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Comparative Approach to the Backward Elimination and forward Selection Methods in Modeling the Systematic Risk Based on the ARFIMA-FIGARCH Model

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ABSTRACT

The present study aims to model systematic risk using financial and accounting variables. Accordingly, the data for 174 companies in Tehran Stock Exchange are extracted for the period of 2006 to 2016. First, the systematic risk index is estimated using the ARFIMA-FIGARCH model. Then, based on the research background, 35 affective financial and accounting variables are simultaneously used with the help of the backward elimination and forward selection method for modeling. After analyzing and evaluating the variables in Eviews software, the four variables of debt ratio (CL. E), size (SIZE), net profit to sales ratio (NETP. S), and interest rate coverage ratio (ICR) are selected in the backward elimination method. In the forward selection method, in addition to the above variables, operating profit margin (OPM) is also chosen. The estimated model of these variables in both methods shows a low ratio of R2 coefficient that is approximately 7%. In the test case, the model of forward selection method has less error in all four criteria of root mean squared error (RMSE), mean absolute error (MAE), mean absolute percentage error (MAPE) and Tile coefficient (TIC) compared to the backward elimination method.

1 Introduction

In recent years, global financial markets have been faced with considerable fluctuations and uncertainties, so that the uncertainty associated with the return on invested assets has worried many investors and financial analysts. As investors point out, uncertainty is the most important factor in pricing any financial asset. The financial crises of 2007 and 2008 have attracted more attention to systematic risk assessment by investors and financial analysts. Afterwards, more than 30 systematic risk criteria and subsequent adjustments were developed [38]. Stock prices are affected by both systematic and non-systematic risks. But investors who diversify their investment are only concerned about systematic risk. Hence, identifying and measuring factors affecting this risk is necessary. Managers every day

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affect companies' risk by financial decision making and they can manage company's risk and increase the wealth of company's shareholders by understanding how these decisions affect financial ratios and consequently companies' risk. Investigators have been able to offer multivariate models for predicting systematic risk by combining these ratios. Financial ratios make it easy to disclose some relevant facts about the operations and financial position of a profit unit [35, 37, 32, 20, 15, 19, 24, 14].
One of the criteria for the systematic risk estimation is market beta variable in the capital asset pricing model (CAPM) presented by William Sharp in 1964. One of the important assumptions of the classic CAPM model is that investors use the expected returns and the matrix of variance of the same covariance in determining the optimal risk of holdable assets' portfolio. However, the beta index is fixed [18]. It should be noted that this assumption suppresses many of the economic facts that are rapidly experiencing structural changes. Based on studies, they suppress the change in the risk of financial firms' cash flow during business cycles, the change in various economic situations, and the updating of the information set during the beta index stability period [17, 21]. Empirical studies have also rejected the assumption of beta index stability [22, 17]. Therefore, the use of the least squares estimation method in estimating the beta index is not practically possible, since the application of this method involves the establishment of many assumptions such as the stability of the parameters and the covariance of the error components of the model [21]. This is while heteroscedasticity, variability and fluctuation are an integral part of the financial markets. The main goal of this research is to use metaheuristic algorithms and their combinations in order to choose optimal variables from among accounting variables affecting systematic risk, and accordingly, provide a model for estimating systematic risk. Therefore, the present study, while measuring the systematic risk using ARFIMA-FIGARCH model, will model the accounting variables affecting systematic risk index through backward elimination method and forward selection method in parallel and examine the power of the models.

2 Theoretical foundation

One of the most important risks of financial markets is systematic risk, which means risk associated with market returns. Systematic risk is the risk of a market that investors cannot avoid by diversification [30]. The modern portfolio theory founded the basis of Sharp and Linton's capital asset pricing model. The basic idea of the CAPM model is based on the assumption that the return rate of an asset equals the risk-free rate plus risk premium. This model is used to theoretically estimate the rate of return required for a specific risk level, usually called beta. The CAPM model and the beta concept, as a systematic risk assessment criterion, have many uses in portfolio management. The overall risk of investing in a stock is divided into two parts: systematic risk and non-systematic risk. The first is market risk or systematic risk that is inevitable and cannot be eliminated by diversification, and the latter is a non-systematic risk that is specific to a company or stock and can be minimized or eliminated by diversification [10]. Capital asset pricing model is a pricing regression model whose equation is as follows:

$$K\,j = Rf + \beta\,(Rm - Rf)$$

Where Rf is the risk-free return rate, β is the sensitivity coefficient and (Rm-Rf) is risk premium. The key factor in this model is the beta coefficient, which is of great importance to measure explanation power and compare the actual return rate. The beta coefficient measures the sensitivity of the expected additional return on assets compared to the expected additional market return, which is obtained from the following relation based on the Sharp model:

$$\beta = \frac{cov(r_i, r_m)}{var(r_m)}$$

A systematic risk for assets is taken from the regression model, the asset characteristic line, whose general equation is as follows:

$$\tilde{R}_{it} = \alpha_i + \beta_{is}\tilde{R}_{Mt} + \mu_{it}$$

Where β is the sensitivity coefficient (systematic risk) of the i^{th} asset [3].

One of the main and classic assumptions of econometrics was the constant variance of error terms, which was a limiting assumption. Engel, in the ARCH essay, set up a new method for emanating from this assumption. He has performed cluster turbulence modelling with the assumption that the conditional variance is an auto correlated function being affected by previous residuals. Engel showed that, when the degree of correlation is strong in the residuals, the efficiency of using the ARCH method is much higher in comparison with the ordinary least squares method. Therefore, because the time series data used in this study are daily and have a high frequency, it is expecting that there is an ARCH effect that can be detected by the test. On the other hand, observing the effects of ARCH indicates that coefficients' estimation is not reliable. For this reason, variance modelling and using GARCH models, which are generalizations of the ARCH model of Engel, are required. GARCH models are much smaller than ARCH model. In this regard, GARCH (1.1) model is the most common structure used for many financial time series [36]. The GARCH (1.1) model can be written as an ARMA (1.1) model using squared residuals. Generally, the following relation holds for the GARCH (p, q) model:

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

The above equation can easily be written as the following relationship:

$$\phi(L)\varepsilon_t^2 = a + b(L)u_t$$

Where,

$$u_t = \varepsilon_t^2 - \sigma_t^2$$

$$\phi(L) = 1 - \phi_1 L - \phi_2 L^2 - \ldots - \phi_m L^m$$

$$b(L) = 1 - b_1 L - b_2 L^2 - \ldots - b_q L^q$$

In addition, $m = \max(p, q)$ and $\varphi_i = a_i + b_i$. It is clear that the mentioned term indicates the ARMA (p, q) process, whose residuals are squared, and u_t is the error term of Martingale difference sequence. Long stay in GARCH models can indicate that the $\varphi(z) = 0$ polynomial has a unit root, in which case the GARCH model is converted to the integrated GARCH model (IGARCH). In order to allow modelling with high durability and long-term memory modelling in conditional variance and in order to avoid the complexity of IGARCH models, similar to the transformation of ARMA (m, q) process into the ARFIMA (m, d, q) process, the proposed expression can be expanded as follows:

$$\phi(L)(1-L)^d \varepsilon_t^2 = a + b(L)u_t$$

When all the $\varphi(z) = 0$ and $b(z) = 0$ roots fall out of the unit root circle and when d=0, the above expression is converted to a typical GARCH model; when d=1, it converts to the IGARCH model;

and when$0 < d < 1$, the fractionally differential-residual squares, $(1-L)^d \varepsilon_t^2$, follow a stationary ARMA (m, q) process. The above ARFIMA process for ε_t^2 can be rewritten according to the conditional variance of σ_t^2 as follows:

$$b(L)\sigma_t^2 = a + [b(L) - \phi(L)(1-L)^d]\varepsilon_t^2$$

Bollerslev and Mikkelsen [13] called the above model as fractionally integrated GARCH or FIGARCH (m, d, q) model. When$0 < d < 1$, the coefficients in $\varphi(L) = 0$ and $b(L) = 0$ indicate the short-term dynamics of turbulence, and the partial differential parameter d models the long-term turbulence. If the $(1-L)^d$operator is expanded by McLaren expansion, the following relations are obtained:

$$(1-L)^d = \sum_{k=o}^{\infty} \frac{\Gamma(k-d)}{\Gamma(k+1)\Gamma(-d)} L^k \Rightarrow$$
$$= 1 - dL + \frac{(1-d)(-d)}{2} L^2 + \frac{(2-d)(1-d)(-d)}{3!} L^3 + \ldots$$

In the case where k is very large:

$$\frac{\Gamma(k-d)}{\Gamma(k+1)} \approx k^{-d-1}$$

The above relation shows that when $0 < d < 1$, the impact of shock on conditional turbulence decreases with the hyperbolic rate, so turbulence has a long-term memory.
In this method, using the long-term memory process, the trend of the systematic risk beta index for the companies listed in Tehran Stock Exchange is investigated. A new method has been used for estimating the maximum likelihood function with the ARFIMA-FIGARCH process, which has a fractional integration of I(d) with an ARMA stationary component in its conditional mean. This long-term memory process creates fractional integrated conditional heteroscedasticity of the FIGARCH type.

3 Research Background

Ibrahim and Haron [26] examined the impact of corporate leverage and corporate finance policies on the systematic risk of non-financial companies listed in the Malaysian stock exchange and analysed financial data for 824 companies for the years 2000 to 2013 using panel data and fixed-effects models. The results showed the high impact of financial leverage on the systematic risk of companies, but the impact of other control variables on systematic risk was not confirmed. Lee [28] examined the relationship between systematic risk in the stock of airlines with financial indicators and crises that were broken in the second half of 2008. The beta was criterion of capital asset pricing model was a measure of systematic risk. The results of the study on 28 international airlines during the period from 1997 to 2002 and 2007 to 2012 indicated that: 1) the systematic risk has a reverse relationship with profitability and direct relationship with the size of the company; 2) there is an inverse relationship between systematic risk and operational efficiency; 3) systematic risk has a direct relationship with financial leverage; 4) in the first period, the systematic risk has had a positive relationship with liquidity; and 5) there is no significant relationship between systematic risk and growth. The statistical method used in this research was panel data.

Valipour et al. [39] used artificial neural networks and financial ratios to predict the beta index of systematic risk in Tehran Stock Exchange between 2009 and 2013 and compare it with a simple regression model. The results of the study of financial ratios of 109 sample companies showed a very high ability of neural networks compared to simple regression models.

Fong and Lee [23] stressed the importance of the beta factor of systematic risk based on the CAPM model in economic and investment decision-making, arguing that recent findings indicate the fluctuation of this factor, which has disrupted the potential to predict this factor. As a result, they attempted to provide a systematic risk estimation model reviewing 88 listed companies in Taiwan from 2001 to 2010 using a regression and optimization model by genetic algorithm. The results show the high power of this optimized model in predicting and estimating systemic risk. Koussis and Makrominas [27] examined the relationship between growth, profitability, financial leverage, and operating leverage and the systematic risk of capital. The results obtained from the multivariate regression model indicated that the beta values have a direct relationship with the financial and operational leverage, the fluctuations in the return, and size of the company and a reverse relationship with the ratio of book value to market value and return on assets.

Salari [37] examined the relationship between the systematic risk of ordinary shares and the financial ratios using the capital asset valuation model. In this study, the relationship between the 8 financial ratios with the systematic risk system was tested by simple and multivariate regression for the data extracted for 226 companies during the years 2006-2009. Finally, the relationship between the current ratio and the quick ratio and the debt to the asset ratio with systematic risk was approved.

Dibiase and Apolito [20] examined the systematic risk of the Italian banking system. The results of time series analysis and regression models showed that the beta value of bank's assets has a positive correlation with the size of the bank, the volume of loans, and intangible assets and has a reverse relationship with profitability and liquidity levels. Hosseinpour and Saeedi [4] investigated the relationship between financial ratios and systematic risk in the cement industry in Tehran Stock Exchange. Financial information of 25 companies for 7 financial periods of 2007-2013 was gathered and analysed through the panel data method in Eviews software using the Limer, Chow, and Bruce-Pogan tests. Results indicated a significant relationship between return on assets and profit growth before interest and tax with systematic risk, while there was no significant relationship between equity and account balance circulation with systematic risk.

Kiani et al. [7] argued that one of the most important metaheuristic methods for solving stock market optimization models is genetic algorithm. The purpose of their research was to investigate its effectiveness in optimizing stock portfolios by reducing the level of systematic risk. For this purpose, using the genetic algorithm, optimal efficient frontier has been obtained and compared with the efficient frontier obtained from the exact solution method. In order to achieve this goal, 25 active companies were selected from Tehran Stock Exchange. The research calculations were performed by MATLAB software. The results of this study indicate that the optimal efficient frontier obtained using the genetic algorithm is equal with that obtained from the exact solution method, which indicates the high efficiency of the genetic algorithm in the optimization of the portfolio. Also, the results indicate that by comparing the optimal portfolios obtained from solution with the systematic and non-systematic risk function, stock diversification in portfolios with non-systematic risk function was much higher than portfolios with systematic risk function.

Eslami Bigdeli and Tayebi Sani [2] presented a heuristic algorithm for solving the limited problem of portfolio optimization with respect to value at risk (VAR) as a risk measure using the combined antler algorithm and genetic algorithm. It was showed that the proposed hybrid algorithm is able to solve the portfolio optimization problem with respect to VAR, taking into account the integer limit for the number of shares in the stock portfolio. In order to demonstrate the efficiency of the algorithm, the proposed algorithm was used to optimize portfolios of the indices of industries in the Tehran Stock Exchange. The results showed that the hybrid algorithm gives better results than the results obtained from the genetic algorithm alone.

Saeedi and Rameshe [6] identified the determinants of the systematic risk of shares of companies in stock exchanges of Iran through the multivariate regression method for mixed data between 1997 and 2008. Their research findings showed that there is a significant relationship between the beta value and the variables of operating profit growth, operational profitability variability, operating profit correlation and the market portfolio index and the growth power. Ahmadpour and Jamkarani [1] investigated the relationship between accounting information and corporate risk in Iran using simple and multiple linear regression methods, and t-test. Results showed that there is no significant relationship between accounting information and corporate risk.

Namazi and Khajavi [9] used the simple regression method and the method of sequential selection of variables called "backward elimination" to examine the usefulness of accounting variables in predicting the systematic risk of companies accepted in Tehran Stock Exchange. They ultimately proposed a model based on 12 variables and estimation using simple regression method for estimating systematic risk.

4 Research Methodology

The present study is applied in terms of its objective. For the selection of the statistical population, the companies accepted in Tehran stock exchange have been considered because: firstly, the information of the companies accepted in Tehran stock exchange is audited by the statutory auditors of the securities and stock market organization; therefore, the information of these companies is more reliable than other companies. Secondly, access to information of these companies is easier than access to other companies. The statistical population of this research includes companies that have the following conditions:

1. They have been accepted in Tehran Stock Exchange by the end of the year 2005.
2. Their fiscal year ends at the end of March and no change has been made in the period under review.
3. They should not be investment and insurance companies, banks, and financial intermediaries.
4. The financial information required for this research has been fully submitted during the period from 2006 to 2015.

As a result of the application of the above conditions and considerations, 174 companies are selected from the statistical population, the names of which are given in Appendix 1. The research period is 10 consecutive years, so the final volume of the sample is 1740 companies-years (174 * 10).

5 Research Hypothesis

First main hypothesis: accounting variables affect the systematic risk index.

First sub-hypothesis: Liquidity ratios affect the systematic risk index.

Second sub-hypothesis: Leverage ratios affect the systematic risk index.

Third sub-hypothesis: Activity ratios affect the systematic risk index.

Fourth sub-hypothesis: Profitability ratios affect the systematic risk index.

Second main hypothesis: the prediction accuracy of the model based on forward selection method is more than backward elimination method.

5.1 Variables' measurement and research model

To test the hypotheses presented in this research, following Rahmani et al. (2014), the following model is used to estimate the systematic risk beta:

$$\tilde{R}_{it} = \alpha_i + \beta_{is}\tilde{R}_{Mt} + \mu_{it}$$

Where:

i = 1 .... 174, the number of companies used in the sample

t = 1 .... 360, the number of operating days in the stock market in an annual period

S = number of years the data is available

$\tilde{R}_{it}$ = the return on stock i at time t.

α_i = The intersection of the regression with the vertical axis (intercept).

β_{is} = is the beta coefficient of stock i in period s.

$\tilde{R}_{Mt}$ = represents the profitability of the market portfolio at time t, which is calculated from the following ratio:

$$\tilde{R}_{Mt} = Ln\frac{I_t}{I_{t-1}}$$

Where:

I_t = is stock market index selected as market portfolio (cash profit and price index (TEDPIX)) at the end of period t

I_{t-1} = is stock market index selected as market portfolio (cash profit and price index (TEDPIX)) at the end of period t-1

The beta of the model is estimated as the systematic risk index using the ARFIMA-FIGARCH model with the following equation:

$$\emptyset(\mathrm{L})(1-\mathrm{L})^{\mathrm{d}}\ln\sigma_t^2 = \mathrm{a} + \sum_{j=1}^{q}(\mathrm{b_j}\left|\mathrm{x_{t-j}}\right| + \gamma_j \mathrm{x_{t-j}})$$

Where the definition of $\emptyset$(L) is in accordance with the previous definition for the FGARCH model, $\gamma_{j \neq 0}$ allows leverage to be taken into account in the model and x_t is the standardized residuals:

$$x_t = \frac{\varepsilon_t}{\sigma_t}$$

Considering the research hypotheses and previous research, accounting variables are as follows: 1. Current ratio (CR), 2. Quick ratio (QR), 3. Current assets growth (CAG), 4. Fixed assets growth (FAG), 5. Financial leverage (FL), 6. Operating leverage (OL), 7. Profit distribution ratio (DPS .

EPS), 8. Interest coverage ratio (ICR), 9. Return on assets ratio (ROA), 10. Size of the company (SIZE) 11. Sales growth (SG), 12. Return on equity (ROE), 13. Net profit to sales ratio (NETP. S), 14. Net profit growth (NETPG) [9, 1, 24], 15. The market value of the company to the book value (MV. BV) [14, 15], 16. The ratio of working capital to assets (WC-TA), 17. The total asset turnover ratio (TAT) [37], 18. Price to earnings ratio (P. E) [19], 19. Net profit margin (NPM), 20. Operating profit margin (OPM), 21. Gross profit margin (GPM), 22. Earning to gross profit ratio (E. GP) [32], 23. Return on working capital (RWC) [33], 24. Liquidity ratio (LR), 25. Liquidity adequacy ratio (LAR), 26. Cash turnover ratio (CTR) [20, 32, 35], 27. Fixed asset turnover ratio (FAT), 28. Debt ratio (D. E), 29. Fixed asset to eigenvalue ratio (FA. E), 30. Long-term liabilities to eigenvalue ratio (LTL. E), 31. Current liabilities to eigenvalue ratio (CL. E) [11], 32. Equity ratio (ER), 33. Debt coverage ratio (DCR), 34. Financial costs to net profit ratio (FC. NP 35), 35. Financial costs to operating profit (FC. OP) [15].

For modelling based on the above variables, a stepwise regression method has been used in this research, which is described below.

Forward selection: In this method, in the first step, the model has only a constant value. In each step, a variable is added to the model to generate the largest change in the R^2 coefficient parameter. This change in R^2 should be such that it can reject the assumption that the real value of the change is zero. This model introduces a variable until there is no other variable that can produce a significant increase in R^2.

Backward elimination: In this method, all variables are first presented in the model. In each step, a variable that makes the smallest change in the value of R^2 is eliminated from the model. This change in R^2 must be such that it cannot reject the assumption that the real value of the change in R^2 is zero. Elimination of variables from the model stops when eliminating any of the variables from the model creates a meaningful change in the R^2.

6 Research Findings

6.1 ARFIMA-FIGARCH modelling

Reliability is very important in the models of GARCH family. Therefore, the reliability test for two variables of models, namely return on asset and market index, is performed using the Dickey-Fuller test. The results are shown in Table 1.

As can be seen in Table 1, all variables are reliable and GARCH models can be used in this regard. Also, non-stationary of time series is rejected because of the absence of the unit root, which means that there are constant moments for the returns.

- GARCH model estimation results

To estimate the GARCH effects on the data time series, an initial model was first estimated and then the Lagrange coefficient analysis of the ARCH effect was investigated. The results are given in Table 2.

Table 1: Results of unit root test using augmented Dickey-Fuller method

Variable	Test type	Test statistics	p-value	Critical values at 1%, 5%, and 10%
Ri	Augmented Dickey-Fuller	-77.1129	.0001	-3.43033
				-2.86141
				-2.56674
Rm	Augmented Dickey-Fuller	-41.1812	.0000	-3.43033
				-2.86141
				-2.56674

Table 2: The results of model estimation and ARCH effect test (Lagrange coefficient) -dependent variable

Variable	Coefficient	SD	t-statistics	p-value
Intercept	.213729	.016238	13.16	.0000
Rm	.106459	.053539	1.988	.0468
ARCH effect test				
ARCH(p,q)		F-statistics	p-value	Results
ARCH(1,3)		2.7345	.0420	ARCH effect is approved

In the table above, the results of estimating the least squares model and the Lagrange coefficient test are specified. As it is seen, considering that the probability of rejecting the third-order ARC effect hypothesis in the Lagrange coefficient test is .042 and less than .05, it can be said that the model has ARCH effects. The results of GARCH model estimation are presented in Table 3.

Table 3: GARCH model estimation

Parameters	Coefficients	T-statistics	P-value
Intercept	-.04609	-.6286	.0042
Rm	.16097	2.587	.0097
ARCH(Alpha1)	.457914	2.307	.0211
ARCH(Alpha2)	-.31009	-1.156	.0000
ARCH(Alpha3)	-.12722	-.7626	.00005
GARCH(Beta1)	.984619	222.5	.0000
Conditional Heteroscedasticity of Tse		RBD(2)=.153861	Result
PROB.		.9259544	Lack of heteroscedasticity

In the above model, the coefficients and parameters related to the GARCH (1.3) model are shown for the systematic risk model of the share of companies under study. As it is seen, the coefficient of 1α related to the GARCH model is significant, which indicates well fit of the GARCH model of P = 1. Also, the conditional variance model with meaningful parameters of 1β indicates that the choice of the order q = 1 is suitable for the conditional variance equation and the model is perfectly convergent. Also, the results of the test of heteroscedasticity show that the model does not have the problem of heteroscedasticity.

- Estimation of the ARFIMA-FIGARCH model

In order to carry out the ARFIMA-FIGARCH model, it is necessary to perform an accurate estimation with ARFIMA method. Then, the results of the initial estimation of the ARFIMA model, in which the optimal time interval of the autoregressive process and the mean and degree of coagulation is determined by the Lagrange coefficient test, should be investigated in terms of ARCH effects. Ultimately, ARFIMA-FIGARCH model can be estimated after specifying intervals of ARFIMA model and observing order of ARCH effects. Based on this, the ARFIMA (1, d, 1) model was first estimated. The results along with the ARCH effect test are shown in Table 4:

Table 4: ARFIMA model estimation results and ARCH effect test (Lagrange coefficient)

Variable	Coefficient	SD	t-statistics	p-value
Intercept	.213857	.040271	5.31	.0000
Rm	.095552	.047559	2.009	.0445
D-ARFIMA	.086786	.018634	4.657	.0000
AR(1)	-.27507	.029485	-.9329	.0147
MA(1)	.336802	.27502	1.225	.0000
ARCH effect test				
ARCH(p,q)		F-statistics	p-value	Results
ARCH(1,1)		25.899	.0000	ARCH effect is approved

As shown in the above model, the D-ARFIMA parameter is significant and states that the fit of the ARFIMA model has contributed to the explanatory power of the model. Considering that the probability of rejecting the hypothesis of the ARCH effect of first-order in the Lagrange coefficient test is .0000 and less than .05, it can be said that the model has ARCH effects. The ARFIMA-FIGARCH estimation results are presented in Table 5.

Table 5: the results of estimating ARFIMA(1,0,D,1)-FIGARCH(1,D,1) model

Parameters	Coefficients	SD	T-statistics	P-value
Intercept	.060081	.049828	1.206	.0325
Rm	.136666	.063723	2.145	.032
D-ARFIMA	-.08883	.043591	-2.014	.0365
AR(1)	-.05501	.02238	-2.4895	.0245
MA(1)	.372352	.099327	3.749	.0002
Cst(V)	75.30711	61.851	1.218	.0497
D-FIGARCH	.402467	.08138	4.945	.0000
ARCH(Phil1)	.676048	.26979	2.506	.0122
GARCH(Beta1)	.814708	.19661	4.144	.0000
Conditional Heteroscedasticity of Tse			RBD(2)=.0119453	Result
PROB.			.9940452	Lack of heteroscedasticity

This is the best estimate of the ARFIMA (1.0, D, 1) -GARCH (1, D, 1) model because it did not have the convergence capability by adding other intervals.

According to the results of Table 8, it is observed that the D-FIGARCH coefficients are significant and since the above coefficient is less than one, this shows the stationary covariance of the conditional variance process. The tse conditional heteroscedasticity test also shows that the model does not have a heteroscedasticity problem. Considering the significance of the market index coefficient (Rm) and the significance of the D-FIGARCH coefficient, it can be said that fitting with ARFIMA-FIGARCH method has added to the fitting power of the model. Accordingly, systematic risk's beta was calculated for all sample companies based on the ARFIMA-FIGARCH model and calculated over a period of 10 years.

6.2 Stepwise regression results

One of the important points of the descriptive statistics is the normality of data. Given that the probability of the Jarque-Bera statistic is less than .05, none of the variables have met the normality conditions, and normality was not met even using the conversion of the various variables performed on the data.

According to the principle of the central limit and its application for non-normal data, it is proved that if the volume of the data is large enough, the asymptote of the efficiency conditions for estimating the regression by the least squares method is established [31, 25].
Co-linearity is another issue that has to be considered before the estimate. In addition to resulting in high coefficients of determination for regression, the co-linearity problem makes explanation coefficients insignificant.

In order to investigate this issue, according to Monte Carlo studies, if the interstitial correlation coefficient of the independent variables is less than .8, there is no acute co-linearity problem in the models [8]. Hence, correlations above .8 were only found between QR and CR or between DE, FAE, LTLE and CLE, each group referring to commonly calculated indices in each group of liquidity and leverage ratios. However, there is no concern about the emergence of a co-linearity problem in the backward elimination and forward selection methods due to the stepwise selection of variables.

This is because it can be said that these methods have a systematic approach to the treatment of co-linearity by selecting or eliminating the problematic variable.
It can be said that the basis of inferential analysis in the science of statistics is hypothesis testing that can be performed in various ways based on the type of data and its distribution.
In this regard, the hypothesis testing method using regression estimation and investigation of significance of estimated equation's coefficients is a common method in the researches of recent decades in various sciences, which is also used in this study. In the inferential statistics literature, there are several methods for estimating regression and testing the existing hypothesis, among which the conventional least squares method can be used to estimate the slope of the regression model line.
To use the least squares method, it must be ensured that the classic assumption of the data used is maintained. One of the most important assumptions is the assumption of the reliability of the variables. If the data are not reliable, the regression that fit the data is not interpretable since the relation obtained from the least squares method is false in these conditions.
Therefore, in this research, before using the least squares test, the reliability test of the variables was performed. The results are shown in Table 6. As can be seen in this table, all variables are reliable.

Therefore, it can be concluded that the use of the least squares method is possible.

Table 6: The results of the reliability test

Variable	Test type	Chi-square	P-value	result
beta	Augmented Dickey-Fuller	1263.75	.0000	Static- I(0)
CAG	Augmented Dickey-Fuller	976.432	.0000	Static- I(0)
CLE	Augmented Dickey-Fuller	504.862	.0000	Static- I(0)
CR	Augmented Dickey-Fuller	428.204	.0021	Static- I(0)
CTR	Augmented Dickey-Fuller	726.156	.0000	Static- I(0)
DCR	Augmented Dickey-Fuller	480.285	.0000	Static- I(0)
DE	Augmented Dickey-Fuller	491.162	.0000	Static- I(0)
DSP/ESP	Augmented Dickey-Fuller	769.145	.0000	Static- I(0)
EGP	Augmented Dickey-Fuller	624.882	.0000	Static- I(0)
ER	Augmented Dickey-Fuller	394.298	.0439	Static- I(0)
FAE	Augmented Dickey-Fuller	540.456	.0000	Static- I(0)
FAG	Augmented Dickey-Fuller	941.602	.0000	Static- I(0)
FAT	Augmented Dickey-Fuller	441.124	.0005	Static- I(0)
FCNP	Augmented Dickey-Fuller	625.846	.0000	Static- I(0)
FCOP	Augmented Dickey-Fuller	625.944	.0000	Static- I(0)
GPM	Augmented Dickey-Fuller	542.692	.0000	Static- I(0)
LAR	Augmented Dickey-Fuller	736.764	.0000	Static- I(0)
LIR	Augmented Dickey-Fuller	394.138	.0444	Static- I(0)
LR	Augmented Dickey-Fuller	560.813	.0000	Static- I(0)
LTLE	Augmented Dickey-Fuller	541.36	.0000	Static- I(0)
MVBV	Augmented Dickey-Fuller	684.539	.0000	Static- I(0)
NETPS	Augmented Dickey-Fuller	721.459	.0000	Static- I(0)
NPM	Augmented Dickey-Fuller	560.496	.0000	Static- I(0)
OPM	Augmented Dickey-Fuller	461.97	.0000	Static- I(0)
ROA	Augmented Dickey-Fuller	518.784	.0000	Static- I(0)
ICR	Augmented Dickey-Fuller	659.534	.0000	Static- I(0)
OL	Augmented Dickey-Fuller	625.944	.0000	Static- I(0)
PE	Augmented Dickey-Fuller	745.314	.0000	Static- I(0)
QR	Augmented Dickey-Fuller	509.669	.0000	Static- I(0)
ROE	Augmented Dickey-Fuller	570.758	.0000	Static- I(0)
RWC	Augmented Dickey-Fuller	974.348	.0000	Static- I(0)
SG	Augmented Dickey-Fuller	867.96	.0000	Static- I(0)
SIZE	Augmented Dickey-Fuller	569.924	.0000	Static- I(0)

What is presented before the final model is the results of the heteroscedasticity test and unit root of the residuals of the forward and backward models. The probability values for the Lm Brush - Godfrey test, associated with heteroscedasticity, are shown in Table 7. What was obtained from the results of this test for both models was that, given that the probability value of the test is more than .05, there is no heteroscedasticity problem in the estimation of the models. Also considering that the probability value of the test statistic of the augmented Dickey-Fuller test for the residuals of both models is less than .05, it can be said that the residual series of both models are reliable and the estimated regressions are valid and interpretable.

Table 7: Results of estimation accuracy tests

Heteroscedasticity test			
Model	Test type	f-statistics	P-value
Forward selection	Lm Brush – Godfrey	.073296	.9293
Backward elimination	Lm Brush – Godfrey	.129395	.8786
Residual reliability test			
Variable	Test type	Chi-square	P-value
Residuals of forward selection	Augmented Dickey-Fuller	454.013	.0000
Residuals of backward elimination	Augmented Dickey-Fuller	469.377	.0000

Table 8: Results of estimating research model using backward elimination

Variable	Coefficient	SD	t-statistics	P-value
C	-1.59867	.766373	-2.08602	.0373
CLE	.049368	.01347	3.665054	.0003
SIZE	.183539	.055058	3.333565	.0009
OPM	-.01069	.005526	-1.93377	.0535
NETPS	.150076	.057848	2.594304	.0097
ICR	.000934	.000421	2.217294	.0269
NPM	-.00264	.004729	-.55754	.5773
OL	-2.29E-06	3.88E-05	-.05911	.9529
DPS-EPS	-.2622	.164291	-1.59595	.1109
TAT	-.14663	.164305	-.89242	.3725
Coefficient of determination	.071385	Durbin-Watson	1.299369	No. of observations
F-statistics	6.090036	p-value	0	870
Eliminated variables	GPM	CAG	CTR	FAT
	EGP	ROE	ER	FCOP
	LIR	DCR	PE	FAG
	FCNP	LTLE	CR	WATA
	RWC	DE	LAR	NETPG
	MVBV	FAE	LR	QR
	SG			

The results of estimating the research model using backward elimination method are presented in Table 8. Before addressing hypotheses, the general characteristics of estimation using backward elimination are stated. The results of the estimation of the backward elimination model indicate that, firstly, the regression is generally significant because the F-statistic of the regression is 6.090036, whose null hypothesis that all regression coefficients are insignificant is rejected at the error level of .05. On the other hand, by observing the coefficient of determination that is .071385, it can be concluded that the independent variables of the study in total account for about 7.1% of the dependent variable varia-

tions, which reflects the weakness of the fit of the model.
Given that none of the variables relating to the liquidity ratio remain in the model, the first sub-hypothesis that liquidity ratio affect the systematic risk is rejected. Also, the coefficients of the interest coverage ratio (ICR) and the current liability to eigenvalue ratio (CLE) are significant at the error level of .1 and the second sub-hypothesis that characteristics of leverage ratios are useful in explaining the systematic risk of the company is confirmed with 90% confidence. However, the relationship between the selected operating leverage (OL) and the systematic risk was rejected due to insignificance at the error level of 1.
The third sub-hypothesis states that the activity ratios affect the systematic risk index. Given the significance of the variable of the company size (SIZE) at the error level of .1, this hypothesis cannot be rejected. However, the relationship between the selected variable of the total asset turnover (TAT) with systematic risk was not confirmed because of insignificance. The fourth sub-hypothesis referred to the impact of the profitability ratios, which ultimately confirmed the significance of the coefficients of net profit to sale ratio (NETPS) and operating profit margin (OPM) variables at 90% confidence level and the sub-hypothesis was approved.

Table 9: Results of estimating research model using forward selection

Variable	Coefficient	SD	t-statistics	P-value
C	-2.05826	.746844	-2.75594	.006
CLE	.04953	.013417	3.691584	.0002
SIZE	.191174	.054793	3.489015	.0005
OPM	-.01423	.004277	-3.32673	.0009
NETPS	.151281	.053441	2.830778	.0048
ICR	.001034	.000416	2.482461	.0133
SG	.269862	.165354	1.632027	.1031
QR	.276208	.166205	1.661857	.097
DPS_EPS	-.27801	.162759	-1.70813	.088
Coefficient of determination	.077295	Durbin-Watson	1.29854	No. of observations
F-statistics	7.476443	p-value	.0000	870
Added variables	CLE	SIZE	OPM	NETPS
	SG	QR	DPS_EPS	ICR

However, the relationship between the selected variables of the earnings per share ratio (DPS / EPS) and the net profit margin (NPM) was not approved due to insignificance at the error level of .1. Hence, the final model obtained in the forward selection method is as follows:

$$Beta_{Arfima-Figarch} = -1.59867 + 0.049368(CLE) + 0.183539(SIZE) - 0.01069(OPM) + 0.150076(NETP/S) + 0.000934(ICR)$$

The results of estimating the research model using forward selection method are presented in Table 9. Before addressing hypotheses, the general characteristics of estimation using forward selection are stated. The results of the estimation of the forward selection model indicate that, firstly, the regression is generally significant because the F-statistic of the regression is 7.476443, whose null hypothesis that all regression coefficients are insignificant is rejected at the error level of .05. On the other hand, by observing the coefficient of determination that is .077295, it can be concluded that the independent variables of the study in total account for about 7.7% of the dependent variable variations, which reflects the better fit of the model compared to backward elimination.

Given that the variable of quick return (QR) is significant at the error level of .1, the first sub-hypothesis is confirmed with 90% confidence level with only one representative in the forward selection model. Also, the coefficients of the interest coverage ratio (ICR) and the current liability to eigenvalue ratio (CLE) are significant at the error level of .1 and the second sub-hypothesis that characteristics of leverage ratios are useful in explaining the systematic risk of the company is confirmed with 90% confidence.

The third sub-hypothesis states that the activity ratios affect the systematic risk index. Given the significance of the variable of the company size (SIZE) at the error level of .1, this hypothesis cannot be rejected. The fourth sub-hypothesis referred to the impact of the profitability ratios, which ultimately confirmed the significance of the coefficients of net profit to sale ratio (NETPS), net profit to sales ratio (NETP/S) and operating profit margin (OPM) variables at 90% confidence level and the sub-hypothesis was approved. Therefore, the final model obtained in the forward selection model is as follows:

$$Beta_{Arfima-Figar} = -2.5826 + 0.04953(CLE) + 0.191174(SIZE) - 0.01423(OPM) + 0.151281(NETP/S) + 0.001034(ICR) + .276208(QR) - 0.27801(DPS/EPS)$$

For choosing one of the forward and backward models, four criteria of regression model prediction power measures were used in this research. In Fig. 1, the estimated beta models of the backward elimination model and in Fig. 2, the estimated beta models of the forward selection model are shown. The comparative results of the two methods are shown in Table 10:

Table 10: criteria of measuring research models' power

Comparing the power of backward elimination and forward selection methods				
Method	RMSE	MAE	MAPE	TIC
Backward elimination	6.428708	1.555606	749.2775	.744113
Forward selection	4.345639	1.370646	399.3546	.692918
Estimation period		2011 to 2015		

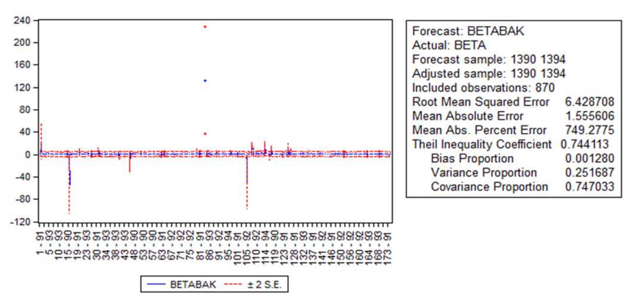

Fig 1: Estimated Beta of the backward elimination model

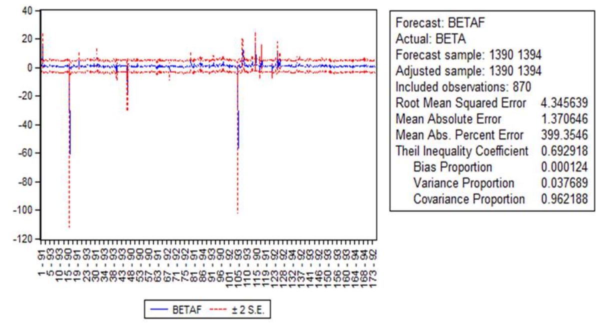

Fig 2: Estimated Beta of the forward selection model

As seen in the table above, the power of the forward model is higher. Because these criteria state that a model is better that its TIC value and other criteria are smaller. Hence, according to the results of the prediction power comparison, for the purpose of interpreting the hypotheses, the coefficients of estimation of the forward selection model have been used.

7 Conclusion

In the first main hypothesis, the effect of accounting variables on the systematic risk index was investigated. Since the main purpose of this research was designing and explaining a systematic risk estimation model for modelling data from 2006 to 2010, two stepwise regression approaches and metaheuristics algorithms were used in modelling.

Due to the difference of the methods, confirmation or rejection of sub-hypotheses was separately examined, and the results are presented separately in each of the methods as follows:

7.1 Analysis of the results of sub-hypotheses testing in the backward elimination method

The results of the estimation of the backward elimination model indicate that, firstly, the regression is generally significant because the F-statistic of the regression is 6.090036, whose null hypothesis that all regression coefficients are insignificant is rejected at the error level of .05. On the other hand, by observing the coefficient of determination that is .071385, it can be concluded that the independent variables of the study in total account for about 7.1% of the dependent variable variations, which reflects the weakness of the fit of the model.
Given that none of the variables relating to the liquidity ratio remain in the model, the first sub-hypothesis that liquidity ratio affect the systematic risk is rejected. This is in line with the findings of Namazi and Khajavi [9], Ahmadpour and Jamkarani [1], Rahmani et al. [5], Chun and Ramasamy [18], Mulli [32] and in contrast with the findings of Salari [37] and Park and Kim [35]. Also, the coefficients of the interest coverage ratio (ICR) and the current liability to eigenvalue ratio (CLE) are significant at the error level of .1 and the second sub-hypothesis that characteristics of leverage ratios are useful in explaining the systematic risk of the company is confirmed with 90% confidence. However,

the relationship between the selected operating leverage (OL) and the systematic risk was rejected due to insignificance at the error level of .1. The results of this sub-hypothesis are in line with the study of Namazi and Khajavi [9], Rahmani et al. [5], Bowman [14], Mulli [32], Dibiase and Apolito [20], Park and Kim [35], and Alqaisi [11], and in contrast with the results of Salari [37] and Brimble and Hodgson [15].

The third sub-hypothesis states that the activity ratios affect the systematic risk index. Given the significance of the variable of the company size (SIZE) at the error level of .1, this hypothesis cannot be rejected. However, the relationship between the selected variable of the total asset turnover (TAT) with systematic risk was not confirmed because of insignificance. These findings are in line with the findings of Rahmani et al. [5], Namazi and Khajavi [9], Park and Kim [35], Dibiase and Apolito [20], Alqaisi (2011), Brimble and Hodgson (2007), and in contrast with the findings of Ahmadpour and Jamkarani [1], Salari [37], and Mulli [32]. The fourth sub-hypothesis referred to the impact of the profitability ratios, which ultimately confirmed the significance of the coefficients of net profit to sale ratio (NETPS) and operating profit margin (OPM) variables at 90% confidence level and the sub-hypothesis was approved. However, the relationship between the selected variables of the earnings per share ratio (DPS / EPS) and the net profit margin (NPM) was not approved due to insignificance at the error level of .1. The results are in line with the study of Rahmani et al. [5] and Alqaisi (2011) and in contrast with the study of Namazi and Khajavi [9] and Mulli [32].

7.2 Analysis of the results of sub-hypotheses testing in the forward selection method

The results of the estimation of the forward selection model indicate that, firstly, the regression is generally significant because the F-statistic of the regression is 7.476443, whose null hypothesis that all regression coefficients are insignificant is rejected at the error level of .05. On the other hand, by observing the coefficient of determination that is .077295, it can be concluded that the independent variables of the study in total account for about 7.7% of the dependent variable variations, which reflects the better fit of the model compared to backward elimination.

Given that the variable of quick return (QR) is significant at the error level of .1, the first sub-hypothesis is confirmed with 90% confidence level with only one representative in the forward selection model. This is consistent with the study of Salari [37] and in contrast with the study of Namazi and Khajavi [9]. Also, the coefficients of the interest coverage ratio (ICR) and the current liability to eigenvalue ratio (CLE) are significant at the error level of .1 and the second sub-hypothesis that characteristics of leverage ratios are useful in explaining the systematic risk of the company is confirmed with 90% confidence. The results of this sub-hypothesis are in line with the study of Namazi and Khajavi [9], Rahmani et al. [5], Bowman [14], Mulli [32], Dibiase and Apolito [20] Park and Kim [35], and Alqaisi [11], and in contrast with the results of Salari [37] and Brimble and Hodgson [15].

The third sub-hypothesis states that the activity ratios affect the systematic risk index. Given the significance of the variable of the company size (SIZE) at the error level of .1, this hypothesis cannot be rejected. The results are in line with the study of Rahmani et al. [5], Namazi and Khajavi [9], Park and Kim [35], Dibiase and Apolito [20], Alqaisi (2011), and Brimble and Hodgson [15] and in contrast with the results of Ahmadpour and Jamkarani [1], Salari [37], and Mulli [32]. The fourth sub-hypothesis referred to the impact of the profitability ratios, which ultimately confirmed the significance of the coefficients of net profit to sale ratio (NETPS), net profit to sales ratio (NETP/S) and

operating profit margin (OPM) variables at 90% confidence level and the sub-hypothesis was approved. However, the relationship of sales growth (SG) was not confirmed at .1 error level due to insignificance. The results are consistent with the study of Rahmani et al. [5] and Alqaisi [11] and in contrast with Namazi and Khajavi [9] and Mulli [32].
In the second main hypothesis, the accuracy of the systematic risk beta prediction by means of the backward elimination and forward selection methods was investigated. Given that the estimated model using forward selection method had the lowest error in all four criteria for evaluating the performance of the models including the root mean squared error (RMSE), mean absolute error (MAE), mean absolute percentage error (MAPE), and Tile coefficient (TIC), it can be claimed that the model estimated by forward selection method has the highest accuracy compared to the backward elimination model. It is suggested to pay special attention to the variables and financial ratios of each company in the systematic risk analysis and decisions regarding the purchase and sale of companies' shares. It has been proved that the systematic risk of each company varies even in the same industries, and one of the reasons for this difference lies in its specific financial features. Therefore, it is emphasized that in corporate risk analysis, leverage, leverage ratios, activities, profitability, and liquidity of each company should be considered individually. Since reducing the risk of investing in a company attracts investors and shareholders due to the relative assurance of achieving expected returns, all of which ultimately increases the value of the company and the shareholders' wealth, it is suggested to the managers of the bourse companies to pay particular attention to financial ratios, especially leverage and profit ratios, in their decision making. This is because, as the ratio of these ratios and the systematic risk of companies has been approved in this research and previous researches, the company's risk level can be reduced through the positive effect of these variables with a correct decision.
Regarding the importance of systematic risk, it seems that further research will help clarify this issue by taking into account other aspects. This research can be used as a model for further research. Due to the wide range of factors affecting the risk and complexity of the market structure, future researches are suggested to use artificial intelligence techniques and effective components in risk modelling. It is also proposed, in addition to using macro-level variables and integrating them with accounting and financial variables, the power of the systematic risk model based on these variables and the model based on value at risk is investigated by determining its correlation with the preferences of investors in stock purchases and sales.

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