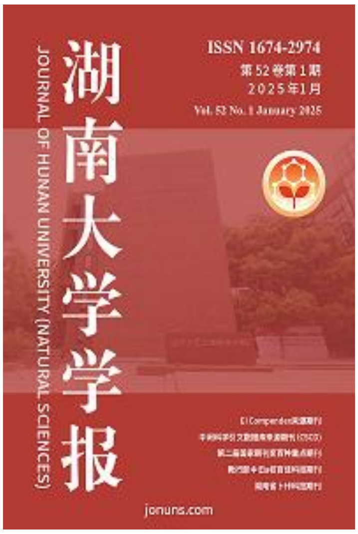

Journal of Hunan University

(Natural Sciences)

Vol. 52 No. 1

January 2025

Available online at

https://jonuns.com

Original research article

https://doi.org/10.55463/issn.1674-2974.52.1.7

Predicting the Relation Between Audit Quality and Share Return Using Artificial Neural Networks

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Article History:

Received: November 18, 2024
Reviewed: December 20, 2024
Revised: January 15, 2025
Accepted: January 25, 2025
Published: February 28, 2025

Abstract: Agency problems arise due to conflicts of interest between managers and shareholders. Auditing is considered an effective solution to limit managers' power in contractual relationships. This study aims to predict the effect of audit quality on stock return changes. For this purpose, data on companies listed on the Tehran Stock Exchange for the period 2006-2023 were extracted, and a nonlinear prediction approach using artificial neural networks was used to predict stock returns. The outputs obtained from the estimation of the artificial neural networks and the results obtained from the estimation using this method with evaluation scales are (MAE = 0.017, MSE = 0.075, and R=0.986). Concerning the random amount and comparing it with R = 0.986, we find a meaningful relationship between audit quality and share returns.

However, such a network had the least error compared to the other networks (MAE=0.027, MSE = 0.004). In this study, using a nonlinear approach, an attempt was made to consider issues related to collinearity between variables and latent factors.

Keywords: audit quality, prediction, artificial neural networks, stock return.

利用人工神经网络预测审计质量与股票收益之间的关系

摘要：代理问题是由于管理者和股东之间的利益冲突而产生的。审计被认为是限制管理者在合同关系中权力的有效解决方案。本研究旨在预测审计质量对股票收益变化的影响。为此，提取了 2006 年至 2023 年期间在德黑兰证券交易所上市的公司的数据，并使用人工神经网络的非线性预测方法预测股票收益。从人工神经网络估计中获得的输出和使用此方法与评估量表估计获得的结果为（MAE = 0.017，MSE = 0.075，R = 0.986）。关于随机量并将其与 R = 0.986 进行比较，我们发现审计质量与股票收益之间存在有意义的关系。然而，与其他网络相比，这种网络的误差最小（MAE = 0.027，MSE = 0.004）。在本研究中，使用非线性方法，尝试考虑与变量和潜在因素之间的共线性相关的问题。。

关键词：审计质量、预测、人工神经网络、股票回报。

1. Introduction

This study examines stock return changes based on audit quality. This study draws on economics and management accounting literature and examines behavioral changes in audit quality that can be useful for auditors, managers, audit committees, and regulators. Pricing and market competition for audit services are important issues for regulators, researchers, and investors [1]. As observed in [2], the nature of auditing as a credit commodity leads to higher auditing costs and time. With increasing audit market concentration and the occurrence of some audit failures, the issue of audit quality has also been considered. Audit committees, auditing individuals, and competitive markets have created incentives for innovation and creativity in auditing. As concluded in [3], the market is highly concentrated in some sectors and has deprived clients of their ability to make decisions regarding auditor selection. Therefore, it is important to examine fluctuations in auditing services in the context of market competition for these services.

Despite the extensive literature on audit quality, its details, including the cost of audit quality, limitations, and other aspects, have not been fully discussed and examined. Auditor behavior over time has not been fully identified, and examining audit behavior in the long term reflects our understanding of the audit market. Research on fluctuations and changes in audit quality is limited, including those in [4] and [5].

Because neural network model application is significantly more difficult and time consuming than simple regression models, predictors may use only nervous neural models because these difficulties and complexities are useful and applicable [6, 7]. One of the reasons for employing neural networks is their nonlinear aspect of prediction [6-8]. The nonlinear aspect may be the complex relations between the dependent or independent variables in the up or down thresholds for affecting the independent variables or the difference between the upper and lower limits of the predictions related to the dependent variable [7]. According to [9, 10], continuous changes in the nature of financial relations are a factor in the traditional approach to change to an artificial neural network approach and abandon traditional techniques. This operation is performed using one reversible approach, in which researchers eliminate the traditional observation with accessibility to new observations simultaneously with the production of new time series for prediction. Prediction refers to the perception of variables that are used to explain variable reactions, which means the clear perception need of timing relations between many variables and the perception statistic value of these relations as well as the training that variables are more appropriate with respect to their signals to predict marker changes.

A better prediction regarding the increasing financial market disturbance by investing flows is the key element to better financial decisions. Financial experts can simply state the actions of obvious assets on market value in the form of a model. However, this capability is not related to unobvious actions. Time series models stated by financial theories have been the basis for predicting data in the recent century. One of the most desirable procedures for converting market value to as a model uses intelligent systems, including artificial neural networks that do not include a standard formula, and may simply insert market changes there.

2. Research Background

According to [11], audit quality is defined as the market's assessment of the auditor's ability to detect material misstatements and report detected misstatements. As emphasized in [11], an auditor who detects and reports misstatements is truly independent. Therefore, according to this definition, the two important components of audit quality are the auditor's ability and competence to detect accounting misstatements, and the market's assessment of the auditor's ability and independence in reporting the detected misstatements. Although many factors may affect the quality of audit services, limited research has been conducted to develop a conceptual framework or model to describe the structure of audit service quality.

A model introduced in [12] showed that audit quality is a function of two factors related to audit performance: auditor capabilities (including knowledge, experience, adaptability, and technical efficiency) and professional performance (including independence, objectivity, and care). Empirical findings in Iran show that audit quality is mainly a function of two key variables related to audit performance (audit firm): competence (knowledge and experience) and the independence and professional performance of audit operations. Field findings and professional experience suggest that audit quality is strongly affected by these two factors. Audit quality refers to the detection of material misstatements (competence) and their reflections in the audit report (independence).

Agency theory, as a part of the positive theory, states that a company based on the contract between suppliers of financial resources (investors) and managers (agents) was formed, and it aims to control and appropriately use these resources. In corporations, managers do not always maximize their efficiency. Therefore, a fundamental problem arises in relation to shareholder interests. Aspects of corporate executives and agency costs due to conflicts of interest between investors and managers have been created. Auditing procedures for forcing managers to use in order to maximize the interests of investors and reduce their conflict of interest. An audit is a tool to control the behavior of managers by investors and increase investor interest. Therefore, we can expect that with increasing agency problems, auditors spend more time reviewing the operations of client firms to increase audit quality.

Many changes and events that occur in the share market cannot be stated directly as a model; that is, this states the type of limitation in the regression models. In recent years, the exploration of nonlinear researchers and financial analysts have focused by various relationships in the financial market. Nonlinear statistical methods are used to achieve better predictions; however, many techniques and approaches are axial models that require these nonlinear models to be regulated before estimating the determinate parameters. In contrast, neural networks are axial data approaches that do not require regulation in model processing because they encompass independent inherent relations between variables. Therefore, neural networks can perform nonlinear models without primary knowledge rather than the relations of output and input variables.

2.1. Artificial Neural Networks

In this type of plan, there exists the concept of learning that this learning is obtained by identifying and gathering relations between one output and input set. In simple terms, learning in these plans is obtained by expanding the set of memories inside the inputs with the set of outputs with knowledge of the set of example results. Artificial neural networks have shown good performance as a modern method in modeling and forecasting nonlinear and nonpermanent time series of processes for which there is no clear solution and relation to their exact identification and description. The total ability of artificial neural networks is the application of a nonlinear relation between data and result generalization for other data. Artificial neural network models with the instruction that has been observed may forecast system behavior without a clear mathematical relation. Two types of highly applicable neural networks in the financial department are multilayer perceptrons and generalized feed-forward. The perception network is defined as the set of interconnected neurons that produce the result by receiving one input series of neurons and fulfilling a certain operation; if the result is more than the given threshold, it yields one amount as the output. In this type of network, the input of the first layer of neurons is connected to the next layer, and this subject is true at every level until it reaches the output layer.

The most common types of networks in forecasting and solving nonlinear problems are networks, known as multilayer perceptrons, which use the error back propagation algorithm inputs of these networks as a vector x (x_1, x_2. …x_n) and every input of is connected to the related node by one weight; finally, the sequence of weights is connected to the considered node, as weight vector w

The GFF neural network is another type of network that is used in the generalized feed-forward neural network. A generalized feed forward means that the artificial neuron is located in the sequence layers and the forward output (signal) itself. The back propagation term also means that the errors are fed in the back of the network to correct the weights thereafter, and again repeat itself forward route input to output.

During the last two decades, we have witnessed the successful use of artificial neural networks in management and financial issues, and many articles have been presented. Training ideas for solving problems of identification of complex patterns using intelligent data factors for university researchers has been very challenging. Neural networks are a valuable tool for a wide range of financial and management fields, and as a vital component of most data collection systems, the change of the approach of people and organizations to the relationship among data. To build and use a neural network model, we must identify the network topology**.** In this step, the number of layers and network nodes, network type, and basis and stimulated functions are selected. Therefore, appropriate software for the network was selected and prepared.

Therefore, network learning is necessary. The aim of work learning is the value correction of network weights for multiple samples with respect to the type of learning algorithm. Information related to the considered patterns is shown as educational data several times in the network, and the network corrects the value of their weights during the learning process for each group of educational patterns. After repeating this action for high frequency, weights such that the view information of each pattern is used to retrieve it. With the change in the transfer functions, the number of layers and nodes per layer and the effective factors on the weights learning as error and attempt to achieve the desired output. Finally, the test or network generalization improved the prediction. After the training phase was completed, to ensure the optimum performance of the network, it was tested for known information, and possible defects were removed. After completing this phase, the network is ready for use. In network design, the determination of the type of network and the learning method–determination of these variables–are important. The number of input nodes, the number of hidden layers and hidden nodes, and the number of output nodes that select the number of inputs in the neural network have special importance, since each input pattern includes important information about the structure of complex correlated data, and most researchers obtain the number of input patterns using the trial-and-error method. In this study, the number of input patterns was selected with respect to the sample size and with the trial-and-error method. In issues related to the prediction that the prediction horizon is usually one step forward, and with respect to, the number of output nodes depends on the prediction horizon, and the output node is one node. Hidden layers and nodes also play important roles in neural networks. hidden layers in the hidden nodes allow the neural network to detect and identify data characteristics and establish complex nonlinear records between the input and output variables. In theory, neural networks can achieve the desired accuracy for function approximation by using a sufficient number of hidden nodes in the hidden layer. In this study, we selected the number of hidden layers using the trial-and-error method and the results. Different models were used for determining the appropriate topology of the tested neural networks, and by changing the number of layers and neurons in the hidden layers, we selected the basic model of prediction. After performing various tests, the number of desired layers in this study was three (one input layer, one hidden layer, and one output layer) with four neurons.

3. Materials and Methods

3.1. Sample selection

This study is based on firms listed on the Tehran Stock Exchange of Iran. We begin with an initial sample of 4,983 firm-year observations from 2008 to 2018. Rahavard software was used to provide the relevant variables. A total of 1,067 firm-year observations related to finance, investment, equity trust, and funds were excluded because of their different practices. In addition, financial institutions have distinct requirements for holding cash to meet operating and financing activities; therefore, they were excluded from the sample. Furthermore, we exclude all firm-year observations when CEO compensation variables are not available. Therefore, the final sample comprised 1,309 firm-year observations. Table 1 shows the sample distributions across the different industries.

Table 1. Sample distribution based on industry (compiled by the authors)

2-digit-SIC Code	Industry Name	Firm-years	%Sample
13	Mining	165	12.6
34	Automotive	297	22.7
42	Food	165	12.6
43	Pharmaceuticals and Health Care	165	12.6
44	Petrochemicals	88	6.7
49	Ceramic and Tile	99	7.5
53	Cement	110	8.4
-	Non-classifiable Establishments	220	16.9
Total		1,309	100

3.2. Dependent Variable Measure

In this study, share returns are considered as dependent variables. It consists of the total dividend obtained from investment in a specific period, plus the price difference in company shares.

3.3. Independent Variables Measure

In this study, three criteria were used to examine audit quality. The first criterion is the size of the auditing firm. The size of the audit firm is a dummy variable, such that if the company's auditor is a large audit firm, it takes the value of one and zero otherwise. Second, auditor industry expertise is defined as the total assets of all clients of a particular audit firm in a particular industry divided by the total assets of clients in that industry. If the value obtained is above the average, it takes the value of one, and zero otherwise. The third criterion is auditor tenure, which is the number of consecutive years an auditor is responsible for auditing a specific company.

After the data collection, the data homogeneity test was reviewed. Next, the most appropriate type of neural network with the best scales for evaluation was selected. By performing the above approach, in the two simulation and estimation models, the number of hidden layers, the effective neuron in each of the layers, and the number of repetitions were determined. It is noteworthy that this research goal is to reduce the mean square error (MSE) to evaluate the accuracy of the artificial neural network model.

To predict the share return using research variables, a feed-forward neural network approach, which is generally called multilayer perceptron networks (MLP), is used to train the above neural network using the error back propagation learning rule. This law comprises two main routes. The first path is called the went path, which in this route is applied to the multilayer perceptron network, and the effects are transferred through the intermediate layer to the output layers. The output vector formed in the output layer provides a real solution. In this route, the network parameters are fixed and unchanged. The second path is called the back-path. In this route, unlike the went path, the network parameters of the multilayer perceptron network change and are set. This adjustment was performed in accordance with the error correction law. An error signal is formed in the output layer of the network. The error vector is equal to the difference between the determined and actual answers of the network. After the calculation, the error value was distributed in the back path of the output layer and through the network layers in the entire network. Because the recent distribution is in contrast to the synapse weight communication route, the word back error propagation is selected to describe the network behavior correction of the network. The network parameters were adjusted such that the real answer of the network was closer to the optimal answer. The learning algorithm used in this research is the back-error propagation algorithm, and faster learning uses the reactionary back-error propagation algorithm. The number of replications in this study was 1000, and the tables of the prediction value, real values, and other tables obtained from the neural networks are shown in the figures below. As mentioned previously, some common performance measures are used to demonstrate the learning of data communication in neural networks. In terms of prediction issues, these measures are mainly related to the error between the predicted outputs and the real desired output. The common performance measures for prediction problems (linear and nonlinear) previously mentioned in the first three cases are the families of standard error mean calculation standard mean squared error (MSE) and root mean squared error (RMSE). R^2 is the coefficient of determination that indicates the direction of the independent or dependent variable. Another measure for evaluating the performance of a neural network is the mean absolute error (MAE).

4. Results and Discussion

The methods of artificial neural networks with the use of sensitivity analysis will determine the correlation between the input variables (independent) and output (dependent). Therefore, the network is designed based on the optimal plan and data input and output, and these relationships are tested.

The objective of the audit is to increase the safety and reliability of the information provided by the company to attract investment. Therefore, detailed information and share returns increase when audit quality increases.

In this step, two types of multilayer perceptron neural networks and feed forward with transfer function change and training low type are constructed and performed to select the transfer function type and appropriate training law.

Table 2 shows the results obtained from the simulation; the sigmoid transfer function and momentum training law possess the best evaluation results.

Table 2. Error and trial test for selecting the best structure multilayer perception (compiled by the authors)

Struc.	Network	Learning Rule	test		
			MSE	MAE	R
R1	MLP	Moment. (0.1-0.9) Tan Axon	0.042	0.081	0.891
R2			0.098	0.004	0.885
R3			**0.027**	**0.004**	**0.980**
R4			0.097	0.098	0.907
R5			0.035	0.078	0.934
R6			0.071	0.084	0.896
R7			0.037	0.076	0.909
R8			0.067	0.082	0.907
R9			0.092	0.095	0.886
R10		Moment. (0.1-0.9) Sig Axon	0.014	0.098	0.903
R11			0.023	0.084	0.905
R12			0.021	0.081	0.916
R13			0.074	0.088	0.893
R14			0.012	0.018	0.943
R15			**0.010**	**0.082**	**0.949**
R16			0.072	0.028	0.886
R17			0.077	0.019	0.892
R18			0.059	0.085	0.901

Next, the results shown in Table 2 prioritize the feed-forward neural network over the multilayer perceptron type.

Tables 2 and 3 show the error and trial results of selecting the best multilayer perceptron and feed-forward structures, respectively. Next, other related structures were tested to obtain the best basis.

These tests are the conjugate gradient and Levenberg–Marqant, which are calculated dependently for both the multilayer perceptron and feed-forward structures.

It is possible to compile the models that are used in the training of law, value, and momentum value, how is regulated as trial and error that performed models possess the most accuracy. This action was applied for every three transfer-function types. To find the best number of hidden layers and neurons, applied networks were constructed and performed with one to three hidden layers, and the results showed that a network constructed with a hidden layer and two neurons was more appropriate.

Table 3. Error and trial test for selecting the best structure feed-forward neural network (compiled by the authors)

Struc.	Network	Learning Rule	test		
			MSE	MAE	R
R19	GFF	Moment. (0.1-0.9) Tan Axon	**0.032**	**0.015**	**0.977**
R20			0.065	0.015	0.875
R21			0.044	0.024	0.966
R22			0.056	0.099	0.915
R23			0.038	0.101	0.947
R24			0.072	0.034	0.914
R25			0.049	0.017	0.917
R26			0.052	0.068	0.900
R27			0.083	0.093	0.894
R28		Moment. (0.1-0.9) Sig Axon	**0.017**	**0.075**	**0.986**
R29			0.075	0.012	0.843
R30			0.059	0.038	0.897
R31			0.088	0.044	0.873
R32			0.053	0.009	0.911
R33			0.041	0.102	0.926
R34			0.063	0.047	0.895
R35			0.072	0.058	0.865
R36			0.044	0.033	0.927

The results obtained in this section are presented in Table 4. By reviewing Table 3 and performing comparisons, we specified that the best structure for multilayer perception is TanhAxon, and that for feed forward is SigmoidAxon.

Table 4. Characteristics of the artificial neural network) compiled by the authors

Transfer	Learning Rule	MAE	MSE	R
MLP Tan	Momentum	**0.027**	**0.004**	**0.980**
	Conjugate Gradiant	0.054	0.086	0.922
	Levenberg Marqant	0.057	0.079	0.914
MLP Sigmoid	Momentum	0.010	0.082	0.949
	Conjugate Gradiant	0.049	0.082	0.930
	Levenberg Marqant	0.042	0.062	0.935
GFF Tan	Momentum	0.032	0.015	0.977
	Conjugate Gradiant	0.051	0.068	0.933
	Levenberg Marqant	0.039	0.024	0.958
GFF Sigmoid	Momentum	**0.017**	**0.075**	**0.986**
	Conjugate Gradiant	0.060	0.045	0.912
	Levenberg Marqant	0.035	0.038	0.943

Consider Table 4 among multilayer perceptron and feed-forward structures that introduced the best structure, and a feed-forward neural network with a sigmoid transfer function in this section is determined. It also represents the correlation between the actual and training variables and the share return. The results show a meaningful relationship between these variables and share returns.

5. Conclusion

In this study, an attempt was made to identify and control for nonlinear effects by removing the limitations related to the direct relationship between variables. On the other hand, the external aspects affecting the change in returns have been examined in the form of audit quality to show that high-quality and effective supervision can also lead to an increase in stock returns by changing the perspective of shareholders and investors. As mentioned earlier in this research, the artificial neural network is used as a factor to predict and estimate. With respect to the fact that neural network reviews the nonlinear relations between variables (by sampling of human neural network), the results are representative of the meaningful relations (R= 0.986) among research variables (audit quality variables). One of the reasons for using a neural network is the optimization of the selected prediction parameters because exploring the parameters is time consuming in a normal situation.

The results of this research show the relative success of neural network models in describing the relationship between research variables and share returns. With regard to the results obtained from modeling, the use of neural networks can lead to improved results. However, the use of a genetic algorithm in the neural network structure may lead to better results. The relationship between audit quality and the dependent variable at different industry levels is not the same and stable, and this correlation could change for different reasons over various functions. In addition, the modeling optimal results indicate that the use of all the basis information will not be followed by the best results as an input index for modeling. It is suggested that this method be further reviewed in future research.

The following recommendations are presented in the direction of the results. By considering the meaningful nonlinear relationships among the research variables, it is suggested that investors also focus on external factors. In other words, appropriate influencing factors must be considered, such as the composition of the board of directors, organizational structure, and profit distribution uniformity.

In this research, some criteria have been used to measure and calculate audit quality, and this is in a situation where the appropriate criterion for audit quality may differ according to the company's operating environment in each country.

Declarations

Author Contributions

Conceptualization, N.R.N. and M.H.; methodology, N.R.N. and M.H; software, H.F.K.A.; validation, N.R.N. and M.H.; formal analysis, H.F.K.A.; investigation, N.R.N., M.H. and H.F.K.A.; resources, N.R.N.; data curation, N.R.N.; writing—original draft preparation, all authors contributed equally.; writing—review and editing, N.R.N.; visualization, H.F.K.A.; supervision, N.R.N.; project administration, N.R.N. All authors have read and agreed to the published version of the manuscript.

Data Availability Statement

The data presented in this study are available on request from the corresponding author.

Funding

Funding information is not available.

Conflicts of Interest

The authors declare no conflicts of interest regarding the publication of this manuscript. In addition, ethical issues, including plagiarism, informed consent, misconduct, data fabrication and/or falsification, double publication and/or submission, and redundancies, have been completely observed by the authors.

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Word count: 4,409 words, excluding references.

Peer review information:

The reviewer reports submitted in first round: 3 reports

The reviewer reports submitted in 2nd round: 2 reports

The revision rounds stages: 2 rounds

Final revised version submitted: January 15, 2025

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