Post-Merger Performance Prediction

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Abstract

In this 21th century, merger and acquisition is becoming the trends for most businesses to growth—to meet the limitation of timing and technology change. This study built artificial neural network models to predict post-merger performance of merged companies. Three types of models—horizontal, vertical, and total—were built. A new approach integrating a statistical technique, backward STEPDISC, and feedforward neural networks, was developed. To compare and evaluate the performance of this proposed method, statistical methods were also constructed.

Results obtained by using the combination of backward STEPDISC and feedforward neural network method significantly outperformed other methods in predicting post-merger performance.

【Keywords】：merger and acquisition, post-merger performance, corporate growth, artificial neural networks.

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INTRODUCTION

During the 1970s, mergers and acquisitions became common methods of growth for companies, and in the late 2000s, this form of growth activity reached its peak in popularity. That popularity has continued to the present times. Because of this prevalent method of corporate growth, there have been several studies to determine why companies merge with or acquire other companies. Researchers also wanted to analyze the impact mergers and acquisitions had on the stock market as well as on the performance of the firms involved.

Growth is one of the most important factors in becoming and maintaining status as a successful company or business. Growth is an aspect that can be an indicator of a firm's performance and can also attract management talent while increasing capital. Growth also increases opportunities for employees and allows businesses to gain access to new products and a better labor market pool.

There are two ways a company can grow. The first procedure is through internal growth, which can be done by acquiring productive assets. A second way a company can grow is through external growth, which is accomplished by acquiring productive and profitable businesses. Although internal and external growth methods essentially have the same objectives, the external growth tends to attract more attention from stockholders, management, and professionals such as investment groups, academics, and politicians.

A merger means creating one firm from two or more firms, and an acquisition occurs when one firm buys control of a target firm. Mergers and acquisitions must be negotiated by the management teams of both firms and they must be approved by the owners and shareholders of both companies. The management of the acquiring firm might elect to negotiate directly with the target firm's shareholders through tender offers.

Based on the relationship between the merger and acquisition participants, mergers can be classified as horizontal, vertical, or conglomerate. There is a horizontal when both firms are in a similar business. When two firms are in the same business but are at different stages of production, the merger is vertical. Firms that are completely unrelated in the merger and acquisition actions are known as a conglomerate merger.

There are many reasons for mergers (Stevens, 1973) including: (1) to accomplish corporate growth, (2) to avoid bankruptcy by the target firm, and (3) to gain diversification. Furthermore, Copeland and Weston (1983), addressed other reasons for mergers and acquisitions: (4) tax consideration, (5) management inefficiency, (6) an undervalued company, (7) synergistic purposes, (8) market power or antitrust considerations, and (9) strategic realignment to changing environment. Dietrich and Sorensen (1984) also discussed another logical reason for a merger and acquisition: (10) shareholders of the target firm have windfall gains. Given today's merger wave and the advantages involved in a merger, it is worthwhile to predict the post-merger performance of this business movement.

The common methodology used to develop prediction models of the past research includes two phases: variable selection and model building. In the variable selection phase, several statistical methods (factor analysis, stepwise of discriminant analysis, and stepwise of logistic regression analysis) were used to select significant input variables for a model. With the selected variables, statistical approaches—such as discriminant analysis, logistic regression, and probit analysis—were used to build the prediction models. A major drawback of these statistical model building methods is that the selection procedure of each of the variable selection methods requires a criterion to identify significant variables; but the criterion, in general, might not be directly related to the performance of the prediction model generated, based upon the variables selected according to the criterion.

The objective of this study is to build artificial neural network models to predict whether or not a company will be a success merger or acquisition. An approach of simultaneously considering variable selection and model building, a method integrating backward STEPDISC and feedforward neural networks, was developed. Each model for horizontal, vertical, and total mergers. (Conglomerate model was not considered in this study because the set of data of conglomerate mergers is small.) To compare and evaluate the performances of these models, statistical models were also developed.

LITERATURE REVIEW

This section discusses previous studies pertaining to the merger and acquisition of companies. Considerations included techniques used for selecting accounting, financial, and market variables as input to the predictive models and the methodologies of model building of the previous studies. Three types of studies will be discussed: (1) multiple discriminant analysis, (2) logistic regression analysis, and (3) artificial neural networks. Several of these studies that will be discussed might not appear to be specifically related to this study; however, they contribute to the development of merger and acquisition theories.

Multiple Discriminant Analysis Studies

Stevens (1973) used MDA to study the target firms that merged in 1966. Eighty firms, including 40 target firms that were listed in the Federal Trade Commission (FTC) and 40 nontarget firms that were pair-matched based on total assets, were used to develop the MDA model. Factor analysis was used to reduce the variables to six factors and to overcome the high multicollinearity problem. Six factors, which accounted for 82.5 percent of the total variance, were: (1) leverage, (2) dividend policy, (3) liquidity, (4) profitability, (5) activity, and (6) price earnings. To develop the MDA model, six variables, with one variable for each factor, were used to build the model. Using the stepwise of MDA, four of the six variables were found to be significant to the model. The variables found to be significant to the model were: (1) earnings before income and taxes/sales, (2) net working capital/assets, (3) sales/assets, and (4) long-term liabilities/assets.

The model's classification accuracy rate was 70 percent for the training sample, where a higher accuracy rate was obtained with the target firms. A validation was used on two samples of 20 firms each, taken from 1967 and 1968; a 70 percent classification accuracy rate was achieved.

Wansley (1984) discussed 12 discriminant models that were used to examine the sensitivity of MDA to a variable selection; 20 variables were selected to represent 10 factors. Forty-four firms that merged in 1975 and 1976 were selected from the COMPUSTAT research file. Twelve samples of 44 firms remaining nonmerged in 1982 were selected and matched at fiscal year-end in the same reporting period. The major objectives of Wansley's study were to determine if different discriminant models built to classify target firms consistently contained the same variables and had the same level of classification accuracy. Classification accuracy rates were 75 percent for the best model and 61.4 percent for the worst model.

Barnes (1990) reviewed the literature on predicting target firms for mergers and acquisitions and focused on its contrast to the efficient market hypothesis, which states that the current stock prices reflect what is knowable from the study of historical prices and trading volume. This study addressed the stability problem of using ratios and the efficiency of using an industry-relative ratio on data obtained on United Kingdom firms.

As a result of using factor analysis, Barnes found five ratios that explained 91.5 percent of the variance. These ratios were: (1) quick assets/current liabilities, (2) current assets/ current liabilities, (3) pre-tax profit margin, (4) net profit margin, and (5) return on shareholders' equities. A linear MDA model was developed. This model correctly classified 68.5 percent of the firms in the training sample. On the validation sample, the classification ability increased to 74.4 percent.

Logistic Regression Analysis Studies

Dietrich and Sorensen (1984) used a logistic regression analysis to predict target mergers. They defined the merger decision as any other capital asset acquisition, and merger targets as a source of cash flow to the buyer firms. The following ratios were used to build the logistic model: (1) price earnings, (2) profit margin, (3) long-term debt/total assets, (4) time interest earned, (5) dividends/earnings, (6) capital expenditures/total assets, (7) asset turnover, (8) current ratio, (9) market value of the equity, and (10) trading volume in the year of acquisition.

In order to account for industry variations, this study was limited to four industries, and the variables were transformed to relative deviations from industry averages. Industries selected for this study were in the areas of food and beverages, chemicals, electronics, and transportation. Data were collected from the COMPUSTAT research file using 24 target firms that were merged between 1969 and 1973, and a matched (by industry SIC code) sample of 43 nontarget firms, which were not targets for mergers within a two-year period following 1973, was used. There were 22 firms used in the validation model. This model correctly classified 92.5 percent of the firms into target and nontarget in the training sample. A 91-percent accuracy rate correctly classified the validation sample into target firms and nontarget firms.

Palepu (1986) investigated the methodological flaws of past research and suggested improvements. He identified three major imperfections that would make the reported prediction accuracy unreliable. The statistical shortcomings Palepu criticized included: (1) a sampling flaw for the training model, (2) sampling flaws for validation, and (3) the use of arbitrary cutoff probabilities. In his study, to prevent the statistical flaws, he developed his own unbiased methodologies. He used logistic regression analysis to select the variables and to develop the model. Variables used were specifically determined to test the following six hypotheses for merger: (1) inefficient management, (2) growth-resource mismatch, (3) industry disturbance, (4) size, (5) market-to-book value, and (6) price-earnings. Palepu concluded the model that consisted of all variables used to test the above six hypotheses was statistically significant, although it had a low explanatory power. These findings are contradictory to earlier studies that were believed to have had higher explanatory power.

Artificial Neural Network Studies

Tam and Kiang (1990) compared the predictive accuracy of a bank failure prediction models constructed by using MDA, logistic regression analysis, k-nearest-neighbor, and neural networks. A back-propagation based neural networks was used. Exploratory experiments were employed to decide on the topology of the network, and two networks, one with no hidden neurons (one-layer) and the other with 10 hidden neurons (two-layer), were constructed.

One hundred sixty-two (81 failed and 81 nonfailed) banks were used for training the networks. Two test groups, one with 44 (22 failed and 22 nonfailed) banks and one with 40 (20 failed and 20 nonfailed) banks, were used to validate the networks for a 1-and 2-year periods, respectively. Nineteen variables, consisting of four factors, were employed and used in the models. The factors included capital adequacy, asset quality, earnings, and liquidity. The two-layer network model with 19 input neurons, 10 hidden neurons, and 1 output neuron provided the highest accuracy rate. According to Tam and Kiang (1990), neural networks offer a competitive alternative, especially under the following conditions: (1) the samples are within group clusters, (2) the sample’s data need an adaptive adjustment, and (3) there are no assumptions on distribution and functional form of the sample's input variables.

Fletcher and Goss (1993) reported that they applied the logistic regression analysis and the back-propagation based neural networks to bankruptcy data. Data from 18 bankrupt companies were pair-matched to 18 non-bankrupt companies. The independent variables used were current ratio, quick ratio, and income ratio.

Training efficiency, prediction accuracy, variance in errors, and prediction risk were the criteria used to compare the performances of the two techniques. The two-layer networks with 3, 4, 5, 6, and 7 hidden neurons were implemented. The two-layer network with 4 hidden neurons was selected as the most efficient prediction model. In terms of prediction accuracy, variance in errors, and prediction risk, it achieved 82.4 percent, 2 percent, and 0.143, respectively.

According to Fletcher and Goss (1993), their findings will bridge the gap between pure statistical methods and neural networks. Their research demonstrated neural networks as being a possible alternative to more traditional methods of estimating causal relationships in data. In addition, it offered a new model of computational capabilities to the business practitioner. They concluded that back propagation neural networks outperformed logistic regression analysis in this problem.

Yoon, Swales, and Margavio (1993) compared a discriminant analysis (DA) model with a back propagation based neural network model in predicting stock price performance, and they examined their capabilities and limitations in classifying data.

The data set was gathered from two magazines, Fortune 500 and Business Week's Top 1000. The final data set consisted of 151 firms with four independent input variables, including: (1) price/earnings, (2) price/sales, (3) current ratio, and (4) return on equity. These companies were classified into two groups— those whose stock prices performed well and those whose stock prices performed poorly, based on market value or total return. Seventy-six companies were used in the training phase, and 75 firms were used to validate the performance of the techniques.

In their study, Yoon, Swales, and Margavio (1993) found: (1) the increase in the number of hidden layers improved the model, (2) the increase in the number of hidden neurons, up to a certain limit, would also improve the model, and (3) the performance of the artificial neural network model was better than the DA model. A two-layer network, containing four input neurons, two output neurons, and seven hidden neurons, was the best model for this problem. The neural network model outperformed the DA model by 23 percent in the training phase and 13 percent in the validation phase. Findings also revealed that the current ratio had a negative influence on the model. On the other hand, return on equity, price/earning, and price/sales were positive indicators of stock price performance.

Post-Merger Performance Studies

Bradley et al. (1988) investigated 236 successful tender offers completed between 1963 and 1984 in which the target and the buyer firms were listed on the New York Stock Exchange (NYSE) or the American Mercantile Exchange (AMEX) at the time of acquisition. Their study found that there was a synergistic gain created by the tender offers, representing a 7.4-percent increase in the combined wealth of the stockholders of the target and buyer companies, with more of the gains captured by the target firms' stockholders. This finding is compatible with Bradley et al. (1983), but contradictory to Roll (1986).

Healy et al. (1992) observed the post-merger cash flow performances of the 50 largest U.S. public companies that merged between 1979 and 1984. This study found that most merged firms showed significant improvements in asset productivity relative to their industries in operating cash flow returns. The study also demonstrated a strong relationship between post-merger increases in operating cash flows, and abnormal stock returns at the merger announcement. This improvement is not due to the reduction of long-term capital expenditures and is stronger exclusively for firms with highly overlapping businesses. These results are inconsistent with Ravenscraft and Scherer (1987) and Herman and Lowenstein (1988) studies that claimed merged firms after takeover did not demonstrate improved operating cash flows.

Agrawal et al. (1992) examined the post-merger performance of 937 mergers and 227 tender offers between NYSE buyers and NYSE/AMEX targets from 1955 to 1987.

This study found that, after adjusting for the firm size effect and beta risk, the stockholders of the buyer firms experienced a statistically significant wealth loss of about 10 percent over 5 years after the merger completion date. The study claimed this loss was possibly due to the fact the market was slow adjusting to takeovers.

This finding is consistent with Roll (1986).

METHODOLOGY

This section focuses on the following subject areas: (1) sample selection, (2) input variable identification, (3) variable selection method, (4) model building method, and (5) proposed model building methods. Sample selection will describe the procedure for selecting appropriate data in this study. The input variable identification will address the procedure for identifying potential input variables for the prediction models. The subjects of variable selection method and model building methods are the two phases of the traditional two-phase methods for general model building problems. The last subject area will describe the proposed model building methods for this research.

Sample Selection

For this study, the sample used for building the models consisted of those firms acquired during the period from January 1, 1981, through December 31, 1990. This time frame was chosen because of the business merger and acquisition activities, which combined assets of billions of dollars, and the need for a large sample size. Firms that were acquired during the period of January 1, 1991, through December 31, 1993, were used for validation samples. A total of 439 target firms (242 horizontal targets and 197 vertical targets) were selected from the Mergerstat Review 1981 to 1993, the 1994 version of COMPUSTAT industrial data file, and COMPUSTAT research file. In the post-merger performance prediction models, a combination of the target and buyer firms was used as the sample.

Input Variable Identification

Financial ratios represent the primary source of input data for a number of merger prediction studies, including Simkowitz and Monroe (1971), Deakin (1972), Stevens (1973), Belkaoui (1978), Dietrich and Sorensen (1984), Palepu (1986), and Bartley and Boardman (1986 and 1990). Two major reasons for using ratios are: (1) financial ratios were used to study the effects of size on the financial variables under investigation, and (2) the use of financial ratios supports comparability among enterprises and other firms within the same industry (Barnes, 1987).

The variables used in this study were chosen based on (1) their acceptance in the literature, (2) their possibilities to influence the takeover event, and (3) availability in the COMPUSTAT research file. These variables were collected based on two-year averages of the annual financial statements from the years before and after the merger event.

Variable Selection Method

Determining a dependable set of variables was critical in generating good prediction models and reducing the costs and training times to reasonable levels.

Intuitively, a model that had more input variables yielded better results. However, in practice, this was not always true. In this study, the technique used to determine the significant variables that yielded better input to the prediction models was the backward STEPDISC procedure of Statistical Analysis System (SAS) for Windows.

Model Building Method

Recent accounting and financial study has applied artificial neural networks to a variety of prediction models in an attempt to develop prediction models that offered a higher degree of accuracy. Studies involving tasks, such as bond ratings (Dutta and Shekhar, 1988), bank failures (Tam and Kiang, 1990, 1992), and price changes of the S&P 500 Index (Barr and Mani, 1994), have incorporated artificial neural networks. Results of these recent studies indicated that, in most cases, the artificial neural network models performed as well as statistical models. Most of the previous studies employed a variety of statistical methods in an attempt to derive models capable of predicting merger targets. Most of them stressed the importance of fitting statistical models appropriate to the tasks. An introduction to artificial neural networks and a discussion of the applicability of these models to the target merger prediction tasks will be presented.

Artificial Neural Networks

Artificial neural networks (ANNs) provide promising applications in the fields of engineering, science, business, and others. ANNs were originally inspired from biological neural systems, such as the human brain, which can deal with a large amount of data and provide high levels of success in decision-making processes. ANNs also can solve major complex tasks through their substantially parallel computing mechanisms. Based on the paraphrasing of Hecht-Nielsen, Caudill (1990) described an ANN as "a computing system that builds up by a number of simple and highly interconnected processing units, which processes the external inputs by its dynamic state response." An ANN has two basic elements: processing units (neurons) and connections. Each neuron is a simple computation device that receives input signals from other neurons. Based on the input, it either activates an output signal or it does not activate an output. The output signal is then transmitted as an input signal to other neurons along the connections between neurons.

Three principal components that comprise an ANN are: (1) topology, the architecture of the ANN that arranges the neurons and their connections; (2) the transfer or activation function, a control structure that dictates when neurons will activate; and (3) a learning algorithm, which is a training rule that controls changes to the strength of connections among neurons relative to the neuron's input.

Feedforward Neural Networks Method

A feedforward neural network (Masters, 1993) contains neurons organized into two or more layers—an input and an output—each with at least one neuron. Neurons in the input layer are purely theoretical constructs. The input neurons do not process, and their outputs are determined by the network input vector. Normally there are one or more hidden layers between the input and output layers. Outputs from neurons in the previous layer are given as inputs to neurons in the following layers. The output of each neuron in the network is a function of that neuron's input.

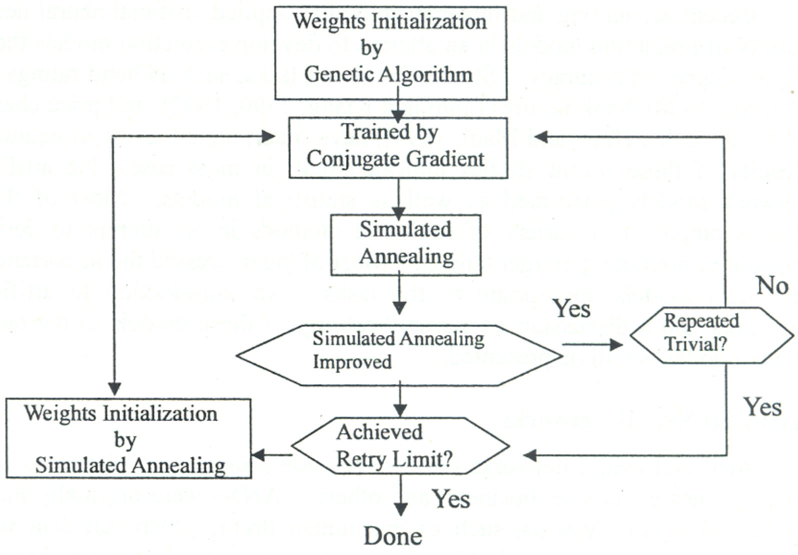

Figure 1 Flow Chart of the Feedforward Neural Network Trained By Conjugate Gradient Algorithm

In summary, this learning algorithm (figure 1) starts with weights initialized using the genetic algorithm. Then the conjugate gradient algorithm is applied to minimize the mean-squared error. When the minimum is found, it uses simulated annealing to try to break through what might be a local minimum. If simulated annealing reduces the error, then it again uses the conjugate gradient algorithm. This process is repeated until several iterations consecutively produce only a small (trivial) improvement. If that happens, or if simulated annealing causes no improvement at all, it will use simulated annealing to generate a whole new set of starting weights, and then again will try the conjugate gradient algorithm (Masters, 1993, p.409).

The Feedforward Neural Network's Architecture

A number of experiments were run in order to identify the most favorable combination of neurons in the input layer, the hidden layer, and the output layer. For each experiment, actual data from the sample were input. The desired output (with two output neurons) was a 0 and 1 or a 1 and 0, depending on whether or not the firm had been declared a merger. In this study, the feedforward neural network's program used was written in C++ by Masters (1993). This is a general purpose program for training and validation. A single threshold of 0.5 was used to determine whether or not the output will be a nontarget or a target. An output of a given sample, generated by the neural network, will be classified as a nontarget if the result of the first neuron's output is greater than or equal to 0.5, and the result of the second neuron's output is less than 0.5. When the result of the first neuron's output is less than 0.5, and the result of the second neuron's output is greater than or equal to 0.5, the sample is classified as a target. The sum of the first neuron's output and the second neuron's output is equal to 1.0. The objective of these experiments was to determine the network architecture that forms the basis for all target-predicting uses.

After trying several architectures, the two-layer network (with a configuration of 15 hidden neurons, 2 output neurons, and the number of input neurons depending on the number of input variables) was selected for all the networks in predicting a target merger. The stopping criterion was assigned a quit error equal to 0.5 percent (figure 2).

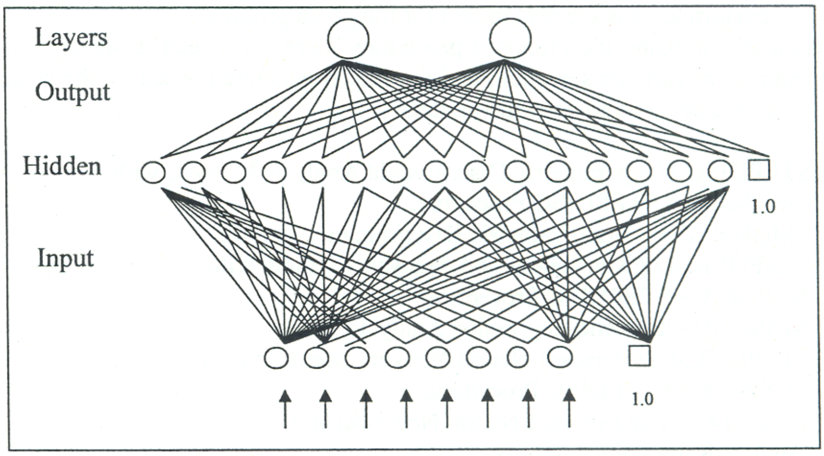

Figure 2 The Feedforward Neural Network for Target Merger Prediction Model

Proposed Model Building Methods

In the literature, most studies in this area separate the variable selection phase and the model building phase. As mentioned previously, the major drawback of this traditional two-phase method is that the criteria used in variable selection, in general, are not directly related to the performance of the prediction model built, based upon the variables selected according to the criteria. For instance, if the STEPDISC procedure is used to select the variables, the criterion used to determine variables to enter or leave a model might include F-statistic, Wilk's Lambda, or Average Squared Canonical Correlation (ASCC). Suppose the F-statistic is selected as the criterion, and an F value is specified. Then only the variables with F values larger than the specified F value will be selected for the following model building. There are two problems in implementing this procedure: first, how is the F value specified? Secondly, how will it be known which selected variables will result in a good model in model building? These problems result from the previously mentioned drawback of the two-phase methods.

Therefore, in this research, an approach that simultaneously considers variable selection and model building in building a model is proposed. The variable selection method is defined as Method A and the model building method as Method A'. Given a problem with a given set of input variables, the procedure of the proposed approach is as follows:

Step 1: Run Method A' to build a model, based on the given set of variables, and measure the performance (accuracy of prediction) of the model.Let the performance be the best performance.

Step 2: Run Method A, and eliminate the variable with the worst value of a specified criterion.

Step 3: Run Method A' to build a model, based on the set of variables that resulted from Step 2, and measure the performance of the model.If the performance is better than the best performance, then update the best performance and go to Step 2; otherwise, the model with the best performance is the best model for the given problem.

It is clear that, using the proposed procedure, there is no need to specify values for any criterion in variable selection, and the model generated based on the selected variables is expected to be an accurate model.

(1) STEPDISC-Nonparametric Discriminant Analysis Method, with
Method A = STEPDISC Procedure,
Method A' = Nonparametric Discriminant Analysis;
(2) STEPDISC-Logistic Regression Analysis Method, with
Method A = STEPDISC Procedure,
Method A' = Logistic Regression Analysis;
(3) STEPDISC-Feedforward Neural Network Method, with
Method A = STEPDISC Procedure,
Method A' = Feedforward Neural Network; and
(4) Logistic Regression Analysis.

EMPIRICAL RESULTS OF THE EXPERIMENTS

This section discusses the results obtained by using the four methods described in previous section. The target merger prediction models are developed, and each model includes the following types of models: horizontal, vertical, and total merger. Each section also discusses the sample firms, input variables, empirical results, and comparison of the performance of the proposed methods and the traditional two-phase methods.

Sample Firms

In this section, a defined target/buyer firm is used to represent the sample throughout this research. A target/buyer firm is defined as a combination of the target merger and its buyer firm before the merger event, and this is used to predict the post-merger performance. The financial ratio of this target/buyer firm is used as the input variable for the model predicting. These ratios are calculated based on the weighted average of the target and its buyer's total assets. For example, to determine the current ratio of a target/buyer firm, the weighted average of the target and the buyer's current ratio are used (Healy et al., 1992).

A merger is considered successful when the operating cash flow of the after-merged firm is higher or equal to the operating cash flow of the target/buyer. The operating cash flow is defined as sales, minus cost of goods sold and selling and administrative expenses, plus depreciation and goodwill expenses. This measure is deflated by the market value of assets, which is market value of equity plus book value of net debt (Healy et al., 1992). In this research, the cash flows were taken for a two-year average, based on the two years before and the two years after the merger was announced.

Sources of the target and the buyer firms were collected from The Mergerstat Review. The sample consisted of 100 horizontal target/buyer firms, 10 companies for each year, from 1981 to 1990 (100 targets and 100 buyer firms). There were 100 vertical target/ buyer firms, 10 firms for each year, from 1981 to 1990 (100 targets and 100 buyer firms). The target firms are similar to the target firms in predicting target merger. For validation, the sample consisted of 60 horizontal target/buyer firms and 39 vertical target/buyer firms for the years 1991 and 1992. Just as the sample in the target merger prediction, there were firms with incomplete data. The firms with missing data were eliminated.

The final sample for this research, after deleting firms with missing data consisted of 70 target/buyer firms for horizontal mergers; 29 for successful mergers and 41 for failing mergers; 58 target/buyer firms for the vertical mergers; 27 for successful mergers and 31 for failing mergers; 128 target/buyer firms for the total merger, with 56 successful mergers and 72 failing mergers. For validation purposes, there were 36 horizontal target/buyer firms, 20 successful mergers and 16 failing mergers, 27 vertical target/buyer firms, 7 successful mergers and 20 failing mergers, 63 total target/buyer firms, 27 successful mergers, and 36 failing mergers. The final target firms of this sample might not be the final sample in predicting target merger.

Input Variables

In this research, eight input variables were used to predict the event of a success or failure of a merger. These ratios were chosen from previous research based on (1) their possibility to influence the success or failure of a merger and (2) their availability on the COMPUSTAT research file, version 1994.

To illustrate the success and failure status of the target/buyer company, a dichotomous (zero-one) dependent variable was chosen. Each successful firm was appointed a dependent variable of 0, and each failure firm was specified a value of 1. These ratios are presented in the Table 1.

Table 1. Potential Input Variables for Target Merger Prediction

Variable	Description	Reference
Dependent Variable:		
Merger Status	Binary variable. A non-target merger company is assigned 0, a target merger company is assigned 1.	
Independent Variables: *		
CR	CURRENT RATIO	Belkaoui [1978], Dietrich & Sorensen [1984], Barnes [1990], Bartley & Boardman [1990]
NWC_TA	NET WORKING CAPITAL / TOTAL ASSETS	Stevens [1973], Rege [1984]
NI_TEQ	NET INCOME / TOTAL EQUITY	Belkaoui [1978], Palepu [1985], Barnes [1990], Bartley & Boardman [1990]
LTD_TA	LONG-TERM DEBT / TOTAL ASSETS	Stevens [1973], Belkaoui [1978], Wansley & Lane [1983], Dietrich & Sorensen [1984]
SALE_TA	SALES / TOTAL ASSETS	Stevens [1973], Rege [1984], Dietrich & Sorensen [1984], Barnes [1990]
MKPR_EPS	MARKET PRICE PER SHARE / EARNING PER SHARE	Simkowitz & Monroe [1971], Wansley & Lane [1983], Palepu [1985], Bartley & Boardman [1990]
MV_BV.	MARKET VALUE PER SHARE / BOOK VALUE PER SHARE	Wansley & Lane [1983], Palepu [1985]
CD_ERN	CASH DIVIDENDS / EARNING	Simkowitz & Monroe [1971], Rege [1984], Dietrich & Sorensen [1984], Bartley & Boardman [1990]
EBIT_SALE	EARNING BEFORE INTERESTS AND TAXES / SALES	Stevens [1973], Dietrich & Sorensen [1984], Barnes [1990]
CF_TEQ	CASH FLOWS / TOTAL EQUITY	Belkaoui [1978], Bartley & Boardman [1990]
CAPEX_TA	CAPITAL EXPENDITURE / TOTAL ASSETS	Dietrich & Sorensen [1984]
CSTR_CSO	COMMON STOCK TRADED / COMMON STOCK OUTSTANDING	Simkowitz & Monroe [1971], Dietrich & Sorensen [1984], Bartley & Boardman [1990]

* Data collected from COMPUSTAT tapes version 1994. Based on two years average, the year before the merger.

Empirical Results

The performance measurements applied to the training and validation samples are presented in the same format as that in the target merger prediction. After the firms with missing data were eliminated, the final sample for training samples consisted of 70 horizontal target/buyer firms, 58 vertical target/buyer firms, and 128 total target/buyer firms. The final sample for validation samples consisted of 36 horizontal target/buyer firms, 27 vertical target/buyer firms, and 63 total target/buyer firms.

Table 2 and table 3 show summary of the selected variables for post-merger performance prediction and the comparison accuracy rate by using the proposed methods with the accuracy rate generated by using the traditional two-phase methods. By comparing the accuracy rate using the proposed methods with the use of the traditional two-phase methods, Table 3 confirms that the proposed methods, in general, are better than the traditional two-phase methods in predicting a merger success. In the training samples, the proposed methods performed better than the traditional two-phase methods. Examining the validation results shows that the vertical model of STEPDISC-nonparametric discriminant analysis, the horizontal and total models of STEPDISC-logistic regression analysis, and the horizontal and total models of logistic regression analysis of the proposed methods were more successful than the traditional methods. This superiority is even more apparent in the STEPDISC-feedforward neural network method, where its models have more variables and are significantly better than the STEPDISC-feedforward neural network models of the traditional method (16 percent).

Table 2. Summary of the Selected Variables for Target Merger Prediction Models By Using Proposed Methods

Variables	Horizontal				Vertical				Total			
	STEPDISC			Logit	STEPDISC			Logit	STEPDISC			Logit
	npar	logit	fnn		npar	Logit	fnn		npar	Logit	Fnn	
CR					*	*	*	*	*	*	*	*
NWC_TA											*	
NI_TEQ	*	*	*	*	*	*	*	*	*	*	*	*
LTD_TA					*	*	*	*			*	
SALE_TA	*	*	*	*					*	*	*	*
MKPR_EPS	*	*	*	*	*	*	*	*			*	
MV_BV			*		*	*	*	*			*	
CD_ERN			*			*	*	*			*	
EBIT_SALE	*	*	*	*	*	*	*	*	*	*	*	*

CF_TEQ			*				*		*	*	*	*
CAPEX_TA	*	*	*	*	*	*	*	*	*	*	*	*
CSTR_CSO	*	*	*	*	*	*	*	*	*	*	*	*

Table 3. Comparison of the Target Merger Prediction Models Obtained by Using Proposed Methods and the Traditional Two Phase Methods

		Training(accuracy)		Validation(accuracy)	
		propose	2-phase	Propose	2-phase
STEPDISC-npar	H	55.9%	55.9%	53.4%	53.4%
	V	62.4%	53.0%	51.2%	52.0%
	T	55.8%	53.4%	54.6%	49.1%
STEPDISC- Logit	H	61.5%	61.5%	41.4%	41.4%
	V	67.1%	65.1%	52.9%	52.1%
	T	61.6%	58.9%	50.2%	52.5%
STEPDISC-fnn	H	100%	99.3%	90.8%	82.2%
	V	100%	100%	85.12%	70.3%
	T	100%	99.7%	93.9%	88.8%
Logit	H	61.5%	61.5%	41.4%	41.4%
	V	67.1%	65.1%	52.9%	52.1%
	T	61.6%	61.3%	50.2%	51.9%

CONCLUSIONS

In this study, an approach integrating backward STEPDISC and feedforward neural networks was developed for building prediction models for post-merger performance. This method differs from the traditional two-phase methods: first, it simultaneously considers the two phases, variable selection and model building, when generating models; secondly, a variable is selected based on its contribution to the accuracy rate of the prediction model, instead of on some statistical criteria, such as significant level of the variable. In order to evaluate the performance of the proposed method, according to the same ideas, three other methods, backward STEPDISC and nonparametric discriminant analysis, backward STEPDISC and logistic regression analysis, and logistic regression analysis, were developed and applied to the candidate problems.

Three types of models, horizontal, vertical, and total, were generated for each of the post-merger performance models. Four methods were applied to each of the three models. The results showed that the method integrating backward STEPDISC and the feedforward neural networks significantly outperformed the other methods for all models. The prediction accuracy rate of the method for post-merger performance prediction models ranged from 77 percent to 85 percent. This is highly superior to the prediction accuracy rate reported in the literature. These results demonstrate that this method is satisfactory for real-world applications.

REFERENCES

1. Agrawal, A., Jaffe, J.F., and Mandelker, G.N., "The Post-Merger Performance of Acquiring Firms: A Reexamination of an Anomaly," The Journal of Finance, Vol. 47(4), 1605-1621 (September, 1992).
2. 2.Barnes, P., "The Analysis and Use of Financial Ratios: A Review Article," Journal of Business Finance and Accounting, Vol. 14(4), 449-461 (Winter, 1987).
3. Barnes, P., "The Prediction of Takeover Targets in the U.K. by Means of Multiple Discriminant Analysis," Journal of Business Finance and Accounting, Vol. 17(1), 73-84 (Spring, 1990).
4. Barr, D.S., and Mani, G., "Using Neural Nets to Manage Investments," AI Expert, 16-21 (February, 1994).
5. Bartley, J.W., and Boardman, C.M., "Replacement Cost-Adjusted Valuation Ratio as a Discriminator Among Takeover Target and Nontarget Firms," Journal of Economics and Business, Vol. 38, 41-55 (1986).
6. Bartley, J.W., and Boardman, C.M., "The Relevance of Inflation Adjusted Accounting Data to the Prediction of Corporates Takeovers," Journal of Business Finance and Accounting, Vol. 17(1), 53-72 (Spring, 1990).
7. Belkaoui, A., "Financial Ratios as Predictors of Canadian Takeovers," Journal of Business Finance and Accounting, Vol. 5, 93-107 (Spring, 1978).
8. Bradley, M., Desai, A., and Kim, E.H., "Synergistic Gains from Corporate Acquisitions and Their Division between the Stockholders of Target and Acquiring Firms," Journal of Financial Economics, Vol. 21, 3-40 (1988).
9. Brealey, R.A.; Myers, S.C.; Marcus, A.J.; Financial Management , Mc Graw Hill,566-590（2003）.
10. Brigham, E.F.; Ehrhardt, M.C.; Financial Management Theory and Practice, 10th ,South-Western, 969-1015（2002）.
11. Caudill, M., Neural Networks Primer, Miller Freeman Publications, San Fransisco, California (1990).
12. Collins, R.A., and Green, R.D., "Statistical Methods for Bankruptcy Forecasting," Journal of Economics and Business, Vol. 34, 4, 349-354 (1982).
13. Copeland, Thomas E., and Weston, Fred J., Financial Theory and Corporate Policy, Addison-Wesley, Reading, MA (1983).
14. Dietrich, J. Kimball, and Sorensen, Eric, "An Application of Logit Analysis to Prediction of Merger Targets," Journal of Business Research, Vol. 12, 393-402 (1984).

15. Elgers, P.T., and Clark, J.J., "Merger Types and Shareholder Return: Additional Evidence," Financial Management, 66-72 (Summer, 1980).
16. Fletcher, D., and Goss, E., "Applications Forecasting with Neural Networks: An Application Using Bankruptcy Data," Information and Management, Vol. 24, 159- 167 (1993).
17. Gilbert, E.S., "On Discrimination Using Qualitative Variables," Journal of The American Statistical Association, 1399-1412 (December, 1968).
18. Glantz, S.A., and Slinker, B.K., Primer of Applied Regression and Analysis of Variance, McGraw-Hill, New York, NY (1990).
19. Grimm, W.T. and Co., Mergerstat review, Chicago, IL (1981-1993).
20. Hand, D.J., "A Comparison of Two Methods of Discriminant Analysis Applied to Binary Data," Biometrics, Vol. 39, 683-694 (September, 1983).
21. Hansen, J.V., and Messier, W.F., "Artificial Neural Networks: Foundations and Application to a Decision Problem," Expert Systems With Applications, Vol. 3, 135-141 (1991).
22. Healy, P.M., Palepu, K.G., and Ruback, R.S., "Does Corporate Finance Improve after Merger?," Journal of Financial Economics, Vol. 31, 135-175 (1992).
23. Hocking, R.R., "The Analysis and Selection of Variables in Linear Regression," Biometrics, Vol. 32, 1-49 (1976).
24. Joachimsthaler, E.A., and Stam, A., "Four Approaches to the Classification Problem in Discriminant Analysis: An Experimental Study," Decision Sciences, Vol. 19, 322- 333 (1988).
25. Kennedy, J.J., and Bush, A.J., An Introduction to the Design and Analysis of Experiments in Behavioral Research, University Press of America Inc., Lanham, MD (1985).
26. Klecka, W.R., Discriminant Analysis, Sage, Beverly Hills, CA (1980).
27. Lamalie Associates, Dun's Business Month, 107 (Jan. 1982).
28. Mandelker, G., "Risk and Return: The Case of Merging Firms," Journal of Financial Economics, 121-144 (December, 1974).
29. Masters, T., Practical Neural Network Recipes in C++, Academic Press, San Diego, CA (1993).
30. McClelland, T.L., Rumelhart, D.E., and the PDP Research Group, Parallel Distributed Processing, The MIT Press, Cambridge, MA (1986).
31. Minsky, M., and Papert, S Perceptrons, The MIT Press, Cambridge, MA (1969).
32. Palepu, K.G., "Predicting Takeover Targets," Journal of Accounting and Economics, Vol. 8, 3-35 (April, 1986).
33. Qin, S.Z., Intergration and Comparison of Neural Networks and Conventioanl Modeling Techniques, Unpublished Ph.D. Dissertation, University of Maryland College Park MD, (1992).
34. Rege, U.P., "Accounting Ratios to Locate Take-over Targets," Journal of Business Finance and Accounting, Vol. 11(3), 301-311 (Autumn, 1984).
35. Roll, R., "The Hubris Hypothesis of Corporate Takeovers," Journal of Business, Vol. 59(2), 197-216 (1986).
36. Ross, S.A.; Westerfield, R.W.; Jaffe, J.; Corporate Finance, 7th, Mc Graw

Hill, 816-847（2005）.

37. Simkowitz, M.A., and Monroe, R.J., "A Discriminant Analysis Function for Conglomerate Targets," Southern Journal of Business, 1-16 (November, 1971).
38. .Stevens, Donald L., "A Multivariate Analysis," Journal of Financial and Quantitative Analysis, 149-158 (1973).
39. Tam, K.Y., and Kiang, M., "Predicting Bank Failures: A Neural Network Approach," Applied Artificial Intelligence, Vol.4, 265-282 (1990).
40. Tam, K.Y., Kiang, M., "Managerial Applications of Neural Networks: The Case of Bank Failure Predictions," Management Science, Vol 38(7), 926-947 (July, 1992).
41. U.S. Bureau of the Census, Statistical Abstract of the United States, Washington, D.C. (1988-1995).
42. Wansley, J.A., "Discriminant Analysis and Merger Theory," Review of Business and Economic Research, 77-85 (Fall, 1984).
43. Yoon, Y., Swales, G.S., and Margavio, T.M., "A Comparison of Discriminant Analysis Versus Artificial Neural Networks," Journal of Operation Research Society, Vol. 44(1), 51-60 (1993).
44. Zmijewski, M.D., "Methodological Issues Related to the Estimation of Financial Distress Prediction Models," Journal of Business, Finance and Accounting, 59-82, (Supplement, 1984)