Multiple States of Financially Distressed Companies : Tests using a Competing-Risks Model

Nongnit Chancharat[a]
Gary Tian[b]*
Pamela Davy[c]
Michael McCrae[d]
Sudhir Lodhe[e]

Abstract

This study examines the determinants of multiple states of financial distress by applying a competing-risks model. It investigates the effect of financial ratios, market-based variables and company-specific variables, including company age, size and squared size on three different states of corporate financial distress: active companies; distressed external administration companies; and distressed takeover, merger or acquisition companies. A sample of 1,081 publicly listed Australian non-financial companies over the period 1989 to 2005 using a competing-risks model is used to determine the possible differences in the factors of entering various states of financial distress. It is found that specifically, distressed external administration companies have a higher leverage, lower past excess returns and a larger size; while distressed takeover, merger or acquisition companies have a lower leverage, a higher capital utilisation efficiency and a larger size compared to active companies. Comparing the results from both the single-risk model and the competing-risks model reveals the need to distinguish between financial distress states.

Keywords: Financial distress; Survival analysis; Competing-risks model.

JEL Classification: G10; C30.

[a b d e] School of Accounting and Finance, University of Wollongong, Australia. * gtian@uow.edu.au

[c] School of Mathematics and Applied Statistics, University of Wollongong, Australia.

Acknowledgement: We are grateful to the comments from the participants in *The 2007 European Applied Business Research Conference,* Italy (2007), and *The FINSIA-Melbourne Centre for Financial Studies Banking and Finance Conference,* RMIT Melbourne (2007) on the early version of the paper. Despite the helpful comments received responsibility still lies with the authors for any errors and omissions.

1. Introduction

Over the last decade there exists evidence of an increasing number of corporate collapses including Enron, WorldCom, Tyco and HealthSouth. In Australia, notable failures include HIH Insurance, OneTel, Ansett Airlines and Fincorp. Such collapses of financially distressed companies often entails significant direct and indirect costs to many stakeholders. There is a view that these costs can be avoided if financially distressed companies are identified well before their ultimate failure. Lau (1987) argues that such companies face a continuum of financial distress states before they go bankrupt. Hensher, Jones and Greene (2007) argue that a model that incorporates multiple states of financial distress provides a wider range of distress scenarios that public companies typically face in the real world. The literature on the predictions of traditional corporate financial distress in general focusses on the conventional failing and non-failing dichotomy. For example, Altman (1968b), Ohlson (1980) and Shumway (2001) examine the companies that actually went bankrupt. Jones and Hensher (2007) argue that the inclusion of multiple states of financially distressed companies in the model provides an opportunity to examine the effect of explanatory variables across the diverse states of financial distress.

A company may exit the market for several different reasons: such as through merger, acquisition, voluntary liquidation and bankruptcy; and each type of exit is likely to be affected by different factors (Schary 1991; Harhoff, Stahl & Woywode 1998; Prantl 2003; Rommer 2004). Johnsen and Melicher (1994) examined the added value of the information provided in predicting corporate bankruptcy by defining three states of financial distress, namely: non-bankrupt, financially weak and bankrupt firms. Dickerson, Gibson and Tsakalotos (1999) investigated the determinants of UK manufacturing companies making acquisitions and being acquired. Wheelock and Wilson (2000) assumed that the causal processes for acquisitions and failures were different, and utilised the competing-risks hazard model to identify the characteristics that made individual US banks more likely to fail or be acquired. Harhoff, Stahl & Woywode 1998, Prantl (2003) and Rommer (2004) also confirmed the importance of distinguishing between different types of corporate exits.

In the Australian context, Jones and Hensher (2004) introduced the three-state financial distress model to examine the listed companies in the ASX (Australian Stock Exchange). This study was extended by Hensher, Jones and Greene (2007) and Jones and Hensher (2007), who added the *distressed merger* as an additional important state of financial distress. These studies used the advanced logit model (i.e. the mixed logit, multinomial error component logit and nested logit model). However, none of these studies considered ‘time to failure’ as an integral factor in corporate distress analysis. We use a competing risks Cox proportional hazard model, which enables the incorporation of time to event as the dependent variable in corporate distress analysis. Also, the variables used in the model are time-dependent variables (i.e. they can change in value over the study period).

Our analysis is based on three main categories of variables: financial ratios, market-based data and company-specific variables. We use a sample of publicly listed Australian companies (except those in the financial sector), during the period 1989 to 2005. In so doing, three different states of financial distress are employed: active companies, distressed external administration companies and distressed takeover, merger or acquisition companies. The determinants of each state are examined and interpreted through the competing-risks model.

In order to examine the determinant of the three states of these financial distresses, we investigate the effects of financial data, market-based variables and company-specific variables on the three unordered states of financially distressed Australian companies. We also compare the pooled model with the competing-risks model. However, it should be mentioned that most existing studies do not distinguish between states of financial distress, while some only suggest discriminating between the different types of exit or financial distress (Lau 1987; Rommer 2004; Rommer 2005).

The reason for selecting Australia is that it follows the English common law tradition that is prevalent in the US and the UK. Furthermore, Australia follows free market policies like the US. We seek to provide external validation of the results documented based on studies on the US market. We argue that this study is the first attempt to apply the competing-risks Cox proportional hazards approach for modelling multiple states of corporate financial distress in an Australian context. We expect that the factors driving companies to enter various states of financial distress are different. More specifically, that distressed external administration companies will have a higher leverage, lower past excess returns and a larger size; while distressed takeover, merger or acquisition companies will have a lower leverage, a higher capital utilisation efficiency and a larger size compared to active companies.

The remainder of this paper is organised as follows. Section 2 reviews previous studies on predicting multiple states of financial distress. Section 3 describes the methodology employed in the study. Section 4 describes the data and sample. Section 5 presents and discusses the empirical results. The final section presents the conclusion and draws possible future extensions of this research.

2. Literature Review

This section reviews the existing background literature. The first sub-section elaborates the literature on the multiple states of the financial distress prediction model. The second sub-section reviews the background literature on the application of the competing-risks model in the multiple states of financial distress prediction.

Multiple States of Financial Distress

Most of the existing corporate financial distress prediction literature focusses on the two-state failure model. For example, Altman (1968b), Ohlson (1980) and Shumway (2001) examine the financial distress factors of companies that went bankrupt. Schary (1991) argues that a firm may exit the business in several ways including through merger, acquisition, voluntary liquidation or bankruptcy. Each form of these exits is likely to be caused by different factors. Hensher, Jones and Greene (2007) argue that outright failure does not capture the full spectrum of financial distress in practice. They argue that there are reasons for this, such as: financially distressed firms seeking merger or amalgamations; firms eliminating dividend payments; and firms defaulting on loans or raising capital to alleviate financial distress. The focus on the dichotomy of conventional failing and non-failing only provides a limited representation of the financial distress spectrum typically faced by companies in practice (Lau 1987; Hensher Jones & Greene 2007). Models that explain failure without considering acquisition (Harhoff, Stahl & Woywode 1998), or models that allow for acquisition without considering failure, are both likely to suffer from a sample selection problem and thus the estimation results can be biased (Koke 2002).

Several other studies also examine the relationships between multiple states of corporate financial distress. For example, Lau (1987) utilises multivariate logit analysis to estimate the probability that a firm will enter each of the five ranked financial states.[1] The results of this study show that multivariate logit analysis outperforms multivariate

[1] The considered five multiple states are as follows: *State 0 (zero)* – financial stability; *State 1* – omitting or reducing dividend payments; *State 2* – technical defaults and default on loan payments; *State 3* – protection under Chapter X or XI of the American bankruptcy act (US House of Representatives, 2005); and *State 4* – bankruptcy and liquidation.

discriminant analysis, and that for some explanatory variables, the empirical results agree with the expectation of the models of prediction time horizons.

Johnsen and Melicher (1994) also used multinomial logit models to examine the value of information in predicting corporate bankruptcy. Their study identifies three states of financial distress: non-bankrupt, financially weak and bankrupt firms. The results confirm that adding the 'financially weak' state can reduce the misclassification error, and the three states of financial health appear to be independent.

Although Lau (1987) improved the two-state failure prediction model by using a five-state model, it was not without limitations. For example, the multinomial logit used was not robust enough for violations of the independent and identically distributed (IID) data and independence for irrelevant alternatives (IIA) assumptions. These assumptions are considered in several studies including Jones and Hensher (2004), Hensher and Jones (2007), Hensher, Jones and Greene (2007) and Jones and Hensher (2007).

In the context of financial distress prediction, Jones and Hensher (2004) demonstrated the empirical usefulness of a mixed ordered logit model. Their study introduced a three-state financial distress model: *State 0 (zero)* – non-failed firms; *State 1 (one)* – insolvent firms; and *State 2 (two)* – firms that filed for bankruptcy and appointed either liquidators or insolvency administrators or receivers. Their results also confirmed the superiority of the mixed logit over multinomial logit models.

In a recent study, Hensher and Jones (2007) further extended several ways to optimise the explanatory and predictive performance of the mixed logit model in forecasting corporate bankruptcy. They investigated five applications of the ordered mixed logit model using a three-state failure model. The results revealed that the unconditional triangular distribution for random parameters offers the best population-level predictive performance in a hold-out sample.

Hensher, Jones and Greene (2007) also extended the Jones and Hensher (2004) study and found that the error component logit model offered an improved explanatory power over a standard logit specification. Jones and Hensher (2007) also extended their previous study, and found that the nested logit model outperformed a standard logit model. These advanced logit models further improved the power of the probability predicting of financial distress.

Competing-risks Model Application

While the standard logit and advanced logit models reviewed in the previous section are powerful for predicting the probability of financial distress, they do not deal with the 'time to event'.[2] It is the survival analysis techniques which allow the modelling of time to event by incorporating it as the dependent variable. Harhoff, Stahl & Woywode (1998) employed the competing-risks model to develop an important conceptual and empirical distinction between two modes of exit (voluntary liquidation and bankruptcy). Their study was based on German firms. The results reveal that pooling exit types is a major source of misspecification. Prantl (2003) also examined bankruptcy and voluntary liquidation of the newly founded firms in Germany by using the competing-risks model.

Utilising a competing-risks proportional hazards model, Perez, Llopis and Llopis (2002) also found differences in the factors determining exit. They argue that the determinant is mainly dependent on the exit route in terms of firm and industry characteristics. Their study was based on Spanish firms. Their results further confirmed the findings of Harhoff,

[2] Koke (2002) suggest that acquisition and failure tend to be influenced by common factors. This implies that they should be examined in combination.

Stahl & Woywode (1998) in that pooling exit routes into the same analysis is a major source of misspecification.

Dickerson, Gibson and Tsakalotos (1999) also employed the competing-risks model, specifically the Weibull hazard model and the semi-parametric hazard model, to investigate the determinants of UK manufacturing companies making acquisitions. The study confirmed that companies making acquisitions can reduce their conditional probability of being taken over.

Rommer (2004) examined three types of exit by Danish non-financial public and private limited liability companies using the competing-risks model. The three types of firms they investigated included financially distressed firms, voluntarily liquidated firms and merger or acquisition firms. It was found that the proportion of correct predictions was higher in the competing-risks model than in the pooled logit model.

Wheelock and Wilson (2000) further utilised a competing-risks model to identify the characteristics that made individual US banks more likely to fail or to be acquired. It was assumed that the causal processes for acquisitions and failures were different, and that the occurrence of either event precluded the other, so the competing-risks hazard model was used to identify characteristics leading to each outcome.

To investigate the determinants of time to bankruptcy and time to merger jointly, and also to investigate their interdependence, Yu (2006) used the dependent competing-risks model assuming that time to bankruptcy and time to merger were interdependent in credit cooperatives in Japan. It is argued that the independent competing-risks model, which assumed the independence of the two hazards, might not fully describe the failure and merger processes, and may thus generate inconsistent estimates. The bankruptcy and merger processes can be interrelated, and some unobservable, firm-specific characteristics may exist that can affect both bankruptcy and merger processes. Yu (2006) suggests that the common practice of assuming the independence of the competing risks would produce biased estimates and a lower predictive accuracy.

3. Methodology

In order to examine the determinants of multiple states of corporate financial distress we employed the survival analysis model within the competing-risks framework.

Survival Analysis Technique

Survival analysis is a class of statistical method to examine the occurrence and timing of events. In survival analysis, an ‘event’ is defined as a qualitative change that can be situated in time (Allison 1995, p2). Since companies may change state – from ‘healthy’ to ‘financial distress’ – the event of interest in our study is defined as a company entering into a financially distressed state.

Compared to the traditional methods (for example, the Multiple Discriminant Analysis (MDA), logit and probit models), two key benefits of survival analysis emerge. These include the ability to handle time-varying variables and censored observations.

Time-varying variables are the explanatory variables that change with time. We used financial ratios, market-based data and company-specific variables (which are similar to time-varying variables), because their values can change over time. We argue that the symptoms of financial distress are observable from the deterioration of financial ratios, or that the effect of such ratios on corporate failures do not stay constant over time (Luoma & Laitinen 1991).

Censored observations are those that have never experienced the event during the observation time. Censoring occurs when the duration of the study is limited in time. In our study, censored observations are only made on active companies that have not entered into a financially distressed state.

Survival analysis contains two key functions: the survival function and the hazard function. The survival function, *S(t)*, gives the probability that the time until the firm experiences the event, *T,* is greater than a given time, *t*. Thus *T* is a random variable that defines the time event for particular observations. The survival function is stated as follows:

$$S(t) = \Pr(T > t) \tag{1}$$

The hazard function defines the instantaneous risk of an event occurring at time *t*, assuming that the firm survives to time *t*. The hazard function is also known as the ‘hazard rate’ because it is a dimensional quantity that has the number of events per interval of time. The hazard function is defined as follows:

$$h(t) = \lim_{\Delta t \to 0} \frac{\Pr(t \le T < t + \Delta t | X, T \ge t)}{\Delta t} \tag{2}$$

The relationship between the survival function and the hazard function is that the hazard function equals the change in the log-survivor function, as follows:

$$h(t) = -\frac{d \ln(s(t))}{dt}. \tag{3}$$

The Cox proportional hazards model is a semi-parametric model used for survival analysis. The Cox (1972) study contains two significant innovations – the proportional hazards model and maximum partial likelihood. The proportional hazards model is stated as follows:

$$h_i(t) = h_0(t) \exp(X_i \beta) \tag{4}$$

where $h_0(t)$ is an arbitrary, unspecified baseline hazard rate that measures the effect of time on the hazard rate for an individual whose variables have values of zeros. *X* represents the vector of variables that influences the hazard, and β is the vector of their coefficients.

Equivalently, the regression model is written as follows:

$$\log h_i(t) = \alpha(t) + \beta_1 X_{i1} + \beta_2 X_{i2} + \ldots + \beta_k X_{ik} \tag{5}$$

where $h_i(t)$ is hazard function for individual *i* and $\alpha(t) = \log h_0(t)$ and $h_0(t)$ is an arbitrary, unspecified baseline hazard rate (LeClere 2000).

This model does not require the particular probability distribution specification of the survival times. It possesses the property that different individuals have hazard functions that are proportional and are thus stated as follows:

$$\frac{h_i(t)}{h_j(t)} = \exp[\beta_1 (X_{i1} - X_{j1}) + \beta_2 (X_{i2} - X_{j2}) + \ldots + \beta_k (X_{ik} - X_{jk})] \tag{6}$$

The ratio of the hazard functions for two individuals does not vary with time *t*. This special property makes the Cox proportional hazard model more robust.

To estimate the coefficients of β, Cox (1972) proposes a partial likelihood function based on a conditional probability of failure by assuming that no tied values exist in the survival times. The function was later modified to handle ties (Efron 1977). We used SAS PROC PHREG (a SAS programming code for constructing a Cox model) to complete the estimation.

Competing-risks Model

The risk of entering into any state of financial distress is modelled using a framework in which each identified company is concurrently under risk for all states of financial distress over the selected period. The undertaken three different states of financial distress are considered to be mutually exclusive events (i.e. the occurrence of one type of event removes the firm from being at risk for all other types of event), and therefore the competing-risks model is deemed to be more appropriate.

We have estimated the survival likelihood for two subsets of firms (which were delisted due to financial distress or takeovers and acquisitions) using a competing-risks Cox's model; where, in addition to survival time, the different causes of an event are observed (Andersen, Abildstrom & Rosthoj 2002).

There are several ways that the problem of competing risks can be approached, but the most common approach is to begin by defining a type-specific or cause-specific hazard function (Ghilagaber 1998). We have denoted R as representing the different states of financial distress which are indexed by the cause-specific hazard for each company (r). r is an identification code for each company. Therefore, $R \geq 2$ – since our analysis focusses on the multiple states of financial distress, including active companies, distressed external administration companies and distressed takeover, merger or acquisition companies. The random variable C represents the cause of failure and therefore in the presence of R a cause-specific hazard function can be defined as follows:

$$h_r(t) = \lim_{\Delta t \to 0} \frac{\Pr(t \leq T < t + \Delta t, C = r \mid T \geq t)}{\Delta t}, r = 1, ..., R \tag{7}$$

Where $h_r(t)$ is the instantaneous rate of occurrence of type r at time t and in the presence of R-1 events.

The overall hazard of financial distress is the sum of all of the type-specific hazards, which is expressed as:

$$h(t) = \sum_{r=1}^{R} h_r(t) \tag{8}$$

Narendranathan and Stewart (1991) show that the log-likelihood for the competing-risks model is additive and can be separated into terms where each term is a function of the parameters of a single, cause-specific hazard. Thus, in order to estimate competing-risks Cox proportional hazards models, the estimation must first be preceded with the estimation of single-risk hazard, treating durations of exit for other reasons than filed for external administration process or subject to a takeover, merger or acquisition arrangement as censored at the point of completion.

Therefore, a further estimation model is needed and stated as follows:

$$h_{ri}(t) = h_{r0}(t) \exp(X_{ri(t)} \beta_r) \tag{9}$$

Where $r = f$ (distressed external administration, distressed takeover, merger or acquisition).

Two separate Cox proportional hazards models are also estimated for the competing risks, and the other states of financial distresses are considered as censored observations.

4. Data and sample

To apply the competing-risks Cox proportional hazards form of survival analysis to the population of all companies listed on the ASX, we used annual data of financial ratios, stock prices and company-specific variables of *Age* and *Size* for the period 1989 to 2005. We excluded the companies in the financial sectors from the analysis because of their different financial statements structure.[3]

For our analysis, financial distress is defined in three unordered mutually exclusive states, as follows:

State 0: Active companies.

State 1: Distressed external administration companies. These companies are defined as financially distressed companies which have filed for an external administration process. As per the *Corporations Act 2001 (Cth),* four categories of external administration process exist: (1) voluntary administration; (2) scheme of arrangement; (3) receivership; and (4) liquidation (Attorney-General's Department 2005). The date of entering into external administration was purchased from the Australian Securities and Investments Commission (ASIC)[4].

State 2: Distressed takeover, merger or acquisition companies. This state is defined as financially distressed companies which were delisted from the ASX because they were subject to a takeover, merger or acquisition arrangement. The data for delisted reasons, company announcement and delisted date are collected from the *FinAnalysis* database.

As pointed out by Clark and Ofek (1994), if a firm experiences operating or financial difficulties then there exist several potential actions. One such remedy is to restructure financially distressed firms through a merger. Therefore, including distressed takeover, merger or acquisition provides an opportunity to further examine more diverse states of financial distress.

A sample of active and distressed companies in *State 0, State 1* and *State 2* was collected for the period from 1989 to 2005. The final sample consisted of 891 active listed companies, 50 distressed external administration companies and 140 distressed takeover, merger or acquisition companies.

Time to event or survival time is defined as follows: for distressed companies, the survival time is the total number of years from the first year when data is available to the year of financial distress. This definition is applied to both distressed external administration companies and distressed takeover, merger or acquisition companies. For active companies, the survival time is the total number of years from the first year when data is available to the last year observed. During the study period, each of the companies were analysed to follow up whether they experienced an event in one of the multiple states of financial distress (e.g. filed for an external administration process or were subjected to a takeover, merger or acquisition arrangement).

[3] Ideally, we would have liked to use the information from the entire history of a company since its establishment, but such financial statement information was not available prior to the fiscal year 1989. Therefore, the models presented in this study are based on duration data truncated to the left, because they pertain only to the period since 1989.

[4] The authors are grateful to the School of Accounting and Finance and the School of Mathematics and Applied Statistics, University of Wollongong, for financial support in obtaining the data.

The explanatory variables used in the model are financial ratios, market-based data and company-specific variables. Financial ratios have long been widely used in explaining the possibility of corporate financial distress (see Beaver (1966); Altman (1968a); Bongini, Ferri & Hahm (2000); Routledge & Gadenne (2000); Catanach & Perry (2001); and Rommer (2005)). In a seminal study, Beaver (1966) used financial ratios with a univariate technique. According to Beaver (1966), six financial ratios were the best predictors in financial failure prediction: (1) cash flow to total debt; (2) net income to total assets; (3) total liabilities to total assets; (4) working capital to total assets; (5) current ratio; and (6) no credit interval. Altman (1968a) develops the well-known Z score model utilising multivariate discriminant analysis as the technique including the financial ratios as explanatory variables. It was found that five financial ratios are the best predictors in the corporate bankruptcy prediction model: (1) working capital to total assets; (2) retained earnings to total assets; (3) earnings before interest and taxes to total assets; (4) market value equity to par value of debt; and (5) sales to total assets.

We have incorporated financial ratios measured in four main categories of firms including profitability, liquidity, leverage and activity ratios in the model. The selection criteria is based on the following: (1) data availability in the *FinAnalysis* database consisting of financial statements of Australian firms; (2) the selected predictive variables from previous studies; and (3) the significance of the selected variables. Finally, there are nine financial ratios considered in the model as follows: earnings before interest and taxes margin (EBIT margin), return on equity and return on assets are used to measure profitability; current ratio, quick ratio and working capital to total assets ratio are used in order to measure firm liquidity; debt ratio is used to measure a firm’s leverage; and capital turnover and total asset turnover are used to measure the efficiency of a firm’s assets utilisation.

Market-based data is also used to investigate the relationship of market returns and the likelihood of financial distress. Shumway (2001) used two market-driven variables including a firm’s past excess returns (or market-adjusted returns) and idiosyncratic standard deviation of firm’s stock returns in forecasting bankruptcy. The hazard model results of this study indicate that the use of the market variable is only representative at the 5% significance level. However, when both market and accounting variables are used, the idiosyncratic standard deviation of a firm’s stock is not a significant variable in forecasting bankruptcy. These results are also consistent with Mossman et al. (1998). According to Mossman et al. (1998), for a 12 month period, the market-adjusted return variable is significant in bankruptcy prediction model while the standard variation variable of market-adjusted return is not significant in forecasting bankruptcy.

As financial ratios can be window-dressed using creative accounting to show improved financial figures, we include the company’s past excess returns as market-based data in the model. The standard deviation of a firm’s stock returns is omitted due to a lack of available data for the company’s monthly stock returns.

Company specific variables (such as age, size and squared size) are also included in the analysis. We use the natural logarithm of sales as the proxy for company size, and the number of years since registration as the proxy for company age to test the association between company age and size for corporate endurance.

To allow for the non-linear relationship between company size and the likelihood of financial distress, we also include the square of size. This is consistent with the previous literature relating to ownership structure and firm performance. For example, Himmelberg, Hubbard and Palia (1999) and Kumar (2003) incorporate the squared company size to allow for the non-linearity in examining the relationship between ownership structure and firm value or performance.

The detail of the variables used in this study is shown in Table 1 (see Appendices).

5. Empirical Results

To examine the determinants of multiple states of financial distress, both the single-risk and competing-risks model are estimated. This section provides the empirical results obtained from both the univariate model and the multivariate model. To provide an overall picture about the characteristics of the data employed in the model, the next section will describe the empirical results regarding descriptive statistics and the correlation coefficient. Then, the following sections will discuss the results of the single-risk and competing-risks models.

Descriptive Statistics

Table 2 presents the descriptive statistics (see Appendices). Sample means, medians, standard deviations, skewness, kurtosis and the number of observations are presented for each financial distress state.

The Kruskal-Wallis test and its *p*-value are the result of a non-parametric test showing the difference between the group means. Variables with a significant difference within the group means are expected to add information to a regression analysis. The results show that all variables display a significant difference between the three states of financial distress at the 5% level except for the variable *Age*.

It is important to note that before truncation the financial ratios employed have very large standard deviations. This is due to several outliers which might have influenced the results. Unlike many previous studies, we use the truncation technique to minimise the effect of the outliers. All observations with variable values higher than the 99^{th} percentile for each variable are set to truncate the values. All variable values lower than the 1^{st} percentile of each variable are then truncated. This is consistent with Shumway (2001). After truncation, the behaviour of the data (especially the financial ratios) has significantly improved as their standard deviations are much smaller than before the truncation. However, it is important also to note that the 99^{th} percentile and the 1^{st} percentile are just arbitrary values[5]. Table 2 reports these values after truncation.

As shown in Table 2, the means of earnings before taxes (*EBT*) of all states of the company are negative, which show the low ability of the company to generate profit. This shows that the financially distressed companies lost earnings compared to the active companies. The means of return on equity (*ROE*) for distressed takeover, merger or acquisition companies are positive, which implies that these companies have a higher ability to generate earnings than both active and distressed external administration companies. Similar results are observed for return on assets (*ROA*). The mean of *ROA* is also positive for distressed takeover, merger or acquisition companies, while it is negative for active and distressed external administration companies.

For liquidity ratios, the means of financially distressed companies for both current ratio (*CUR*) and quick ratio (*QUK*) are lower than those of the active companies. This shows that distressed companies have a greater ability to meet their current obligations compared to the active companies.

It is found that financially distressed companies in all states have a lesser capacity to pay off their long term liabilities compared to the active companies, which indicates the means of debt ratio (*DET*).

For activity ratios, capital turnover (*CPT*) and total asset turnover (*TAT*), the mean values of both ratios show mixed results. For the variable *CPT*, the mean value for active companies is higher than for distressed external administration companies but lower than for

[5] The values are considered arbitrary here because we do not know exactly what the optimal threshold to be used is.

distressed takeover, merger or acquisition companies. However, the means of *TAT* for financially distressed companies in all states are higher than the active companies.

The mean value of companies' *SIZE* implies that the size of financially distressed companies in all states is larger than the size of active companies. The *Age* of distressed external administration and distressed takeover, merger or acquisition companies is higher than the size of the active companies.

Finally, the mean of excess returns (*EXR*) suggests that the past excess returns for active companies is higher than for the distressed external administration companies but lower than for the distressed takeover, merger or acquisition companies.

Correlation Coefficients

In order to investigate the relationships between the variables, an examination of the correlation coefficients across the variables was carried out. The Pearson correlation coefficients are shown in Table 3 (see Appendices). The results indicate weak relationships across most of the variables except for current (*CUR*) and quick (*QUK*) ratios which are highly correlated. Since both these two financial ratios measure liquidity, we only use *CUR* as the proxy for liquidity ratios in the following regressions. These results suggest that most of the employed variables in the study provide unique information for the model.

The Model Estimation Results

In order to examine the determinants of multiple states of financial distress, and to compare pooled data with the competing-risks model, nine financial ratios, a market-based variable and three company specific variables are analysed into Cox's model. The variables used are time-dependent variables covering the period from 1989 to 2005. The estimation results of the competing-risks model are presented in Table 4 (see Appendices).

In order to highlight the effect of allowing for multiple states of financial distress, the estimation results are presented from both the single-risk model or pooled model (where all states of financial distress are pooled together) and the competing-risks model. Panel (A) contains the results for the single-risk model while Panel (B) contains the competing-risks model estimation. The coefficients estimation for each panel with the relative p-values for testing the null hypothesis is shown in the first two columns and the hazard ratio is presented in the last column.

The hazard ratio is obtained by computing e^{β}, where β is the coefficient in the proportional hazards model. A hazard ratio equal to 1 indicates that the variable has no effect on survival. A hazard ratio greater (less) than 1 indicates a faster (slower) hazard timing.

Single-risk Model Estimation

When we pooled all of the different states of financial distress together, three variables were found to be highly significant at the 5% level. These variables are *TAT*, *SIZE* and *SIZE2* with the coefficients of -0.1825, 1.2398 and -0.0302 respectively. The variables *ROA* and *DET* are also significant at 10% with the estimated coefficients -0.4461 and 0.3275 respectively.

The coefficient of *TAT* is negative, indicating an increase in the firm's ability to utilise assets which can decrease the hazards of becoming financially distressed. The hazard ratio for *TAT* is 0.8330. This indicates a unit increase in the total assets turnover ratio, and the risk of becoming financially distressed decreased by 16.7%. The positive sign of *SIZE* indicates that the larger the size of a company the higher the likelihood that it becomes financially distressed. This is because a large company might have inflexible management and have problems monitoring managers and employees; consequently, the company may have inefficient communication and then face financial difficulties (Rommer 2004).

Considering *SIZE2*, the result suggests that the effect of company size on financial distress is the inverted U-shaped or bell-shaped curve. However, this finding is not consistent with Rommer (2004), who suggests a U-shaped relationship between firm size and the likelihood of financial distress.

One possible explanation for this is that the sample used is not totally representative of the population for both publicly listed and non-listed Australian companies. The sample with a relatively large size might have captured only the effect of size on the likelihood of financial distress for those companies. In other words, the results might not have captured the effect of company size on financial distress for non-publicly listed companies which are relatively small in size.

In addition, the coefficient of *ROA* is negative, indicating that an increase in a firm's ability to generate earnings can decrease the hazard of becoming financially distressed. The hazard ratio for *ROA* is 0.6400 which indicates a unit increase in *ROA*, and the risk of becoming financially distressed decreases by 36%. This is consistent with the expectation that companies with a high ability to generate earnings are less likely to face financial difficulties.

The estimated variable *DET* is positive, indicating that the company with a low debt ratio is less likely to become financially distressed. The hazard ratio for *DET* is 1.3880. That is, for every unit increase in debt ratio, the risk of becoming financially distressed increases by 38.8%.

Competing-risks Model Estimation

The empirical results are reported in Table 4 (see Appendices). From the estimation results, we found that the working capital to total assets ratio (*WCA*) and *EXR* are significant factors in explaining the risk of financial distress through an external administration process but they do not significantly affect the risk of the takeover, merger or acquisition of a company.

It is also found that *WCA* significantly affects the risk of filing an external administration process, but it does not drive the risk of the takeover, merger or acquisition of a company. The coefficient of WCA is positive, indicating an increase in working capital to total assets ratio which can enhance the possibility of the hazard facing an external administration process. The ratio used for measuring the company liquidity, as considered in Altman (1968a), shows that a firm experiencing consistent operating losses will have shrinking current assets in relation to total assets. This result contrasts the expected results in that a company with a high liquidity should have a lower likelihood of facing financial difficulties.

For *EXR*, the coefficient is negative, indicating an increase in a company's past excess returns which decreases the hazards of becoming financially distressed. The hazard ratio for *EXR* is 0.4710 indicating an increase of one unit in a company's past excess returns which implies a 52.9% decrease in the risk of financial distress. This indicates the potential of market data as a good predictor of corporate financial distress. Shumway (2001) and Partington et al. (2006) also reported similar consistent findings.

The variables *DET* and *SIZE* significantly affect the hazard of entering financial distress both through external administration and through takeover, merger or acquisition. The variable *DET* has different signs between the distressed external administration model and the distressed takeover, merger or acquisition model. In the distressed external administration model, *DET* has a positive coefficient, while in the distressed takeover, merger or acquisition model, *DET* has a negative coefficient. These results imply that the company with a lower debt to total assets ratio is less likely to file an external administration process but is more likely to be a candidate for takeover, merger or acquisition. Schary (1991) also found that debt ratio is negatively related to the probability of a merger. The reasonable explanation for this result is that companies with lower leverage ratios are likely to be attractive targets to acquirers who have perhaps taken on debt to enable them to purchase the company (Dickerson, Gibson & Tsakalotos 1999).

The coefficient sign of *SIZE* is positive in both models. The positive sign of *SIZE* indicates that the larger the size of a company the higher the likelihood of entering into financial distress; both through the external administration process and through takeover, merger or acquisition. One reason for this is that a large company might have inflexible management and thus have problems monitoring managers and employees thus leading to inefficient communication (Rommer 2004). Perez, Llopis and Llopis (2002) also report consistent results showing that the risk of acquisition increases with company size and suggest that large firms tend to be involved in mergers.

The covariant *CPT* and squared size of the company (*SIZE2*) are found to significantly affect the risk of the takeover, merger or acquisition of a company, but this is not significantly related to the probability of entering an external administration process.

The coefficient sign of *CPT* is positive, implying an increase in the operating revenue to operating invested capital, indicating an increased hazard for the takeover, merger or acquisition of the company. A reasonable explanation for this is that a company which uses its assets efficiently will increase its income and liquidity position, and therefore it is more attractive for its takeover, merger or acquisition. Wheelock and Wilson (2000) also found consistent results in identifying the determinants of bank failure and acquisition. The authors suggest that inefficient banks, in terms of excessive use or payment for physical plant or labour, are less likely to be acquired.

The estimated coefficient for *SIZE2* of distressed takeover, merger or acquisition is negative. This suggests that the effect of company size on distressed takeover, merger or acquisition is the inverted U-shaped or bell-shaped curve. This finding is consistent with Bhattacharjee et al. (2004), who also found a bell-shaped relationship between firm size and the likelihood of being acquired. In particular, their findings support medium-sized listed firms being more likely candidates for acquisition.

In summary, our results suggest that there are differences in the factors determining which companies enter the different states of financial distress. Specifically, distressed external administration companies have a higher leverage, lower past excess returns and a larger size compared to active companies. In comparison, distressed takeover, merger or acquisition companies have a lower leverage, a higher capital utilisation efficiency and a larger size compared to active companies.

Comparing the Models

Comparing the estimation results between the single-risk model and the competing-risks model, we found that *DET* and *SIZE* are common significant variables in both the single-risk model and the competing-risks model.

The coefficient signs of *DET* in the single-risk and the distressed external administration in the competing-risks model are both positive, which indicates that the company with the lower debt-to-total assets ratio is less likely to become financially distressed. However, the sign of the parameter for *DET* is negative for a distressed takeover, merger or acquisition in the competing-risks model. This indicates that the company with the higher debt has a lower probability of becoming a distressed takeover, merger or acquisition company.

The coefficient *SIZE* is positive in the single-risk model as well as the two specifications in the competing-risks model. This result implies that company size has the same effect on the hazard for financial distress in the single-risk model as on the hazard for filing an external administration process and the hazard for distressed takeover, merger or acquisition in the competing-risks model. In particular, the results suggest that the larger the size of the company, the greater the likelihood of becoming financially distressed.

It should be noted that some variables (i.e. *ROA* and *TAT*) that affect the hazard of financial distress in the single-risk model may not significantly affect the hazard of distressed external administration and distressed takeover, merger or acquisition in the competing-risks model.

The estimation of the competing-risks model shows that the covariant *ROA* is negative, which implies that a company with a high profitability has a decreased likelihood of facing financial difficulties. It is found that the variable *TAT* has a negative estimated sign, which suggests that companies with a higher ability to utilise assets are less likely to fail.

The variable *AGE* was never found to be significant in explaining financial distress for all model specifications. This finding is consistent with the results of Shumway (2001).

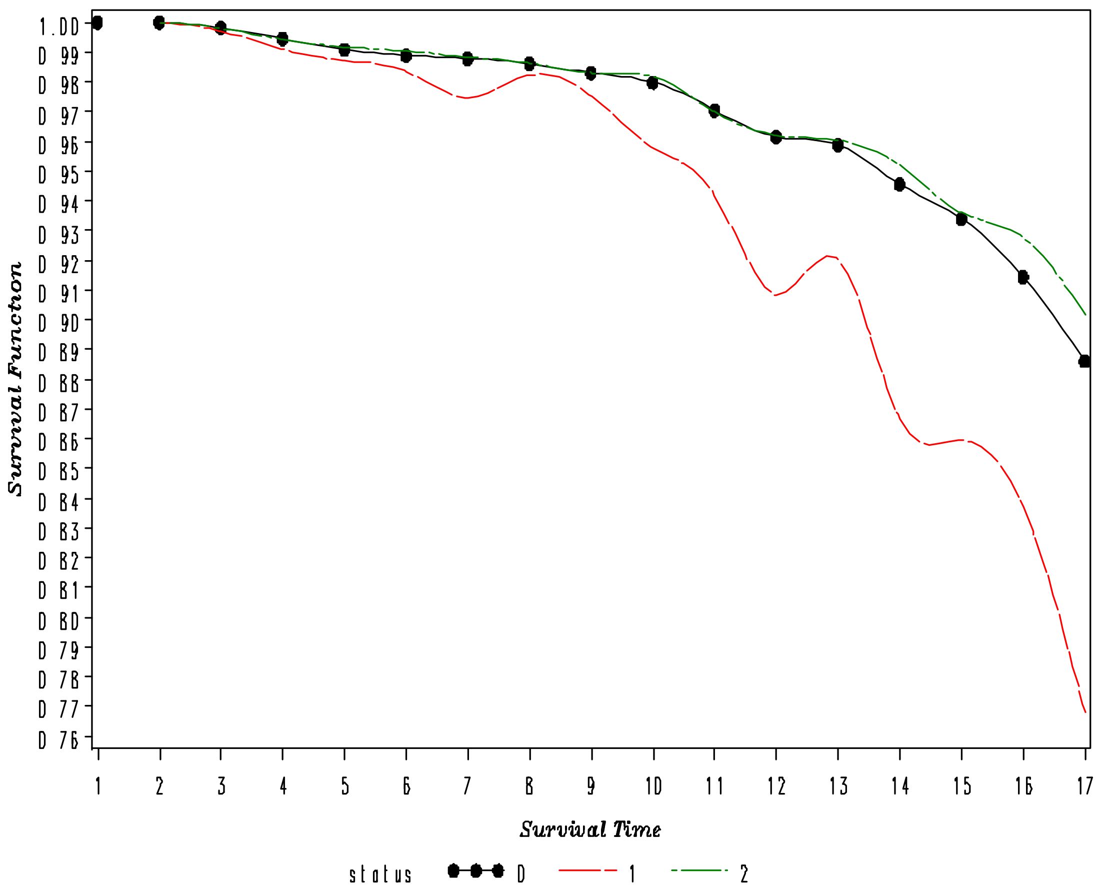
Considering the three-state financial distress model specifically (comprising active companies, distressed external administration companies and distressed takeover, merger or acquisition companies within the framework of a competing-risks model), it is found that each state of financial distress is caused by different factors. The empirical estimation results of a single-risk and a competing-risks model are also compared. The results indicate that both model specifications result in different significant variables for explaining financial distress. Therefore, we conclude that distinguishing the financial distress states is an important consideration to develop the model. This finding is consistent with Harhoff, Stahl and Woywode (1998), Perez, Llopis and Llopis (2002) and Rommer (2004). Harhoff, Stahl and Woywode (1998) conclude that a separate consideration of the modes of corporate exit is highly desirable, they reveal that pooling exit types is a major source of misspecification, and they also show how the econometric results may be misleading if the distinction between exit modes is not made.

Survival Probability Evaluation for Multiple States of Financial Distress

The survival functions of typically active, distressed external administration and distressed takeover, merger or acquisition companies are presented in Figure 1 (below). The survival function defines the probability that a company will survive longer than t time units. The function starts with 1 at the beginning, and declines as more companies become financially distressed.

The survival function shown in Figure 1 is produced by averaging the estimated survival probability of companies by the different states of financial distress (that is, *State 0:* active companies; *State 1:* distressed external administration companies; and *State 2:* distressed takeover, merger or acquisition companies).

Figure 1
Graph of Survival Function and Survival Time by Financial Distress States



According to Figure 1, the survival probability of typical financially distressed external administration companies is lower than that of typical active companies and distressed takeover, merger or acquisition companies. The survival probability starts with 1 and slightly declines afterward. The noticeable decrease in corporate survival for distressed external administration companies occurs after 9 years as more companies become financially distressed.

The probability of survival beyond 17 years for active and distressed takeover, merger or acquisition companies is approximately 88.61% and 90.18% respectively; while that for distressed external administration companies is approximately 76.77%. The survival profile of active companies and distressed takeover, merger or acquisition companies is very similar. Additionally, the probability that distressed takeover, merger or acquisition companies will survive beyond year 12 to year 14, and also year 16 to year 17, is slightly higher than that of active companies. One possible explanation for these results is that distressed takeover, merger or acquisition companies have a lower leverage, a higher capital utilisation efficiency and a larger size compared to active companies. Therefore, these companies have a slightly higher probability of survival than active companies.

6. Conclusion

Companies face a range of financial health states, and may exit the market in several ways such as through merger, acquisition, voluntary liquidation or bankruptcy, where each form of exit is likely to be caused by different factors. Models that allow for multiple states of financial distress provide a wider range of distress scenarios that public companies typically face in reality. Therefore this study focussed on examining the determinants of multiple states of financial distress using the competing-risks model and comparing the empirical results to the pooled model.

To examine the determinants of multiple states of financial distress, this study provided an unordered three-state financial distress model based on a sample of publicly listed Australian non-financial companies, which combined traditional financial ratios, market-based variables and company-specific variables with a survival analysis technique in the form of the competing-risks Cox proportional hazards model. The three-state financial distress was defined as: *State 0:* active companies; *State 1*: distressed external administration companies; and *State 2*: distressed takeover, merger or acquisition companies.

We incorporated 891 active companies, 50 distressed external administration companies and 140 distressed takeover, merger or acquisition companies over the period 1989 to 2005, by utilising the competing-risks Cox proportional hazards model with the proposed variables. Four main categories of financial ratios (profitability, liquidity, leverage and activity) were used as indicators of financial distress. The company's past excess returns were additionally used as a proxy for market-based data. The relationships between company-specific variables (age, size, squared size and corporate endurance) were also examined.

The results show that differences exist in the factors which determine whether companies enter different states of financial distress. Specifically, distressed external administration companies have a higher leverage, lower past excess returns and a larger size compared to active companies. Meanwhile, distressed takeover, merger or acquisition companies have a lower leverage, a higher capital utilisation efficiency and a larger size compared to active companies. The conclusion from comparing the results from the single-risk model and the competing-risks model is that distinguishing between financial distress states is important. However, the results do not support the importance of the company age factor in explaining financial distress.

Further implications of this study relate to future research on potential factors for predicting corporate failure which need to be considered, such as corporate governance variables and macroeconomic variables.

References

Allison, P D 1995, *Survival analysis using the SAS system: A practical guide*, SAS Institute, Cary, N C.

Altman, E I 1968a, 'Financial ratios, discriminant analysis and the prediction of corporate bankruptcy', *Journal of Finance*, vol.23, no.4, pp589-609.

Altman, E I 1968b, 'The prediction of corporate bankruptcy: A discriminant analysis', *Journal of Finance*, vol.23, no.1, pp193-194.

Andersen, P K, Abildstrom, S Z & Rosthoj, S 2002, 'Competing risks as a multi-state model', *Statistical Methods in Medical Research*, vol.11, no.2, pp203-215.

Beaver, W H 1966, 'Financial ratios as predictors of failure', *Empirical Research in Accounting: Selected Studies*, supplement to vol.4, pp71-111.

Bhattacharjee, A, Higson, C, Holly, S & Kattuman, P 2004, *Macroeconomic conditions and business exit: Determinants of failures and acquisitions of UK firms*, Working paper, University of Cambridge, Cambridge, pp1-31.

Bongini, P, Ferri, G & Hahm, H 2000, 'Corporate bankruptcy in Korea: Only the strong survive?', *Financial Review*, vol.35, no.4, pp31-50.

Catanach, A H & Perry, S E 2001, 'An evaluation of the survival model's contribution to thrift institution distress prediction', *Journal of Managerial Issues*, vol.13, no.4, pp401-417.

Clark, K & Ofek, E 1994, 'Mergers as a means of restructuring distressed firms: An empirical investigation', *Journal of Financial and Quantitative Analysis*, vol.29, no.4, pp541-565.

Attorney-General's Department 2005, *Corporations Act 2001 (Cth)*. Accessed 1 March, 2007, at: http://www.comlaw.gov.au/ComLaw/Legislation/ActCompilation1.nsf/

Cox, D R 1972, 'Regression models and life-tables', *Journal of the Royal Statistical Society, Series B (Methodological)*, vol.34, no.2, pp187-220.

Dickerson, A P, Gibson, H D & Tsakalotos, E 1999, *Is attack the best form of defence? A competing risks analysis of acquisition activity in the UK*, Working paper, University of Kent, Canterbury.

Efron, B 1977, 'The efficiency of Cox's likelihood function for censored data', *Journal of the American Statistical Association*, vol.72, no.359, pp557-565.

Ghilagaber, G 1998, 'Analysis of survival data with multiple causes of failure', *Quality and Quantity*, vol.32, no.3, pp297-324.

Harhoff, D, Stahl, K & Woywode, M 1998, 'Legal form, growth and exit of West German firms: Empirical results for manufacturing, construction, trade and service industries', *Journal of Industrial Economics*, vol.46, no.4, pp453-488.

Hensher, D A & Jones, S 2007, 'Forecasting corporate bankruptcy: Optimizing the performance of the mixed logit model', *Abacus*, vol.43, no.3, pp241-264.

Hensher, D A, Jones, S & Greene, W H 2007, 'An error component logit analysis of corporate bankruptcy and insolvency risk in Australia', *Economic Record*, vol.83, no.260, pp86-103.

Himmelberg, C P, Hubbard, R G & Palia, D 1999, 'Understanding the determinants of managerial ownership and the link between ownership and performance', *Journal of Financial Economics*, vol.53, no.3, pp353-384.

Johnsen, T & Melicher, R W 1994, 'Predicting corporate bankruptcy and financial distress: Information value added by multinomial logit models', *Journal of Economics and Business*, vol.46, no.4, pp269-286.

Jones, S & Hensher, D A 2004, 'Predicting firm financial distress: A mixed logit model', *The Accounting Review*, vol.79, no.4, pp1011-1038.

Jones, S & Hensher, D A 2007, ‘Modelling corporate failure: A multinomial nested logit analysis for unordered outcomes’, *The British Accounting Review*, vol.39, no.1, pp89-107.

Koke, J 2002, ‘Determinants of acquisition and failure: Evidence from corporate Germany’, *Structural Change and Economic Dynamics*, vol.13, no.4, pp457-484.

Kumar, J 2003, *Does ownership structure influence firm value? Evidence from India*, Working paper, Indira Gandhi Institute of Development Research, Mumbai, pp1-44.

Lau, A H-L 1987, ‘A five-state financial distress prediction model’, *Journal of Accounting Research*, vol.25, no.1, pp127-138.

LeClere, M J 2000, ‘The occurrence and timing of events: Survival analysis applied to the study of financial distress’, *Journal of Accounting Literature*, vol.19, pp158-189.

Luoma, M & Laitinen, E 1991, ‘Survival analysis as a tool for company failure prediction’, *Omega*, vol.19, no.6, pp673-678.

Mossman, C E, Bell, G G, Swartz, L M & Turtle, H 1998, ‘An empirical comparison of bankruptcy models’, *Financial Review*, vol.33, no.2, pp35-54.

Narendranathan, W & Stewart, M B 1991, ‘Simple methods for testing for the proportionality of cause-specific hazards in competing risks models’, *Oxford Bulletin of Economics & Statistics*, vol.53, no.3, pp331-340.

Ohlson, J A 1980, ‘Financial ratios and the probabilistic prediction of bankruptcy’, *Journal of Accounting Research*, vol.18, no.1, pp109-131.

Perez, S E, Llopis, A S & Llopis, J A S 2002, *A competing risks analysis of exit for Spanish manufacturing firms*, University of Valencia.

Prantl, S 2003, *Bankruptcy and voluntary liquidation: Evidence for new firms in East and West Germany after unification*, Discussion paper no.03-72, ZEW, Centre for European Economic Research, London, pp1-42.

Rommer, A D 2004, *Firms in financial distress: An exploratory analysis*, Working paper no.17, Danmarks Nationalbank and Centre for Applied Microeconometrics (CAM), Institute of Economics, University of Copenhagen, Copenhagen, pp1-68.

Rommer, A D 2005, *A comparative analysis of the determinants of financial distress in French, Italian and Spanish firms*, Working paper no.24, Danmarks Nationalbank and Centre for Applied Microeconometrics (CAM), Institute of Economics, University of Copenhagen, Copenhagen, pp1-76.

Routledge, J & Gadenne, D 2000, ‘Financial distress, reorganization and corporate performance’, *Accounting and Finance*, vol.40, no.3, pp233-259.

Schary, M A 1991, ‘The probability of exit’, *The Rand Journal of Economics*, vol.22, no.3, pp339-353.

Shumway, T 2001, ‘Forecasting bankruptcy more accurately: A simple hazard model’, *Journal of Business*, vol.74, no.1, pp101-124.

US House of Representatives 2005, *Title 11-Bankruptcy,* Retrieved 1 March, 2007. Available at: http://uscode.house.gov/download/title_11.shtml.

Wheelock, D C & Wilson, P W 2000, ‘Why do banks disappear? The determinants of US bank failures and acquisitions’, *Review of Economics and Statistics*, vol.82, no.1, pp127-138.

Wong, B, Partington, G, Stevenson, M & Torbey, V 2007, ‘Surviving chapter 11 bankruptcies: Duration and payoff?’, *ABACUS*, vol.43, no.3, pp363-387.

Yu, X 2006, *Competing risk analysis of Japan's small financial institutions*, Discussion Paper no.2006-E-7, Institute for Monetary and Economic Studies, Bank of Japan, pp1-47.

Appendices

Table 1
The Covariates used in the Study

Category	No.	Covariate	Code	Definition
Profitability	1.	EBIT margin	EBT	EBIT / operating revenue
	2.	Return on equity	ROE	NPAT before abnormals / (shareholders equity-outside equity interests)
	3.	Return on assets	ROA	Earnings before interest / (total assets-outside equity interests)
Liquidity	4.	Current ratio	CUR	Current assets / current liabilities
	5.	Quick ratio	QUK	(Current assets-current inventory) / current liabilities
	6.	Working capital/total assets	WCA	Working capital / total assets
Leverage	7.	Debt ratio	DET	Total debts / total assets
Activity	8.	Capital turnover	CPT	Operating revenue / operating-invested capital before goodwill
	9.	Total asset turnover	TAT	Operating revenues / total assets
Company-Specific	10.	Size of company	SIZE	Natural logarithm of sales
	11.	Squared size	SIZE2	The square of natural logarithm of sales
	12.	Age of company	AGE	The number of years since registration
Market Based	13.	Excess returns (year *t*)	EXR	A company's stock return in year *t-1* minus ASX 200 index return in year *t-1*

Note: All data were obtained from the *FinAnalysis* Database, Aspect Huntley Company — except for the S&P/ASX 200 monthly index data, which were obtained from the *Dx* Database.

Table 2
Descriptive Statistics of the Data

	ROE	ROA	CUR	QUK	WCA	DET	CPT	TAT	SIZE	SIZE2	AGE	EXR
Active (n = 891)												
Mean	-0.1404	-0.1301	7.2254	6.9260	0.0415	0.3942	3.3850	0.7713	15.4840	253.6566	19.4838	-0.1211
Median			1.7600	1.3000	0.0128	0.3433	0.9230	0.4394				
Min	-0.0081	-0.0085	0.0500	0.0400	-1.0000	0.0047	0.0002	0.0002	15.9391	254.0548	14.0000	-0.0805
Max			155.0900	155.0900	0.6999	3.5587	82.7817	5.7367				
Std. Dev.	-4.2639	-2.3701			0.2201	0.4282		0.9912	6.7708	45.8436	1.0000	-2.2731
Skewness			18.6848	18.7216	-0.9343	3.9324	9.9278	2.3255	22.5982	510.6794	90.0000	
Kurtosis	2.5722	0.3884	5.4057	5.3990	5.8129	23.7046	6.3372	6.9079				2.0433
	0.7526	0.4061	33.4315	33.3725			44.3049		3.7188	111.9211	18.4983	0.7280
	-2.4059	-3.3643							-0.3126			-0.0737
										0.1798	2.0393	
	13.9761	13.5418							-0.5608	-0.6265	4.1816	1.1784
Distressed External Administration (n = 50)												
Mean	-0.1022	-0.1587	5.1382	4.9091	0.0282	0.5859	2.9237	0.8548	15.8297	259.8330	22.0454	-0.2475
Median			1.3200	1.0400	0.0106	0.4556	0.8820	0.4533				
Min	0.0025	-0.0062	0.0500	0.0400	-1.0000	0.0047	0.0004	0.0002	16.4390	270.2389	17.0000	-0.2096
Max	-4.2639		155.0900	155.0900	0.6999	3.5587	51.4800	5.7367				
Std. Dev.		-2.3701			0.2756	0.7348		1.1424	7.4396	55.3470	1.0000	-2.2731
Skewness	2.5722		17.3525	17.3967	-1.4149	2.9279	6.9209	2.6287	21.5449	464.1840	90.0000	
Kurtosis	0.7766	0.3884	7.2412	7.2240	5.0272	8.6108	4.8427	7.9975				2.0433

	ROE	ROA	CUR	QUK	WCA	DET	CPT	TAT	SIZE	SIZE2	AGE	EXR
	-1.5362	0.5007	55.7535	55.5423			26.4602		3.0109	89.6430	16.6491	0.8061
		-3.2754							-0.6863	-0.2302		-0.0785
	10.7583									-0.3737	1.3985	
		10.7957							-0.0097		2.6935	1.0194
Distressed Takeover, Merger or Acquisition (n = 140)												
Mean	0.0270	0.0124	3.6748	3.2616	0.0827	0.4907	3.7742	1.0201	17.9684	329.6880	22.2363	-0.0691
Median	0.0825	0.0538	1.5000	1.0100	0.0460	0.4663	1.5115	0.8167				
Min	-4.2639	-2.3701	0.0500	0.0400	-1.0000	0.0047	0.0003	0.0002	18.1779	330.4352	14.0000	-0.0556
Max			155.0900	155.0900	0.6999	3.5587	82.7817	5.7367				
Std. Dev.	2.5722	0.3884			0.1951	0.4269		0.9212	6.9078	47.7171	1.0000	-2.2731
Skewness	0.5037	0.2137	11.7242	11.7859	-0.3701	4.9554	9.1551	2.1054	22.4284	503.0313	90.0000	
Kurtosis	-3.8848	-6.4543	8.5974	8.5643	4.7533	32.1249	5.8140	6.7491				2.0433
			87.2817	86.6035			39.5832		2.6052	86.8882	20.6510	
	38.0125	57.7766							-1.0868	-0.5215		0.5769
										0.2680	1.4579	
									1.7751		1.4020	0.1276
												2.9682
Kruskal-Wallis Test	43.4135	64.7073	33.3688	37.5854	9.3162	22.3618	7.2498	21.2755	70.2482	70.6205	2.6275	9.9025
p-value	<.0001	<.0001	<.0001	<.0001	0.0095	<.0001	0.0267	<.0001	<.0001	<.0001	0.2688	0.0071

Note: Descriptive statistics are grouped by company status. Kruskal-Wallis test from a non-parametric test of equality of group means.

Table 3
Pearson Correlation Coefficients

Covariate	EBT	ROE	ROA	CUR	QUK	WCA	DET	CPT	TAT	SIZE	SIZE2	AGE	EXR
EBT	1.0000*	0.1027 <.0001	0.1692 <.0001	-0.0919 <.0001	-0.0948 <.0001	0.0763 <.0001	0.0931 <.0001	0.0638 <.0001	0.1756 <.0001	0.4567 <.0001	0.3843 <.0001	0.0686 <.0001	-0.0017 0.8579
ROE		1.0000	0.4624 <.0001	-0.0176 0.0572	-0.0200 0.0306	0.0467 <.0001	0.1441 <.0001	0.0008 0.9295	0.1562 <.0001	0.2395 <.0001	0.2454 <.0001	0.0740 <.0001	0.0817 <.0001
ROA			1.0000	-0.0262 0.0047	-0.0307 0.0009	0.3627 <.0001	-0.2213 <.0001	-0.0370 <.0001	0.1096 <.0001	0.3738 <.0001	0.3773 <.0001	0.1085 <.0001	0.1242 <.0001
CUR				1.0000	**0.9995** **<.0001**	0.0885 <.0001	-0.2531 <.0001	-0.0513 <.0001	-0.1821 <.0001	-0.3051 <.0001	-0.2966 <.0001	-0.0951 <.0001	-0.0172 0.0640
QUK					1.0000	0.0773 <.0001	-0.2525 <.0001	-0.0496 <.0001	-0.1864 <.0001	-0.3125 <.0001	-0.3038 <.0001	-0.1000 <.0001	-0.0181 0.0503
WCA						1.0000	-0.3456 <.0001	-0.1213 <.0001	0.0665 <.0001	0.1979 <.0001	0.1973 <.0001	0.1327 <.0001	0.0624 <.0001
DET							1.0000	0.1252 <.0001	0.3926 <.0001	0.2719 <.0001	0.2683 <.0001	0.0696 <.0001	-0.0372 <.0001
CPT								1.0000	0.3770 <.0001	0.1291 <.0001	0.1190 <.0001	-0.0250 0.0069	-0.0461 <.0001
TAT									1.0000	0.5000 <.0001	0.4940 <.0001	0.1346 <.0001	0.0109 0.2408
SIZE										1.0000	**0.9900** **<.0001**	0.2905 <.0001	0.0639 <.0001
SIZE2											1.0000	0.3130 <.0001	0.0728 <.0001
AGE												1.0000	0.0644 <.0001
EXR													1.0000

Note: * Pearson correlation coefficients. The p-value is under the null hypothesis of zero correlation.

Table 4
Single-risk and Competing-risks Cox Proportional Hazards Model Estimation

Covariate	(A) Single-Risk Model			(B) Competing-Risks Model: Distressed External Administration Companies			(B) Competing-Risks Model: Distressed Takeover, Merger or Acquisition Companies		
	Coefficient	***p*-Value**	**Hazard Ratio**	**Coefficient**	***p*-Value**	**Hazard Ratio**	**Coefficient**	***p*-Value**	**Hazard Ratio**
EBT	-0.0018	0.1790	0.9980	-0.0006	0.7029	0.9990	-0.0019	0.5152	0.9980
ROE	-0.0254	0.7962	0.9750	-0.0805	0.5584	0.9230	0.0195	0.9083	1.0200
ROA	-0.4461*	0.0584	0.6400	-0.4143	0.1766	0.6610	-0.3871	0.3597	0.6790
CUR	-0.2703	0.1742	0.7667	-0.6156	0.1789	0.5435	-0.1787	0.4446	0.8359
WCA	0.2065	0.6242	1.2290	0.9740*	0.0738	2.6490	-0.3987	0.5314	0.6710
DET	0.3275*	0.0968	1.3880	0.9205**	<.0001	2.5100	-0.7975*	0.0596	0.4500
CPT	0.0086	0.2060	1.0090	-0.0053	0.7541	0.9950	0.0131*	0.0915	1.0130
TAT	-0.1825**	0.0497	0.8330	-0.1919	0.2401	0.8250	-0.1554	0.1809	0.8560
SIZE	1.2398**	0.0001	3.4550	0.8393*	0.0753	2.3150	1.6956**	0.0003	5.4500
SIZE2	-0.0302**	0.0008	0.9700	-0.0223	0.1161	0.9780	-0.0412**	0.0014	0.9600
AGE	-0.0031	0.4312	0.9970	-0.0014	0.8751	0.9990	-0.0028	0.5224	0.9970
EXR	-0.1375	0.2219	0.8720	-0.7538**	0.0002	0.4710	0.1167	0.3925	1.1240
Number of events	190			50			140		

Note: * Significant at the 10% level. ** Significant at the 5% level.