Forecasting stock systematic risk using Heuristic Algorithms

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Abstract

Systematic risk forecast is considered in several studies in which has been used of financial ratios as variables to predict risk, most of these studies has used of traditional statistic models, especially simple and multiple regression models. In this study of artificial neural network model as artificial intelligence model and of multivariate regression models, Blume's simple regression model (1975) and ST as linear models were compared together. The sample used in this study consists of 109 companies among the accepted companies in Tehran Stock Exchange between 2009 to 2013. The results showed that artificial neural network model has a higher ability to predict stock systemic risk using financial ratios than linear regression models, Blume and ST simple prediction model.

Key words: systemic risk, financial ratios, artificial neural network.

Introduction

Making decision on economic and financial issues is always risky due to the future uncertainty. So, one way to help investors is providing forecast patterns about the general prospects and future status of company. The more these predictions are closer to reality, decisions that are made based on such predictions, will be more accurate. Investment is one of the basic and essential items in the economic development process of each country. Investors to predict future net cash flow usually need information about the expected time and amount of cash flows of business unit, the risk of achieving them, as well as the appropriate interest rate for discounting these cash flows, therefore one of the information required by investors is investment risk. Risk can be defined as the probability of the difference between the actual return of expected return (Jahankhani, 1997). Risk and return has a key role in investment. If future events are not completely predictable and some events are reference to other events, there is a risk factor (Shabahang 1993). Now that we found the importance of risk in financial decisions and investments so one of the issues that can help investors on how make their decisions, is the existence of appropriate tools and models to predict systemic risk. In this study of artificial intelligence and statistical models: artificial neural networks, multivariate regression, Bloom's simple regression model (1975) and ST are compared with each other, in order to determine which of the above models classify the systematic risk of companies listed on the stock exchange, that consumers and investors could use of their investment opportunities in the country well.

Theoretical foundation

Systematic risk

Several economists have defined investment risk as return dispersion. For example, Keynes has defined it as the probability of deviation from return mean. According to Keynes, a person who invests in asset that its return yields a high degree of dispersion, must get surplus because of the risk it tolerate. (Levy & Sarnat 1984).

The total market risk can be divided into two general categories: systematic risk and unsystematic risk. Unsystematic risk is the risk that results from the specific characteristics of company including product kind of
major shareholders capital structure and etc. Systemic results from total developments in the market and economy, and is not for a specific company; in the other words, systemic risk is due to the general movements in the market. According to portfolio theory, unsystematic risk can be eliminated with diversification of stock portfolio but systemic risk remains.

Capital asset pricing model is formed based on Markowitz's "Portfolio Selection" model (Markowitz, 1959), Markowitz was the first to produce a specific standard for developing portfolios model and the relationship between risk and expected return (Mashayekh, 2003). This model can be a method for portfolios risk assessment and the risk relationship with its rate of return (Zainal et al., 1994). The capital assets pricing model (CAPM) is based on the assumption that the expected return rate of investment has a direct and linear relationship with its systematic risk rate; or in other words, the expected return is a function of beta coefficient (as indicator of stock systemic risk).

\[ R_{it} = a_i + \beta_i R_{mt} + \varepsilon \]

Where \( R_{it} \) is return of asset \( i \) in \( t \) time, \( \beta_i \) line slope of asset \( i \), \( a_i \) constant coefficient for asset \( i \), \( R_{mt} \) market return in \( t \) time and \( \varepsilon \) is measurement error.

The variance for a risky asset is as follows:

\[
Var(R_{it}) = Var(a_i + b_i R_{mt} + \varepsilon)
\]

\[
= Var(a_i) + Var(b_i R_{mt}) + Var(\varepsilon)
\]

\[ Var(\beta_i R_{mt}) \] is the variance of an asset returns in relation to the market returns variance (systematic risk or variance).

Also, \( Var(\varepsilon) \) is the remaining variance of return on an asset that is not associated with the market portfolio. The remaining variance is the variability that is named as unsystematic risk or unique risk and results from individual characteristics of each asset. Therefore:

\[ Var(R_{it}) = \text{systematic variance} + \text{unsystematic variance} \]

In a fully diversified portfolio including market portfolio, unsystematic variance of an asset is not relevant to the decisions making by investors, because they can remove it by diversifying. Therefore, investors should not expect that achieve additional return for this unique risks. Only the systematic risk is concerned only in decision-making, because it cannot be eliminated by diversification. The source of those factors is macroeconomic that impact on all assets.

The Measurement criterion of systematic risk is beta (\( \beta \)), which measure the approximation of oscillation return rate on a specific exchange, compared with return rates of all available exchanges on the market (Shabahang 1993).

\[ \beta = \frac{\text{Cov}(R_{mt}, R_i)}{\delta^2_{Rm}} \]

The Use of financial statements and accounting information of companies, in determining the risk rate

Financial experts and academic theorists have long attempted to identify the relationship between risk and exchange return rate but has not achieved so much success. Determining the specific relationship between risk and return is not simple. However, several researches has done on the analysis of accounting information published by companies (such as balance sheets and profit and loss statements and cash flows) and their financial ratios (liquidity ratios, leverage, profitability, activity, etc. ...) and their relationship with risk rate and stock returns in the stock market. The results of Ferri and Jones (1972) indicates that company size, the kind of industry, and the company's operating leverage degree influence on the use of the firm's debt risk. Results of Keith Lam (2002) suggest that firm size and book-to-market variables can explain the difference between the average return on the Hong Kong stock exchange. Belkoui (1993) pointed out in his study that there is a significant relationship between three variables; value added, profit and cash flow with return on stocks. In a study, Fama and French (1993) approved the relationship between firm size and B / M ratios of companies stock with their profitability. Extensive researches has been conducted in Iran, Namazi and Zare (2004) showed that systematic risk can be estimated by using information analysis and financial reports, there is a significant relationship between the entropy of information contained in the balance sheet and profit and loss statement.
with systematic risk. In another study, Namazi and Khajavi (2007) concluded that there is a meaningful relationship between liquidity ratios, profitability and accounting variables with systematic risk.

**Literature review**

Forecasting systemic risk is considered in several studies that in many of these studies, has been used of financial ratios as variables to predict risk, most of researches were used of traditional statistical models, particularly simple and multiple regression models. [For example, researches conducted by Lev (1974), Belkoui (1978), Mandelker and Rhee (1984), Ahmadpour (1999), Namazi and Khajavi (2004).] Also, many capital market-based accounting researches, has stated the usefulness of accounting information in determining the risk of stock exchange (Brimbel, 2003). In recent years, in addition to the statistical methods, has been used of artificial intelligence methods for prediction in the capital market. In 1995, Wittkemper and Steiner used artificial neural networks to predict systematic risk (Wittkemper and Steiner, 1996). In 2000, Shah and Merteza, offered a model using ANN for bankruptcy prediction (Shah and Murtaza, 2000). Edward, Hairong, Chen and Menger in 2009, performed the study of Australian companies bankruptcy. The results showed that artificial neural network model performed better than other compared models (Edward et al, 2009). In the limited studies on bankruptcy prediction using genetic programming method (GP), results show the superiority of this model to the other statistical models (Etemadi et al, 2009). Matoussi has used of artificial neural network method for credit risk assessment of Tunisian bank (Matoussi, 2009). Pawar and Das (2010) studied the literature on the use of artificial neural network to predict stock market (Pawar and Dase, 2010). In a study, Yuhong Li (2010) studied the use of artificial neural network to predict prices on financial markets (Lee, 2010).

**Research hypothesis**

The hypothesis in this study include: "Artificial neural networks model has a higher ability to predict the systematic risk of stock than linear models of higher ability." Measurement standard of forecast in this study is mean square error (MSE). To test the research hypothesis, it must be written in the form of statistical hypothesis. To do this, the research hypothesis has become to three sub-hypotheses as follows:

**hypothesis 1:**
Artificial neural networks model has not a higher ability to predict the systematic risk of stock than linear regression model.

\[ H_0 : \mu_{MSE_{ANN}} \geq \mu_{MSE_{Reg}} \]

Artificial neural networks model has a higher ability to predict the systematic risk of stock than linear regression model.

\[ H_1 : \mu_{MSE_{ANN}} < \mu_{MSE_{Reg}} \]

**hypothesis 2:**
Artificial neural networks model has not a higher ability to predict the systematic risk of stock than Blume linear model.

\[ H_0 : \mu_{MSE_{ANN}} \geq \mu_{MSE_{Blume}} \]

Artificial neural networks model has a higher ability to predict the systematic risk of stock than Blume linear model.

\[ H_1 : \mu_{MSE_{ANN}} < \mu_{MSE_{Blume}} \]

**hypothesis 3:**
Artificial neural networks model has not a higher ability to predict the systematic risk of stock than simple linear model ST (Simplest technique).

\[ H_0 : \mu_{MSE_{ANN}} \geq \mu_{MSE_{ST}} \]

Artificial neural networks model has a higher ability to predict the systematic risk of stock than simple linear model ST (Simplest technique).
H1: \( \mu_{MSE_{ANN}} < \mu_{MSE_{ST}} \)

**Methodology:**

In this study, population consisted of all companies listed on the Tehran stock exchange between 2009 to 2013 that has the following characteristics.

1. Have been accepted in Tehran Stock Exchange up to the end of 2008.
2. Its stocks were traded continuously on the Tehran Stock Exchange over the years 2009 to 2013.
3. Their fiscal year is (March).
4. Is not an investment and intermediation company.

Investment companies were excluded from this research population because of the nature of their activities and statistics indicated in the financial statements. According to the four above-mentioned limits, 109 companies were included in the population of this study that all these companies were chosen as sample.

**Independent variables**

Accounting information used in this study include 17 financial ratios as follows:

- RGPS = Gross profit on sales
- PM = Margin profit
- ROA = Return on assets ratios
- ROE = Return ratio on assets
- CR = Current ratio
- QR = Quick ratio
- CC = Charges collection period
- TAT = Total assets turnover
- DR = Debt ratio to asset
- DER = Debt ratio to the rights of share holders
- ER = Equity ratio
- RSG = Ratio of sale growth
- RGPG = Ratio of gross profit growth
- RCA = Ratio of current asset growth
- WC = Working capital ratio
- SIZE = Natural logarithm of total company assets
- \( \beta_{t-1} \) = Last year Beta

To select the optimal variables of the 17 variables was used of Pearson correlation test. The correlation between above 17 variables and current year Beta, of which 10 variables were correlated (Table 1):

<table>
<thead>
<tr>
<th>Variable</th>
<th>Correlation coefficient</th>
<th>sig</th>
<th>Variable</th>
<th>Correlation coefficient</th>
<th>sig</th>
</tr>
</thead>
<tbody>
<tr>
<td>CR</td>
<td>0.104*</td>
<td>0.015</td>
<td>ROA</td>
<td>0.108*</td>
<td>0.012</td>
</tr>
<tr>
<td>CC</td>
<td>0.034</td>
<td>0.431</td>
<td>ROE</td>
<td>0.025</td>
<td>0.562</td>
</tr>
<tr>
<td>PM</td>
<td>0.015</td>
<td>0.735</td>
<td>ROE</td>
<td>0.025</td>
<td>0.562</td>
</tr>
<tr>
<td>ER</td>
<td>0.104*</td>
<td>0.015</td>
<td>RSG</td>
<td>0.102*</td>
<td>0.017</td>
</tr>
<tr>
<td>DR</td>
<td>-0.104*</td>
<td>0.015</td>
<td>RGPG</td>
<td>0.009</td>
<td>0.830</td>
</tr>
<tr>
<td>QR</td>
<td>0.075</td>
<td>0.081</td>
<td>RCA</td>
<td>0.099*</td>
<td>0.021</td>
</tr>
<tr>
<td>RGPS</td>
<td>0.086*</td>
<td>0.045</td>
<td>WC</td>
<td>0.021</td>
<td>0.631</td>
</tr>
<tr>
<td>TAT</td>
<td>-0.091*</td>
<td>0.034</td>
<td>( \beta_{t-1} )</td>
<td>0.269**</td>
<td>0.000</td>
</tr>
</tbody>
</table>
** The correlation coefficient is significant at 0.01 level.
* The correlation coefficient is significant at the 0.05 level.

According to the correlation coefficients and significance level, variables CR, ER, DR, RGPS, TAT, ROA, RSG, RCA, SIZE and \( B_{t-1} \) are correlated with current year's Beta.

In the following, all the above variables were used to create regression models using backward elimination regression that finally in the final stage, the best regression model has been selected with independent variables which are presented in Table 2. It should be noted that this regression test, is also a variable for selecting independent variables of research on artificial neural network model.

| Table 2- The results of multivariate regression model |
|----------------|----------------|--------|
| Variables  | B coefficient | t-test | Sig    |
| CR          | 0.1939         | 2.213  | 0.029  |
| ER          | - 2.2791       | - 4.201| 0.000  |
| DR          | - 2.3804       | - 5.148| 0.000  |
| RGPS        | - 0.7184       | - 2.521| 0.021  |
| RSG         | 0.3361         | 2.921  | 0.009  |
| SIZE        | 0.1992         | 6.545  | 0.000  |
| \( B_{t-1} \) | 0.1417         | 3.516  | 0.000  |
| R Square    | 0.431          | F      | 43.666 |
| Adjusted R Square | 0.421   | Sig    | 0.000  |
| Durbin-Watson | 1.704       |        |        |

According to the t-test and significant level showed in table 2, the above variables are selected as independent variables of research.

**Dependent variable**

**\( \beta \) Systematic risk**

Is part of risk that can not be decreased by stock diversification. Measure of systematic risk is beta (\( \beta \)), which measure the approximation of return rate oscillation on an stock exchange, compared with return rates of all available exchanges on the market (Shabahang 1993).

\[
\beta = \frac{\text{Cov}(R_a, R_m)}{\sigma^2_{R_m}}
\]

**Training and test data**

In this study, were used of 82 companies for validation (75% of the total sample) for training sample in the neural network (equation determination in the linear models) as well as 27 companies remaining as test samples (25% of the total sample). Measurement standard of forecast in this study is mean square error (MSE). Forecast for each of the five years has been done separately and then, mean square error for all models was derived and calculated for five years. In the following, to confirm or disapprove the hypothesis is used of criteria averages comparison test (mean square error) specified for five years.

**Linear Regression Models design**

Multivariate regression model: in this study of multivariate linear regression model is used of backward elimination method. Also, this regression has been used for selection criterion of research independent variables. According to table 2, the structure of linear regression model is as follows:
\[ \beta_t = 0.1939 \times CR_t - 2.2791 \times ER_t - 2.3804 \times DR_t - 0.7184 \times RGPS_t + 0.3361 \times RSG_t + 0.1992 \times SIZE_t + 0.1417 \times \beta_{t-1} + \epsilon \]

Blume model: In this model, it is assumed that there is a linear relationship between the systematic risk of current year and last year. Using univariate regression, according to table 3, the relationship is calculated as follow:

\[ \beta_t = 0.4932 + 0.2221 \times \beta_{t-1} + \epsilon \]

<table>
<thead>
<tr>
<th>Variables</th>
<th>B coefficient</th>
<th>t-test</th>
<th>Sig</th>
</tr>
</thead>
<tbody>
<tr>
<td>(Constant)</td>
<td>0.493</td>
<td>10.285</td>
<td>0.000</td>
</tr>
<tr>
<td>(B_{t-1})</td>
<td>0.222</td>
<td>5.466</td>
<td>0.000</td>
</tr>
<tr>
<td>R Square</td>
<td>0.068</td>
<td>F</td>
<td>29.872</td>
</tr>
<tr>
<td>Adjusted R Square</td>
<td>0.066</td>
<td>Sig</td>
<td>0.000</td>
</tr>
<tr>
<td>Durbin-Watson</td>
<td>1.701</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

**ST model:** is the simplest model for forecasting systematic risk. According to this model, \( \beta \) is equal for \( i \) stock in \( t \) term with last term.

\[ \beta_t = \beta_{t-1} \]

**Designing artificial neural network based model**

The neural network used in this research, is back propagation network (BP), one kind of feed forward networks (ff). This network is a multilayer network with a non-linear transition function and learning rule Levenbery-Marqwardt. The method tries to reduce calculation by failing to calculate Hessian matrix. Hessian matrix can be estimated as follows.

\[ H = J^T J \]

The slope is calculated as follows:

\[ G = J^T e \]

J is Jacobian matrix that consists of first derivative of network errors toward the weights and bias, and \( e \) is the network error vector. Jacobian matrix can be calculated through standard techniques (BP) and the complexity of its computation is much lower than calculating Hessian matrix. In this study, The TrainLM learning function is used to train the network.

In this study, using rule 2n+1 (n represents the number of neurons in the input layer) for different number of neurons in the middle layer, and by setting other parameters, it was concluded that the existence of 15 neurons in the middle layer can be led to a better performance, especially in terms of interoperability. So, the overview of used networks is as below in figure 1.

Figure 1 - the overview of neural networks used in this research

The transfer function used in this study, is a sigmoid function, the formula is:

\[ f(\text{net}) = \left( 1 + e^{-\text{net}} \right)^{-1} \]

That the purpose of net is the weighted sum of input variables from the previous layer. Using this function, the value of output variable will be a number between zero and one. Performance Function is considered for network training, mean sum of squared error (MSE), that is:

\[ F = MSE = \frac{1}{n} \sum_{i=1}^{n} (e_i)^2 \]
The use of this function will cause that the network has smaller weights and biases and in turn, this would forced the network to provide easier answers. With this function, the final results were very satisfactory.

**The output for determining the best neural network model**

To determine the learning rate and frequencies have been used of 10 kinds of neural network with different learning rate and frequencies randomly for 2009. That is shown in Table 4 below:

<table>
<thead>
<tr>
<th>ANN</th>
<th>n</th>
<th>Lr</th>
<th>mc</th>
<th>Frequency</th>
<th>Fitting</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>15</td>
<td>0.01</td>
<td>0.5</td>
<td>500</td>
<td>0.000351</td>
</tr>
<tr>
<td>2</td>
<td>15</td>
<td>0.01</td>
<td>0.5</td>
<td>1000</td>
<td>0.000586</td>
</tr>
<tr>
<td>3</td>
<td>15</td>
<td>0.01</td>
<td>0.5</td>
<td>2000</td>
<td>0.000804</td>
</tr>
<tr>
<td>4</td>
<td>15</td>
<td>0.1</td>
<td>0.5</td>
<td>1000</td>
<td>0.000135</td>
</tr>
<tr>
<td>5</td>
<td>15</td>
<td>0.1</td>
<td>0.5</td>
<td>2000</td>
<td>0.000464</td>
</tr>
<tr>
<td>6</td>
<td>15</td>
<td>0.1</td>
<td>0.5</td>
<td>3000</td>
<td>0.000841</td>
</tr>
<tr>
<td>7</td>
<td>15</td>
<td>0.5</td>
<td>0.5</td>
<td>1000</td>
<td>0.000873</td>
</tr>
<tr>
<td>8</td>
<td>15</td>
<td>0.5</td>
<td>0.5</td>
<td>2000</td>
<td>0.000957</td>
</tr>
<tr>
<td>9</td>
<td>15</td>
<td>0.7</td>
<td>0.5</td>
<td>1000</td>
<td>0.000992</td>
</tr>
<tr>
<td>10</td>
<td>15</td>
<td>0.7</td>
<td>0.5</td>
<td>2000</td>
<td>0.001038</td>
</tr>
</tbody>
</table>

n= the number of neurons in hidden layer, Lr = learning rate, mc = maximum amount of weights changes

By examining the mean squared error related to the training part for the above 10 models, the best model is ANN4 with learning rate of 0.1 and 1000 frequencies. In figure 2 is shown the process of error reduction during 1,000 times frequency to train for 2009.

**Figure 2- The error reduction diagram of ANN₄ model during 1000 frequency**

![Error Reduction Diagram](image)

**Results**

Table 5 shows the mean sum square error of each of the 5 years studied from 2009 to 2013, and also the sum and the mean of the criteria for 5 years and for each model of artificial neural network, regression, Blume and simple prediction of ST.
Table 5- Mean square error of case study models

<table>
<thead>
<tr>
<th>Year</th>
<th>ST</th>
<th>Blume</th>
<th>Regression</th>
<th>ANN</th>
</tr>
</thead>
<tbody>
<tr>
<td>2009</td>
<td>3.554843</td>
<td>1.237926</td>
<td>1.10873</td>
<td>0.016485</td>
</tr>
<tr>
<td>2010</td>
<td>1.851445</td>
<td>0.984123</td>
<td>0.861876</td>
<td>0.012762</td>
</tr>
<tr>
<td>2011</td>
<td>0.821127</td>
<td>0.664429</td>
<td>0.595049</td>
<td>0.013703</td>
</tr>
<tr>
<td>2012</td>
<td>0.910154</td>
<td>0.915207</td>
<td>0.780203</td>
<td>0.011194</td>
</tr>
<tr>
<td>2013</td>
<td>1.170981</td>
<td>0.53591</td>
<td>0.655714</td>
<td>0.012503</td>
</tr>
<tr>
<td>Sum</td>
<td>8.30825</td>
<td>4.337594</td>
<td>4.001572</td>
<td>0.066647</td>
</tr>
<tr>
<td>Mean</td>
<td>1.66165</td>
<td>0.867519</td>
<td>0.800314</td>
<td>0.013536</td>
</tr>
</tbody>
</table>

Figure 3 shows the error rate of prediction as well as the volatility of forecast error for each of linear and nonlinear models in this study for 5 years.

Figure 3- The forecast Volatility diagram of studied models

Figure 3 shows that artificial neural network model have less volatility during 5 years in forecasting error than other linear models and has passed a proper process in anticipation of systemic risk. Figure 3 also shows that simple prediction linear model ST has the most volatility in anticipation of systemic risk and has the lowest reliability and confidence than other models. After the artificial neural network model, regression model and Blume model have a high reliability and confidence to predict the stock systemic risk respectively. To prove the hypothesis, has been used of inferential statistics and pair mean comparison test for each of secondary hypotheses. Means comparison test was performed using SPSS software.

In this test, the mean standard error of 5 years was compared for artificial neural network and multivariate regression models, Blume and ST models were compared. The program output is shown in Table 6:

Figure 6- the pairs mean comparison test between ANN model and regression model

<table>
<thead>
<tr>
<th>Pair</th>
<th>Paired Differences</th>
<th>95% Confidence Interval of the Difference</th>
<th>T</th>
<th>df</th>
<th>Sig.</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Mean</td>
<td>Std. Deviation</td>
<td>Lower</td>
<td>Upper</td>
<td></td>
</tr>
<tr>
<td>ANN - Regression</td>
<td>-0.78699</td>
<td>0.20020</td>
<td>-1.03557</td>
<td>-0.53840</td>
<td>-8.790</td>
</tr>
</tbody>
</table>
In Table 6, t-test, significance level (sig) and the negativity of high and low limit shows that MSE mean for artificial neural network model is less than multivariate regression, Blume and ST model; so we can reject H₀ at 5% level error and accept H₁. It means that in the significant level of 95, it can be said “artificial neural network model to predict stock systemic risk using financial ratios than regression linear models, Blume and simple prediction ST model have higher ability.”

Conclusion

Investment is an important factor in the development of country and the stock exchange is the most important tool that can use of capitals for more activity of different industries. Therefore, the most important factor that is effective in decision making about purchasing stocks, is return and its risk in comparison to the other investment opportunities. Financial management, one of the most important part of management in corporate decision-making, deals with different methods discussions of financing, how to invest and use funds, profit sharing policy, cash management and debt and … . Recent studies in the field of forecasting risk, has focused on the establishment and use of artificial intelligence and machinery learning methods. In the present study, after determining the structure of artificial neural network has been focused on the neural network training and testing. Obtained MSE mean for each model of artificial neural networks, multivariate regression, Blume simple regression ST is 0.013536, 0.867519, 0.800314 and 1.66165 respectively. According to the present study, the results showed that machinery learning methods such as artificial neural network have been more successful than other available statistical patterns in the field of forecasting risk. However, it is expected that in the future using new techniques and variables, predictive risk models form with high accuracy and easy intelligibility for users.

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