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THE STUDY OF CORPORATE BANKRUPTCY PREDICTION MODELS: UNIVARIATE ANALYSIS AND LOGISTIC REGRESSION

Abstract. *Corporate failure has become a major academic research over the last fifty years. During this time, various failure prediction models and bankruptcy theories were developed. From the initial univariate analysis to market-based models of the twenty-first century, the accuracy of the prediction models are improved continually and their link with corporate governance is attracting more attention. However, the emergence of new prediction methods does not mean the decline of traditional empirical analysis. To inspect the relationship between accounting ratios and bankruptcy risk, this paper investigates the efficacy of univariate analysis and logit model to predict bankruptcy problems with a sample of 52 failed and 518 non-failed companies over the period from 2004 to 2008. Further, comparing with the model incorporated with corporate governance information, including number of directors, female percentage, board average age, average tenure and outside directors percentage, I find corporate governance can enhance the accuracy of the prediction model. After combining these corporate governance variables, the accuracy of the prediction model has been improved. Based on the findings of this study, I explore the evidence of factors contributed to the bankruptcy of companies during the financial crisis.*

Keywords: Logistic Regression; The logit model; Receiver Operating Characteristics (ROC); corporate governance information

Introduction

Bankruptcy occurs when a corporation fails to fulfill its obligations and repay its outstanding debts or liquidate its assets to the federal court (Bryan, Fernando, and Tripathy, 2013). Companies' failure can bring a series of tremendous unfavorable influence to the diverse stakeholders, economic safety and social public interest, having a butterfly effect in that a failure could have effects elsewhere in the economic system. Therefore, the ability to predict corporate insolvency correctly can largely avoid the social resources being wasted and this is beneficial to maintain the normal economy order. Numerous studies have been dedicated to verifying the validity of the bankruptcy prediction model and the related study continues.

The early academic study of bankruptcy prediction tended to apply statistical models such as univariate analysis (Beaver, 1966), multiple discriminant analysis (Altman, 1968) and logit analysis (Ohlson, 1980). Though these traditional statistical failure prediction models have long been applied before, due to the differences of sample selections, the focus of research and other method details, the conclusions may not be entirely consistent in different ages. Entering the twenty-first century, the economic environment and enterprise's development pattern is changing greatly, and the forecasting ability of these classic models make researchers interested again. Therefore, many academic studies sought to compare their research results with the previous studies and present an overview of these classic statistical methods (Sofie Balcaen and Hubert Ooghe, 2006). In this paper, I will use the univariate analysis and retest the predictive ability of one of the classic multivariate model - logit model. The accuracy is examined by Receiver Operating Characteristics (ROC) curve.

Corporate governance and its association with the risk of bankruptcy is another area of interest in recent years. Ethical and corporate governance issues are playing more significant roles in corporate risk prediction. Poor corporate governance can offer an early signal to bankruptcy, which is particularly good for regulators and policy-makers (Ali F. Darrat et.al, 2014). The purpose of this study is to investigate what extent can accounting and financial data be used to provide business failure forecasts and how corporate governance information can improve the predictive ability of the prediction model. Importantly, the main factors which caused the failure of corporate during the financial crisis are analyzed.

Literature Review

More than half a century ago, Beaver (1966) examined the accuracy of financial ratios as predictors of failure and concluded that the cash flow/debt was the optimal single ratio. He was one of the first researchers to use modern statistical models to predict corporate risk and his study was viewed as a milestone of univariate analysis in this area. Further, Beaver pointed out in his research that a multivariate analysis using several different ratios may predict better.

In 1968, Altman (1968) established the Z-score model, which utilized a number of financial ratios to assess the firm's bankruptcy potential. In his model, a combination of five financial ratios were selected to predict the financial distress of 33 pairs of manufacturing firms. He tested a series of predictors up to five years prior to failure and the accuracy on his sample 1 year before failure was around 95%. Though the use of Z-score models showed a decreasing trend since the 1980s, the applications and examinations of the Z-score model keep moving.

However, multiple discriminant analysis (MDA) is not perfect and some problems are unavoidable. Critics maintain that the output of this model has little intuitive interpretation and its violations of the statistical assumptions. To handle these problems, research started to shift to logit analysis, which estimates the possibility of corporate failure under less restrictive statistical assumptions. Ohlson (1980) was the first researcher to use this model in company failure prediction. Using logit model, Ohlson selected nine financial ratios for 105 failed and 2058 non-failed companies over the period of 1970 to 1976, and he concluded that predictive ability of any model depends upon the extent to which information is available. Zavgren (1985) stated that the conditional probability models such as the logit model are more useful in predicting corporate failure because there is no linearity assumption. Nevertheless, the logit model also has some limitations. Tucker (1996) argued that logit regression is extremely sensitive to multicollinearity and this problem may be serious because the majority of financial ratios used in the model are highly correlated. Even so, conditional logit analysis still occupies a dominant position in the field of discriminant analysis. Nowadays, the rapid development of the computer technology create conditions for insolvency prediction researchers to apply more approaches and artificially Intelligent Expert Systems (AIES) began to spring up, such as neural networks (Odom & Sharda, 1990; Coats & Fant, 1993; Charitou et al., 2004).

In recent decades, there is renewed interest in the relationship between corporate governance and bankruptcy risk. Previous research tends to focus on the information in the financial statements rather than firm characteristics. However, corporate governance builds the connecting bridge between boards, shareholders, top management and other stakeholders, and many researchers realize that its influence on the risk of bankruptcy cannot be ignored. In the 1990s, some research indicated that the size of a board can affect the possibility of bankruptcy (Lipton and Lorsch, 1992; Jensen, 1993; Yermack, 1996; and Eisenberg et al. 1998), although it was proved not exactly accurate, more attention was paid in that field. Fich and Slezak (2008) argued that the probability of bankruptcy can be influenced by corporate governance. Further, Ali F. Darrat et.al (2014) examined how the risk of business failure influenced by the firm's characteristics, especially the degree of firm's complexity and its requirement for specialized knowledge. The association between corporate governance and bankruptcy risk has been proved to be true of the word and further research is needed.

Methodology and Model evaluation approaches

My discussion is based on the univariate analysis and logit model. This section describes these statistical methods and model evaluation approaches.

Univariate analysis

Traditionally, univariate analysis concentrates on financial ratio analysis. It's fairly simple and only contains one financial ratio as a variable. The ratio which has a good predictive ability is expected to have a significant difference across the failed and non-failed groups. According to the performance of the firm's ratios, an optimal cut-off point is selected. Beaver (1966) examined 30 financial ratios and successfully proved that accounting data imply a potential to predict the business failure.

Logit model

The logit model has a wide range of applications in financial distress prediction. It is a form of regression model which utilizes the non-linear maximum log-likelihood method to express the possibility of corporate failure based on a logistic distribution. Meanwhile, this regression helps to present the multivariate regression between dependent and independent variables (Lee, Ryu & Kim, 2007). Logit regression is frequently used because it's not required to follow linearity assumption, however, it needs to make assumptions on dichotomous dependent variable and error costs should be taken into account when defining the optimal cut-off score (Balcaen, S., & Ooghe, H, 2006). In the logit model, the probability of Y=1 is viewed as the cumulative standard logistic distribution function. The resulting model can be written as follows:

$$\Pr\left(Y = 1/X\right) = \frac{1}{1+e^{-(a+B_1X_1+B_2X_2.....+BnXn)}} = \frac{1}{e^{-z}}$$

The estimation of parameters B1, B2……Bn is via the approach of maximum likelihood procedure. The purpose of the maximum likelihood is to maximize the value of Log Likelihood Function (LLF). Using statistical software, the values of parameters can be obtained as the given Y is as high as possible. LIF is described as the following form:

$$LIF = \sum_{1}^{n} Yi(z) - \sum_{k=1}^{n} Ln(1+e^{z})$$

This paper attempts to examine the forecasting ability of a logit model. The data of this study is relevant to US companies over the period from 2004 to 2008. Using the five financial ratios introduced below, I incorporate these univariate measures into the logit model.

The ROC curve

Receiver Operating Characteristics (ROC) curve is one of the most common ways to measure the accuracy of the different models. Different from contingency tables, it doesn't require researchers to determine the best accurate cut-off point. The ROC divides the model's possibilities into percentiles resulting in 101 cut-points and plots sensitivity (True Positive Rate TPR) against-specificity (1-True Negative Rate TNR) for all these cut-offs. The TPR and TNR are calculated as TP/(TP+FN) and TN/(TN+FP) respectively.

Engelmann, Hayden and Tasche (2003) proved that the model's accuracy is a linear transformation which is represented by the area under the ROC curve. The value of this area is bounded by 0 and 1 and a perfect model has a value of 1.

Data

This section mainly describes data collection, sample and variables selection of my study.

Data collection

The accounting data for these 570 US companies is collected from Wharton Research Data Services (https://wrds-web.wharton.upenn.edu). I conduct my empirical analysis with data from 2004 to 2008. In addition, all corporate governance data of the companies are provided by the course in Exeter Learning Environment (ELE), which includes the number of directors, female percentage, average age, average tenure and outside directors proportion.

Sample selection

This study covers 52 failed firms and 518 non-bankrupt firms. All the non-failed corporations are selected from a list of 2984 healthy companies provided by the course in ELE and I ensure that they are covered in the North America-Annual updates database. These healthy companies were deemed to be alive during 2009 and the database can provide sufficient data over a 5 year period for predicting analysis. Meanwhile, in order to avoid any selection basis and appearance of a general characteristic with abnormal frequency in the sample, I make sure the proportions of the selected non-failed firms with similar characteristics (mainly industry and size) are appropriate and they can be representative of the all 2984 firms. It's important because non-random samples with certain general characteristics under-represented may make the prediction model inefficient. Sofie Balcane and Hubert Ooghe (2006) stated that non-random samples may result from several reasons, such as over-sampling the failing companies, applying a 'complete data' sample selection and using matched pairs. Thus, this study gives up using matched pairs to avoid the biased result which may be caused by non-random samples. In this paper, the proportion of failed and non-failed companies (1:10) meets the requirement of unpaired analysis that selecting much more healthy firms in relation to the failed ones, meanwhile, it permits inferences regarding a single observation (Beaver, 1966) and this scale can better represent the percentage of failures in reality.

Variables selection

There is a great diversity of financial ratios in finance, but not all of them can be good predictors of failure. In univariate analysis, researchers expect their average financial ratios can present the obvious separation between failed and non-failed companies. In this paper, I select 6 financial variables: (1) total debt/total equity, (2) cash/current liability, (3) sales/total assets, (4) net income/sales, (5) total dividends/net income, (6) log (total assets). These ratios are widely used in the field of corporate finance and they measure different perspectives of a company. Total debt/total equity ratio is applied to evaluate a firm's leverage; cash/current liability can assess the liquidity of a company and net income/sales judge earning ability. Beaver have used both of them in 1966; sales/total assets can measure the firm's efficiency to generate revenue with its assets; dividend payout ratio reflects the percentage of earnings paid to shareholders in dividends. It is related to a company's business performance and dividend policy; log (total assets) is used to compare the (book) size of the companies. Just like Beaver, I plot the average of these ratios and examine their predictive accuracy.

Results

This section presents the results of univariate analysis and logit models with and without incorporating corporate governance information.

Predictability of single financial ratios

Figure 1 shows the mean ratios of failed and non-failed firms for the period 2004 to 2008. What can be observed is that cash/current liabilities, net income/sales and sales/total assets have good separation between failed and non-failed firms and their ratios of the non-failed group are much higher than failed ones. Total debt/total equity presents a different trend from 2007 but it has a tendency of merging in the early years. In addition, total dividends/net income seems to be converging as we approach 2009 and the average size of failed firms is slightly larger than non-failed ones over the five year period. To test the significance of these average financial ratios, t-test can be used to examine the value in 2008 (one year before failure).

As shown in table 1, the t-tests confirm that cash/current liabilities, net income/sales and sales/total assets can do well in distinguishing the failed and non-failed firms because all of their p-values are less than 5% and their average ratios of the non-bankrupt group are higher than the bankrupt group. However, the variation trend of profit margin is different from the other two ratios. From figure 1, we can see its average ratio of failed firms dropping drastically during this period and there's a separative trend in the last few years before failure.

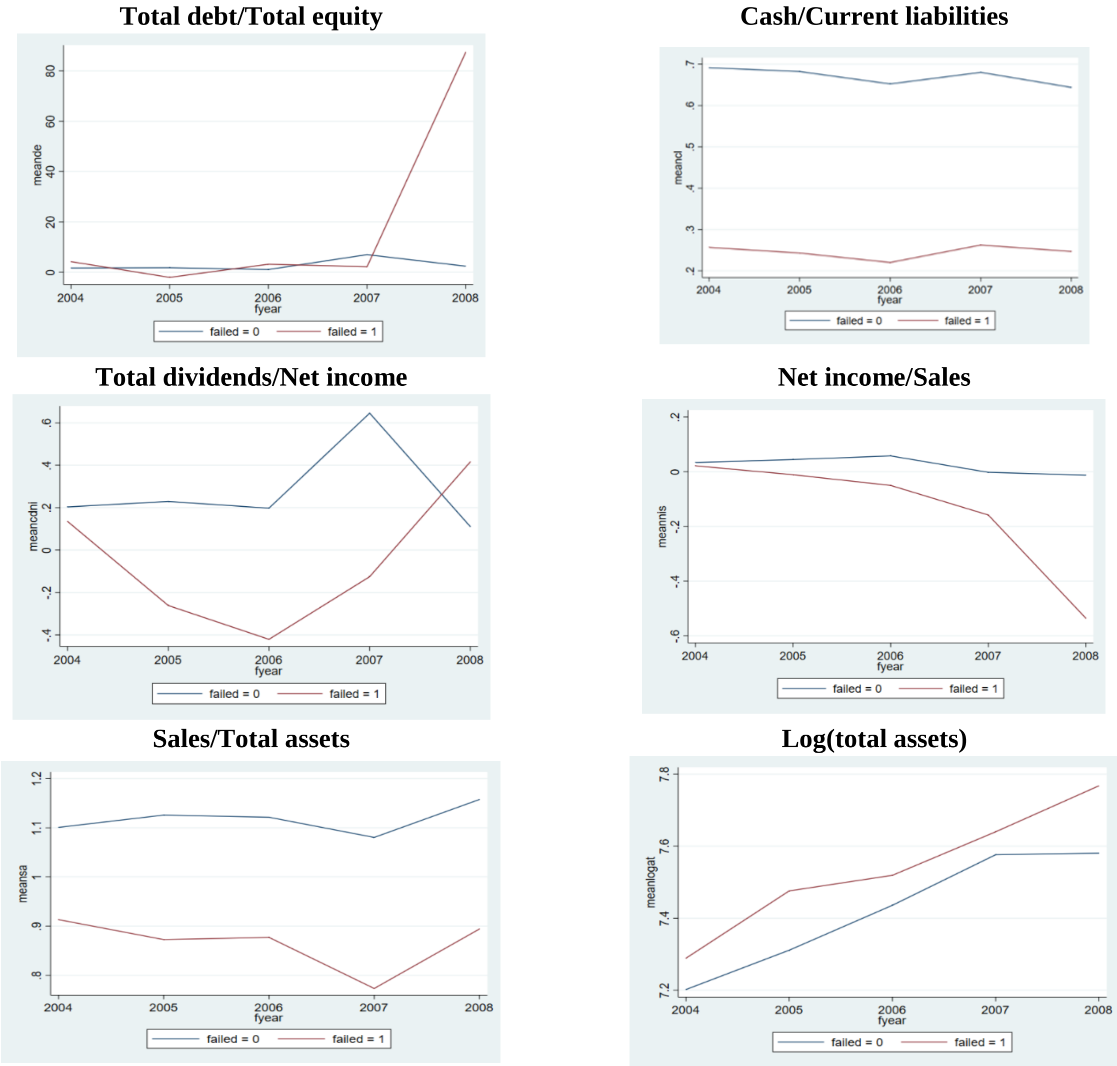


Figure 1 – Comparision of mean values

Table 1 ***– T-test of ratios in 2008***

Variables	Mean (failed)	Mean (non-failed)	Value of P
Total debt/Total equity	87.4167	2.382913	0.1457
Cash/Current liabilities	.2469838	.645454	0.0000
Total dividends/Net income	.4162471	.1103018	0.2545
Net income/Sales	-.5357317	-.0130705	0.0004
Sales/Total assets	.8941049	1.154049	0.0382
Size (log(total assets))	7.767531	7.580646	0.2343

The ROC results are presented numerically in table 2. The ROC area of the net income/sales is the highest at 87%, while the other single financial ratios are in the range 52% to 69%. Comparing to the results of t-test, we can find that the accuracy of cash/current liabilities is next to dividend payout ratio but it has a significant influence on the result. Log (total assets) is the lowest and its p-value is also greater than 5%.

Generally, the results proved that net income/sales can predict corporate accurately in the financial crisis to a large extent and cash/current liabilities also shows good predictive ability. Conclusions of t-test and ROC curves are not exactly consistent and this may result from outliers, correlation issues or the small sample size. The accuracy of single ratios in insolvency prediction has differences, in other words, there is considerable variability in the forecasting ability of different ratios. Before combining these financial ratios in a multivariate model, it's essential to check for their correlation issues. According to table 3, there are no very high correlations between the variables and it's unnecessary to eliminate any of these ratios.

Table 4 shows the regression results of the logit model of 2008 and over a five year period. In this table, the coefficient and p-value of the accounting ratios and firm characteristics are shown, and different from model 1, model 2 represents the new model incorporated with corporate governance information.

Model 1 consists of six accounting financial ratios I selected. From this model, we can see that cash/current liabilities, total dividends/net income and net income/sales are significant in the regression where p<0.05. We also find that the coefficient of total debt/total equity, sales/total assets, cash dividends/net income and size are close to 0, which means they have a very weak relationship with the probability of failure. On the contrary, the cash ratio and profit margin have an obvious reducing effect on the possibility of bankruptcy. For example, the coefficient of cash/current liabilities is -2.567 in 2008, so its odds ratio is $e^{-2.567}$=0.077, which means failure is less likely to occur as cash/current liabilities increases. In conclusion, the company with higher cash ratio and profit margin has a lower probability of failure.

Table 2 ***– ROC – Asymptotic Normal***

Variables	Area	Std. Err	[95% Conf. Interval]	
Total debt/Total equity	0.5894	0.0935	0.40619	0.77263
Cash/Current liabilities	0.6621	0.0535	0.55722	0.76693
Sales/Total assets	0.5647	0.0693	0.42890	0.70050
Net income/Sales	0.8680	0.0313	0.80667	0.92936
Total dividends? Net income	0.6843	0.0421	0.60172	0.76694
Size (log(total assets))	0.5203	0.0473	0.42749	0.61306

Table 3 ***– correl failed in 2008***

Failed	TDTE	CCL	SAT	NIS	CDNI	SIZE	
Failed	1.0000						
TDTE	0.1958	1.0000					
CCL	-0.0858	0.0316	1.0000				
STA	0.0199	-0.0511	0.1993	1.0000			
NIS	0.2219	0.0310	-0.01038	0.1128	1.0000		
DTNI	-0.0127	-0.0032	0.0178	0.0249	0.0425	1.0000	
SIZE	-0.0229	-0.0092	-0.2974	0.1431	0.2118	0.0671	1.0000

Logit model and corporate governance information

Table 4 ***– Coef. and P value (P value is below Coef. in brackets)***

Accounting ratios and firm characteristics	One year prior to bankruptcy		Over a five year period 2004-2008	
	Model 1	Model 2	Model 1	Model2
TDTE	.0021504 (0.248)	.0023552 (0.337)	.0006092 (0.257)	.0002768 (0.612)
CCL	-2.566769 (0.004)	-3.271936 (0.001)	-1.909589 (0.000)	-2.219269 (0.000)
STA	.1865464 (0.424)	.3488069 (0.171)	-.1431923 (0.171)	-.0145133 (0.912)
NIS	-2.021693 (0.000)	-1.798303 (0.000)	-.3328927 (0.000)	-.6770378 (0.015)
DTNI	-.0022573 (0.985)	-.0784698 (0.655)	-.0615432 (0.012)	-.0396073 (0.311)
SIZE	-.0577484 (0.713)	-.2435077 (0.252)	-.1932146 (0.000)	-.1996644 (0.019)
Number of Directors		.1270401 (0.006)		.0546332 (0.006)
Female_pct		1.211766 (0.732)		-2.744668 (0.077)
Avg_age		.000382 (0.996)		.0462783 (0.140)
Avg_tenure		-.4609009 (0.000)		.4028436 (0.000)
Outside_director_pct		-2.086446 (0.300)		-1.72001 (0.023)
_cons	-2.350683	1.096448	-.4832173	-.276963

Model 2 adds some firm characteristics such as the number of directors, female percentage, average age, average tenure and outside director proportion. They indeed bring some changes to the logit model. What we can observe is that the number of directors, average tenure and outside directors proportion have a significant effect. The coefficient of the first two characteristics is insignificantly different from zero so they have no relationship with the probability of bankruptcy. From 2004 to 2008, firms are more likely to fail if it is less diversified in gender and the impact of female percentage is significant at the significance level of 10%. The outside director proportion also plays an important role. Though its p-value is greater than 5% in 2008, over the five year period, outside director proportion has a significant influence on the possibility of bankruptcy, as its percentage increases, the probability of bankruptcy can be reduced.

The question of whether corporate governance information can improve the forecasting ability can be answered by ROC. As shown in figure 2, ROC of model 1 are listed on the left side and the model 2 with corporate governance information are on the other side. We can see that the area under the ROC curve of model 1 in 2008 is 81.94%. After incorporating with corporate governance information, the new logit model obtains an accuracy of 91.98%. Identically, the predictive ability of logit model 2 with corporate governance data also performs better than model 1 over the 5 year period and its accuracy is improved to 86.95%, which is pretty good. It proves that corporate governance information can enhance the accuracy of the multivariate model.

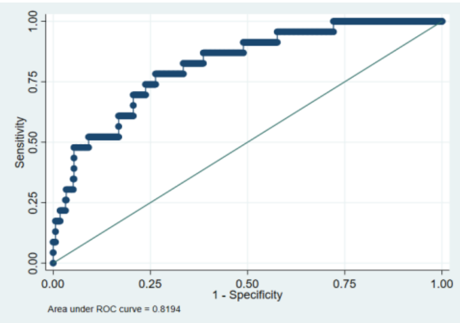
However, this research has its limitations. Because of the lack of some company information in the last few years, the number of failed observations of 2008 is only 34, and considering the outliers and small sample size, the accuracy of the prediction model may be influenced.

In addition, the traditional view is that the closer to the failure year, the higher accuracy of the model can be obtained (Beaver, 1966), but my result is not completely consistent with Beaver's finding. It's likely caused by differences of observations and the time period in sample selection. In short, this study proves that combining financial ratios into a multivariate model can get comparatively ideal predictive accuracy, and through comparing the initial logit models with new models of the same year, the positive effect of corporate governance information can be observed.

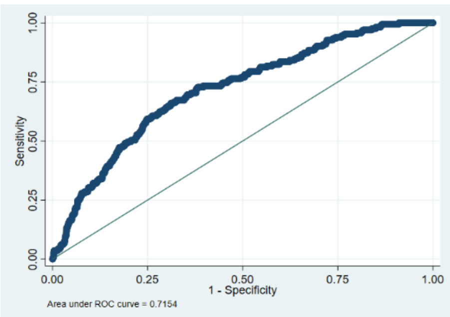
Analysis

This study applies univariate analysis and multivariate model to forecast corporate failure in the financial crisis. The corporate governance information is also considered into the logit model and its competency to improve the predictive accuracy has been verified. Based on the result above, we would find that the main causes contributing to the bankruptcy of the companies in 2009. In univariate analysis, the ratio of cash/current liabilities and net income/sales demonstrate the great ability to separate the failed and non-failed company over the period of 2004 to 2008. The logit model also proves these financial ratios have a significant influence on the probability of corporate failure. To be precise, the US company which has lower cash ratio and profit margin is more likely to fail in the financial crisis.

Model 1

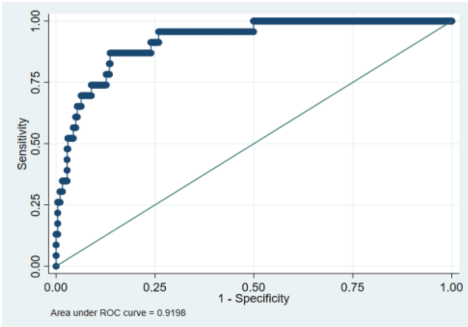


2008

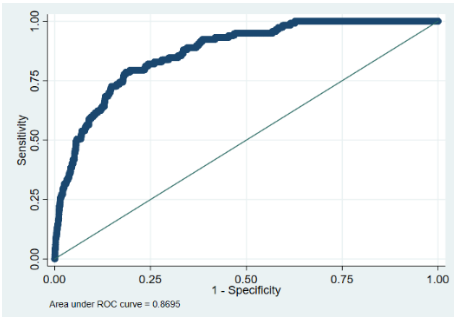


2004-2008

Model 2



2008



2004-2008

Figure 2 – Roc of the logit model

The financial crisis in 2009 was the greatest jolt to the world and numerous firms went bankrupt in one night. It seems might likely that the cash ratio and the profit margin can be part of the explanation. Cash ratio is a kind of important liquidity ratio to measure the company's ability to pay off short-term debt and cash is the most liquid assets to perform this obligation. The crisis emphasized the significance of liquidity to the normal functioning of financial sectors and banking industry (Larry Li, 2017). Before the recession, surface prosperity of the economy would make entrepreneurs to raise funds at low costs to finance the operation. Loose credit conditions for US banks also made firms hold more debt easily. Meanwhile, the role of credit analysis was weakened as the emergence of originate-to-distribute lending which allows bankers to sell on the loan to other institutions or investors (Buckley & Adrian, 2011). We have seen that debt to equity ratio of failed firms is much higher than non-failed firms in one year prior to failure in figure 1. High leverage had laid a hidden danger for the bankruptcy of enterprises. Because of the great expectations for the market, entrepreneurs believed their liability obligation can be paid off when they obtain the prospective earnings. However, as the financial crisis brought down the financial system, the market faced with shrinking demand and companies failed to gain the profits to repay the debt. The rapid reversal of market conditions evaporated the liquidity of the companies. These firms had no choice but kept their base price low and even sold at a loss. That's why failed companies had such a low-profit-margin before the crisis. Comparing to non-failed firms, the cash ratio of failed companies is also much lower in 2008. Without adequate funding, the low profit gained from the sale can't support the operation of enterprises and their current assets were not enough to satisfy the loan, let alone cash on hand. It was impossible to raise funds because funding was not available at low costs like before and banks were drowned in bad debts. In this case, the capital chain of many firms broke. Thus, they had to stop production, as the global recession deepened, bankruptcy was inevitable.

Corporate governance also has an obvious impact on the possibility of corporate failure. The empirical result of this study indicates that a company is more likely to fail if it has a lower percentage of outside directors and female percentage over the five years. Ali F. Darrat et.al (2014) stated that outside directors can play an active role when it is informed about the firm's operations more easily and a high percentage of outside directors is more likely to reduce failure risk in circumstances requiring relatively little specialist knowledge. They also pointed out that firms can perform better with relatively high percentage female directors. Comparing to insiders, outside directors are not employees of the company so they are more independent and can provide unbiased opinions to the company. A high proportion of outside directors who have rich expertise and experience can improve the quality of strategic decision-making and supervise the company management. Similarly, board gender diversification also contributed to improving monitoring (Adams and Ferreira, 2009). Thus, firms have a higher percentage of outside directors and female percentage are related to the lower probability of failure in the sample.

Conclusion

In summary, 6 financial ratios I selected presents different predictive accuracy in univariate analysis. Net income/sales have a relatively good ability to distinguish failed and non-failed firms and its predictive accuracy achieves the anticipated results, which is the highest of these 6 ratios. Overall, the forecasting ability of a single ratio is often limited because there is no one ratio can generalize all the characters of a company and not all financial ratios can be good predictors of insolvency prediction. Further, the result obtained by using a group of variables in a multivariate model to predict insolvency is more persuasive. In the logit model, I find cash/current liabilities and net income/sales play important roles relating to the probability of business failure. In addition, corporate governance information is proven to be able to improve the accuracy of the prediction model. Good corporate governance can reduce the probability of corporate failure and help companies survive in the financial crisis. It is true that management and investors should pay more attention to corporate governance information rather than being limited by accounting data.

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ВИВЧЕННЯ МОДЕЛЕЙ ПРОГНОЗУВАННЯ КОРПОРАТИВНОГО БАНКРУТСТВА: УНІВЕРСАЛЬНИЙ АНАЛІЗ ТА ЛОГІСТИЧНА РЕГРЕСІЯ

Анотація. *Провал корпорацій став головним науковим дослідженням за останні п'ятдесят років. За цей час були розроблені різні моделі прогнозування збоїв та теорії банкрутства. Від первинного універсального аналізу до ринкових моделей двадцять першого століття точність моделей прогнозування постійно вдосконалюється, а їх зв'язок з корпоративним управлінням привертає все більше уваги. Однак поява нових методів прогнозування не означає занепаду традиційного емпіричного аналізу. Для перевірки взаємозв'язку між коефіцієнтами бухгалтерського обліку та ризиком банкрутства у цьому документі досліджено ефективність універсального аналізу та моделі логіта для прогнозування проблем банкрутства для вибірки 52 невдалих та 518 невдалих компаній протягом періоду з 2004 по 2008 рік. Далі моделі порівнюються. До інформації про корпоративне управління включено: кількість директорів, відсоток жінок, середній вік правління, середній термін роботи та відсоток поза межами директорів. Отже, корпоративне управління може підвищити точність моделі прогнозування. Після поєднання цих змінних корпоративного управління точність моделі прогнозування була вдосконалена. На основі результатів цього дослідження наведено фактори, що сприяли банкрутству компаній під час фінансової кризи.*

Ключові слова: логістична регресія; модель Logit; експлуатаційні характеристики приймача (ЕХП); інформація про корпоративне управління

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