行政院國家科學委員會專題研究計畫 成果報告

財務危機預測：複層次離散時間存活風險預測模型分析
研究成果報告(精簡版)

計 畫 類 別 ：個別型
計 畫 編 號 ：NSC 96-2416-H-004-034-
執 行 期 間 ：96 年 08 月 01 日至 97 年 07 月 31 日
執 行 單 位 ：國立政治大學會計學系

計 畫 主 持 人 ：張清福

計畫參與人員： -兼任助理人員：林佳慧
-兼任助理人員：蔡蓓華

處 理 方 式 ：本計畫可公開查詢

中 華 民 國 98 年 05 月 25 日

附件：封面格式

行政院國家科學委員會補助專題研究計畫成果報告

※※※※※※※※※※※※※※※※※※※※※※※※※
※　　　　　　　　　　　　　　　　　　　　　　　　※
※　財務危機預測：複層次離散時間存活風險預測模型分析　※
※　　　　　　　　　　　　　　　　　　　　　　　　※
※※※※※※※※※※※※※※※※※※※※※※※※※

計畫類別：■個別型計畫　　□整合型計畫
計畫編號：NSC 96 - 2416 - H - 004 - 034 -
執行期間：96 年 08 月 01 日至 97 年 07 月 31 日

計畫主持人：張清福
計畫參與人員：林佳慧、蔡蓓華

本成果報告包括以下應繳交之附件：
□赴國外出差或研習心得報告一份
□赴大陸地區出差或研習心得報告一份
□出席國際學術會議心得報告及發表之論文各一份
□國際合作研究計畫國外研究報告書一份

執行單位：國立政治大學

中　華　民　國　98 年　05 月　20 日

行政院國家科學委員會專題研究計畫成果報告
國科會專題研究計畫成果報告撰寫格式說明
Preparation of NSC Project Reports

計畫編號：NSC 96-2416-H-004-034-
執行期限：96 年 8 月 1 日至 97 年 7 月 31 日
主持人：　　張清福　　（國立政治大學）
計畫參與人員：林佳慧、蔡蓓華　　（國立政治大學）

中文摘要

多數財務危機預測之研究採用羅吉斯迴歸方法，有單期羅吉斯迴歸模型以及多期羅吉斯迴歸模型，Shumway (2001) 將離散時間涉險模型應用於財務危機預測，使得羅吉斯迴歸方法在該議題之研究運用上向前邁進一步。本研究運用複層次離散時間涉險預測模型預測財務危機，希冀能進一步提高模型之預測能力。

複層次離散時間涉險預測模型兼具離散時間涉險模型以及複層次羅吉斯迴歸模型之特性，較能細緻地考慮到『公司分屬於產業』之複層次特性，此一思考應能提高財務危機研究之預測能力。目前文獻上的財務危機預測模型，將各產業的財務風險視為一致，此一隱含之假設恐與事實有所出入。實際上，不同的產業在不同的景氣循環階段，面臨不同程度的風險；而同一產業內的公司，應該共同享有某種程度的共同風險。如果能夠把此一產業共同的風險濾析出來，模型的預測應可提高。本研究在考慮公司財務危機風險存在複層次性之本質下，首先說明複層次離散時間涉險預測模型方法，接著以 Altman (1968) 之財務變數為模型自變數，比較離散時間涉險預測模型與複層次離散時間涉險預測模型之預測能力。

複層次離散時間涉險預測模型將不只用來預測公司財務危機，更可以提供金融機構應用於 Base II 協定所建議之 IRB 信用風險評估系統中。

關鍵詞：財務危機預測、離散時間涉險預測模型、複層次離散時間涉險預測模型

Abstract

Subsequent to Shumway (2001), I try to advance the prediction of bankruptcy by proposing a multilevel discrete-time survival model which is a hybrid of both multilevel model and discrete-time survival model. While the discrete-time survival models are proved more accurately predict bankruptcy than single-period models, I argue that multilevel discrete-time survival models further outperform discrete-time survival models in predicting bankruptcy. As firms can be hierarchically organized by industry, bankruptcy prediction becomes an issue concerning multilevel phenomenon.

Traditional prediction of bankruptcy disaggregating industry data consisting of all sample firms into the individual level ignores the difference in bankruptcy risk between industries, and hence its estimation is biased. By considering the multilevel attribute of the bankruptcy risk, I describe a multilevel discrete-time survival model and then use the accounting ratios that have been used in previous models to compare the proposed models with single-period models and discrete-time survival models.

Multilevel discrete-time survival models not only can be applied to bankruptcy prediction but also credit risk prediction. The latter is a recent focus of Basel II accord.

Keywords: Bankruptcy Prediction, Multilevel Model, Discrete-time Survival Model, Multilevel Discrete-time Survival Model

1. Motivation and Purposes

The logistic bankruptcy prediction models in literature have evolved from single-period logistic regression model, multi-period logistic regression model, and then the discrete-time survival models (Shumway 2001; 吳清在與謝宛庭 2004). All these models haven't considered the multilevel attribute of the sample firms. However, in essence, firms can be grouped into industries that have different attributes bankruptcy risks. Up to now, we haven't had a model in literature to deal with this sophisticated concern.

This study argues that multilevel discrete-time survival models outperform discrete-time survival models by comparing their prediction capability based on Altman's (1968) Z-score accounting-based explanatory variables. In addition, this study proposes a multilevel discrete-time survival model incorporating accounting-based variables, audit opinions, and corporate governance variables as explanatory variables.

The Basel Committee on Banking Supervision issued a revised framework on International Convergence of Capital Measurement and Capital Standards ("Basel II" or the "revised Framework") in June 2004. The Committee advocates that banks apply the "internal ratings-based" (IRB) approach to Basel II. According to IRB, banks use their own internal measures for key drivers of credit risk as primary inputs to their minimum regulatory capital calculation. If the proposed models outperform the state-of-the-art discrete-time survival models, it could also contribute to the credit risk rating for the banking industry.

2. Literature Review

The issue of bankruptcy prediction has been extensively studied. Although the formal quantitative studies on this issue can be dated back to 1930s, Altman's (1968) Z-score model is mostly cited. He uses multiple discriminant analysis (MDA) to address the bankruptcy prediction models. Altman develops his Z-score model by using manufacturing firms that filed a bankruptcy petition under Chapter XI of the national bankruptcy act from 1946 to 1965. The model has 5 explanatory variables including Net Working Capital/Total Assets, Retained Earnings/Total Assets, Market Value of Equity/Book Value of Total Liabilities, Earnings before Interest and Taxes/Total Assets, and Sales/Total Assets. Altman find that firms with Z-score less than 1.81 go bankrupt within one year while firms with Z-scores greater than 2.99 fell into the non-bankrupt group. Firms with Z-scores between 1.81 and 2.99 fell into a 'gray area' where misclassifications often arise. He found that a cutoff of Z-score equal to 2.675 minimizes the total of type I and type II errors.

Starting from 1980s, some complex estimation methods such as logit and probit models are used to compute the probability of bankruptcy. Ohlson (1980) uses a logit model to investigate the probability of bankruptcy. He find that using a probability cutoff of 3.8% for classifying firms as bankruptcy minimizes type I and type II errors and the model correctly classifies 87.6% of his bankrupt firms and 82.6% of normal firms.

In Taiwan, 陳明賢(1986), 潘玉葉(1990), and 王俊傑(2000) use logit models to predict bankruptcy while 郭志安(1997) and 陳渭淳(200) use survival analysis to examine the issue. Pagano et al. (1998) and Denis and Sarin (1997) use multi-period logit model which combines survival analysis and logit model to predict bankruptcy. Louwers et al. (1999) employs baseline hazard model to test if the auditor's opinion matters in the issue.

Recently, Shumway (2001) employs discrete-time survival model. It's noteworthy. This model uses multiple years of data for each sample firm, and treats each firm as a single observation. He finds this model outperforms MDA and logit models, and that the model incorporating accounting ratios and market-based variables outperforms including only accounting ratios.

As we know from the above literature, the logit regression used in the literature on bankruptcy evolves from single-period logit models, multi-period logit models, baseline hazard models, and discrete-time survival models. However, the multilevel attribute of the bankruptcy hasn't been tackled with. This issue would be the main focus of this study.

3. Methodology

Multilevel discrete-time survival models are a hybrid of multilevel models and discrete-time survival models for binary response.

In the studies of bankruptcy, single-period logit models have been extensively used, such as Ohlson (1980), Zmijewski (1984) and others. For the event cases, single-period logit models take the risk factors just before bankruptcy into consideration while multi-period logit models incorporate risk factors information for several years before bankruptcy occurs. Allison (1982, 1984), Tuma and Hannan (1984) and Yamaguchi (1991) extend multi-period logit models to discrete-time survival models.

Bankruptcy or credit risk researchers frequently ask whether and when events occur. However, the sound statistical methods for analyzing such issues are not readily available until the development of discrete-time survival models.

Most logistic regression models applied to predicting bankruptcy in previous research are single-period models. Discrete-time survival models have not been applied to this issue until recent work of Shumway (2001).

A multilevel model concerns the multilevel attribute of the sample and has the level-1 case as the linear regression. A linear regression is therefore a special case of multilevel models. Multilevel models can be extended to deal with binary response data. In this case, a multilevel model consists of three parts: a sampling model, a link function, and a structural model (Raudenbush and Bryk 2002).

This study synthesizes discrete-time survival model Shumway (2001) and Multilevel model (Raudenbush and Bryk 2002) to be the multilevel discrete-time survival model.

4. Research Design

This study compares the prediction capabilities of a multilevel discrete-time survival model and a discrete-time survival model based on Altman (1968). That means, in order to make comparison of the prediction capabilities of the above two models, I use the explanatory variables as those in Altman (1968). The explanatory variables of Altman are classical ones. Shumway (2001) hence uses the same prediction variables as the ones in Altman (1968). Following Shumway (2001), this study also includes Altman's variables in the model only.

In the multilevel discrete-time survival model, level-1 and level-2 predictors have been centered around their group means. The multilevel discrete-time survival model can be written as follows.

Level 1 Model

$$\mathrm{Prob}(Y_{ij}=1|\beta_i) = \varphi_{ij}$$

$$\mathrm{Log}[\varphi_{ij}/(1-\varphi_{ij})] = \eta_{ij}$$

$$\begin{aligned}\eta_{ij} = \beta_{0i} + \beta_{1i}\,&(TATO_{ij} - AVG(TATO_{.j})) + \\ &\beta_{2i}\,(WCTA_{ij} - AVG(WCTA_{.j})) + \\ &\beta_{3i}\,(RETA_{ij} - AVG(RETA_{.j})) + \\ &\beta_{4i}\,(EBITTA_{ij} - AVG(EBITTA_{.j})) + \\ &\beta_{5i}\,(MVETL_{ij} - AVG(MVETL_{.j}))\end{aligned}$$

Level 2 Model

$$\beta_{0i} = \gamma_{00}$$

$$\beta_{1i} = \gamma_{10} + \gamma_{11}(MTATO_j - AVG(MTATO.))$$

$$\beta_{2i} = \gamma_{20} + \gamma_{21}\,(MWCTA_j - AVG(MWCTA.))$$

$$\beta_{3i} = \gamma_{30} + \gamma_{31}\,(MRETA_j - AVG(MRETA.))$$

$$\beta_{4i} = \gamma_{40} + \gamma_{41}\,(MEBITTA_j - AVG(MEBITTA.))$$

$$\beta_{5i} = \gamma_{50} + \gamma_{51}\,(MMVETL_j - AVG(MMVETL.))$$

where

Y: binary response, 1 for bankruptcy

occurs, otherwise non-bankruptcy

AVG(.): mean of a variable
TATO: Total Assets Turnover
WCTA: Working Capital/Total Assets
RETA: Retained Earnings/Total Assets
EBITTA: EBIT/Total Assets
MVETL: Market Value of Equity/Total Assets
MTATO: mean TATO by industry
MWCTA: mean WCTA by industry
MRETA: mean RETA by industry
MEBITTA: mean EBITTA by industry
MMVETL: mean MVETL by industry

The final sample consists of 6,481 listed and OTC firms together, which includes 86 bankrupt firms and 6,396 firms in normal operation during the 1996-2005 period. All data are retrieved from Taiwan Economic Journal (TEJ) database.

The sample consists of 6,481 listed and OTC firms together within 24 industries. Descriptive statistics are found in Table 1. As shown in the table, both level-1 and level-2 have five variables. The bankruptcy frequency is presented in Table 2. In the sample, there are 86 bankrupt firms and 6,396 firms in normal operation.

5. Empirical Results

This section compares the empirical results between discrete-time survival model (Shumway 2001) and multilevel discrete-time survival model. The latter is a synthesis of discrete-time survival model and multilevel model (Raudenbush and Bryk 2002). Both discrete-time survival model and multilevel discrete-time survival model have the same sample while the models are different.

Table 1 presents the descriptive statistics for two-level data. The level-1 descriptive statistics of the multilevel discrete-time survival model is the same as the descriptive statistics of the discrete-time survival model.

TABLE 1
Descriptive Statistics for Two-Level Data

Level-1 Descriptive Statistics						
Variable	N	Min	Mean	Median	Std Dev	Max
WCTA	6481	-1.075	0.19	0.177	0.188	0.849
RETA	6481	-2.629	0.045	0.057	0.155	0.66
EBITTA	6481	-2.441	0.055	0.057	0.107	0.583
MVETL	6481	0	0.003	0.002	0.009	0.284
TATO	6481	-0.16	0.857	0.72	0.621	6.85
Level-2 Descriptive Statistics						
Variable	N	Min	Mean	Median	Std Dev	Max
MWCTA	24	0.041	0.18	0.166	0.092	0.361
MRETA	24	-0.031	0.062	0.055	0.061	0.263
MEBITTA	24	0.021	0.068	0.061	0.046	0.222
MMVETL	24	0	0.003	0.003	0.002	0.01
MTATO	24	0.039	0.847	0.84	0.406	2.24

Table 2 describes the frequency of bankrupt firms in the sample.

TABLE 2
Bankruptcy Frequency

Y	Frequency	Percent
0	6,395	98.67
1	86	1.33

Table 3 presents the results from discrete-time survival model in which the ratio of market value of equity to total liabilities and total assets turnover are insignificant.

Table 3. Discrete-time Survival Model

Analysis of Maximum Likelihood Estimates

Parameter	Estimate	Std Err	Wald Chi-Sq	Pr > Chi-Sq
Intercept	-3.94	0.23	285.27	<.0001
WCTA	-5.00	0.74	45.11	<.0001
RETA	-3.59	0.67	28.99	<.0001
EBITTA	-1.50	1.13	1.75	0.1862
MVETL	-45.70	39.41	1.34	0.2462
TATO	-0.12	0.27	0.19	0.6628

Table 4 shows the results from multilevel discrete-time survival model in which all the coefficients of prediction variable are significant.

Table 4
Estimation of fixed Effects

Fixed Effect	Coef	Std Err	t-ratio	p-value
For INTRCPT1, β0				
INTRCPT2, γ00	-5.444	-0.021	250.577	0.000
For TATO slope, β1				
INTRCPT2, γ10	-0.372	0.031	-11.662	0.000
MTATO, γ11	3.103	0.103	29.891	0.000
For WCTA slope, β2				
INTRCPT2, γ20	-5.478	0.086	-63.311	0.000
MWCTA, γ21	27.566	0.893	30.843	0.000
For RETA slope, β3				
INTRCPT2, γ30	-4.397	0.103	-42.479	0.000
MRETA, γ31	-33.131	4.069	-8.142	0.000
For EBITTA slope, β4				
INTRCPT2, γ40	-0.111	0.175	-0.637	0.524
MEBITTA, γ41	78.259	7.762	10.082	0.000
For MVETL slope, β5				
INTRCPT2, γ50	-72.101	5.144	-14.014	0.000
MMVETL, γ51	24260	1941	12.493	0.000

5. Conclusions

One merit of this study is that the multilevel discrete-time survival model is shown superior to the discrete-time survival model in terms of the improvement on the significance of coefficients of prediction variables while the comparison of prediction power f two models needs further investigation.

6. References

王俊傑，2000，財務危機預警模式－以現金流量觀點，國立台北大學企業管理學系碩士論文。

吳清在、謝宛庭，2004，財務困難公司下市櫃之離散時間涉險預測模式，會計評論，第 39 期。

郭志安，1997，以Cox 模式建立財務危機預警模式，私立逢甲大學統計與精算學系碩士論文。

陳渭淳，2001，上市公司失敗預測之實證研究，國立台北大學企業管理學系博士論文。

陳明賢，1986，財務危機預測之計量分析研究，國立台灣大學商學系碩士論文。

潘玉葉，1990，台灣股票上市公司財務危機預警分析，私立淡江大學管理科學學系所博士論文。

Allison, P. 1982. Discrete-time methods for the analysis of event histories. *Sociological Methodology*: 61-98.

Allison, P. 1984. *Event History Analysis*. Beverly Hill: Sage Publications.

Altman, E. 1968. Financial ratios, discriminant analysis and the prediction of corporate bankruptcy. Journal of Finance 6 (1): 4-19.

Cox, D. 1972. Regression models and life-table. *Journal of the Royal Statistical Society* 34 (2): 187-200.

Denis, D. J., D. K. Denis, and A. Sarin. 1997. Ownership structure and top executive turnover. *Journal of Financial Economics* 45 (2): 193-221.

Goldstein, H. 2003. *Multilevel Statistical Models*. New York, NY: Oxford University Press Inc.

Heck, R. H. and S. L. Thomas. 2000. *An Introduction to Multilevel Modeling Techniques*. Mahwah, NJ: Lawrence Erlbaum Associates, Inc.

Hox, J. 2002. *Multilevel Analysis: Techniques and Applications*. Mahwah, NJ: Lawrence Erlbaum Associates, Inc.

Louwers, J., M. Messina, and D. Richard. 1999. The auditor's going-concern disclosure as a self-fulfilling prophecy: A discrete-time survival analysis. *Decision Sciences* 30 (3): 805-824.

Ohlson, J. 1980. Financial ratios and the probabilistic prediction of bankruptcy. *Journal of Accounting Research* 18 (1): 109-131.

Pagano, M., F. Panetta, and L. Zingales. 1998. Why do companies go public? An empirical analysis. *The Journal of Financ*e 53 (1): 27-64.

Raudenbush, S. W., and Bryk, A. S. 2002. *Hierarchical Linear Models: Applications and Data Analysis Methods*, Second Edition. Newbury park, CA: Sage.

Shumway, T. 2001. Predicting bankruptcy more accurately: A simple hazard model. *Journal of Business* 74 (1): 101-124.

Snijders, T. A. B. and R. J. Bosker. 2003. *Multilevel Analysis: An Introduction to Basic and Advanced Multilevel Modeling*. Thousands, CA: Sage Publications Ltd.

Tuma, N. B. and M. T. Hannan. 1984. *Social Dynamics: Models and Methods*. New York, NY: Academic.

Yamaguchi, K. 1991. *Event History Analysis*. Newbury Park, CA: Sage Publications.

Zmijewski, M. 1984. Methodological issues related to the estimation of financial distress prediction models. *Journal of Accounting Research* 22 (Supplement): 59-82.