4. FINANCIAL INFORMATION FRAUD RISK WARNING FOR MANUFACTURING INDUSTRY - USING LOGISTIC REGRESSION AND NEURAL NETWORK

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Abstract

This study aims to use financial variables, corporate governance variables, and cash flow variables to construct financial information fraud warning models for the manufacturing industry, and applies logistics regression and back propagation neural network (BPNN) to determine the accuracy rate of identifying normal company samples and fraudulent company samples. In a ratio of '1:2', this study collects the data of 96 fraudulent company samples and 192 normal company samples, over a period of 3 years (a total of 288 samples) for prediction. The results indicate that debt ratio and shareholding ratio of board directors are two important financial variables for the identification of manufacturing industry frauds. Logistic regression has better identification capacity than BPNN in both cases of normal and fraudulent company samples. This study provides a set of correct and real-time financial information fraud warning models for the manufacturing industry, which can predict financial information frauds by observing the changes of various financial variables and shareholding ratio of the board directors in real-time. These findings can serve as a reference to financiers and the manufacturing industry for establishing credit policies.

Keywords: financial information fraud warning models, Back Propagation Neural Networks, manufacturing industry, credit policy

JEL Classification: G32, C45

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1. Introduction

The manufacturing industry has a dominating role in the global economy, according to the World Bank (2009), the output of the manufacturing industry accounted for approximately 18% of the global GDP in 2008. The manufacturing industries in China, the U.S., and Europe account for about 33%, 14%, and 25% of the global share, respectively. As the manufacturing industry is the source of the daily life goods and materials, the manufacturing industry will continue to play an important role in global economic development, regardless of the economic environment. Thus, when large-scale manufacturers are involved in frauds, and thus, cannot carry out normal operations, there would be great impact on the economy and stock market. At present, the global manufacturing industry is dominated by small and medium enterprises (SMEs), which have less financial controls and inferior accounting systems than large-scale enterprises, and are prone to financial statement frauds. To strengthen fraud controls and management systems, the U.S. and other countries have enacted regulations, such as Sarbanes-Oxley Act, Federal Sentencing Guidelines, to increase the responsibility of the management regarding fraud risks. This is sufficient to suggest that fraud risk management has become a trend. For the prevention of manufacturing industry frauds, in addition to the external legislation and the establishment of goods enterprise internal control, causes for frauds are usually traceable. Therefore, it is necessary to design and construct objectively and scientifically a set of financial information fraud warning models for the manufacturing industry.

As the financial statement is the most direct tool to present the overall performance of an enterprise, financial statements are often used as a financial distress warning assessment tool (Mensah, 1984; Gentry *et al*., 1987; Beaver, 1996; Wu, 2004). However, the frequent financial statement frauds involving small and medium manufacturers seem to suggest that traditional financial distress warning systems are unable to effectively detect financial information frauds. Hence, related studies have applied other indicator variables to construct new warning models that better detect fraud risks (Dechow *et al*., 1996; Beasley, 1996; Ward and Foster, 1997; Abbott *et al*., 2000). Therefore, this study employs the concepts of financial distress warnings and enterprise bankruptcy predictions as reference for the construction of financial information fraud risk warning models in the manufacturing industry.

Early studies focused on Beaver (1966) and Altman (1968) and the introduction of univariate and multivariate discriminant analysis (MDA) to assess whether the financial condition is robust. Related studies have focused on the forecast of different model, such as logistic model and back propagation neural network (BPNN) (Martin, 1977; Ohlson, 1980; Zmijewski, 1984; Zavgren, 1985; Coats and Fant, 1993). The univariate model cannot take into account multivariate changes. Models constructed by MDA cannot measure the probability of risk occurrence. However, the independent variables used by logistic regression models can be abnormal, and such models are suitable for non-linear analysis. In addition, the application of BPNN complies with the characteristics of non-linear and non-structural reality, and has a high degree self-learning and differentiation capability. Hence, logistic regression and BPNN methods are gradually recognized and applied, in particular, in the fields of financial distress warning and stock price prediction (Altman *et al*., 1994; Ahn *et al*., 2000; Shively, 2003; Black and McMillan, 2004; Jasic and Wood, 2004; Rapach and Wohar, 2005). Therefore, this study uses specific financial indicators, variables including corporate governance and cash flow to construct a set of financial information fraud warning models, and predict the possibility of manufacturing industry financial information fraud by using logistic regression and BPNN. It also compares the prediction accuracy rates of the two methods. This paper is organized as follows. Section 2 introduces the theoretical background. The model construction and implementation are shown in Section 3. An empirical study is presented in Section 4. Finally, discussion and conclusions are given in Section 5.

2. Literature review

Recently, the exposure of fraudulent financial reporting caused business fraud that made a great impact on global financial market. However, business fraud not only included the financial fraud, but also there are some fraudulent behavior usually occurs in employee. Based on Statement on Auditing Standards No. 53 (SAS NO.53), the business fraud events included the employee fraud and management fraud. The management fraud usually denote the financial statement fraud, and the higher management level, the more difficult the effective detection of accountants. Employee fraud is the misappropriation of assets. It usually occurs in the asset management of the employee, and can be audited by effective internal control.

In addition, according to SAS No. 82, the risk of fraudulent misstatement divided into fraudulent financial reporting and misappropriation of assets. Misappropriation of assets included that susceptibility of assets to misappropriation and controls (These involve the lack of controls designed to prevent or detect misappropriations of assets). The risk factors of fraudulent financial reporting included management's characteristics and influence over the control environment, industry conditions, operating characteristics and financial stability. Based on the above description, the financial fraud is the most common type of business fraud.

In the development process of traditional financial distress warning models, Beaver (1966) first constructed a crisis-warning model with the univariate method, however, the univariate method could not take into account the multivariate changes. Therefore, Altman (1968) further used the MDA in the construction of a crisis-warning model, which was named the Z-score model. Moreover, in the model constructed, the related variables involved have received considerable attention by both academics and practitioners. Some studies have been specified financial variables (Loebbecke *et al*., 1989; Bell *et al*., 1991; Platt and Platt, 2002; Foreman, 2003; Chi and Tang, 2006), and other related research focus the various corporate governance variables were integrated into the financial distress warning (Beasley, 1996; Dechow *et al*., 1996, Abbott *et al*., 2000; Bell and Carcello, 2000; Sharma, 2004; Wolfe and Hermanson, 2004; Shih *et al*., 2008; Wang *et al*., 2010).

In addition, Beaver (1966) was the first scholar to use statistical methods to discuss enterprise financial distress, as well as the first to use a cash flow ratio to detect business crisis warnings. Largay and Stickney (1980) integrated cash flow of operational activities into a bankruptcy-warning model in a case study. Gombola and Ketz (1983) extended the samples to cover all industries, using the cash flow of the operational activities to predict enterprise financial distress. Gentry *et al*. (1985) used MDA, probit, and logistic methods in bankruptcy warning empirical studies, and found that cash flow variables from operational activities could increase model validity (Casey and Bartczak, 1985; Foster, 1997; Cochran *et al*., 2006; Wang *et al*., 2010).

Nevertheless, a MDA-constructed model was still unable to measure effectively the crisis probability. The empirical study results suggested that logistic regression is better than the probit model in terms of prediction accuracy, thus, logistic regression is considered a data analysis method that can effectively construct warning models (Martin, 1977; Ohlson, 1980; Zmijewski, 1984). According to its characteristics, logistic regression is mainly to address problems in the classification of data by variables. The occurrence of manufacturing industry frauds requires dual classification variables, and thus, and it is suitable to use logistic regression for prediction.

Moreover, real world, non-linear relations exist in between variables, and it is difficult to present such relations by general mathematical models, while the neural network of the artificial intelligence field is able to solve various non-linear and non-structural problems. Based on the study of the brain and neural system, BPNN is an information processing technology of a group of data composed of input and output data to establish a relation system between the two. The model can be applied in the estimation, prediction, decision-making, diagnosis, and construction of non-linear models, which accepts variables of various types as input. Its network learning model, high degree of self-learning, and differentiation capacity has been recognized by scholars from various fields (Zobel *et al*., 2004; Lu *et al*., 2006; Wang *et al*., 2007; Niaki and Abbasi, 2007, Hwarng, 2008; Lin *et al*., 2008; Chen and Wang, 2009), and then, was gradually extended to the business field in the 1990s, on topics such as financial distress warning, stock price prediction, and loan risk warning (Cao *et al*., 2005; Becerra *et al*., 2005; Tseng *et al*., 2008; Tsai *et al*., 2009; Chen and Du, 2009). Past studies suggested that the prediction capability of the neural network is actually better than the traditional statistical methods (Malhotra *et al*., 1999; Salchenberger *et al*., 1992; Chen and Huang, 2003; Baesens *et al*., 2005; Wang, 2009). This study mainly uses financial indicators, corporate governance, and cash flow variables to construct the manufacturing industry financial information fraud warning models, using logistic regression and BPNN for model construction and fraud warning, respectively, and discussing the prediction capacity.

3. Methodology

3.1. Sample selection and data source

Data selection of this study is mainly based on the annual reports of companies in Taiwan's manufacturing industry, with applications of integrated financial statements as additional conditions for sample selection. Most studies on financial information fraud model adopted the matching ratio of 1:1, namely one fraud sample to one normal sample (Beaver, 1966). This study considered practical situations, and to avoid the dilution of normal samples by oversampling, which may lead to sampling errors of the selection basis (Zmijewski, 1984), it increased the number of normal company samples to improve model fitness. A total of 96 manufacturers with financial information fraud from 1998 to 2008 were selected (abnormal company samples), and 192 normal companies (normal company samples) of similar capital scale were selected for comparison. The ratio of normal samples to those with financial information fraud was 1:2, for the construction of warning models.

The data were sourced from the Taiwan Economic Journal (TEJ), the top ten commercial banks in Taiwan, Market Observation Post System, Investors Protection Center, the major financial information fraud cases published by the Financial Supervisory Commission, Executive Yuan, and judgments from the jurisprudence database of the Judicial Yuan. Data were sourced for a period of three years, starting from the year of financial information fraud exposure t, namely t, $t-1$, $t-2$. Normal company samples were acquired in the same manner.

3.2. Research variables

Based on literature reviews, this research selected five financial indicators, one corporate governance indicator, and one cash flow indicator as the prediction variables for manufacturing industry fraud warning. The definitions of various prediction variables are as follows:

1. Dependent variable

The dependent variable is defined as whether there is financial information fraud. Similar to the variables used by Beasley (1996) in a dichotomous approach, it is a virtual variable. The occurrence of financial information fraud is set as 1, otherwise, 0.

2. Prediction variable

(1) Current ratio

Current ratio (*CR*) is defined as: current asset (*CA*) divided by current liability (*CL*), representing the year of the fraud occurrence. Current ratio (*CR*) measures the short-term debt-paying ability of an enterprise (one year or a business cycle) to creditors; a higher *CR* means an increased possibility of repayment. The company may improve its *CR* by increasing current assets, such as receivables of higher liquidity, bills, and stocks; or decreasing short-term liabilities such as receivable accounts, and bills. Therefore, a higher *CR* means stronger company debt-paying ability and lower chances of fraud. Current ratio (*CR*) estimation equation is as shown by equation (1).

$$CR_i = \frac{CA_i}{CL_i} \tag{1}$$

(2) Debt ratio

Debt ratio (*DB*) is defined as: total liability (*TL*) divided by total asset (*TA*), indicating the year of fraud occurrence. Debt ratio (*DB*) measures the enterprise's financial structure, reflecting that the enterprise capital comes from shareholder investment or debts. Higher *DB* means higher financial risks, and increased relative possibility of fraud. The debt ratio (*DB*) estimation equation is as shown by equation (2).

$$DB_i = \frac{TL_i}{TA_i} \tag{2}$$

(3) Growth rate of total assets

The growth rate of total assets (g_t) is defined as: current average total assets minus previous term's average total assets, then divided by previous term's average total assets. The growth rate of total assets is able to measure enterprise growth. The fast growth of an enterprise is an important warning of financial information fraud (Loebbecke *et al.*, 1989; Bell *et al.*, 1991; Beasley, 1996). If the company has experienced abnormally faster growth than its industrial peers, it would be more easily for the management to bear the operational pressure, at times of economic recession, possibly leading to financial statement fraud to create a false image of stable growth. Therefore, this study includes the total asset growth rate as a model construct indicator, since higher total asset growth rate represents better current term growth of the company, and the higher possibility of future fraud. g_t Estimation equation is as shown by equation (3).

$$g_t = \frac{Avg(TA_{t-1};TA_t) - Avg(TA_{t-2};TA_{t-1})}{Avg(TA_{t-2};TA_{t-1})} \tag{3}$$

where: $Avg(TA_{t-1};TA_t) = \frac{TA_{t-1} + TA_t}{2}$; $Avg(TA_{t-2};TA_{t-1}) = \frac{TA_{t-2} + TA_{t-1}}{2}$

(4) Return on assets (*ROA*)

ROA measures the profit making capacity of an enterprise. The company may improve the net profit created by unit assets through increasing the net profit or asset turnover rate. The maximization of profits through assets is the aim of an enterprise; therefore, a higher *ROA* means stronger earning capacity and lower chances of fraud. *ROA* estimation equation is as shown by equation (4).

$$ROA_t = \frac{EBIT_t}{Avg(TA_{t-1};TA_t)} \tag{4}$$

where: $EBIT_t$ denotes current term earnings, before interest and taxes.

(5) Total asset turnover (*TAT*)

Total asset turnover is defined as: the net current term business revenues divided by the average total assets, both at the beginning and the end of the term. *TAT* can be used to measure operational capacity, inspect the overall use of assets, and the properness of investments, indicating the business revenue each unit asset can create. Higher *TAT* represents better operational capacity, and lower probability of fraud. TAT_t calculation is as shown by equation (5).

$$TAT_t = \frac{Sales_t}{Avg(TA_{t-1};TA_t)} \tag{5}$$

(6) Shareholding ratio of board directors (HRD)

Since the proposal of the agency theory by Jensen and Meckling (1976), the conflict between the right to control and the control of cash flow has been continually studied by follow-up scholars. Companies of higher shareholding ratios of board directors can better focus on creating value for the company, and have lower possibilities of conflicts with the interests of shareholders. Therefore, this study expects that higher shareholding ratio of board directors means lower possibility of fraud. The estimation of shareholding ratio of board directors (*HRD*) is the total general shares held by the board of directors at the end of the term, divided by the total outstanding general shares at the end of the term.

(7) Operating cash flow cover ratio (*OCFC*):

Operating cash flow cover ratio measures the cash flow created by the enterprise, in the form of debts. Its estimation is cash flow from operational activities, divided by the current term total debts. The cash flow viewpoint can measure the stability of an enterprise's long-term debt-paying capacity, and monitor the demands on short-term capital. Higher *OCFC* represents stronger due debt-paying ability of the enterprise, and lower fraud probability. $OCFC_i$ calculation equation is as shown by equation (6).

$$OCFC_i = \frac{OCF_i}{TL_i} \tag{6}$$

where: $OCFC_i$ denotes cash flow from operational activities.

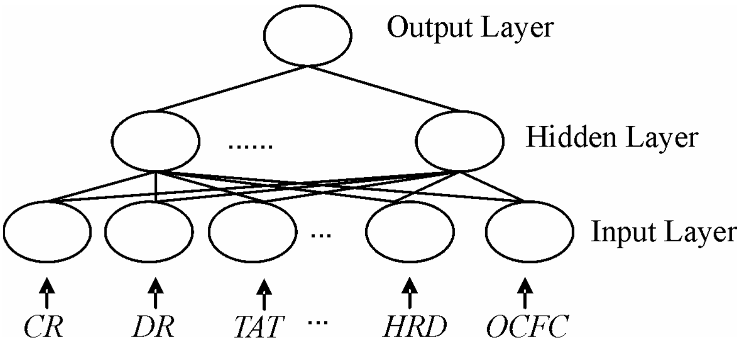
3.3. Research methods

According to literature reviews, there are many types of warning methods for enterprise financial distress, such as the univariate regression analysis, MDA, logistic regression analysis, and artificial intelligence. The logistic regression method can solve the problem of explaining abnormal variables of MDA. In addition, neural network is an information processing and computing system that used an enormous amount of simple linking artificial nerves to simulate the capability of biological neural network (Freeman and Skapura, 1992), the application of back propagation neural network (BPNN) has high degree of self-learning and differentiating capabilities, among which, BPNN is the most representative and popular for issues of classification and prediction (Vellido, Lisboa, and Vaughan, 1999), and learning and recalling were applied for numerical estimations.

In Figure 1, this study employs one hidden layer for BPNN. The process determines the numeric weights for the connections among the nodes based on data training, yielding a minimized least-mean-square error measure of the actual, and the estimated values from the output. The connections weights are assigned initial values (Wang, 2009). Moreover, the error between the predicted and actual output values is back propagated via the network for updating the weights. The supervised learning procedure then attempts to minimize the error between the desired and forecast outputs. The BPNN must be trained before being applied for forecasting. During the training procedure, the BPNN learns from experience based on the proposed hypotheses (Lin and Yeh, 2006; Wang, 2009).

Figure 1

One Hidden Layer of BPNN



Most importantly, the financial distress warning models, as established by logistic regression and back propagation neural network (BPNN), have relatively higher accuracy rate of prediction. Therefore, this study employed logistic regression and back propagation neural network (BPNN) to predict manufacturing industry fraud risks. This study selected five financial indicators, one corporate governance indicator, and one cash flow indicator as the prediction variables for manufacturing industry fraud warning.

4. Empirical results

To construct financial information fraud warning models for the manufacturing industry, this study employed financial variables, corporate governance variables, and cash flow variables as the prediction variables. Logistic regression and BPNN were used as the warning methods. The relationships between various variables and manufacturing industry fraud are as shown in Table 1. With the exception of DB, other prediction variables are negatively related to "fraud or not". Then, this study used logistic regression and BPNN to test the accuracy rate of the warning models, and selected the most suitable cutoff values by probability classification, providing an optimized warning model.

Table 1

Variable indicators

Categories	Variable indicator	Relationship to Financial Information Fraud	Indicato r
Financial Variables	Current Ratio (*CR*)	-	x_i^c
	Debt Ratio (*DR*)	+	x_i^d
	Total Assets Turnover (*TAT*)	-	x_i^{at}
	Return on Asset (*ROA*)	-	x_i^r
	Total Asset Growth Rate (*g*)	-	x_i^{ag}

Categories	Variable indicator	Relationship to Financial Information Fraud	Indicator
Corporate Governance Variable	Shareholding Ratio of Board Directors (*HRD*)	-	x_i^b
Cash Flow Variable	Operating Cash Flow Cover Ratio (*OCFC*)	-	x_i^{cf}

4.1 Logistic Model

First, related coefficients were used to analyze relations between the various prediction variables and the dependent variable (fraud or not). As shown in Table 2, current ratio, *ROA*, shareholding ratio of board directors, and operating cash flow cover ratios have significant negative impact on the fraud situation of manufacturing industry. Only debt ratio has a significant positive impact on the fraud situation.

Table 2

Correlation Matrix of Dependant and Independent Variables

Indicator	Mean(S.D.)	x_i^c	x_i^d	x_i^{at}	x_i^r	x_i^{ag}	x_i^b	x_i^{cf}	y_i
x_i^c	213.97(162.93)	1.00							
x_i^d	42.89(18.89)	-0.65***	1.00						
x_i^{at}	17.22(28.53)	0.14*	-0.02	1.00					
x_i^r	0.41(5.00)	0.21**	-0.29**	0.36**	1.00				
x_i^{ag}	0.24(0.20)	-0.08	0.22**	0.28**	0.15*	1.00			
x_i^b	26.34(14.29)	0.08	-0.22**	-0.12	0.11	-0.08	1.00		
x_i^{cf}	0.07(0.19)	0.60***	-0.46**	-0.07	0.13*	-0.08	0.09	1.00	
y_i	0.32(0.47)	-0.15*	0.30**	0.01	-0.17**	-0.02	-0.36**	-0.14*	1.00

*Notes : *p<0.05, **p<0.01, ***<0.001.*

The chi-square value of the financial information fraud for manufacturing industry using logistic regression is 64.728, indicating that the logistic regression model has good explanatory power and fitness degree. In the model, if the event occurrence probability value is P > 0.5, it is regarded as a fraudulent company sample, otherwise, if P <0.5, it is a normal company sample. The results of logistic regression analysis are as shown in Table 3, which indicate that debt ratio is significantly positively related to fraud, indicating that higher manufacturing industry DB means higher possibility of financial information fraud. The shareholding ratio of board directors is strongly and significantly negatively related to fraud, indicating that higher manufacturing industry shareholding ratio of board directors means lower financial information fraud possibility.

Table 3

Results of Logistic Regression

Indicator	coefficient	S.E.	Wald
x_i^c	0.001	0.002	0.050
x_i^d	0.031*	0.013	5.844
x_i^{at}	0.001	0.006	0.031
x_i^r	-0.020	0.030	0.441
x_i^{ag}	-0.954	0.792	1.453
x_i^b	-0.075***	0.015	24.300
x_i^{cf}	-0.437	1.038	0.177
constant	-0.005	0.893	0.000

*Notes : *p<0.05; ***p<0.001.*

According to the logistic regression results, this research constructed the manufacturing industry fraud warning model, as shown by equation (7).

$$Logit(P_i) = -0.005+0.001\, x_i^c +0.031\, x_i^d + \\ +0.001\, x_i^{at} -0.02\, x_i^r -0.954\, x_i^{ag} -0.075\, x_i^b -0.437\, x_i^{cf} \quad (7)$$

Logistic regression model training and prediction results are shown in Table 4. If predicting by the normal company samples, there are 192 normal companies at the beginning of model training, with 24 companies being misjudged as fraudulent, indicating the training accuracy rate is 87.5%. If predicting by the fraudulent company samples, 28 of the 96 fraudulent company samples are misjudged as normal, indicating the training accuracy rate is 60.4%. The overall model judgment accuracy rate is 78.5% on average. The results indicate that the capacity of identifying normal company samples is higher than the fraudulent company samples in the logistic regression warning model. The model constructed in this study has relatively significant accurate results when predicting the normal company samples. The research findings suggest that the warning indicators of the proposed logistic regression model have better capacity of identifying companies of financial information fraud.

Table 4

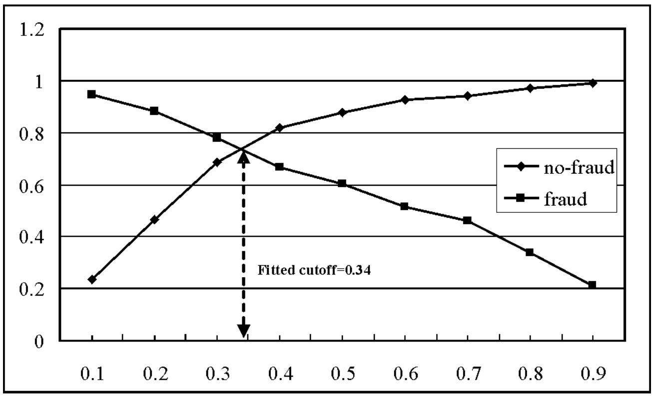
The Prediction Results of Logistic Regression Model (cutoff value is 0.5)

Training Sample		Prediction Result		Validity
		Normal Sample	Fraud Sample	
Test Sample	Normal Sample	168	24	87.5%
	Fraud Sample	28	58	60.4%
Overall Validity				78.5%

As seen, the capacity of identifying fraudulent company samples is far below that of the normal company samples when the general probability is 0.5. This results in judgment imbalance and increased intangible costs of prediction. The capacity of identifying fraudulent company samples can be improved by selecting the most suitable cutoff values. Figure 2 shows the judgment accuracy rates in cases of different cutoff values. As seen, the intersection point of judging normal company samples and fraudulent company samples is 0.34. Therefore, it can be used as the fittest judgment cutoff value for another logistic regression model to balance the prediction capacity of the normal company samples and the fraudulent company samples.

Figure 2

Discriminant Analysis of Fitted Cutoff (Logistic Regression)



Therefore, this study employed the fittest cutoff value of 0.34 to retest the manufacturing industry financial information fraud warning models (Table 5). In the prediction results, the judgment accuracy rates for normal company samples, fraudulent company samples and overall samples are 77.6%, 77.1%, and 77.4%, respectively. Although the judgment accuracy rates of the overall samples and normal company samples when the fittest cutoff value are slightly lower than those in case of judgment cutoff value at 0.5, the judgment accuracy rate is close to 80%, with a considerably increased judgment accuracy rate of defaults. In consideration of risk costs, the fittest cutoff value at 0.34 can achieve the aim of balancing the judgment of normal company samples and fraudulent company samples, as well as relatively good fraud prediction capacity.

Table 5

The Prediction Results of Logistic Regression Model (cutoff value is 0.34)

Training Sample		Prediction Result		Validity
		Normal Sample	Fraud Sample	
Test Sample	Normal Sample	149	43	77.6%
	Fraud Sample	22	74	77.1%
Overall Validity				77.4%

4.2 Neural networks model

This study used back propagation neural network (BPNN) to construct financial information fraud warning models in the manufacturing industry. After inputting 7 categories of variables, which are financial variables, corporate governance variable, and cash flow variables, the smallest root-mean-square value after convergence of the training model is 0.0284. In the aspect of training results (Table 6), the accuracy rate of judging normal company samples is 84.4%, with 30 out of 192 companies being misjudged, while the training accuracy rate of judging fraudulent company samples is 51.0%, with 47 out of 96 companies being misjudged. The overall hit rate is as high as 73.3%, which indicates that the prediction capacity of BPNN is relatively lower than that of the logistic regression model.

Table 6

The Prediction Results of BPNN (cutoff value is 0.5)

Training Sample		Prediction Result		Validity
		Normal Sample	Training Sample	
Test Sample	Normal Sample	162	30	84.4%
	Fraud Sample	47	49	51.0%
Overall Validity				73.3%

Both the output value of the BPNN and the logistic regression are a probability value. General models all set same occurrence probability of normal company samples and fraudulent company samples, using 0.5 as the threshold value. However, the prediction results of the logistic regression model suggested that, if the fittest judgment cutoff value is selected as the new threshold value, the judgment capacity of normal company samples and fraudulent company samples can be balanced. Based on the same viewpoints, the judgment accuracy rates of the BPNN when the fittest cutoff value is 0.36 different cutoff values. In such a case, the testing results (Table 7) indicate that the number of misjudged normal company samples increases from 30 to 53 with accuracy rate dropping to 72.4%, while the number of misjudged fraudulent company samples drops from 47 to 26, and the overall hit rate is 72.6%. It indicates that the BPNN has lower judgment accuracy rate than logistic regression model, regardless of the prediction of normal company samples, or the judgment of fraudulent company samples after adjusting the judgment values.

Table 7

The Prediction Results of BPNN Model (cutoff value is 0.36)

Training Sample		Prediction Result		Validity
		Normal Sample	Training Sample	
Test Sample	Normal Sample	139	53	72.4%
	Fraud Sample	26	70	72.9%
Overall Validity				72.6%

To determine relatively proper warning models, this research compared the prediction capacity of a verified logistic regression and a BPNN-warning model in various aspects and Press' Q (Table 8). The results revealed that, regardless of the judgment cutoff value, the logistic regression model has significantly higher capacities of judging both normal company and fraudulent company samples than BPNN. The Press' Q of the logistic regression and BPNN reached a significant level, indicating the good fitness of the various models. The logistic regression model's Press' Q is higher than that of the BPNN, indicating that the logistic regression method has good predication capacity for manufacturing industry fraud warning model.

Table 8

Comparison of Logistic Regression and BPNN Prediction Results

	Normal Sample Validity	Fraud Sample Validity	Overall Validity	Press' Q
Logistic regression–0.5	87.5%	60.4%	78.5%	93.4***
Logistic regression–0.34	77.6%	77.1%	77.4%	82.347***
BPNN–0.5	84.4%	51.0%	73.3%	62.3***
BPNN–0.36	72.4%	72.9%	72.6%	58.7***

*Notes: ***p<0.001.*

5. Discussion and conclusion

Recently, due to drastic changes of the global financial environment, the topic of risk assessment and control has become relatively important to financial institutions in response to the implementation of *Basel* II (the second of the *Basel* Accords). Financial institutions around the world have actively established various risk assessment and prediction models to detect risks of financial information frauds in the credit granting process. The accuracy rate of the models is determined by the key prediction variables integrated in the models. Therefore, the rationality and effectiveness of the variables adopted should be occasionally inspected. Meanwhile, manufacturing industry occupies an important position in the overall development of the world economy, and is a major transaction partner of financial institutions. Once financial information fraud occurs, the loss will be difficult to estimate, therefore, it is of considerable importance to establish a set of fraud risk warning models for the manufacturing industry.

This study aimed to use financial variables, corporate governance, and cash flow variables to construct financial information fraud warning models for the manufacturing industry, and use logistics regression and BPNN as verification methods. The results show that logistic regression has a higher capacity than the BPNN in judging normal company and fraudulent company samples. When the fittest cutoff value is 0.34, the judgment capacity of logistic regression for normal and fraudulent company samples can reach a balanced state with a prediction capacity close to 80%, being higher than those with a fit cutoff value of 0.36. In addition, the logistic regression results suggested that the debt ratio variable of the financial variables, and the shareholding ratio of board directors of the corporate governance variables, are major indicators to judge financial information fraud for manufacturing industry. It is proved that financial and corporate governance variables are irreplaceably important to the prediction of manufacturing industry fraud. Therefore, it is suggested that judgment of financial information fraud of the manufacturing industry may start with preliminary inspection of debt ratio and shareholding ratio of board directors.

Moreover, the impact of other financial and cash flow variables (liquidity ratio, total asset growth rate, ROA, total asset turnover rate, and operating cash flow cover ratio) on "manufacturing industry fraud or not" has not reached a significant level. It is probably because manufacturers involved in financial information frauds in recent years are very skillful in altering financial statements, and using large sums of fake transactions that exaggerate profits and rapidly build assets. These acts are not easily detected, even if investors have disclosed the information. The research results are consistent with Keasey and Watson (1987), who suggested that manufacturers tend to alter financial statements. Therefore, no financial information fraud warning model is "absolutely" perfect. Only by constant adjustment of prediction variables in a timely manner could the warning models have "relatively" effective judgment capacity at different time points. The research findings also verified the conclusions of past studies (Dechow *et al*., 1996, Abbott *et al*., 2000; Bell and Carcello, 2000; Wang and Deng, 2006) that the integration of corporate governance variables into warning models can help improve judgment capacity.

To construct financial information fraud warning models for the manufacturing industry, this research collected sample data in a ratio of 1:2, for fraudulent samples to normal samples. Meanwhile, to increase the sample data of fraudulent company samples for identifying data of fraudulent company samples, this study integrated the data of the sample companies of the previous year (t-1), and the year before the previous year (t-2) for analysis. The above data selection method caused the overall prediction accuracy of the models to be below 95%. Future studies can increase related quantitative and qualitative indicators according to time and space, and use other research methods (Grey Theory, MDA, DEA-DA, RST) for preliminary screening to establish financial information fraud warning models, thereby perfecting the identification capacity of warning models for the manufacturing industry, and lowering losses resulting from inaccurate classifications.

According to research institution IDC, Taiwan has become the third largest manufacturer of electronics products, and the world's fourth largest supplier for the high-technology industry. Hence, following the international high-tech countries like the United States and Japan have already been focused on the consumer electronic products, Taiwan will have assembled a complete core electronics manufacturer industry supply chain (Lin *et al*., 2008). However, most of the enterprises of Taiwanese manufacturing industries are small- and medium-sized enterprises, and their operating ability and capital turnover are usually not as good as the stability of large-sized enterprises. Hence, to construct consistent with characteristics of small- and medium-sized manufacturing patterns of financial information fraud warning model is an important part of risk prevention, it can minimize the risk of bad debts in the economic system and enhance capital market structure and competitive advantage of emerging industries.

References

Abbott, L. J. Park, Y. and Parker, S. (2000), "The Effects of Audit Committee Activity and Independence on Corporate Fraud", *Managerial Finance*, 26(11): 55-67.

Ahn, B. S. Cho, S. S. and Kim, C. Y. (2000), "The Integrated Methodology of Rough set Theory and Artificial Neural Network for Business Failure Prediction", *Expert Systems with Applications*, 18: 65-74.

Altman, E. I. (1968), "Financial Ratios, Discriminant Analysis and the Prediction of

Corporate Bankruptcy", *Journal of Finance*, 22: 589-609.

Altman, E. Marco, G. and Varetto, F. (1994), "Corporate Distress Diagnosis: Comparisons Using Linear Discriminant Analysis and Neural Networks", *Journal of Banking & Finance*, 18: 505-529.

Baesens, B. Gestel, T.V. Stepanova, M. Poel, D.V.D. and Vanthienen, J. (2005), "Neural Network Survival Analysis for Personal Loan Data", J*ournal of the Operational Research Society*, 56: 1089-1098.

Beaver, W.H. (1966), "Financial Ratios as Predictors of Failure", *Journal of Accounting Research*, 4: 71-111.

Beasley, M.S. (1996), "An Empirical Analysis of the Relation Between the Board of Director Composition and Financial Statement Fraud", *The Accounting Review*, 71(4): 443-465.

Becerra, V. Galvao, R. and Abou-Seada, M. (2005), "Neural and Wavelet Network Models for Financial Distress Classification", *Data Mining and Knowledge Discovery*, 11(1): 35-55.

Bell, T.B. and J. V. Carcello (2000), "A Decision Aid for Assessing the Likelihood of Fraudulent Financial Reporting", *Auditing: A Journal of Practice & Theory*, 19(1): 169-185.

Black, A.J. and McMillan, D. G. (2004), "Nonlinear Predictability of Value and Growth Stocks and Economic Activity", *Journal of Business Finance & Accounting*, 31: 439-474.

Blum, M. (1974), "Failing Company Discriminant Analysis", *Journal of Accounting Research*, 74(12): 1-25.

Cao, Q. Leggio, K.B. and Schniederjans, M.J. (2005), "A Comparison Between Fama and French's Model and Artificial Neural Networks in Predicting The Chinese Stock Market", *Computers and Operations Research*, 32(10): 2499-2512.

Casey, C.J. and Bartczak, N.J. (1985), "Using Operating Cash Flow Data to Predict Financial Distress: Some Extensions", *Journal of Accounting Research*, 23: 384-401.

Chen, M.C. and Huang, S.H. (2003), "Credit Scoring and Rejected Instances Reassigning Through Evolutionary Computation Techniques", *Expert Systems With Applications*, 24: 433-441.

Chen, W.S. and Du, Y.K. (2009), "Using Neural Networks and Data Mining Techniques for the Financial Distress Prediction Model", *Experts Systems with Applications*, 36(2): 4075-4086.

Chen, Y.L. and Shih, K.H. (2006), "A Research on the Criminal Motives, Models and Investigation of Financial Frauds", *Police Science Quarterly*, 37 (2): 21-40. (in Chinese)

Chen, Z. and Wang, L. (2009), "Adaptable Product Configuration System Based on Neural Network", *International Journal of Production Research*, 47(18): 5037-5066.

Chi, L.C. and T. C. Tang (2006), "Bankruptcy Prediction: Application of Logit Analysis in Export Credit Risks", *Australian Journal of Management*, 31(1): 17-27.

Coats, P.K. and Fant, L.F. (1993), "Recognizing Financial Distress Patterns Using a Neural Network Tool", *Financial Management*, 22(3): 307-327.

Cochran, J.J. Darrat, A.F. and Elkhal, K. (2006), "On the Bankruptcy of Internet Companies: An Empirical Inquiry", *Journal of Business Research*, 59: 1193-1120.

Dechow, P.M., Sloan, R.G.. and Sweeney, A.P. (1996), "Cause and Consequences of Earnings Manipulation: An Analysis of Firms Subject to Enforcement Actions by the SEC", *Contemporary Accounting Research*, 13(1): 1-36.

Freeman, J.A. and Skapura, D.M. (1992), *Neural Networks Algorithms, Applications, and Programming Techniques*, New York: Addison-Wesley.

Foreman, R.D. (2003), "A Logistic Analysis of Bankruptcy within the US Local Telecommunications Industry", *Journal of Economics and Business*, 5(2): 135-166.

Gentry, J.A. Newbold, P. and Whitford, D.T. (1987), "Funds Flow Components, Financial Ratios, and Bankruptcy", *Journal of Business Finance and Accounting*, 14(4): 595-606.

Gombola, M.J. and Ketz, J.E. (1983), "A Note on Cash Flow and Classification Patterns of Financial Ratios", Accounting Review, 58(1): 105-114.

Hwarng, H.B. (2008), "Toward Identifying the Source of Mean Shifts in Multivariate SPC: A Neural Network Approach", *International Journal of Production Research*, 46(20): 5531-5559.

Jasic, T. and Wood, D. (2004), "The Profitability of Daily Stock Market Indices Trades Based on Neural Network Predictions: Case Study for the S&P 500, the DAX, the TOPIX and the FTSE in the Period 1965-1999", *Applied Financial Economics*, 14: 285-297.

Jensen, M.C. and Meckling, W.H. (1976), "Theory of the Firm: Managerial Behavior, Agency Cost and Ownership Structure", *Journal of Financial Economics*, 3: 305-360.

Largay, J.A. and Stickney, C.P. (1980), "Cash Flows, Ratio Analysis and W. T. Grant Bankruptcy", *Financial Analysts Journal*, 50-54.

Lin, C.S. Chiu, J.S., Hsieh, M.H., Mok, M. S., Li, Y. C. and Chiu, H. W. (2008), "Predicting Hypotensive Episodes During Spinal Anesthesia with the Application of Artificial Neural Networks", *Comput Methods Programs Biomed*, 92: 193-197.

Lin, C.T. and Yeh, H.Y. (2006), "Empirical Study of the Taiwan Stock Index Option Price Forecasting Model- Applied Artificial Neural Network," *Applied Economics*, 41(15): 1965-1972.

Lin, C.T. and Yeh, H.Y. (2006), "Empirical Study of the Taiwan Stock Index Option Price Forecasting Model- Applied Artificial Neural Network," *Applied Economics*, 41(15): 1965-1972.

Lu, C.J. Wu, C.M., Keng, C.J. and Chiu, C.C. (2006), "Integrated Application of SPC/EPC/ICA and Neural Networks", *International Journal of Production Research*, 46(4): 873-893.

Loebbecke, J. K. Eining, M.M. and Willingham, J.J. (1989), "Auditors' Experience with Material Irregularities: Frequency, Nature, and Detect Ability", *Auditing: A Journal of Practice & Theory*, 9(1): 1-28.

Malhotra, M.K. Sharma, S. and Nair, S.S. (1999), "Decision Making Using Multiple Models", *European Journal of Operational Research*, 114(1): 1-14.

Martin, D. (1977), "Early Warning of Banking Failure", *Journal of Banking and Finance*, 1: 249-276.

Mensah, M.Y. (1984), "An Examination of the Stationarity of Multivariate Bankruptcy Prediction Models: A Methodological Study", *Journal of Accounting Research*, 22(1): 380-395.

Niaki, S.T.A. and Abbasi, B. (2007), "Detection and Classification Mean-shifts in Multi-attribute Processes by Artificial Neural Networks", *International Journal of Production Research*, 46(11): 2945-2963.

Ohlson, J.A. (1980), "Financial Ratios and the Probabilistic Prediction of Bankruptcy", *Journal of Accounting Research*, 18(1): 109-131.

Rapach, D.E. and Wohar, M.E. (2005), "Valuation Ratios and Long-horizon Stock Price Predictability", *Journal of Applied Econometrics,* 20: 327-344.

Salchenberger, L.M., Cinar, E.M. and Lash, N.A. (1992), "Neural Networks: A New Tool for Predicting Thrift Failures", *Decision Sciences*, 23(4): 899-916.

Sharma, V.D. (2004), "Board of Director Characteristics, Institutional Ownership, and Fraud: Evidence from Australia", *Auditing: A Journal of Practice & Theory*, 23(2): 105-117.

Shih, K.H. Chen, Y. Jian, D. and Lin, W. (2008), "An Exploration on Motives of Financial Frauds- Criminal Investigation Perspective", *Police Science Quarterly*, 38(6): 79-107.(in Chinese)

Shively, P.A. (2003), "The Nonlinear Dynamics of Stock Prices", *Quarterly Review of Economics and Finance*, 13: 505-517.

The World Bank (2009), http://www.ifc.org/ifcext/gms.nsf/Content/Home

Tsai, M.C. Lin, S.P. Cheng, C.C. and Lin, Y.P. (2009), “The Consumer Loan Default Predicting Model–An Application of DEA-DA and Neural Network”, *Expert 9Systems with Applications*, 36(9): 11682-11690.

Tseng, C.H. Cheng, S.T. Wang, Y.H. and Peng, J.T. (2008), “Artificial Neural Network Model of the Hybrid EGARCH Volatility of the Taiwan Stock Index Option Prices,” *Physica A: Statistical Mechanics and its Applications*, 387(13): 3192-3200.

Vellido, A. Lisboa, P.J.G. and Vaughan, J. (1999), “Neural Networks in Business: A Survey of Applications (1992–1998)”, *Expert Systems with Applications*, 17: 51-70.

Wang, Y.H. (2009), “Using Neural Networks to Forecast Taiwan Stock Index Option Prices: A Hybrid GARCH Approach”, *Quality & Quantity*, 43(5): 833-843.

Wang, Y.H. (2009), “Nonlinear Neural Network Forecasting Model for Stock Index Option Price: Hybrid GJR-GARCH Approach”, *Expert Systems With Applications*, 36(1): 564-570.

Wang, Y.H. Chuang, C.C. and Lee, S.Y. (2010), “Impact of Compositions and Characteristics of Board of Directors and Earnings Management on Fraud”, *African Journal of Business Management*, 4(4): 496-511.

Wang, Z.J. and Deng, X.L. (2006), “Corporate Governance and Financial Distress”, *The Chinese Economy*, 39(5): 5-27.

Wang, C.H. Kuo, W. and Qi, H. (2007), “An Integrated Approach for Process Monitoring Using Wavelet Analysis and Competitive Neural Network”, *International Journal of Production Research,* 45(1): 227-244.

Ward, T. J. and Foster, B. P. (1997), “A Note on Selecting a Response Measure for Financial Distress”, *Journal of Business Finance and Accounting*, 24: 869-879.

Wolfe, D.T. and Hermanson, D. R. (2004), “The Fraud Diamond: Considering the Four Elements of Fraud”, *The CPA Journal*, 72(4): 38-42.

Wu, C.Y. (2004), “Using Non-financial Information to Predict Bankruptcy: A Study of Public Companies in Taiwan”, *International Journal of Management*, 21(2): 194-201.

Zavgren, C.V. (1985), “Assessing the Vulnerability to Failure of American Industrial Firms: A Logistic Analysis”, *Journal of Business, Finance and Accounting*, 12(1): 19-45.

Zobel, C.W. Cook, D.F. and Nottingham, Q.J. (2004), “An Augmented Neural Network Classification Approach to Detecting Mean Shifts in Correlated Manufacturing Process Parameters”, 42(4): 741-758.

Zmijewski, M.E. (1984), “Methodological Issues Related to the Estimation of Financial Distress Prediction Models”, *Journal of Accounting Research*, 22: 59-82.