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碩 士 論 文

財務比率與總體經濟因素對財務危機預警之影響

The Impact of Financial Ratios and Macro-variables
on
Financial Distress Determination

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財 務 比 率 與 總 體 經 濟 因 素 對 財 務 危 機 預 警 之 影 響

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摘　　要

本論文之主要目的在研究財務比率與總體經濟因素對財務危機預警之影響。根據公司的財務比率資料以及總體經濟相關指標，以Logit模型來研究公司的財務狀況和預測未來的破產機率。本文用1992到2007年的歷史資料來估計建立模型參數，並將建立之預測模型，針對2008-2009年期間樣本公司分析違約機率來驗證所建立財務預測模型之準確性。本論文採用加入與未加入總體經濟因素的兩種模型，來判斷經濟指標對財務危機預警模型之影響，實證結果顯示出總體經濟因素對於預測模型的重要性。此研究指出對於破產預測、投資組合管理和公司的內部與外在表現分析的應用可能性，並可提供給投資者做參考避免重大損失發生。

關鍵詞：財務危機預警模型；Logit；總體經濟因素

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ABSTRACT

The purpose of this paper is to investigate the impact of financial ratios and macroeconomic variables on financial distress. According to the information with respect to the financial ratios and macroeconomic related indicators, Logit model can research on the firms' financial situation and predict the bankruptcy probability in the future. The parameters are estimated by the historical data from 1992 to 2007, and then the model can be constructed and verified by the evaluation the default probability of the firms during 2008-2009 and the detection whether firms fail or not. This paper adopts two models with and without macroeconomical factors to detect the influence of macroeconomic indicators on financial distress prediction model. The empirical results show the importance of macroeconomic factors within the failure prediction model. This study indicates the potential important application on the failure prediction, management portfolio and the internal and external performance analysis of the companies. Moreover, this paper provides the suggestion to investors and avoids the enormous loss occurring.

Keywords: Financial distress prediction model; Logit; Macroeconomic factors

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I. Introduction

The world was stunned when East Asia, the highest growth region during 1990s, was broken by a banking crisis in 1997 and the burst of Internet bubbles followed in 2000. Recently, since subprime mortgage crises broke out in August, 2007, economical recession occurs again and enormous companies encounter financial difficulties and defaults. The investors are afraid of vast loss due to liquidity and bankruptcy risk of financial institutions and firms. The research related to credit risk and financial distress prediction model hence isof vigorousness development to protect investors from enormous loss.

The default of a firm can be detected according to information, for example, financial statement, firm's announcement, financial market or economic index. According to that significant information, the investors can avoid the loss of false portfolio through the investment of healthy firms. The purpose of this paper is to provide a convictive model with financial information and economic indexes, evaluate the default probability of companies, and enhance the accuracy of failure prediction for investors. Then the investors can refer to result of this model for the choice of portfolio.

Prior literatures provide several methods to calculate the default probability and to forecast the firm's situation in the future. The prediction models can be categorized into univariate discriminant analysis (Beaver, 1966), multivariate discriminant analysis (Altman, 1968), Logit model (Ohlson, 1980), Probit model (Zmijewski, 1984). This paper based on Logit model and a proper cut-off point, could predict the default possibility for investors as the suggestion of investment. Although previous paper effectively incorporated historical financial data into model and presented significant practical results, the various financial ratios changing over time are neglected. The macroeconomic factors would influence microeconomic variables seriously, and then the accuracy of models would be unstable and unconvinced. In hence, this paper engages in the combination of macroeconomic variables and financial ratios to analysis whether firm would fail or not.

This paper is organized as follows. Starting from introduction of purpose and motivation about prediction of failure firms, next section expresses the previous literatures related to our methodology and provides prior studies which deal with economical factors. Section 3 proposes our model and section 4 states the data and the explanatory variables. Section 5 shows the empirical results and analysis accuracy of prediction with and without macroeconomic factors. Finally, section 6 would make a conclusion and discuss the imperfections of this thesis and the recommendation for the future research.

II. Literature Review

Financial distress prediction models can be approximately classified into many categories. The investigation of corporate failure prediction models begins from univariate analysis (Beaver, 1966) and multivariate discriminant analysis (Altman, 1968). One of the classic works in the field of bankruptcy classification was provided by Beaver (1966). Beaver firstly employed dichotomous classification test to build financial distress prediction model. This univariate analysis including bankruptcy indicators set the stage for the multivariate attempts, which replace several variables by one factor to detect failed firms.

The pioneering work in the area of bankruptcy prediction using multivariate techniques is generally contributed to Altman (1968). The multivariate discriminant analysis (hereafter called MDA) improves the drawback of univariate analysis which only uses one financial ratio as the variable in the model. The discriminant model included five explanatory variables that affect firm's liquidity, profitability, leverage, solvency and activity and capture various financial dimensions of the firm. According to these predictable factors, Altman regression model calculates the discriminant score to distinguish whether the firm defaults or not. Very briefly, the variables in the regression model (called Z-score model) are: 1. Net working capital/total assets, 2. Retained earnings/total assets, 3. Earnings before interest and taxes/total assets, 4. Market value equity/book value of total debt, and 5. Sales/total assets. In the evidence from MDA model, Altman shows the discriminant score (Z-score) 2.675 as the cut-off point which could distinguish the sound firms from the default firms. If firm's Z-score larger (smaller) than 2.675, the firm is classified as a non-failed firm (a failed firm).

Specifically, according to the sample of 33 bankrupt and non-bankrupt firms, Altman's linear MDA model was able to classify accurately 95 percent of the original sample using financial data one reporting period prior to bankruptcy. However, the accuracy of prediction in Z-score model declines as the length of time increasing. The classification accuracy declined to less than 72 percent for data two years prior to bankruptcy and to 36 percent for data dating from five years before bankruptcy. Subsequent research (Deakin, 1972; Blum 1974; Sinkey, 1975) largely focused on improvements in the selection of explanatory variables which yielded the better result in terms of prediction accuracy over the 1968 Altman model.

The previous studies mostly use the 1968 Altman model as a benchmark because of its popularity in the literature. Later, Altman, Haldeman, and Naraynana (1977) constructed a second generation model with the enhancement to the original Z-score approach. Due to economical factors vary with time, the adjusted Z-score model called ZETA model incorporated seven significant variables with respect to business failures. The seven factors are Return on assets (ROA), Stability of earnings, Debt service, Cumulative profitability, Liquidity, Capitalization, and Size. The variables are respectively measured by (1) earnings before interest and taxes/total assets, (2) the standard error of estimate around a ten-year trend in ROA, (3) earnings before interest and taxes/total interest payments, (4) retained earnings/total assets, (5) current ratio, (6) common equity/total capital, and (7) total assets. The ZETA model successfully enhanced the effectiveness in classifying bankrupt firms up to five years prior to failure on the 53 sample of manufacturers and retailers. The results show the prediction of accuracy is 96% in one year and 70% in five years prior to failure.

Generally, we use qualitative choice model when the dependent variables in the regression belong to discrete data, for example, dependent variable given 1 as failure and otherwise given 0. Ohlson (1980) firstly adopts Logit model to calculate the default probability. Logit model assumes that the probability of event happening follows Logistic distribution. The purpose of using Logit methodology is to avoid some well known problems related to MDA. The unprecedented assumption of distribution in financial distress prediction improved the drawback of MDA model which only can predict failure but cannot evaluate the default probability. The output of the application of MDA model is a score (Z-score) which is indirectly related to decision policy of bankruptcy. Thus the misclassification may result from decision problem. Furthermore, there are certain statistical requirements in MDA model imposed on the distributional properties of the predictors. For instance, the variance-covariance matrices of the predictors should be the same for failed and non-failed firms groups. Also, the "matching" procedures in MDA model constrained the sample number. Thus, the use of Logit analysis essentially avoids all of the problems discusses associated with MDA. That is why Ohlson can choose sample with 105 failed firms and 2058 non-failed firm in contrast with 53 firms in each groups. In Logit model, nine variables are: 1. Log(total assets/GNP price-level index), 2. Total liabilities/total assets, 3. Working capital/total assets, 4. Current liabilities/current assets, 5. Bankruptcy dummy variable (one if total liabilities exceeds total assets, zero otherwise), 6. Net income/total assets, 7.Funds provided by operations/total liabilities, 8. Net income dummy variable (one if net income was negative for the last two years, zero otherwise), and 9. Change in net income. Under 0.5 as cut-off point, the predictions of accuracy are 96.12%, 95.55% and 92.84% related to the failure sample in period 1977, 1978, and 1977~1978 respectively.

Previous studies subsequently extend the application of Logit model to financial distress prediction. Lau (1987) classifies companies into five groups according to the soundness situation. Queen and Roll (1987) separate the eliminated firms into two groups according to the reason for emerge or default. Then analyze these firms via Logit model with five variables. Hopewood, Mckeown and Mutchler (1994) state the prediction of Logit model consistent with the accountant's opinion. Platt and Platt (1990) consider that the financial ratios would vary unsteadily over time because of economical factors such as business cycle, inflation, and interest rate. They assert that the accuracy of prediction would increase if focusing on the firms in the same industry. Hwang, Lee and Liaw (1997) predict the bankruptcy of bank in America during the period from 1985 to 1988 via Logit model with 48 financial ratios as variables. Kane, Patricia and Richardson (1998) investigate the influence of economic recession on financial distress prediction. The evidence illustrates the importance of economics recession factor and shows the significance of cash flow/ total assets and net income/total assets in Logit model. Compared to the occurrence of event following Logistic distribution in Logit model, Probit model and Probabilistic model assume the occurrence of event following Normal distribution and Cauchy distribution respectively. The unprecedented application of Probit model to financial distress prediction originated with Zmijewski (1984). However, in general, Logit model easily deals with the data, most papers usually construct financial distress prediction model based on Logit model.

The previous research on the failure of company mostly focuses on financial ratios to enhance the accuracy of financial distress prediction. However, only use firm's internal information such as financial statement seems not enough to predict firm's situation due to the significant effect of economical factors on these microeconomic variables (Platt and Platt, 1990; Kane, Patricia and Richardson, 1998). Suetorsak (2006) examines interactions between micro and macro variables in explaining the risk positions of East Asian banks. The analysis shows that macroeconomic policies significantly impacted the bank's micro-economic decision. Suetorak (2006) states that macro conditions and government policies influences bank's reactions to their microeconomic variables and the level of risk they take. Therefore, the macroeconomic factors are of importance in the investigation on the bankruptcy of firms. In this paper, financial ratios combined with macroeconomic factors engage in the analysis of the default and failure companies to increase the accuracy of prediction.

III. Methodology

In this study, we established a financial distress model by Logit Model. We tried to verify whether macroeconomic factors affect financial distress model or not. Therefore we used financial ratios as our basic factors of inputs, and compared the performance of models which without macroeconomic factors and the other with macroeconomic factors. In this section, we start with introducing the methodology used in this study.

3.1 Logit Model

The outcomes of the financial distress are between two discrete alternatives, failed or non-failed. Thus the binary choice model is an appropriate method for us to apply. The dependent variable Y_k takes the value of 1 when the company suffers financial distress, and takes the value of 0 when otherwise. Logit Model assumes that the bankruptcy probability has a Logistic distribution. In a dummy regression equation of company k, suppose the continuously dependent variable y_k^* represent the possible situation of financial distress, and x_k 's are its linear independent variables. The event will happen when the continuously dependent variable crosses a value of threshold, say T. y_k is the value we can observe. For example, let T = 0 as a divide such that the firm encounters financial distress if the dependent variable value is negative and the sound firm if the dependent variable value is positive. The equation can be expressed as following:

$$y_k^* = \alpha + \sum_{i=1}^{m} \beta_{ik} x_{ik} + \varepsilon_k \qquad (3\text{-}1)$$

$$y_k = \begin{cases} 1 & (y_k^* > \mathrm{T},\ \mathrm{T}=0) \\ 0 & (y_k^* < \mathrm{T},\ \mathrm{T}=0) \end{cases} \qquad (3\text{-}2)$$

Assume ε_k follows the logistic distribution. Then we have the conditional probability of which company k suffers financial distress.

$$
\begin{aligned}
p_k = P(y_k = 1 \mid x_k) &= P(\alpha + \sum_{i=1}^{m} \beta_{ik} x_{ik} + \varepsilon_k > 0) \\
&= P(\varepsilon_k > -\alpha - \sum_{i=1}^{m} \beta_{ik} x_{ik}) \\
&= P(\varepsilon_k \le \alpha + \sum_{i=1}^{m} \beta_{ik} x_{ik}) \\
&= \frac{1}{1 + e^{-(\alpha + \sum_{i=1}^{m} \beta_{ik} x_{ik})}}
\end{aligned}
\tag{3-3}
$$

Or written in the form of logit function of bankruptcy probability

$$\ln\left(\frac{p_k}{1-p_k}\right) = \alpha + \sum_{i=1}^{m} \beta_{ik} x_{ik} \tag{3-4}$$

In order to figure out the probability of this model, we have to estimate the parameters α and β_{ik}. In the linear regression models, the OLS (ordinary least squares) is frequently used to estimate the parameters. However, we cannot use the OLS to estimate the coefficients due to bias. Thus, we use the MLE (maximum likelihood estimator) to estimate. Suppose Y_1, Y_2, …, Y_n are identically independent distribution of Bernoulli(p_k). Then we have the probability

$$f(y_k) = p_k^{y_k} (1-p_k)^{1-y_k} \tag{3-5}$$

and the likelihood function is:

$$L(\alpha, \beta \mid y) = \prod_{k=1}^{n} p_k^{y_k} (1-p_k)^{1-y_k} \tag{3-6}$$

By equation (3-6), we can get the log-likelihood function as:

$$\ln\left[L(\alpha, \beta \mid y)\right] = \ln\left[\prod_{k=1}^{n} p_k^{y_k} (1-p_k)^{1-y_k}\right]$$

$$
\begin{aligned}
&= \sum_{k=1}^{n} \left[y_k \ln(p_k) + (1-y_k)\ln(1-p_k) \right] \\
&= \sum_{k=1}^{n} \left[y_k \ln\left(\frac{p_k}{1-p_k} \right) + \ln(1-p_k) \right] \\
&= \sum_{k=1}^{n} \left[y_k \left(\alpha + \sum_{i=1}^{m} \beta_{ik} x_{ik} \right) + \ln\left(1 - \frac{e^{\alpha + \sum_{i=1}^{m} \beta_{ik} x_{ik}}}{1 + e^{\alpha + \sum_{i=1}^{m} \beta_{ik} x_{ik}}} \right) \right] \\
&= \sum_{k=1}^{n} \left[y_k \left(\alpha + \sum_{i=1}^{m} \beta_{ik} x_{ik} \right) - \ln\left(1 + e^{\alpha + \sum_{i=1}^{m} \beta_{ik} x_{ik}} \right) \right] \qquad (3\text{-}7)
\end{aligned}
$$

where y_k equals to one if the firm goes bankruptcy and equals to zero otherwise.

We take differentiating with respect to $\alpha, \beta_1, \beta_2, \ldots\ldots, \beta_m$ for maximizing equation (3-7), and set it to zero. Then, we can get the normal equations:

$$
\begin{cases}
\dfrac{\partial \ln\left[L(\alpha, \beta \mid y) \right]}{\partial \alpha} = \displaystyle\sum_{k=1}^{n} \left[y_k - \frac{e^{\alpha + \sum_{i=1}^{m} \beta_{ik} x_{ik}}}{1 + e^{\alpha + \sum_{i=1}^{m} \beta_{ik} x_{ik}}} \right] = 0 \\[2ex]
\dfrac{\partial \ln\left[L(\alpha, \beta \mid y) \right]}{\partial \beta_j} = \displaystyle\sum_{k=1}^{n} \left[y_k - \frac{e^{\alpha + \sum_{i=1}^{m} \beta_{ik} x_{ik}}}{1 + e^{\alpha + \sum_{i=1}^{m} \beta_{ik} x_{ik}}} \right] x_{jk} = 0 \qquad j = 1, \ldots, m
\end{cases}
\qquad (3\text{-}8)
$$

By solving this equation (3-8), we can get the parameters $\alpha, \beta_1, \beta_2, \ldots\ldots, \beta_m$.

3.2 Cut-off point

After implementing the Logit Model, we can classify every firm as default group or non-default group by using a cut-off point. Traditionally, we use 0.5 as our cut-off point. This means that if the predicted bankruptcy probability of a company is higher than 0.5, we will classify the firm as the default group; if the predicted bankruptcy probability of a company is lower than 0.5, we will classify the firm as the non-default group. But whether the best value of cut-off point is 0.5 is a debatable problem. So we then employ the maximum KS value method (Mays,2001) to find the better cut-off point. KS value is the difference between cumulated percentages of default firm's number and the non-default one. The range that max KS value falls in is the cut-off point we want. Table3.1 shows the general guide to the quality of the KS.

Table 3.1 The Quality of the KS Value

KS value	quality
Less than 20%	The scorecard's probably not worth using
20%-40%	Fair
41%-50%	Good
51%-60%	Very good
61%-75%	Awesome
Greater than 75%	Probably too good to be true (be suspicious that something is wrong)

IV. Data

This section can be separated into three parts. The first part states the definition of financial distress according to TEJ database; the part about sample data expresses the period and the number of the samples; the final part is the independent factors choosing.

4.1 Definition of Financial Distress

A company encounters financial difficulties and defaults when it fails to service its debt obligation. Many researchers have studied corporate bankruptcy; different people have come up with different definitions that basically reflect their special interest in the field. In this study, we will use the definitions of financial distress and quasi financial distress in TEJ database as default event.

4.2 Sample Data

Our sample firms must be listed on Taiwan Stock Exchange Corporation (TSE) or GreTai Security Market (GTSM or OTC). Because the characteristics of banking, security and insurance industries are different from others, we exclude these industries from our sample firms. Besides, we also exclude the firms of which financial reports are incomplete.

We collect data of the sample firms from TEJ database. The study period is 1992-2009. If the firms experienced the financial distress situations mentioned in section 4.1 during this period, we classify these firms as default group. The non-default firms are firms that remain trading on TSE or GTSM during 1992-2009. The healthy or non-default firms we select are chosen on 1:1 basis. The industry and size of the healthy firm match with the default one. That is, the non-default firm's industry and firm size is similar to the default one.

We have two kinds of data, financial ratios and macroeconomic factors. We choose financial ratios from financial year report one year before the firms suffering from financial distress. We use sum of season macroeconomic factors. If financial distress breaks out in time t year, then we collect the first and second quarter of time t year, third and fourth quarter of the last year of time t year, and then sum these four quarts data together.

We use the observations between 1992 and 2007 as the estimation sample, and the observations from 2008 to 2009 as the prediction sample validation group to examine the model's accuracy. Finally, there are 174 non-default firms and 174 default firms in the estimation sample, and 29 non-default firms and 29 default firms in the prediction sample. The number of estimation sample and prediction sample firms is shown in Table 4.1.

Table 4.1 Number of Sample Companies

	Sample period	No. of non-default firms	No. of default firms
Estimation sample	1992~2007	174	174
Prediction sample	2008~2009	29	29

The data comes from TEJ database which the period is from 1992 to 2009. The sample firms are listed either on Taiwan Stock Exchange Corporation (TSE) or on GreTai Security Market (GTSM or OTC).

4.3 Factors choosing

The chosen independent variables can be classified into two kinds of variables, that is, financial ratios and macroeconomic factors respectively. The detail of these factors would be discussed subsequently.

4.3.1 Financial ratios

In this study, we collect inputs according to six category measures as follows.

1. Long-term solvency measure

Long-term solvency ratios are intended to address the firm's long-run ability to meet its obligations, or more generally, its financial leverage. We choose "Debt Ratio" and

“$\dfrac{\text{Equity + Long-term liabilities}}{\text{Fix assets}}$” in this category.

2. Short-term solvency or Liquidity measure

Short-term solvency ratios as a group are intended to provide information about a firm’s liquidity. The primary concern is the firm’s ability to pay its bills over the short run without undue stress. Consequently, these ratios focus on current assets and current liability. We choose “Current Ratio” and “Quick Ratio” (Acid Test Ratio) in this category.

3. Asset management or Turnover measure

Turnover ratios are intended to describe how efficiently, or intensively, a company uses its assets to generate sales. We choose “Inventory Turnover Ratio”, “Receivables Turnover Ratio”, and “Total Asset Turnover Ratio” in this category.

4. Profitability measure

Profitability measures are intended to measure how efficiently the company uses its assets and how efficiently the company manages its operations. The focus in this group is on net income. We choose “Profit Margin” and “Return on Total Assets” in this category.

5. Cash flow measure

A firm’s cash flow measures reveal whether the firm makes money or not, and whether the money generated in this period can meet its obligations. We choose “Cash Ratio” and “Change in Cash flow” in this category.

6. Firm’s Size

The company with different size will have different ability of overcome financial distress. We use the natural log of firm’s size as an input.

Table 4.2 shows the code and calculation of the financial ratios used in this paper. Table 4.3 shows the descriptive statistics of the financial ratios.

Table4.2 The Summary of Chosen Financial Ratios

Category	Code	Variable	Equation
Solvency measure	FR1	Debt Ratio	$\frac{\text{Total Liabilities}}{\text{Total Assets}}$
	FR2	$\frac{\text{Equity + Long-term liabilities}}{\text{Fix assets}}$	
Liquidity measure	FR3	Current Ratio	$\frac{\text{Current Assets}}{\text{Current Liabilities}}$
	FR4	Quick Ratio	$\frac{\text{Current Assets} - \text{Inventory}}{\text{Current Liabilities}}$
Turnover measure	FR5	Inventory Turnover Ratio	$\frac{\text{Cost of good sold}}{\text{Inventory}}$
	FR6	Receivables Turnover Ratio	$\frac{\text{Sales}}{\text{Accounts receivable}}$
	FR7	Total Asset Turnover Ratio	$\frac{\text{Sales}}{\text{Total assets}}$
Profitability measure	FR8	Profit Margin	$\frac{\text{Net income}}{\text{Sales}}$
	FR9	Return on Total Assets	$\frac{\text{Net income}}{\text{Total assets}}$
Cash flow	FR10	Cash Ratio	$\frac{\text{Cash}}{\text{Current liabilities}}$
	FR11	Change in Cash flow	
Size	FR12	Size	Ln(Size)

The total number of variables is twelve. The solvency ability is measured by debt ration and (equity + long-term liabilities) / fix assets; the liquidity ability is measured by current ratio and quick ratio; the turnover ability is measured by inventory turnover ratio, receivable turnover ratio and total asset turnover ratio; the profitability is measured by profit margin and return of total assets (ROA); the cash flow aspect is measured by cash ratio and change in cash flow; the size measure equation is the log of size value.

Table4.3 Descriptive Statistics of Financial Ratios

Variable	Mean	Std	Maximum	Minimum
FR1	53.08892	21.49304	175.25	1.82
FR2	921.7876	4430.586	75199.76	-211.05
FR3	169.0488	171.9555	1732.41	10.56
FR4	104.9144	157.3101	1730.63	1.59
FR5	17.30365	81.09258	1381.73	-0.03

FR6	9.051305	31.01726	587	-1.48
FR7	0.882635	0.707633	4.73	-0.03
FR8	-34.4377	241.0873	73.67	-3668
FR9	-1.27308	18.08898	66.5	-93.38
FR10	0.151685	0.602335	4.869454	-1.61291
FR11	-155772	2812215	10869450	-4.6E+07
FR12	14.93189	1.405555	19.48802	10.79561

The variable codes are explained in Table 4.2.

4.3.2 Macroeconomic factors

In this study, we choose eight macroeconomic indicators which are listed in table 4.4. The correlation of these indicators must not too large. So we check the correlations of these factors. Table 4.5 shows the coefficient correlation of them. Table 4.6 shows the descriptive statistics of macroeconomic indicators.

Table4.4 The Summary of Chosen Macroeconomic Factors

Code	Variable
MF1	Real Estate Determine Score
MF2	Monitoring Indictors Score
MF3	Leading Index
MF4	Floor area of Building Permit - Taiwan (Epd)
MF5	Saving Rate--R.O.C(YEAR)
MF6	Unemployment Rate – U.S.A.
MF7	New privately owned housing started-U.S.A.
MF8	Import Goods – U.S.A.

MF1 data comes from Architecture and Building Research Institution, Ministry of the Interior; MF2 to MF5 measures are from Council for Economic Planning and Development; MF6 data is from US Department of Labor; MF7 data is from US Census Bureau; and MF8 data is from United States International Trade Commission (USITC). All factors are annual datum.

Table4.5 Correlation Coefficient of Macroeconomic Factors

	MF1	MF2	MF3	MF4	MF5	MF6	MF7	MF8
MF1	1.0000	0.6458	0.1035	0.6187	0.0218	-0.0076	0.4032	-0.0111
MF2	0.6458	1.0000	0.0380	0.6134	0.1856	-0.1030	0.3590	-0.0687

MF3	0.1035	0.0380	1.0000	0.0451	-0.1043	-0.3651	0.3019	0.9850
MF4	0.6187	0.6134	0.0451	1.0000	0.3073	0.0924	0.2350	-0.0457
MF5	0.0218	0.1856	-0.1043	0.3073	1.0000	0.3831	-0.4929	-0.0833
MF6	-0.0076	-0.1030	-0.3651	0.0924	0.3831	1.0000	-0.6188	-0.3407
MF7	0.4032	0.3590	0.3019	0.2350	-0.4929	-0.6188	1.0000	0.1965
MF8	-0.0111	-0.0687	0.9850	-0.0457	-0.0833	-0.3407	0.1965	1.0000

The codes MF1 to MF8 can be referred to Table 4.4 which shows the detail of macroeconomic factors.

Table4.6 Descriptive Statistics of Macroeconomic Factors

Variable	Mean	Std	Maximum	Minimum
MF1	40.84211	8.98309	60	27
MF2	92.15789	21.92478	135	48
MF3	300.5842	72.86198	423.7	193.9
MF4	9049.105	2984.417	13611	4134
MF5	27.13158	1.636847	31.25	24.15
MF6	22.28947	4.401375	31.4	16.2
MF7	5908.421	1417.039	7916	2489
MF8	380578.9	165694	704411	164530

The codes MF1 to MF8 can be referred to Table 4.4 which shows the detail of macroeconomic factors.

V. Empirical Result

In this study, we compare the financial distress models with and without macroeconomic factors. We use “Model 1” represent the model without macroeconomic factors, and “Model 2” represent the model with macroeconomic factors. In section 5.1, we show the estimation result of Model 1. In section 5.2, we show the estimation result of Model 2. In section 5.3, we show the performance of prediction sample and compare the difference of the two models.

5.1 Without Macroeconomic factors

In section 3.1, we have introduced the Logit Model method. Equation (3-3) shows the probability concept of Logit Model. We use MLE to estimate the coefficients in Logit model, these coefficient estimates of model 1 is shown in Table 5.1. The regression for company k is as following

$$\hat{y}_k^* = c + \beta_{1k}\mathrm{FR1} + \beta_{2k}\mathrm{FR2} + \beta_{3k}\mathrm{FR3} + \beta_{4k}\mathrm{FR4} + \beta_{5k}\mathrm{FR5} + \beta_{6k}\mathrm{FR6}$$
$$+\beta_{7k}\mathrm{FR7} + \beta_{8k}\mathrm{FR8} + \beta_{9k}\mathrm{FR9} + \beta_{10k}\mathrm{FR10} + \beta_{11k}\mathrm{FR11} + \beta_{12k}\mathrm{FR12}$$

where FR1 is debt ratio, FR2 is equity plus long-term liabilities over fix assets, FR3 is current ratio, FR4 is quick ratio, FR5 is inventory turnover ratio, FR6 is receivables turnover ratio, FR7 is total asset turnover ratio, FR8 is profit margin, FR9 is return on total assets, FR10 is cash ratio, FR11 is change in cash flow, FR12 is ln(size).

So the probability equation of company *k* is

$$p_k = \frac{1}{1 + e^{-(c + \sum_{i=1}^{12} \beta_{ik} FR_{ik})}} \qquad (5\text{-}1)$$

According to the parameters estimated in Table 5.1, the regression of the equation (5-1) is as following:

$$\hat{y}_k^* = -3.2677 + 0.0629\mathrm{FR1} + 0.0001\mathrm{FR2} - 0.0111\mathrm{FR3} + 0.0146\mathrm{FR4} - 0.0007\mathrm{FR5} + 0.0037\mathrm{FR6}$$
$$-1.3707\mathrm{FR7} - 0.0062\mathrm{FR8} - 0.0742\mathrm{FR9} - 0.5977\mathrm{FR10} + 0.0000\mathrm{FR11} + 0.0899\mathrm{FR12}$$

Table5.1 Coefficient Estimate of Model 1

	B	S.E.	Wald Test	P-value	Exp(B)
FR1	0.0629	0.0116	29.4197	0.0000*	1.0649
FR2	0.0001	0.0001	0.5519	0.4575	1.0001
FR3	-0.0111	0.0037	8.9826	0.0027*	0.9890
FR4	0.0146	0.0043	11.6940	0.0006*	1.0147
FR5	-0.0007	0.0045	0.0267	0.8703	0.9993
FR6	0.0037	0.0042	0.7729	0.3793	1.0037
FR7	-1.3707	0.3317	17.0795	0.0000*	0.2539
FR8	-0.0062	0.0064	0.9276	0.3355	0.9939
FR9	-0.0742	0.0213	12.1457	0.0005*	0.9285
FR10	-0.5977	0.4357	1.8819	0.1701	0.5501
FR11	0.0000	0.0000	0.0344	0.8529	1.0000
FR12	0.0899	0.1307	0.4727	0.4917	1.0940
Constant	-3.2677	2.1709	2.2658	0.1323	0.0381

FR1 is debt ratio, FR2 is equity plus long-tern liabilities over fix assets, FR3 is current ratio, FR4 is quick ratio, FR5 is inventory turnover ratio, FR6 is receivables turnover ratio, FR7 is total asset turnover ratio, FR8 is profit margin, FR9 is return on total assets, FR10 is cash ratio, FR11 is change in cash flow, FR12 is ln(size). In P-value column, signal * means 1% significant. The Exp(B) is the exponential value of coefficient B for the calculation of failure probability in equation (5-1).

The estimated parameters illustrate that debt ratio, current ratio, quick ratio, total asset turnover ratio, and ROA are very significant at 1%. However, other financial ratios are of insignificance.

After estimating the coefficients, we have prediction probability of every company. The following step is to find a better cut-off point in order to sort companies into failed or non-failed catalogs. We use the Maximum KS value method to select cut-off value. Table 5.2 shows the summary of selection process. Figure 5.1 shows the figure of cumulative percentage of failed and non-failed companies. The max KS value is 66.09% and in the score range of 0.35 to 0.45. Thus we choose the upper bound 0.45 as Model 1's cut-off point.

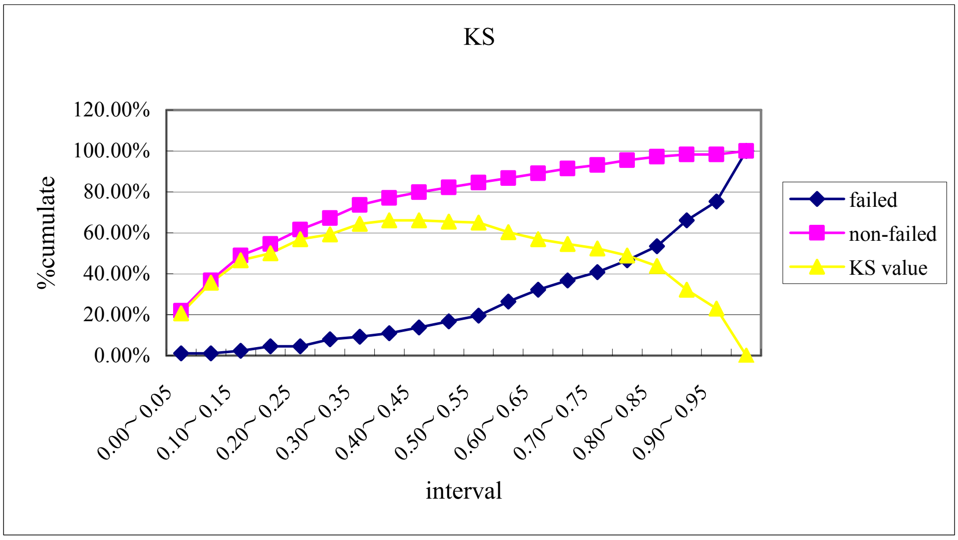
Table 5.3 shows the performance of estimation sample using Model 1, the correct prediction percentage of failed firms is 86.21%, the correct prediction percentage of non-failed firms is 79.89%, and the correct percentage of total prediction is 83.05%. Thus the prediction ability performance of the model which uses financial ratios as its inputs is well. Note that table 5.3 also implies the type I error rate is 13.79% and type II error rate is 20.11%.

Table5.2 The Process of Finding Maximum KS Value

Score range	Number		Cumulative Number		Number %		Cumulative %		KS value
	F	N	F	N	F	N	F	N	
0.00～0.05	2	38	2	38	1.15%	21.84%	1.15%	21.84%	20.69%
0.05～0.10	0	26	2	64	0.00%	14.94%	1.15%	36.78%	35.63%
0.10～0.15	2	21	4	85	1.15%	12.07%	2.30%	48.85%	46.55%
0.15～0.20	4	10	8	95	2.30%	5.75%	4.60%	54.60%	50.00%
0.20～0.25	0	12	8	107	0.00%	6.90%	4.60%	61.49%	56.90%
0.25～0.30	6	10	14	117	3.45%	5.75%	8.05%	67.24%	59.20%
0.30～0.35	2	11	16	128	1.15%	6.32%	9.20%	73.56%	64.37%
0.35～0.40	3	6	19	134	1.72%	3.45%	10.92%	77.01%	**66.09%**
0.40～0.45	5	5	24	139	2.87%	2.87%	13.79%	79.89%	**66.09%**
0.45～0.50	5	4	29	143	2.87%	2.30%	16.67%	82.18%	65.52%
0.50～0.55	5	4	34	147	2.87%	2.30%	19.54%	84.48%	64.94%
0.55～0.60	12	4	46	151	6.90%	2.30%	26.44%	86.78%	60.34%
0.60～0.65	10	4	56	155	5.75%	2.30%	32.18%	89.08%	56.90%
0.65～0.70	8	4	64	159	4.60%	2.30%	36.78%	91.38%	54.60%
0.70～0.75	7	3	71	162	4.02%	1.72%	40.80%	93.10%	52.30%
0.75～0.80	10	4	81	166	5.75%	2.30%	46.55%	95.40%	48.85%
0.80～0.85	12	3	93	169	6.90%	1.72%	53.45%	97.13%	43.68%
0.85～0.90	22	2	115	171	12.64%	1.15%	66.09%	98.28%	32.18%
0.90～0.95	16	0	131	171	9.20%	0.00%	75.29%	98.28%	22.99%
0.95～1.00	43	3	174	174	24.71%	1.72%	100.00%	100.00%	0.00%
total	174	174			100.00%	100.00%			

The max KS value is 66.09% noted by bold number in the table and we choose the upper bound 0.45 as the cut-off point of Model 1.

Figure5.1 KS Value in Model 1



This picture is to find the maximum KS value which is denoted by the line with triangle spots. The line with diamond spot is the cumulative percentage of failed companies and the line with square spot is the cumulative percentage of non-failed companies. The KS value is calculated by the cumulative percentage of non-failed companies minus the cumulative percentage of failed companies.

Table5.3 Model 1 Performance of Estimation Sample

	Sample Number	Correct Prediction	Incorrect Prediction	Percentage Correct	Overall Correct Percentage
Observed Failed	174	150	24	86.21%	83.05%
Observed Non-Failed	174	139	35	79.89%	
Total	348	289	59		

The estimation sample is to evaluate the coefficients of parameters in model 1. Based on the coefficients calculated via MLE method, the correct percentage of observed failed firms is 86.21% and the correct percentage of observed non-failed firms is 79.89%. The overall correct percentage is 83.05% where the cut-off point is 0.45.

5.2 With Macroeconomic factors

Similarly, the coefficient estimate of model 2 is shown in Table 5.4. The regression for company k is as following:

$$\begin{aligned}\hat{y}_k^* &= c + \beta_{1k}\mathrm{FR1} + \beta_{2k}\mathrm{FR2} + \beta_{3k}\mathrm{FR3} + \beta_{4k}\mathrm{FR4} + \beta_{5k}\mathrm{FR5} + \beta_{6k}\mathrm{FR6} + \beta_{7k}\mathrm{FR7} \\ &+ \beta_{8k}\mathrm{FR8} + \beta_{9k}\mathrm{FR9} + \beta_{10k}\mathrm{FR10} + \beta_{11k}\mathrm{FR11} + \beta_{12k}\mathrm{FR12} + \lambda_{1k}\mathrm{MF1} + \lambda_{2k}\mathrm{MF2} \\ &+ \lambda_{3k}\mathrm{MF3} + \lambda_{4k}\mathrm{MF4} + \lambda_{5k}\mathrm{MF5} + \lambda_{6k}\mathrm{MF6} + \lambda_{7k}\mathrm{MF7} + \lambda_{8k}\mathrm{MF8}\end{aligned}$$

where FR1 is debt ratio, FR2 is equity plus long-tern liabilities over fix assets, FR3 is current ratio, FR4 is quick ratio, FR5 is inventory turnover ratio, FR6 is receivables turnover ratio, FR7 is total asset turnover ratio, FR8 is profit margin, FR9 is return on total assets, FR10 is cash ratio, FR11 is change in cash flow, FR12 is ln(size). MF1 is real estate determine score, MF2 is monitoring indictors score, MF3 is leading index, MF4 is floor area of building permit –Taiwan (Epd), MF5 is saving rate-R.O.C(year), MF6 is unemployment rate-U.S.A., MF7 is new privately owned housing started (SA), MF8 is import goods-U.S.A.

And the probability equation of company *k* is

$$p_k = \frac{1}{1 + e^{-(c + \sum_{i=1}^{12} \beta_{ik} FR_{ik} + \sum_{j=1}^{8} \lambda_{jk} MF_{jk})}} \tag{5-2}$$

where β_{ik} and λ_{jk} are the coefficients of financial ratios parameters and macroeconomic factors, and c is the constant term.

According to the coefficients of parameters estimated in Table 5.4, the regression in equation (5-2) is as following:

$$\begin{aligned}\hat{y}_k^* &= -4.5398 + 0.0645\mathrm{FR1} + 0.0001\mathrm{FR2} - 0.0106\mathrm{FR3} + 0.0141\mathrm{FR4} - 0.0006\mathrm{FR5} + 0.0036\mathrm{FR6} \\ &- 1.3940\mathrm{FR7} - 0.0067\mathrm{FR8} - 0.0716\mathrm{FR9} - 0.6137\mathrm{FR10} + 0.0000\mathrm{FR11} + 0.1112\mathrm{FR12} + 0.0304\mathrm{MF1} \\ &+ 0.0028\mathrm{MF2} - 0.0061\mathrm{MF3} - 0.0001\mathrm{MF4} + 0.0131\mathrm{MF5} - 0.0151\mathrm{MF6} + 0.0000\mathrm{MF7} + 0.0000\mathrm{MF8}\end{aligned}$$

Table5.4 Coefficient Estimate of Model 2

	B	S.E.	Wald	P-value	Exp(B)
FR1	0.0645	0.0118	29.7136	0.0000*	1.0667
FR2	0.0001	0.0001	0.3307	0.5653	1.0001
FR3	-0.0106	0.0038	7.7754	0.0053*	0.9894
FR4	0.0141	0.0044	10.2917	0.0013*	1.0142
FR5	-0.0006	0.0045	0.0183	0.8924	0.9994
FR6	0.0036	0.0044	0.6929	0.4052	1.0036
FR7	-1.3940	0.3412	16.6904	0.0000*	0.2481
FR8	-0.0067	0.0070	0.9086	0.3405	0.9933
FR9	-0.0716	0.0221	10.4931	0.0012*	0.9309
FR10	-0.6137	0.4492	1.8670	0.1718	0.5413
FR11	0.0000	0.0000	0.0178	0.8938	1.0000
FR12	0.1112	0.1374	0.6555	0.4182	1.1177
MF1	0.0304	0.0400	0.5773	0.4474	1.0308
MF2	0.0028	0.0127	0.0470	0.8283	1.0028
MF3	-0.0061	0.0233	0.0688	0.7931	0.9939
MF4	-0.0001	0.0001	0.3173	0.5732	0.9999
MF5	0.0131	0.3190	0.0017	0.9673	1.0132
MF6	-0.0151	0.0682	0.0493	0.8243	0.9850
MF7	0.0000	0.0004	0.0110	0.9165	1.0000
MF8	0.0000	0.0000	0.1324	0.7160	1.0000
Constant	-4.5398	8.3923	0.2926	0.5885	0.0107

FR1 is debt ratio, FR2 is equity plus long-tern liabilities over fix assets, FR3 is current ratio, FR4 is quick ratio, FR5 is inventory turnover ratio, FR6 is receivables turnover ratio, FR7 is total asset turnover ratio, FR8 is profit margin, FR9 is return on total assets, FR10 is cash ratio, FR11 is change in cash flow, FR12 is ln(size). MF1 is real estate determine score, MF2 is monitoring indictors score, MF3 is leading index, MF4 is floor area of building permit –Taiwan (Epd), MF5 is saving rate-R.O.C(year), MF6 is unemployment rate-U.S.A., MF7 is new privately owned housing started (SA), MF8 is import goods-U.S.A. In P-value column, signal * means 1% significant. The Exp(B) is the exponential value of coefficient B for the calculation of failure probability in equation (5-2).

The estimated parameters of model 2 illustrate the same results as model 1 which debt ratio, current ratio, quick ratio, total asset turnover ratio, and ROA are very significant at 1%. However, all macroeconomic factors are not significant.

Table 5.5 shows the summary of selection process. Figure 5.2 shows the figure of cumulative percentage of failed and non-failed companies. The max KS value is 66.67% and in the score range of 0.45 to 0.50. Thus we choose the upper bound 0.5 as Model 2's cut-off point.

Table 5.6 shows the performance of estimation sample using Model 2, the correct prediction percentage of failed firms is 83.33%, the correct prediction percentage of non-failed firms is 83.33%, and the correct percentage of total prediction is 83.33%. Thus the prediction ability performance of the model which adds macroeconomic factors as its inputs is better than the model only use financial ratios as its inputs. From table 5.6, we know the type I error rate is 16.67% and type II error rate is 16.67%.

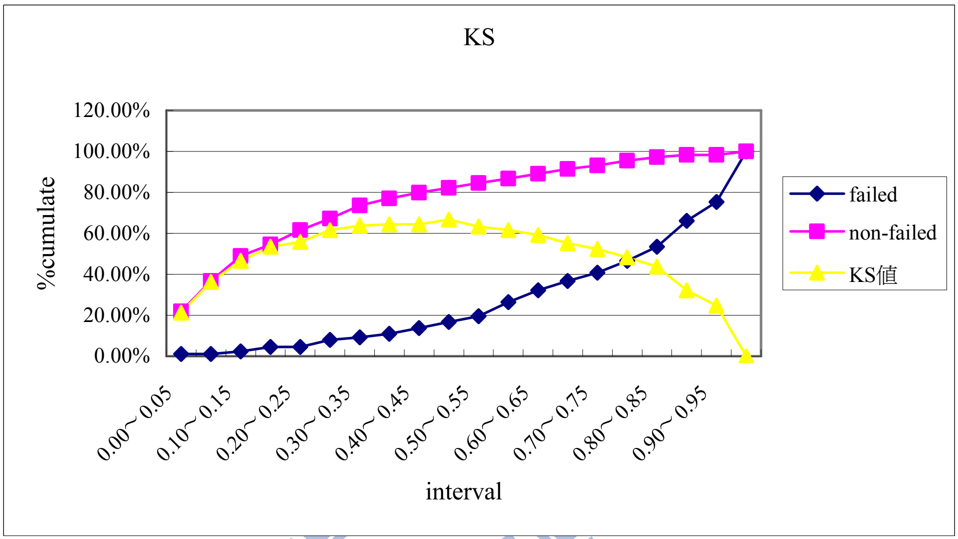
Table5.5 The Process of Finding Maximum KS Value

Score range	Number		Cumulative Number		Number %		Cumulative %		KS value
	F	N	F	N	F	N	F	N	
0.00～0.05	2	39	2	39	1.15%	22.41%	1.15%	22.41%	21.26%
0.05～0.10	0	26	2	65	0.00%	14.94%	1.15%	37.36%	36.21%
0.10～0.15	2	20	4	85	1.15%	11.49%	2.30%	48.85%	46.55%
0.15～0.20	1	13	5	98	0.57%	7.47%	2.87%	56.32%	53.45%
0.20～0.25	6	10	11	108	3.45%	5.75%	6.32%	62.07%	55.75%
0.25～0.30	2	12	13	120	1.15%	6.90%	7.47%	68.97%	61.49%
0.30～0.35	3	7	16	127	1.72%	4.02%	9.20%	72.99%	63.79%
0.35～0.40	4	5	20	132	2.30%	2.87%	11.49%	75.86%	64.37%
0.40～0.45	6	6	26	138	3.45%	3.45%	14.94%	79.31%	64.37%
0.45～0.50	3	7	29	145	1.72%	4.02%	16.67%	83.33%	**66.67%**
0.50～0.55	9	3	38	148	5.17%	1.72%	21.84%	85.06%	63.22%
0.55～0.60	5	2	43	150	2.87%	1.15%	24.71%	86.21%	61.49%
0.60～0.65	9	5	52	155	5.17%	2.87%	29.89%	89.08%	59.20%
0.65～0.70	10	3	62	158	5.75%	1.72%	35.63%	90.80%	55.17%
0.70～0.75	8	3	70	161	4.60%	1.72%	40.23%	92.53%	52.30%
0.75～0.80	11	4	81	165	6.32%	2.30%	46.55%	94.83%	48.28%
0.80～0.85	12	4	93	169	6.90%	2.30%	53.45%	97.13%	43.68%
0.85～0.90	22	2	115	171	12.64%	1.15%	66.09%	98.28%	32.18%
0.90～0.95	14	1	129	172	8.05%	0.57%	74.14%	98.85%	24.71%
0.95～1.00	45	2	174	174	25.86%	1.15%	100.00%	100.00%	0.00%

total	174	174		100.00%	100.00%

The max KS value is 66.67% noted by bold number in the table and the score range is 0.45 to 0.5. Here we choose the upper bound 0.5 as the cut-off point of Model 2.

Figure5.2 KS Value in Model 2



This picture is to find the maximum KS value which is denoted by the line with triangle spots. The line with diamond spot is the cumulative percentage of failed companies and the line with square spot is the cumulative percentage of non-failed companies. The KS value is calculated by the cumulative percentage of non-failed companies minus the cumulative percentage of failed companies.

Table5.6 Model 2 Performance of Estimation Sample

	Sample Number	Correct Prediction	Incorrect Prediction	Percentage Correct	Overall Correct Percentage
Observed Failed	174	145	29	83.33%	83.33%
Observed Non-Failed	174	145	29	83.33%	
Total	348	290	58		

The estimation sample is to evaluate the coefficients of parameters in model 2. Based on the coefficients calculated via MLE method, the correct percentage of observed failed firms is 83.33% and the correct percentage of observed non-failed firms is 83.33%. The overall correct percentage is 83.33% based on the cut-off point 0.5.

5.3 Prediction Sample Performance

In previous sections, we have figure out the coefficients and cut-off point. The coefficients of Model 1 are shown in Table 5.1; the coefficients of Model 2 are shown in Table 5.4; the cut-off point of Model 1 is 0.45; the cut-off point of Model 2 is 0.50. So we use these information to see how the prediction performance of the two models.

Table 5.7 shows the prediction performance of Model 1. The correct prediction percentage of failed firms is 86.21%, the correct prediction percentage of non-failed firms is 82.76%, and the correct percentage of total prediction is 84.48%. The type I error rate is 13.79% and type II error rate is 17.24%.

Table 5.8 shows the prediction performance of Model 2. The correct prediction percentage of failed firms is 86.21%, the correct prediction percentage of non-failed firms is 86.21%, so the correct percentage of total prediction is also 86.21%. The type I error rate is 13.79% and type II error rate is 13.79%, too.

Therefore, the model with macroeconomic factors is better than the model without ones. This result proves that the factor of macroeconomic affects firms' financial situation in Logit default model.

Table5.7 Model 1 Performance of Prediction Sample

<table>
<tr><th></th><th>Sample Number</th><th>Correct Prediction</th><th>Incorrect Prediction</th><th>Percentage Correct</th><th>Overall Correct Percentage</th></tr>
<tr><td>Observed Failed</td><td>29</td><td>25</td><td>4</td><td>86.21%</td><td rowspan="2">84.48%</td></tr>
<tr><td>Observed Non-Failed</td><td>29</td><td>24</td><td>5</td><td>82.76%</td></tr>
<tr><td>Total</td><td>58</td><td>49</td><td>9</td><td></td><td></td></tr>
</table>

The prediction sample is to verify the currency of model 1. The correct percentage of observed failed firms is 86.21% and the correct percentage of observed non-failed firms is 82.76%. The overall correct percentage is 84.48% based on the cut-off point 0.45.

Table5.8 Model 2 Performance of Prediction Sample

	Sample Number	Correct Prediction	Incorrect Prediction	Percentage Correct	Overall Correct Percentage
Observed Failed	29	25	4	86.21%	86.21%
Observed Non-Failed	29	25	4	86.21%	
Total	58	50	8		

The prediction sample is to verify the currency of model 2. The correct percentage of observed failed firms is 86.21% and the correct percentage of observed non-failed firms is 86.21%. The overall correct percentage is 86.21% based on the cut-off point 0.5.

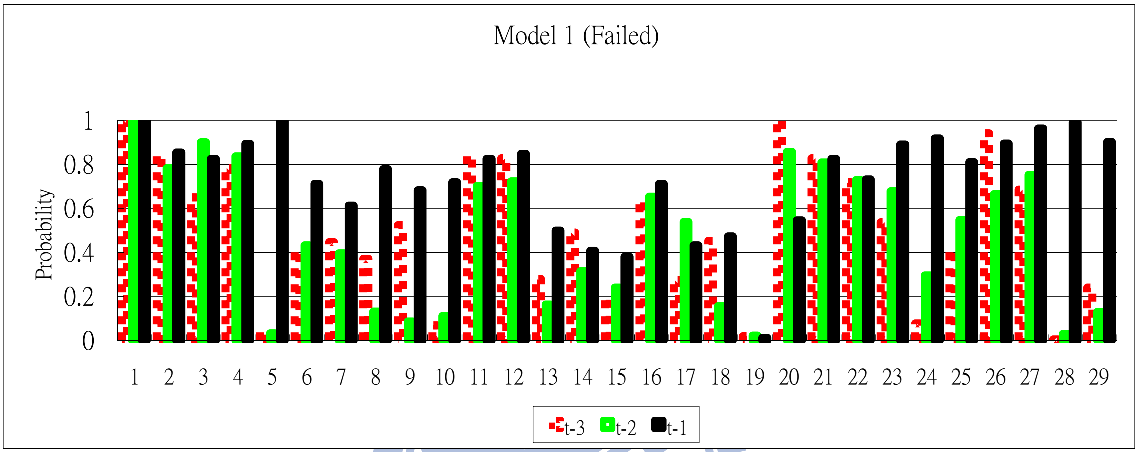
We also compare the probabilities of the 29 prediction sample in 3-year before financial distress occur. Let year t be the time of financial distress occurs. Figure5.3 to figure5.6 show the firms' probabilities of year t – 1, t – 2, and t – 3.

In figure 5.3, we can see the failed firms' changes of probability in each year by using Model 1. There are 12 positive changes from year t – 3 to t – 2, and 23 positive changes from year t – 2 to t – 1. In figure 5.4, we can see the non-failed firms' changes of probability in each year by using Model 1. There are 16 positive changes from year t – 3 to t – 2, and 5 positive changes from year t – 2 to t – 1.

Similarly, in figure 5.5, we can see the failed firms' changes of probability in each year by using Model 2. There are 19 positive changes from year t – 3 to t – 2, and 13 positive changes from year t – 2 to t – 1. In figure 5.6, we can see the non-failed firms' changes of probability in each year by using Model 2. There are 19 positive changes from year t – 3 to t – 2, and 2 positive changes from year t – 2 to t – 1.

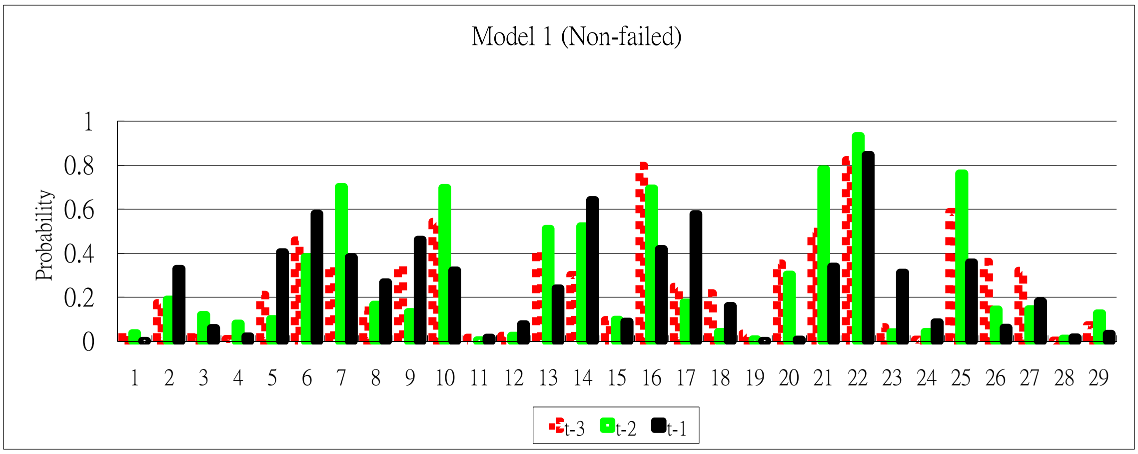
This means no matter Model 1 or Model 2, if a firm's change of default probability is positive, then it is more possibility for this firm to default. Moreover, no matter how many years prior to the failure time, the accuracy of prediction would increase with the inclusion of the macroeconomic factors even though these variables are not significant.

Figure5.3 Probability of Model 1 (Failed)



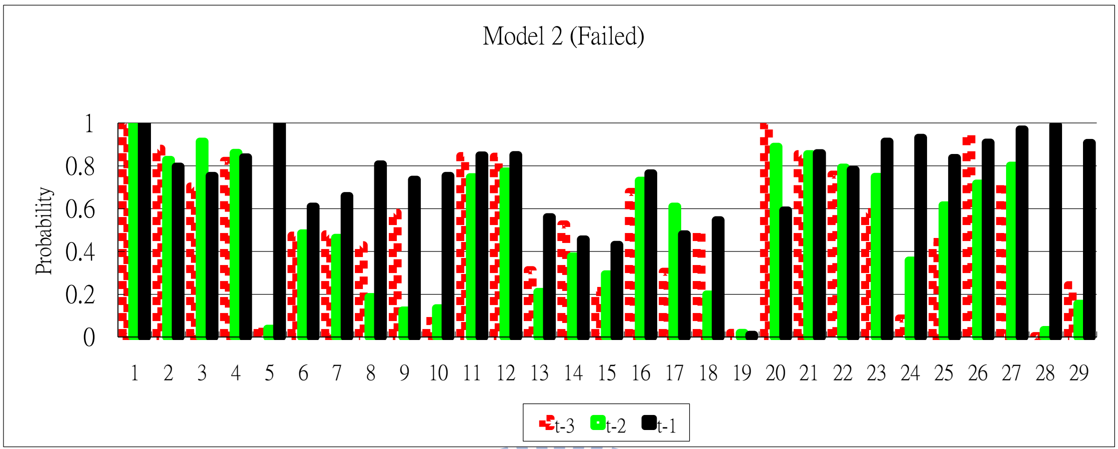
The probability of each failed firm is calculated by model 1 without the macroeconomic factors. The time t-1 means the time of prediction is one year prior to time t year, the time t-2 means the time of prediction is two year prior to time t year, and the time t-3 means the time of prediction is three year prior to time t year. The cut-off point of model 1 is 0.45. Total sample for model verification is 29 firms.

Figure5.4 Probability of Model 1 (Non-failed)



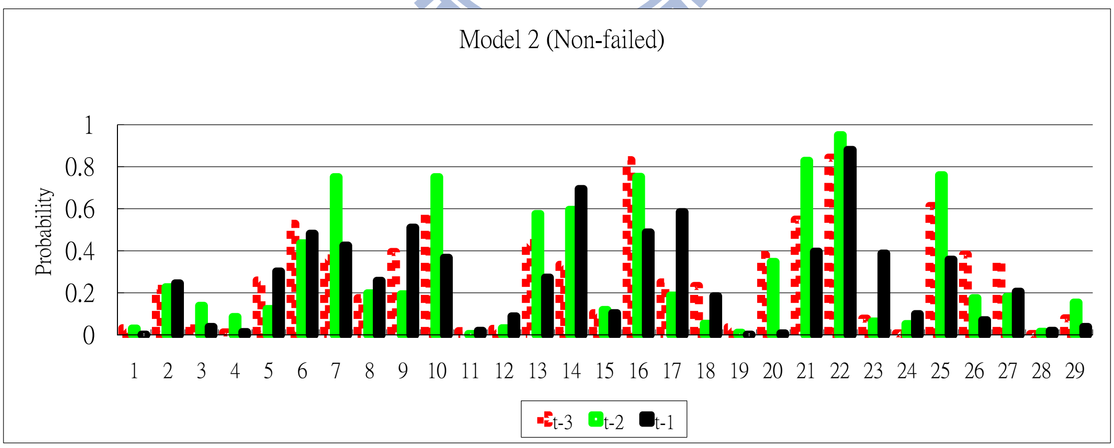
The probability of each non-failed firm is calculated by model 1 without the macroeconomic factors. The time t-1 means the time of prediction is one year prior to time t year, the time t-2 means the time of prediction is two year prior to time t year, and the time t-3 means the time of prediction is three year prior to time t year. The cut-off point of model 1 is 0.45. Total sample for model verification is 29 firms.

Figure5.5 Probability of Model 2 (Failed)



The probability of each failed firm is calculated by model 2 without the macroeconomic factors. The time t-1 means the time of prediction is one year prior to time t year, the time t-2 means the time of prediction is two year prior to time t year, and the time t-3 means the time of prediction is three year prior to time t year. The cut-off point of model 2 is 0.45. Total sample for model verification is 29 firms.

Figure5.6 Probability of Model 2 (Non-failed)



The probability of each non-failed firm is calculated by model 2 without the macroeconomic factors. The time t-1 means the time of prediction is one year prior to time t year, the time t-2 means the time of prediction is two year prior to time t year, and the time t-3 means the time of prediction is three year prior to time t year. The cut-off point of model 2 is 0.45. Total sample for model verification is 29 firms.

6. Conclusion and Discussions

This paper not only provides an accurate financial distress prediction model to avoid enormous loss of investment, but also gives investors a suggestion about the choice of portfolio to increase their wealth.

The contribution of this study results from the application of the combination of microeconomic and macroeconomic factors in Logit model, and differentiates from mostly previous paper which only focused on the financial ratios and ignored the influence of economic environment on firms. An appropriate cut-off point for the determination of failed and non-failed firm is chosen by maximum KS value method instead of 0.5 given in Ohlson's paper. The proper cut-off point contributes to the explicit separation for default and non-default groups.

The evidence from empirical analysis illustrates that the Logit model with macroeconomic variables is slightly better than it without macro factors, especially in non-failed firms group. Therefore, the macroeconomic factors are of necessary and importance in the financial distress prediction model due to their influence on firm's financial situation. Moreover, no matter adding macroeconomic variables or not, the default probability of the model can classify failed and non-failed firms correctly when the prediction time close to the failure date. Nevertheless, even the three year prior to failure time, the model with macro factors presents better currency of prediction on failed firms than it without those factors.

In conclusion, our model albeit uses Logit model without extension, the advantage of this paper contributes to the exhibition of important influence of macroeconomic factors on failure prediction. Thus, when any model predicts the default situation of company, we should take account of macroeconomic aspect which would affect microeconomic variable such as financial ratios.

There are imperfections in this thesis to point out for future reference. As shown in table 4.5, MF3 Taiwan Leading Index has a high correlation with MF8 Import Goods-USA. FR3 current ratio is also highly correlative to FR10 cash ratio. These might affect the accuracy of the model.

Second imperfection is the significance of variables. FR5 inventory turnover ratio, FR11 change in cash flow have a poor significance on this distress model and also FR2 Long term capital adaptive rate, FR12 firm size have less significance. MF5 Saving rate-R.O.C. and MF7 New privately owned housing started –U.S.A. have poor significance. Less significant variables won't crumble the prediction model, but adding more significant variables will enhance the accuracy of this financial distress prediction model. In the future the interest rate, currency exchange might be the parameters to test.

Also, in the future, we can add these variables in different failure prediction models and then compare each model's effectiveness. If other models consistently show significant results, the necessary of macroeconomic factors would be more convictive and persuasive.

Appendix A

The firm list: the samples for parameters estimation

Failed Firms

8094 卓立	3343 聯宗光電	2333 碧悠	1228 台芳	2506 太設	5504 信南	8709 峰安
3190 新典	5414 磐英	3295 宇極	1212 中日	2318 佳錄	2019 桂宏	8704 大業
6110 艾群	4413 飛寶	6252 艾爾法	9801 力霸	2594 德利	2518 長億	2005 友力
8276 連邦	2523 德寶	3039 宏傳	1207 嘉食化	5502 龍田	5313 皇旗	8708 大鋼
1557 金豐	1601 台光	2407 欣煜	3053 鼎營	1450 新藝	1505 楊鐵	8382 美式
6114 翔昇	6262 鼎太國際	6181 宇詮	5307 耀文	5518 大日	2334 國豐	5002 住聯
3096 碩良	3142 遠茂	4910 陽慶	5372 十美	1438 裕豐	4424 民興	8716 尖美
4801 碼斯特	5395 圓方	5325 大騰	4404 百成行	3258 誠洲	2714 華國	8706 金緯
8060 力竑	6249 蕃薯網	6193 洪氏英	2445 南方	5503 榮美開發	1107 建台	2529 仁翔
6238 勝麗	2496 卓越	5376 東正元	1221 久津	1458 嘉畜	2521 宏總	2016 名佳利
6111 大宇資	2479 和立	9936 欣錩	5702 統合	1491 東榮工	1462 東雲	8719 宏福
2418 雅新	6137 新寶科	1534 新企	1602 太電	1407 華隆	2528 皇普	8707 中精機
3348 中華聯	8934 世一旦	3004 豐達科	5011 久陽	3159 彩華科	2628 正利	8712 國產車
8017 展茂	3328 亞微電	2490 皇統	8007 商合行	1224 惠勝	1209 益華	8717 瑞圓
3401 南暐	8061 東聖科	5207 飛雅	3239 帝華	1408 中紡	8907 三粹	1918 萬有
3179 華科	5467 聯福生	8031 鉅業	2525 寶祥	8720 元富	9922 優美	1238 正義
6294 智基科	3137 瑞積	2491 吉祥全	5304 鼎創達	8724 立大	8725 三采	1425 福昌
5532 竟誠建築	6132 銳普	6250 宇加	2512 寶建	2517 長谷	8711 大穎	8701 正豐
2569 開立	6254 菘凱	3184 微邦	1807 羅馬	6702 復航	8713 延穎	8721 尙鋒
6236 凌越	3084 光威	2398 博達	2435 台路	2902 中信	8710 易欣	8702 羽田
2410 鼎大	5204 得捷	2494 廣業科	2326 亞瑟	8718 工礦	8714 紐新	1501 台機
8106 寰訊	1204 津津	2335 清三	1306 合發	2540 金尙昌	5901 中友	2202 三富
2429 永兆	6162 鴻源科	3001 協和	5336 華特	9906 興達	1431 新燕	2052 同光
5318 佳鼎	3116 寬頻	2533 昱成	5385 瑩寶	5008 長銘	2553 啓阜	2309 國勝
3364 達康網	1432 大魯閣	8143 晶揚	8722 尙德	2058 彥武	2322 致福	

Non-Failed Firms

8101 華冠	8069 元太	3038 全台	8905 裕國	9945 潤泰新	2504 國產	2009 第一銅
3236 千如	3515 華擎	6188 廣明	1219 福壽	3060 銘異	2015 豐興	6285 啓碁
6218 豪勉	1476 儒鴻	5209 新鼎	8033 雷虎	5534 長虹	2501 國建	2012 春雨
3527 聚積	5521 工信	6172 互億	1210 大成	5508 永信建	2352 佳世達	5016 松和
1527 鑽全	1611 中電	2377 微星	6271 同欣電	1418 東華	1583 程泰	9935 慶豐富
5464 霖宏	5212 凌網	6259 百徽	2316 楠梓電	5514 三豐	2301 光寶科	9958 世紀鋼
6140 訊達	2495 普安	5388 中磊	5439 高技	4401 東隆興	4413 飛寶	5531 鄉林
9949 琉園	3523 迎輝	2403 友尚	1439 中和	2489 瑞軒	2707 晶華	1445 大宇
3287 廣寰科	3570 大塚	2365 昆盈	3466 致振	5533 皇鼎建設	2524 京城	5523 宏都
6231 系微	4903 聯光通	6210 慶生	1201 味全	1460 宏遠	5512 力麒	2031 新光鋼
3546 宇峻	8935 邦泰	8941 關中	5905 南仁湖	1474 弘裕	1455 集盛	2511 太子
2313 華通	3024 憶聲	5384 捷元	1605 華新	1409 新纖	2534 宏盛	4534 慶騰
5443 均豪	1537 廣隆	3552 同致	5007 三星	6219 富旺	2609 陽明	2207 和泰
3049 和鑫	6182 合晶	6180 橘子	6146 耕興	1232 大統益	1201 味全	1446 宏和
2482 連宇	8048 德勝	5201 凱衛	6199 精威	1402 遠紡	5516 雙喜	1902 台紙
9912 偉聯	6265 方土昶	5403 中菲	5522 遠雄	6605 帝寶	9934 成霖	1218 泰山
6209 今國光	6195 旭展	3050 鈺德	8101 華冠	1217 愛之味	6212 理銘	1473 台南
5519 隆大	3296 勝德	3221 台嘉碩	2534 宏盛	2542 興富發	1313 聯成	6508 惠光
1535 中宇	6179 世仰	8047 星雲	1809 中釉	2618 長榮航	1307 三芳	4305 世坤
3268 海德威	2442 美齊	2393 億光	5480 統盟	5902 德記	2543 皇昌	2204 中華
3010 華立	2471 資通	8082 捷超	4905 台聯電	2906 高林	9927 泰銘	1539 巨庭
5201 凱衛	1213 大飲	4909 新復興	1316 上曜	6177 達麗	2905 三商行	2201 裕隆
3229 晟鈦	5355 佳總	3083 網龍	8066 福陞	8936 國統	1443 立益	5015 華祺
2367 燿華	3466 致振	2509 全坤興	8111 立碁電	5009 榮剛	5511 德昌	2434 統懋
3130 一零四	1465 偉全	2425 承啓	1235 興泰	2008 高興昌	2314 台揚	

Appendix B

The firm list: the samples for model verification

Failed Firms

2348 力廣	6101 弘捷	2341 英群	3051 力特	2396 精碟	6149 禾鴻
1456 怡華	8027 鈦昇	6242 聯豪科	3369 鐵研	1606 歌林	8130 聯達電
5206 經緯	5346 力晶	5506 長鴻	8028 昇陽	3065 大眾電	3252 海灣科
1805 寶徠	5387 茂德	3099 頂倫	3397 協泰	3144 新揚科	6103 合邦
5432 達威	3469 銓祐科	2438 英誌	6130 亞全	6232 仕欽	

Non-Failed Firms

8271 宇瞻	6108 競國	6277 宏正科	3049 和鑫	2349 錸德	6221 晉泰
1468 昶和	5493 三聯	3511 矽瑪	2431 聯昌	1604 聲寶	5481 華韡
6218 豪勉	2303 聯電	2546 根基	3016 嘉晶	3045 台灣大	8277 商丞
9949 琉園	3474 華亞科	5349 先豐	8088 品安	3354 律勝	6104 創惟
8049 晶采	6222 上揚	6235 華孚	5314 世紀	5465 富驊	

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