Failure Prediction of Chinese A-Share Listed Companies

--Comparisons Using Logistic Regression Model and Neural Network Analysis

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Abstract

This study compares the relative prediction accuracy of corporate failure between two prediction methods –logistic regression model and neural network analysis– based on a sample of 3598 observations and companies data obtained from the Chinese A-Share market during the period 1991 to 2002. Seven criteria have been set up to define failure according to attributes of Chinese listed companies. Using forty financial ratios and seven misclassification cost ratios of Type I and Type II error, two models achieve ranges of minimal misclassification cost at optimal cut-off points for two years prior to business failure; The logistic regression model is slightly superior to neural network analysis. Compared with random prediction, both models are efficient. In addition, the study points out that Total Asset Turnover (TATR), Cash Ratio (CASR), Earning per Share (EPS), Total Debt to Total Asset (TDTA), Return on Assets (ROA) and the natual log of Total Market Value (MVLN) could be significant financial indictors of corporate failure. Results of the study have important implications in credit evaluation, internal risk control and capital market investment guidelines.

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1. Introduction

The development of the Chinese stock market has made great gains since 1990s. At the end of December 2003, in the ShangHai and ShengZhen stock exchanges together, there were more than 1200 listed companies and the total market value reached RMB 4246 billion. However, as the number of listed companies is increasing, the quality is declining. Many Chinese investors blamed the phenomenon on the increasing number of loss-making firms and the declining overall performance of the market. Until November 2004, there were more than 140 listed companies that had been classified S.T. (special treatment), among them 15 companies were suspended trading and 14 companies had been delisted from ShangHai and ShengZhen Stock Exchanges.

Therefore, there is a growing demand to develop a procedure to give early warning of financial distress, and the analysis of corporate failure in China becomes more crucial and necessary. Corporate failure prediction has been a subject of study for 70 years worldwide. Accurate prediction of corporate failure is important to investors, creditors and auditors. It can help shareholders, creditors and governments to avoid heavy losses stemming from surprise bankruptcies; and using analytic tools and data from corporate financial reports, future financial performance can be evaluated and predicted.

Studies of failure prediction in China are still in the early stage; Shi and Zou (2001) studied the credit problems of Chinese A-share part list companies during 1999-2000 by means of canonical discriminate analysis. Li (2001) classified list companies by distinguishing function by using data from the Shanghai and Shenzhen Stock Exchange covering the period of 1997-1999. Most of these studies used discriminant analysis, but Zhang (2003) indicated that the Logistic Regression Model and Neural Network Analysis might be good choice for the Chinese market in predicting the corporate failure.

The major purpose of this paper is to compare the accuracy of Logistic Regression Model and Neural Network Analysis in predicting corporate failure. It is hoped to answer the following questions:

(1) Which method is better to predict the failure of Chinese listed companies?

(2) Which factors explain the corporate failure in China?

Compared with previous studies, this study is distinctive in that we set seven classify criteria to identify firms as failed or non-failed; the failed firms consist in the earlier phases of financial distress while the ultimate condition of either de-listing or bankruptcy is not known at the time of selecting. Hence, the failure predication derived from this study intends to develop an early warning system to help management to recognise the ailing of the firm, enable appropriate action to improve efficiency, and avoid the risk of de-listing or bankruptcy. Knowledge of the likelihood of failure would also assist investors in setting risk premiums and advocate a rational investment.

The preliminary results of this study indicate that both methodologies yield reasonable predictive accuracy across the range of cost ratios, with the logistic regression model performing slightly better than the neural network analysis. Compared with random prediction, both models are efficient. Additionally, the selected financial ratios indicate that firms with low operating efficiency, low cash flow, low profitability, high financial leverage and declining market value could have a high probability of failure.

The organization of this study is as follows: Section 2 reviews literature on business failure and prediction technique. Section 3 describes the data and methodology; section 4 presents and discusses the results. Conclusions and further research are formulated in section 5.

2. Literature Review

2.1 Definitions of Failure

There are various possible descriptions of term "failure", the most commonly used term are "distress", "insolvency", "default" and "bankruptcy", extremely it can mean liquidation or bankruptcy, at the other it could just mean reporting a profit figure below that expected.

The McGraw-Hill Dictionary of Modern Economics (1973) defined business failures as "The cessation of operations by a business concern because of involvement in court procedures or voluntary actions which will result in loss to its creditors." Beaver (1967) and Altman (1968) concluded that the definition of failure varied across different studies depending on purpose and scopes of studies. Ling and Mathews (1982) stated that failure was a distinct phenomenon of capitalist societies where owners of capital may choose where to invest and disinvest funds. Economists often refer to business success and failure as a real reflection of the efficiency of the "invisible hand" in allocating the scarce resources of the economy.

According to Altman (1993), failure "means that the realized rate of return on invested capital, with allowances for risk consideration, is significantly and continually lower than prevailing rates of similar investment". This is a term of an economic sense and does not indicate the discontinuity of a firm. Insolvency illustrates a negative performance indicating liquidity problems. The term default refers to the firm that violates a condition of an agreement with a creditor and can cause legal action. Bankruptcy indicates a net worth of a firm or a court judgement that leads the firm either to liquidation or restructuring.

Ross (2003) claimed that the financial distress could be defined in several ways:

- Business Failure - This term is usually used to refer to a situation in which a business terminated with a loss to creditors.
- Legal Bankruptcy - Firms or creditors bring petition to a federal court for bankruptcy. Bankruptcy is a legal proceeding for liquidating or reorganizing a business.
- Technical Insolvency -Technical insolvency occurs when a firm is unable to meet its financial obligations.
- Accounting Insolvency-Firms with negative net worth are insolvent on the books. This happens when the total book liabilities exceed the book value of the total assets.

Morris (1997, P.24,) listed a spectrum of potential indicators of financial distress:

1. Creditors' or voluntary liquidation, appointment of a receiver;
2. Suspension of Stock Exchange listing;
3. Going concern qualification by the auditors;
4. Composition with the creditors;
5. Protection sought from creditors (e.g. under Chapter 11 of US Bankruptcy Code);
6. Breach of debt covenants, fall in bond or credit rating, new charges taken over the assets of the company or its directors;
7. Company reconstruction;
8. Resignation of directors, appointment of a company doctor, etc;
9. Take-over (although not all take-overs are witness to financial distress, of course);
10. Closure or sale of part of the business;
11. A cut in dividends or the reporting of losses;
12. The reporting of profits below a forecast or acceptable level; and/or the fall in a company's relative share price.

So a large number of definitions found in the literature have reflected a series of events such as violation of loan provisions, consistent omission of dividends, appointment of a receiver, liquidation, and winding up. Some may consider technical insolvency but others would consider a negative net worth as the point of failure, liquidation or bankruptcy proceedings appear to be the most commonly used definitions. Karels and Prakash (1987, pp.576) presented a summary table of a diverse set of definitions bankruptcy/failure used by researchers in the empirical studies of business failure.

Table 2.1 Business Failure/Bankruptcy Definitions

Author	Term Used	Definition
Altman (1968)	**Bankruptcy**	Those firms that legally bankrupt and either placed in receivership or have been grated the right reorganize under the provision of the National Bankruptcy Act.
Beaver (1966)	**Failure**	The inability of a firm to pay its financial obligations as they mature. Operationally, a firm is said to have failed when any of the following events have occurred: bankruptcy, bond defaults, an overdrawn bank account, or non-payment of a preferred stock dividend.
Blum (1974)	**Failure**	Events signifying an inability to pay debts as they come due, entrances into a bankruptcy proceedings or an explicit agreement with creditors to reduce debts.
Booth (1983)	**Failure**	No explicit definition provided. Companies were de-listed from trading on any Australian Stock Exchange.
Deakin (1972)	**Failure**	The firms, which experience bankruptcy, insolvency, or were otherwise, liquidated for the benefit of creditors.
Edminster(1972)	**Failure**	Author identifies both Beaver's and Blum's definitions.
Elam (1975)	**Bankruptcy**	Firms are identified as bankrupt when they have undertaken at least one of the following actions: 1) filed for reorganization under Chanter XI of the Federal Bankruptcy Act;2)filed for reorganization under Chapter X of the Chandler Act; 3)voted in a stockholder's meeting to file either under Chapter X or Chapter XI; 4) reached agreement with creditors to reduce firm's liabilities a loss to the creditors.
EL Hennawy & Marris (1983)	**Failure**	Failure was define as a business, which was liquidated, wound up by court order or to which a receiver was appointed.
Libby (1975)	**Failure**	Same as Deakin's definition
Taffler (1982)	**Failure**	Failure was defined as receivership, voluntary liquidation (creditors), winding up by court order or government action undertaken as an alternative.

Source: Karels and Prakash (1987, pp.576)

As yet, in finance studies there is no unifying theory to define failure. Sharma and Mahajian (1980) listed some reasons:

- The very negative connotation of the term "failure."
- The notion that the failure process for each product or firm is atypical and hence does not lend to a scientific study.
- Lack of a systematic body of knowledge related to the failure process.
- The nature of the reward criteria used by management.
- The belief that failure is a sudden rather than a gradual process.

2.2 Causes of Failure

The study of corporate failure must be dealt through the search of its causes. Edmister (1972), Taffler & Tisshaw (1977), and Lau (1987) indicated that failure could be produced by both internal and external causes. Newton (2003, pp.23) stated that the general signs of business in financially difficulty included decreasing sales, slowing of sales growth, declining cash flow and net income positions, and increasing large debt. Beaver (1967) stated that firms usually entered bankruptcy because it was unable either to generate sufficient cash internally or to obtain needed cash from external sources to sustain operating, investing and financing activities.

Argenti (1976) developed his "A-score" approach by identifying several different types of problem that may face a company. Morris (1997, P.197,) summarised as follows:

1. There are five possible management defects: the style of the chief executive is too autocratic, the posts of chairman and chief executive are not separated, the board is passive, the board lacks all-round skills, the finance director has little authority, and there is a lack of management depth below board level.

2. There are three potential weaknesses in the accounting system: budgetary control is inadequate, the cash flow projection (if it exists) is out of date, and managers have little idea of costs of the activities they supervise.

3. The company may be slow to appreciate the changes in the environment in which it operates and even slower to react to it.

4. There can be mistakes that frequently lead to failure: too high a level of borrowing, overtrading, and a lack of diversification (often characterised by overreliance on one customer or on a major project).

5. There are various symptoms as a company approaches failure: key financial ratios decline (though probably only in the last two years before collapse), the company engages in creative accounting to try to hide unpalatable facts, there are non-financial signs of weakness (e.g. basic expenditures are cut, investments are delayed, staff turnover rises, etc), and ultimately there are terminal signs of collapse immediately before the receiver is called in.

Likewise, Slatter (1984) identifies a number of factors that seemed to be the principal causes of corporate decline.

1. Four are associated with poor management: an autocratic chief executive, an ineffective board of directors, neglect of the core business, and a lack of general management skills.

2. There is inadequate financial control, characterised by: poorly designed management accounting systems, poor use of management accounting information, overcentralisation which impedes effective control, and costs are distorted by inappropriate methods of allocating overheads.

3. There is an inability to respond to competition, with a reluctance to develop and/or introduce new products; or a failure to respond to price competition by focusing on market demands, by differentiating the product, or by trimming costs to match those of rivals.

4. Costs are too high: in relative terms because of an inability to take advantage of scale economies or to benefit from learning effects; in absolute terms because of lack of access to raw materials, know-how, appropriate location, or skilled labour at a competitive price; high overheads because of a particular diversification strategy or organisation structure; inefficient operators (e.g.

because of poor maintenance, production planning, plant layout, etc); and unfavourable government policies.

5. Adverse changes in market demand can seriously affect a firm: e.g. because of secular or cyclical declines in demand, or because of a change in tastes.

6. Adverse movements in commodity prices can severely damage a firm's viability; often as a result of changes in exchange rate parities.

7. Marketing may be ineffective: e.g. because of poorly motivated workforce, ineffective advertising, lack of market research, an outdated product, or poor after sales service.

8. Overreliance on a major project, for which capital requirements may have been underestimated, on which there may have been start up difficulties, for which capacity was inadequate, for which the costs of penetrating a new market were underestimated, or where the contract price was set too low.

9. Acquisition strategies sometimes go sour: this can arise for a variety of reasons (e.g. "losers" are acquired, too high a price has been paid for a company, or post-acquisition management is poor).

10. Financial policy is flawed (e.g. because gearing is too high, not enough resources are invested to meet demand, or there is a failure to raise suitable finance).

11. Finally overtrading, where a company's sales grow at a faster rate than it is able to sustain from internally generated cash flow and it faces capital rationing conditions.

Although a company disappears when it goes bankrupt, before this happens the company has gone through a long period of crisis. Taking into account the senses of the concept of failure, they are divided into two main stages: economic and financial. The economic failure starts when the profitability of the invested capital is under its costs of opportunity, receiving its owner an investment yield lower than other alternative opportunities with the same risk. As the economical failure settles down in the company, the incomes start to be lower than the expenses producing the first negative results.

If the deterioration produced during the economic failure process is not corrected, the company will descend into technical insolvency, the first stage of financial failure. In this situation the company does not have enough liquidity for the payments as these are increasing. The breaking point of this ruinous process will be reached when the company is not only unable to pay off its due debt but is also in a situation of negative net asset, which could soon lead the company to its bankruptcy.

2.3 Failure Firms in China

In China, state-owned enterprises are under protection of the government, despite the *Law of the People's Republic of China on Enterprise Bankruptcy*, which was promulgated on December 2, 1986, and came into effect on November 1, 1988. Two main obstacles have prevented more losing making firms from going into bankruptcy; they are China's already substantial unemployment problem and the fragility of the financial system. Aware of the problems associated with bankruptcies, the government encourages company mergers over bankruptcies. Also the existing Bankruptcy Law is hard to implement, much of its content does not adequately address the complex economic realities of China and it is fraught with ambiguities and deficiencies, so in China the government plays a special role, they control the number of state owned enterprises going bankrupt.

Failed listed firms undergo special treatment in China's capital market. According to *The Company Law* effective on July 1,1994, listed firms that show losses for three consecutive years should be suspended from trading by the Securities Regulatory Commission. Article 158 further requires that suspended firms should be removed from the market if they fail to gain profits before a deadline.

According to *the Listing Rules* set forth by Shenzhen and Shanghai Stock Exchanges, effective on January 1,1998, a listed firm might become "ST" (Special Treatment) if any of the following four criteria has been achieved: 1) the external auditors express negative opinions or clearly state that they are unable to express opinions on a firm's annual report; 2) the firm's financial conditions are considered to be abnormal by the stock exchanges or China Security Regulator Commission (CSRC); 3) a firm shows that the company has suffered losses for two continuous years and 4) the audited report shows that the shareholder's equity is lower than registered capital.

Furthermore, according to the *Regulations Concerning Suspension of Trading* promulgated by Shenzhen and Shanghai Stock Exchanges on June 16, 1999, the ST symbolized firms that made a loss for a further year should be suspended from trading and their shares should be labelled as "PT" (i.e. particular transfer). The mark of "PT" shows firms involved have a high potential risk of trading termination and bankruptcy; these shares can only be traded on each Friday with a price limit of 5 percent fluctuation on a single day. On February 22, 2001, the China Securities Regulatory Commission (CSRC) announced the *Measures for the Implementation of Suspension and Termination of Trading for Loss-firms*, requiring that "PT" firms should be allowed to apply for a grace period of 12 months. If these firms failed to show a turnaround from their losses during the grace period or given disclaimer opinion in audit reports, their stocks would be terminated from trading on the market.

From February 25, 2002, new *Listing Rules* of Shenzhen and Shanghai Stock Exchanges have been operated. According to the new rules, the grace period is shortened to six months and Particular Transfer (PT) firms face the fate of being tossed out of the bourses if they fail to report a profit in the next half a year.

Until November 2004, more than 140 listed companies had been on special treatment, among which 15 companies were suspended from trading and 14 companies had been removed from Shenzhen and Shanghai Stock Exchanges (www.stockstar.com). For a long time, Chinese stock market has been improperly stressing the role of raising funds, ignoring its more important role in resources distribution. The adopting of delisting mechanism indicates that the government determines to intensify market supervision; the listed companies can no longer rest under the protective umbrella of the government, which ensures them a lifetime in the security markets.

2.4 Financial Ratios as Failure Indictors

Financial ratios reflect key relationships among financial variables and provide basic guidelines for financial planning and analysis. Ratios are frequently used as a basis for interpreting a firm's performance trends, its business, financial and market risk pattern, and various corporate strategic decisions such as mergers, consolidations and bankruptcy. Researchers and practitioners have found that financial ratios perform as effective indicators of dimensions of profitability and risk. The recent studies of Morse (1999) and Schmidgall & Damitio (1999) point out that financial ratio analysis is a popular technique for predicting bankruptcy.

A large number of ratios have been proposed in the literature. Beaver's (1967) was the first reported research that tested the usefulness of financial ratios to predict business failure. Courtis (1978) attempted to identify the variables useful in predictive studies. In his survey, 79 financial ratios were identified from various studies and were grouped in three main categories: 1) profitability ratios, 2) managerial performance ratios and 3) solvency ratios. Later studies proposed additional financial ratios for inclusion in failure prediction analysis. Lee (1985) grouped ratios into seven categories: Return on Investment, Financial Leverage, Capital Turnover, Short-term Liquidity, Cash Position, Inventory Turnover, and Receivables Turnover. Altman and Narayanan (1997) did a survey (Table 2.2) throughout the world. Most studies found that financial ratios measuring profitability, leverage, and liquidity had the most statistical power in differentiating defaulted from non-defaulted firms.

TABLE 2.2: International Survey of Financial Ratio

STUDIES CITED	EXPLANATORY VARIABLES
United States	
Altman (1968)	EBIT/assets; retained earnings/ assets; working capital/assets; sales/assets; market value (MV) equity/book value of debt.
Japan	
Ko (1982)	EBIT/sales; working capital/debt; inventory turnover 2 years prior/inventory turnover 3 years prior; MV equity/debt; standard error of net income (4 years).

Takahashi et al. (1984)	Net worth/fixed assets; current liabilities/assets; voluntary reserves plus unappropriated surplus/assets; interest expense/sales; earned surplus; increase in residual value/sales; ordinary profit/assets; sales - variable costs.
Switzerland	
Weibel (1973)	Liquidity (near monetary resource asset – current liabilities)/ operating expenses prior to depreciation; inventory turnover; debt/assets.
Germany	
Baetge, Huss and Niehaus (1988)	Net worth/(total assets – quick assets – property & plant); (operating income + ordinary depreciation + addition to pension reserves)/assets; (cash income – expenses)/short-term liabilities.
Von Stein and Ziegler (1984)	Capital borrowed/total capital; short-term borrowed capital/output; accounts payable for purchases & deliveries / material costs; (bill of exchange liabilities + accounts payable)/output; (current assets – short-term borrowed capital)/output; equity/(total assets – liquid assets – real estate); equity/(tangible property – real estate); short-term borrowed capital/current assets; (working expenditure – depreciation on tangible property)/(liquid assets + accounts receivable – short-term borrowed capital); operational result/capital; (operational result + depreciation)/net turnover; (operational result + depreciation)/short-term borrowed capital; (operational result + depreciation)/total capital borrowed.
England	
Marais (1979), Earl & Marais (1982)	Current assets/gross total assets; 1/gross total assets; cash flow/current liabilities; (funds generated from operations – net change in working capital)/debt.
Canada	
Altman and Lavallee (1981)	Current assets/current liabilities; net after-tax profits/debt; rate of growth of equity – rate of asset growth; debt/assets; sales/assets.
The Netherlands	
Bilderbeek (1979)	Retained earnings/assets; accounts payable/sales; added value/ assets; sales/assets; net profit/equity.
Van Frederikslust (1978)	Liquidity ratio (change in short-term debt over time); profitability ratio (rate of return on equity).
Spain	
Fernandez (1988)	Return on investment; cash flow/current liabilities; quick ratio/ industry value; before tax earnings/sales; cash flow/sales; (permanent funds/net fixed assets)/industry value.
Italy	
Altman, Marco, and Varetto (1994)	Ability to bear cost of debt; liquidity; ability to bear financial debt; profitability; assets/liabilities; profit accumulation; trade indebtedness; efficiency.
Australia	

Izan (1984)	EBIT/interest; MV equity/liabilities; EBIT/assets; funded debt/ shareholder funds; current assets/current liabilities.
Greece	
Gloubos and Grammatikos (1988)	Gross income/current liabilities; debt/assets; net working capital/assets; gross income/assets; current assets/current liabilities.
Brazil	
Altman, Baidya, & Ribeiro-Dias,1979	Retained earnings/assets; EBIT/assets; sales/assets; MV equity/ book value of liabilities.
India	
Bhatia (1988)	Cash flow/debt; current ratio; profit after tax/net worth; interest/ output; sales/assets; stock of finished goods/sales; working capital management ratio.
Korea	
Altman, Kim and Eom (1995)	Log(assets); log(sales/assets); retained earnings/assets; MV of equity/liabilities.
Singapore	
Ta and Seah (1981)	Operating profit/liabilities; current assets/current liabilities; EAIT/paid-up capital; sales/working capital; (current assets – stocks – current liabilities)/EBIT; total shareholders' fund/liabilities; ordinary shareholders' fund/capital used.
Finland	
Suominen (1988)	Profitability: (quick flow – direct taxes)/assets; Liquidity: (quick assets/total assets); liabilities/assets.
Uruguay	
Pascale (1988)	Sales/debt; net earnings/assets; long-term debt/total debt.
Turkey	
Unal (1988)	EBIT/assets; quick assets/current debt; net working capital/sales; quick assets/inventory; debt/assets; long-term debt/assets.

Source: Altman and Narayanan (1997).

The use of financial ratio in failure prediction is based on the assumption that the failure process is characterized by a systematic deterioration in the values of the ratios. There may, however, be a problem in the context of failure prediction since failing firms may have different failure processes in terms of the behaviour of financial ratios. The existence of alternative failure processes in a sample of failed firms may result in inaccuracy in failure prediction models based on an assumption of a common uniform process. For example, the Z-score model completed by Taffler (1982) in the year of 1974 was comprised of five financial ratios estimated for UK firms. However, his later model updated in 1976 was quite different containing four other ratios from those in the previous model.

Financial ratios are rarely used to test hypotheses and theories of economic and financial behaviour. They are usually simply selected from data statistically without any rigorous hypotheses on the behaviour of the firm before failure. Zavgren (1983, p.32) stated that in the absence of a theory that indicated the important dimensions, the selection of various closely related ratios in the model might lead to sample-specific results and to the instability of the prediction model.

Although the statistical models used and the relevant financial ratios vary with the numerous studies, certain commonalities appear as well. Stickney, Brown and Wahlen (2003) summarized the following factors that seem to explain business failure most consistently across various studies:

- Investment Factors related to the asset side of the balance sheet
    - Relative Liquidity of a firm's asset
    - Rate to Asset Turnover

- Financing Factors related to the liability side of the balance sheet
    - Relative Proportion of Debt in the Capital Structure
    - Relative Proportion of Short-term Debt in the Capital Structure

- Profitability Factors related to the operating activities of a firm
    - Relative Level of Profitability
    - Variability of operations

- Other Possible Explanatory Variables examined in bankruptcy research
    - Size
    - Growth
    - Qualified Audit Opinion

2.5 Methods for Predicting Failure

Failure prediction has long been an important and widely studied topic since an early study of Fitzpatrick in 1930's; during the last 70 years an impressive body of theoretical and empirical research concerning this topic has been evolved. This section briefly discusses some commonly used prediction models.

Dimitras, Zanakis, and Zopounidis (1996) collected the failure prediction methods from 47 studies that were presented in *Journal of Banking & Finance, Journal of Business Finance & Accounting, Journal of Accounting Research, Omega, Decision Science, Journal of Finance and European Journal of Operational Research.* These studies concerned 12 different countries, as presented in Table 2.3.

Table 2.3: Number of studies by country in the study of Dimitras et al. (1996)

Country	No of studies
Australia	2
Canada	1
Finland	4
France	5
Greece	7
Israel	1
Italy	2
Japan	1
Sweden	1
The Netherlands	1
UK	9
USA	13

Two main approaches in failure prediction studies can be distinguished as: the first and most often used empirical approach searching for predictors that lead to lowest misclassification rates; the second approach concentrating on the search for statistics methods that lead to improve prediction accuracy.

At the beginning of the research period of failure prediction by Fitzpatrick (1932), there were no advanced statistics methods or computers available for researchers. Bankruptcy prediction research represents an effort of integrating traditional financial statement analysis and statistical modelling methods.

Beaver (1967) was recognised as the first researcher to focus on the ability of financial ratios to predict failure. He analysed a sample of 79 large, failed, and publicly owned, industrial companies, from 38 different industries, using univariate models to assess the usefulness of individual random variables as predictive indicators of corporate failure. Beaver found that a number of indicators could discriminate between matched samples of failed and non-failed firms, the best predictor of failure was the cash flow to total debt ratio, the ratio correctly predict bankruptcy for 87% of the sample firms one year prior to failure, the results also showed that this ratio was a reasonable predictor up to five years prior to failure.

Altman (1968) developed the five-variable Z-score model using multiple discriminant analysis, which showed a prediction accuracy rate above 90 percent. This five variable model proved to be extremely accurate, predicting bankruptcy correctly in 94% of the initial sample with 95% of all firms in the bankrupt and non-bankrupt groups assigned to their actual group classification. The discriminant function was accurate in several secondary samples introduced to test the reliability of the model. Investigation of the individual ratio movements prior to bankruptcy corroborated the model's findings that bankruptcy can be accurately predicted up to two years prior to actual failure with the accuracy diminishing rapidly over period longer than two years. After Altman, a number of studies corroborated this result; multiple discriminant analysis then became the dominant approach.

Although early bankruptcy studies used MDA to identify failing companies, its suitability rests on two assumptions. First, the explanatory variables are assumed to have a multivariate normal distribution. Second, the samples of failing and non-failing companies are assumed to be drawn at random from their respective populations. Most MDA studies have used a linear classification rule, which is only optimal if the restriction of equal group covariance matrices is satisfied.

Such problems with MDA have led researchers to use the logit model, Martin (1977) and Ohlson (1980) were among the first to apply these techniques, followed by Mensah (1983), Zavgren (1983), Casey and Baztczak (1985), and Peel (1987). The logit technique allows direct modelling of the relationship between the observable variables and the rating class or the default probability. Logit techniques apply for modelling zero-one variables, categories or numerical values in the zero to one range, such as default probabilities. Martin (1977) used both logit and discriminant analysis to predict bank failures in the 1975-1976 period, a time when 23 banks failed. Both models gave similar classifications in terms of identifying failures/non-failures. Ohlson (1980) applied the logit model to a sample of 105 bankrupt firms and 2,000 surviving US companies over the period 1970-76, the ratios used were the log of a price-level deflated measure of total assets, total liabilities/total assets, working capital/total assets, current liabilities/current assets, net income/total assets, flow of funds/total liabilities, and a dummy variable where total assets were greater than total liabilities. The model did not discriminate between failed and non-failed firms as well as the MDA/MRA models reported in previous studies did. But this might have been because the methodology differed in several important aspects, most obviously because of the relatively unbiased sampling procedure used by Ohlson, which suggested that previous researchers might have overstated the discriminatory power of their models. Zavgren (1983), despite using a matched pair technique, found misclassification errors for a 45 failed company sample similar to those reported by Ohlson, and somewhat surprisingly also found the profit/(equity+debt) ratio was not significantly different between the two groups of companies, although liquidity and gearing measures were. Platt and Platt (1991) applied the Logit model to test whether industry relative accounting ratios, rather than simple firm specific accounting ratios, are better predictors of corporate bankruptcy. Despite this, previous studies had argued that, in practice, the explanatory power of logit model was similar to that of discriminant analysis (Press and Wilson, 1978).

Beginning in the mid-1980s, neural network, a non-linear forecasting model became popular in predicting business failure. One of the first applications was the work by Odom and Sharda (1990). They used the same five ratios employed by Altman (1968) in his original multiple discriminant analysis (MDA) study, applying them to a sample of 65 failed and 64 non-failed US companies, where the former went bankrupt between 1975 and 1982. The training set comprised 38 failed and 36 non-failed companies, the remainder being used as a validation sample. A three layered network was created with five hidden nodes. Convergence was reached after 24 hours and 191,400 iterations. The NN model correctly identified all failed and non-failed companies in the training sample, compared to a successful classification rate of only 86.8 percent for a benchmark discriminant model. Both models were then tested on the hold out sample using prior probability of failure estimates of 50:50, 20:80 and 10:90. The neural network model correctly classified bankrupt firms in 77.7 percent or more occasions under all probability priors – a far better record than the discriminant model, which could only manager between 59 percent and 70 percent. However, for the non-failed businesses there was little to choose between the models, the correct classification rates being between 79 percent and 89 percent.

A further NN model developed in a bankruptcy context is that of Tam (1991), this was constructed on a sample of 59 Texas banks which failed between the year of 1985 and 1987, and another group of 59 matched Texas banks which survived over that period. Each bank was described over a two years period in terms of 19 financial ratios, reflecting capital adequacy, asset quality, earnings and liquidity. These were normalised by transformation and reduced to a set of 6 for constructing one year prior to failure MDA model, and to 7 for two year prior to failure MDA model. Other models were developed to provide benchmarks for assessing the NN models, including logit and artificial intelligence models. Two and three layer NN models were developed for each period, the latter having 10 hidden nodes. Different prior probability rates of failure and different misclassification costs were used. Both the one and two year NN models were an improvement over the other models in their ability to discriminate, with the three layer NN models doing best. However, the superiority was less obvious in the second year before failure, possibly suggesting that the failing and non-failing banks comprised a more homogeneous population at that stage than in the last year of a failing bank's life. The results were checked out on hold out samples, comprising 22 failed and 22 non-failed banks in the last year before failure; and 20 failed and 20 non-failed banks in the previous year. The two layer NN model was less effective in some respects than the MDA and logit models, but the three layers NN model again was more accurate than all others. However, the misclassification errors were much higher than on the original sample, especially for the Type I errors one year prior to failure, which for even the three layer NN model were around 20 percent.

In a subsequent study, Salchenberger, Clinar and Lash (1992) applied the NN procedure to discriminate between 100 US savings-and-loan (S&L) companies which failed in the year of 1986-1987 and a similar number of non-failed matched pairs. Applying five ratios, the NN model consistently outperformed a logit model, although both on the face of it were impressive in their forecasting accuracy. However, the performance of both models fell away slightly with respect to failing S&Ls as the time interval before collapse was lengthened, although only marginally in the case of the NN model. Moreover, when the model was applied to a sample where the proportion of non-failed to failed S&Ls was more realistic, the NN model still performed tolerably well, although the misclassification errors for failing firms were much larger.

Fletcher and Goss (1993) used backpropagation NN models to identify US corporate bankruptcies from a sample of 18 matched pairs of companies. Using three accounting ratios as the explanatory variables (the current ratios, the quick ratio, and net profit/working capital), they investigated the impact on the performance of their NN models of the number of neurons in the hidden layer. The results showed that NN models with between 3 and 7 hidden nodes were better able to discriminate than comparable logit models, though only marginally so, with the 4 hidden node model performing best. However, the 82 percent correct prediction rate (compared with only 71 percent for the logit model) was only achieved without adjusting for sampling bias, which suggested that none of the models would be very helpful in practice.

Another NN bankruptcy study is that of Coats and Fant (1993). They used going concern audit qualifications as their criterion of failure, identifying 94 listed US manufacturing companies over the period of 1970-1989, which met this requirement. Against these they also used 188 non-failed listed companies, almost half of which however were not in the manufacturing sector. Eight sets of company data were created, two for each of the four years prior to failure, one being used to derive the NN model, the other as a hold out sample to assess its predictive power. Each year's training and test sets comprised 47 failed and 94 non-failed companies, membership of the training set in each of the four years being determined by random selection. As in Odom and Sharda's study, the variables in the training set data were the five accounting ratios used in Altman's 1968 MDA study, and the latter's ability to identify failing companies correctly was used as the benchmark against which to assess the NN model's performance. Working to a 100 percent correct classification objective, some of the networks developed required up to 1,400 training cycles and installed as many as 8 hidden nodes. The MDA models correctly identified over 90 percent of the non-failed companies over the four years, but did far less well in classifying the failed companies, only achieving success rates of between 64 percent and 70 percent over the four years. By contrast, the NN models did far better in identifying failed companies, achieving a success rate of over 80 percent and almost matching the MDA models' ability to identify non-failures. Coats and Fant concluded that, after allowance was made for misclassification costs, the NN model appeared to be making a useful contribution to the task of identifying firms that might be the subject of on going concern, especially when the time interval before this type of "failure" was extended.

A more recent examination of the NN technique had been undertaken by Altman, Marco and Varetto (1994). They tested a number of NN models against the existing MDA predictions provided by a consortium of Italian banks. These were derived annually for a population of nearly 40,000 medium and small sized businesses. The MDA diagnostic procedures were in fact applied in two phases: first, to distinguish healthy from vulnerable firms; and then with respect to the latter to separate those which are prima facie failures from those which are not. Using a 404 matched pair analysis sample and a 150 matched pair hold out group, the first phase model was very successful in discriminating both over the estimation period and over a control period. However, the classificatory accuracy of the second phase model was somewhat weaker. It was also based on a 404 matched pair analysis sample and a 150 matched pair hold out group, but only around 80 percent of failing firms were correctly identified. Various NN models were then developed to see how they performed in relation to the MDA models. One, two and three layer NN models were devised with different numbers of hidden nodes and with different learning times. The best results in distinguishing between healthy and vulnerable firms were initially achieved with a three layer network, the second layer having four hidden neurons. The inputs comprised 10 financial ratios, and training was interrupted after 1,000 cycles. When the number of layers in the network was varied, the most satisfactory results were achieved after 2,000 cycles for a three layer model, with 15 neurons in the first layer and 6 in the second. The model was able to discriminate with 97 percent accuracy compared to between 86 percent and 90 percent for the corresponding MDA model.

Podding (1994), using data on 300 French firms collected over three years, claimed that neural networks outperformed credit scoring models in bankruptcy prediction. However, he found that not all artificial neural systems were equal, noting that the multi-layer perception (or back propagation) network was best suited for bankruptcy prediction. Yang, Platt and Platt (1999) used a sample of oil and gas company debt to show that the back propagation neural network obtained the highest classification accuracy overall, when compared to the probabilistic neural network and discriminant analysis (Allen (2002)).

Despite a number of studies advocating usefulness of Neural Networks (NN), there are flaws in these models too. As noted by Shin and Lee (2002), finding an appropriate NN model to reflect problem characteristics is not an easy job. It is because there are a number of network topologies, learning methods and parameters. Most importantly, NNs are characterized as 'black boxes' due to inability of the users to readily comprehend the final rules acquired by NNs to solve the problem. Additionally, Altman and Varetto (1994) noted that long processing time to complete the NN training stage, requirement of having a large number of tests to identify appropriate NN structure, and the problem of over fitting could considerably limit the use of NNs.

The general conclusions from this extensive research review seem to be that each study by itself provides a reasonable discrimination between failed and non-failed firms, but also, and perhaps more significantly, that the various studies show little agreement. This discord of conclusions can partly be attributed to the fact that virtually there is lack a theoretical framework to guide the empirical research effort.

Studies of failure prediction in China are still in the early stages. Shi and Zou (2001) studied the credit problem of Chinese A-share part listed companies during the year of 1999-2000 by means of canonical discriminate analysis. Li (2001) classified listed companies by distinguishing function with data of the Shanghai and Shenzhen Stock Exchange covered the period of 1997-1999. Almost of these studies used discriminant analysis, Zhang (2003) indicated that the Logit Model and Neural Network might be good choice for the Chinese market in predicting the business failure.

So business failure prediction studies evolved between the mid-1960 and mid-1990 from relatively simple univariate models to multivariate models. Empirical studies reveal that multiple discriminant analysis; logit and probit models are frequently developed to classify firms as failures or healthy. Recently, there has been considerable interest in the development of the neural network predication model. Neural network model requires fewer assumptions, achieves a higher degree of prediction accuracy and is more robust.

Accurate prediction of corporate failure is very important. First, as "early warning systems", such models are very useful to those (managers, authorities, etc.) that can act to prevent failure. These actions include the decision about merger of the distressed firm, liquidation or reorganization type and associated costs (Casey et al., 1986). Second, such models can be useful aiding investor and financial institutions in the firms' evaluation and selection, avoiding heavy losses stemming from surprise delisting or bankruptcies.

3. Data and Methodology

3.1 Research Design

In this study, the data mining technique[1] will be used to test failure prediction methods. To derive the causes of failure, the analysis focuses on two alternative techniques: Parametric method Logistic Regression Model (LRM) and Neural Network Analysis (NN) which is a nonparametric method frequently used in data mining. The process for the development of failure prediction models consists mainly of three parts:

1. Sample selection and collection of data (dependent variables and sample size).
2. Selection of a method and the specific variables (financial ratios) to develop a predictive model.
3. Model validation, i.e. statistical significance and accuracy of results.

3.2 Data Collection

3.2.1 Ratio Variables

The annual financial statement data is extracted from the China Stock Market & Accounting Research (CSMAR) and Data Stream database during the period of December 1991 to December 2002. The ratio variables include both financial-based ratios and equity-based ratios. The financial-based ratios are taken from China Stock Market & Accounting Research (CSMAR) database and verified by actual balance sheets, income statements and cash flow statements. The equity-based ratio are collected from Data Stream and verified by price and market value. The data comes from the public listed companies on both the Shanghai (SHSE) and Shenzhen (SZSE) Stock Exchange. In this study, we use A-shares part listed companies.

[1] Data mining refers to the practice of analysis data with little or no underlying theory in the hope of finding statistically significant relationships.

Based on extensive literature review, 40 popularly used financial ratios have been computed and divided into seven categories: 1) Liquidity, 2) Asset Utilization, 3) Long-term Solvency, 4) Profitability, 5) Cash Flow, 6) Growth, and 7) Market Value (see Appendix 1). The time factor is an essential concern; Deakin (1972) concluded two years as the minimum for a model to be useful, so in this study, we use ratios two years prior to failure.

3.2.2 Sample Description

Group classification is critically important in failure study, The assumptions of most failure prediction methods are based on that firms can generally be split into two groups: the group of healthy firms and the group of failed firms. In China, most problematic listed companies are financially distressed but non-bankrupt. Based on the failed firms' commonalities summarized by Stickney, Brown and Wahlen (2003) and new *Listing Rules* of Shenzhen and Shanghai Stock Exchanges, we build seven criteria to define business failure; each criterion represents one problem type of failed firms. The seven criteria are:

According to new *Listing Rules,* listed companies will be special treatment under condition of:

1. Shareholder's equity is lower than registered capital;
2. Suffered losses for two consecutive years;

Based on Stickney, Brown and Wahlen (2003) study, failed firms show some commonalities (the threshold levels are determined by personal experience and judgement):

3. Profitability problem: net profit <0, and sale growth <0.8;
4. Liquidity problem: net profit <0, current ratio <1 and change level <1;
5. Insolvency problem: net profit <0, total debt / equity >1 and change level >1;
6. Growth problem: two continues year sale growth <0.8;
7. Non-invest value problem: two continues year market value growth <0.8.

According to the above criterion, failed group firms are assigned a dummy variable of 1 while the healthy firms 0. The failed group firms consist in the earlier phases of financial distress, the ultimate condition of either de-listing or bankruptcy is not known at the time of selecting. Hence, the failure predication derived from this study intends to develop an early warning system to help the management to recognise the ailing of the firm, enable appropriate action to improve efficiency, and avoid risk of de-listing or bankruptcy.

The preliminary sample comprised 6099 observations firms, divided by five sectors: industry, utility, property, commercial and others (see table 3.1). After matched by two year before ratios, 2501 observations have been eliminated and there are just 3598 observations left in the sample.

Table 3.1: Sector Breakdown of Observations

Sector	Original Observations	Matched Observations
Industry	3315	1906
Utility	1010	536
Property	303	214
Commercial	587	381
Others	884	561
Total	6099	3598

A cross-validation procedure is applied in this study, as explained by Bishop (1995, p. 372):

"Since our goal is to find the network having the best performance on new data, the simplest approach to the comparison of different networks is to evaluate the error function using data which is independent of that used for training. Various networks are trained by minimization of an appropriate error function defined with respect to a **training** data set. The performance of the networks is then compared by evaluating the error function using an independent **validation** set, and the network having the smallest error with respect to the validation set is selected. This approach is called the **hold out method.** Since this procedure can itself lead to some overfitting to the validation set, the performance of the selected network should be confirmed by measuring its performance on a third independent set of data called a **test** set."

The procedure for the analysis is as follows. First, a prediction model is drawn by comparing failed firms with healthy firms using the financial ratio two year prior to failure. After setting up the prediction model, a test for reliability of the model is conducted. An estimation sample is used for determination of the model, while a holdout sample is used to measure the accuracy of the model. Using repeated random partition; the sample set is divided into training, validation and testing sets (Table 3.2). 40% of the sample set is chosen for training and 30% for validation, the other 30% is for testing. Hence, cross-validation avoids "over-fitting" when attempting to build more effective model.

Table 3.2 Sample Size

	Sample	Training	Validation	Test	Total
Criterion one	Failure	94	58	58	210
	Non-Failure	1344	1022	1022	3388
	Total	1438	1080	1080	3598
Criterion two	Failure	74	48	48	170
	Non-Failure	1364	1032	1032	3428
	Total	1438	1080	1080	3598
Criterion three	Failure	98	68	68	234
	Non-Failure	1340	1012	1012	3364
	Total	1438	1080	1080	3598
Criterion four	Failure	105	77	77	259
	Non-Failure	1333	1003	1003	3339
	Total	1438	1080	1080	3598
Criterion five	Failure	125	89	89	303
	Non-Failure	1313	991	991	3295
	Total	1438	1080	1080	3598
Criterion six	Failure	91	50	50	191
	Non-Failure	1347	1030	1030	3407
	Total	1438	1080	1080	3598
Criterion seven	Failure	163	96	96	355
	Non-Failure	1275	984	984	3243
	Total	1438	1080	1080	3598

Note: Criterion One: Shareholder's equity is lower than registered capital
Criterion Two: Suffered losses for two consecutive years
Criterion Three: Net profit <0, and sale growth <0.8
Criterion Four: Net profit <0, current ratio <1 and change level <1
Criterion Five: Net profit <0, total debt / equity >1 and change level >1
Criterion Six: Two continues year sale growth <0.8
Criterion Seven: Two continues year market value growth <0.8

Table3.2 illustrates a significantly low frequency rate of failed firms in our sample. This finding is consistent with that of White and Turnbull (1975) and Zmijewski (1983) who revealed that the proportion of failed firms in the economy was substantially smaller than the proportion of non-failed firms. Previous studies typically estimated financial distress prediction models on non-random samples. Estimating models on such sample might result in biased parameter and probability estimates if no appropriate techniques were used. DeaKin (1977), Ketz (1978), Dambolena and Hkoury (1980), Ohlson (1980) and Zmijewski (1983) addressed this criticism by using a larger proportion of non-bankrupt firms. They statistically confirmed that the sample frequency of more highly distressed firms might lead to lower prediction errors in both distressed firms and non-distressed firms estimated error rates. Therefore, in this study we selected samples of non-matched pairs for prediction models.

3.3 Methodology

3.3.1 Logistic Regression Model

Logistic Regression Model (or logit model) has commonly been used to investigate the relationship between binary or ordinary response probability and explanatory variables; it is a statistical method that attempt to obtain a functional relationship between a transformation - from a qualitative variable - called logit and *p* predictor variables which can be either quantitative or qualitative.

It is used to develop a model that attempts to sufficiently describe the relation between the result (dependent variable or the response) and the set of independent (or explanatory) variables. The fundamental characteristic of this regression is that the dependent variable is dichotomous. Mathematically the function used in logistic distribution is extremely flexible and easy to use. The advantage of this method is that it does not assume multivariate normality and equal covariance matrices, and incorporates non-linear effect.

Indicating the dichotomous variable to predict by Y and the P predictor variables by x_1, .., x_p, assuming that 1 indicates failure and 0 indicates non-failure, the objective is to determine the coefficients $\beta_0, \beta_1, ..., \beta_p$ in order to satisfy the logit transformation formula:

$$\mathrm{g(X)} = \ln\frac{P(Y=1)}{P(Y=0)} = \beta_0 + \beta_1 x_1 + \ldots + \beta_p x_p$$

The determination of the coefficients (β_0 is the intercept and $\beta_1, \ldots, \beta_p$ are the p parameters) is carried out by the method of maximum likelihood, and the predictor variables selection can be carried out by three methods: forward, backward or stepwise. In this study the stepwise method is used. The procedure starts by estimating parameters for variables determined by the model such as intercept and first possible explanatory variables, next, the procedure computes the adjusted chi-squared statistic for all the variables not in the model and examines the largest of these statistics, a 5% entry significance level is specified in this study for a variable entered into the model, each step is followed by one or more elimination steps, the stepwise selection process terminates when no further variable is added to or removed from the model.

After obtaining g (X), a classification model can be constructed. The probability of a firm i go to failure is described by the following formula:

$$P(Y=1) = \frac{1}{1+e^{-g(X)}}$$

It is used to classify a firm as failed or healthy from the following rules:

" If $P(Y=1) >$ cut-off point, then the firm is classified as 1,

otherwise it is classified as 0".

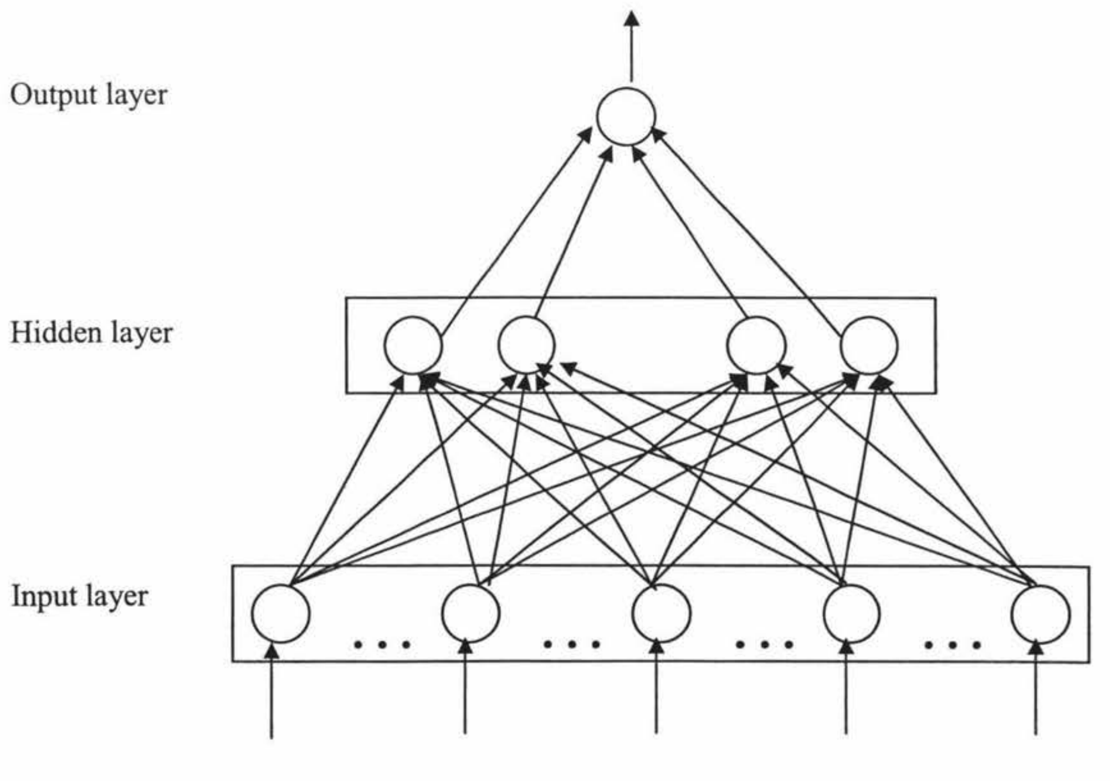
So the greater the probability $P(Y=1)$ is above cut-off point (range from 0-1), the greater chance the firm is classified as failure.

3.3.2 Neural Network Analysis

This is a sequential process, one case is considered at a time, as compared with other multivariate techniques, which consider an entire set of cases simultaneously (Hair, 1992). The most basic element in a neural network is neuron, a self-contained processing unit that acts in parallel with other neurons, also called "processing elements" or "nodes". Like real neurons, these nodes are connected to each other through "weighted interconnections" (synapses in neuroscience terms). Nodes are organized in layers. Each node takes delivery of joins, and converts input signals into a single output signal via weighted interconnections. This output signal is accepted as the classifying decision if it satisfies the researcher; otherwise it is transmitted again as an input signal to many other nodes (possibly including itself). This process keeps going until the researcher is satisfied.

The neural networks used in this study consist of three layers: input, hidden, and output (see Figure 3.1).

Figure 3.1 Neural Network Design



The input layer receives data from the outside world. The input layer neurons send information to the hidden layer neurons. The hidden neurons are all the neurons between the input and output layers. They are part of the internal abstract pattern, which represents the neural network's solution to the problem. The hidden layer neurons feed their output to the output layer neurons, which provide the neural network's response to the input data.

Neurons process input and produce output. Each neuron takes in the output from many other neurons. Actual output from a neuron is calculated using a transfer function. In this study, a sigmoid transfer function is chosen because it produces a continuous value in the range [0,1]. A neuron (n_i) in a given layer is connected to neurons (n_j) in the previous layer. The connection from n_j to n_i has the weight w_{ji}. The weights of the connections are initially assigned an arbitrary value between 0 and 1. The appropriate weights are determined during the training phase. Input to the n_i is obtained using the following equation:

$$Input_i = \sum_j w_{ji} \times output_j + \varphi_i$$

Where: w_{ji} is the connection weight between neuron *i, j* and

φ_i is the bias of neuron *i*.

Output from the n_i is calculated using a sigmoid transfer function as:

$$Output_i = \frac{1}{1 + e^{Input_i}}$$

The multiplayer perception (MLP) is selected for neural network architecture, the input nodes obtain the values of input variables and optionally standardize those values, the hidden nodes perform internal computations, providing the non-linearity that makes neural network powerful. Increasing the size of the nodes makes the network more powerful but introduces the risk of over-fitting[2], so we need find equilibrium between generalisation and representation. A three layer network structure with four hidden nodes in the hidden layer has been set in this study, following Altman, Marco and Varetto (1994).

In this study, the "backpropagation[3] learning algorithm" is employed to train the network; It is a gradient descent method that minimizes the mean squared error by moving down the gradient of the error curve. The error surface is multi-dimensional and may contain many local minima. As a result, training the network often requires experimentation with starting position, adjusting the weights during training, and modifying various learning parameters. After training has been completed, the NN can be used for prediction, the new input firms arising from the final unit of the network is classified as failure or non-failure.

Neural network models are distribution free and adaptive to the real world problems. However, there are some problems in their application such as: the impossibility to describe them in terms of parameter values and much more computational complexity than other methods. Altman, Marco and Varetto (1994) mentioned that NNs behaved like a "black box" in a decision making approach and made the acceptance and application of them difficult.

3.3.3 Cost of Prediction Errors

In general terms, Type I error is incorrectly identifying a failed firms as non-failed and Type II error is incorrectly identifying a non-failed firms as failed. Most classification systems for predicting bankruptcy have attempted to minimize the misclassification rate, assuming that Type I and Type II error costs are equal, however, in reality the cost of a Type I error is much greater than a Type II error. For example, the investors could lose the total investment if they invest in a failed firm, whereas in making a Type II error the investors just lose the opportunity to earn dividend and capital gain. Since the distinctions between the two types of error are

[2] Over-fitting refers to the situation where a model fits exceptionally well on to the data from which it is derived, but far less well on to other data from a hold out sample.

[3] backpropagation refers to the method for computing the error gradient for a feedforward network, a straightforward application of the chain rule of elementary calculus.

important, following by Koh (1992), we incorporate asymmetric costs for Type I and Type II error in attempt to find the minimum overall cost of misclassification.

The following function is used to calculated the expected misclassification cost:

$$TotalCost = \sum_i F(i)C(i)$$

$$AverageCost = TotalCost / \sum_i F(i)$$

Where, $F(i)$ is the frequency for case i (Type I or Type II error);

$C(i)$ is the misclassification cost of case i.

In this study, a range of Type I and Type II error cost ratios from 6:4, 7:3, 8:2, 9:1, 10:1, 25:1 to 50:1 are assumed to investigate the sensitivity of optimal cut-off points. Based on the optimal cut-off points, then, we compare the average cost of logistic regression model and neural network to judge which model is more appropriate to predict failed firms in China.

3.3.4 Random Prediction

In order to prove both models are useful, we produce a random prediction for target variables based on Bernoulli distribution. The Bernoulli distribution is a discrete distribution having two possible outcomes labelled by $n = 0$ and $n = 1$, in which $n = 1$ ("failure") occurs with probability p and $n = 0$ ("success") occurs with probability $q=1-p$, where $0<p<1$. It therefore has probability function:

$$P(n) = \begin{cases} 1-p & \text{for } n = 0 \\ p & \text{for } n = 1, \end{cases}$$

The corresponding distribution function is

$$D(n) = \begin{cases} 1-p & \text{for } n = 0 \\ 1 & \text{for } n = 1. \end{cases}$$

While p=0.5 is set to generate random variables based on sample size. Then comparing with actual target value, we can get Type I, Type II errors and total misclassification cost.

3.4 Used Software

In this study, the statistical software SAS 8e, including SAS base and SAS Enterprise Miner, are used for estimation and assessment of the logistic regression model and the neural network analysis. The random prediction is produced on Excel spreadsheet Bernoulli distribution function.

4 Empirical Results

In this study, our aim is to find out which prediction model performs well, relying on minimizing total misclassification costs of Type I and Type II error. As mentioned earlier, cross-validation procedure has been used to avoid over-fitting; so following results are achieved from the test sample and presented separately by different criterion.

4.1 Failure Criterion One-- Shareholder's equity is lower than registered capital

4.1.1 Optimal cut-off points

The optimal cut-off points (defined as the value which produces the lowest average cost) corresponding to cost ratio are summarised in Table 4.1. As can be seen, both models are rather sensitive to different relative misclassification costs. For logit model, the optimal cut-off points decrease from 0.4 to 0.05 as the type I error costs increase. (Because of type I cost > type II cost, type I error should be reduced through adjusted cut-off points, total cost is trade-off between type I error and type II error to find out optimal cut-off points). For neural network, the optimal cut-off points decrease from 0.45 to 0 as type I error costs increase.

4.1.2 Prediction errors

The prediction error rates of the model at different levels of relative misclassification costs are also presented in Table 4.1. For logit model, type I error decreases from 74% to 12% while type II error increases from 1% to 29%; however, the total misclassification rate goes up, from 5% to 28%. (As in non-paired samples, the non-failure firms have more weight on total sample). For neural network, type I error decreases from 76% to 0%, type II error increases from 1% to 100%, and the total misclassification rate goes up, from 5% to 95%.

4.1.3 Misclassification costs

The minimum average misclassification costs of the model at different optimal cut-off points are presented in Table 4.1. For logit model, based on optimal cut-off points of 0.4, 0.3, 0.2, 0.15, 0.1, 0.05, and 0.05, the average costs are 0.2722, 0.2824, 0.3111, 0.2815, 0.3046, 0.4342 and 0.5963, respectively; For neural network, based on optimal cut-off points of 0.45, 0.35, 0.35, 0.25, 0.05, 0.05, and 0, the average cost are 0.2815, 0.3194, 0.3259, 0.2935, 0.3139, 0.5565 and 0.9463, respectively. At each level of expected misclassification cost, the logit model is superior to neural network, so in this criterion, logit model exceeds neural network. Compared with the Bernoulli distribution prediction, the average costs of both models are far less than random prediction.

Table 4.1 Prediction Errors and Misclassification Cost

(Criterion One-- Shareholder's equity is lower than registered capital)

It is believed that the cost of type I error (misclassifying a financial failure firm as a healthy firm) is greater than the cost of type II errors (misclassifying a healthy firm as financial failure firm). Average cost is the total misclassification cost per observation. Optimal cut-off point is the threshold that minimizes average cost. Random prediction is based on Bernoulli simulation.

Type I/ II error cost ratio	**6:4**	**7:3**	**8:2**	**9:1**	**10:1**	**25:1**	**50:1**
A: Logit model							
Type I error	74%	66%	66%	45%	33%	12%	12%
Type II error	1%	1%	2%	7%	14%	29%	29%
Total misclassification rate	5%	5%	5%	9%	15%	28%	28%
Average cost	**0.2722**	**0.2824**	**0.3111**	**0.2815**	**0.3046**	**0.4342**	**0.5963**
Optimal cut-off points	0.4	0.3	0.2	0.15	0.1	0.05	0.05
B: Neural Network							
Type I error	76%	67%	57%	48%	17%	29%	0%
Type II error	1%	2%	4%	6%	23%	17%	100%
Total misclassification rate	5%	6%	7%	9%	23%	18%	95%
Average cost	0.2815	0.3194	0.3259	0.2935	0.3139	0.5565	0.9463
Optimal cut-off points	0.45	0.35	0.35	0.25	0.05	0.05	0
C: Random Prediction							
Type I error	45%	45%	45%	45%	45%	45%	45%
Type II error	50%	50%	50%	50%	50%	50%	50%
Total misclassification rate	49%	49%	49%	49%	49%	49%	49%
Average cost	2.0259	1.5796	1.1333	0.6870	0.7111	1.0722	1.6741

4.2 Failure Criterion Two-- Suffered losses for two consecutive years

4.2.1 Optimal cut-off points

The optimal cut-off points corresponding to cost of type I and type II errors for criterion two are summarised in Table 4.2. For logit model, the optimal cut-off points decrease from 0.35 to 0.05 as type I error costs increase. (At cost ratio 8:2 is exceptional, optimal cut-off points increase to 0.25, total cost is a trade-off between type I error and type II error to adjust cut-off points). For neural network, the optimal cut-off points decrease from 0.1 to 0.05 as type I error costs increase (but at cost ratio 8:2, optimal cut-off points jump to 0.65).

4.2.2 Prediction errors

The prediction error rates of the model at different levels of relative misclassification costs are presented in Table 4.2. For logit model, type I error decreases from 94% to 21%, type II error increases from 0% to 35%, and the total misclassification rate goes up, from 4% to 35%. For neural network, type I error decreases from 100% to 25%, type II error increases from 0% to 25%, and the total misclassification rate goes up, from 4% to 25%.

4.2.3 Misclassification costs

The minimum average misclassification costs of the model at different optimal cut-off points are presented in Table 4.2. For logit model, based on optimal cut-off points, the average cost are 0.2611, 0.3111, 0.3407, 0.3666, 0.3759, 0.5583 and 0.8018, respectively; for neural network, based on optimal cut-off points, the average cost is 0.2666, 0.3111, 0.3555, 0.3268, 0.3639, 0.5129 and 0.7907, respectively. At lower type I error cost ratio 6:4 and 8:2, the average costs of logit model are smaller than neural network, however, at higher type I error cost ratio from 9:1 to 50:1, the neural network surpasses logit model; at cost ratio 7:3, average cost is equal for both models.

Compared with the Bernoulli distribution prediction, both models average costs are less than random prediction.

Table 4.2 Prediction Errors and Misclassification Cost

(Criterion Two- Suffered losses for two consecutive years)

It is believed that the cost of type I error (misclassifying a financial failure firm as a healthy firm) is greater than the cost of type II errors (misclassifying a healthy firm as financial failure firm). Average cost is the total misclassification cost per observation. Optimal cut-off point is the threshold that minimizes average cost. Random prediction is based on Bernoulli simulation.

Type I/ II error cost ratio	**6:4**	**7:3**	**8:2**	**9:1**	**10:1**	**25:1**	**50:1**
A: Logit model							
Type I error	94%	100%	90%	67%	60%	21%	21%
Type II error	0%	0%	1%	10%	11%	34%	35%
Total misclassification rate	4%	4%	5%	13%	13%	34%	35%
Average cost	**0.2611**	***0.3111***	**0.3407**	0.3666	0.3759	0.5583	0.8018
Optimal cut-off points	0.35	0.1	0.25	0.1	0.1	0.05	0.05
B: Neural Network							
Type I error	100%	100%	100%	38%	63%	25%	25%
Type II error	0%	0%	0%	19%	9%	25%	25%
Total misclassification rate	4%	4%	4%	19%	11%	25%	25%
Average cost	0.2666	0.3111	0.3555	**0.3268**	**0.3639**	**0.5129**	**0.7907**
Optimal cut-off points	0.1	0.1	0.65	0.1	0.2	0.05	0.05
C:Random Prediction							
Type I error	46%	46%	46%	46%	46%	46%	46%
Type II error	50%	50%	50%	50%	50%	50%	50%
Total misclassification rate	50%	50%	50%	50%	50%	50%	50%
Average cost	2.0259	1.5704	1.1148	0.6593	0.6796	0.9852	1.4944

4.3 Failure Criterion Three--Net profit <0, and sale growth <0.8

4.3.1 Optimal cut-off points

At criterion three (see table 4.3), the optimal cut-off points decrease from 0.1 to 0 as type I error cost increases for logit model, most cut-off points are around 0.1; for neural network, the optimal cut-off points decrease from 0.1 to 0 as type I error cost increases, (but at cost ratio 8:2, optimal cut-off points jump to 0.8).

4.3.2 Prediction errors

The prediction error rates of the model at different levels of relative misclassification costs are presented in Table 4.3. For logit model, type I error decreases from 100% to 0%, type II error increases from 0% to 100%, and the total misclassification rate goes up, from 6% to 94%. For neural network, type I error decreases from 100% to 0%, type II error increases from 0% to 100%, and the total misclassification rate goes up, from 6% to 94%.

4.3.3 Misclassification costs

The minimum average misclassification costs of the model at different optimal cut-off points are presented in Table 4.3. For logit model, based on optimal cut-off points, the average costs are 0.3778, 0.4324, 0.4889, 0.5435, 0.5879, 0.937 and 0.937, respectively; For neural network, based on optimal cut-off points, the average costs are 0.3778, 0.4407, 0.5037, 0.4991, 0.5305, 0.7704 and 0.937, respectively. At lower type I error cost ratio from 7:3 to 8:2, the average costs of logit model are superior to neural network, however, at higher type I error cost ratio from 9:1 to 25:1, the neural network exceeds logit model; and at cost ratio 7:3 and 50:1, average cost is equal for both models. Compared with the Bernoulli distribution prediction, both models average cost are better than random prediction.

Table 4.3 Prediction Errors and Misclassification Cost

(Criterion Three-- Net profit <0, and sale growth <0.8)

It is believed that the cost of type I error (misclassifying a financial failure firm as a healthy firm) is greater than the cost of type II errors (misclassifying a healthy firm as financial failure firm). Average cost is the total misclassification cost per observation. Optimal cut-off point is the threshold that minimizes average cost. Random prediction is based on Bernoulli simulation.

Type I/ II error cost ratio	**6:4**	**7:3**	**8:2**	**9:1**	**10:1**	**25:1**	**50:1**
A: Logit model							
Type I error	100%	96%	96%	79%	85%	0%	0%
Type II error	0%	0%	0%	10%	5%	100%	100%
Total misclassification rate	6%	6%	6%	14%	10%	94%	94%
Average cost	***0.3778***	**0.4324**	**0.4889**	0.5435	0.5879	0.937	0.937
Optimal cut-off points	0.1	0.15	0.15	0.1	0.1	0	0
B: Neural Network							
Type I error	100%	100%	100%	50%	50%	25%	0%
Type II error	0%	0%	0%	23%	23%	40%	100%
Total misclassification rate	6%	6%	6%	25%	25%	39%	94%
Average cost	0.3778	0.4407	0.5037	**0.4991**	**0.5305**	**0.7704**	***0.937***
Optimal cut-off points	0.1	0.1	0.8	0.1	0.1	0.05	0
C: Random Prediction							
Type I error	44%	44%	44%	44%	44%	44%	44%
Type II error	50%	50%	50%	50%	50%	50%	50%
Total misclassification rate	49%	49%	49%	49%	49%	49%	49%
Average cost	2.0259	1.5889	1.1519	0.7148	0.7426	1.1593	1.8537

4.4 Failure Criterion Four--Net profit <0, current ratio <1 and change level <1

4.4.1 Optimal cut-off points

At criterion four (see table 4.4), the optimal cut-off points decrease from 0.1 to 0.05 as type I error cost increases for logit model, (there is exceptional at cost ratio 7:3 and 8:2). For neural network, the optimal cut-off points decrease from 0.45 to 0 as type I error cost increases.

4.4.2 Prediction errors

The prediction error rates of the model at different levels of relative misclassification costs are presented in Table 4.4. For logit model, type I error decreases from 100% to 14%, type II error increases from 0% to 44%, and the total misclassification rate goes up, from 7% to 42%. For neural network, type I error decreases from 100% to 0%, type II error increases from 0% to 100%, and the total misclassification rate goes up, from 7% to 93%.

4.4.3 Misclassification costs

The minimum average misclassification costs of the model at different optimal cut-off points are presented in Table 4.4. For logit model, based on optimal cut-off points, the average costs are 0.4278, 0.4815, 0.5444, 0.4722, 0.4963, 0.7861 and 0.9204, respectively. For neural network, the average costs are 0.4278, 0.4991, 0.5704, 0.4379, 0.4555, 0.7333 and 0.9287, respectively. At lower type I error cost ratio from 7:3 to 8:2 and higher ratio 50:1, the average costs of logit model are superior to neural network, however, at higher type I error cost ratio from 9:1 to 25:1, the neural network surpasses logit model; at cost ratio 6:4, average cost is equal for both models. Compared with the Bernoulli distribution prediction, both models average cost are better than random prediction.

Table 4.4 Prediction Errors and Misclassification Cost

(Criterion Four-- Net profit <0, current ratio <1 and change level <1)

It is believed that the cost of type I error (misclassifying a financial failure firm as a healthy firm) is greater than the cost of type II errors (misclassifying a healthy firm as financial failure firm). Average cost is the total misclassification cost per observation. Optimal cut-off point is the threshold that minimizes average cost. Random prediction is based on Bernoulli simulation.

Type I/ II error cost ratio	**6:4**	**7:3**	**8:2**	**9:1**	**10:1**	**25:1**	**50:1**
A: Logit model							
Type I error	100%	95%	88%	39%	40%	12%	14%
Type II error	0%	0%	2%	24%	23%	62%	44%
Total misclassification rate	7%	7%	8%	25%	24%	59%	42%
Average cost	***0.4278***	**0.4815**	**0.5444**	0.4722	0.4963	0.7861	**0.9204**
Optimal cut-off points	0.1	0.35	0.25	0.1	0.1	0.05	0.05
B: Neural Network							
Type I error	100%	100%	100%	36%	23%	21%	0%
Type II error	0%	0%	0%	22%	31%	39%	100%
Total misclassification rate	7%	7%	7%	23%	31%	38%	93%
Average cost	0.4278	0.4991	0.5704	**0.4379**	**0.4555**	**0.7333**	0.9287
Optimal cut-off points	0.45	0.4	0.1	0.1	0.05	0.05	0
C: Random Prediction							
Type I error	48%	48%	48%	48%	48%	48%	48%
Type II error	50%	50%	50%	50%	50%	50%	50%
Total misclassification rate	50%	50%	50%	50%	50%	50%	50%
Average cost	2.0574	1.6287	1.2000	0.7713	0.8056	1.3194	2.1759

4.5 Failure Criterion Five--Net profit <0, total debt /total equity >1 and change level >1

4.5.1 Optimal cut-off points

At criterion five (see table 4.5), the optimal cut-off points decrease from 0.1 to 0 as type I error cost increases for logit model. For neural network, the optimal cut-off points decrease from 0.95 to 0 as type I error cost increases.

4.5.2 Prediction errors

The prediction error rates of the model at different levels of relative misclassification costs are presented in Table 4.5. For logit model, type I error decreases from 100% to 14%, type II error increases from 0% to 100%, and the total misclassification rate goes up, from 8% to 92%. For neural network, type I error decreases from 100% to 0%, type II error increases from 0% to 100%, and the total misclassification rate goes up, from 8% to 92%.

4.5.3 Misclassification costs

The minimum average misclassification costs of the model at different optimal cut-off points are presented in Table 4.5. For logit model, based on optimal cut-off points, the average costs are 0.4944, 0.5768, 0.6111, 0.5481, 0.5731, 0.9176 and 0.9176, respectively. For neural network, the average costs are 0.4944, 0.5731, 0.6166, 0.5426, 0.6018, 0.8731 and 0.9176, respectively. Basically these two models perform equally well in the prediction. Compared with the Bernoulli distribution prediction, both models' average costs are less than random prediction.

Table 4.5 Prediction Errors and Misclassification Cost

(Criterion Five-- Net profit <0, total debt /total equity >1 and change level >1)

It is believed that the cost of type I error (misclassifying a financial failure firm as a healthy firm) is greater than the cost of type II errors (misclassifying a healthy firm as financial failure firm). Average cost is the total misclassification cost per observation. Optimal cut-off point is the threshold that minimizes average cost. Random prediction is based on Bernoulli simulation.

Type I/ II error cost ratio	**6:4**	**7:3**	**8:2**	**9:1**	**10:1**	**25:1**	**50:1**
A: Logit model							
Type I error	100%	100%	76%	30%	30%	0%	0%
Type II error	0%	0%	6%	35%	35%	100%	100%
Total misclassification rate	8%	8%	12%	35%	35%	92%	92%
Average cost	0.4944	0.5768	**0.6111**	0.5481	**0.5731**	0.9176	0.9176
Optimal cut-off points	0.1	0.1	0.2	0.1	0.1	0	0
B: Neural Network							
Type I error	100%	99%	75%	51%	47%	25%	0%
Type II error	0%	0%	7%	18%	23%	40%	100%
Total misclassification rate	8%	8%	12%	21%	25%	38%	92%
Average cost	***0.4944***	**0.5731**	0.6166	**0.5426**	0.6018	**0.8731**	***0.9176***
Optimal cut-off points	0.95	0.85	0.35	0.15	0.15	0.05	0
C: Random Prediction							
Type I error	46%	46%	46%	46%	46%	46%	46%
Type II error	50%	50%	50%	50%	50%	50%	50%
Total misclassification rate	49%	49%	49%	49%	49%	49%	49%
Average cost	2.0500	1.6324	1.2148	0.7972	0.8352	1.4046	2.3537

4.6 Failure Criterion Six--Two continues year sale growth <0.8

4.6.1 Optimal cut-off points

At criterion six (see table 4.6), for Logit model, the optimal cut-off points decrease from 0.45 to 0.05 as type I error cost increases. For neural network, the optimal cut-off points decrease from 0.55 to 0.05 as type I error cost increases.

4.6.2 Prediction errors

The prediction error rates of the model at different levels of relative misclassification costs are presented in Table 4.6. For logit model, type I error decrease from 100% to 26%, type II error increase from 0% to 35%, and the total misclassification rate goes up from 5% to 34%. For neural network, type I error decrease from 100% to 0%, type II error increase from 0% to 100%, and the total misclassification rate goes up, from 5% to 95%.

4.6.3 Misclassification costs

The minimum average misclassification costs of the model at different optimal cut-off points are presented in Table 4.6. For logit model, based on optimal cut-off points, the average costs are 0.2778, 0.3241, 0.3611, 0.3917, 0.4231, 0.8787 and 0.9324, respectively. For neural network, the average costs are 0.2778, 0.3241, 0.3704, 0.3889, 0.4139, 0.8222 and 0.9537, respectively. Basically these two models perform equally well in the prediction. Compared with the Bernoulli distribution prediction, both models average costs are better than random prediction.

Table 4.6 Prediction Errors and Misclassification Cost

(Criterion Six-- Two continues year sale growth <0.8)

It is believed that the cost of type I error (misclassifying a financial failure firm as a healthy firm) is greater than the cost of type II errors (misclassifying a healthy firm as financial failure firm). Average cost is the total misclassification cost per observation. Optimal cut-off point is the threshold that minimizes average cost. Random prediction is based on Bernoulli simulation.

Type I/ II error cost ratio	**6:4**	**7:3**	**8:2**	**9:1**	**10:1**	**25:1**	**50:1**
A: Logit model							
Type I error	100%	100%	96%	68%	68%	40%	26%
Type II error	0%	0%	0%	11%	11%	44%	35%
Total misclassification rate	5%	5%	5%	14%	14%	43%	34%
Average cost	***0.2778***	***0.3241***	**0.3611**	0.3917	0.4231	0.8787	**0.9324**
Optimal cut-off points	0.45	0.45	0.3	0.1	0.1	0.05	0.05
B: Neural Network							
Type I error	100%	100%	96%	54%	54%	42%	0%
Type II error	0%	0%	1%	17%	17%	35%	100%
Total misclassification rate	5%	5%	5%	19%	19%	36%	95%
Average cost	0.2778	0.3241	0.3704	**0.3889**	**0.4139**	**0.8222**	0.9537
Optimal cut-off points	0.55	0.1	0.3	0.1	0.1	0.05	0.05
C: Random Prediction							
Type I error	40%	40%	40%	40%	40%	40%	40%
Type II error	50%	50%	50%	50%	50%	50%	50%
Total misclassification rate	49%	49%	49%	49%	49%	49%	49%
Average cost	2.0000	1.5463	1.0926	0.6389	0.6574	0.9352	1.3981

4.7 Criterion Seven--Two continues year market value growth <0.8

4.7.1 Optimal cut-off points

At last criterion (see table 4.7), for logit model, the optimal cut-off points decrease from 0.45 to 0.05 as type I error cost increases. For neural network, the optimal cut-off points decrease from 0.75 to 0.05 as type I error cost increases.

4.7.2 Prediction errors

The prediction error rates of the model at different levels of relative misclassification costs are presented in Table 4.7. For logit model, type I error decreases from 75% to 6%, type II error increases from 3% to 46%, and the total misclassification rate goes up, from 9% to 42%. For neural network, type I error decreases from 83% to 10%, type II error increases from 2% to 46%, and the total misclassification rate goes up, from 9% to 43%.

4.7.3 Misclassification costs

The minimum average misclassification costs of the model at different optimal cut-off points are presented in Table 4.7. For logit model, based on optimal cut-off points, the average costs are 0.5111, 0.5546, 0.5889, 0.3954, 0.3935, 0.625 and 0.6954, respectively. For neural network, the average costs are 0.5259, 0.5629, 0.5518, 0.4139, 0.4351, 0.6481 and 0.8796, respectively, logit model exceeds neural network except at cost ratio 8:2. Compared with the Bernoulli distribution prediction, both models average cost are less than random prediction.

Table 4.7 Prediction Errors and Misclassification Cost

(Criterion Seven-- Two continues year market value growth <0.8)

It is believed that the cost of type I error (misclassifying a financial failure firm as a healthy firm) is greater than the cost of type II errors (misclassifying a healthy firm as financial failure firm). Average cost is the total misclassification cost per observation. Optimal cut-off point is the threshold that minimizes average cost. Random prediction is based on Bernoulli simulation.

Type I/ II error cost ratio	**6:4**	**7:3**	**8:2**	**9:1**	**10:1**	**25:1**	**50:1**
A: Logit model							
Type I error	75%	65%	46%	16%	14%	10%	6%
Type II error	3%	6%	14%	30%	30%	43%	46%
Total misclassification rate	9%	11%	17%	28%	29%	40%	42%
Average cost	**0.5111**	**0.5546**	0.5889	**0.3954**	**0.3935**	**0.625**	**0.6954**
Optimal cut-off points	0.45	0.35	0.2	0.1	0.1	0.05	0.05
B: Neural Network							
Type I error	83%	65%	55%	24%	24%	16%	10%
Type II error	2%	6%	9%	24%	24%	33%	46%
Total misclassification rate	9%	11%	13%	24%	24%	31%	43%
Average cost	0.5259	0.5629	**0.5518**	0.4139	0.4351	0.6481	0.8796
Optimal cut-off points	0.75	0.35	0.25	0.1	0.1	0.05	0.05
C: Random Prediction							
Type I error	45%	45%	45%	45%	45%	45%	45%
Type II error	49%	49%	49%	49%	49%	49%	49%
Total misclassification rate	49%	49%	49%	49%	49%	49%	49%
Average cost	2.0426	1.6315	1.2204	0.8093	0.8491	1.4463	2.4417

4.8 Overall Discussion

From the above results of each criterion, it can be seen that optimal cut-off points are affected by the misclassification costs of type I and type II error. For example, the cut-off point that is optimal when cost ratio is 6:4 is not optimal when cost ratio is 50:1. However, sometimes the optimal cut-off points are insensitive to different level of cost ratio. For example, at criterion seven, 0.1 is optimal cut-off point at cost ratio 9:1 and 10:1 for both models.

The Type I error and Type II error goes to different trend as cost ratio changes. Basically the Type I error goes down as its cost increases, and Type II error goes up as its cost decrease. Both model's total misclassification rate is increasing because the sample has more non-failure firms than failure firms, so the Type II error has more weight in total misclassification rate.

The misclassification cost results are mixed across seven criteria and seven different cost ratios, 24 times logit model is superior to neural network, and neural network leads at 17 times, there are 8 times both models get same results. It seems that neural network performs well at higher cost ratio and logit model does better at lower cost ratio. Compared with the random prediction, both models surpass random prediction according to average cost.

4.9 Predictor Ratios

A stepwise procedure was used in Logit Model to select predictors on the basis of Chi-squared statistic at 5% level of significance; as nonparametric method Neural Network, we add variable selection node identify what ratios are useful for predicting target variables, using R-square selection criterion. Table 4.8 lists a diversified set of predictor selected in each method, the SAS outputs are presented in appendix 2.

Table 4.8: Predictor Selection

	Criterion 1	Criterion2	Criterion 3	Criterion4	Criterion 5	Criterion 6	Criterion 7
	TDTA	CASR	EPS	EPS	RETA	EPS	MVLN
	ROA	TATR		TATR	ROA	FATR	TALN
Logit	TATR	EPS		CASR	LQR	TLDTD	LQR
Model	WCPTR			CR	CASR	TATR	MVTD
	MVTD			WCPTA	TATR	CASR	
	CASR				MVTD		
					Growth_TE		
	Growth_TE	Growth_TE	CASR	Growth_TP	EPS	Growth_TP	MVLN
	Growth_TA	MVLN	TATR	WCPTA	NCOTA	EPS	MVTD
	MVLN	EPS	TDTE	TATR	TDTA	EBITTA	PB
	NCOTS	ROE	EBITTA	TDTA	TATR	TLDTD	TDTA
R-square	ROA	ROA	EPS	TDTE	CASR	CASR	WCPTA
Selection	RETA	RETA		RETA			CASR
	TDTE	EBITTA		OPM			Growth_MV
	TDTA	TDTE		ROA			
	TATR	TDTA		ROE			
	WCPTR	TATR		NCOTS			
		WCPTA		EPS			
		CASR		MVLN			

Note: see the appendix 1 for the ratios definition.

Based on the selection frequency, we pay attention to what predictors are common to all methods. Table 4.9 indicates that TATR, CASR, EPS appears to be the most commonly selected predictor, be selected 10, 10 and 9 times, respectively; followed by TDTA, ROA, MVLN, each be chose 6, 5 and 5 times; so these ratios could be significant indictor of business failure.

Table 4.9: Predictor Selection Frequency

Ratio Variables	TATR	CASR	EPS	TDTA	ROA	MVLN
Frequency	10	10	9	6	5	5

5. Conclusions and Future Study

Corporate failure is certainly not desirable and an early detection of distress is desirable. In this study, two models, Logistic Regression Model and Neural Network Analysis are used to test the seven types of failure Chinese A-Share listed companies. Based upon our assumption of cost of Type I and Type II errors, the average misclassification cost produces in a range from 0.2611 to 0.9537 for two years prior to failure, and both models are superior to random prediction. So the results have important implications for investor, creditor and management in making failure assessments and evaluation if the misclassification cost of Type I and Type II errors can be quantified.

Seven criteria have been set up to define failure according to attributes of Chinese listed companies, which are:

1. Shareholder's equity is lower than registered capital;
2. Suffered losses for two consecutive years;
3. Profitability problem: net profit <0, and sale growth <0.8;
4. Liquidity problem: net profit <0, current ratio <1 and change level <1;
5. Insolvency problem: net profit <0, total debt / equity >1 and change level >1;
6. Growth problem: two continues year sale growth <0.8;
7. Non-invest value problem: two continues year market value growth <0.8.

Throughout the seven criteria, the logit model performs significantly well at criterion 1 and 7; and at other criteria, the results are mixed, it seems that the neural network performs well at higher Type I error cost ratios and logit model does better at lower Type I cost ratios. Compared with random prediction, both models are efficient prediction methods as average costs are concerned.

Additionally, the study also shows that the financial ratios are useful to predict corporate failure in China. Six most significant predictors are Total Asset Turnover (TATR), Cash Ratio (CASR), Earning per Share (EPS), Total Debt to Total Asset (TDTA), Return on Assets (ROA) and the natual log of Total Market Value

(MVLN). The selected predictors indicate that firms with low operating efficiency, low cash flow, low profitability, high financial leverage and declining market value could have a high probability of business failure.

This study is working on a sample of firms from different industry, however, the financial characteristics of a failed or non-failed firm in one industry might not be the same as in others, and so the sector analysis could be done in future study. Furthermore, non-financial ratio indicators could give early warning of financial failure and establish the underling economic causes of failure. Due to data limitation, this study does not use non-financial ratios, which could be adopted in further study.

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Appendices

APPENDIX 1 :FINANCIAL RATIOS

Liquidity

1. **CR** Current Ratio = Current Assets / Current Liabilities
2. **QR** Quick Ratio = Current Assets – Inventories / Current Liabilities
3. **CASR** Cash Ratio = Cash + Marketable securities / Current Liabilities
4. **WCPTA** Net Working Capital to Total Asset = Net Working Capital / Total Asset

Asset Utilization

5. **IVETR** Inventory Turnover = Cost of goods sold / Inventories
6. **ARTR** Accounts Receivable Turnover = Total sales / Total Accounts receivable
7. **WCPTR** Net Working Capital Turnover = Net Working Capital / Total Sales
8. **FATR** Fixed Asset Turnover = Sales / Net fixed assets
9. **TATR** Total Asset Turnover = Sales / Total Assets

Long-term Solvency

10. **TDTA** Debt Ratio = Total Debt / Total Assets
11. **TDTE** Debt-Equity Ratio = Total Debt / Total Equity
12. **TLDTD** Long Term Financial debt / Total debt
13. **FATLD** Net Fixed Asset / Long Term Financial debt
14. **TSETA** Total Equity / Net Fixed Asset
15. **EBITTA** Eaening Before Interest and Tax / Total Asset
16. **INTCR** Coverage Interest Ratio = EBIT / Interest expenses
17. **RETA** Retained Earning / Total Asset
18. **LQR** (Total Asset – Total Intangiable Asset & Other Assets) / Total Liability

Profitability

19. **NPM** Net Profit Margin = Net income / Total sales
20. **OPM** Operating Profit Margin = Operating Profit / Total sales
21. **ROA** Return on assets = Net Income / Total Assets
22. **ROE** Return on equity = Net Income / Shareholders' equity

Cash Flow

23. **NCOTD** Net Cash Flow from Operating / Total Debt
24. **NCOTA** Net Cash Flow from Operating / Total Asset
25. **NCOTS** Net Cash Flow from Operating / Total Sales
26. **NCOTP** Net Cash Flow from Operating / Net Profit

Market Value

27. **EPS** Earning per share = Net Income / Total Number of share
28. **PE** Share price / Earning per share
29. **PB** Share price / Book value per share
30. **NCFOS** Net Cash Flow from Operating / Total number of share
31. **MVTD** Equity Market Value / Total Debt Book value
32. **MVLN** The natual log of Total Market Value
33. **TALN** The natual log of Total Asset

Growth

34. **Growth_TA** The Asset Growth rate = Total Asset / Last year Total Asset
35. **Growth_TE** The Equity Growth rate = Total Equity / Last year Total Equity
36. **Growth_TS** The Sales Growth rate = Total sales / Last year Total Sales
37. **Growth_EBIT** The EBIT Growth rate = EBIT / Last year EBIT
38. **Growth_TP** Total profit Growth rate = Total Profit / Last year Total Profit
39. **Growth_CF** Cash Flow Growth rate = Net Cash Flow from Operating / Last year Net Cash Flow from Operating
40. **Growth_MV** The Market Value Growth rate = Total Market Value / Last year Total Market Value

APPENDIX 2: RATIO SELECT

Criterion One-- Shareholder's equity is lower than registered capital

Analysis of Maximum Likelihood Estimates: logit model

Parameter	DF	Estimate	Standard Error	Wald Chi-square	Pr > Chi-square
Intercept	1	-4.3087	0.6780	40.39	<.0001
CASR	1	-3.4276	0.9762	12.33	0.0004
MVTD	1	0.0885	0.0211	17.56	<.0001
ROA	1	-4.4383	1.3912	10.18	0.0014
TATR	1	-2.2635	0.5736	15.57	<.0001
TDTA	1	5.4533	1.0009	29.69	<.0001
WCPTR	1	0.0899	0.0264	11.63	0.0006

Effects Chosen for Target: R-Square Selection

Effect	DF	R-Square	F Value	p-Value
ROA	1	0.120900	197.626925	<.0001
TDTE	1	0.030562	51.721481	<.0001
TDTA	1	0.012611	21.649216	<.0001
TATR	1	0.008839	15.324243	<.0001
Growth_TE	1	0.004211	7.333176	0.0068
NCOTS	1	0.003378	5.903349	0.0152
WCPTR	1	0.002732	4.787015	0.0288
Growth_TA	1	0.001825	3.203006	0.0737
MVLN	1	0.001773	3.116102	0.0777
RETA	1	0.000760	1.335884	0.2480

Criterion Two- Suffered losses for two consecutive years

Analysis of Maximum Likelihood Estimates: logit model

Parameter	DF	Estimate	Standard Error	Wald Chi-square	Pr > Chi-square
Intercept	1	-1.3014	0.2424	28.83	<.0001
CASR	1	-3.0524	0.7766	15.45	<.0001
EPS	1	-0.8568	0.2719	9.93	0.0016
TATR	1	-1.7351	0.5428	10.22	0.0014

Effects Chosen for Target: R-Square Selection

Effect	DF	R-Square	F Value	p-Value
EPS	1	0.042259	63.405001	<.0001
TDTE	1	0.013259	20.159386	<.0001
ROE	1	0.009335	14.325227	0.0002
TATR	1	0.004896	7.546676	0.0061
CASR	1	0.004144	6.412767	0.0114
EBITTA	1	0.003174	4.924922	0.0266
RETA	1	0.003633	5.655209	0.0175
MVLN	1	0.002721	4.244408	0.0396
TDTA	1	0.002475	3.869615	0.0494
Growth_TE	1	0.001791	2.803382	0.0943
WCPTA	1	0.001043	1.632895	0.2015
ROA	1	0.000836	1.308761	0.2528

Criterion Three-- Net profit <0, and sale growth <0.8

Analysis of Maximum Likelihood Estimates: logit model

Parameter	DF	Estimate	Standard Error	Wald Chi-square	Pr > Chi-square
Intercept	1	-2.5783	0.1156	497.70	<.0001
EPS	1	-0.8182	0.2547	10.32	0.0013

Effects Chosen for Target: R-Square Selection

Effect	DF	R-Square	F Value	p-Value
EPS	1	0.012357	17.979110	<.0001
TDTE	1	0.006098	8.920775	0.0029
TATR	1	0.005121	7.526365	0.0062
CASR	1	0.003626	5.344562	0.0209
EBITTA	1	0.000569	0.838559	0.3600

Criterion Four-- Net profit <0, current ratio <1 and change level <1

Analysis of Maximum Likelihood Estimates: logit model

Parameter	DF	Estimate	Standard Error	Wald Chi-square	Pr > Chi-square
Intercept	1	0.3905	0.5738	0.46	0.4961
CASR	1	-2.3612	0.7641	9.55	0.0020
CR	1	-1.2051	0.5047	5.70	0.0170
EPS	1	-0.7662	0.2598	8.70	0.0032
TATR	1	-1.7255	0.4492	14.75	0.0001
WCPTA	1	1.5590	1.2142	1.65	0.1991

Effects Chosen for Target: R-Square Selection

Effect	DF	R-Square	F Value	p-Value
EPS	1	0.044557	67.013629	<.0001
TDTA	1	0.019599	30.073456	<.0001
TATR	1	0.008383	12.969944	0.0003
TDTE	1	0.006719	10.463704	0.0012
WCPTA	1	0.004880	7.635816	0.0058
Growth_TP	1	0.003839	6.027949	0.0142
NCOTS	1	0.003592	5.658677	0.0175
RETA	1	0.005280	8.359555	0.0039
ROE	1	0.002622	4.159923	0.0416
MVLN	1	0.002082	3.309008	0.0691
ROA	1	0.001856	2.954382	0.0859
OPM	1	0.001393	2.218570	0.1366

Criterion Five-- Net profit <0, total debt /total equity >1 and change level >1

Analysis of Maximum Likelihood Estimates: logit model

Parameter	DF	Estimate	Standard Error	Wald Chi-square	Pr > Chi-square
Intercept	1	-0.0319	0.3996	0.01	0.9364
CASR	1	-2.1880	0.5879	13.85	0.0002
Growth_TE	1	0.2761	0.1303	4.49	0.0340
LQR	1	-0.7450	0.1948	14.63	0.0001
MVTD	1	0.0572	0.0225	6.45	0.0111
RETA	1	9.6844	2.0699	21.89	<.0001
ROA	1	-12.1634	2.6937	20.39	<.0001
TATR	1	-1.2273	0.3778	10.55	0.0012

Effects Chosen for Target: R-Square Selection

Effect	DF	R-Square	F Value	p-Value
TDTA	1	0.017673	25.853605	<.0001
TATR	1	0.010195	15.059235	0.0001
CASR	1	0.005204	7.723082	0.0055
EPS	1	0.003429	5.102813	0.0240
NCOTA	1	0.000677	1.007833	0.3156

Criterion Six-- Two continues year sale growth <0.8

Analysis of Maximum Likelihood Estimates: logit model

Parameter	DF	Estimate	Standard Error	Wald Chi-square	Pr > Chi-square
Intercept	1	-1.6056	0.2543	39.87	<.0001
CASR	1	-1.2462	0.4754	6.87	0.0088
EPS	1	-0.9125	0.2882	10.03	0.0015
FATR	1	0.0368	0.0118	9.75	0.0018
TATR	1	-1.1977	0.4441	7.27	0.0070
TLDTD	1	-3.4403	1.1223	9.40	0.0022

Effects Chosen for Target: R-Square Selection

Effect	DF	R-Square	F Value	p-Value
EPS	1	0.029953	44.371318	<.0001
TLDTD	1	0.007294	10.879465	0.0010
CASR	1	0.002594	3.876987	0.0491
Growth_TP	1	0.002597	3.889407	0.0488
EBITTA	1	0.000613	0.917828	0.3382

Criterion Seven-- Two continues year market value growth <0.8

Analysis of Maximum Likelihood Estimates: logit model

Parameter	DF	Estimate	Standard Error	Wald Chi-square	Pr > Chi-square
Intercept	1	-20.0116	2.5974	59.36	<.0001
LQR	1	-0.1442	0.1088	1.76	0.1851
MVLN	1	2.2889	0.2966	59.56	<.0001
MVTD	1	0.0309	0.0270	1.31	0.2526
TALN	1	-1.5027	0.2803	28.74	<.0001

Effects Chosen for Target: R-Square Selection

Effect	DF	R-Square	F Value	p-Value
MVTD	1	0.056023	85.283401	<.0001
MVLN	1	0.025194	39.376906	<.0001
PB	1	0.004555	7.148931	0.0076
Growth_MV	1	0.002928	4.607390	0.0320
WCPTA	1	0.001647	2.594463	0.1075
CASR	1	0.002853	4.505503	0.0340
TDTA	1	0.001871	2.958223	0.0857