A Study on Recursive Defaults for Taiwan Industries: A Competing Risk Approach

Dr. Yi-Kuan Joey Jong*

*Department of Business Administration, St. John's University, TAIWAN. E-Mail: ykjong{at}mail{dot}sju{dot}edu{dot}tw

***Abstract*—**In default risk analysis, the discriminate analysis for default and probit or logit models for default probability are common used. For these analyses, we only consider the effects of financial variables without time effects. In this study, we want to compare the default factors in four different industries, Traditional industry, Metallurgic industries and Electrical industries, Electronic industry, and others. We use two approaches in survival analysis to find the effects of defaults with time effect. First we consider the competing risk model to find whether there is a difference in survival rates between industries. Then we are using Cox proportional hazard rate (PH) model to model default probability. Risk factors of Capital structure analysis, Liquidity analysis, Operating performance analysis, Return on investment analysis and Cash flow are considered. We find it is necessary to separate the industrial types for the analyses since the survival rate for each industry are different. Also the risk factors are different. Financial institute such as Banks can use this model for predict default probability and reduce the risk for holding default customers. The empirical analysis of TEJ data gives the evidence for model adequacy.

***Keywords*—**Competing Risk Analysis; Cox PH Regression; Default Risk Analysis; Survival Analysis.

***Abbreviations*—**Cox Proportional Hazard Rate Model (PH); Internal Rating-based Approach (IRB); Return on Asset (ROA); Return on Equity (ROE); Taiwan Economic Journal (TEJ).

I. INTRODUCTION

1.1. Introduction

During the past 20 years, firms in Taiwan face the competitions from China and Southeast Asia by their low labor cost. Some of the firms moved to China to reduce the operating cost. Firms in Taiwan have encountered either financial crises such as receiving bounded checks, restructured or gone bankrupt. In this study, we focus on the firm which encounters financial crisis. For each crisis, we treat it as one default of the company and we will restart the lifetime after it passes the crisis.

For the bank, we need to evaluate the firms' performance before loan approval. If we can predict the financial performance of a firm especially when default occurs, we will have a better chance to avoid the loss accordingly.

The Basel Committee on Banking and Supervision issued a revised frame work on 2004. In the first pillar, there are two ways to access a company's credit risk, the standard approach and the Internal Rating-Based approach (IRB). In the standard approach, bank can use the credit risk evaluated by external rating from credit rating companies. The second method allow a bank to evaluate default risk under supervision. When using IRB approach validation are required after we calculate default risk.

In default risk analysis, the discriminate analysis for default and probit or logit models for default probability are common used. For these analyses, we only consider the effects of financial variables without time effects and group effect such as difference in industries. In this study, we first use competing risk model to compare the survival curve across the industries. Then we are using Cox proportional hazard rate (PH) model to model default probability. Also a competing risk analysis will give us a tool to compare the risk between distinct groups of samples. We want to use these methods to explore the relation between default and financial ratios of a company for firm.

1.2. Literature Review

For traditional approach of defaults, Altman (1968) used multivariate discriminate analysis to predict financial risk. He combined different financial variables to create good financial discriminate functions. Ohlson (1980) use Conditional Logit Model to predict financial risk. He used 9 financial variables to model the financial risk for a company, the result was better than the one analyzed by multivariate discriminate model. Gentry et al., (1985) cash-based funds flow to predict financial risk, he found the most important factor on financial risk was equity. Using this model, they find case-based fund are useful for predicting a company's financial crisis. Lo (1986) study 38 companies who faced financial crises between 1975 and 1983. He used both multivariate discriminate model and logit model to analyze whether a company was defaulted. He found that if the data is from normal samples the multivariate discriminate model is better than logit model. Otherwise, the logit model is better.

Kaplan & Meier (1958) provides a method for estimating the survival function. Lawless (1982) provides the background on survival analysis and Kaplan-Meier estimators. Cox (1972) using generalized linear model to develop regression model with survival data. It is successful to model to time to events with fixed covariates. Kleinbaum & Klein (2005) provide basic introduction for competing risk models. Fine & Gray (1999) and Gray (1988) provide some theoretic background on competing risk analysis. Scrucca et al., (2007) provides an example of performing competing risk model in R Language.

Srinivasan et al., (2008) used competing risk model to study the effects of product diversity, number of patents, number of trademarks, sale growth and other macro economic variables on the survival of high tech firms. They find the number of patents, number of trademarks, Competitive intensity, employees and NASDAQ index have significant impact on high tech firms' survival. Esteve-Pérez et al., (2010) use the competing risk model to study the exit of Spanish firm between 1990 and 2000. They find the age, size of the firms, labor productivity, price cost margin, R&D and advertising activities have significant impact on firms' exit. He et al., (2010) study the effect of capital structure variables on corporate survival for Hong Kong firms'. They find the firms' financial performances has significant impact whether they will go private or not. The book edited by Engelmann & Rauhmeier (2006) provides methodology to analyze default risk under the Basel Accord regulation.

II. SURVIVAL ANALYSIS AND COMPETING RISK MODELS

Survival analysis is a common tool in biostatistics and reliability. It is used to model the time to failure of a of a patient or a physical component. It is also can be used to model the time to default of a company. In this study we define the a company is defaulted if its credit rating is downgraded.

2.1. Survival Distribution and Hazard Rate Function

Let T lifetime of a company. The function $F(\cdot)$ and $f(\cdot)$ be the distribution function and the probability density function of T. We define the survival function $S(t)$ of T.

$$S(t) = P(T > t) = \int_t^{\infty} f(x)\ dx \tag{1}$$

We can express the pdf $f(\cdot)$ as the derivative of the distribution function $f(t) = F'(t)$. The hazard function $h(t)$ specifies the instantaneous rate of failure at $T = t$ given that the individual survived up to time t and defined as $h(t) = f(t)/S(t)$. It can be explained as instantaneous time of failure.

2.2. Right-Censoring and Estimating Survival Probability

A company is said to be default if it encounter financial crisis such as receiving bounded checks, restructured before the end of study.

For the lifetime of a company, we consider the right-censoring model. We collected our data during a period of time. The lifetimes are set to be 0 at the time the company enters the study or when the company has recovered from financial crisis.

The lifetime of a company is defined as the lifetime of a company is the time of years for it in the study when there is no default occurred for a company during the study. Otherwise, the lifetime is defined as the time of years between the time of default and the beginning of the study if it is the first time of default

We define the observation is censored if no default occurs at the end of study.

We use the company data with both complete and censoring lifetimes to estimate the survival function.

The most common way to estimate the survival probability $S(t)$ is Kaplan-Meier estimator. Lawless (1982) discuss the detail of this method.

2.3. Cox Proportional Hazards (PH) Model

In Cox (1972), he purposed a new regression model on the lifetime distribution called proportional hazards (PH) model, he define the hazard function $h(t \mid \vec{x}) = h_0(t)\ \exp(\vec{x}'\vec{\beta})$ where $h_0(t)$ is an unspecified baseline hazard function free of the covariates $\vec{x}$. The covariates act multiplicatively on the hazard. For two different points $\vec{x}_1$ and $\vec{x}_2$, the hazard ratio

$$\frac{h(t \mid \vec{x}_1)}{h(t \mid \vec{x}_2)} = \frac{h_0(t)e^{\vec{x}_1'\vec{\beta}}}{h_0(t)e^{\vec{x}_2'\vec{\beta}}} = \exp((\vec{x}_1' - \vec{x}_2')\vec{\beta}) \tag{2}$$

is constant respected to time t. This defines the proportional hazards property.

2.4. Cumulative Incident Function and Competing Risk Model

In order to compare the survival curve, we compare the cumulative incidence functions estimated by industries. The cumulative incidence function is defined as the probability of failing from cause r ($r=1,\ldots, k$ where k is the number of industries) up to a certain time point t. Formally, it may be written as

$$I_r(t) = P(T \le t, R = r) = \int_0^T \lambda_r(u)S(u)du \tag{3}$$

where $r(t)$ is the cause specific hazard rate and $S(t) = P(T \ge t)$ is the survival function. Non-parametric MLE of (cause specific) CIF is computed as follows:

$$\hat{I}_r(t) = \sum_{j:t_j \le t} \frac{d_{rj}}{n_j} S_j(t_{j-1}) \tag{4}$$

where d_{rj} is the number of failures at time t_j from industry r, n_j is the number of companies at risk at time t_j, and $S(t_j)$ is the Kaplan–Meier estimate of the overall survival function.

To test whether there is difference in survival curve, we perform the following hypothesis

H_0 : $S_1(t_0) = S_2(t_0) = S_3(t_0) = S_4(t_0)$ versus H_1:At least one of $S_i(t_0)$ are different, for predetermined t_0.

Or we can write it in terms of cumulative incidence functions

H_0: $CI_1(t_0) = CI_2(t_0) = CI_3(t_0) = CI_4(t_0)$

Versus

H_1: At least one of $CI_i(t_0)$ are different, for predetermined t_0.

III. RESULT

3.1. Data Set

The data contain the information of financial ratio provided by TEJ for the Taiwan industries during the 2000 and 2014. It contains 803 companies information. After we transfer the data into survival lifetime, we have 522 observations in the final data set. It contains 62 complete lifetimes and 769 censored lifetimes.

3.2. Analysis Procedures

We analyze data by the following way

(1) We separate the data into 4 groups: a) Electronic industry, b) Metallurgic industry and Electrical industry, c) Traditional industry and d) others.
(2) We consider 5 dimensions of financial ratios: Capital structure analysis, Liquidity analysis, Operating performance analysis, Return on investment analysis and Cash flow
(3) We fit Cox PH model by the four sets of variables and the whole variables with the complete data set as well as the 4 groups of data sets.

3.3. Result for Survival Function Estimations

We first use Kaplan-Meier estimator to fit the survival distribution of 4 different groups. It is shown in figure 1 Comparing the survival function of these four groups, we first find the Electronic Industries have the highest rate of survivals and the Metallurgic industries and Electrical industries have the lowest survival rate. It indicates that the electronic industries are the most industrial force for exporting in Taiwan. For the Metallurgic industries and Electrical industries, it has faced the competition from Southeast Asia and China. Some of the companies have closed their operation in Taiwan and moved their factories to China or other countries with cheap labor.

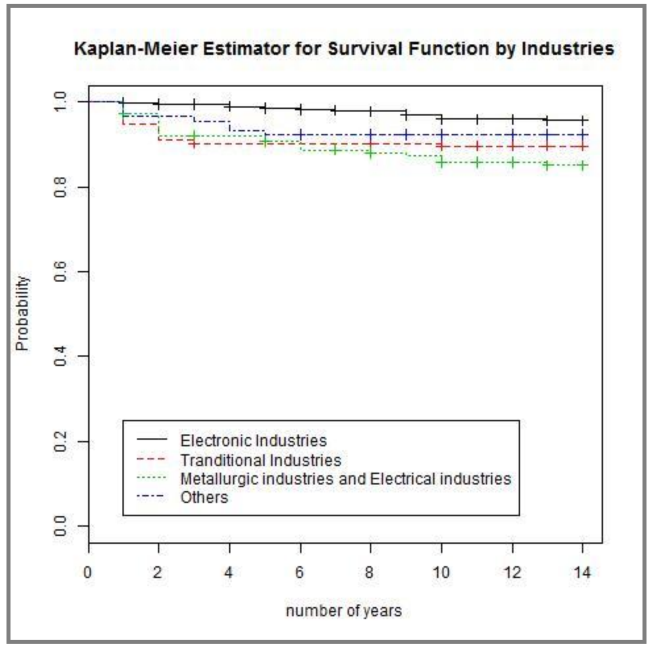

Figure 1: The Kaplan Meier Estimation of Survival Time

3.4. Result for Competing Risk Analysis

The result for the cumulative incidence function is shown on figure 2. We test the hypothesis

H_0 : There is no difference of the incidence functions between four industries

Versus

H_1:At least one cumulative incidence function is different from others for predetermined t_0 The result of comparing cumulative incidence function is shown in Table 1. At level of significance $\alpha = 0.05$,

we have enough evidence to show that there are difference in cumulative incidence function by industries.

Table 1: Result for Comparing Cumulative Incidence Functions

Test equality across groups:

	Statistic	p-value	df
0	19.4	0.0002258	3

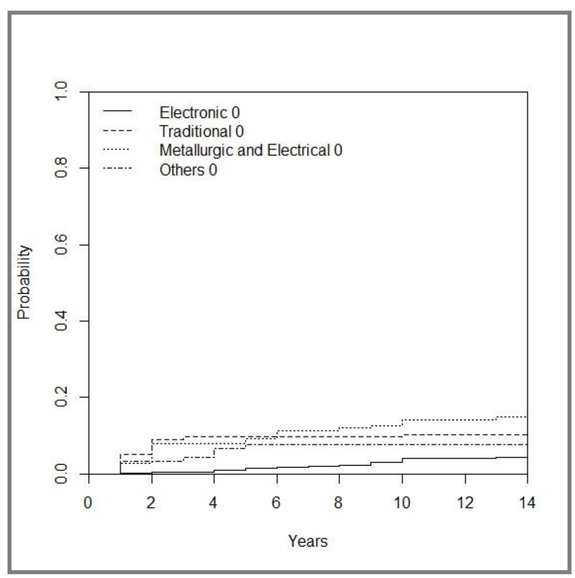

Figure 2: The Cumulative Incidence Functions by Industries

3.5. Result for Survival Function Estimations

Seventeen financial ratios of five dimensions are considered. There ratios are ROA, ROE, Operating profit ratio, YOY%-Pre-Tax Income, YOY%-Total Assets, YOY%-Total Equity, YOY%-Return on TA, Current %, Acid Test, Interest Expenses, Liabilities, Total Asset Turnover, A/R & N/R Turnover, Equity Turnover, Days-A/P Turnover, Degree of Fin. Lever, Sales Per Employee. We fit the Cox PH model for all data and with 4 categories of industries. The result shown in table 2.

Table 2: Parameter Estimation for Cox PH Regression

Variable	Industries				
	All	Electronic	Metallurgic, et	Traditional	Others
ROA	-0.00223	-0.03366	-0.09447	0.0627	-6.65595
	(0.0055)	(0.03494)	(0.14523)	(0.05375)	(6590)
ROE	-0.00496	-0.02069	-0.04625	-0.05108	-3.49601
	(0.00417)	(0.01353)	(0.0451)	(0.02632)	(3471)
Operating profit ratio	-3.6E-05*	0.000028	-0.000036	0.0001195	0.07637
	(1.39E-05)	(0.000408)	(0.0000208)	(0.0005666)	(11.64024)
YOY%-Pre-Tax Income	-6.58E-06	-0.00012	-0.0002634	-6.62E-06	-0.03793
	(5.7E-06)	(0.000343)	(0.0003032)	(0.0000223)	(15.75959)
YOY%-Total Assets	0.00237*	0.0143*	0.02503	0.00704	0.90781
	(0.00141)	(0.00643)	(0.01865)	(0.00678)	(977.78916)
YOY%-Total Equity	-0.00238	-0.02869*	0.0005168	-0.04372*	-1.02322
	(0.00363)	(0.01316)	(0.00489)	(0.02136)	(650.52709)
YOY%-Return on TA	0.02354*	0.05086	0.0457	0.00637	-0.5371
	(0.00794)	(0.04802)	(0.03708)	(0.01065)	(591.36931)
Current %	-0.00705*	-0.00254	-0.01633	-0.04893*	-2.81149
	(0.00344)	(0.00678)	(0.01072)	(0.01431)	(983.799)
Acid Test	-0.0023	-0.00611	0.00454	-0.0047	-0.0352
	(0.00136)	(0.01233)	(0.00276)	(0.00291)	(44.80422)
Interest Exp. %	-0.00049	-0.00325	0.00336	-0.00188*	0.00129
	(0.000262)	(0.00303)	(0.00329)	(0.0008579)	(2.40297)
Liabilities %	-0.05095*	-0.07969*	-0.00567	0.01672	-1.80545
	(0.01031)	(0.03316)	(0.05129)	(0.02088)	(706.4785)
Total Asset Turnover	0.00019	-0.17072	0.00212	-0.04793	0.11248
	(0.00055)	(0.08831)	(0.00289)	(0.03745)	(34.17364)
A/R&N/R Turnover	0.000412	-0.01975	0.01007	-0.00121	0.14465
	(0.4774)	((0.0145)	(0.00726)	(0.0012)	(48.33318)
Equity Turnover	-0.0097*	0.00203	-0.01776	-0.02666*	-0.49359
	(0.0116)	(0.01304)	(0.01699)	(0.01238)	(242.1875)
Days-A/P Turnover	6.35E-05	0.00525	-0.0001314	0.0003453	0.00221
	(0.2231)	(0.00508)	(0.0003258)	(0.0003643)	(8.82933)
Degree of Fin. Lever	-5.97E-06	-6.58E-07	0.0000256*	-0.000052	0.00208
	(3.41E-01)	(9.49E-06)	(0.0000104)	(0.000043)	(0.79449)
Sales Per Employee	-8.61E-06	-2.1E-05	-0.0000615	0.0000729	0.01881
	(0.5188)	(2.55E-05	(0.0000625)	(0.0003329)	(11.82931)

* 0.05 level of significance

For the complete data, we find Operating profit ratio, Current ratio, Acid Test, Interest Expense ratio, Liabilities, Equity Turnover, Electronic industries have negative effects on default. And YOY%-Total Assets, YOY%-Return on TA have positive effects on defaults.

For Electronic industry, we found YOY%-Total Equity, Liabilities and Total Asset Turnover have negative effects on default. Also YOY%-Total Assets has positive effects on defaults

For the Traditional Industries, we found YOY%-Total Equity, Current ratio, Interest Expense ratio and Equity Turnover have negative effects on defaults.

For the Metallurgic and Electrical operating profit ratio has negative effects on defaults and Degree of Financial Lever has positive effects on defaults.

For the other Industries, the estimation is not significant since there are not enough complete lifetime for the data

IV. CONCLUSION

In this study, we use the 17 financial factors to use Cox PH model to predict default rates. We have found that the survival rate for electronic industries, electrical industrial, traditional industries and other industrial are different. Also the risk factor for each type of industries are different.

If we did not separate the data by industrial, the variables on Return on investment analysis are most significant.

For electronic industrial, variables for Return on investment are useful in predicting default of a company.

For Metallurgic and Electrical Industries, variables on Operating performance analysis are useful in predicting default of a company.

For Traditional Industries, variables on Capital structure are useful in predicting default of a company

Therefore, when considering the default risk factors, we need to separate the type of industries in order to have a better prediction results.

In this study, we only consider the variables from financial statement. We may consider macro economical variables such as GNP and unemployment rates.

Acknowledgement

I like to thank the reviewers for providing valuable comment.

References

[1] E.L. Kaplan & P. Meier (1958), "Nonparametric Estimation from Incomplete Observations", *J. Amer. Statist. Assoc.*, Vol. 53, Pp. 457–481.

[2] E.I. Altman (1968), "Financial Ratios, Discriminant Analysis and the Prediction of Corporate Bankruptcy", *Journal of Finance*, Vol. 23.

[3] D.R. Cox (1972), "Regression Models and Life Tables (with Discussion)", *Journal of Royal Statistical Society, Series B* 34, Pp. 187–220.

[4] J.M. Ohlson (1980), "Financial Ratios and the Probabilistic Prediction of Bankruptcy", *Journal of Accounting Research*, Vol. 18, No. 1, Pp. 109–131.

[5] J.F. Lawless (1982), "Statistical Models and Methods for Lifetime Data", New York: *Wiley*.

[6] J. Gentry, A.P. Newbold & D.T. Whitford (1985), "Funds Flow Components, Financial Rations, and Bankruptcy", *Journal of Business Finance and Accounting*, Vol. 14, No. 4, Pp. 595–606.

[7] A.W. Lo (1986), "Logit versus Discriminant Analysis: A Specification Test and Application to Corporate Bankruptcies". *Journal of Econometrics*, Pp. 151–178.

[8] R.J. Gray (1988), "A Class of K-sample Tests for Comparing the Cumulative Incidence of a Competing Risk", *Ann Stat*, Vol. 16, Pp. 1141–1154.

[9] J.P. Fine & R.J. Gray (1999), "A Proportional Hazards Model for the Subdistribution of a Competing Risk", *J. Amer. Statist. Assoc.*, Vol. 94, Pp. 496–509.

[10] D.G. Kleinbaum & M. Klein (2005), "Survival Analysis A Self-Learning Text", 2nd ed, *Springer*.

[11] B. Engelmann & R. Rauhmeier (2006), "The Basel II Risk Parameters", *Springer-Verlag Berlin Heidelberg*.

[12] L. Scrucca, A. Santucci & F. Aversa. (2007), "Competing Risk Analysis using R: and Easy Guide for Clinician", *Bone Marrow Transplant*, Vol. 40, Pp. 381–387.

[13] R. Srinivasan, G.L. Lilien & A. Rangaswamy (2008), "Survival of High Tech Firms: The Effects of Diversity of Product–Market Portfolios, Patents, and Trademarks", *Intern. J. of Research in Marketing*, Vol. 25, Pp. 119–128.

[14] S. Esteve-Pérez, A. Sanchis-Llopis & J.A. Sanchis-Llopis (2010), "A Competing Risks Analysis of Firms' Exit", *Empir Econ*., Vol. 38, Pp. 281–304.

[15] Q. He, T. Chong, L. Li & J. Zhang (2010), "A Competing Risks Analysis of Corporate Survival", *Financial Management*, Vol. 39, No. 1, Po. 1697–1718.

Yi-Kuan Joey Jong received his Ph. D. degree from Department of Statistics, University of Pittsburgh, PA, USA. He is an assistant professor in Department of Business Administration, St. John's University, Taiwan. His research interests are survival analysis applied in risk managements and bathtub distribution in reliability theory.

