Corporate Performance Prediction Based on BP Neural Network

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Abstract: Top Management Team (TMT), as the most important presence in corporate decision-making, is an integral part of corporate research. Its impact on corporate performance is a topic that cannot be ignored. This paper uses earnings per share (EPS) to represent corporate performance, and the shareholding ratio of executives (SHARE) is used as TMT characteristics. Based on the BP neural network, the input layer of the model is set as five nodes, the implied layer as two nodes, and the output layer as one node. We use 75% of the data of listed information technology companies from 2017-2019 as the training set to derive the performance prediction model. In this study, 25% of the test set is used to validate the final valid performance prediction model obtained. This study integrates TMT characteristics into predicting corporate performance, helping to optimize the non-economic indicators used to assess and predict corporate performance.

Keyword: Top Management Team Characteristics, R&D Investment, Corporate Performance, BP Neural Network.

1 INTRODUCTION

The top management team (TMT), as the makers and executors of corporate decisions [2], has been a high research topic around the world (Hambrick and Mason, 1984). Since the upper echelons theory was proposed, many studies have been conducted by domestic and international scholars on the demographic characteristics of TMT and Pay Dispersion in TMT on corporate performance [3][6]. However, the results of TMT characteristics and corporate performance have not reached unity, and numerous theories have been born to explain their relationship [1].

With the advent of the 5G era and the IoT technology revolution, people are paying more attention to R&D, and R&D investment is increasingly reflecting a country’s level of economic development. According to the “2020 National Science and Technology Expenditure Statistics Bulletin” published by the National Bureau of Statistics, the Ministry of Science and Technology, and the Ministry of Finance in 2021, China’s R&D investment has increased in 2020 and has maintained a double-digit growth rate since the “13th Five-Year Plan”, a record high growth rate.

Previous studies have tended to focus on economic indicators and ignore the impact of TMT [8]. Therefore, this paper focuses on the prediction model of earnings per share (EPS) by adding TMT characteristics variables and using information technology-listed companies as research samples.

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2 THEORETICAL BACKGROUND AND HYPOTHESES

TMT, as the most important presence in corporate decision-making [2], is an integral part of accounting research and its impact on corporate performance is a topic that cannot be ignored. According to the most popular explanation of agency theory, in the case of information asymmetry, it is the executive team members as *Economic Men*. Individuals will constantly seek to maximize their own interests, making them inconsistent with the interests of the firm, leading to free-riding [9][11].

Agent theory suggests that increasing the shareholding of TMT will reduce this goal inconsistency (Garvey, 1992). Giving shares to the executive team is a form of equity incentive. The higher the shareholding ratio, the more it reduces the short-sighted effect of the executive team on R&D investment activities and motivates the executive team to invest in R&D. In the information technology industry, a large part of a company's performance relies on its degree of technological innovation. It is not difficult to imagine that the higher the intensity of R&D investment, the stronger the technological innovation. In summary, we posit that: Executive team shareholding, R&D investment increase corporate performance.

3 METHOD AND MATERIAL

3.1 BP Neural Network

BP neural network is a multiple-feedforward network trained according to the error back propagation algorithm [7]. It can store and learn a large amount of input and output data by simulating the function of human neurons. It does not need to describe the mapping relationship of variables, using input and output data to the model. It has a solid ability to simulate nonlinear systems. The BP neural network often consists of input, output, and hidden layers. The neurons between layers are connected in a fully interconnected manner, interconnected by corresponding network weight coefficients. The neurons within each layer are not connected. See Figure 1 for an illustration.

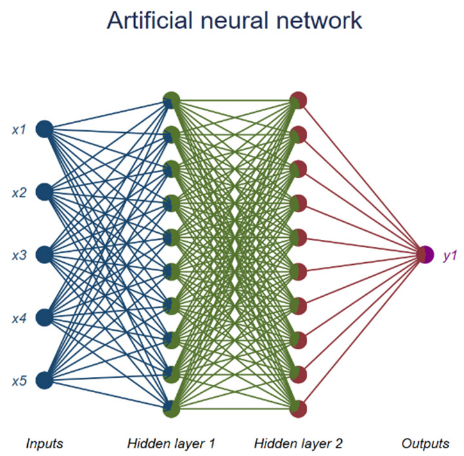

Figure 1: BP neural network topology.

The BP neural network training process is as follows [10]. We suppose that there are A training samples to train the network, one of which is a. For a, the input to the neuron n in layer i is as follows.

$$net_{na}^{(i)} = \begin{cases} x_n, & i = 1 \\ \sum_{j=1}^{N_{i-1}} w_{nj}^{(i)} o_{ja}^{(i-1)} - \theta_n^{(i)}, & i = 2 \end{cases} \tag{1}$$

Where x_n is the input of the neuron n, $w_{nj}^{(i)}$ is the connection of weight between neuron n of the layer i and neuron j of the layer *(i-1)* in equation (1). $o_{ja}^{(i-1)}$ is the output of neuron j of the layer *(i-1)* of sample a in equation (1).

The output of the neuron n of the layer i is as follows.

$$o_{na}^{(i)} = \begin{cases} net_{na}^{(i)}, & i = 1 \\ f(net_{na}^{(i)}), & i = 2 \end{cases} \tag{2}$$

Where *f(.)* is the activation function in equation (2).

3.2 Sample Selection

In this paper, the listed companies in the information technology industry in the SSE A-share and SZSE A-share in 2017 year and 2018 year are used as the research sample. The data on corporate performance is obtained from the 2018 year and 2019 year data because of the lagging effect of the growth effect of corporate performance brought about by considering R&D investment.

According to the collected samples, the following treatments were performed: (1) eliminating samples with missing relevant variables; (2) eliminating samples of ST and *ST enterprises; (3) Winsorize all variables from 1% to 99% in order to remove the influence of extreme values, and finally, 1045 samples were obtained. The data were all obtained from the CSMAR database.

3.3 Input Layer, Hidden Layer, Output Layer

In this study, 75% of the data were used as training samples and 25% as test samples. The input layers are SHARE, RD, Size, Growth, and AGE and the output layer is EPS.

The shareholding ratio of executives (SHARE): The shareholding ratio of the executive team is represented by the ratio of the number of shares held by executives to the total number of shares of the company. R&D investment (RD): R&D investment can be measured by the intensity of R&D investment. Corporate performance (EPS): We collect EPS for 2018-2019 as the dependent variable for this study. Company size (Size): Liu and Liu proposed that company size is closely related to research investment. Company growth (Growth): Companies with higher growth will care more about their corporate performance the following year. Age of the firm (AGE): The older the company, the greater stability of executive team characteristics such as executive shareholding ratio. Table 1 shows the variable descriptions.

Table 1: Variable descriptions.

Variable Name		Variable descriptions
Corporate Performance	EPS	Net profit for the year / Total number of ordinary shares
Shareholding ratio of executives	SHARE	Percentage of shares held by executives to total shares
R&D investment	RD	R&D expenditure/total assets
Company Size	Size	Log of total assets for the year
Company Growth	Growth	Operating income growth rate
Company age	AGE	Difference between the year of company statistics and the year of company establishment

There is no definite formula for calculating the number of stages of the hidden layer. Therefore, when selecting an implicit layer, its reasonable range of values in equation (3) is usually calculated based on an empirical formula.

$$k = \sqrt{m+n} - a, (0 < a < 10) \tag{3}$$

Where k is the number of nodes in the hidden layer, n is the number of nodes in the input layer, and m is the number of nodes in the output layer. Therefore, the number of nodes in the hidden layer in this study is 2.

3.4 Model Design

We construct a multiple linear regression model and use BP neural network to test. We further establish equation (4).

$$EPS = a_0 + a_1 SHARE + a_2 RND + a_3 Size + a_4 Growth + a_5 AGE + \varepsilon \tag{4}$$

4 RESULT

4.1 Data Processing

In this study, we cleaned the data and tested and plotted the hypotheses using Stata 17.0 and Python 3.8.

Table 2 presents the results of descriptive statistics for all variables. Figure 2 presents that the data which correspond to normal distribution were analyzed.

Table 2: Descriptive statistics.

Variables	N	Mean	S. E	Mini	Max
SHARE	1045	0.119	0.158	0	0.662
RD	1045	0.044	0.032	0.000	0.160
EPS	1045	0.312	0.986	-3.280	3.68

Size	1045	9.519	0.498	8.341	11.73
Growth	1045	0.250	2.375	-0.777	55.04
AGE	1045	17.35	5.438	3	43

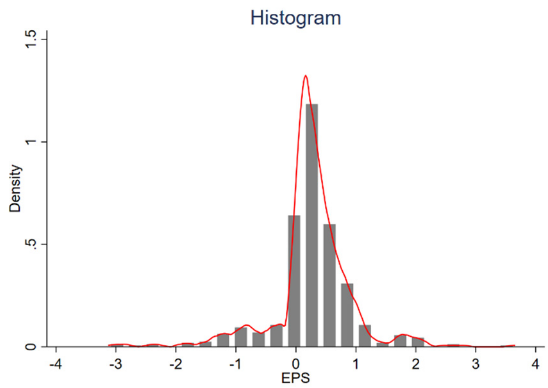

Figure 2: Normal distribution histogram.

Each variable has a different physical unit and represents a different economic significance. In this paper, to avoid large differences between the values of the variables, we have dimensionless processed the sample data according to the equation (5) and equation (6) as follows.

$$x_{ij} = \frac{(var_{ij} - \min(var_{in}))}{(\max(var_{in}) - \min(var_{in}))} \quad (5)$$

$$x_{ij} = \frac{(\max(var_{in}) - var_{ij})}{(\max(var_{in}) - \min(var_{in}))} \quad (6)$$

The results of the treatment are shown in Table 3. Furthermore, the results of correlation analysis are shown in Table 4.

Table 3: Dimensionless processing data.

Variables	N	Mean	S. E	Min	Max
SHARE	1045	0.188	0.239	0	1
RD	1045	0.258	0.179	0	1
EPS	1045	0.412	0.067	0	1
Size	1045	0.364	0.151	0	1
Growth	1045	0.019	0.049	0	1
AGE	1045	0.276	0.143	0	1

Table 4: Results of correlation analysis.

	1	2	3
EPS	1		
RD	0.235***	1	
SHARE	0.157***	0.126***	1
Size	-0.021	-0.072*	-0.245***
Growth	-0.010	-0.031	-0.031
AGE	-0.0280	-0.082*	-0.180***
	5	6	7
Size	1		
Growth	0.101**	1	
AGE	0.176***	-0.054	1

Furthermore, we use the Stata17.0 graphing tool and Python 3.8 to present the correlation between SHARE, R&D, EPS more clearly in the figures. Figure 3 shows the relationship between EPS and SHARE, which is the plotted result of Model 1, and the relationship between R&D and SHARE, which is the plotted result of Model 3. A 3D result plot of SHARE, R&D, and EPS is shown, demonstrating a visible surface in Figure 4, which is the plotted result of SHARE-R&D-EPS relationship.

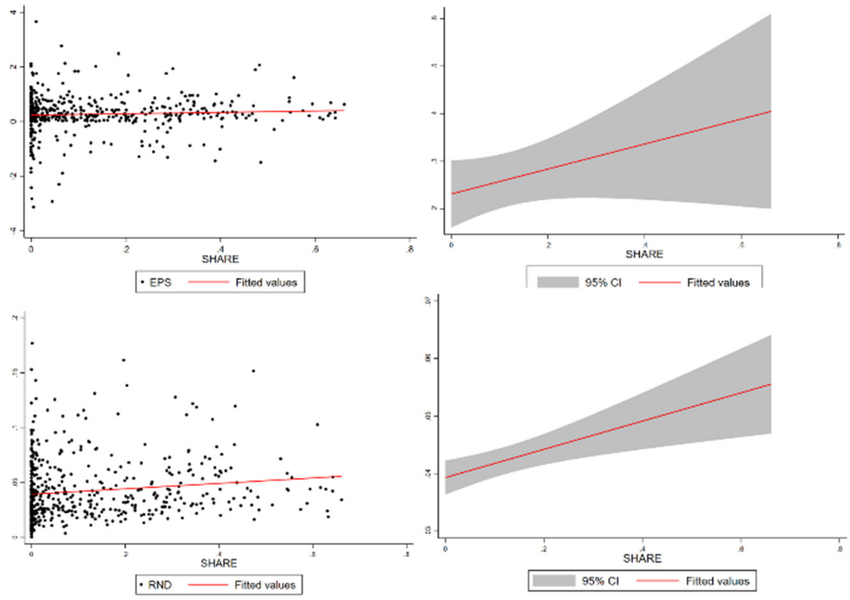

Figure 3: The correlation between SHARE and EPS and the correlation between SHARE and RND.

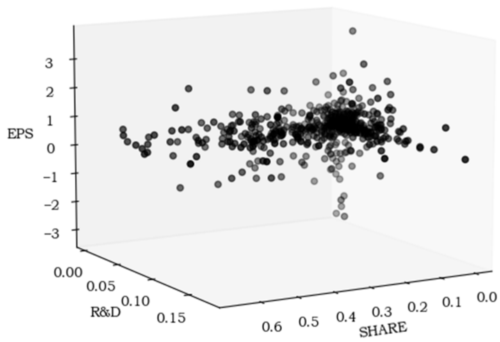

Figure 4: The SHARE-R&D-EPS relationship.

4.2 Training and Testing of Neural Network Predictive Model

In this paper, the model is analyzed using Stata 17.0, and the input layer is set to 5 nodes, the hidden layer is set to 2 nodes, and the output layer is set to 1 node. BP neural network is established after 200 iterations, and the error of its model reaches the requirements of the set criteria, that is, the corporate performance-based prediction model. The error of the network training is shown in Figure 5.

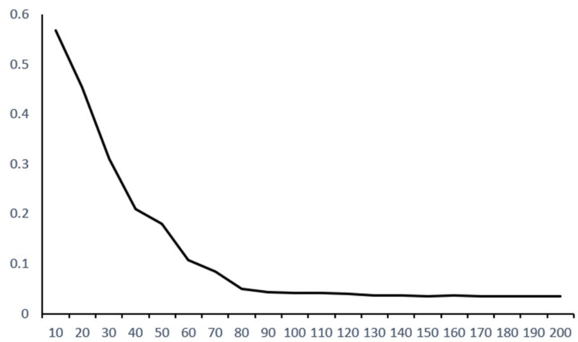

Figure 5: The error of the network training.

The "Tansig" function is selected for the activation function of the neurons in the hidden layer of the first layer and the neurons in the output layer of the second layer.

In addition, we compared the R-squared of the BP neural network-based model with that of the OLS-based model. It is found that the BP neural network model R-squared is significantly larger than the OLS method model, indicating that the BP neural network method prediction method is better than the OLS method. See Table 5 for more details.

Table 5: The compared of OLS and BP neural network.

Method	R-Squared
BP Neutral Network	0.78
OLS	0.25

In order to test whether the BP neural network predictive model has good generalization ability, the model also needs to be tested. Using the remaining 25% of the data, we performed the test. The test results are shown in Figure 6.

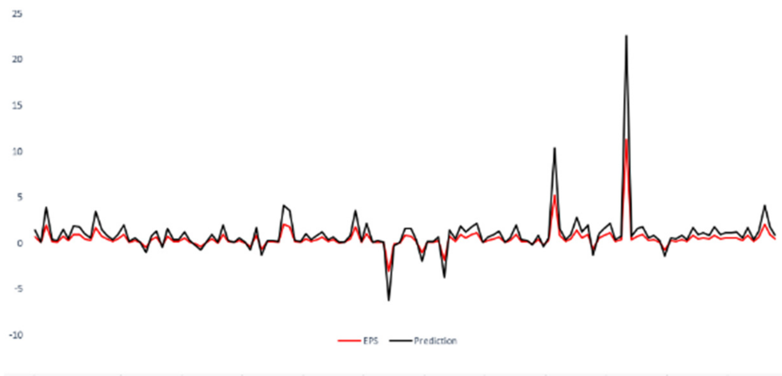

Figure 6: Test results of BP neural network predictive model.

From the Figure 6, the model trained using 75% of the data in this study as training can predict the remaining 25% of the corporate performance level very well. The relative errors of the test sets are all relatively small, implying that this BP neural network model has good generalization ability and can have good corporate performance prediction for Chinese IT-listed companies.

5 CONCLUSION AND FUTURE RESEARCH DIRECTION

5.1 Conclusion

In this paper, we add top management team characteristics to predict corporate performance, which only remedies the previous evaluation of corporate performance around economic indicators. In addition, neural networks are utilized to optimize the construction of multiple linear models compared to OLS. Furthermore, this study integrates TMT characteristics into predicting corporate performance, helping to optimize the non-economic indicators used to assess and predict corporate performance.

This study establishes a BP neural network predictive model for testing the prediction of EPS . The findings verify the positive impact of the shareholding ratio of the top management team on corporate performance. This study reveals that the amount of the principal's shareholding in the executive team as an equity incentive aligns the agent with its goals to make long-term, correct investments in R&D investment, increasing corporate performance.

From the perspective of Chinese culture, compensation represents having a higher income and a status symbol. The shareholding ratio can also bring higher satisfaction to the higher-level executive members, and the decisions are more in the hands of the executives at the higher compensation levels, so increasing the shareholding ratio of the executive team will increase corporate performance.

5.2 Future Research Direction

This study has considered the effect of top management team characteristics, but ignored the full range of economic indicators. Future research should focus on integrating top management team characteristics and economic indicators to explore the prediction of corporate performance evaluation.

In addition, this study only regarded the data before the epidemic. Future research could adopt the DID (Differences-in-Differences) method and consider whether there is a change in the prediction for corporate performance evaluation in the epidemic context.

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