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Improving Returns on Strategy Decisions through Integration of Neural Networks for the Valuation of Asset Pricing: The Case of Taiwanese Stock

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Abstract: Most of the growth forecasts in analysts' evaluation reports rely on human judgment, which leads to the occurrence of bias. A back-propagation neural network (BPNN) is a financial technique that learns a multi-layer feedforward network. This study aims to integrate BPNN and asset pricing models to avoid artificial forecasting errors. In terms of evaluation, financial statements and investor attention were used in this case study, demonstrating that modern analysts should incorporate the evaluation advantages of big data to provide more reasonable and rational investment reports. We found that assessments of revenue, index returns, and investor attention suggest that stock prices are prone to undervaluation The levels of risk-taking behaviors were used in the classification of robustness analysis. This study showed that when betas range from 1% to 5%, both risk-taking levels of investors can hold buying strategies for the long term. However, for lower risk-taking preferences, only when the change exceeds 10 percent, the stock price is prone to overvaluation, indicating that investors can sell or adopt a more cautious investment strategy.

Keywords: evaluation; back-propagation neural network; asset pricing; investor attention; risk-taking; investment strategy

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1. Introduction

The fundamental principle of financial evaluation is to estimate the reasonable stock price that should be obtained through the estimation of future cash flow. Although this method has been widely accepted and used by most analysts in their evaluation reports, there is still a no more standardized approach to cash-flow forecasting.

Classic financial theory suggests using a single-factor capital asset pricing model (CAPM) and multi-factor arbitrage models to estimate (Sharpe 1964; Ross 1976) as prediction models. Afterwards, new risk factors are proposed to estimate individual stocks or portfolio forecasting methods (Fama and French 1995; Carhart 1997). Regardless of the traditionally important fundamental analysis and technical methods, there are some existing problems. For example, long-term forecasts are required for basic analysis efficiency to reduce the risk of bias, including cash-flow risk and discount-rate risk (Campbell and Vuolteenaho 2004) and illiquidity risk (Acharya and Pedersen 2005).

The previous studies have clearly made contributions to the field of neural network technology in business (Wong et al. 1997) and finance (Wong and Selvi 1998), although neural network processing has been applied in the application areas, in terms of bankruptcy prediction of banks/firms, stock performance/selection prediction, bond trading, loan analysis, IPO pricing, portfolio selection, asset value forecasting, property values evaluation, and so on (Ahmed et al. 2022). Nevertheless, stock price forecasting and determining the timing to help decisions has always been an interesting subject for investors and institutional investors. However, the persistent problems are that there are a noticeable absence of the use of neural network in the extension models for the time series of finance and economy in terms of nonlinear times series (Tealab 2018) and highly nonlinear problems. In recent years, studies of neural network technology have led to widespread applications such as machine-learning (ML) and deep-learning technologies. Ahmed et al. (2022) explored the effect of different major subjects, and collected 348 articles from journals of Scopus indexed from 2011 to 2021, and provided the use of artificial intelligence (AI) and ML to market participants especially in financial technologies (Fintech) and finance companies for their decision-making.

In the past, data was limited, so exploration methods and technologies were also limited in their development. Now in the big-data-information environment, it is very easy to obtain a large amount of data. Artificial intelligence has become a specialism in this field and been applied to the fields of finance and accounting (Kim 2003, 2006) to investigate and predict changes in the stock index, for example, through big-data analysis (Ou and Penman 1989; Bollen et al. 2011; Wang 2002; Chang and Liu 2008; Kohara et al. 1997; Kim and Lee 2004). In stock-return forecasting, a deep-learning method for volatility in asset management is widely used (Petrozziello et al. 2022). Similar to the method of using artificial machine learning, the value of the company is evaluated through simulation and prediction. The use of linear and non-linear methods is to predict stock returns, such as decision trees, logistic regression, and BPNN (Chen et al. 2006; Pavlidis et al. 2006; Ren et al. 2006; Wang and Chan 2006; Huang et al. 2008; Lai et al. 2009; Lee 2009; Hadavandi et al. 2010; Nair et al. 2010; Chang 2011; Chen 2011; Kara et al. 2011; Khan et al. 2011; Tsai et al. 2011; Wang et al. 2011; Sun et al. 2014; Ticknor 2013; Patel et al. 2015). Neural networks, which are mainly used for information processing, are also used for exchange rates (Huang et al. 2004; Pavlidis et al. 2005). Following the trend with the evolution of technology and the appearance of big data, the financial-services industry has transformed (Königstorfer and Thalmann 2020), and its applications have allowed for to improvements in operations and efficiency (Mhlanga 2020). Goodell et al. (2021) provided an assessment of AI and ML in finance through the identification of three groups, including (1) portfolio construction, valuation, and investor behavior, (2) financial fraud and distress; and (3) sentiment inference, forecasting, and planning.

The Google Search Volume Index (SVI) has become an important tool for predicting future trends in financial markets through online behavioral patterns (Da et al. 2011). Investors also rely on the Internet for sources of financial information on transactions. Prior studies have suggested that the SVI can provide financial valuation benefits. Internet searches, for example, can help inform investors' trading decisions. People allocate their limited attention to specific interests, which ultimately improves the quality of asset valuations (Hirshleifer et al. 2011; Vozlyublennaia 2014).

This study focuses on predictive analysis, the use of the learning process of neural networks, and combines financial evaluation models to predict the optimal theoretical price. Finally, an analyst report is produced through evaluation theory and simulation prediction results.

The remainder of the paper is organized as follows: In Section 2, the neural network estimation and evaluation model is described. In Section 3, the use of the data and the examination of the results are investigated. In Section 4, numerical simulations of the evaluation model and a sensitivity analysis for the robustness of the prediction results are carried out. Section 5 gives a brief conclusion and suggestions for future research.

2. Neural-Network Estimation and Evaluation Model

2.1. Neural Network

The most commonly used method in traditional statistics is the maximum likelihood estimation, and the iterative learning mechanism of neural-like networks uses the backward transfer network model (Hecht-Nielsen 1992) to iteratively modify the weights to obtain parameters. It can be used to solve the disadvantage that the dependent variable cannot be treated as a categorical variable in the traditional regression model.

Neural-network-like (Yao 1993) content simulates the operation of biological nerves and uses intelligent learning and error correction to achieve the correct output. The main characteristics of the neural network are its ability to generate large flat areas and non-linear output, and the ability to predict multilayer structures. The processing element (PE) is the most basic unit of the neural network. The output of each processing element must be combined with the processing unit in the next layer. The sum of the output values of each processing unit is shown in the figure below.

The equation of the output value and input value of the processing unit can generally be expressed by the function of the sum of the input value and the weighted product of the unit:

$$Y_j = f(net) = f(\sum_i w_{ij} x_i + \theta_j) \tag{1}$$

where Y_j is the output signal of the neural network processing unit, x_i is the input variable, net is the integration function, θ_j is the threshold value of the unit at the neural network, w_{ij} is the knot weight between each unit of the neural network (its symbol indicates the strength of the correlation between the i-th unit in the previous layer and the j-th unit in the subsequent layer), and f is the transfer function of the processing unit of the neural network (it uses the sum of the input value input from other processing units and the weight of the knot to obtain the output value through the process of converting between units).

The back-propagation neural network (BPNN) used in this study is shown in Figure 1.

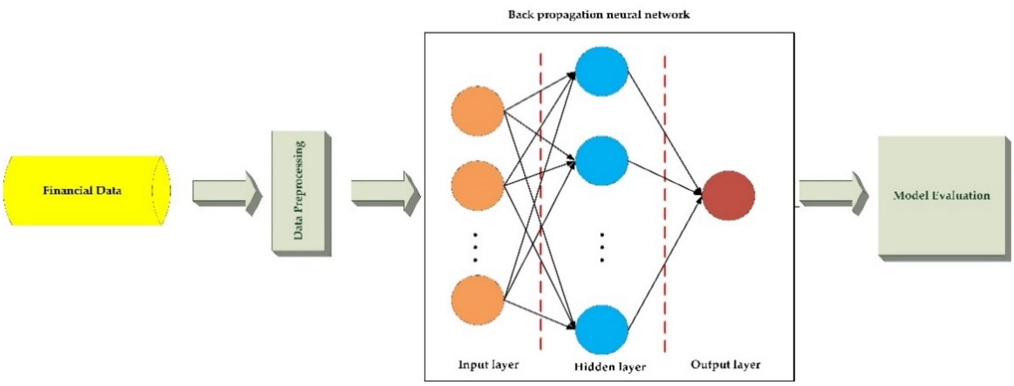


Figure 1. Back-propagation neural network.

The consideration of hidden layers is a model that can adapt to complex problems. The BPNN has a hidden layer that can simulate any continuation function. According to the process of approximating the real model, the nodes of the hidden layer with multiple dimensions are used. However, in practice, a neural network with one hidden layer and more than a thousand processing units is generally not used. Instead, it is more desirable to use more hidden layers and fewer neurons. In this study, convergence and generalization were tested as the stability criterion of the BPNN (Refenes and Azema-Barac 1994).

The learning rate has an influence on the convergence properties. The BPNN principle uses the gradient-steepest-descent method to minimize the error function. Whenever a training example is entered, the network slightly adjusts the size of the weighting value. The magnitude of the adjustment and the sensitivity function of the error function are directly proportional to the weighting value. The model is as follows:

$$\Delta W = -\eta \frac{\partial E}{\partial W}, \ E = \frac{1}{2} \sum (T_j - Y_j)^2 \tag{2}$$

where η is the learning rate, which can control the magnitude of the modification of the weight value; E is the error, if the value is larger, the quality is worse; T_j is the training process and outputs the target output value of the j-th hierarchy unit; and Y_j is the training process and outputs the inferred output value of the j-th hierarchy unit.

In the second part, we discuss the basic evaluation of finance and accounting. This is also the most commonly used evaluation method in analyst reports. The major problem is that few people can determine the growth rate of the company, that is, the change in g. Data exploration is helpful for exploration and evaluation, which are two of the main purposes of this study.

2.2. Evaluation Model

Past research has primarily measured the cost of stock in terms of ex-post realized stock returns such as CAPM. This method may be less accurate (Fama and French 1995). Generally, a simple evaluation is to predict the future income or earnings per share of the target company without providing a forecast of the company's future cash dividends. Therefore, the discounted dividend model cannot be used to estimate the company's equity cost. The discounted-cash-flow (DCF) model evaluated by financial theory is as follows:

$$V = \sum_{t=1}^{t=n} \frac{CF_t}{(1+r)^t} \tag{3}$$

where r is the discount rate and reflects the risk level of the estimated cash flow, n is the economic life of the asset, and CF is the cash flow in period t.

In this basic model, because the definition of free cash flow (FCF) and discount rate can be used to obtain the value of the company or the shareholder, respectively, the evaluation model is as follows:

$$V = \sum_{t=1}^{t=n} \frac{FCF_t}{(1+WACC)^t} \tag{4}$$

where $WACC$ is the weighted average cost of capital. It refers to the total capital cost calculated by an enterprise by weighting the cost of various long-term capital with the weight in the total capital of the enterprise. The cash flow referred to in the enterprise-evaluation model refers to the free cash flow of the enterprise after deducting all operating expenses and taxes (including investment expenses), but without deducting interest expenses (and its tax-shield effect).

In the evaluation, the future growth of the company should be considered, and the intrinsic value of the stock (Gordon's growth model) should be evaluated according to the dividends that will grow at a certain rate in the future. The multi-stage model is as follows:

$$V_0 = \sum_{t=1}^{n} \frac{FCF_i}{(1+WACC_1)^n} + \sum_{j=n+1}^{p} \frac{FCF_j}{(1+WACC_2)^j} + \frac{1}{(1+WACC_1)^n(1+WACC_2)^{p-n}} \times \frac{FCF_{p+1}}{WACC_3+g_3} \tag{5}$$

where g is the company's future growth forecast value. The g forecast is the theoretical analysis through the data of the financial database, and then the searched network database is used as the basis for the actual query, and the neural network method is used to predict.

3. Data and Results

In this study, evaluation was performed using a Taiwanese optical lens manufacturer company. The open data was from the "Taiwan Stock Exchange" (https://www.twse.com.tw/zh/, accessed on 18 October 2022), and the use of the web search volume was Google Chrome (http://www.Google.com/trends, accessed on 27 December 2019). The data covers a period from January 2011 until December 2017. Figure 2 shows the trend graphs for individual stock price returns, market index returns (Rm), and search volume index (SVI). The SVI indicates the percentage of searches for a given keyword of the total number of searches over time. We used the following Google search keywords: "Company X" for a predictive model of stock price returns. The search probability measures were converted into natural logarithms (Da et al. 2011).

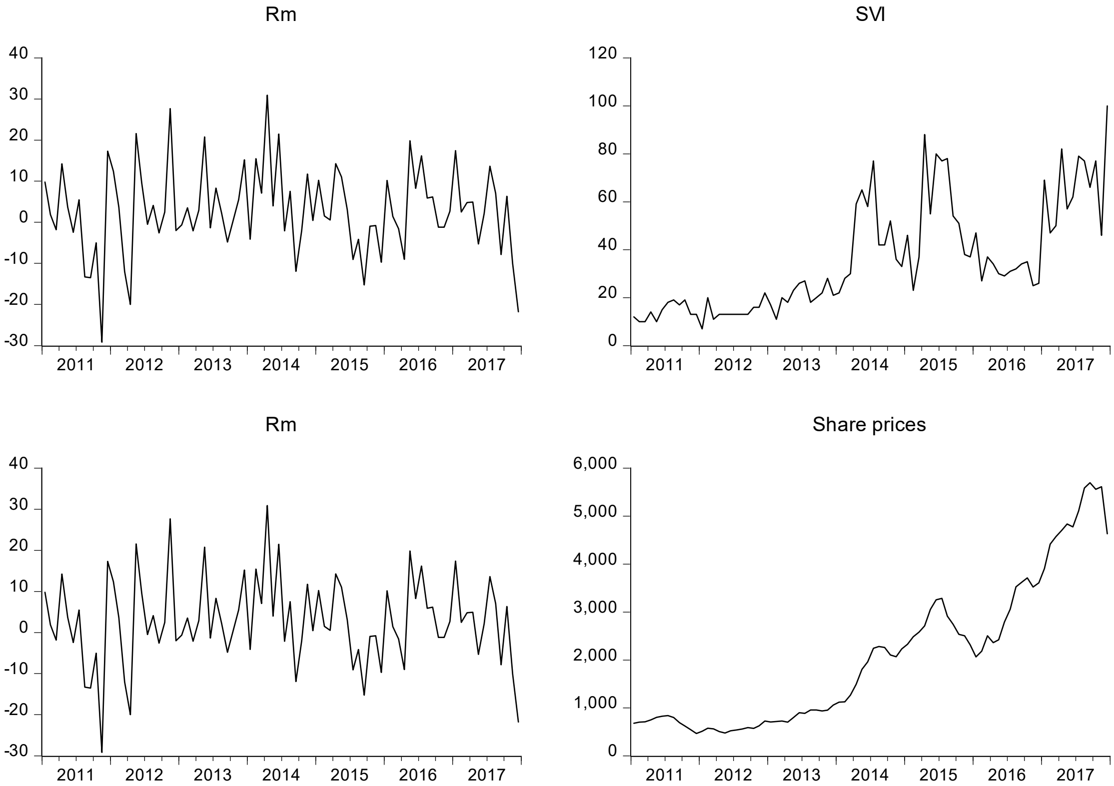


Figure 2. *Rm* is the market index; *Share prices* are the stock price; *SVI* is the search volume index.

3.1. Descriptive Statistics

Table 1 presents the descriptive statistics of the financial statement variables. Panel B, Panel C, and Panel D display quarterly summary statistics of financial indicators, including profitability, debt-paying ability and operating capacity, respectively. This study examined the sensitivities of these categories to the impact of future growth rates in valuation theory. By calculating the characteristics of each financial index data, it was found that there was no abnormal variable and the index value was a stable sequence.

Table 1. Descriptive Statistics.

	Mean	**Max.**	**Min.**	**S. Dev.**	**Skew.**	**Kur.**	**JB**	**Obs.**
Panel A: Index								
Share prices	2119.69	5830.00	418.89	1533.47	0.77	2.52	9.03	84
Rm	2.76	30.90	−29.15	10.63	−0.09	3.66	1.64	84
SVI	35.69	100.00	7.00	22.93	0.89	2.77	11.34	84
Panel B: Profitability								
Gross profit margin	0.53	0.71	0.38	0.11	0.13	1.73	1.96	28
NOPAT margin	0.38	0.49	0.22	0.07	−0.64	2.47	2.23	28
Growth of profit before tax	0.39	1.25	−0.23	0.43	0.26	2.10	1.28	28
Return on total assets	0.17	0.35	0.04	0.09	0.24	1.87	1.75	28
Return on assets	0.17	0.35	0.04	0.09	0.24	1.87	1.75	28
Return on equity	0.22	0.46	0.05	0.12	0.21	1.97	1.44	28
Operating margin	44.92	61.87	29.20	10.55	0.05	1.65	2.14	28

Table 1. *Cont.*

	Mean	Max.	Min.	S. Dev.	Skew.	Kur.	JB	Obs.
Panel C: Debt-Paying Ability								
Current ratio	310.88	458.86	194.49	58.06	0.39	3.04	0.73	28
Quick ratio	284.22	416.36	177.50	57.42	0.41	2.53	1.03	28
Operating cash-flow ratio	0.75	1.43	0.29	0.37	0.56	1.95	2.75	28
Current debt/debt	0.99	1.00	0.98	0.00	−1.65	6.74	29.01	28
Equity/assets	0.76	0.85	0.64	0.04	−0.79	4.08	4.27	28
Debt/equity	0.31	0.57	0.18	0.08	1.24	5.36	13.66	28
Panel D: Operating Capacity								
Inventory turnover	5.58	7.90	3.41	1.21	0.32	2.48	0.78	28
Accounts payable turnover	4.01	4.86	3.28	0.47	−0.07	1.96	1.28	28
Assets turnover	0.65	0.92	0.39	0.14	−0.18	2.05	1.21	28
Sell expense/sales	0.09	0.10	0.07	0.01	−0.43	2.24	1.54	28
Admin expense/sales	0.02	0.03	0.02	0.00	0.25	3.02	0.29	28

Notes: Index series are monthly data; financial report indicators are quarterly data.

3.2. BPNN Forecasting and Estimation

This study used a variety of algorithms to predict the results, estimates the theoretically set hidden layer numbers, and used the network architecture to estimate the results. It also considered different learning rates and inertia factors to simulate the final results. The following demonstrations achieved the best convergence state through a lot of time calculations and tests. If the optimal convergence state is reached, it means that all variables can effectively learn and predict the possibility of the future for searched variables, stock price returns, and growth rates. Table 2 shows the outcomes for the learning models in the training and the test sets and the optimal learning rates were selected to be 0.02 to 0.2. In each panel, the comprehensive analysis shows that learning rate is convergence and stability of the BPNN. Meanwhile, this does not mean that they are perfect models. As the results of learning rates were different between 0.02 to 0.3, the BPNN model may fall into local optimal solutions due to the changes in the initial weights and biases from the initial random numbers in a certain range (Wang and Bi 2022). However, it performed acceptably in the learning model's errors and prediction. We focus on the performance of the model that resulted from an important stage of optimization, it follows the process of forward-propagation based on the error back-propagation algorithm, and repeats the pre-set training until the expectation of MSE is obtained. A similar simulation of the working mechanism of the BPNN model has been brought forward by many studies (see Desai et al. 2019; Jiang et al. 2019; Liang et al. 2019; Yan et al. 2019).

Table 2. The network architecture results.

Term	Hidden Layers	Network Architecture	Learning Rate	Inertia Factor	MSE in Training	MSE in Testing
Panel A: *SVI* for four-quarter						
1	3	19-7-3	0.1	0.01	0.0842	0.0030
2	3	19-6-3	0.3	0.4	0.0794	0.0028
3	3	19-4-1	0.2	0.05	0.0752	0.0026
4	3	19-6-3	0.3	0.3	0.0590	0.0021
5	3	19-6-3 *	0.2	0.1	0.0528	0.0018
Panel B: *SVI* for eight-quarter						
1	3	19-6-3	0.3	0.5	0.0865	0.0030
2	3	19-6-3	0.2	0.05	0.0750	0.0026
3	3	19-6-3	0.2	0.1	0.0509	0.0018
4	3	19-7-4	0.3	0.4	0.0460	0.0016
5	3	19-4-3 *	0.2	0.04	0.0414	0.0014

Table 2. *Cont.*

Term	Hidden Layers	Network Architecture	Learning Rate	Inertia Factor	MSE in Training	MSE in Testing
Panel C: *Ri* (stock return) for four-quarter						
1	3	19-6-5	0.3	0.1	0.4676	0.0167
2	3	19-10-5	0.2	0.2	0.3967	0.0141
3	3	19-10-5	0.2	0.1	0.2771	0.0098
4	3	19-9-3	0.2	0.3	0.2655	0.0094
5	3	19-9-3 *	0.2	0.2	0.2327 *	0.0083
Panel D: *Ri* (stock return) for eight-quarter						
1	4	19-7-3	0.05	0.1	0.3586	0.0128
2	3	19-5-4	0.2	0.2	0.2427	0.0086
3	3	19-9-3	0.2	0.3	0.2352	0.0084
4	3	19-5-4	0.2	0.3	0.1987	0.0070
5	3	19-7-3 *	0.1	0.05	0.1304	0.0046
Panel E: *Ri* (revenue growth rate) for four-quarter						
1	3	19-4-1	0.02	0.03	0.0347	0.0347
2	3	19-4-1	0.03	0.02	0.0219	0.0007
3	3	19-4-1 *	0.02	0.01	0.0168 *	0.0006
Panel F: *Ri* (revenue growth rate) for eight-quarter						
1	3	19-4-1	0.02	0.03	0.0347	0.0347
2	3	19-4-1	0.03	0.02	0.0219	0.0007
3	3	19-4-1 *	0.02	0.01	0.0168 *	0.0006

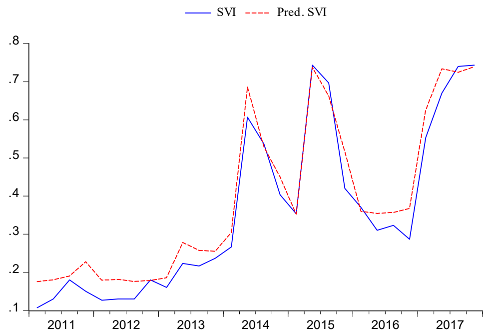
Notes: The results of the error values during training are sorted by the MSE error value from largest to smallest; * is the minimum estimated value of MSE. The training model is a modified sigmoid distribution; where the layer equals to $\sqrt{input \times output}$ and $\ln(\text{nodes}_{layer-1})$ (Refenes and Azema-Barac 1994).

In the parameter setting of the neural network, the convergence of the model prediction needs to be considered. When training a neural network, we set the training sample to repeat the learning cycle multiple times until the error converges. According to the evaluation-theory model, this study used simulation to predict the growth rate change in different periods as important evaluation information in company value evaluation. The study also used the daily data of *SVI*, *Ri* (stock return), and *Ri* (Revenue growth rate) as training and simulation estimates, and considered using four quarters and eight quarters as the company's future growth forecast as demonstrated in Figure 3. Table 3 displays the results, which show a similar trend, as evidenced by the significantly outcomes of the *Slope* set and high r^2 of the regression.

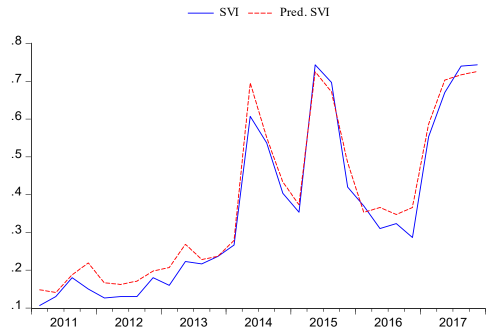
Table 3. Regression results.

Variable	Reg. (r^2)	Slope	Intercept
SVI for four-quarter	0.9901	1.0400 *	−0.0483
SVI for eight-quarter	0.9779	0.9458 *	0.0452
Ri (Stock return) for four-quarter	0.8987	0.9937 *	0.0701
Ri (Stock return) for eight-quarter	0.9039	0.8876 *	0.0701
Ri (Revenue growth rate) for four-quarter	0.9893	0.9904 *	−0.0029
Ri (Revenue growth rate) for eight-quarter	0.9958	0.9904 *	0.0198

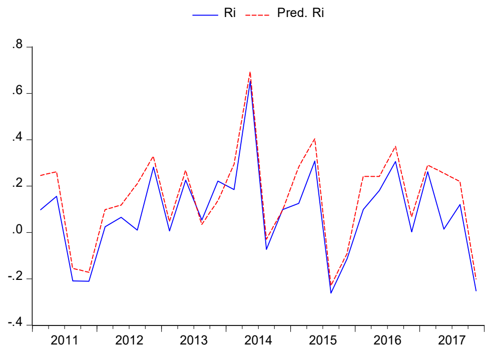
Notes: * indicates p-value < 0.001.



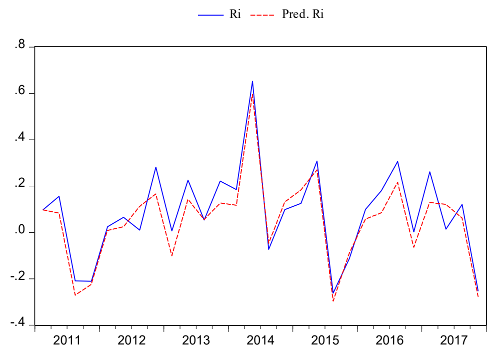
SVI for four-quarter



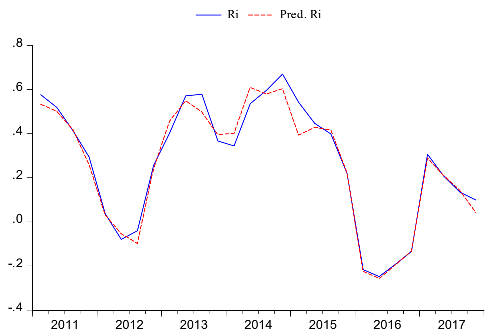
SVI for eight-quarter



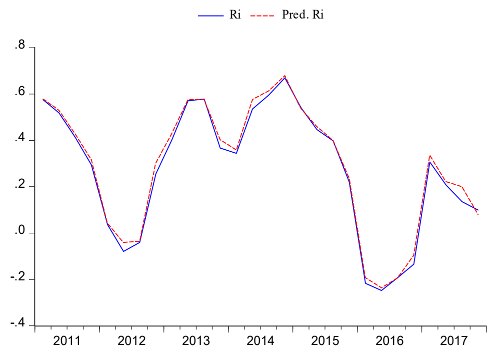
Ri (stock return) for four-quarter



Ri (stock return) for eight-quarter



Ri (revenue growth rate) for four-quarter



Ri (revenue growth rate) for eight-quarter

Figure 3. Actual and predicted trend graphs of BPNN model.

The back-propagation neural network (BPNN) used in the training and post-learning prediction for the growth ("g") results is shown in Table 4. The results show reasonable performance predictions for each indicator and help provide an alternative to computationally learning systems. Next, using all g estimation results, predictions of the models were used for the DCF evaluations.

Table 4. "g" estimation results for each season.

Periods	SVI	Stock Return	Revenue Growth Rate
2018.03	0.3529	−0.1932	0.0568
2018.06	0.3657	−0.2363	0.0854
2018.09	0.3471	−0.1933	0.2158
2018.12	0.3660	−0.0967	−0.0639
2019.03	0.5866	0.3357	0.1291
2019.06	0.7028	0.2220	0.1208
2019.09	0.7171	0.1996	0.06185
2019.12	0.7254	0.7996	−0.2763

4. Evaluation, Analysis, and Discussion

Actual evaluators, especially financial analysts, often mistakenly believe that the growth rate, g, of discounted cash flow (DCF) can be arbitrarily assumed. In fact, the data must adhere to some principles. This study believes that analysts can set the data for each stage according to the three scenarios of (1) the most optimistic, (2) the most likely to occur, and (3) the most pessimistic. Looking at the comparison between the estimated stock price and the actual stock price in the three cases, the upper and lower ranges of the stock price can be estimated. If the actual stock price falls outside the range, the evaluation analyst will have considerable confidence that the current stock is mispriced.

The key factors influencing the evaluation—changes in sales growth rate, marginal profit rate, tax rate, investment rate, return on invested capital (ROIC), WACC, n, and reinvestment rate—can all cause different degrees of impact on the estimated stock price. Sensitivity analysis helps the evaluator to make decisions about the key factors that affect the value of the enterprise and can reconfirm and collect information on the key factors.

Evaluators can test what evaluation data reflects the current stock price by changing the evaluation data. For example, the company's stock price of $250 may reflect the evaluation results of the first-stage sales growth rate of 58% and the marginal profit rate of 12%. After the evaluator understands the implicit evaluation data, he can wait for the company's future revenue and dividend interest rates. Once the revenue growth rate or marginal profit rate is different from 58% or 12%, the evaluator can judge whether the stock price of $250 is too high or too low.

4.1. *Evaluation and Calculation of Discounted Cash Flow*

In the evaluation method, we considered several important brokerage analyst reporting methods, such as professional reports of investment analysts (internal analysts) of Standard & Poor's, Merrill Lynch, and JP Morgan. These important evaluation indicators include different general financial analyses. Before the evaluation, this study established an evaluation model using the basic assumptions and theoretical basis in the evaluation. The company's basic financial cash flows are shown below. The data sources are calculated based on the financial report data. Table 5 is the discounted free cash-flow statement, expressed in each year.

Table 5. DCF valuation.

Indicator	FY11	FY12	FY13	FY14	FY15	FY16	FY17
Panel A: DCF Valuation Assumptions							
Risk-free rate (%)	1.36	1.36	1.36	1.36	1.21	1.04	1.04
Market risk premium (%)	−20.46	11.21	15.36	10.42	−8.29	13.03%	18.96
Beta	1.43	1.35	1.55	1.42	1.68	1.91	1.76
Debt/value of capital (%)	20.47	26.05	21.15	24.33	24.53	20.84	20.28
Cost of debt (%)	0.03	0.02	0.03	3.85%	0.00	0.00	0.00
Years of growth (%)	94.44	4.37	−20.29	119.44	134.69	−30.27	36.49
Years of growth (%)	28.54	7.29	72.29	102.27	24.27	−5.89	14.26
Panel B: Key DCF Drivers							
Sales growth (%)	29.41	25.57	36.67	66.99	21.96	−13.45	9.88
EBIT margin (%)	36.52	33.93	41.92	50.14	52.19	58.43	60.16
NOPAT margin (%)	74.74	69.93	82.96	83.16	74.54	53.08	47.87
Net fixed assets turns (%)	4.19	4.57	8.54	8.36	5.39	5.61	4.81
Net WC turns (%)	2.41	3.5	2.43	2.33	1.91	2.01	1.68
ROIC (%)	20.87	17.88	24.89	31.84	28.76	23.42	22.41
EPS	38.57	41.3	71.81	144.34	179.93	169.32	193.49

Notes: Cost of debt (%) is the cost of debt after tax, which is equal to the interest-bearing debt ratio × (1 − tax rate); NOPAT margin (%) is the return on operating assets, which is equal to the net operating income/operating assets; net fixed assets turns (%) is the turnover rate of fixed assets, which is equal to the net operating income/net fixed assets; net WC turns (%) is the turnover rate of working capital, which is equal to the net operating income/cash flows from operations; the return on invested capital is equal to earnings before interest and tax (EBIT) × (1 − tax rate)/invested capital.

4.2. Evaluation Results and Judgement

In this study, the BPNN model was used for simulation and prediction and was evaluated through a learning process of algorithms and simulation results. This study tested three indicators for forecasting, including search-volume indicators, returns, and revenue growth rates, and completed analysis and evaluation reports. As shown in Table 6, the results of each case analysis show that the estimates included in the search-volume indicators were the best, followed by the revenue growth rate, and finally the stock price return. The simulation verification also found that the short-term (based on one year) prediction accuracy rate was as high as 0.891. The long-term (up to two years) was consistent with the stock price highs of the past two years and could be used as a reference for investors' evaluation.

Table 6. BPNN model for the results of prediction and judgement.

Periods	Real Price	Pred. Price	Pred. Gaps	Judgement
2018.03	3237.65	2159.456	−0.3330	Underestimated
2018.06	4339.42	2769.627	−0.3618	Underestimated
2018.09	3571.21	2970.950	−0.1680	Underestimated
2018.12	3158.58	3823.144	0.2104	Overestimated
2019.03	4519.28	4383.435	−0.0301	Underestimated
2019.06	3787.35	4617.363	0.2192	Overestimated
2019.09	4450.00	4835.738	0.0866	Overestimated
2019.12	4995.00	5176.731	0.0363	Overestimated

Notes: "Pred. Gaps" indicates the percentage of predicted and actual gaps.

4.3. Sensitivity Analysis

The stock price predicted by the BPNN model may lead to evaluation errors, causing investors or analysts to make wrong decisions and suffer losses. Mispricing also leads to managers and investors having problems of corporate governance. Within a reasonable forecast interval, we analyzed the sensitivity and difference of the price to give a reasonable assessment of the price. We used daily data and monthly data and check whether there is a significant difference from the predicted value. Considering the delay in the forecast of the time effect, we also used rolling data to make predictions. Beta can be considered as a changing factor in market risk. We tested whether the observations of the most volatile first 10% and the most stable last 10% of the market would affect the difference in predictions. Sensitivity analysis is shown in Tables 7 and 8.

Table 7. Sensitivity results for daily, monthly, and rolling data.

Periods	Daily	Pred. Gaps	Monthly	Pred. Gaps	Rolling (Daily)	Pred. Gaps
2018.03	3675.56	−0.412 ***↓	3559.81	−0.393 ***↓	3675.56	−0.412 ***↓
2018.06	3825.74	−0.276 ***↓	3888.40	−0.288 ***↓	3751.93	−0.262 ***↓
2018.09	4540.51	−0.346 ***↓	4390.31	−0.323 ***↓	4029.23	−0.263 ***↓
2018.12	3273.68	0.168 ***↑	3253.55	0.175 ***↑	3830.40	−0.002 ↓
2019.03	3980.65	0.101 ***↑	4172.15	0.051 ↑	3857.36	0.136 ***↑
2019.06	4106.97	0.124 ***↑	4019.86	0.149 *↑	3899.42	0.184 ***↑
2019.09	4012.00	0.205 ***↑	4171.81	0.159 ***↑	3916.11	0.235 ***↑
2019.12	4577.90	0.131 ***↑	4633.33	0.117 ***↑	4000.36	0.294 ***↑

Notes: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. ↑ indicates overestimated; ↓ indicates underestimated.

Table 8. Sensitivity results for beta.

Periods	Beta Top_10%	Pred. Gaps	Rolling Top_10%	Pred. Gaps	Beta Last_10%	Pred. Gaps	Rolling Last_10%	Pred. Gaps
2018.03	3571.09	−0.395 ***↓	3571.09	−0.395 ***↓	3958.63	−0.454 ***↓	3958.63	−0.454 ***↓
2018.06	3202.45	−0.135 ***↓	3372.59	−0.179 ***↓	4303.99	−0.357 ***↓	4147.01	−0.332 ***↓
2018.09	4953.13	−0.400 ***↓	3925.78	−0.243 ***↓	3734.14	−0.204 ***↓	4001.29	−0.258 ***↓
2018.12	3182.44	0.201 ***↑	3733.06	0.024 ↑	3338.70	0.145 ***↑	3828.44	−0.001 ↓
2019.03	4266.30	0.027 ↑	3830.01	0.144 ***↑	3195.91	0.372 ***↑	3715.49	0.180 ***↑
2019.06	4548.75	0.015 ↑	3955.79	0.167 ***↑	3608.06	0.280 ***↑	3696.53	0.249 ***↑
2019.09	4111.43	0.176 ***↑	3978.97	0.215 ***↑	4116.47	0.175 ***↑	3759.52	0.286 ***↑
2019.12	4373.57	0.184 ***↑	4030.12	0.285 ***↑	4936.67	0.049 ***↑	3913.06	0.323 ***↑

Notes: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. ↑indicates overestimated; ↓indicates underestimated.

4.4. Further Discussion and a Robust Test

Table 9 is a robustness test that examines the relationship between market fluctuations and individual stock returns. The risk-taking behaviors, including higher risk-taking levels and lower risk-taking levels, were considered in the robustness analysis and are reflected in their attitudes toward risk (Kahneman and Tversky 1979). As risk-taking behaviors of investors' decision-making (Bekaert et al. 2009), it reflects investors' choices of expected return levels in investment decisions. In fact, risk appetite refers to the willingness of investors to take risks (Chan and Lakonishok 2004; Qadan and Jacob 2022). β can be used to measure the degree to which the individual stocks invested are affected by systemic risks. When the beta is greater than 1, the return (value at risk) of the invested stock is more volatile than the market fluctuation, and vice versa. In this study, we assumed that higher risk-taking-level investors consider a positive β change of 1% to 10%, while lower risk-taking-level investors set a negative β change of 1% to 10%. In the interactive relationship test, we considered the relationship between future growth and changes in shareholders' equity. The setting WACC_1% represents a 1% change in the weighted average capital cost, and G_1% represents a 1% increase in growth rate. From Table 9 it can be found that for higher risk-taking investors, on average, when the beta changes by 1 to 10 percent, the evaluation showed that the stock price was undervalued, and the values were all less than 1. For the lower risk-taking investors, when the beta changed by 1 to 5 percent, the evaluation also showed that it was undervalued, and when the beta change exceeded 10%, it showed that the stock price is overvalued. The results reveal that a new aspect links the value premium (Qadan and Jacob 2022) and pricing evaluation with investors' risk appetite.

Table 9. Robust test of the changes in Beta.

Types	Higher Risk-Taking Levels			Lower Risk-Taking Levels		
	Beta+1%	Beta+5%	Beta+10%	Beta-1%	Beta-5%	Beta-10%
Panel A: Using Revenue Growth with BPNN						
G_1%	1.161 *	1.138 *	1.110 *	1.173 *	1.198 *	1.231 *
G_5%	1.186 *	1.162 *	1.134 *	1.198 *	1.224 *	1.258 *
G_10%	1.218 *	1.193 *	1.164 *	1.230 *	1.257 *	1.292 *
WACC_1%	1.158 *	1.146 *	1.131 *	1.165 *	1.178 *	1.196 *
WACC_5%	1.059 *	1.049 *	1.036 *	1.065 *	1.077 *	1.092 *
WACC_10%	0.955	0.946	0.935	0.960	0.970	0.983
Panel B: Using Stock's Return with BPNN						
G_1%	0.924	0.905	0.882	0.933	0.954	0.981
G_5%	0.949	0.929	0.906	0.959	0.980	1.008 *
G_10%	0.980	0.960	0.936	0.991	1.013 *	1.042 *
WACC_1%	0.920	0.910	0.897	0.925	0.937	0.952
WACC_5%	0.843	0.834	0.823	0.848	0.858	0.871
WACC_10%	0.762	0.754	0.745	0.766	0.775	0.786
Panel C: Using SVI with BPNN						
G_1%	0.920	0.903	0.883	0.928	0.946	0.970
G_5%	0.945	0.927	0.907	0.954	0.972	0.997
G_10%	0.976	0.958	0.937	0.986	1.005 *	1.031 *
WACC_1%	0.916	0.907	0.897	0.920	0.930	0.943
WACC_5%	0.843	0.836	0.827	0.847	0.856	0.867
WACC_10%	0.767	0.760	0.753	0.770	0.778	0.787
Panel D: A Summary						
Mean	0.971	0.957	0.939	0.979	0.995	1.016 *
S.D.	0.136	0.132	0.127	0.139	0.143	0.150

Note: The value is the estimated value relative to the accuracy of the evaluation. * Indicates that the stock price is overvalued, and its value is greater than 1. If less than 1, it indicates that the stock price is undervalued.

5. Conclusions

The purpose of this study was to evaluate the company's equity value, which is the most important valuation method of financial theory. Traditionally, an evaluation method using only financial statements may not be able to accurately reflect the actual value of the company. Therefore, considering the concerns of market investors regarding the company's operations, the search volume can represent investors' concerns about the company and some of the factors affecting the market. In this study, we use the BPNN method and evaluation theory and examine the sensitivity of its evaluation. The main contributions of this study are: first, it adopts the self-learning network methods and predictions to achieve prediction capabilities by using the multi-layer architecture of backward transitive neural networks and incorporating financial statements and search-volume evaluation methods; second, it effectively finds the best valuation and growth rate and reasonably predicts the short-term and long-term changes; third, its rigorous data analysis and convergence tests ensure the rationality of the evaluation; and finally, it completes a reasonable evaluation report and process. This study proves that the BPNN method has a good forecasting ability to predict the stock price. When the beta range is between 1 and 5 percent, the stock price appears to be reasonably undervalued, and it is prone to overvalue when the market exceeds 10%. For both higher and lower risk-taking investors, it can be used as a reference for long-term buying signals. For lower risk-taking investors, it is recommended that the stock price is overvalued, indicating that it can be sold or a more cautious investment strategy should be undertaken.

Future research may consider the evaluation in diversified portfolios or use more big data for pricing or diversification for safe-haven assets. Considering the behavioral biases for mispricing, the data may consist of a balanced industry-level dataset covering longer periods. In data processing, it may be possible to filter data through multi-factor analysis or other more advanced analysis models, such as the family of deep-learning models. Regarding the results, the optimal parameters selected should be considered for overfitting issues from the limited data (Brownlee 2018).

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