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Nongnit Chancharat
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**AN EMPIRICAL ANALYSIS OF FINANCIALLY DISTRESSED AUSTRALIAN
COMPANIES: THE APPLICATION OF SURVIVAL ANALYSIS**

A thesis submitted in fulfilment of the requirements for the
award of the degree of

DOCTOR OF PHILOSOPHY

from

UNIVERSITY OF WOLLONGONG

by

NONGNIT CHANCHARAT

B.B.A. (Finance) First Class Honours, Khon Kaen University, Thailand
M.S. (Applied Statistics), National Institute of Development Administration, Thailand

SCHOOL OF ACCOUNTING AND FINANCE

2008

CERTIFICATION

I, Nongnit Chancharat, declare that this thesis, submitted in fulfilment of the requirements for the award of Doctor of Philosophy, in the School of Accounting and Finance, University of Wollongong, is wholly my own work unless otherwise referenced or acknowledged. The document has not been submitted for qualifications at any other academic institution.

Nongnit Chancharat

26 September 2008

To my dear parents, my husband and my son

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LIST OF ABBREVIATIONS

AFT	Accelerated Failure Time Model
AGE	Age of Company
ANN	Artificial Neural Network
ASIC	Australian Securities and Investments Commission
ASX	Australian Stock Exchange
BACK	Underwriter Backing
BD_INDP	Percentage of Independent Directors
BD_SIZE	Board Size
BE/ME	Book to Market Equity Ratio
BIG5	Auditor Reputation
CEO	Chief Executive Officer
CM_DUAL	Dual Leadership Structure
CM_NEXC	Non-Executive Chairman
CPT	Capital Turnover
CUR	Current Ratio
C_SIZE	Size of IPO Company
DET	Debt Ratio
EBIT	Earnings Before Interest and Taxes
EBT	EBIT Margin
EXR	Excess Returns
GICS	Global Industry Classification Standard
GNP	Gross National Product
IIA	Independent of Irrelevant Alternatives Assumption
IID	Independent and Identically Distributed Assumption

IPOs	Initial Public Offerings
IPO_9900	A Company that Issued Stock Between 1999 and April 2000
ITSA	Insolvency and Trustee Service Australia
MDA	Multivariate Discriminant Analysis
MSCI	Morgan Stanley Capital International
NUM_RISK	Number of Risk Factors in the Prospectus
OF_AGE	Offering Age
OF_PRICE	Offering Price
OF_SIZE	Offering Size
QUK	Quick Ratio
RETAIN	Retained Ownership
ROA	Return on Assets
ROE	Return on Equity
RPA	Recursive Partitioning Analysis
SIZE	Size of Company
SIZE2	Squared Size of Company
TAT	Total Assets Turnover
TOP20	Top 20 Shareholders
WCA	Working Capital to Total Assets Ratio

ABSTRACT

This thesis provides an empirical analysis of financially distressed companies in the Australian context using survival analysis techniques. Three main assays are developed and presented in the thesis.

The first assay explores the effect of financial ratios and other variables on corporate financial distress and identifies the probability of corporate survival in a given time frame. The four main categories of financial ratios are profitability, liquidity, leverage and activity ratios and control variables which are a market-based variable and company-specific variables; for example, company age, company size and squared size are employed in the analysis. The Cox proportional hazards model was estimated using time-varying variables based on a sample of 1,117 publicly listed Australian companies over the period 1989 to 2005. Empirical results found that financially distressed companies have higher leverage measured by debt ratio, lower past excess returns and larger size compared to active companies.

Researchers argue that a company may exit the market in several different ways, such as through merger, acquisition, voluntary liquidation and bankruptcy and each type of exit is likely to be affected by different factors. Consequently, the second assay investigates the determinants of multiple states of financial distress by applying a competing risks Cox proportional hazards model. The unordered three-state financial distress model is defined as follows: state 0: active companies, state 1: distressed external administration companies and state 2: distressed takeover, merger or acquisition companies. The effect of financial ratios, market-based variable and company-specific variables including company age, company size and squared size on three different states of corporate financial distress are investigated based on a sample of 1,081 publicly listed Australian companies over the period 1989 to 2005.

The results indicate that it is important to distinguish between the different financial distress states. Additionally, the results suggest that distressed external administration companies have higher leverage, lower past excess returns and a larger size while distressed takeover, merger or acquisition companies have lower leverage, higher capital utilization efficiency and a bigger size compared to active companies.

In addition to examining financial ratios as the main variables, this thesis further explores the effect of corporate governance attributes on IPO companies' survival focusing on a particular sector. Accordingly, the third essay examines the influence of corporate governance mechanisms on the survival of 127 new economy IPO companies listed on the ASX between 1994 and 2002. In addition to the three main categories of corporate governance attributes include board size, board independence and ownership concentration; control variables, for example, offering characteristics, financial ratios and company-specific variables, are also included in the model.

The Cox proportional hazards model estimation results found ownership concentration significantly negative related to the survival of new economy IPO companies. For offering characteristics variables, the offering size and the underwriter backing are a significant variable in explaining IPO companies' survival; however, the estimated signs are in contrast to the expectations. Specifically, those IPO companies with a larger offering size are less likely to survive than are those that offer a smaller size. Furthermore, the results found that the hazard of financial distress for companies with an offer that is underwritten is greater than the hazard for those for which the offer is not underwritten. For financial ratios, the results indicate that the debt ratio is statistically significant in explaining IPO firms' survival. In particular, IPO companies with a low total debts to total assets ratio are less likely to fail.

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CHAPTER 1

INTRODUCTION

1.1 Introduction

This chapter presents the introduction and background of this research. The research objectives and questions are presented in order to place the succeeding component chapters in the context of the whole thesis. This chapter begins with the statement of the problem and the motivation of the study in the next section, Section 1.2. The definitions of a financially distressed company adopted in this study are discussed in Section 1.3. Section 1.4 discusses the background of the financial distress prediction model in order to provide the information regarding previous literature in the research areas, followed by the formulation of the research objectives and research questions in Sections 1.5 and 1.6 respectively. The contribution of the study to knowledge is provided in Section 1.7 and, finally, Section 1.8, describes the organization of the study; brief details of each chapter are also given in this section.

1.2 Statement of the problem and motivation of the study

The continuous entrances and exits of companies are natural components in the economic system. Throughout the centuries, a huge number of businesses have succeeded, while others have struggled for survival and subsequently failed.

Interest in corporate financial distress prediction has grown rapidly in recent years with the global increase in the number of corporate collapses, for example, Parmalat in Europe, Enron and WorldCom in the US and HIH and Ansett Airlines in Australia.

In the US, 34 corporations with liabilities greater than 1 billion dollars filed for protection under Chapter 11 of the bankruptcy code during 1989-1991. Furthermore, in the three-year period 2001-2003, 100 companies with liabilities greater than 1 billion

dollars filed for protection under the same chapter. Among these companies, the first three major corporate bankruptcies included Conceco, WorldCom and Enron with the liabilities of 56,639.30, 45,984.00 and 31,237.00 billion dollars, respectively (Altman and Hotchkiss, 2006).

Across the Pacific, Australia has also experienced a series of corporate collapses since the early 1990s. Major collapses include HIH Insurance in March 2001, Harris Scarfe in April 2001, One.Tel in May 2001, Ansett Airlines in March 2002, and most recently, FIN Corp in 2007.

Corporate failure often results in significant direct and indirect costs to many stakeholders including shareholders, managers, employees, creditors, investors, auditors, suppliers, customers and the community. For example, as a result of the collapse of Australia's second largest carrier, Ansett Airlines, in March 2002, approximately 16,000 people lost their jobs directly. The collapse brought about an indirect loss of 54,880 jobs in 105 sectors of the Australian economy. Losses were particularly marked in retail trade, business services, education, health services, accommodation, cafes and restaurants (Valadkhani, 2003), which had been the fastest growing industries in terms of employment during the 1985-2000 period. According to Robbie Holdaway, who spent 25 years as an Ansett cabin manager, about 40 former Ansett members of staff have committed suicide and another half-dozen have suffered heart attacks or died from stress-related illnesses since the collapse (Birnbauer, 2004).

According to Altman (1983), financial distress can cause direct and indirect costs to the firm. Direct costs are the tangible, out-of-pocket expense of either liquidity or an attempted reorganization of the ailing enterprise. These include bankruptcy filing fees and legal fees, accountants' fees and the costs of other professional services, such as lawyers' fees.

The primary indirect cost is the lost sales and profits of the firm due to the perceived potential bankruptcy. These losses are primarily due to customer reluctance. Customers often need assurance that firms are sufficiently stable to deliver on promises and they will be reluctant to buy from a firm that might fail. Similarly, a firm's potential for financial distress will affect the relationship between the firm and the suppliers. Suppliers providing goods and services on credit are likely to reduce the generosity of credit terms or even stop supplying the firm. In a financial distress situation, employees may become demotivated, as a result of perceived job insecurity. Furthermore, the high-potential staff will start to move to safer enterprises. The additional indirect cost is the loss of managerial time and the loss of opportunities. The management has to spend daily time dealing with liquidity problems and focusing on the short term cash flow rather than on long term shareholder wealth.

In addition to the economic costs resulting from corporate failure, there exist the social costs relating to corporate collapse. Argenti (1976) pointed out that corporate collapse has always brought huge mental pain to proprietors, entrepreneurs, managers and their families. Failure ruins lives, destroys the health of its victims, and pushes the victims to the edge of suicide and beyond.

Many of these costs might be avoided if financially distressed companies could be identified well before failure occurs and if estimates could be made of their survival probability within a given time frame.

Therefore, this thesis focuses on examining the financial distress of publicly listed Australian companies based on survival analysis techniques. The significant factors that influence corporate financial distress in Australia and the survival probability of a company within a given time frame will be identified. Early identification of potential failure in companies could provide the parties concerned with an early indication of

problems thus enabling companies to improve the decision-making. An early warning system would enable the management to take action to prevent corporate bankruptcy or failure and to mitigate or reduce the failure-induced costs.

1.3 Definition of financial distress

Over the past three decades, a vast body of literature has emerged concerned with the development of statistical models designed to predict whether firms will enter into financially difficult situations.

The most common terms used to describe the situations of firms facing financial difficulty are ‘bankruptcy’, ‘failure’, ‘insolvency’ and ‘default’. Although these terms are sometimes used interchangeably, they are distinctly different in their formal usage (Altman and Hotchkiss, 2006). Altman and Hotchkiss (2006) provide a completed description and definition of these terms.

According to Altman and Hotchkiss (2006), ‘bankruptcy’ is defined as a failed formal petition of bankruptcy with the courts under the National Bankruptcy Act. ‘Failure’ is the situation where the realized rate of return on invested capital, with allowances for risk consideration, is significantly and continually lower than the prevailing rates of similar investments. ‘Insolvency’ is defined as a situation that illustrates a negative performance, indicating liquidity problems. The term is defined in two ways: technical insolvency and insolvency in the bankruptcy sense. Specifically, technical insolvency is the situation when a firm cannot meet its current obligations signalling a lack of liquidity while insolvency in a bankruptcy sense is more critical and usually indicates a chronic rather than a temporary condition. A firm is in this situation when its total liabilities exceed a fair valuation of its total assets, which means that the real net worth of the firm is negative. Finally, ‘default’ is the situation in which a firm violates a condition of an agreement with a creditor and causes legal action to be taken.

This thesis uses the term ‘financial distress’ to describe the situations of firms that face financial difficulty. The definition of financial failure or bankruptcy is diverse and it is not uniform in the literature. The definitions of financial distress range from the strict legal sense to the less formal indicators of financial distress, for example, suspension or delisting from the stock exchange.

Some studies adopt the legal definition; for example, Altman (1968a) defined bankrupt firms as firms that have failed a formal petition of bankruptcy with the courts under the National Bankruptcy Act. Ohlson (1980) and Zmijewski (1984) also define a bankrupt firm using the legal definition of firms filing a bankruptcy petition in the sense of Chapter X, Chapter XI or some other notification indicating bankruptcy proceedings. Similarly, Lindsay and Campbell (1996) and LeClere (2002) define a bankrupt firm as a firm that has filed for bankruptcy under Chapter XI of the Bankruptcy Act.

Other studies employ the suspension or delisting definition; for instance, Persons (1999) defines failed finance companies as those companies forced by the Bank of Thailand (BOT) to suspend their operations in mid 1997. Similarly, Tirapat and Nittayagasetwat (1999) define financially distressed firms as firms required by the Bank of Thailand or the Stock Exchange of Thailand (SET) to submit restructuring plans. The restructuring plans include the companies that were designated as C (Compliance) or SP (Suspension) by the SET.

In the Australian context, most previous studies define financially distressed firms according to the legal concepts; for example, Castagna and Matolcsy (1981), Izan (1984), Lincoln (1984), Liu (1993), Ryan (1994) and Seow (1998) define financially distressed firms as firms that enter into receivership or liquidation.

In this thesis, a company is defined as being in financial distress when it has entered into the external administration process; otherwise, the company is referred to

as an active company. The external administration process includes one of the following states: 1) voluntary administration, 2) schemes of arrangement, 3) receivership and 4) liquidation (For the definition and details of each state, see Appendix A).

According to the Corporations Law, the term ‘bankruptcy’ is not technically correct in the Australian context because only individuals can be bankrupt in Australia. The Insolvency and Trustee Service Australia (ITSA) is the Commonwealth government agency responsible for administering and regulating Australia’s personal insolvency system under the Bankruptcy Act 1966 and its related legislation. A company will generally be described as ‘insolvent’, which refers to the situation where an individual or a business is unable to pay debts as and when they fall due for payment. ASIC (Australian Securities & Investments Commission) is the government agency responsible for administering and regulating Australia’s company insolvency system under the Corporations Law.

The definition mentioned above is set in the context of the conventional failing vs. non-failing dichotomy model while some researchers argue that a company may exit the market for several different reasons, such as through merger, acquisition, voluntary liquidation and bankruptcy, and that each type of exit is likely to be affected by different factors (Schary, 1991; Harhoff, Stahl and Woywode, 1998; Prantl, 2003; Rommer, 2004).

Therefore, this thesis additionally examines the multiple states of financial distress. A three-state financial distress model is developed. Specifically, the model is defined as follows: state 0: active companies, state 1: distressed external administration companies and state 2: distressed takeover, merger or acquisition companies.

Accordingly, the distressed takeover, merger or acquisition state is defined in addition to the distressed external administration state. A distressed external

administration company is defined as a financially distressed company that has filed for external administration process. A company is classified as being in state 2 when the company is delisted from the Australian Stock Exchange (ASX) having been subject to a takeover, merger or acquisition arrangement due to its financially distressed position. This definition is also used in Hensher, Jones and Greene (2007) and Jones and Hensher (2007b), who define four unordered states of financial distress of public Australian companies and include distressed merger as an important state of financial distress.

Furthermore, this thesis additionally investigates the survival likelihood of new economy companies after they have gone public. In this study, new economy IPO companies that are delisted or suspended from the ASX due to their financially distressed condition are defined as non-survival companies. This definition is consistent with previous survival studies of IPO firms, for example, Welbourne and Andrews (1996) and Lamberto and Rath (2008).

Table 1.1 summarizes the definitions of financial failure adopted in previous Australian studies.

Table 1.1: Definitions of financial failure in previous Australian studies

No.	Studies	Definition of Failure
1.	Castagna and Matolcsy (1981), Izan (1984), Lincoln (1984), Liu (1993), Ryan (1994) and Seow (1998)	Receivership or liquidation
2.	Crapp and Stevenson (1987)	Failure is defined as the phenomenon where a credit union exits the industry due to implied pressures of financial distress
3.	Houghton and Smith (1992)	Corporate failure is defined as following states: <ul style="list-style-type: none"> • Receivership

No.	Studies	Definition of Failure
		<ul style="list-style-type: none"> • Voluntary liquidation • Compulsory liquidation • Provisional liquidation • Corporate affairs/ NCSC investigation • Other signs of distress, such as ASX delisting for non-technical reasons (for example, delayed payment of listing fees)
4.	Tan and Dihadjo (2001)	The Credit Unions that were placed under direction or placed under notice of direction (such as forced mergers, voluntary mergers)
5.	Jones and Hensher (2004) and Hensher and Jones (2007)	<p>Different states of financially distressed firms are defined as follows:</p> <p>State 1: Insolvent firms are defined as:</p> <ul style="list-style-type: none"> • Failure to pay ASX annual listing fees • Capital raising specifically to generate sufficient working capital to finance continuing operations • Loan default • A debt/total equity restructure due to a diminished capacity to make loan repayments <p>State 2: Firms that filed for bankruptcy followed by the appointment of liquidators, insolvency administrators or receivers</p>
6.	Hensher, Jones and Greene (2007) and Jones and Hensher (2007b)	<p>Different states of financially distressed firms are defined as follows:</p> <p>State 1: Insolvent firms are defined as:</p> <ul style="list-style-type: none"> • Loan default

No.	Studies	Definition of Failure
		<ul style="list-style-type: none"> • Failure to pay ASX annual listing fees as required by ASX Listing Rules • Capital raising specifically to generate sufficient working capital to finance continuing operations • A debt/total equity restructure due to a diminished capacity to make loan repayments <p>State 2: Financially distressed firms who were de-listed from the ASX because they were subject to a merger or takeover arrangement</p> <p>State 3: Firms that filed for bankruptcy followed by the appointment of receiver managers/liquidators</p>

1.4 Background of financial distress prediction model

The literature investigating bankruptcy or financial distress can be classified into two broad categories based on the adopted approaches, namely, the qualitative approach and the quantitative approach.

The studies employed a qualitative method to demonstrate and explore the business failure in the case studies, to provide the histories and to draw some conclusions from them. For example, Fernandez (2002) examined the warning signs of four major collapses in Australia, namely, Ansett, HIH, One.Tel and Harris Scarfe, that might have been evident to a company's stakeholders. Leung and Cooper (2003) also highlighted the corporate governance issue in corporate collapses such as HIH, One.Tel and Harris Scarfe.

In the US, Sridharan, Dickes and Caines (2002) discussed the social and financial impact of Enron's failure. The roles played by the management and the board of directors were additionally discussed. Similarly, Zandstra (2002) also focused on the roles played by the Chief Executive Officer (CEO) and other executives during the failure of Enron. In addition, Boyd (2003) highlighted the WorldCom failure case relating to the authorization of personal loans to its CEO or fellow directors. Leung and Cooper (2003) also provided an insight into the accounting profession, the regulators and the general public in the US regarding the case of the failure of Enron and WorldCom. Furthermore, Sidak (2003) discussed the collapse of American telecommunications after deregulation in the US.

One of the in-depth corporate failure studies that adopted the qualitative approach was done by Argenti (1976). Argenti provided an extensive qualitative analysis of the causes and symptoms of corporate collapse based on the summary of a number of books and articles about failure written by leading writers, on interviews with experts in the field of failure, for example, insolvency managers, accountants, receivers, bankers, and investment analysts, and an analysis of Altman's book, 'Corporate Bankruptcy in America', and Altman's 1968 Z score model. By integrating the views of a considerable number of writers and experts, the twelve elements (in italics) that are the causes and symptoms of failure are linked in the dynamic model as follows.

If *management* of a company is poor then two things will be neglected: the system of *accountancy information* will be deficient and the company will not respond to *change*. (Some companies, even well-managed ones, may be damaged because powerful *constraints* prevent the managers from making responses they wish to make.) Poor managers will also make at least one of three other mistakes: they will *overtrade*, or they will launch a *big project* that goes wrong, or they will

allow the company's *gearing* to rise so that even *normal business hazards* become constant threats. These are the chief causes, neither fraud nor bad luck deserve more than a passing mention. The following symptoms will appear: certain *financial ratios* will deteriorate but, as soon as they do, the managers will start *creative accounting* which reduces the predictive value of these ratios and so lends greater importance of *non-financial symptoms*. Finally, the company enters a characteristic period in its *last few months*. (Argenti, 1976, p. 122)

Another category of the approach adopted by bankruptcy studies is the quantitative method. Various bankruptcy or financial distress studies have focused on using a statistical method with potential explanatory variables. Then the significant variables that influence financial distress are reported.

Various statistical methodologies have been employed by previous bankruptcy or financial failure literature, for example, univariate analysis (Beaver, 1966; 1968a), Multivariate Discriminant Analysis (Altman, 1968a; Laitinen, 1992), logit analysis (Ohlson, 1980; Nikitin, 2003), probit analysis (Zmijewski, 1984) and Artificial Neural Networks (Odom and Sharda, 1990; Tan and Dihadjo, 2001).

While often effective in predicting ultimate corporate failures, these approaches are static models. Static models are inappropriate for forecasting bankruptcy because the models can consider only one set of explanatory variables for each firm and ignore the fact that firms change through time as the firm's characteristics change from year to year (Shumway, 2001). Furthermore, the models do not allow an estimation of survival probabilities or the 'time to corporate failure' to be calculated.

This thesis utilizes survival analysis techniques; these incorporate failure time as a dependent variable in the model and allow the estimation of survival probability within a given time frame given the company's characteristics to be calculated. Survival

analysis is appropriate for studying the occurrence and timing of an interested event (Allison, 1995). The main application of survival analysis in accounting research has been in the area of financial distress.

Two techniques under survival analysis are employed with proposed variables in examining corporate financial distress, namely, the Cox proportional hazards model and the competing risks model. Specifically, this study aims to examine publicly listed financially distressed companies in Australia, both established and Initial Public Offerings (IPO) companies. This will provide the opportunity to explore the significant factors driving financial distress for companies under different business constraints and environments since established companies are relatively more settled and familiar with the business environments compared to IPO companies.

Considering the variables used, this thesis investigates the relationship of various potential variables and financial distress. In particular, the explanatory variables used in this thesis cover both financial and non-financial data. Specifically, the financial ratios and control variables, for example, market-based data and company-specific variables, are examined in the context of established companies. Furthermore, this thesis further examines the influence of non-financial data, for example, corporate governance variables, on the survival likelihood of new economy IPO companies controlling for offering characteristics, financial ratios and company-specific variables. These potential variables are carefully selected based on previous empirical results and the relevant theoretical framework.

In addition, unlike in previous studies, this study uses time-varying variables rather than using merely time-invariant variables as in Luoma and Laitinen (1991) and Henebry (1996; 1997). LeClere (2005) suggested that proportional hazards models with

time-varying variables outperform proportional hazards models with time-invariant variables in determining the influence of covariates on financial distress.

Among the literature of financial distress in the Australian context, only Crapp and Stevenson (1987) and Peat (2007) employed survival analysis to examine financial distress. Although these studies make a significant contribution to the financial distress literature, they did not employ time-varying variables.

By employing the Cox proportional hazards model and competing risks model with time-varying variables based on both established and new economy IPO companies, this thesis will contribute to the existing bankruptcy or financial distress literature.

1.5 Research objectives

This thesis focuses on examining financially distressed Australian companies in the framework of survival analysis techniques. The research objectives include the following aims.

- 1. To examine the relationship between financial ratios and control variables with the likelihood of corporate financial distress.*

To achieve this objective, the annual data on four main categories of financial ratios, that is, profitability, liquidity, leverage and activity ratios, are incorporated in a Cox proportional hazards model controlling for stock prices and company-specific variables of age and size.

- 2. To identify the probability of corporate survival in a given time frame based on the state of the financial health of a company.*

Using the Cox proportional hazards form, the survival function that defines the probability that a company will survive longer than t time units is estimated. The survival function is produced by averaging the estimated survival probability of companies by company status, distressed and active company. (For details, see Chapter 4).

The above research objectives are set in the context of a single risk model. In other words, the research focuses on the conventional failing vs. non-failing dichotomy model while, as mentioned previously, some researchers argue that 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 and Woywode, 1998; Prantl, 2003; Rommer, 2004).

These studies are the motivation of this thesis as it aims to explore further multiple states of corporate financial distress rather than simply focusing on the conventional failing vs. non-failing dichotomy model. Consequently, the research objectives include the following aims.

3. *To identify whether the factors that influence the single risk model and the multiple risks model are different.*

To accomplish this objective, the competing risks model based on three different states of financial distress, namely, active companies, distressed external administration companies and distressed takeover, merger or acquisition companies is estimated. Then, the pooled model wherein all financial distress states are pooled together is estimated. Next, the competing risks model and pooled model are compared in terms of the significance and sign of the variables.

Then, this study further explores the determinants driving each financial distress state within a multiple-financial distress framework. The additional research objective is as follows:

4. *To examine the determinants of three different states of financial distress, namely, active companies, distressed external administration companies and distressed takeover, merger or acquisition companies.*

Within a multiple states failure model, the effect of financial ratios, a market-based variable and company-specific variables on the three unordered states of financially distressed Australian companies is investigated using a competing risks model. The significant factors that affect each state of financial distress are compared in terms of the significant variables and the signs of coefficient estimation. (For details, see Chapter 5).

In addition to financial ratios, the existing literature suggests that corporate governance variables are significantly related to corporate performance and long-term survival. Furthermore, between late 1998 and early 2000, there existed a speculation in increasing stock values and growth in new economy companies. Many IPO companies rapidly implemented new business models and developed new products in the new economy sector during the boom period. Then, the boom or bubble period was followed by a dramatic period of collapsing stock prices, exits and bankruptcies (Cockburn and Wagner, 2007).

Since corporate governance is the system that influences how the objectives of the company are set and achieved, how risk is monitored and assessed and how performance is optimized (ASX, March 2003), this thesis further explores the influence of corporate governance on the new economy IPO companies' survival.

The research objectives are specified as follows.

5. *To explore extensively the corporate governance attributes and control variables that influence the likelihood of the survival of new economy IPO companies.*

To accomplish this objective, the Cox proportional hazards model is estimated based on core explanatory variables and control variables. The core explanatory variables are three measurements of corporate governance, namely, board size, board independence and ownership concentration. Control variables include offering characteristics, financial ratios and company-specific variables.

The additional research objective is.

6. *To examine the survival probability of new economy IPO companies after going public.*

To achieve this objective, the Cox proportional hazards model is employed to identify the likelihood of survival of a company after the IPO. The survival function is produced by averaging the estimated survival probability of companies by company status, namely, non-survival and survival IPO companies. (For details, see Chapter 6).

1.6 Research questions

It can be expected that the symptoms of financial distress are observable from the deterioration of financial ratios, or that the effect of such ratios on corporate failure do not stay constant over time. Various studies in the literature, for example, Beaver (1966), Altman (1968a), Routledge and Gadenne (2000) and Rommer (2005), incorporated financial ratios in predicting bankruptcy or financial failure and confirmed that financial ratios are the significant indicators of corporate failure. However, there is inconclusive evidence regarding the significant financial ratios since each study reported different financial ratios as the significant indicators of financial distress.

Therefore, this thesis aims to investigate the relationship between financial ratios and corporate financial distress and identify corporate survival probability within a given time frame. Accordingly, the research questions are set as follows.

1. Are financial ratios significantly related to corporate financial distress?

To answer this question, this thesis incorporates financial ratios from four main categories, that is, profitability, liquidity, leverage and activity ratios, as the core variables. Consequently, the extended Cox proportional hazards model using time-dependent variables is estimated.

This thesis additionally employs control variables, for example, a market-based variable, company age, company size and squared size, in the model. The relevant research questions are specified as follows.

2. Is a market-based variable significantly associated with the likelihood of corporate financial distress?

In this study, to account for the criticism arising from the use of solely financial ratios, market-based data are employed in the analysis. Specifically, a company's past excess returns are included in the Cox proportional hazards model.

Other control variables used in this study are company-specific variables and the relevant research question is set as follows.

3. Do company-specific variables significantly affect corporate endurance?

To answer this question, company-specific variables used in the model include company age, company size and squared size. Specifically, the natural logarithm of

sales is used as a proxy of company size, and company age is measured by the number of years since registration. (For details, see Chapter 4).

In addition to focusing on the conventional failing vs. non-failing dichotomy and defining a financially distressed company in a single event model, this thesis further examines the effect of explanatory variables across the diverse states of financial distress. Accordingly, the research questions are set as follows.

4. Are the significant factors that influence financial distress in single risk and multiple risks models different?

To answer this question, a three-state financial distress model, including state 0: active companies, state 1: distressed external administration companies and state 2: distressed takeover, merger or acquisition companies, is estimated using a competing risks Cox proportional hazards model. Then, a single risk or pooled model in which all financial distress states are pooled together is estimated. Consequently, the results of the two model specifications are compared in terms of their significance and the sign of the variables.

5. Are the significant factors that influence each financially distressed state different within a competing risks framework?

The significant factors or determinants of each particular financially distressed state are identified using a competing risks model. Then, the similarities and differences of the factors that drive each state of financial distress are compared in terms of the significant variables and estimated signs within multiple the states of a financial distress model. (For details, see Chapter 5).

Regardless of the success of financial ratios in explaining financial distress, there are some criticisms about financial ratios; for example, financial ratios are subject to window dressing (Moses, 1990; Ryan, 1994) and are affected by a lack of theoretical foundation to guide the ratios selection (Aharony, Jones and Swary, 1980; Ryan, 1994; Charitou, Neophytou and Charalambous, 2004). Furthermore, ratios are historical rather than prospective or *ex-post* in nature (Johnson, 1970; Moses, 1990).

Many studies suggest the importance of non-financial data, for example, corporate governance, as a significant indicator of corporate performance and survival. Accordingly, this thesis additionally examines the influence of corporate governance mechanisms on IPO companies' survival by focusing on companies from the new economy sector.

The relevant research question is set as follows.

6. *Do corporate governance attributes significantly influence the survival likelihood of new economy IPO companies?*

To answer this question, the Cox proportional hazards model is utilized with three main categories of corporate governance attributes, namely, board size, board independence and ownership concentration, and controlling for relevant variables.

In addition to exploring the influence of corporate governance as the core variable on IPO companies' survival, this study further investigates the relationship between control variables, for example, offering characteristics, financial ratios and company-specific variables, and the likelihood of survival of IPO companies. Consequently, the research questions are specified as follows.

7. *Are offering characteristics variables significantly associated with new economy IPO companies' survival probability?*

To answer this question, several IPO firms' offering characteristics variables are employed in the model including offering price, offering size, offering age, retained ownership, underwriter backing, auditor reputation and the number of risk factors in the prospectus.

8. Are financial ratios significantly related to new economy IPO companies' survival probability?

To answer this question, four ratios, that is, current ratio, ROA, debt ratio and total assets turnover, are used as a measure of four categories of financial ratios, that is, liquidity, profitability, leverage and activity ratios.

9. Do company-specific variables significantly affect new economy IPO companies' survival probability?

To answer this question, two company-specific variables are included in the model: company size and timing of the IPO. Company size is measured by the logarithm of the firms' total assets. For timing of the IPO, a dummy variable is used indicating whether a company issued stock between 1999 and April 2000. (For details, see Chapter 6).

1.7 Contribution of the study

This thesis examines corporate financial distress utilizing survival analysis techniques with time-varying variables in the context of both established and new economy Australian IPO companies. This thesis will contribute to the existing financial distress literature.

First, since a limited number of studies have employed survival analysis to examine financial distress in the Australian context, this thesis uses the Cox

proportional hazards analysis, which is the sub-discipline of survival analysis will contribute to the literature on corporate financial distress.

Furthermore, no literature in Australia has adopted the Cox proportional hazards model with time-varying variables. By using time-varying variables based on the Cox proportional hazards model, the thesis will contribute to the literature on corporate financial distress based on survival analysis techniques in the Australian context. This feature allows for deterioration in the variables of financial ratios and company-specific variables over time, since it is unlikely that their values or effects would remain constant with the progression of the corporate failure process (Luoma and Laitinen, 1991). This is a reasonable application of the statistical method because financial distress does not occur immediately, but is preceded by a deterioration in a firm's financial health over a number of years (LeClere, 2000).

Secondly, this thesis extensively explores the various potential explanatory variables in the financial distress prediction problem. The adopted variables include both financial data and non-financial data. Particularly, financial ratios and control variables, for example, a market-based variable and company-specific variables, are included in the model based on the Cox proportional hazard model (*see Chapter 4 for details*) and a competing risks model (*see Chapter 5 for details*). Additionally, this study further explores the influence of non-financial data, for example, corporate governance attributes on new economy IPO companies' survival. The offering characteristics, financial ratios and company-specific variables are also employed in the analysis (*see Chapter 6 for details*).

Thirdly, this thesis also examines financial distress in the multiple states of a financial distress framework using a competing risks Cox proportional hazards model. Since, as mentioned previously, a company might exit business in various forms, the

determinant of each form could be different (Schary, 1991; Harhoff, Stahl and Woywode, 1998; Prantl, 2003; Rommer, 2004). By developing a multi-state failure model, this thesis will provide an opportunity to examine further the effect of explanatory variables across the diverse states of financial distress observable in practice.

In the Australian context, Jones and Hensher (2004) introduced a three-state financial distress model to examine the corporations in the ASX. The study was extended by Hensher, Jones and Greene (2007) and Jones and Hensher (2007b) by adding distressed merger as an additional important state of financial distress. However, these studies used advanced logit models, for example, mixed logit, multinomial error component logit and nested logit models, which is different from this thesis.

To the author's best knowledge, this is the first study to utilize a competing risks Cox proportional hazards model in examining a multiple states of financial distress model in the Australian context. Compared to other methods, the Cox proportional hazards model allows failure rates to be estimated as a function of time and also allows time-varying variables to be incorporated. The latter feature is important because it is expected that the value of the financial ratios will deteriorate as failure approaches.

Finally, this thesis provides a survival analysis of financially distressed Australian companies in the context of both established and IPO companies. The latter is explored with particular focus on the new economy sector; this means the study is able to restrict the analysis to a relatively homogenous sample of firms. Existing empirical evidence shows that the performance of IPO firms varies widely in different industries (Ritter, 1991; Levis, 1993). Hensler, Rutherford and Springer (1997) and Lamberto and Rath (2008) also found that the survival likelihood of IPO companies varies between industries. Audretsch and Lehmann (2004) further pointed out that firms in the new

economy or knowledge-based industries differ in their governance structure from traditional firms. Therefore, the study's focus on the survival analysis of Australian IPO firms solely within the new economy sector is justified.

By examining the both established companies and IPO companies, this thesis will be able to explore the factors that influence financial distress for companies in different business environment contexts. This will contribute to the literature in the field of financial distress.

1.8 Organization of the study

The study is organized into seven chapters. A brief summary of each chapter is set out below.

Chapter 1: Introduction

The chapter provides an introduction to the study, beginning with a statement of the problem and the motivation of the study. The definitions of a financially distressed company adopted in this study are also discussed. Next, the background of the financial distress prediction model is described. The research objectives and research questions are defined as this improves understanding of the specific questions that the researchers need to answer. This chapter also presents the organization of the thesis and the contribution it makes.

Chapter 2: Classification of financial distress prediction models

The classification of the financial distress prediction models is presented in this chapter, including classical statistical financial distress prediction models and alternative statistical financial distress prediction models. The background, relevant previous studies, and the advantages and disadvantages of each methodology are also presented.

Chapter 3: Financial distress predictors

This chapter contains a comprehensive review of the previous studies relating to the predictors of financial distress. Two main categories of financial distress predictors are presented: financial data and non-financial data. The details of each category and the empirical results based on the literature are discussed.

Chapter 4: Examining financially distressed companies: The Cox proportional hazards model

This chapter investigates the relationship between financial ratios and the likelihood of corporate financial distress and identifies the survival probability of companies within a given time frame, for example, the probability of companies surviving more than two years. A sample of 1,117 publicly listed Australian companies was examined over the period 1989 to 2005. The Cox proportional hazards model with four main categories of financial ratios and control variables including a market-based variable and company-specific variables is estimated and discussed.

Chapter 5: Multiple states of financially distressed companies: The competing risks model

This chapter demonstrates the application of a competing risks model, which is the sub-discipline of survival analysis, by examining multiple states of financially distressed Australian companies. The financial ratios, market-based variables and company-specific variables of 1,081 publicly listed Australian companies during the period 1989 to 2005 are investigated. The competing risks Cox proportional hazards model is developed for three states of financial distress. The significant variables for each state of

financial distress are discussed and compared. Furthermore, the significant determinants of a multiple risks model are compared with those of a single risk or pooled model. In addition, the survival probability of each state of financial distress is identified.

Chapter 6: Corporate governance mechanisms and new economy Australian IPO companies' survival

This chapter investigates the influence of corporate governance mechanisms on the survival of 127 new economy Australian IPO companies listed on the ASX between 1994 and 2002. Three main categories of corporate governance variables with offering characteristics variables, financial ratios and company-specific variables are employed in the Cox proportional hazards model. The empirical results are reported and discussed relating the significant factors of the IPO companies' survival and the probability of survival after the initial public offering.

Chapter 7: Summary and conclusion

This final chapter summarizes the overall picture of the thesis and discusses the empirical results. The policy implications that are derived from the findings are also presented. The chapter ends by identifying the limitations of the study and proposing suggestions for future research.

CHAPTER 2

CLASSIFICATION OF FINANCIAL DISTRESS

PREDICTION MODELS

2.1 Introduction

Academic researchers and practitioners from all over the world have been developing a large number of corporate financial distress prediction models based on various types of methodologies (Balcaen and Ooghe, 2004b). For example, Altman (1984) gave an overview of business failure prediction models developed in different countries. Keasey and Watson (1991) indicated the usefulness of, and limitations associated with adopting financial distress prediction models. Ooghe, Joos and Bourdeaudhuij (1995) reported an overview of the literature of financial distress models in Belgium. Dimitras, Zanakis and Zopounidis (1996) produced another important study, which presented a comprehensive survey of literature on business failure prediction models. Altman and Narayanan (1997) examined the studies on business failure classification models in 21 different countries. Cybinski (2001) also examined, described and explained the evolution of bankruptcy studies. These studies justify the importance of corporate financial distress prediction models.

This chapter aims to explain and classify the models employed in financial distress prediction. The classifications of the models are presented including classical statistical financial distress prediction models in Section 2.2 and alternative statistical models presented in Section 2.3. Finally, Section 2.4 presents the conclusions drawn from this chapter.

According to Balcaen and Ooghe (2004b), the evolution of financial distress prediction models starts from the classical statistical methods and goes on to the

application of several alternative methods. This section presents two groups of financial distress models categorized by the analytical techniques.

2.2 Classical statistical financial distress prediction models

The classical statistical methods have been widely used for the development of corporate failure prediction models. These models are called ‘single period’ classification models or ‘static’ models (Shumway, 2001). These techniques include univariate analysis, multivariate analysis and conditional probability models. This section elaborates on the different classical statistical models by explaining the features of each method, the previous studies that applied the models, and the advantages and drawbacks of the method.

2.2.1 Univariate analysis

Background

Univariate analysis is the statistical technique that involves an individual financial ratio as the single predictor of corporate failure. A classification procedure is organized separately for each ratio in the model. In the process of classifying a firm, the optimal cut off point of the measure is developed on the basis of minimizing the percentage of misclassifications. If the firm’s ratio value is below the cut off point, then it is classified as a failed firm; otherwise, it is classified as a non-failed firm. The classification accuracy can be measured by the total misclassification rate and the percentage of type I and type II errors.

Existing studies

Beaver (1966) pioneered the development of a corporate failure prediction model with financial ratios using a univariate analysis model. The sample of the study consisted of 79 failed firms during 1954 to 1964 and a paired sample of non-failed firms matched by

industry and asset sizes. Univariate analysis was applied to investigate the predictive ability of six financial ratios selected from the original thirty different financial ratios on the basis of the lowest percentage of error. The six ratios as the predictors of financial failure were cash flow to total debt, net income to total assets, total debt to total assets, working capital to total assets, current ratios and the no-credit interval. Beaver concluded that ratio analysis can be useful in the prediction of failure for at least five years before failure and cash flow to total debt is suggested as the best overall predictor.

Beaver (1968a) extended his 1966 study by using the same data to illustrate a method for evaluating alternative accounting measures as the predictors of failure. The groups of non-liquid asset ratios and liquid asset ratios were used in solvency determination and analysed at three levels including 1) the dichotomous classification test, 2) the comparison of mean values of ratio components and 3) the likelihood ratio analysis. The results indicated that the non-liquid asset measures predict failure better than do the liquid asset measures.

Advantages and disadvantages

Although the simplicity of the univariate model is appealing, this model shows some important disadvantages. As univariate analysis involves an individual financial ratio as a single predictor of failure, an inconsistency problem can occur. The model may give inconsistent and confused classifications results for different ratios for the same firm (Altman, 1968a). Furthermore, the univariate model differs from reality in that the financial status of a company is a complex issue that cannot be analysed by one single ratio. There are various factors that can describe the financial status of the firm; hence, a single financial ratio cannot include all the information (Edmister, 1972).

2.2.2 Multivariate discriminant analysis

Background

To overcome the problems resulting from the univariate analysis method, in 1968, Altman introduced the statistical multivariate analysis technique into the problem of company failure prediction and estimated a model called the ‘Z-score model’. Since then, this study has dominated the literature relating to financial failure or bankruptcy prediction models. There have been many studies based on Altman’s Z-score model, such as Joy and Tollefson (1975), Libby (1975), Altman, Haldeman and Narayanan (1977), Dambolena and Khoury (1980), Taffler (1982), Appetiti (1984), Frydman, Altman and Kao (1985) and Laitinen (1992).

Multivariate discriminant analysis (MDA) is used to classify an observation into one of several a priori groups depending on the observation’s individual characteristics. The MDA model consists of a linear combination of variables where the objective is to obtain the linear combination of the independent variables that maximizes the variance between the populations relative to within-group variance. The main idea of multivariate analysis is to combine the information of several financial ratios into a single weighted index, unlike the univariate analysis, which analysed the predictive ability of a single ratio (Laitinen, 1993b). The method estimates a discriminant function that is a coefficient vector $A = (a_1, a_2, \dots, a_n)$ and a constant term a_0 . The linear combination of the variables provides for each firm a Z-score as shown below.

$$Z_i = a_0 + a_1X_{i1} + a_2X_{i2} + a_3X_{i3} + \dots + a_nX_{in} \quad (2.1)$$

Where Z_i = Z-score or discriminant score for firm i

X_{ij} = Value of the independent variable X_j (with $j = 1, \dots, n$) for firm i

a_j = Linear discriminant coefficients with $j = 0, \dots, n$

A cut-off score is calculated according to the *a priori* probabilities of group membership and the costs of misclassification. Based on its Z-score and the cut-off score, a firm is then classified as belonging to the failure or the non-failure group. Particularly, the firm is placed in the failed group if its Z-score is less than the cut off point and it is placed in the non-failed group if its discriminant score exceeds or equals the cut off point (Balcaen and Ooghe, 2004a). The classification accuracy of an MDA model is measured mostly on the basis of rates of type I and type II errors as well as the percentage of correct classifications.

Existing studies

In Altman's study (1968a), the sample comprised 66 manufacturing corporations with 33 failed firms in the period 1946 to 1965 and 33 non-failed firms pair matched on the basis of year, industry and asset size. Altman's Z-score model utilized five financial ratios from twenty-two variables as the best predictors of financial failure. The discriminant model that performed the best overall job of predicting bankruptcy is presented as follows.

$$Z = 0.012X_1 + 0.014X_2 + 0.033X_3 + 0.006X_4 + 0.999X_5 \quad (2.2)$$

Where Z = Discriminant value or Z value

X_1 = Working capital/total assets

X_2 = Retained earnings/total assets

X_3 = Earnings before interest and taxes/total assets

X_4 = Market value equity/par value of debt

X_5 = Sales/total assets

This model predicts that the lower the Z-score, the greater a firm's distress potential. The optimal or cut off scores are 1.81 and 2.67 and the scores between 1.81

and 2.67 represent the grey area, called the zone of ignorance. Altman concluded that the MDA model's result was superior to a comparable univariate study by Beaver, (Beaver, 1966, reported a type I error of 22 percent and a type II error of 5 percent with an overall accuracy of 87 percent) and was an accurate predictor of failure up to two years prior to bankruptcy.

Based on Altman's (1968) model, Joy and Tollefson (1975) criticized the predictive ability, the relative discriminatory power of variables and the classification efficiency of MDA. Joy and Tollefson pointed out that those studies with the application of discriminant analysis to dichotomous classification problems have paid relatively little attention to the design and interpretation difficulties associated with discriminant analysis; consequently, the conclusions and generalizations that can be drawn from such studies are frequently tenuous and questionable.

The ZETA model developed by Altman, Haldeman and Narayanan (1977) was further improved due to the dramatic change in size, financial profile, financial and accounting standards and the retail business's expansion. By using a quadratic discriminant analysis to overcome the assumption of equal dispersion matrices required by linear discriminant analysis, the ZETA model improved the original Z-score model in terms of a higher accuracy rate for one to five years prior to failure.

To introduce various measures of ratio stability as the predictors in the corporate failure prediction model, Dambolena and Khoury (1980) used the stability of all financial ratios over time as well as the level of these ratios as explanatory variables in MDA. The results indicated that there was a substantial degree of instability, which is measured by 1) the standard deviation of the financial ratios, 2) the standard error of the estimation and 3) the coefficient of variation, in the ratios of bankrupt firms; this instability significantly increased over time as the corporation approached failure.

Taffler (1982) described an operational discriminant model for the identification of British companies at risk of failure and discussed the results of the discriminant analysis model. Using discriminant analysis and financial ratio data, the derived model appeared to outperform extant US-based models.

For Italian firms, Appetiti (1984) used discriminant analysis to develop a predictive model to forecast the solvency of those firms and also compare the ability of this model with that of the model that incorporates the trends of ratios over three years. The results confirmed that balance sheet ratios could also be a helpful instrument in analysing firms in Italy and the trend variables provided more information than did static values at least three years before bankruptcy.

In addition, Laitinen (1992) used univariate analysis and multivariate analysis to develop the failure prediction model of a newly founded firm. The author pointed out that the classification accuracy of the univariate model can be improved by using a combination of several variables, which is a linear discriminant function; however, the improvement in the accuracy of the results is rather small.

Advantages and disadvantages

The multivariate analysis is able to combine the information of several financial ratios into a single weighted index, unlike the univariate analysis, which analysed the predictive ability of a single ratio, therefore, it overcomes the problems resulting from the univariate analysis method. Although MDA is the most frequently used modelling technique in failure prediction, it has some serious disadvantages. MDA requires three restrictive assumptions. Firstly, the independent variables included in the model are multivariate normally distributed. Secondly, the group dispersion matrices or ‘variance-covariance matrices’ are equal across the failing and the non-failing group. Finally, the prior probability of failure and the misclassification costs are specified. In practice, it

seems that the first assumption of multivariate normality is often violated (Deakin, 1976), which might result in a significant bias (Eisenbeis, 1977; Mcleay and Omar, 2000). Furthermore, most corporate failure studies did not attempt to analyse whether the data satisfy this assumption, as in practice, the data rarely satisfy the three statistical assumptions. These situations result in questions being raised relating to the conclusions and generalizations with respect to the MDA technique, which is often applied in an inappropriate way (Joy and Tollefson, 1975; Eisenbeis, 1977).

2.2.3 Conditional probability models

Background

MDA is commented on as a violation of the assumption of the multivariate normal distribution of independent variables and as such is unsuitable for the interpretation of independent variables (Eisenbeis, 1977). The main criticism of MDA resulted in the introduction of conditional probability models in which no assumptions are made regarding the distribution of the independent variables (Ohlson, 1980). These models included logit analysis and probit analysis. Ohlson (1980) pioneered using logit analysis with financial ratios in order to predict company failure while Zmijewski (1984) was the pioneer in applying probit analysis.

Logit and probit techniques are parametric techniques based on a cumulative probability function. The techniques produce the results in the forms of probability of a firm being classified as belonging to an *a priori* group according to the financial characteristics of the firm. The logit and probit techniques are nonlinear probability models in which a dependent variable is not continuous, but performs a discrete characteristic, such as distressed or non-distressed firms. The coefficients of the model are obtained by maximizing the log-likelihood function. The difference between logit and probit models is the form of the cumulative distribution function; the logit

represents the cumulative logistic distribution function while the probit represents the cumulative normal distribution function.

In logit analysis, a non-linear maximum likelihood estimation procedure is used to obtain the estimates of the parameters of the following logit model (Gujarati, 2003).

$$P_1(X_i) = \frac{1}{1 + e^{-(B_0 + B_1 X_{i1} + B_2 X_{i2} + \dots + B_n X_{in})}} = \frac{1}{1 + e^{-D_i}} \quad (2.3)$$

Where $P_1(X_i)$ = Probability of failure given the vector of attributes X_i

B_j = Coefficient of attribute j with $j = 1, \dots, n$

B_0 = Intercept

X_{ij} = Value of the attribute j (with $j = 1, \dots, n$) for firm i

D_i = The “logit” for firm i

The logit analysis model combines several characteristics or ‘attributes’ to give a multivariate probability score for each company, which indicates the ‘failure probability’ or the ‘vulnerability to failure’. If D_i approaches minus infinity, P_1 will be zero and if D_i approaches plus infinity, P_1 will be 1. In logit analysis, failure probability P_1 follows the logistic distribution (Laitinen and Kankaanpaa, 1999).

Existing studies

Ohlson (1980) employed logit analysis to compute the probability of failure of 105 failed firms and 2,058 non-failed firms during the period 1970 to 1976. By constructing nine variables in a firm failure prediction model, the predictability of the model was high at 96 percent for a year prior to the event.

Another study that has extended logit analysis to classify and predict financial distress was Lau (1982). According to Lau, thirteen financial ratios were used to construct a multilogit model, which was used to predict financial distress. As a result of

developing a process of financial distress that divides the stage of financial distress into five states, Lau argued that the consideration of these various states of financial distress leads to a more realistic financial model.

In addition, Flagg, Giroux and Wiggins (1991) developed a failure prediction model to determine whether bankrupt and non-bankrupt firms could be correctly classified when the sample consisted only of failed firms. The logistic regression model reached 94 percent for overall accuracy prediction. The authors suggested that the probabilities of moving one failure event to another can be analysed in greater detail by using new methods such as Markov processes or survival analysis.

Johnson and Melicher (1994) examined the added value of two types of information provided by multinomial logit models to explain and predict corporate bankruptcy. The two types of information include 1) the information obtained by expanding the outcome by including a third state of financial distress and 2) secondary classification information. The significant reductions in misclassification error rates for the multinomial model were found and the results also suggested that secondary classification information can be used to improve the ability to predict bankrupt firms correctly as well as predicting financially weak firms that will suffer impending financial distress.

Ward and Foster (1997) applied a logistic regression model to test the results by using different definitions of a distress event and found that using the loan default definition as a response measure produces better results than using the legal bankruptcy definition.

Nikitin (2003) analysed plant failure and survival in the Indonesian financial crisis by adopting logit regression models to examine how the bankruptcy or survival determinants changed during the crisis. The study found that the major determinants of

business survival probability from 1993 to 1998 in Indonesia were the size of the establishment, the age of the establishment and the percentage of capacity utilised.

The logit model seems to be a much more popular model compared with the probit model because probit techniques require more computations (Dimitras, Zanakis and Zopounidis, 1996). The study by Tan and Dihadjo (2001) applied the probit model in the failure prediction model. They found that artificial neural network models performed as well and in some cases better than the probit models as an early warning predictor for Credit Union financial distress.

Advantages and disadvantages

No assumptions are made regarding the distribution of the independent variables in logit and probit models, while a violation of the assumption of multivariate normal distribution of independent variables exists in MDA (Eisenbeis, 1977; Ohlson, 1980)

However, standard logit models are limited by the restrictive assumption associated with the independent and identically distributed (IID) condition, which can result in significant information loss in model estimation and could affect the predictive performance of the model (Jones and Hensher, 2004; Jones and Hensher, 2007a).

Recent studies by Jones and Hensher (2004; 2007a; 2007b), and Hensher, Jones and Greene (2007) have introduced advanced probability modelling in the prediction of corporate bankruptcies, insolvencies and takeovers. These advanced models include the nested logit model (Jones and Hensher, 2007b), the mixed logit model (Jones and Hensher, 2004), the latent class multinomial logit model (Jones and Hensher, 2007a), and more recently, the error component logit model (Hensher, Jones and Greene, 2007).

These advanced probability models provide significantly greater explanatory and statistical power than did the standard logit models widely used in previous research.

The researchers concluded that all advanced models could potentially enhance the predictive performance of corporate bankruptcy and takeover probability models.

An important enhancement of the mixed logit model relative to the standard logit models used in most previous research is that the mixed logit model relaxes the highly restrictive assumption associated with the IID condition or constant variance error component and incorporates parameters that capture observed and unobserved heterogeneity both within and between firms (Hensher and Jones, 2007).

2.3 Alternative statistical financial distress prediction models

Besides the classical statistical methods, researchers have also been using alternative statistical financial distress prediction models for analysing and predicting business failure. The methods include decision trees, artificial neural networks (ANN) and survival analysis. This section explains the features of each method, the existing studies that applied the methods, and the advantages and drawbacks of each method.

2.3.1 Decision trees

Background

Decision trees based on a certain decision-tree-building algorithm have been used in financial distress prediction models since the mid 1980s. A decision tree is a collection of branches (paths from the root to the leafs), leaves (classes of objects) and nodes (containing decision rules or ‘splitting rules’), that classifies some ‘objects’ according to their attributes (Quinlan, 1986). The decision-tree-building algorithm determines the most important aspects of the decision tree: 1) the way to find the attribute that best discriminates between the two classes of firms (failing and non-failing) and 2) the appropriate approach for reducing the size of the tree. Consequently, the choice of this

algorithm is extremely important. In the context of financial distress prediction, different algorithms have been used.

Existing studies

Frydman, Altman and Kao (1985) applied the recursive partitioning algorithm and called it the 'Recursive Partitioning Analysis' or RPA. RPA is a non-parametric classification technique that starts with the sample of firms, the firms' financial characteristics, the actual group classification, the prior probabilities and the misclassification costs. A binary classification tree is built, where a rule is associated to any node. These are, usually, univariate rules, that is, a certain financial characteristic and a cut-off point that minimize the cost of misclassification for the rest of the firms. After the classification tree is constructed, the risk of the final nodes and the risk for the entire tree are calculated. For the classification of any new object (firm), the object descends the tree and falls into a final node that identifies the group membership for the specific firm and the associated probability.

Advantages and disadvantages

There are no strong statistical requirements concerning the data in the training sample in the decision trees method. Furthermore, it can handle incomplete and qualitative data (Joos et al., 1998).

According to Quinlan (1986), decision trees can deal with noise or non-systematic errors in the values of attributes. However, the decision tree method also has some drawbacks (Frydman, Altman and Kao, 1985; Dimitras, Zanakakis and Zopounidis, 1996). First, just like the classical statistical method of MDA, decision trees require the specification of prior probabilities and misclassification costs. Moreover, the decision

trees method is more sensitive to changes in misclassification costs and prior probabilities than is MDA (Balcaen and Ooghe, 2004b).

2.3.2 Artificial neural networks

Background

ANN is becoming a very popular research subject with applications in many areas such as medicine, business, politics and technology (Charalambous, Charitou and Kaourou, 2000).

In 1990, the ANN technique was been applied in the field of business failure prediction and it became a very popular technique that dominated the literature on business failure in the second half of the 1990s. In 1990, Odam and Sharda were the first researchers to apply ANN to the prediction of company failure (Balcaen and Ooghe, 2004b). According to Hawley, Johnson and Raina (1990), the Artificial Neural System (ANS) or Artificial Neural Network (ANN) can be described as follows.

ANS is a computer program that simulates the physical neural process by which human learning and intuition take place. The system is not programmed with any preexisting rules or structure, it actually learns through experience and trial and error. The ANS requires a training procedure through which it is repeatedly exposed to correct input/output information sets. Based on these, the system 'learns' the nature of the relationship between the inputs and outputs.

The networks consist of a number of highly interconnected processing elements, called 'neurons'. In ANN, the independent variables offered to the network are called 'inputs', the dependent variables are known as 'training values' and the estimated values are called 'output values' (Shachmurove, 2002).

An ANN has a particular architecture or structure. An example of a frequently used architecture is the feed-forward layered network, in which the neurons are divided into different subsets, called 'layers'. This kind of layered network contains 1) an input layer of neurons containing the input information, 2) internal or 'hidden' layers of a number of neurons and 3) an output layer of one neuron (Coats and Fant, 1993). As the number of hidden neurons increases, the network becomes more complex.

Existing studies

Several studies reported the superiority of the neural networks to other methods in predicting financial distress or bankruptcy areas.

For example, Salchenberger, Cinar and Lash (1992) compared the predictive performance between a neural network and a logit model in discriminating failed and surviving saving and loan associations (S&Ls). The financial data on 3,479 S&Ls for the period January 1986 to December 1987 were incorporated in the models. The study concluded that the neural network performed as well or better than did the logit model in classifying thrift institutions as failed or non failed, achieved a higher degree of prediction accuracy, and was more robust.

Using a data sample comprising Texas banks that failed in the period 1985 to 1987, Tam and Kiang (1992) also reported that ANN had a better predictive accuracy than did discriminant analysis, logit, k Nearest Neighbor (kNN) and decision tree analysis. The empirical results showed that the neural network is a promising method of evaluating bank conditions in terms of predictive accuracy, adaptability and robustness.

In addition, comparing a neural network with MDA in predicting financial distress using data covering the period 1970 to 1989, Coats and Fant (1993) found that MDA produced excellent results for the year of the going-concern opinion; however, the

Cascade Correlation (Cascor) neural network did better by comparison in the earlier years' classification.

Fletcher and Goss (1993) applied a back propagation neural network to a sample of 18 failed companies matched with 18 non failed companies by industry and size. The authors pointed out that the back propagation neural network methodology predicted bankrupt firms more accurately than did the logit model.

Fanning and Cogger (1994) examined the efficiency of a generalized adaptive neural network algorithm (GANNA) processor in comparison to the efficiency of a standard back propagation artificial neural network, logistic regression and model-based predictors to the classification problem of discriminating between failing and non failing firms. The results indicated that the results produced by neural networks are often superior to those of logit and model based predictors; furthermore, GANNA is easy to use and offers potential time saving.

Using the data, specifically 65 bankrupt firms and 64 non bankrupt firms matched on industry and year and covering the period 1975 to 1982, Wilson and Sharda (1994) compared the predictive capabilities for firm bankruptcy of neural networks and classical MDA. Their results also indicated that neural networks performed significantly better than did MDA at predicting firm bankruptcies.

By comparing ANN with logit and nonparametric multiple discriminant analysis in predicting the three-state outcome, that is, specifically acquired, emerged and liquidated after the bankruptcy filing of publicly traded firms, Barniv, Agarwal and Leach (1997) found that ANN provided significantly better results than did logit and nonparametric multiple discriminant analysis.

Bell (1997) was another study that insisted on the high performance of the neural network in comparison with a traditional statistical model such as a logistic regression

analysis. Bell modelled regulator's decisions to close commercial banks using logistic regression and a neural network and compared their ability to predict commercial bank failures over a 12-month period. The results suggested that the predictive accuracy of both methodologies is similar across the range of all possible cutoff values. Specifically, a neural network performs marginally better in the grey area where some failing banks appear to be less financially distressed than others.

Comparing two types of ANN, namely, categorical learning/instar ANN and probabilistic ANN with traditional MDA and a logit model when examining 148 failed and 991 healthy banks from all regions of the US covering the period 1986 to 1988, Etheridge and Sriram (1997) also found that when relative error costs were considered, the neural network performed better than did the traditional logit model or MDA.

These results were consistent with the findings of Charalambous, Charitou and Kaourou (2000); they compared the predictive performance of three neural network methods, namely, the learning vector quantization, the radial basis function and the feed-forward network with logistic regression, and the back propagation algorithm. Using 139 matched pairs of bankrupt and non-bankrupt US firms covering the period 1983 to 1994, the results showed that the three neural network methods provided superior results to the logistic regression and back propagation algorithm.

Additionally, comparing ANN to the probit model as an early warning model for predicting Australian credit unions in distress, Tan and Dihadjo (2001) demonstrated that the ANN model is a robust technique in the application of bankruptcy prediction.

However, using data from the US oil and gas industry, Yang, Platt and Platt (1999) indicated that whereas probabilistic neural networks without pattern normalization and Fisher discriminant analysis achieve the best overall estimation results, discriminant analysis produces superior results for bankrupt companies.

Balcaen and Ooghe (2004b) also concluded that although a sophisticated method such as a neural network is a more complex computation than are classical statistical methods, which offer univariate analysis, MDA, and probit and logit analysis, it is not clear that neural networks performed better than did those classical methods.

Advantages and disadvantages

Compared to other models, ANN has several advantages in the application of predicting financial distress or bankruptcy. ANN has the ability to analyse complex patterns quickly and to represent better the nonlinear discriminant function with a high accuracy level (Tam and Kiang, 1992). Unlike linear discriminant analysis, ANN does not require restrictive assumptions about the probability distribution of the data, which results in an unbiased analysis.

In addition, an ANN is able to deal with missing or incomplete data (Shachmurove, 2002; Hawley, Johnson and Raina, 1990). Furthermore, Tam and Kiang (1992) reported that ANN has the ability to adopt to the changing environment by adjusting the model.

However, ANN also shows some limitations. The most important problem related to the use of neural networks is the ‘black box’ problem. A neural network does not reveal the significance of each of the variables in the final classification and the derived weights cannot be interpreted. Additionally, the technique does not reveal the knowledge concerning how and why the network classifies companies into the failing and non-failing groups, which might restrict the use of this modelling technique (Balcaen and Ooghe, 2004a; Hawley, Johnson and Raina, 1990; Salchenberger, Cinar and Lash, 1992).

Furthermore, there is no formal theory for determining optimal network topology; the development and interpretation of neural network models requires more expertise

from the user than do traditional statistical models (Salchenberger, Cinar and Lash, 1992). The neural network produced the best results when used in conjunction with an expert since there is no structured methodology available for choosing, developing, training and verifying neural networks (Shachmurove, 2002).

2.3.3 Survival analysis

Background

Studies have been published that have reviewed and criticized current statistical techniques in financial distress prediction models that include univariate analysis, linear and quadratic discriminant analysis, logistic regression and probit analysis. However, a financial distress literature that employs the statistical technique of survival analysis has emerged. The main application of survival analysis in accounting research has been in the area of financial distress.

As a result of survival analysis techniques being discovered and adopted by researchers in several different fields, several different terms have been used to refer to survival analysis, such as reliability analysis, failure time analysis, event history analysis, duration analysis or transition analysis. For example, the researchers in engineering use the term ‘reliability analysis’ to study the reliability of machines and electronic components. In medical sciences, survival analysis is used to examine the survival time of the patient analysis under a specific treatment. These different terms do not imply any real difference in techniques, although different disciplines may emphasise slightly different approaches (Allison, 1995).

Survival analysis is a class of statistical methods for studying the occurrence and timing of events (Allison, 1995). The hazard function $h(t)$ is an important function in survival analysis, because it models the hazard rate, which is the basic concept of survival analysis. The hazard function models the probability of failure in the next

period given that the firm was active at time t . Given that T is a random variable that defines the event time for some particular observation, then the hazard function is modelled as follows:

$$h(t) = \lim_{\Delta t \rightarrow 0} \Delta t [P(t < T < t + \Delta t | T \geq t) / \Delta t] \quad (2.4)$$

There are three different techniques in survival analysis for constructing survival analysis models: non-parametric, semi-parametric and parametric technique. Non-parametric models are useful for conducting a preliminary analysis of survival data and for estimating and comparing survivor function. The two main methods are the Kaplan-Meier method and the Life-Table method. Parametric models are referred to as accelerated failure time (AFT) models. The key issue is to specify a probability distribution for the time of event. Common distributions include the exponential, Weibull, log-normal, log-logistic and gamma distribution. Semi-parametric models, unlike the parametric models, do not require specification of the probability distribution of hazard function over time. The most widely used semi-parametric regression model for survival data is the Cox proportional hazards model proposed by Cox (1972). The Cox proportional hazards model is a popular statistical model used in financial distress research (LeClere, 2000).

According to Allison (1995), there are many reasons for the popularity of the Cox proportional hazards model. Firstly, it is a semi-parametric approach that does not require the particular probability distribution to represent survival times. Secondly, it is easy to incorporate into the method time-dependent covariates, that is, the covariates that might change in value over the course of the observation period. Thirdly, it permits a kind of stratified analysis that is very effective in controlling for nuisance variables. Fourthly, the method is easy to adjust to allow for periods of time in which an

individual is not at risk of an event. Finally, the Cox proportional hazards model can readily accommodate both a discrete and a continuous measurement of event times.

In Cox's (1972) study, there are two significant innovations: the proportional hazards model, and partial likelihood or maximum partial likelihood. The proportional hazards model is represented as:

$$h_i(t) = \lambda_0(t) \exp\{\beta_1 x_{i1} + \dots + \beta_k x_{ik}\} \quad (2.5)$$

This equation shows that the hazard for individual i at time t is the product of two factors. The first factor is a baseline hazard function $\lambda_0(t)$, which is the hazard function for an individual whose covariates all have values of 0. The second factor is an exponentiated set of a linear function of a set of k fixed covariates.

Equivalently, the regression model is written as:

$$\log h_i(t) = \alpha(t) + \beta_1 X_{i1} + \beta_2 X_{i2} + \dots + \beta_k X_{ik} \quad (2.6)$$

Where $\alpha(t) = \log h_0(t)$ and $h_0(t)$ is an arbitrary unspecified baseline hazard rate (LeClere, 2000).

The model does not require the particular probability distribution specification of the survival times, but it possesses the property that different individuals have hazard functions that are proportional, that is,

$$\frac{h_i(t)}{h_j(t)} = \exp[\beta_1 (X_{i1} - X_{j1}) + \beta_2 (X_{i2} - X_{j2}) + \dots + \beta_k (X_{ik} - X_{jk})] \quad (2.7)$$

The ratio of the hazard functions for two individuals does not vary with time t . These special properties make the Cox proportional hazards model robust and popular amongst researchers.

The proportional hazards model is estimated with the method of partial likelihood (Cox, 1972). What is remarkable about partial likelihood is that the β coefficients of the proportional hazards model can be estimated without there being any need to specify the baseline hazard function $\lambda_0(t)$.

The likelihood function for the proportional hazards model of Equation (2.5) can be factored into two parts; one part depends on both β and $\lambda_0(t)$; the other part depends

on β alone. The partial likelihood discards the first part and treats the second part as though it were an ordinary likelihood function. Partial likelihood still has two of the three standard properties of maximum likelihood estimates. They are consistent and asymptotically normal (in large samples they are approximately unbiased and their sampling distribution is approximately normal). Partial likelihood estimates depend only on the ranks of the event times, not their numerical values. This implies that any monotonic transformation of the event times will leave the coefficient estimates unchanged (Allison, 1995).

The partial likelihood is a product of the likelihoods for all the events that are observed. A general expression for the partial likelihood for data with fixed covariates from a proportional hazards model is:

$$PL = \prod_{i=1}^n \left[\frac{e^{\beta x_i}}{\sum_{j=1}^n Y_{ij} e^{\beta x_j}} \right]^{\delta_i} \quad (2.8)$$

Where PL = The partial likelihood

$$Y_{ij} = 1 \text{ if } t_j \geq t_i \text{ and } Y_{ij} = 0 \text{ if } t_j < t_i$$

t_i = The time to failure or the time of censoring

δ_i = An indicator variable with a value of 1 if t_i is uncensored or a value of 0 if t_i is censored

When the partial likelihood is constructed, it can be maximized with respect to β .

To maximize the logarithm of the likelihood, the function is:

$$\log PL = \sum_{i=1}^n \delta_i \left[\beta x_i - \log \left(\sum_{j=1}^n Y_{ij} e^{\beta x_j} \right) \right] \quad (2.9)$$

Most partial likelihood programs use some version of the Newton-Raphson algorithm to maximize this function with respect to β (Allison, 1995).

Existing studies

Studies that applied a Cox proportional hazards model include Luoma and Laitinen (1991), Chen and Lee (1993), Wheelock and Wilson (1995), Henebry (1996), Turetsky and McEwen (2001) and LeClere (2002).

Luoma and Laitinen (1991) applied a Cox proportional hazards model to point out the advantages and shortcomings of survival analysis in company failure prediction and found that the best Cox proportional hazards model was composed of six financial variables and an interaction term; however, the classification results of survival analysis were outperformed by MDA and the logistic model.

In order to examine financial distress in the oil and gas industry, Chen and Lee (1993) employed a Cox proportional hazards model to determine the length of time between the onset of economic adversity and the onset of financial distress. The result indicated that the liquidity ratio, leverage ratio, operating cash flows, success in exploration, age and size are significant factors affecting corporate endurance. Additionally, the study compared survival analysis with the traditional logit model and found that these two models result in largely the same significant variables but the survival analysis provided an additional feature of prediction, that is, the capability to show the probability that a firm could endure until each given time interval.

Wheelock and Wilson (1995) also applied a Cox proportional hazards model to estimate the time to failure of banks in Kansas during the years 1910 through to 1928. Three specifications of the proportional hazards model were estimated. The results showed that undercapitalization, membership in the deposit insurance system and inefficiency increased the hazard rate.

Henebry (1996) also examined the bank failure issue focusing on whether the addition of the cash flow variable improves the performance of the Cox proportional hazards model. The improvement was identified through the comparison of R values, type I and II errors and rank order correlations. The result indicated the cash flow information improves predictive accuracy only in longer horizon models.

Turetsky and McEwen (2001) investigated the influence of certain risk dimensions and firm-specific attributes on the survival of distressed firms using a Cox proportional hazards model. The results showed that the significant accounting covariates tend to change, conditional on a firm having progressed through the diverse stages of distress, and indicated the heterogeneous nature of financial distress and potential business failure. Furthermore, LeClere (2002) examined the sensitivity of a Cox proportional hazards model to the choice of covariate time dependence within a financial distress context. The study found that the Cox proportional hazards models with time-dependent covariates outperformed the models with time-invariant covariates.

Another technique of survival analysis is a competing risks model, which is appropriate for the application of multiple end states (Allison, 1995). For instance, in the area of financial distress, there are many types of financial distress, such as voluntary or involuntary bankruptcy, skipping or reducing a dividend payment or interest payment default. These types of events might result from different covariates. In this situation, the competing risks model seems to be an appropriate method (LeClere, 2000). Studies that applied a competing risks model include Wheelock and Wilson (2000) and Rommer (2004; 2005).

Wheelock and Wilson (2000) used a competing risks model to identify the characteristics that make US banks more likely to fail or to be acquired. The comprehensive model relating the probability of failure to bank characteristics with

special emphasis on management quality was estimated. The authors pointed out that since banks can disappear through either failure or acquisition and because the occurrence of either event precludes the occurrence of the other, the competing risks hazard model seems to be the most appropriate method to identify the characteristics leading to each outcome. This statement is consistent with the study by Rommer (2004), which also employed a competing risks models to predict which firms would end up in financial distress. Since firms in the non-financial sector can go out of business for various reasons, competing risks models were used. The results suggested that the proportion of correct predictions in the competing risks models was better than that in the pooled logit model; this indicates it is important to distinguish between exit types.

Additionally, Rommer (2005) used a competing risks model to estimate the probability of a firm exiting in various states. As firms can exit for reasons other than financial distress, such as merger and voluntary liquidation, a competing risks model was applied in the study. In order to compare the determinants of financial distress in French, Italian and Spanish firms, accounting-based credit scoring models for each country were estimated. The results showed that although there are some similarities across countries, there are also quite a lot of differences in the determinants of financial distress in those countries.

Other studies that applied survival analysis in financial distress or financial failure prediction models in addition to the Cox proportional hazards model and the competing risks model include Audretsch and Mahmood (1995), Hill, Perry and Andes (1996), Honjo (2000), DeYoung (2003), Duffie and Wang (2003) and Saretto (2004).

Audretsch and Mahmood (1995) used a hazard duration model to identify the post entry performance of new businesses by linking the likelihood of their survival to the conditions of technology and market structure environment and the establishment of

specific characteristics. The results demonstrated that the likelihood of a new business surviving was shaped not only by the underlying technological conditions and market structure environment, but also by business specific characteristics, such as ownership status and size.

To examine bankruptcy and financial distress, Hill, Perry and Andes (1996) employed an event history analysis known as a transition rate model in the study. The results suggested that variables differ in identifying financially distressed firms and bankrupt firms.

Honjo (2000) applied a multiplicative hazards model to estimate the determinants of business failure among new manufacturing firms in Tokyo. The author found that a new firm without sufficient capital or a sufficient size has a higher risk of business failure. New firms tend to have more difficulty surviving in an industry with a high entry rate and new firms that enter just before or after the collapse of the economy are more likely to fail.

In order to examine the failure patterns and failure determinants for new banks and compare the results to a benchmark model estimated for small established banks, DeYoung (2003) used a split population duration model in the examination. The results indicated that it is easier to identify early indicators for new banks than for established banks since new banks are more common and have characteristics that are less heterogeneous than have the established ones.

Duffie and Wang (2003) also employed hazard analysis to predict maximum likelihood estimators of multi period corporate failure prediction and found that when comparing the significant dependence of the level and shape of the term structure of the conditional probability of bankruptcy on a firm's distance to default and US personal income growth, specifically, the former has a greater relative effect than has the latter.

Furthermore, Saretto (2004) applied a simple piece wise constant hazard to predict and price the probability of corporate bond defaulting and found that the duration model outperformed existing models in correctly classifying both default and non default firms.

Advantages and disadvantages

Researchers suggest that survival analysis techniques are particularly appropriate for examining corporate endurance (Flagg, Giroux and Wiggins, 1991; Chen and Lee, 1993; Audretsch and Mahmood, 1995; Turetsky and McEwen, 2001).

According to Chen and Lee (1993), the advantage of survival analysis is that it utilizes an *ex ante* approach to track a firm's status and characteristics longitudinally. This is in contrast to other financial distress studies, which typically consider business failure by collecting biased *ex post* data of financial distress.

Furthermore, survival analysis can handle two common features of data, namely, censoring and time-dependent covariates, which are difficult to handle with conventional statistical methods (Allison, 1995). Generally, censored observations arise when the duration of the study is limited. There are firms in the sample that never experience some or all of the potential distress stages. The survival analysis techniques that consider censored observations are able to avoid sampling bias (Turetsky and McEwen, 2001).

Additionally, according to Shumway (2001), survival analysis hazard models resolve the problems of static models by explicitly accounting for time. The dependent variable in hazard models is the survival time. Since the bankruptcy probability that a static model assigns to a firm does not vary with time, survival analysis techniques are preferable to static models both theoretically and empirically. By comparing the forecasting ability of survival analysis to Altman (1968) and Zmijewski (1984),

Shumway reveals that about half of the financial ratios that have been used in previous study models are not statistically related to bankruptcy probability.

Survival analysis techniques are more appropriate than single-period classification models or static models for forecasting bankruptcy. Static models, such as MDA and logit analysis, ignore the fact that firms change through time; therefore, they produce biased and inconsistent bankruptcy probability estimates. Test statistics that are based on static models give incorrect inferences. Hence, survival analysis techniques are more consistent and accurate than are static models (Shumway, 2001).

Survival analysis has important advantages since, unlike MDA, it does not require the distribution of explanatory variables and it seems to be consistent with the reality that firms change over time. Therefore, this study will develop a financial distress prediction model for Australian firms using survival analysis techniques.

2.4 Conclusion

This chapter explained and classified the models employed in financial distress prediction studies. The classification of the models generally progressed from classical statistical financial distress prediction models to alternative statistical models.

Classical statistical financial distress prediction models include univariate analysis, MDA and conditional probability models. Beaver is the pioneer in using univariate analysis in failure prediction. This analysis involves the use of a single financial ratio in a failure prediction model. Altman performed a multivariate analysis of failure by means of MDA. The main idea of that analysis is to combine the information of several financial ratios to form a single weighted index. Many other studies have followed this multivariate methodology: however, the method is statistically valid only if the variables are multivariate normal distribution which is

often violated. This shortcoming has led to the use of logit and probit analysis, which do not assume the multi-normality of the variables.

Alternative statistical financial distress prediction models include decision trees, ANN and survival analysis. Decision trees based on a certain decision trees-building algorithm have been entered into financial distress prediction models since the mid 1980s. The method requires the specification of prior probabilities and misclassification costs like the classical statistical method of MDA. In 1990, ANN was applied in the corporate failure prediction field and became a very popular technique. The technique dominated the literature on business failure in the second half of the 1990s; however, since there is no formal theory for determining optimal network topology, the development of neural network models requires more expertise from the user than do classical statistical models.

The problems associated with classical statistical models, for example, MDA, and logit and probit analysis are as follows: 1) these models assume a steady or static state for the failure process, which is usually violated, 2) the predictions given by these models based on data from alternative years before failure may be biased and 3) while often effective in predicting ultimate corporate failures, these models do not provide any estimations for the time to failure.

These problems could be avoided by using survival analysis, which is a class of statistical methods for studying the occurrence and timing of events. This method permits the estimation of corporate survival probabilities in a given time frame based on a set of variables symptomatic of corporate financial distress, which was not available under previously used techniques.

This chapter also has presented the background of survival analysis and reviewed the existing studies using survival analysis techniques to explain financial distress.

The next chapter will review and discuss the categories of financial distress predictors adopted in the previous literature.

CHAPTER 3

FINANCIAL DISTRESS PREDICTORS

3.1 Introduction

To provide the empirical evidences about the influence of variables on bankruptcy or corporate failure and identify the potential determinants of corporate financial distress, this chapter provides an extensive review of the predictors of corporate bankruptcy or financial distress in the previous literature. The categories of financial distress predictors are identified and the details of each category and the empirical results based on the literature are discussed.

3.2 Categories of financial distress predictors

According to Hossari and Rahman (2005), empirical investigations of corporate failure can be classified into two categories: those studies that do not utilize financial data and those that do utilize financial data. The latter can be further classified into those that employ financial ratios and those that use non-ratio financial data in modelling corporate collapse.

3.3 Financial data

The use of financial statement information for corporate bankruptcy prediction has been extensively explored by researchers. As discussed by Lincoln (1984), analysts should rely on financial statements in examining corporate financial failure because all the factors influencing the success of a company are reflected in its financial statements. Poor management will be reflected in the profit and loss statement, economic downturns will be shown in the company's declining cash flow and tight credit or low levels of money supply growth will be reflected in the balance sheet.

The details of the existing literature regarding the use of financial data in corporate bankruptcy or financial distress prediction are discussed as follows.

3.3.1 Financial ratios

A significant number of academic studies have utilized financial ratios in predicting bankruptcy, financial failure or financial distress.

Since Beaver's (1966) pioneering work in the late 1960s, there has been considerable interest in using financial ratios to predict financial distress with studies such as Altman (1968a), Edmister (1972), Libby (1975), Altman, Haldeman and Narayanan (1977), Ohlson (1980), Lau (1982), Bongini, Ferri and Hahn (2000), Routledge and Gadenne (2000), Catanach and Perry (2001) and Rommer (2005).

Beaver (1966) is the pioneering academician who used financial ratios with a univariate technique to predict financial failure. According to Beaver, ratio analysis can be useful in the prediction of failure for at least five years before failure occurs. The initial thirty financial ratios are reduced to six common element groups. These six financial ratios are cash flow to total debt, net income to total assets, total liabilities to total assets, working capital to total assets, current ratio and no credit interval. Beaver found that cash flow to total debt ratio is the best predictor for five years preceding failure.

Altman (1968a) improved on Beaver's univariate method of analysis by introducing a multivariate approach that allows for the simultaneous consideration of several variables in the analysis. Altman developed the well-known Z score model with financial ratios based on MDA. The results found five financial ratios that are significant predictors in corporate bankruptcy prediction model. These ratios are working capital to total assets, retained earnings to total assets, earnings before interest

and taxes to total assets, market value equity to par value of debt and sales to total assets.

A subsequent study by Deakin (1972) examined fourteen financial ratios used by Beaver (1966), but used MDA in order to propose an alternative model for predicting failure. The results found that it is possible to identify a large number of potential failures correctly up to three years before the firm files for bankruptcy.

Using financial ratios based on the logit model to predict bankruptcy, Ohlson (1980) found four basic factors have a significant effect on the probability of failure within one year: company size, financial structure, performance and current liquidity.

In order to predict corporate failure in Australia, Castagna and Matolcsy (1981) examined ten financial ratios that measure profitability, liquidity, coverage and leverage and capitalization. The results confirm that the ratios group means of failed and surviving companies are significantly different in all five years prior to failure.

Lincoln (1984) explored the usefulness of accounting ratios to describe levels of insolvency risk for Australian firms. Six streams of financial information are defined, that is, profit, cash flow, assets, liabilities, shareholder's funds and working capital, and then combinations of thirty-nine ratios are produced. The study confirms the usefulness of accounting ratios to describe the levels of insolvency risk.

Additionally, Crapp and Stevenson (1987) utilized eighteen ratios from areas including quality of assets, financial risk, managerial efficiency, growth, and economic consequences to develop a method to assess the relevant variables and the probability of financial distress on Australian credit unions. The results indicate that the significant variables in explaining failure in all periods are income capacity, operating efficiency and loan growth.

By comparing four types of bankruptcy prediction models based on financial ratios, cash flows, stock returns and return standard deviations, (Mossman et al., 1998) found that all models are statistically important and the ratio model is the most effective in explaining the likelihood of bankruptcy.

In addition, Lennox (1999) examined the causes of bankruptcy for UK listed companies using financial ratios along with company-specific factors. Those financial ratios are the measure of profitability, leverage and cash flow. The study shows that profitability, leverage and cash flow have important effects on the probability of bankruptcy.

By examining five main categories of financial ratios, namely, operating risk, profitability, liquidity, financial leverage and market perspective risk, Turetsky and McEwen (2001) also confirmed that the significant accounting covariates tend to change conditional on a firm having progressed through the diverse stages of distress.

Koke (2002) investigated the determinants of acquisition and failure for German corporations, separately for public and private corporations. The results suggest that both types of firms are more likely to be acquired or to fail when performance is poor, leverage is high and firm size is small.

Additionally, Lensberg, Eilifsen and McKee (2004) developed a bankruptcy classification model for Norwegian companies. The authors investigated twenty-eight potential bankruptcy predictors including both financial ratios and non-financial ratio variables. The results show that accounting information is more important for larger than for smaller firms. It also suggests that for small firms, the most important information is liquidity and non-accounting information.

According to Altman (2000), in general, ratios measuring profitability, liquidity, and solvency prevailed as the most significant indicators. The order of their importance

is not clear since almost every study cited a different ratio as being the most effective indication of impending problems.

Recently, Hossari and Rahman (2005) have provided a formal ranking of the financial ratios used in existing corporate collapse studies by investigating the usage rate of financial ratios in 53 previous studies from 1966 to 2002. The results reveal that the most popular financial ratio is net income to total assets, which is used in 43 percent of the relevant studies. Furthermore, only five out of forty-eight financial ratios were found useful by more than 25 percent of the studies included in their study. These ratios are net income to total assets, current assets to current liabilities, total liabilities to total assets, working capital to total assets and EBIT to total assets.

As a result of the lack of an established theory in guiding the possible financial ratios for inclusion in corporate failure prediction models (Ball et al., 1982; Gilbert, Menon and Schwartz, 1990), researchers have been employed in data fitting exercises. Previous studies initially consider large sets of independent variables and then use statistical techniques to obtain the selected variables in the final model. For example, Altman reduced the original twenty-two variables to five by searching through various discriminant functions to obtain the one that predicted best. Another approach is employing the variables suggested by the existing literature or those found to be significant by previous corporate failure or financial distress studies.

Due to an absence of any theory to guide the selection of independent variables, this study takes an *ad hoc* approach to the selection of financial ratios as potential indicators of financial distress. The selection criteria is based on 1) the predictive variables in previous studies, 2) the potential of the variables in this study and 3) data availability in *FinAnalysis Database* as financial statements of Australian firms are collected from this database. Finally, four categories of financial ratios, that is,

profitability, liquidity, leverage and activity ratios, are utilized in this study as discussed in the following sections.

1) Profitability ratios

The profitability ratios measure the firm's ability to generate earnings. Profit is one source of funds from operations. The more profit a firm can generate, the greater the increase in funds and liquidity. Many firms face financial distress when they have negative earnings. Therefore, profit is often used as a predictor of financial distress events (Khunthong, 1997). Three types of profitability ratios, namely, EBIT margin, return on equity (ROE) and return on assets (ROA) are used in this study.

Utilizing the logit model, Platt and Platt (2002) found the EBIT margin is a significant variable in predicting financial distress among companies in the automobile supplier industry. Consistent with Platt and Platt (2002), Parker, Peters and Turetsky (2002b) also found the EBIT margin is significantly related to the survival likelihood of distressed firms.

Another profitability measure is ROE, which shows the return on capital provided by a firm's owners. In other words, ROE measures the ability of a firm to utilize assets to generate earnings for shareholders.

According to Khunthong (1997), ROE is found to be one of the significant variables in predicting failure two and three years before failure occurs for companies in Thailand. Gestel et al. (2006) also found ROE to be one of the three most important inputs for the Least Squares Support Vector Machine (LS-SVM) classifier in the analysis of the creditworthiness of a company.

In this study, ROA is defined as EBIT to total assets. As discussed in Altman (1968a), EBIT to total assets is a measure of the true productivity of the firm's assets independent of any tax and leverage factors. This ratio is particularly appropriate for

corporate failure studies since insolvency occurs when the total liabilities exceed a fair valuation of the firm's assets with the value being determined by the earning power of the assets.

The previous literature found ROA is a significant factor in explaining financial failure, for example, Altman (1968a), Altman, Haldeman and Narayanan (1977), Izan (1984), McGurr and DeVaney (1998), Laitinen and Laitinen (2000), Zapranis and Ginoglou (2000), Ginoglou, Agorastos and Hatzigagios (2002) and Beaver, McNichols and Rhie (2005).

Altman (1968a) found that EBIT to total assets outperformed other profitability measures including cash flow. Consistent with Altman (1968a), Izan (1984) also found EBIT to total assets a useful factor in discriminating financially distressed companies in Australia.

Additionally, Beaver, McNichols and Rhie (2005) found ROA to be one of the significant variables in predicting bankruptcy. However, after both financial ratios and market-based variables are combined, ROA is no longer significant. The authors concluded that this is consistent with the notion that the market-based variables contain the financial statement variables as a subset.

2) Liquidity ratios

The liquidity ratios measure a firm's ability to meet its current obligations as they become due. Liquidity ratios also have been used to measure short term solvency. A higher level of liquidity decreases the likelihood of financial failure. Most firms meet illiquidity and then become financially insolvent and eventually become bankrupt while they still operate profitably (Khunthong, 1997). Chen and Lee (1993) confirmed that liquidity ratio is one of the significant factors affecting corporate endurance. Current

ratio, quick ratio and working capital to total assets ratio are used in this study in order to measure the liquidity of the firms.

Studies that found the current ratios useful in predicting bankruptcy include Beaver (1966), Altman, Haldeman and Narayanan (1977), Izan (1984), McGurr and DeVaney (1998), Charalambous, Charitou and Kaourou (2000), Laitinen and Laitinen (2000), Parker, Peters and Turetsky (2002b) and Platt and Platt (2002).

Izan (1984) utilized an industry-relative approach rather than traditional ratios in examining corporate financial distress and found that the current ratio is one variable that is univariately significant.

Since the current asset measure includes cash, marketable securities, account receivable and inventory, Beaver (1968a) claimed that the inclusion of inventory impairs the current asset measure's usefulness. It has been argued that inventory is not a liquid asset because it must be sold before it can be converted into cash or account receivable. This criticism led to the development of the quick asset measure, which includes cash, marketable securities and account receivable, but not inventory.

The quick ratio was found significant as regards financial distress, financial failure or bankruptcy in Laitinen and Laitinen (2000) and Laitinen (2005). Laitinen (2005) used survival analysis to model the duration of time that precedes a firm's initial payment default. The primary covariates used in the study are financial ratios and results; quick ratio has been shown to be one of most significant financial covariates.

Working capital is a measure of the net liquid assets of the firm relative to the total capitalization. Since net working capital is defined as current assets minus current liabilities, Beaver (1968a) pointed out that this measure is free from manipulation through window dressing, for example, the temporary payment of current liabilities just

prior to the financial statement date, which results in a spurious improvement of the current ratio.

According to Altman (1968a), working capital to total assets is the most valuable ratio in predicting corporate financial distress compared to the other two liquidity variables, namely, the quick and the current ratio. Similarly, Beaver (1966) also found that working capital to total assets is a useful factor in predicting bankruptcy.

In addition, Chen and Lee (1993) explored how long firms were able to endure the oil and gas industry turmoil of the early 1980s before facing financial distress. The results confirmed that working capital to total assets is an important determinant of survival time.

By examining listed Thai firms that experienced financial distress in 1997, Tirapat and Nittayagasetwat (1999) also found working capital to total assets to be significantly related to the probability of financial distress.

3) Leverage ratios

The analysis of financial leverage is concerned with the capital structure of the firm. These ratios show the origin of funds provided from external sources in the benefit of shareholders. Leverage ratios also have been used to measure the long term solvency of firms. In other words, the ratios measure the ability of firms to pay long term liabilities (Khunthong, 1997).

This study uses debt ratio as a measure of financial leverage and a potential determinant of corporate financial distress.

The financial distress literature provides specific evidence for the association between financial leverage and a firm's financial distress or failure, for example, Beaver (1966; 1968a), Damolena and Khoury (1980), Flagg, Giroux and Wiggins (1991), Charalambous, Charitou and Kaourou (2000), Laitinen and Laitinen (2000), Zapranis

and Ginoglou (2000), Charitou, Neophytou and Charalambous (2004) and Beaver, McNichols and Rhie (2005).

Based on univariate analysis, debt ratio was found to be one of the six best predictors of financial failure in Beaver (1966). Beaver (1968a) also confirmed that the debt ratio predicts financial failure better than do the other eleven ratios at one, four and five years before failure.

Incorporating financial ratios' stability measurements with MDA in predicting corporate failure, Dambolena and Khoury (1980) found debt ratio to be one of best predictors in discriminant function.

Flagg, Giroux and Wiggins (1991) also found that debt ratio is significantly positively related with a progression towards business failure for firms that enter a potential failure process.

More recently, Beaver, McNichols and Rhie (2005) have suggested that debt ratio is a significant variable for predicting bankruptcy. Additionally, after combining market-based variables with financial ratios, debt ratio remains a significant variable. The authors discussed how leverage remains significant, since the market-based variables do not distinguish between volatility induced by business risk and that induced by financial risk.

4) Activity ratios

The activity ratios present the efficiency of a firm's assets utilization and measure the ability of a firm to use assets to generate revenue or return. If a firm can use assets efficiently, it will earn more revenue and increase liquidity and net income (Khunthong, 1997). Two activity ratios, namely, capital turnover and total assets turnover, are used in this study.

Laitinen (1992) developed a failure prediction model based on financial statement data from newly founded firms. Net sales to total capital or capital turnover were found to contribute significantly to the discriminant model. However, the result is contrary to expectations as net sales to total capital has a negative coefficient, which means a company with a high capital turnover ratio is more likely to fail.

Regarding total assets turnover, Altman (1968a) pointed out that total assets turnover is the standard financial ratio presenting the ability of a firm to generate sales from assets and it is one measure of management's capacity to deal with competitive conditions. It should be noted that total assets turnover ranked second in its contribution to the overall discriminant ability in the Altman Z-score model.

The financial ratios used in this study and their popularity in previous financial failure literature are shown in Table 3.1.

Table 3.1: Financial ratios used in this study and its popularity in previous literature

Category	Financial Ratio	Studies
Profitability	EBIT margin	Edmister (1972), Lee, Han and Kwon (1996), Khunthong (1997), Tirapat and Nittayagasetwat (1999), Parker, Peters and Turetsky (2002b), Platt and Platt (2002), Charitou, Neophytou and Charalambous (2004) and Gestel et al. (2006)
	ROE	Edmister (1972), Dambolena and Khoury (1980), Lee, Han and Kwon (1996), Kumar and Ganesalingam (2000), Ganesalingam and Kumar (2001), Lizal (2002), Platt and Platt (2002), Charitou, Neophytou and Charalambous (2004) and Gestel et al. (2006)
	ROA	Altman (1968a), Edmister (1972), Altman, Haldeman and Narayanan (1977), Dambolena and Khoury (1980), Castagna and Matolcsy (1981), Izan (1984), Zmijewski (1984), Frydman, Altman and Kao (1985), Molinero and Ezzamel (1991), Hill, Perry and Andes (1996), Lee, Han and Kwon (1996), Ward and Foster (1997), McGurr and DeVaney (1998), Dimitras et al.(1999), Doumpos and Zopounidis (1999), Kumar and Ganesalingam (2000), Routledge and Gadenne (2000), Zapranis and Ginoglou (2000), Ganesalingam and Kumar (2001), Turetsky and McEwen (2001), Ginoglou, Agorastos

Category	Financial Ratio	Studies
		and Hatzigagios (2002), LeClere (2002), Lizal (2002), Platt and Platt (2002), DeYoung (2003), Charitou, Neophytou and Charalambous (2004), Lensberg, Eilifsen and McKee (2004), Rommer (2004), Beaver, McNichols and Rhie (2005), Hensher, Jones and Greene (2007) and Lamberto and Rath (2008)
Liquidity	Current ratio	Beaver (1966), Beaver (1968a), Edmister (1972), Altman, Haldeman and Narayanan (1977), Dambolena and Khoury (1980), Ohlson (1980), Castagna and Matolcsy (1981), Izan (1984), Frydman, Altman and Kao (1985), Molinero and Ezzamel (1991), Fletcher and Goss (1993), Lee and Urrutia (1996), Lee, Han and Kwon (1996), Ward and Foster (1997), McGurr and DeVaney (1998), Dimitras et al. (1999), Doumpos and Zopounidis (1999), Charalambous, Charitou and Kaourou (2000), Kumar and Ganesalingam (2000), Routledge and Gadenne (2000), Zapranis and Ginoglou (2000), Elloumi and Gueyle (2001), Ganesalingam and Kumar (2001), Turetsky and McEwen (2001), Ginoglou, Agorastos and Hatzigagios (2002), Parker, Peters and Turetsky (2002b), Platt and Platt (2002), Charitou, Neophytou and Charalambous (2004), Lensberg, Eilifsen and McKee

Category	Financial Ratio	Studies
		(2004), Gestel et al. (2006) and Lamberto and Rath (2008)
	Quick ratio	Beaver (1966), Beaver (1968a), Edmister (1972), Dambolena and Khoury (1980), Castagna and Matolcsy (1981), Frydman, Altman and Kao (1985), Keasey, McGuinness and Short (1990), Luoma and Laitinen (1991), Molinero and Ezzamel (1991), Laitinen (1992), Fletcher and Goss (1993), Laitinen (1993a), Laitinen (1993b), Lee, Han and Kwon (1996), Dimitras et al.(1999), Doumplos and Zopounidis (1999), Kumar and Ganesalingam (2000), Ganesalingam and Kumar (2001), Platt and Platt (2002), Charitou, Neophytou and Charalambous (2004), Laitinen (2005) and Gestel et al. (2006)
	Working capital/total assets	Beaver (1966), Altman (1968a), Beaver (1968a), Edmister (1972), Ohlson (1980), Castagna and Matolcsy (1981), Frydman, Altman and Kao (1985), Keasey, McGuinness and Short (1990), Molinero and Ezzamel (1991), Chen and Lee (1993), Lee, Han and Kwon (1996), Tirapat and Nittayagasetwat (1999), Ginoglou, Agorastos and Hatzigagios (2002), Platt and Platt (2002), Yim and Mitchell (2003), Charitou, Neophytou and Charalambous (2004), Jones and Hensher (2004) and Hensher, Jones and Greene (2007)

Category	Financial Ratio	Studies
Leverage	Debt ratio	Beaver (1966), Beaver (1968a), Gordon (1971), Dambolena and Khoury (1980), Ohlson (1980), Castagna and Matolcsy (1981), Zmijewski (1984), Frydman, Altman and Kao (1985), Lau (1987), Gilbert, Menon and Schwartz (1990), Chan and Chen (1991), Molinero and Ezzamel (1991), Hill, Perry and Andes (1996), Lee, Han and Kwon (1996), Dimitras et al.(1999), Doumplos and Zopounidis (1999), Persons (1999), Charalambous, Charitou and Kaourou (2000), Kumar and Ganesalingam (2000), Zapranis and Ginoglou (2000), Elloumi and Gueyle (2001), Ganesalingam and Kumar (2001), Shumway (2001), Turetsky and McEwen (2001), LeClere (2002), Lizal (2002), Parker, Peters and Turetsky (2002b), Platt and Platt (2002), DeYoung (2003), Charitou, Neophytou and Charalambous (2004), Lensberg, Eilifsen and McKee (2004), Beaver, McNichols and Rhie (2005), Rommer (2005), Gestel et al. (2006) and Yu (2006)
Activity	Capital turnover	Molinero and Ezzamel (1991) and Laitinen (1992)
	Total assets turnover	Altman (1968a), Frydman, Altman and Kao (1985), Molinero and Ezzamel (1991), Lee, Han and Kwon (1996), Ward and Foster (1997), McGurr and DeVaney (1998), Parker,

Category	Financial Ratio	Studies
		Peters and Turetsky (2002b), Platt and Platt (2002), Charitou, Neophytou and Charalambous (2004), Jones and Hensher (2004), Lensberg, Eilifsen and McKee (2004), Hensher, Jones and Greene (2007), Lamberto and Rath (2008) and Van der Goot, Van Giersbergen and Botman (2008)

3.3.2 Non-ratio financial data

The literature utilizing non-ratio financial data in predicting financial distress or failure can be classified into two groups, specifically, those studies that employ market-based variables and those that utilize financial statement items.

The relationship between market-based variables and corporate failure or financial distress has been examined in various studies. The significant market variables that have been confirmed by previous studies as explaining financial failure include a firm's market returns, book to market equity (BE/ME), relative market capital size and the standard deviation of stock returns.

Previous studies support the claim that there is a relationship between the market returns and the likelihood of corporate financial distress. For example, Beaver (1968b) described an investigation into the extent to which changes in the market prices of stocks can be used to predict failure. The study observed the dramatic price decline in the final year before failure, and the failed firms are also riskier in terms of the variability of returns as well as default risk.

In addition, Aharony, Jones and Swary (1980) pointed out that corporate bankruptcy that incorporates accounting ratios has little or no definitive theoretical foundation regardless of the success of the models. The authors argued that market data can provide a satisfying theoretical basis for examining corporate bankruptcy. Based on market risk-return measures, the results found both the total variance and the firm-specific variance behave differently for the bankrupt and for the control groups as much as four years before bankruptcy.

Altman and Brenner (1981) assessed the market response to information about problematic firms. The selected companies were tested using a residual methodology in different variants. Although the results were rather ambiguous, it was found that

bankrupt firms experience a consistent deterioration of capital market returns for at least one year prior to bankruptcy.

Similarly, Clark and Weinstein (1983) examined the stock returns behaviour of bankrupt corporations and suggested that there are negative market returns at least three years prior to bankruptcy.

Lindsay and Campbell (1996) used stock returns in developing a bankruptcy prediction model using non linear dynamics or chaos theory. The results showed that the returns of firms approaching bankruptcy exhibit significantly less chaos than at an earlier period.

Mossman et al.(1998) developed a bankruptcy prediction model based on four types of data: financial ratios, cash flow, stock returns and return standard deviation. The Clark and Weinstein (1983) market return model and the Aharony, Jones and Swary (1980) market return variation model were investigated in this study. The study found that the market adjusts stock prices downward as the probability of bankruptcy increases and the returns standard deviation also shows results consistent with expectations. However, these variables do not display a strong discriminatory ability. The results confirm that the usefulness of ratio and cash flow variables is substantial in comparison with the use of market returns in isolation.

Shumway (2001) developed three market-driven variables along with an accounting variables model to identify failing firms based on a simple hazard model. The market variables include a firm's relative market capital size, past excess returns and the idiosyncratic standard deviation of the firm's stock returns. The accounting data employed are the variables used previously by Altman (1968) and Zmijewski (1984). The results found that half of these variables are statistically unrelated to bankruptcy

probability. Shumway argued that a model that incorporates both financial ratios and market-driven variables is better than a model that uses solely financial ratios.

Three market-based variables, namely, cumulative residual returns, standard deviation of security returns and logarithm of the ratio of the market capitalization of the firm divided by the market capitalization of the market index, are employed in Beaver, McNichols and Rhie (2005). The results showed that the market-based variables are a significant factor in predicting bankruptcy even after market-based variables have been combined with financial ratios.

Previous studies, such as Chan and Chen (1991) and Fama and French (1992), argued that a high BE/ME reflects a low stock price relative to book value, which in turn signals a negative market assessment of a firm's prospects and has a negative effect on the likelihood of a distressed firm's survival. Similarly, Fama and French (1995) showed that firms with a high BE/ME have consistently low earnings, higher financial leverage, and more earnings uncertainty, and are more likely to cut dividends compared to their low BE/ME counterparts.

Turetsky and McEwen (2001) also employed the absolute value of BE/ME to reflect the market perception or market risk of a firm. The results suggest that the likelihood of a dividend reduction, which precedes the subsequent stage of financial distress following the decrease in cash flow from the operations, is higher for firms that are perceived by the market to be a greater risk.

Griffin and Lemmon (2002) examined the relationship between BE/ME, distress risk and stock returns. The results found that among firms with the highest distress risk as proxied by Ohlson's (1980) O-score, the difference in returns between high and low BE/ME securities is more than twice as large as that in other firms.

In contrast, Dichev (1998) used the measures of bankruptcy risk proposed by Ohlson (1980) and Altman (1968a) to identify firms with a high likelihood of financial distress. The results found that firms with a high bankruptcy risk earn significantly lower than average returns since 1980 and suggested that bankruptcy risk is not rewarded by higher returns. These results appear to be inconsistent with the view that firms with high BE/ME earn high returns as a premium for distress risk.

In this study, to counter criticism arising from using solely financial ratios, the market-based data, which is the firm's excess returns, are employed in the analysis. This market variable is also incorporated in Shumway (2001).

In addition to market-based variables, previous studies have employed financial data, specifically, financial statements items in examining financial failure; for example, Honjo (2000) assumed that business failure is a function of the financial strength and profitability of new firms. Financial strength is then measured by the capital of new firms. The variable 'capital' is defined as the logarithm of paid up capital. It has been found that a new firm without sufficient capital has a higher risk of business failure.

To develop a bankruptcy prediction model in Norway, Lensberg, Eilifsen and McKee (2004) employed fifteen financial ratios and thirteen non-financial ratio measures of prior auditor's opinion, fraud indicators, the presence of financial stress and company start-up year using a genetic programming model. The variable analysis process reduced the number of variables from twenty-eight to six. Based on these six variables, the results confirm that the most significant variable in the final model is the prior auditor's opinion.

3.4 Non-financial data

Regardless of the success of financial ratio models, there is some criticism of the use of financial ratios in a financial distress prediction model, such as financial ratios being

subject to window dressing (Moses, 1990; Ryan, 1994), the lack of any theoretical foundation to justify the selection of specific ratios (Aharony, Jones and Swary, 1980; Ryan, 1994; Charitou, Neophytou and Charalambous, 2004) and the fact that ratios are historical rather than prospective or *ex-post* in nature (Johnson, 1970; Moses, 1990).

Accordingly, the influences of non-financial data on corporate financial distress have been investigated by researchers. The non-financial data employed in previous literature can be divided into three categories: corporate governance attributes, company-specific variables and macroeconomic variables. The details of each category are discussed as follows.

3.4.1 Corporate governance attributes

Corporate governance mechanisms have received extensive attention in corporate financial distress prediction researches since the occurrence of a series of corporate collapses in the late 1990s (Becht, Bolton and Roell, 2002).

Studies have explored the relationship between corporate governance attributes with corporate performance in various countries, for example, in Australia (Balatbat, Taylor and Walter, 2004), China (Claessens and Djankov, 1999; Xu and Wang, 1999; Hovey, Li and Naughton, 2003; Bai et al., 2004; Li and Naughton, 2007) and the UK (Weir and Laing, 2001). If corporate governance influences corporate performance, then it is expected that corporate governance attributes will affect the likelihood of corporate survival (Goktan, Kieschnick and Moussawi, 2006). The extensive literature has focused on examining corporate governance mechanisms as potential predictors of financial failure as discussed in more detail in the following sections.

1) Board size

The results regarding the influence of board size on corporate survival are inconclusive. On the one hand, it is expected that a company with a larger board size will be less likely to fail as a result of the greater accountability of the directors (Lamberto and Rath, 2008) and the wider range of views and external connections (Pfeffer and Salancik, 1978). Evidence to support this argument is found in an empirical study by Chaganti, Mahajan and Sharma (1985), which found that non-failed retailing firms tend to have bigger boards than failed ones.

On the other hand, some researchers have argued that small boards can improve firm performance while large boards are ineffective because of the coordination and process problems that often exist when there are many people involved in the decision making process (Lipton and Lorsch, 1992; Jensen, 1993).

Results consistent with this argument are found in Beasley (1996), who indicated that board size increases the likelihood of financial statement fraud. Additionally, Yermack (1996) confirmed that board size has a negative relationship with firm value. Furthermore, companies with small boards show more favourable values for financial ratios and provide stronger Chief Executive Officers (CEO) performance incentives due to compensation and the threat of dismissal. Eisenberg, Sundgren and Wells (1998) also suggested there was a negative correlation between board size and probability in a sample of small and mid-size Finnish firms.

However, it should be noted that some of the previous literature found board size was never significantly related to corporate performance (Elsayed, 2007), firm value (Beiner et al., 2003) or corporate survival (Parker, Peters and Turetsky, 2002b; Lamberto and Rath, 2008).

2) Board diversity

Corporate governance researchers argue that board diversity is potentially positively related to firm performance (Smith, Smith and Verner, 2005) and that directors' gender and age are potential ways to create such diversity (Bohren and Strom, 2007). This section reviews the literature that focuses on examining the influence of board gender and age diversity on firm performance. It should be noted that the same influence of board diversity on corporate survival as in corporate performance is expected since higher performance would lead to a higher likelihood of survival.

It is expected that women directors may be better at reflecting the diversity of a firm's customer base and labour pool, and thereby might enhance firm performance (Farrell and Hersch, 2005).

The empirical evidence on the performance effect of board gender diversity is ambiguous. Some studies found a negative relationship between the percentage of female directors and corporate performance; for example, Bohren and Strom (2007) confirmed that female board membership is negatively related to the market-to-book ratio for Norwegian firms.

Various studies suggest a positive relationship between board gender diversity and firm value, for example, Adams and Ferreira (2003), Carter, Simkins and Simpson (2003), Erhardt, Werbel and Shrader (2003) and Smith, Smith and Verner (2005).

Adams and Ferreira (2003) and Carter, Simkins and Simpson (2003) found a positive relationship between the percentage of women on the board of directors and firm value as measured by Tobin's Q. Erhardt, Werbel and Shrader (2003) also confirmed that there is evidence of a positive relationship between the percentage of women and minorities on the boards of directors and firm performance as measured by return on assets and return on investment. Furthermore, Smith, Smith and Verner (2005)

suggested that the proportion of women in top management jobs tends to have a positive effect on firm performance, as measured by four alternative measures.

Some studies report that board gender diversity does not influence corporate performance. For example, examining data from the Wall Street Journal for 200 large firms, Shrader, Blackburn and Iles (1997) found positive relationships between the firms' total percentage of women managers and corporate performance. However, the percentages of women board members are not related to corporate performance. Farrell and Hersch (2005) also reported the insignificant abnormal returns on the announcement date of a woman added to the board. Similarly, Randoy, Thomsen and Oxelheim (2006) suggest that board gender is not significantly related to stock market value or return on assets based on the 500 largest companies from Denmark, Norway and Sweden.

In contrast to the analysis of board gender diversity, the literature that focuses on investigating the effect of the diversity of the age of directors on the board on corporate performance is relatively limited. Bohren and Strom (2007) also point out that age diversity in the board has not been studied in this context.

Bohren and Strom (2007) explored how board composition influences the conflict of interest between principals and agents, the production of information for monitoring and advice, and the effectiveness of the board. Using the standard deviation of board age as a measure of board age dispersion, the authors found that age diversity is not significantly related to corporate performance as measured by Tobin's Q.

3) Board activity

The activity levels of the boards could be observed from the frequency of board meetings. Since the decisions and information announcements are usually made in either board meetings or shareholder general meetings, it is expected that boards that

meet more frequently are likely to be more effective in monitoring the management (Lipton and Lorsch, 1992; Vafeas, 1999). Vafeas (1999) found that a firm's profitability and asset efficiency improve in years when more frequent board meetings follow a period of poor performance.

Similarly, Adams and Mehran (2003) also report that bank holding companies have meetings slightly more frequently than do manufacturing firm boards, and they argue that the number of meetings may influence the bank's choice of directors and potentially affect the quality of directors willing to serve on the boards.

4) Board independence

While the importance of board independence has been generally acknowledged, there is no common consensus relating to the definition of 'independence' (Brennan and McDermott, 2004; Kang, Cheng and Gray, 2007). Some previous studies use the word 'outside directors' instead of 'independent' to describe directors who are presumed to be independent from the management (Ajinkya, Bhojraj and Sengupta, 2005). Some existing studies simply consider the differences between 'executive' and 'non-executive' directors (Kang, Cheng and Gray, 2007; Lamberto and Rath, 2008).

4.1) Percentage of independent directors

Due to the limited information company directors disclose to external stakeholders, studies exploring director independence face difficulties when comparing definitions of director independence from one company to another (Kang, Cheng and Gray, 2007). For the purpose of this study, all non-executive directors are classified as 'independent directors'. This is consistent with the definition used in Lamberto and Rath (2008).

Based on agency perspective, Fama and Jensen (1983) suggest that if the majority of directors in the board are independent directors, then the opportunity for the CEO and

inside directors to exercise behaviours that are self-serving and costly to the firm's owners will be reduced.

Executive directors are responsible for the day-to-day management of the company. Since executive directors are subordinate to the CEO, it is expected that executive directors are not in a strong position either to monitor or discipline the CEO (Daily and Dalton, 1993).

Non-executive directors are appointed on a part-time basis and it is assumed that the interests of shareholders will be safeguarded by non-executive directors who can exercise independent judgment. In addition, non-executive directors can contribute valuable external business expertise to the business, and can often see risks and opportunities for the company that might have been overlooked by the company's executive directors who are typically immersed in the day-to-day running of the business (Pass, 2004).

Various studies have examined the relationship between the proportion of non-executive directors and corporate performance. The expectation is that a higher proportion of non-executive directors in the board leads to better corporate performance and consequently, a higher probability of corporate survival. Previous literature that found evidence supporting this expectation, for example, Rosenstein and Wyatt (1990), suggested that the announcement of a non-executive director appointment in the board leads to positive excess returns. Similarly, Daily and Dalton (1994) found that firms with lower proportions of independent directors are significantly associated with bankruptcy. Further evidence supporting the importance of outside directors can be found in Beasley (1996), who reported that no-fraud firms have boards with significantly higher percentages of outside directors than have fraud firms.

However, Hermalin and Weisbach (1991), Yermack (1996) and Klein (1998) found a negative relationship between the proportion of outside directors and corporate performance. Furthermore, some studies found no relationship between the proportion of non-executive directors and corporate performance, for example, Vafeas and Theodorou (1998), Laing and Weir (1999), Bhagat and Black (2001) and Balatbat, Taylor and Walter (2004).

4.2) Non-executive chairman

The chairman is responsible for leadership of the board, for the efficient organization and conduct of the board's function and for the briefing of all directors in relation to issues arising at board meetings (ASX, March 2003). A board led by an independent leader will better represent the interests of the shareholders and more effectively monitor the management of the company.

An independent non-executive chairman is more likely to provide an objective opinion on proposals, be a more effective decision monitor and be more likely to promote shareholder interests (Weir and Laing, 2001). Accordingly, it is expected that the presence of a non-executive chairman in the board will lead to higher corporate performance and a higher likelihood of survival. However, on the contrary, Boyd (1995) claims that an executive chairman would be expected to have greater knowledge of a firm and its industry and have greater commitment to the organization than would an external or non-executive chairman.

4.3) Dual leadership structure

A dual leadership structure, or CEO duality, exists when a firm's CEO also serves as a chairman of the board of directors. If different individuals serve in these positions, then the term 'independent structure' is used.

The evidence regarding the effect of CEO duality on corporate performance is mixed (Arthur et al., 1993; Pi and Timme, 1993). Some studies, for example, Fama and Jensen (1983), Rechner and Dalton (1991), Jensen (1993) and Daily and Dalton (1994) argue that a board on which the chairperson and CEO are the same person is ineffective because the CEO duality structure reduces the board's ability to fulfil its governance function and this might constitute a clear conflict of interest. In contrast, advocates of the CEO duality structure argue that it provides a single, clear focus for objectives and operations (Rechner and Dalton, 1991).

It should be noted that Elsayed (2007) found CEO duality has no impact on corporate performance. However, CEO duality attracts a positive and significant coefficient only when corporate performance is low. Furthermore, Brickley, Coles and Jarrell (1997) claimed that proponents of the dual leadership structure base their arguments on a mix of anecdotal evidence and an intuitive appeal to common sense. The authors suggested that there are both costs and benefits involved in using a dual leadership structure. This structure may create a potential for rivalry between the CEO and the chairperson, making it difficult to pinpoint the blame for poor performance.

5) CEO quality

The CEO is an executive of the highest level in the firm with the responsibility to provide leadership and strategic directions for the firm. It is expected that higher quality CEOs are likely to produce higher returns for shareholders, and consequently, decrease the probability of failure.

The quality of decision making by management depends on their capabilities and visions (Rotemberg and Saloner, 2000). These capabilities are derived from the experience and education of members of the management team.

Prior studies have used two variables to measure the quality of the CEO: the length of CEO tenure and the CEO's formal education. CEO tenure is the number of years that the current CEO has been in that position with the company. Shekhar and Stapledon (2007) report that the average CEO tenure in Australian IPO companies during 1996 and 2001 was 7.02 years. It is expected that the length of CEO tenure is positively related to an IPO company's survival, as a CEO who has not performed well can be removed from the position by existing shareholders.

Furthermore, Bates (1990) suggested that the owner's educational background is a major factor of small business failure. The study reported that the higher the entrepreneur's level of education, the less likely the firm is to fail. If formal education is the means for developing human capital, then it can be expected that a CEO with a higher level of formal education will enhance the survival likelihood of an IPO company.

6) CEO compensation structure

Critics of CEO compensation practices argue that since the board of directors is influenced by the CEO, the board does not structure the CEO compensation package to maximize value for outside shareholders (Core, Holthausen and Larcker, 1999).

Mehran (1995) provided evidence supporting advocates of incentive compensation and suggested that firm performance is positively related to the percentage of equity held by managers and to the percentage of their compensation that is equity-based.

In contrast to Mehran (1995), Core, Holthausen and Larcker (1999) suggested that CEOs earn greater compensation when governance structures are less effective and the predicted component of compensation has a statistically significant negative relation to subsequent firm operating and stock return performance.

7) Ownership concentration

Based on the information asymmetry theory, when stockholdings are concentrated, information asymmetries are low, so the ability of stockholders to remove a management team is high and managers are more likely to pursue strategies that are in stockholders' interests. In contrast, when stockholdings are diffused, significant information asymmetries are likely to exist and management is then more likely to pursue strategies inconsistent with stockholders interests (Hill and Snell, 1989).

Based on agency theory, a firm is more likely to survive if ownership concentration is high. This is because shareholders are more likely to have an influence on management's decisions and shareholders will want to expend monitoring costs as their stake in the firm is relatively high (Jensen and Meckling, 1976). Therefore, high ownership concentration is expected to increase corporate performance and, consequently, corporate survival. Investigating publicly listed Chinese companies, Bai et al. (2004) found that a high degree of concentration among other large shareholders enhanced a firm's market value.

In contrast, Woo, Jeffrey and Lange (1995) found that low ownership concentration is related to corporate longevity. Kang, Cheng and Gray (2007) also suggested that ownership concentration is significantly negatively associated with an independent board of directors. This may imply that lower ownership concentration leads to a higher probability of firm survival.

However, using three measures of ownership structure, that is, the percentage of shares owned by the five largest shareholders, the 20 largest shareholders and the Herfindahl index, Demsetz and Lehn (1985) found that corporate ownership concentration is not related to the accounting profit rates of a company. Consistent with

Demsetz and Lehn (1985), Hovey, Li and Naughton (2003) also indicated that ownership concentration does not explain firm performance in China.

It can be seen that the conclusion regarding the effect of ownership concentration on firm survival is unclear. In this study, ownership concentration is measured by the proportion of common stock held by the top 20 shareholders. This measurement is consistent with the studies discussed above.

In this thesis, the influence of various corporate governances on corporate survival focusing on new economy IPO companies will be empirically examined in Chapter 6.

3.4.2 Company-specific variables

This section reviews the company-specific variables, for example, company size, age and industry sector used in the existing literature.

1) Company size

To examine the effect of company size on bankruptcy or financial distress, researchers measure company size in various ways, for example, total assets (Lamberto and Rath, 2008), the logarithm of total assets (Lizal, 2002; Parker, Peters and Turetsky, 2002b; Lensberg, Eilifsen and McKee, 2004; Rommer, 2004; Rommer, 2005; Gestel et al., 2006), the natural logarithm of total assets (Hensher, Jones and Greene, 2007), the logarithm of sales (Laitinen, 1992), the natural logarithm of sales (Chen and Lee, 1993; Hill, Perry and Andes, 1996) and the number of employees (Audretsch and Mahmood, 1995; Lennox, 1999; Audretsch and Lehmann, 2004; Kauffman and Wang, 2007).

In this study, the natural logarithm of sales is used as the proxy for the size of the company. To test for a nonlinear relationship between company size and the likelihood of financial distress, the square of company size is also included in the analysis in

Chapters 4 and 5. In addition, the influence on survival likelihood of an IPO company's size as measured by the logarithm of total assets is also examined in Chapter 6.

According to Rommer (2004), there are two hypotheses regarding the effect of size on the probability of entering financial distress. The first hypothesis suggests that the effect of firm size on the likelihood of financial distress is nearly U-shaped. Small firms have a higher probability of entering financial distress because they are not so resistant to the shocks they might encounter and large firms have a high probability of entering financial distress because they might have inflexible organizations, problems with monitoring managers and employees and difficulties with providing efficient intra-firm communication. The second hypothesis is that the probability of financial distress is a decreasing function of firm size.

Some of the literature supports the claims of a negative relationship between firm size and the likelihood of financial distress, for example, Altman, Haldeman and Narayanan (1977), Ohlson (1980), Audretsch and Mahmood (1995), Lennox (1999), Nikitin (2003), Lensberg, Eilifsen and McKee (2004) and Hensher, Jones and Greene (2007).

However, Altman, Haldeman and Narayanan (1977) found that company size is one of seven significant variables out of an initial twenty-seven variables in the MDA model. Ohlson (1980) concluded that company size is an important predictor of bankruptcy in all three models tested based on logit analysis and found company size had a negatively significant effect on the probability of failure within one year. Similarly, Audretsch and Mahmood (1995) confirmed that the start-up size of the company is negatively related to new firm failure. Furthermore, Lennox (1999) examined the causes of bankruptcy for UK-listed companies and demonstrated that a

small company is more likely to fail than is a large company. Nikitin (2003) also found establishment size is one of the major determinants of business survival in Indonesia.

Lensberg, Eilifsen and McKee (2004) utilized firm size in a developing bankruptcy prediction model in Norway. The results suggest that the bankruptcy risk is negatively related to firm size except when profits are negative, and an unfavourable audit report has a more negative bankruptcy status impact for a big firm than for a small one.

After examining financial distress in the four-state failure framework, Hensher, Jones and Greene (2007) suggested that larger firms have a lower probability of outright failure, but have a higher probability of entering a distressed merger.

Some financial failure studies found a positive relationship between company size and the probability of financial distress, for example, Laitinen (1992) found a negative coefficient of firm size in the multivariate discriminant model, which implies that large size means a company is more likely to fail.

Parker, Peters and Turetsky (2002b) indicated that company size is positively associated with bankruptcy likelihood. The results suggest that larger distressed firms are more likely to go bankrupt as they have greater difficulty in maintaining ongoing operations during periods of financial distress. This result is consistent with Lamberto and Rath (2008), which also suggested that the size of the firm is found to be negatively related to survival.

Some studies report inconclusive empirical results regarding company size; for example, in exploring the determinants of corporate endurance in the oil and gas industry, Chen and Lee (1993) found company size to be a significant factor in bankruptcy prediction analysis. However, the efficient sign of size is inconclusive since different estimated signs were produced when using different methods of variable

selection. Size has a negative sign in models when all variables are included in the analysis, but the sign is positive when stepwise reduction is used. Both results indicated size is a significant factor in explaining bankruptcy at the 1 percent level.

Additionally, Rommer (2005) compared the determinants of financial distress across countries, namely, Italy, France and Spain. Company size is expected to have a significantly negative affect on financial distress. The estimations show that size was an insignificant factor of corporate financial distress in the Spanish case. In the Italian case, size had positive effect while, in the French case, size had the expected sign.

It should be noted that some of the previous studies have not found that company size is significantly related to the likelihood of financial distress; for example, Turetsky and McEwen (2001) examined the relationship between firm size and financial distress and the results showed that size is not significant. This is consistent with Yu (2006), which found that a credit cooperative's size, in terms of total assets relative to those of the local market, did not have a significant effect on the bankruptcy hazard.

2) Company age

In addition to company size, company age is another company-specific variable suggested by the literature that might significantly affect the likelihood of corporate failure. For example, Chen and Lee (1993) investigated the survival of oil and gas companies during the turmoil of the early 1980s and found that company age, which was measured by the number of years the firm had existed up to the end of 1981, was negatively related to corporate failure.

Lensberg, Eilifsen and McKee (2004), when developing their bankruptcy model for Norwegian companies, provided evidence that younger companies have a substantially higher bankruptcy rate than have more established companies.

In developing a four-state failure model based on the error component logit analysis, Hensher, Jones and Greene (2007) defined company age as a dummy variable coded 1 if a firm had been established in the previous six years, and coded 0 otherwise. The finding was that if a firm has been in existence six years or less, the probability of outright failure increases.

Comparing the determinants of financial distress across countries, namely, Italy, France and Spain, company age is expected to have a significantly negative effect on financial distress, according to Rommer (2005). However, the study offers inconclusive results. Specifically, company age was an insignificant predictor of financial distress for Spanish company, had the expected sign in the Italian case and had an unexpected sign based on the French data.

Furthermore, some studies argue that company age and corporate financial failure have a non-linear relationship. For example, Rommer (2004) points out that the effect of age on firms' exit is bell-shaped. When firms are young, they have not yet learned their own potential and the probability of exit is low. As time passes, the firms learn about their own profitability potential and the firms either expand, contract or exit the business.

Similarly, Li, Zhang and Zhou (2005) explored the determinants of firm survival in China's economic transition and found that company age had an inverted U-shaped effect on firm exit.

In this study, the number of years since registration is used as the proxy for company age to test whether the company-specific variable of age is a useful factor in predicting the probability of corporate endurance. Additionally, in Chapter 6, which focuses on the analysis of the survival of new economy IPO companies, the effect of company age on the likelihood of survival when going public is also examined.

3) Company industry sector

Another company-specific variable investigated by the previous literature is industry sector. For example, Mata and Portugal (1994), in examining the survival duration time of Portuguese firms, provided evidence that corporate survival rates differ extensively across industry sectors.

Hensler, Rutherford and Springer (1997) investigated the indicators of IPO firms' survival and found that the survival of American firms varies with industry sector. Specifically, the survival time is negatively affected if the IPO firm is in the computer and data, wholesale, restaurant or airline industries and positively affected if the IPO firm is in the optical or drug industries.

Similar results were found in Lennox (1999), which reported that company industry sector is an important predictor of bankruptcy. Specifically, companies in the construction or financial services are more likely to enter bankruptcy. Rommer (2004) also confirmed that the probability of financial distress varies between different business sectors. The results found that firms in the trade and hotel, transport, business, and public service activities and organizations are less likely to face financial distress compared to manufacturing firms while firms that belong to the self-constructed IT and telecommunications category have a higher financial distress likelihood than all other firms. In addition, Hensher, Jones and Greene (2007) indicated that firms in the finance sector have a higher standard deviation or variance of excess market returns and lesser standard deviation or variance of cash resources to total assets than have firms from the non-finance sector. Examining IPO companies' survival in Australia, Lamberto and Rath (2008) also confirm that firm survival varies across industry sector; for example, firms in the natural resource or finance industries are more likely to survive than are IPO companies in other sectors.

3.4.3 Macroeconomic variables

Bankruptcy prediction models incorporating financial ratios, non-ratio financial data, corporate governance and company-specific variables have been discussed in previous sections. These could be categorized as micro-bankruptcy models (Rose, Andrews and Giroux, 1982). Firms might have a higher likelihood of failing during an economic recession than during a period of economic prosperity; therefore, it seems reasonable that macroeconomic factors also are helpful predictors of corporate failure (Rose, Andrews and Giroux, 1982).

Rose, Andrews and Giroux (1982) evaluated the relationship between macroeconomic factors and business failures. Four groups of business cycle indicators, that is, leading and coincident indicators, supply (cost-push) theories, monetary theories and saving-investment theories, are utilized. Variables presenting all four categories are included in the final six-variable model incorporating lead-lag relationship. The authors conclude that economic conditions influence business failure.

Additionally, Audretsch and Mahmood (1995) examined the link between the business cycle and the exposure to risk by including the macroeconomic variables of unemployment rate and the real interest rate in the analysis. The results suggest that hazard rates are influenced by the unemployment rate. Specifically, the hazard rate for new establishments tends to be greater during periods of high unemployment or macroeconomic downturns.

Hill, Perry and Andes (1996) also confirmed the importance of the prime rate and unemployment rate in explaining the failure process. Consistent with their results (1996), Everett and Watson (1998) also found interest rates and unemployment rate positively associated with small business failure.

In addition, Tirapat and Nittayagasetwat (1999) incorporated the CAMEL categories and macroeconomic factors including monthly changes in the production manufacturing index, consumer price index, interest rates and M2 money supply in the investigation of financially distressed firms in Thailand. The authors found that the sensitivity of firms to economic conditions plays a major role in differentiating the financially distressed companies from the non-distressed ones.

Raj and Rinastiti (2002) examined the failed banks in Asia during the 1997 Asian crisis in order to identify the causes and develop bank failure prediction models. Several macroeconomic variables were utilized including the country's political risk, GNP, international reserve, export, import, the central bank's foreign reserve and the local currency exchange rate to USD. The results suggest that larger size banks that have holding company affiliation and reside in low political risk countries that have a stable exchange rate are less likely to fail; the results additionally show that large size banks that reside in a high GNP country that has a stable exchange rate will have a lower survival rate.

To study the impact of macroeconomic conditions on business exit, bankruptcy and acquisition, macroeconomic activity and macroeconomic instability are included in the study by Bhattacharjee et al. (2004). The results show that adverse macroeconomic conditions increase bankruptcy hazard while at the same time decreasing acquisition hazard.

Finally, Porath (2004) analysed the impact of macroeconomic information for forecasting a bank's defaults. The results show that macroeconomic information significantly improves the default forecasting for German banks.

3.5 Conclusion

The main categories of bankruptcy and financial distress predictors include financial data and non-financial data. The bankruptcy literatures that employ financial data predictors can be further classified into those studies that use financial ratios and those that use non-ratio financial data. Various studies have utilized statistical techniques with financial ratios in examining corporate bankruptcy or financial distress since the late 1960s.

Researchers also acknowledge the usefulness of non-ratio financial data in explaining the likelihood of corporate failure. Those non-financial ratios include market-based variables, for example, stock returns, stock return variations and financial statement items, for example, capital item.

Since there are criticisms relating to the nature of financial data, for example, the issue of window dressing, the lack of any theoretical framework for guiding the variable selection and the *ex-post* nature of financial statements, the bankruptcy or financial distress prediction models comprising solely financial data have been questioned by some researchers.

Researchers have argued that non-financial data could also be useful predictors in explaining financial distress. Three categories of non-financial data, namely, corporate governance variables, company-specific variables and macroeconomic variables, have been examined in the bankruptcy literature.

Based on the extensive review in this chapter, it should be noted that various previous studies have incorporated both financial data and non-financial data in developing financial distress prediction models.

The usefulness of financial ratios as predictors of financial distress controlling for market-based and company-specific variables will be examined based on the Cox

proportional hazards model and the competing risks model in Chapters 4 and 5 respectively. Then, Chapter 6 will focus on the empirical investigation regarding the influence of corporate governance mechanisms on new economy IPO companies' survival.

CHAPTER 4

EXAMINING FINANCIALLY DISTRESSED COMPANIES: THE COX PROPORTIONAL HAZARDS MODEL

4.1 Introduction

Interest in corporate financial distress studies has grown rapidly in recent years with the global increase in the number of corporate collapses. The need for such research is obvious due to the indirect and direct costs involved when a financially distressed company goes bankrupt. The purpose of this chapter is to identify the probability of corporate survival in a given time frame and to examine the relationship between financial ratios, other variables and corporate financial distress.

Australia has also experienced a series of corporate collapses since the early 1990s. Notable failures include HIH Insurance, One.Tel, and Ansett Airlines in 2001, and most recently FIN Corp in 2007. The collapse of HIH entailed huge individual and social costs. The deficiency of the group was estimated to be between \$3.6 billion and \$5.3 billion, 200 permanently disabled people were left with no regular income payments, retirees with superannuation in HIH shares saw their investment disappear and several non-profit organizations were liquidated by the collapse (Commonwealth of Australia, 2003). The collapse of HIH entailed huge individual and social costs, as the HIH group comprised several insurance companies and was a major provider of all types of insurance in Australia (Leung and Cooper, 2003). Many of these types of costs can be avoided if financially distressed companies can be identified well before failure and estimates made of their survival probability within a given time frame.

Previous studies of corporate financial distress prediction have used a variety of methodologies such as univariate analysis, MDA, probit and logit analysis and ANN.

While often effective in predicting ultimate corporate failures, these approaches provide little analysis or insight into the dynamics of corporate failure. As static predictors, they assume a steady state progression of financial distress and omit ‘time to failure’ as an integral factor in corporate distress analysis. While these models estimate a broad prediction of likely corporate failure, they do not allow estimation of survival probabilities or the ‘time to corporate failure’.

To overcome these shortcomings, this study uses the Cox proportional hazards form of survival analysis as a diagnostic tool for estimating the survival probabilities of financially distressed firms and for identifying significant signs or symptoms of such firms. In particular, this study focuses on examining financial distress in Australia. A sample of 1,117 publicly listed Australian companies is examined over the period 1989 to 2005. The Cox proportional hazards model with time-varying variables including financial ratios, a market-based variable and company-specific variables is estimated.

This study differs from previous studies in a number of aspects. First, unlike previous studies, this study uses time-varying variables in the Cox proportional hazards model rather than merely using time-invariant variables as in Luoma and Laitinen (1991) and Henebry (1996; 1997). This feature allows for deterioration in the variables of financial ratios, market-based data and company-specific variables over time, since it is unlikely that their values or effects would remain constant during the progression of the corporate failure process (Luoma and Laitinen, 1991). LeClere (2005) suggested that the potential proportional hazards models with time-varying variables outperforms proportional hazards models with time-invariant variables since it allows testing of the sensitivity of the proportional hazards model to the choice of variable time-dependence in financial distress application.

Second, multiple sets of determinants of financial distress are included rather than just one set as was common in previous studies. For example, Hill, Perry and Andes (1996), Ward and Foster (1997), DeYoung (2003), Nikitin (2003) and Laitinen (2005) used only financial ratios as financial distress predictors; while Altman (1969), Aharony, Jones and Swary (1980), Altman and Brenner (1981), Borenstein and Rose (1995) and Fama and French (1995) used only market-based variables. A combination of financial ratios, market-based data and company-specific variables in the Cox proportional hazards model is able to analyse dynamically the potential influence of these variables on financially distressed Australian firms.

Finally, a limited numbers of studies, including Crapp and Stevenson (1987) and Peat (2007), employ survival analysis to examine financial distress in an Australian context. Furthermore, the existing literature in Australia did not employ time-varying variables, while this study will estimate the corporate survival probability within a given time frame and provide the corporate survival profile evaluation.

The results show that the Cox proportional hazards model can provide meaningful estimates of corporate survival probabilities within a given time frame. Empirical results also support the effectiveness of financial ratios, market-based variables and company size as potential predictors of financial distress. Financially distressed companies appear to exhibit higher leverage ratios, lower historic excess returns and a larger size than active companies. There is no evidence to support the significance of company age as a predictor of the probability of corporate failure.

The remainder of this chapter is organized as follows. The next section reviews the survival analysis application and financial distress predictors used in previous studies. Consequently, the theoretical and empirical literatures are discussed in Section 4.3 in developing the research hypotheses corresponding to the research questions.

Section 4.4 then describes the background and concept of survival analysis techniques and the Cox proportional hazards model. The data and sample utilized in the analysis are discussed in Section 4.5. The empirical results are presented and discussed in Section 4.6. The implications of the results are also presented in this section. The conclusions, limitations of the analysis and possible future extensions are discussed in Section 4.7.

4.2 Literature review

4.2.1 Survival analysis application

Survival analysis techniques form the basis of a number of studies in financial distress areas in the context of various studies. For example, in the USA, using Cox regression model to identify the performance of new USA companies after entering the business, led Audretsch and Mahmood (1995) to conclude that the likelihood of a new business surviving is shaped not only by the underlying technological conditions but also by business specific characteristics, such as ownership status and size. Henebry (1996) used the Cox proportional hazards model to determine whether adding cash flow information would improve current bank failure prediction methods. Wheelock and Wilson (2000) utilized a competing risks hazards model to identify the characteristics that make individual USA banks more likely to fail or to be acquired. Shumway (2001) compared a hazard model to a static model by employing Altman's 1968 variables, Zmijewski's 1984 variables and market-driven variables for 300 bankrupt companies in the USA context. The author found that combining market-driven variables with accounting ratios provided a more accurate model. DeYoung (2003) used a split-population model to examine failure patterns and failure determinants for new banks in the USA and suggested that the financial performance of the typical de novo bank follows a life cycle pattern. Partington et al. (2006) utilized the Cox proportional

hazards model to predict the duration of Chapter 11 bankruptcy and the payoff to shareholders. These studies show the potential of survival analysis techniques as a methodology in predicting corporate failure.

In European countries, Luoma and Laitinen (1991) used the Cox proportional hazards model to consider the application of survival analysis in predicting the failure of Finnish industrial and retailing companies and to compare the results with MDA and the logistic model. However, the study shows that the classification result of survival analysis is outperformed by MDA and the logistic model. Rommer (2004) utilized a competing risks model to predict the Danish firms that end up in financial distress. Types of exit are divided into financial distress, voluntary liquidation and merger or acquisition. The results show that it is important to distinguish between exit types. Consequently, Rommer (2005) compared the financial distress predictors between French, Italian and Spanish companies using a competing risks model. Other corporate failure studies, such as Prantl (2003), Bhattacharjee et al. (2004), Porath (2004) and Laitinen (2005), used survival analysis techniques in the context of European countries.

There are a few studies that investigate corporate financial distress utilizing survival analysis in the Asian context. For example, Honjo (2000) employed a multiplicative hazards model to investigate the business failure of new firms in the Japanese manufacturing industry whereas Raj and Rinastiti (2002) used the Cox proportional hazards model to examine the failed banks in Asia during the 1997 Asian crisis.

Some of the previous corporate failure or bankruptcy studies focused the analysis on a specific industry sector. Chen and Lee (1993) focused their study on the oil and gas industry using the Cox proportional hazards model. Similarly, Lee and Urrutia (1996)

scoped the analysis in a specific industry, that is, the property liability insurance industry.

In Australia, Crapp and Stevenson (1987) included financial ratios and economic influences but omitted market-based data and limited the sample to New South Wales Credit Unions in the banking sector, whereas the sample in this current study includes market-based data as a variable and covers all publicly listed Australian companies. These features provide an expanded application of the dynamic diagnostic tool, which extends the literature regarding corporate financial distress.

Most recently, Peat (2007) used the Cox regression model to examine public Australian companies covering the period 1966 to 1994. While the study made a contribution by introducing a new ‘managerial decision-based approach’ in order to provide an explicit economic basis for selecting the variables for inclusion in a bankruptcy prediction model, Peat did not estimate any corporate survival probability within a given time frame.

4.2.2 Financial distress predictors

According to Hossari and Rahman (2005), empirical investigations of corporate failure can be classified into two categories, that is, the studies that do not utilize financial data and those that do utilize financial data; the latter can be further classified into those that utilize non-ratio financial data and those that utilize financial ratios in modelling corporate collapse.

The use of financial ratios to predict corporate failure or bankruptcy has been well established since the original study by Beaver (1966). Most of the empirical research in this area has used financial ratios and has been successful in discriminating between failed and non failed firms. Regardless of the success of financial ratio models, there is

criticism of the use of financial ratios due to the issue of window dressing. In other words, the firm may use creative accounting to show better financial figures.

To overcome the criticism arising from the use of solely financial ratios in examining a financially distressed company, this study additionally analyses the influence of market-based data on firm survival over time.

A number of studies have employed market data to analyse corporate bankruptcy; for example, Aharony, Jones and Swary (1980) found differences in the behaviour of total and firm-specific variances in returns four years before formal bankruptcy was announced. Altman and Brenner (1981) suggested bankrupt firms experience deteriorating capital market returns for at least a year prior to bankruptcy. Similarly, Clark and Weinstein (1983) suggested that there are negative market returns at least three years prior to bankruptcy. Other studies, such as Mossman et al. (1998), Shumway (2001) and Turetsky and McEwen (2001) also supported the view that there is a relationship between the market-based data and the likelihood of corporate financial distress.

Additionally, company-specific variables, including company age, company size and squared size, are also employed in the study. Previous studies suggest that a company's age and size affect its endurance. Younger or smaller firms are more likely to fail than are established or bigger firms as they do not have sufficient experience in the business, have limited number of business connections and have limited information. Larger firms are expected to manage better and be more protected from financial distress (Audretsch and Mahmood, 1995; Honjo, 2000).

In addition, according to Rommer (2004), there are two hypotheses regarding the effect of size on the probability of entering financial distress. The first hypothesis suggests that the effect of firm size on the likelihood of financial distress is nearly U-

shaped. Small firms have a higher probability of entering financial distress because they have to adapt themselves to the new business environments while large firms have a high probability of entering financial distress because they suffer from inflexible organizations, problems with monitoring managers and employees and difficulties with providing efficient intra-firm communication. The second hypothesis is that the probability of financial distress is a decreasing function of firm size.

The natural logarithm of sales is used as the proxy for company size. This definition of company size is consistent with Chen and Lee (1993) and Hill, Perry and Andes (1996). To test for a nonlinear relationship between company size and the likelihood of financial distress, the square of company size is also included in the analysis. The number of years since registration is used as the proxy for company age to test whether company age is a useful factor in predicting the probability of corporate endurance.

4.3 Hypotheses development

The main explanatory variables used in this study are financial ratios. The usefulness of financial ratios as predictors of corporate financial distress is explored. Additionally, the relationship between corporate survival and control variables, including a market-based variable and company-specific variables, is investigated in this study.

4.3.1 Financial ratios

A financial ratio is 'a quotient of two numbers, where both numbers consist of financial statement items' (Beaver, 1966). Financial ratios are tools for the analysis of a firm's operational success and financial health and have been found useful for analysts in making predictions about the future success of a company. Numerous studies have employed financial ratios to predict corporate failure, for example, Beaver (1966),

Altman (1968a), Edmister (1972), Libby (1975), Altman, Haldeman and Narayanan (1977), Ohlson (1980), Lau (1982), Bongini, Ferri and Hahm (2000), Routledge and Gadenne (2000), Catanach and Perry (2001) and Rommer (2005). However, the use of financial ratios in predicting business failure admittedly lacks any theory that could guide the selection of financial ratios to be entered in a failure model (Ball et al., 1982; Gilbert, Menon and Schwartz, 1990; McGurr, 1996).

In the absence of theoretical foundations for selecting the financial ratios in a failure model, previous studies have employed statistical techniques to reduce the initial large set of financial ratios variables to be incorporated into the final model.

Although the results regarding the significant financial ratios are inconclusive, since each study reported different financial ratios as the significant indicators of financial distress, the specific ratios that have been identified as measuring specific aspects of a firm's operations can be generally categorized into four groups, namely, leverage or solvency ratios, liquidity ratios, profitability ratios and activity ratios (Brigham and Gapenski, 1994).

Accordingly, this study focuses on examining four main categories of financial ratios in explaining financial distress. A number of research hypotheses relating to the research questions specified in Chapter 1 are presented and described as follows.

1) Profitability ratio

Research hypothesis #4.1: A company with high profitability is less likely to enter financial distress.

Profitability ratios measure the ability of a company to generate earnings. The more earnings a company can generate, the greater the increase in funds and liquidity. Many firms face financial distress when they have negative earnings (Khunthong, 1997).

Therefore, it is expected that a high profitability company is less likely to face financial distress.

To test this hypothesis, three measures of profitability ratios, including EBIT margin, return on equity (ROE) and return on assets (ROA), are employed in the model.

2) Liquidity ratio

Research hypothesis #4.2: A company with high liquidity is less likely to enter financial distress.

Liquidity ratios measure a company's ability to pay off its short term debt obligations. This is done by comparing a company's liquid assets to its short term liabilities. In general, the greater the proportion of liquid assets to short term liabilities the better, as it is a clear signal that a company can pay the debts that are coming due in the near future and still fund its ongoing operations. On the other hand, a company with a low coverage rate should raise a red flag for investors, as it may be a sign that the company will have difficulty meeting its running operations, as well as meeting its obligations. Most firms face financial difficulties after suffering illiquidity problems (Khunthong, 1997). Therefore, it is hypothesised that a company with low liquidity is more likely to fail.

To test this hypothesis, three types of liquidity ratios, for example, current ratio, quick ratio and working capital to total assets ratios, are utilized in the model.

3) Leverage ratio

Research hypothesis #4.3: A company with a high level of financial leverage is more likely to enter financial distress.

Leverage ratios measure the long term solvency of a company. The analysis of financial leverage is concerned with the capital structure of the firm. These ratios show the origin

of funds provided from external sources to the benefit of the shareholders. The ratios have been used to examine a company's ability to pay long term liabilities (Khunthong, 1997). The expectation is that a company with high financial leverage is more likely to enter financial distress.

To test this hypothesis, the leverage ratio measured by debt ratio is used in the analysis. The debt ratio compares a company's total debt to its total assets; this is used to gain a general idea of the amount of leverage being used by a company. A low percentage means that the company is less dependent on leverage. The lower the percentage, the less leverage a company is using and the stronger its equity position. In general, the higher the ratio, the greater the risk a company is considered to have taken on.

4) Activity ratio

Research hypothesis #4.4: A company with high activity ratios is less likely to enter financial distress.

Activity ratios measure the ability of a company to utilize its assets to generate revenues or returns (Khunthong, 1997). A company with high efficiency in assets utilization is expected to earn more revenues and net incomes. Consequently, the company is less likely to face financial difficulties.

To test this hypothesis, two activity ratios, that is, assets turnover ratio and capital turnover ratio, are employed in the model.

4.3.2 Market-based variable

In addition to traditional financial ratios, various financial distress studies suggest the potential of market-based variables as predictors of financial distress. The market variables have been suggested by previous studies as significant indicators of financial

failure, for example, stock returns (Beaver, 1968b; Clark and Weinstein, 1983; Lindsay and Campbell, 1996; Mossman et al., 1998), the returns standard deviation (Mossman et al., 1998; Shumway, 2001; Beaver, McNichols and Rhie, 2005) and the book to market equity (BE/ME) (Turetsky and McEwen, 2001; Griffin and Lemmon, 2002).

To counter any criticism arising from the use of solely financial ratios, this study further incorporates a market-based variable in addition to financial ratio variables to examine corporate financial distress. The research hypothesis is set as follows.

Research hypothesis #4.5: A company with high past market returns is less likely to enter financial distress.

To test this hypothesis, a company's past excess returns are included in the Cox proportional hazards model. In general, this process follows Shumway (2001). Shumway (2001) used two market-driven variables including a firm's past excess returns or market-adjusted returns and the idiosyncratic standard deviation of a firm's stock returns in forecasting bankruptcy. The hazard model results indicate that when using market variables only, both of the market driven data are highly significant; 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 quite consistent with Mossman et al. (1998). According to Mossman et al. (1998), for a 12 month period, the only significant variable is market-adjusted returns but this is not true for the returns standard variation in a bankruptcy prediction model.

4.3.3 Company-specific variables

The existing literature has examined the company-specific variables, for example, company age and size in predicting corporate endurance.

According to the Industrial Organization (IO) literature, a firm can survive when the revenues are large enough to cover the costs (Jovanovic, 1982; Hopenhayn, 1992; Cooley and Quadrini, 2001). Since business entry is associated with sunk costs, young and small firms have to spend a huge amount of financial resources for investment in the market. To survive in the market, these companies have to grow and attain a minimum size that allows them to compete in the market (Audretsch and Lehmann, 2004).

This study additionally analyses the relationship between company-specific variables and corporate financial distress as indicated in the following research hypotheses.

1) Company size

Research hypothesis #4.6: Company size significantly affects the likelihood of corporate financial distress.

Previous literature confirms the significance of company size in explaining corporate failure; however, the results are mixed. On the one hand, it is expected that a small company is more likely to fail because of inadequate experience in the market, limited connections and limited financial resources compared to a larger company (Audretsch and Mahmood, 1995; Honjo, 2000). Previous studies confirm the negative relationship between firm size and the likelihood of corporate financial distress, for example, Altman, Haldeman and Narayanan (1977), Ohlson (1980), Audretsch and Mahmood (1995), Lennox (1999), Nikitin (2003), Lensberg, Eilifsen and McKee (2004) and Hensher, Jones and Greene (2007).

On the other hand, some previous studies, for example, Laitinen (1992), Parker, Peters and Turetsky (2002b), Lamberto and Rath (2008) have found that corporate size is positively related to the likelihood of financial distress.

Therefore, this study hypothesises that company size significantly affects the likelihood of financial distress. In particular, since the empirical results in the existing literature are inconclusive, thus, this study has no prior expectation of the effect of company size on firm survival. To test this hypothesis, the natural logarithm of sales is used as a proxy of company size.

2) Squared company size

In addition, this study further explores whether there exists a non-linear relationship between company size and the probability of financial distress. Consequently, the next research hypothesis is identified as follows.

Research hypothesis #4.7: Company size has a non-linear relationship with the likelihood of corporate financial distress.

According to Rommer (2004), a U-shaped relationship between company size and the probability of entering financial distress is suggested in addition to the negative relationship hypothesis. The reason for a U-shaped relationship is that small firms have a higher probability of entering financial distress as these firms are not so resistant to the shocks of the market and large firms have a high probability of entering financial distress because these firms might have inflexible organizations, problems with monitoring managers and employees and difficulties with providing efficient intra-firm communication.

To test this hypothesis, the square of the natural logarithm of sales is utilized in the model. This method is consistent with previous studies relating ownership structure

and firm performance; for example, Himmelberg, Hubbard and Palia (1999) and Kumar (2003) incorporated the squared company size to allow for the nonlinear relationship of company size in examining the relationship between ownership structure and firm value or performance.

3) Company age

In addition to company size, this study also examines the association of company age and corporate endurance as set out in the following hypothesis.

Research hypothesis #4.8: Company age is negatively related to the likelihood of corporate financial distress.

Previous studies, for example, Jovanovic (1982), Chen and Lee (1993), Lensberg, Eilifsen and McKee (2004), Rommer (2004), Li, Zhang and Zhou (2005), Rommer (2005), Hensher, Jones and Greene (2007) have suggested the importance of company age in explaining financial failure. Jovanovic (1982) developed a learning model where age captures the experience of a firm and thus is the major determinant of firm survival. A recently established company or younger company might be more likely to fail as the company has less experience and must overcome several additional hurdles, for example, raising finance, developing a customer base and reputation and establishing effective internal management structures (Jovanovic, 1982; Hopenhayn, 1992; Ryan, 1994).

Accordingly, this study expects that company age be negatively related to the likelihood of corporate financial distress. To test this hypothesis, company age, measured by the number of years since registration, is used to test whether company age is a useful factor in predicting corporate financial distress.

4.4 Survival analysis technique

Survival analysis is a type of statistical method for studying 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). Since the state of companies might vary from ‘healthy’ to ‘financial distress’ and so on to ‘failure or bankruptcy’, the event of interest in this study is defined as a company entering into a financially distressed state.

However, these changes usually occur over a time horizon of several periods rather than instantaneously. The expectation is that the corporate ‘disease’ of financial distress begins with identifiable initial conditions of the ‘symptom’ variables. The symptomatic conditions then change progressively over time as the financial distress worsens.

This study utilizes a survival analysis technique in examining corporate financial distress. Compared to the traditional methods, for example, MDA, and the logit and probit models, there are two key advantages to survival analysis. These advantages include the ability to handle time-varying variables, and censored observations.

Time varying variables are the explanatory variables that change with time. The financial ratios, market-based data and company-specific variables used in this study are time-varying variables as their values change over time. It can be expected that the symptoms of financial distress are observable from the deterioration of financial ratios or that the effect of such ratios on corporate failure do not stay constant over time (Luoma and Laitinen, 1991). In contrast to the traditional method, which examines only the level of a variable at a given point in time as it simply makes the observation at a ‘snap-shot’ in time, the major contribution of the survival analysis method is the estimation procedures that consider changes in the value of variables over time. This is a reasonable application of the statistical method because financial distress does not

occur immediately, but is preceded by the deterioration in a firm's financial health over a number of years (LeClere, 2000).

Censored observations are those observations that have never experienced the event during the observation time. Censoring occurs when the duration of the study is limited in time. In this study, censored observations are the active companies, as they have not entered into a financially distressed state during the study time. Survival analysis makes it possible to use the information from these observations by including them as censored observations and by using the maximum or partial likelihood method to provide consistent parameter estimates. This is in contrast to the traditional methods, which cannot incorporate information from censored observations (Allison, 1995).

Survival analysis contains two key functions, namely, the survivor 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 . Given that T is a random variable that defines the event time for some particular observation, then the survival function is defined as:

$$S(t) = \Pr(T > t) \quad (4.1)$$

The hazard function defines the instantaneous risk of an event occurring at time t given 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 form of the number of events per interval of time. The hazard function is defined as

$$h(t) = \lim_{\Delta t \rightarrow 0} \frac{\Pr(t \leq T < t + \Delta t | X, T \geq t)}{\Delta t} \quad (4.2)$$

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

$$h(t) = -\frac{d \ln(s(t))}{dt} \quad (4.3)$$

To estimate survival and hazard functions, there are parametric and nonparametric models. The advantage of using parametric models is the complete specification of the model leading to better predication of survival time, but this may also produce an inconsistent estimation due to some distributional assumptions. The nonparametric methods are very useful for descriptive purposes.

The Cox proportional hazards model is a semi-parametric model for survival analysis, which is most widely used. In Cox's study (1972), there are two significant innovations, namely, the proportional hazards model and maximum partial likelihood. The proportional hazards model is represented as follows:

$$h_i(t) = h_0(t) \exp(X_i \beta) \quad (4.4)$$

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 all have values of zero. X represents the vector of those variables that influence the hazard and β is the vector of their coefficients. It is the lack of specificity of a baseline hazard function that makes the model semi-parametric or distribution free.

Equivalently, the regression model is written as:

$$\log h_i(t) = \alpha(t) + \beta_1 X_{i1} + \beta_2 X_{i2} + \dots + \beta_k X_{ik} \quad (4.5)$$

Where $\alpha(t) = \log h_0(t)$ and $h_0(t)$ is an arbitrary unspecified baseline hazard rate (LeClere, 2000).

The model does not require the particular probability distribution specification of the survival times, but it possesses the property that different individuals have hazard functions that are proportional, that is,

$$\frac{h_i(t)}{h_j(t)} = \exp[\beta_1 (X_{i1} - X_{j1}) + \beta_2 (X_{i2} - X_{j2}) + \dots + \beta_k (X_{ik} - X_{jk})] \quad (4.6)$$

The ratio of the hazard functions for two individuals does not vary with time t . These special properties make the Cox proportional hazards model robust and popular amongst researchers.

To estimate the coefficients of β , Cox (1972) proposed a partial likelihood function based on a conditional probability of failure by assuming that there are no tied values in the survival times. The function was later modified to handle ties (Efron, 1977). The SAS PROC PHREG can be used to complete the calculation much more easily.

In the above Cox PH model, it is assumed that the ratio of hazard functions for any two individuals is independent of time t , or that the variables are not time-dependent. However, it is common in practice for a study to include both time-dependent and time-independent variables. The most common time-dependent variables are those that are observed repeatedly at different follow-up time points, which is true of most of the variables in the dataset of this study. Other kinds of time-dependent variables include those that change with time according to a known mathematical formula, for example, age. In general, the hazard function of Equation (4.2) depends on the complete time path of regressors $X(t)$, so that Equation (4.2) becomes:

$$h(t) = \lim_{\Delta t \rightarrow 0} \frac{\Pr(t \leq T < t + \Delta t | X(t), T \geq t)}{\Delta t}. \quad (4.7)$$

A time-varying variable may exhibit feedback and this will result in the coefficients β in the regression Equation (4.5) are also depend on time t . This situation should be common in financial studies because a company is always willing to adjust its behaviours according to relative variables. This study assumes that the variables are weakly exogenous; that is, whether the process underlying the time variation is stochastic or deterministic, the parameters of that process in estimating the hazard model under consideration do not need to be considered.

One rather simple solution is to replace the time-dependent variable by its mean value during the spell. A tedious, but useful method for handling one or more time-dependent variables is represented using the counting process style. The subject will be represented as one or more observations, each consisting of a time interval, the status, and the values of fixed variables over the interval. The per-subject residual for a given subject is the sum of residuals for its observations.

4.5 Data and sample

The data in this study include all companies listed on the ASX for the period 1989 to 2005. The annual data on financial ratios, stock prices and company-specific variables of age and size are incorporated in the model. The companies in the financial sector are excluded from the analysis because of a different financial statements structure.

Based on previous financial distress prediction literature, most researchers have adopted a matched pairs technique as the sample selection criteria of distressed and non-distressed companies (Seow, 1998; Lennox, 1999). A sample of non-distressed companies is usually drawn by matching the characteristics of the companies such as company size, industry sector and year of financial distress against the characteristics of distressed companies. Such researches include Beaver (1966), Altman (1968a), Altman, Haldeman and Narayanan (1977), Damolena and Khoury (1980), Castagna and Matolcsy (1981), Lau (1982), Izan (1984), Luoma and Laitinen (1991), Laitinen (1993b), Liu (1993), Henebry (1996; 1997), Seow (1998), Charalambous, Charitou and Kaourou (2000), Frost-Drury, Greinke and Shailer (2000), Gadenne and Iselin (2000), Routledge and Gadenne (2000) and Charitou, Neophytou and Charalambous (2004).

An alternative method of selection basis is matching a greater number of non-distressed companies to a number of distressed companies. For example, Lincoln (1984)

and Coats and Fant (1993) matched two non-distressed companies with one distressed company in the sample.

Lennox (1999) pointed out that the advantage of the matching procedure is the reduction in the cost of data collection; however, some researchers argue that there might be some sample selection problems due to matching procedures.

According to Ohlson (1980), it is not known what is really gained or lost by different matching procedures, including no matching at all. Furthermore, it is not possible to investigate the effects of industry sector, company size or year of failure on the probability of bankruptcy, and the use of relatively small samples may lead to over-fitting (Lennox, 1999). The use of a matched sample to derive the model for populations of companies where the percentage of firms failing is low might result in seriously misleading indications of both a model's external validity and its likely practical value for decision-making purposes (Keasey and Watson, 1991).

Another method is random sampling or the selection of a sample in which the ratio of non-distressed companies to distressed companies represents the actual failure rate. Researchers who adopted this method include Zmijewski (1984), Crapp and Stevenson (1987), Flagg, Giroux and Wiggins (1991), Houghton and Smith (1992), Audretsch and Mahmood (1995), Lennox (1999), Honjo (2000), Shumway (2001), Tan and Dihardjo (2001), Turetsky and McEwen (2001), LeClere (2002), DeYoung (2003) and Rommer (2004; 2005). The proponents of this method argue that the matched pairs method results in choice-based sample bias because the method fails to reflect the actual failure rate in the sample (Zmijewski, 1984). However, Zmijewski (1984) concluded that the existence of the bias did not significantly affect the statistical inferences or the overall classification rates of the model.

To avoid the criticisms of the matched pairs sample basis, this study will use a sample that represents the actual failure rate. The data on a large number of companies over a 17 year period of publicly listed Australian companies on the ASX in all sectors except financial sector will be incorporated. This sampling method allows the effects of company size and industry sector on financial distress likelihood to be evaluated. This study expects that using the whole sector of listed companies will result in the development of an effective financial distress prediction model of the companies in Australia because this sample should be representative of the Australian economy overall.

Finally, there are 50 financially distressed companies and 1,067 active listed companies in the analysis. Financially distressed companies within the sample are defined as companies that have entered into external administration process, which includes one of the following states: 1) voluntary administration, 2) a scheme of arrangement, 3) receivership or 4) liquidation.

Time to event or survival time in this study is the number of years from the start year to the year of financial distress for a distressed company or to the last year observed for an active company. In this study, the start year is the first year when data are available. Since the dependent variable in survival analysis is time to event, the time when a company enters into financial distress is constructed in this study. The date of external administration during 1989 to 2005 was purchased from ASIC.

The explanatory variables used in the model are financial ratios, market-based data and company-specific variables. The four main categories of financial ratios included in the model are profitability, liquidity, leverage and activity ratios. The selection criteria is based on 1) data availability in *FinAnalysis Database* as financial statements of Australian firms are used in this study and were collected from the

FinAnalysis Database, 2) the predictive variables in previous studies and 3) the potential of the variable in this study.

The details of variables used in this study are shown in Table 4.1.

Note: All of the data are obtained from Fin Analysis Database, Aspect Huntley Company except for the S&P/ASX200 monthly index data are obtained from Dx Database.

Consequently, the Cox proportional hazards model, which will be employed in order to assess the relationship of explanatory variables to survival time and to evaluate the corporate survival probability in a given time frame in this study, is shown as follows.

$$\begin{aligned} \log h_i(t) = & \alpha(t) + \beta_1 EBT_i(t) + \beta_2 ROE_i(t) + \beta_3 ROA_i(t) + \beta_4 CUR_i(t) + \beta_5 QUK_i(t) \\ & + \beta_6 WCA_i(t) + \beta_7 DET_i(t) + \beta_8 CPT_i(t) + \beta_9 TAT_i(t) + \beta_{10} SIZE_i(t) + \\ & \beta_{11} SIZE2_i(t) + \beta_{12} AGE_i(t) + \beta_{13} EXR_i(t) \end{aligned} \quad (4.8)$$

Where $h_i(t)$ is the hazard of company i of entering into financial distress at time t . This hazard at time t depends on the value of each variable at time t . $\alpha(t) = \log h_0(t)$ where $h_0(t)$ is the hazard function for an individual that has a value of zero for each of the variables. The variables used in the model are time-dependent variables, which change in value over the study period. This is one of the major advantages of the Cox proportional hazards model in that it allows the use of time-dependent variables.

4.6 Empirical results

4.6.1 Descriptive statistics

Due to there being a number of extreme values among the observations, which might have a significant effect on the statistical results, the observations were truncated at the specified thresholds. All observations with variable values higher than the ninety-ninth percentile of each variable were set to that value. In the same way, all variable values lower than the first percentile of each variable were truncated. These percentiles are empirical values used by Shumway (2001).

Table 4.2 presents the descriptive statistics of the data employed in the study after truncation. The descriptive statistics include the number of observations, minimum, means, medians, inter-quartile range, maximum, standard deviations, skewness and

kurtosis for each company status. The descriptive statistics results before truncation are shown in Table B.1 in the appendix.

It is important to note that the financial ratios before truncation employed in this study behave in an unsatisfactory way as the standard deviations are very large. This is because there are a number of outliers that influence the results. Unlike many previous studies, which do not account for this problem, this study uses the truncation technique to minimize the effect of the outliers.

However, it is important to note that the ninety-ninth percentile and the first percentile which have been using in the study are just the arbitrary values. A better way to handle the outliers is to adopt a heavy-tailed probability distribution such as the student-*t* distribution instead of the normal distribution. Unfortunately, statistical influence using the *t*-distribution is not available in most statistical package including SAS. Furthermore, contaminated normal and heavy-tailed distribution may be used to handle outliers and provide a robust influence. This may efficiently be done using Bayesian methods and can be considered in a future research.

To avoid the extreme values, median and inter-quartile range are used as summary statistics instead of mean and standard deviation which are very sensitive to outliers.

The Chi-square statistics for the median test and its *p*-value are the result of a non-parametric test for a significant difference between the group medians. Variables with significant differences within the group medians will be expected to add information to a regression analysis. The variables EBT, ROA, CUR, QUK, DET and EXR display a significant difference.

According to Table 4.2, the profitability ratios, EBT, ROE and ROA, are all shows that the financially distressed companies have lower ability to generate a profit than have active companies. The medians of EBT for active and distressed companies

are 0.0100 and -0.0214 respectively. That means the financially distressed companies in this study have lower profitability than have the active companies. The median of ROE for active companies is 0.0137 which is higher than the median ROE of financially distressed companies with median value 0.0025. The medians of ROA also behaves in the same way as EBT and ROE. For liquidity ratios, CUR, QUK and WCA, the financially distressed companies have lower medians than have active companies. This shows that a distressed company has less ability to meet its current obligations as they become due than has an active company. The medians of DET shows that the ability to pay long term liabilities of a distressed company is less than that of an active company. For activity ratios, CPT and TAT, the median values of both ratios show that active companies have higher ability of a company to utilize its assets to generate revenues than have financially distressed companies. According to SIZE median values, the sizes of financially distressed and active companies in the study are quite similar. The Chi-square statistics of median test showed that the median company size of the financially distressed companies and active companies in this study are the same. Furthermore, the median age of the financially distressed companies in this study is greater than the median age of the active companies with median values 14.0000 and 17.0000 respectively. Finally, the median of EXR suggests the past company's excess returns for the active companies is higher than for the financially distressed ones.

4.6.2 Correlation coefficients

Table 4.3 reports the Pearson correlation coefficients results to investigate the relationships between the variables used in the study.

The results indicate that most of the variables are significantly correlated but the magnitudes are small.

Table 4.2: Descriptive statistics of the data

	EBT	ROE	ROA	CUR	QUK	WCA	DET	CPT	TAT	SIZE	SIZE2	AGE	EXR
Active (n=1067)													
Min	-1110.0460	-4.2422	-2.3255	0.0500	0.0400	-1.000	0.005	0.0002	0.0002	6.8800	47.3000	1.0000	-2.2730
Mean	-33.6789	-0.1172	-0.1105	6.6559	6.3369	0.0474	0.4078	3.3425	0.8058	15.8317	264.1774	19.9729	-0.1158
Median	0.0100	0.0137	0.0092	1.7100	1.2300	0.0186	0.3701	1.0023	0.4924	16.3499	267.3185	14.0000	-0.0777
IQR	2.1593	0.2819	0.2032	2.8100	2.8000	0.1865	0.4322	2.3921	1.0719	5.2371	166.3267	16.0000	0.7319
Max	1.6308	2.5722	0.4029	147.9600	147.9600	0.699	3.586	76.9763	5.7367	22.6000	511.0000	93.0000	2.0790
Std Dev.	151.4233	0.7208	0.3856	17.5213	17.5638	0.2179	0.4334	9.2804	0.9897	3.6697	111.4845	18.9533	0.7128
Skewness	-5.9371	-2.5236	-3.5101	5.5582	5.5483	-0.9137	4.0685	6.1319	2.2594	-0.4263	0.0540	1.9596	-0.0588
Kurtosis	36.3755	15.4144	14.8926	35.2694	35.1697	5.7940	24.7712	41.8669	6.6206	-0.4726	-0.6828	3.8062	1.3862
Distressed (n=50)													
Min	-318.6193	-4.2422	-2.3255	0.0500	0.0400	-1.000	0.005	0.0004	0.0002	7.4400	55.000	1.0000	-2.2700
Mean	-10.3232	-0.1020	-0.1573	5.0978	4.8686	0.0282	0.5868	2.9237	0.8548	15.8297	259.8330	22.0473	-0.2471
Median	-0.0214	0.0025	-0.0062	1.3200	1.0400	0.0106	0.4556	0.8820	0.4533	16.4390	270.2389	17.0000	-0.2096
IQR	1.2552	0.2360	0.1733	1.9100	1.9800	0.2134	0.4491	2.2523	1.0574	3.5043	113.5213	23.0000	0.8338
Max	1.6308	2.5722	0.4029	147.9600	147.9600	0.699	3.586	51.4800	5.7367	21.5000	460.000	91.0000	2.0008
Std Dev.	45.5936	0.7760	0.4948	17.0073	17.0518	0.2756	0.7384	6.9209	1.1424	3.0109	89.6430	16.6568	0.8072
Skewness	-5.8351	-1.5269	-3.2414	7.1668	7.1494	-1.4149	2.9408	4.8427	2.6287	-0.6863	-0.2302	1.4019	-0.0678
Kurtosis	34.5948	10.7077	10.5475	54.5926	54.3804	5.0272	8.6928	26.4602	7.9975	-0.0097	-0.3737	2.7141	1.0428
Chi-Square	16.3737**	0.7138	5.9812**	45.0747**	11.7515**	0.7138	11.1221**	0.5715	1.2358	1.0463	1.2358	19.9972	17.8448**
p-value	<.0001	0.3982	0.0145	<.0001	0.0006	0.3982	0.0009	0.4497	0.2663	0.3064	0.2663	0.3618	<.0001

Note: Descriptive statistics grouped by company status. Chi-square from a non-parametric test of equality of group medians using median tests.

*** Significant at the 5 percent level.*

Table 4.3: Pearson correlation coefficients

Variable	EBT	ROE	ROA	CUR	QUK	WCA	DET	CPT	TAT	SIZE	SIZE2	AGE	EXR
EBT	1.0000	0.1029 ^a <.0001 ^b	0.1692 <.0001	-0.0937 <.0001	-0.0966 <.0001	0.0760 <.0001	0.0915 <.0001	0.0653 <.0001	0.1734 <.0001	0.4534 <.0001	0.3818 <.0001	0.0686 <.0001	-0.0020 0.8310
ROE		1.0000	0.4636 <.0001	-0.0190 0.0374	-0.0215 0.0183	0.0446 <.0001	0.1455 <.0001	0.0022 0.8132	0.1592 <.0001	0.2410 <.0001	0.2468 <.0001	0.0768 <.0001	0.0805 <.0001
ROA			1.0000	-0.0276 0.0025	-0.0323 0.0004	0.3628 <.0001	-0.2203 <.0001	-0.0346 0.0002	0.1097 <.0001	0.3767 <.0001	0.3802 <.0001	0.1110 <.0001	0.1258 <.0001
CUR				1.0000	0.9995 <.0001	0.0894 <.0001	-0.2528 <.0001	-0.0533 <.0001	-0.1832 <.0001	-0.3085 <.0001	-0.2996 <.0001	-0.0964 <.0001	-0.0168 0.0660
QUK					1.0000	0.0778 <.0001	-0.2522 <.0001	-0.0516 <.0001	-0.1876 <.0001	-0.3162 <.0001	-0.3071 <.0001	-0.1015 <.0001	-0.0178 0.0516
WCA						1.0000	-0.3557 <.0001	-0.1232 <.0001	0.0610 <.0001	0.1982 <.0001	0.1972 <.0001	0.1292 <.0001	0.0632 <.0001
DET							1.0000	0.1280 <.0001	0.3898 <.0001	0.2648 <.0001	0.2612 <.0001	0.0700 <.0001	-0.0381 <.0001
CPT								1.0000	0.3853 <.0001	0.1337 <.0001	0.1236 <.0001	-0.0242 0.0081	-0.0471 <.0001
TAT									1.0000	0.4997 <.0001	0.4944 <.0001	0.1425 <.0001	0.0118 0.1958
SIZE										1.0000	0.9901 <.0001	0.2936 <.0001	0.0653 <.0001
SIZE2											1.0000	0.3168 <.0001	0.0743 <.0001
AGE												1.0000	0.0664 <.0001
EXR													1.0000

Note: a. Pearson correlation coefficients.

b. The p-value under the null hypothesis of zero correlation.

4.6.3 Cox proportional hazards model estimation results

In order to assess the usefulness of financial ratios, market-based data and company-specific variables as the predictors of corporate financial distress are entered into the Cox proportional hazards model along with nine financial ratios, a market-based variable and three company-specific variables. The variables used are time-dependent variables covering 1989 to 2005. A dependent variable is the survival time, specifically, the number of years from the start year to the year of financial distress for a distressed company or to the last year observed for an active company. In this study, the start year is the first year when data are available.

The results of applying the Cox proportional hazards model with financial ratios, a market-based variable and company-specific variables, are reported in Table 4.4.

The variable selection method used in this study is the simplest method and the default in PROC PHREG in SAS. The SAS PROC PHREG fits the complete model as specified in the MODEL statement. The variables are selected from the full model (all variables were included in the model), instead of backward, forward or stepwise selection procedures¹. Table 4.4 reports the results for these significant variables only.

Table 4.4: Cox proportional hazards model estimation

Variable	Coefficient	Standard Error	χ^2 Statistic	p-Value	Hazard Ratio
WCA	0.9792*	0.5445	3.2337	0.0721	2.6620
DET	0.9187**	0.2264	16.4628	<.0001	2.5060
SIZE	0.8271*	0.4710	3.0834	0.0791	2.2870
EXR	-0.7526**	0.2030	13.7499	0.0002	0.4710

Note: *Significant at the 10 percent level.

** Significant at the 5 percent level.

¹ This study has also estimated the model using backward, forward and stepwise but they reported different results. The full model is chosen in this study because it is consistent to the economic intuitive.

Table 4.4 presents the estimated model after truncation. After truncation, the Cox proportional hazards model estimation results improve. Some variables, for example, WCA and DET, become significant after truncation. The empirical results of the Cox proportional hazards model estimation before truncation are presented in Table B.2 in the appendix.

Table 4.4 presents the coefficient estimation, the standard error of this estimate, and the Wald chi-square tests with the relative p -value for testing the null hypothesis that the coefficient of each variable is equal to zero, 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. If the hazard ratio is greater (less) than 1, this indicates the more rapid (slower) hazard timing.

Considering the p -value, two variables are highly significant at the five percent level. These ratios are DET and EXR with the coefficient 0.9187 and -0.7526 respectively. WCA and SIZE are also significant at the 10 percent level with the estimated coefficient 0.9792 and 0.8271 respectively.

The coefficient of WCA has a positive sign, which means that an increase in working capital to total assets ratio increases the hazard of entering into financial distress. The ratio is used for measuring company liquidity and, as mentioned in Altman (1968a), a firm experiencing consistent operating losses will have shrinking current assets in relation to total assets. This result is in contrast to what is expected, as a company with high liquidity should have a lower likelihood of entering into financial difficulties. It should be noted that the finding is counter-intuitive and so should be held out for further inquiry and testing, rather than considered as a primary factor in predicting financial distress.

The coefficient sign of EXR is negative, indicating that an increase in a company's past excess returns decreases the hazard of the company entering into financial distress. The hazard ratio for EXR is 0.4710, which means that for each one unit increase in a company's past excess returns, the hazard of the company becoming financially distressed decreases by an estimated 52.90 percent. The results indicate that the past excess returns or market adjusted returns decrease as the probability of financial distress increases. The results show the potential usefulness of market data for the prediction of corporate financial distress, which is consistent with the results found in Shumway (2001) and Partington et al. (2006).

On the other hand, the sign of the parameter for DET is positive, which means a company with low DET is less likely to file financial distress. The hazard ratio for DET is 2.5060, which means that for every unit increase in debt ratio, the risk of becoming financially distressed changes by a multiple of 2.5060.

The economic interpretation of these results is straightforward. The company with an excessively fast growth compared to profitability will be forced to seek funding from incurring a debt. The high indebtedness brings more financial obligations, which must be paid. The firm's low ability to generate earnings forces the company to incur more and more debt to pay these obligations and, consequently, the company will become involved in the vicious circle and will ultimately fail.

For SIZE, the estimated coefficient is 0.8271. The positive sign of SIZE means that the larger the size of a company, the higher the likelihood of the company entering into financial distress. The hazard ratio of SIZE is 2.2870, which means that for each unit increase in company size, the risk of becoming financially distressed changes by a multiple of 2.2870. As mentioned previously, the reasonable explanation for this result is that the large company might have inflexible organizations and have problems with

monitoring managers and employees, which leads to inefficient communication (Rommer, 2004).

For the sample in this study, the results suggest that the financially distressed companies have higher leverage, lower past excess returns and a larger size than the active companies. However, the study results do not support the importance of company age in explaining financial distress, which is consistent with the study results of Shumway (2001). Furthermore, the variable SIZE2 is not significant, which implies that there is no non-linear relationship between company size and corporate financial distress likelihood.

The expected effect and the estimated effect of the variables are summarized in Table 4.5. The table shows that DET and EXR have the expected sign when the model is estimated, while WCA and SIZE do not have the expected effect.

Table 4.5: Summary of estimated effects of variables on financial distress

Variable	Expected effect	Estimated effect
WCA	-	+
DET	+	+
SIZE	-	+
EXR	-	-

According to Table 4.5, it should be noted that the variables WCA and SIZE are unexpected results and should be held out for future research.

4.6.4 Corporate survival probability evaluation

The hazard function, shown in Equation (4.4), presents the risk that financial distress will occur at time t given that the firm has survived up to time t . There is one term, that is, ‘linear predictor’, which is an interesting term for evaluating a company’s risk of financial distress. Linear predictor is the term $X_i\beta$ in hazard function. X is the vector of

explanatory variables and β is the parameter that needs to be estimated. The larger the value of the linear predictor, the higher the risk of financial distress. The relationship between the average linear predictor and time for active and distressed companies is shown in Figure 4.1.

According to Figure 4.1, the values of the linear predictor of distressed companies are higher than those of active companies; this confirms the view that the risk of financial distress of distressed companies is higher than that of active ones. The dramatic change of linear predictor occurs eight years after the companies enter into the analysis, which implies the high risk of financial distress at that time. The detail of the linear predictor of a company within a given time stratified by company status is shown in Table 4.6.

The survival profiles of a typical distressed and a typical active company are presented in Figure 4.2. Theoretically, survival function is monotonic function but it is not the case in this study because the survival function shown in the figure is produced by averaging the estimated survival probability of companies by company status, for distressed and active companies. It can be inferred that the survival probability of the typical financially distressed companies is lower than that of the typical active companies. Since the survival function denoted a company's probability of surviving past time t , it starts with 1.00 at the beginning and declines as more companies entering financially distressed.

The graph shows that the survival probability of distressed companies is lower than that of active companies and, as time goes by, the survival probabilities for both decreases. The noticeable decrease in corporate survival, especially for distressed companies, occurs eight years after the companies are entered into the analysis. For distressed companies, the survival probability that the companies will survive beyond

17 years is around 76.53 percent and for active ones is around 88.72 percent .This result confirms the result shown in Figure 4.1. The detail of the survival probability of a company within a given time stratified by company status is shown in Table 4.7.

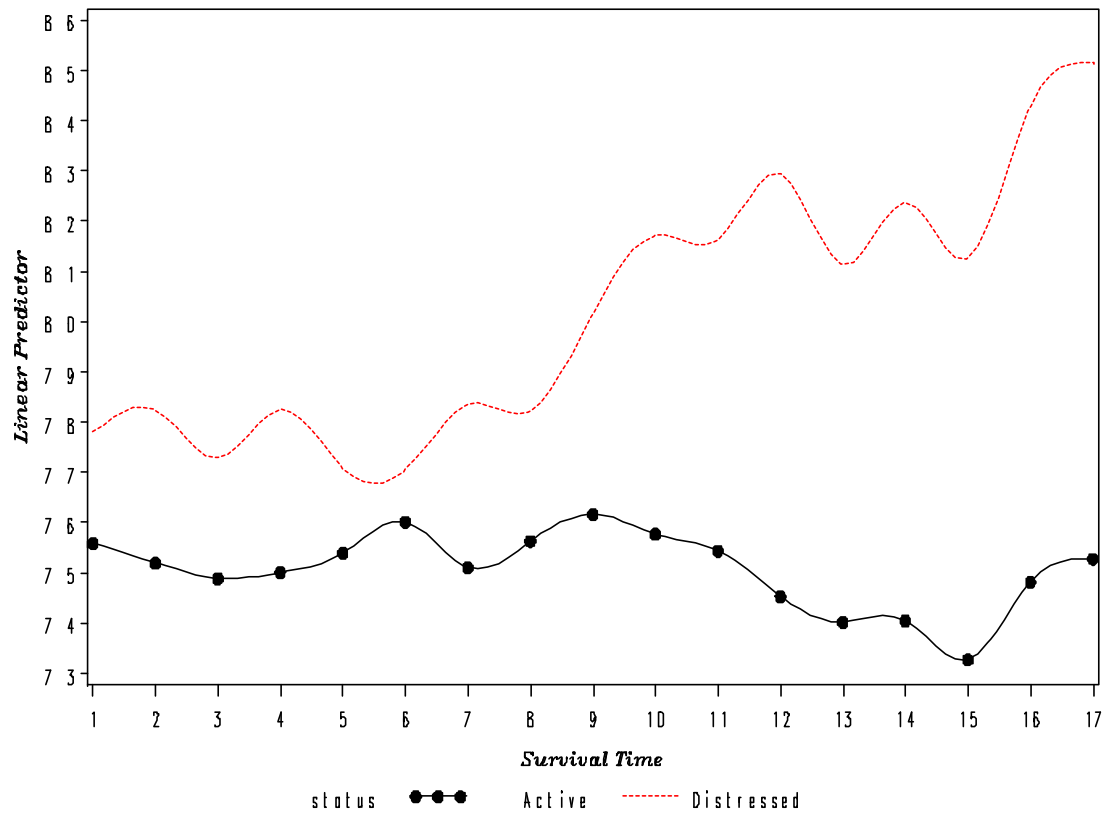


Figure 4.1: Graph of linear predictor and time by company status

Table 4.6: Linear predictors of companies by company status

Survival Time	Linear Predictor	
	Active Companies	Distressed Companies
1	7.5587	7.7799
2	7.5201	7.8236
3	7.4894	7.7287
4	7.5013	7.8251
5	7.5397	7.7088
6	7.6012	7.7060
7	7.5106	7.8351
8	7.5635	7.8237
9	7.6170	8.0185
10	7.5774	8.1720
11	7.5443	8.1638
12	7.4533	8.2936
13	7.4023	8.1141
14	7.4049	8.2375
15	7.3276	8.1264
16	7.4823	8.4300
17	7.5283	8.5143

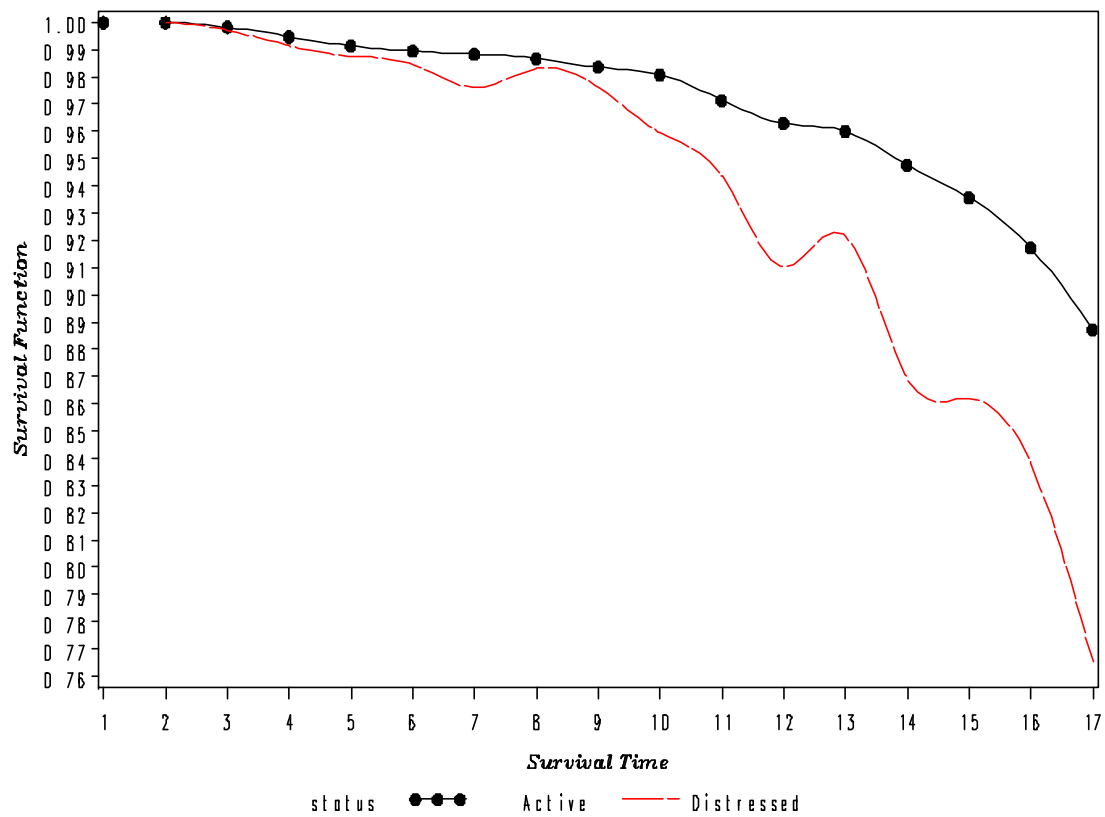


Figure 4.2: Graph of survival function and time by company status

Table 4.7: Survival probabilities of companies by company status

Survival Time	Survival Probability	
	Active Companies	Distressed Companies
1	1.0000	1.0000
2	1.0000	1.0000
3	0.9983	0.9972
4	0.9947	0.9913
5	0.9913	0.9876
6	0.9895	0.9845
7	0.9883	0.9760
8	0.9867	0.9830
9	0.9836	0.9763
10	0.9807	0.9594
11	0.9714	0.9436
12	0.9629	0.9102
13	0.9600	0.9218
14	0.9476	0.8691
15	0.9356	0.8621
16	0.9172	0.8379
17	0.8872	0.7653

4.7 Conclusion

This study provides a financial distress model that combines traditional financial ratios, a market-based variable and company-specific variables with a survival analysis technique in the form of a Cox proportional hazards model. The study extends and improves the previous works in financial distress predication literature, primarily with the application of the Cox proportional hazards model with time-varying variables in the financial distress context in investigating various potential factors of corporate financial distress.

The results show that the Cox proportional hazards model can provide information regarding corporate survival probability in a given time frame, and also support the effectiveness of financial ratios, market-based and company-specific variables as predictors of financial distress. Specifically, financially distressed companies have higher leverage, lower past excess returns and a larger size than the active companies. The results, however, do not support the importance of the company age factors in explaining financial distress.

There are a number of practical implications regarding this study. First, management needs to consider carefully the financial structure of the company in order to prevent possible financial difficulties. Secondly, market-based data are a valuable source of information for detecting the possibility of financial distress. Management and investors might use market data in addition to financial ratios in examining corporate financial distress to make better decisions in relation to predicting corporate failure, which may consequently reduce losses.

This chapter defines financial distress in a single risk model framework; however, some researchers argue that a company might face financial distress in different forms, for example, through merger, acquisition, voluntary liquidation and bankruptcy, and

each type of exit is likely to be affected by different factors (Schary, 1991; Harhoff, Stahl and Woywode, 1998; Prantl, 2003; Rommer, 2004). Therefore, multiple states of financial distress will be defined and examined in the next chapter using a competing risks Cox proportional hazards model.

CHAPTER 5

MULTIPLE STATES OF FINANCIALLY DISTRESSED

COMPANIES: THE COMPETING RISKS MODEL

5.1 Introduction

In recent years, there has been a global increase in the number of corporate collapses such as Enron, WorldCom, Tyco and HealthSouth to name just a few. Australia has also experienced a series of corporate collapses since the early 1990s. Notable failures include HIH Insurance, One.Tel, and Ansett Airlines in 2001, and, most recently, FIN Corp in 2007. The failure or bankruptcy of financially distressed companies often entails significant direct and indirect costs to many stakeholders. These costs can be avoided or reduced if financially distressed companies can be identified well before the ultimate failure occurs. To avoid or reduce the associated costs of corporate financial distress, therefore, corporate financial distress, failure or bankruptcy has attracted the attention of researchers and practitioners.

In practice, companies may face the continuum of financial health (Lau, 1987). Multiple states of a financial distress model would provide a wider range of distress scenarios than public companies typically face in the real world (Hensher, Jones and Greene, 2007). However, most of the traditional corporate financial distress prediction literature has focused on the conventional failing vs. non-failing dichotomy; for example Altman (1968b), Ohlson (1980) and Shumway (2001) focused their studies on companies that go bankrupt. However, focusing on only one form of exit, for example, bankruptcy, and ignoring the others might provide limited empirical estimation results.

The relevance and utility of multiple states of financial distress models is now widely accepted (Jones and Hensher, 2007b). The rationale for defining different states

of financial distress is the inclusion of multiple states of financially distressed companies, and this will provide an opportunity to examine further the effect of explanatory variables across the diverse states of financial distress observable in practice, as a company might 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 and Woywode, 1998; Prantl, 2003; Rommer, 2004).

Multiple states of corporate financial distress have been examined by various studies; for example, Lau (1987) estimated the probability that a firm will enter each of the five ranked financial states. The five states include state 0: 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 Bankruptcy Act and state 4: bankruptcy and liquidation. Johnsen and Melicher (1994) examined the added value of information provided in predicting corporate bankruptcy by defining three states of financial distress: non-bankrupt, financially weak and bankrupt firms. In addition, Dickerson, Gibson and Tsakalotos (1999) investigated the determinants of UK manufacturing companies making acquisitions and being acquired. Furthermore, Wheelock and Wilson (2000) assumed that the causal processes for acquisitions and failures are different. The competing risks hazard model was utilized to identify the characteristics that make individual US banks more likely to fail or to be acquired.

The existing literature focuses on examining different types of corporate exit, namely, merger, takeover or acquisition, for example, Harhoff, Stahl and Woywode (1998), Prantl (2003) and Rommer (2004). These studies confirmed the importance of distinguishing between different types of corporate exit.

In the Australian context, Jones and Hensher (2004) have made a contribution by introducing three-state financial distress models for examining corporations in the ASX. The study was extended by Hensher, Jones and Greene (2007) and Jones and Hensher (2007b), who added distressed merger as an additional important state of financial distress. However, these studies used an advanced logit model, for example, mixed logit, multinomial error component logit and nested logit models which differ from the models used in this study. While often effective in predicting ultimate corporate failures, these approaches omit ‘time to failure’ as an integral factor in corporate distress analysis.

Compared to the literature in the Australian context, this study utilizes a different method, that is, a competing risks model. This method allows time to event to be incorporated into the analysis to explore the multiple states of corporate financial distress.

The purposes of this study are, first, to examine the determinants of three different states of financial distress, namely, active companies, distressed external administration companies and distressed takeover, merger or acquisition companies. The effect of financial data, a market-based variable and company-specific variables on the three unordered states of financially distressed Australian companies is investigated using a competing risks model. The competing risks model will provide information regarding whether the effects of variables are the same or different across the multiple states of financial distress.

Secondly, the study will compare a pooled model with a competing risks model. Most of the existing studies do not distinguish between states of financial distress while some studies have suggested that distinguishing between the different types of exit or financial distress is required (Lau, 1987; Rommer, 2004; Rommer, 2005). In this study,

the use of a competing risks model, which can handle multiple states of financial distress, will provide an opportunity to compare the different specifications of the models.

The contribution of this study to the literature is that this is the first attempt to apply a competing risks Cox proportional hazards model for modelling multiple states of corporate financial distress in the Australian context. A competing risks Cox proportional hazards model allows 'time to event' to be incorporated as the dependent variable in corporate distress analysis. Furthermore, the variables used in the model are time- dependent variables, that is, those that can change in value over the study period. One of major advantages of the Cox proportional hazards model is that it allows for time- dependent variables.

The analysis is based on three main categories of variables: financial ratios, market-based data and company-specific variables. A sample of all publicly listed Australian companies except those in the financial sector is explored. The study period covers 1989 to 2005. Three different states of financial distress, that is, active companies, distressed external administration companies and distressed takeover, merger or acquisition companies, are employed. The determinants of each state are examined and interpreted through the competing risks model.

The results show that a variety of factors drive companies to enter different states of financial distress. More specifically, distressed external administration companies have higher leverage, lower past excess returns and a larger size while distressed takeover, merger or acquisition companies have lower leverage, higher capital utilization efficiency and a bigger size compared to active companies.

After comparing the estimation results from the single risk model and the competing risks model, it can be concluded that the multi-state of financial distress

should be defined when modelling failure prediction rather than company status being classified simply into the binary classification of failure vs. non-failure.

The remainder of the chapter is organized as follows. The next section reviews previous multiple states of financial distress prediction studies. The development of research hypotheses corresponding to the research questions is discussed in Section 5.3. Section 5.4 then describes the methodology employed in the study. The data and sample are described in Section 5.5. The empirical results are presented and discussed in Section 5.6. Finally, the conclusion and possible future extensions are discussed in Section 5.7.

5.2 Literature review

This section reviews the literature starting with a multiple states of financial distress prediction model. Then, the application of a competing risks model in a multiple states of financial distress prediction literature is discussed.

5.2.1 Multiple states of financial distress

Most corporate financial distress prediction literature has focused on a two-state failure model; for example, Altman (1968b), Ohlson (1980) and Shumway (2001) focused their studies on companies that go bankrupt. In practice, a firm may exit business in several ways, for example, through merger, acquisition, voluntary liquidation and bankruptcy and each form of exit is likely to be caused by different factors (Schary, 1991). Furthermore, Hensher, Jones and Greene (2007) pointed out that outright failure does not capture the full spectrum of financial distress in practice; for instance, many financially distressed firms seek merger partners or amalgamations, eliminate dividend payments, and default on loans or raise capital to alleviate financial distress. This implies the significance of defining different states of financial distress. By focusing on

the conventional failing vs. non-failing dichotomy, the model provides only a limited representation of the financial distress spectrum that companies typically face in practice (Lau, 1987; Hensher, Jones and Greene, 2007). Models explaining failure but not taking into account the second form of sample exit, acquisition (Harhoff et al., 1998), or vice versa, are likely to suffer from a sample selection problem and could bias estimation results (Koke, 2002).

Therefore, this study aims to explore the multiple states of corporate financial distress that would provide a wider range of the continuum of financial health that companies face in reality.

A number of studies distinguish between the states of corporate financial distress; for example, Johnsen and Melicher (1994) used multinomial logit models to examine the added value of information provided in predicting corporate bankruptcy. The study identified three states of financial distress: non-bankrupt, financially weak and bankrupt firms. The results confirm that adding the ‘financially weak’ state reduces the misclassification error and the three states of financial health appear to be independent.

Lau (1987) also utilized multivariate logit analysis to estimate the probability that a firm will enter each of the five ranked financial states including state 0: 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 Bankruptcy Act and state 4: bankruptcy and liquidation. The results show that multivariate logit analysis outperforms MDA and, for some explanatory variables, the empirical signs agree with the expected signs for models of some prediction time horizons.

Although Lau (1987) improved the two-state failure prediction model by using a five-state model, the study has a number of limitations. For example, the multinomial logit used in the study is not robust to violations for the independent and identically

distributed (IID) and the independence of irrelevant alternative (IIA) assumptions; these faults are corrected in Jones and Hensher (2004), Hensher and Jones (2007), Hensher, Jones and Greene (2007) and Jones and Hensher (2007b).

Jones and Hensher (2004) demonstrated the empirical usefulness of a mixed ordered logit model in the financial distress prediction context. The study introduced a three-state financial distress model including state 0: non-failed firms, state 1: insolvent firms and state 2: firms that filed for bankruptcy followed by the appointment of liquidators, insolvency administrators or receivers. The results confirm the superiority of mixed logit over multinomial logit models.

Furthermore, Hensher and Jones (2007) discussed a number of ways to optimise the explanatory and predictive performance of the mixed logit model in forecasting corporate bankruptcy. Five applications of the ordered mixed logit model were investigated using a three-state failure model, as in Jones and Hensher (2004). The results suggest that the unconditional triangular distribution for random parameters offers the best population level predictive performance on a hold out sample.

Hensher, Jones and Greene (2007) demonstrated the performance of the multinomial error component logit model, which is an extension of the mixed logit model and relaxes several questionable statistical assumptions associated with the standard logit model. The study extended Jones and Hensher's (2004) study by including distressed merger as another important state of financial distress. They defined four unordered states of financial distress of public Australian companies, namely, state 0: non-failed firms, state 1: insolvent firms, state 2: firms that were delisted from the ASX because they were subject to a merger or takeover arrangement and state 3: firms that filed for bankruptcy followed by the appointment of receiver

managers/liquidators. The study suggests that the error component logit model provides a much improved explanatory power over a standard logit specification.

Jones and Hensher (2007b) also extended their 2004 study by introducing and demonstrating the properties and predictive performance of the nested logit model relative to a standard logit model. Using a four-state failure model with Australian company samples, they obtained results that indicate that the nested logit model outperforms a standard logit model.

The studies mentioned above emphasise the importance of defining financial distress into multiple states that provide the full spectrum of financial distress in practice. However, after examining the determinants of corporate failure and acquisition in Germany, the results of Koke's (2001) study, based on descriptive statistics, confirm that firm failure and acquisition should be analysed in combination. Moreover, using a multinomial logit model with three survival states, namely, survival, acquisition, and failure for each sample firm, Koke (2002) suggested that acquisition and failure tend to be influenced by common factors. This implies that they should be examined in combination.

5.2.2 Competing risks model application

The methodologies utilized in previous studies for examining multiple states of financial distress that were reviewed in previous section included both standard logit and advanced logit models, for example, mixed logit, the multinomial error component logit and nested logit model. While these models are powerful in predicting the probability of financial distress, they do not deal with the 'time to event' issue.

Survival analysis techniques allow time to event to be modelled by incorporating it as the dependent variable. This study uses a competing risks model, which is a

technique of survival analysis and incorporates time to financial distress as the dependent variable in the model.

Most of the studies that employ a competing risks model in corporate financial distress prediction have been conducted in the context of European countries. For example, Harhoff, Stahl and Woywode (1998) and Prantl (2003) explored bankruptcy and liquidation in the German context. Harhoff, Stahl and Woywode (1998) employed a competing risks model to develop an important conceptual and empirical distinction between two modes of exit, namely, the voluntary liquidation and bankruptcy of West German firms. The results reveal that pooling exit types is a major source of misspecification. This result is consistent with Prantl (2003), which modelled the bankruptcy and voluntary liquidation of new firms in Germany using a competing risks model. The study investigated how exit decisions vary between new firms in a transitional and in a comparatively stable market environment. The results confirm that distinguishing between different types of exit augments the understanding of the exit behaviour of new firms.

Moreover, Perez, Llopis and Llopis (2002) utilized a competing risks proportional hazards model to explore the determinants of different exit routes for Spanish manufacturing firms. The different exit types, that is, liquidation, acquisition and merger, are identified. The results show the remarkable difference in the factors determining exit depending upon the exit route in terms of firm and industry characteristics. The result is consistent with Harhoff, Stahl and Woywode (1998), which suggested that pooling exit routes into the same analysis is a major source of misspecification.

In the UK, Dickerson, Gibson and Tsakalotos (1999) employed a competing risks model, specifically, a Weibull hazard model and a semi-parametric hazard model to

investigate the determinants of UK manufacturing companies making acquisitions and being acquired and to examine whether companies can use acquisition as a strategy to reduce the probability of takeover or go bankrupt. The study confirms that companies that make acquisitions can reduce the conditional probability of being taken over.

Using a competing risks hazard regression model with four groups of variables, namely, macroeconomic instability, macroeconomic activity, firm-specific variables and industry dummies of all listed UK companies, Bhattacharjee et al. (2004) suggested that adverse macroeconomic conditions increase the bankruptcy hazard while decreasing the acquisition hazard.

Furthermore, Rommer (2004) examined three types of exit of Danish non-financial public and private limited liability companies using a competing risks model. The three types of firms, that is, financially distressed firms, voluntarily liquidated firms and merger or acquisition firms are identified in order to compare the competing risks model to a pooled logit model (where all exits are pooled) and to a simple financial distress model (where the exit to financial distress is modelled and all other firms are treated as censored). It was found that the proportion of correct predictions in the competing risks model was better than in the pooled logit model, which suggests that it is important to distinguish between exit types.

In addition, Rommer (2005) used a competing risks model to compare the predictors of financial distress in French, Italian and Spanish firms. By including firms that exit for reasons other than financial distress, for example, merger, voluntary exit, unknown reasons and residual category, a competing risks model is set up and the probability of exiting to the various states is estimated. The results show that some of the variables behave similarly across countries while some variables produce the different effect between the countries.

The literature explores multiple states of financial distress in contexts other than European countries using a competing risks model; for example, in the US, Wheelock and Wilson (2000) utilized a competing risks model to identify the characteristics that make individual US banks more likely to fail or be acquired. The study assumes that the causal processes for acquisitions and failures are different and because the occurrence of either event precludes the other, so, the competing risks hazard model is used to identify the characteristics leading to each outcome.

In Japan, to investigate the determinants of time to bankruptcy and time to merger jointly and to investigate their interdependence, Yu (2006) used a dependent competing risks model in examining credit cooperatives in Japan, which assumes that time to bankruptcy and time to merger are interdependent. The author argues that the independent competing risks model assumes the independence of the two hazards might not fully describe the failure and merger processes and might generate inconsistent estimates. Furthermore, the bankruptcy and merger processes are interrelated and there might be some unobservable firm-specific characteristics that affect both processes. The results suggest that the common practice of assuming the independence of the competing risks would produce biased estimates and lower the predictive accuracy.

5.3 Hypotheses development

This study estimates the competing risks Cox proportional hazards model, which allows multiple states of financial distress to be examined. The research hypotheses corresponding to specific research questions presented in Chapter 1 are set as follows.

Research hypothesis #5.1: The significant factors influencing financial distress in single risk and multiple risks models are different.

To test this hypothesis, a three-state financial distress model including state 0: active companies, state 1: distressed external administration companies and state 2: distressed takeover, merger or acquisition companies is estimated using a competing risks Cox proportional hazards model. Then, a single risk or pooled model in which all financial distress state are pooled together is estimated. Consequently, the results of the two model specifications are compared in terms of the significance and sign of variables.

Research hypothesis #5.2: The significant factors driving each state of financial distress are different.

To test this hypothesis, the three-state financial distress model is examined by utilizing the competing risks Cox proportional hazards model. The above hypothesis will be tested based on the proposed variables including annual data of financial ratios, stock prices and company-specific variables. The significant factors or determinants of each particular financially distressed state are identified. Then, the similarity and difference of the factors that drive each state of financial distress are compared in terms of the significant variables and estimated signs within the multiple states of financial distress model.

5.4 Competing risks model

In order to examine the determinants of multiple states of corporate financial distress, this study utilizes a competing risks Cox proportional hazards model. Competing risks is the sub-discipline of survival analysis where, in addition to survival time, the different causes of an event are observed (Andersen, Abildstrom and Rosthoj, 2002).

The risk of entering each state of financial distress is modelled in a framework where each company is concurrently at risk of each state of financial distress during each year of its lifetime. Three different states of financial distress are mutually

exclusive events, which means that the occurrence of one type of event removes the firm from being at risk of all the other event types; therefore, the use of a competing risks model is appropriate.

There are several ways to approach the problem of competing risks but the most common way has been to begin by defining a type-specific or cause-specific hazard function (Ghilagaber, 1998).

In the presence of R ($R \geq 2$) causes of failure indexed by r ($r = 1, \dots, R$), let the random variable C represent the cause of failure. A cause-specific hazard function is defined as follows:

$$h_r(t) = \lim_{\Delta t \rightarrow 0} \frac{\Pr(t \leq T < t + \Delta t, C = r | T \geq t)}{\Delta t}, r = 1, \dots, R \quad (5.1)$$

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

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

$$h(t) = \sum_{r=1}^R h_r(t) \quad (5.2)$$

Narendranathan and Stewart (1991) have shown that the log-likelihood for the competing risks model is additively separable into terms where each of one is a function of the parameters of a single cause-specific hazard. Thus, in order to estimate competing risks Cox proportional hazards models, the researchers must proceed with the estimation of single risk hazards treating durations finishing for other reasons than the one of interest as censored at the point of completion.

Therefore, this thesis will estimate the following models:

$$h_{ri}(t) = h_{r0}(t) \exp(X_{ri(t)} \beta_r) \quad (5.3)$$

Where $r = \{\text{distressed external administration, distressed takeover, merger or acquisition}\}$.

In this thesis, the competing risks of a three-state financial distress model, namely, active companies, distressed external administration companies and distressed takeover, merger or acquisition companies will be estimated using Cox proportional hazards models. Two separate Cox proportional hazards models are estimated for the competing risks where other states of financial distress are considered as censored observations.

5.5 Data and sample

In order to examine the determinants of multiple states of financial distress and to compare the pooled model with the competing risks model in predicting the probability of corporate endurance, the competing risks Cox proportional hazards form of survival analysis is now applied to the population of all companies listed on the ASX using annual data of financial ratios, stock prices and company-specific variables of age and size for the period 1989 to 2005. Companies in the financial sector are excluded from the analysis because of variations in the structure of their financial statements. Ideally, the information of the entire history of a company since its establishment would be used. Unfortunately, financial statement information is not available until the Fiscal year 1989. Therefore, the models presented in this chapter are based on duration data truncated to the left since they pertain only to the period since 1989.

This study defines financial distress 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 that filed for the external administration process. According to the Corporation Act 2001, there are four categories of external administration process: 1) voluntary administration, 2) scheme of arrangement, 3)

receivership and 4) liquidation. The date of entering into external administration is purchased from ASIC.

State 2: Distressed takeover, merger or acquisition companies. This state is defined as financially distressed companies that were delisted from the ASX because they were subject to a takeover, merger or acquisition arrangement. The data of the delisted reason, company announcement and delisted date are collected from *FinAnalysis Database*, which belongs to Aspect Huntley Ltd.

As pointed out by Clark and Ofek (1994), if a firm experiences operating or financial difficulties then several potential actions exist. One remedy is restructuring financially distressed firms through a merger. Therefore, the inclusion of distressed takeover, merger or acquisition provides an opportunity to examine further a more diverse state of financial distress that can be observed in reality.

A sample of active and distressed companies in States 0, 1 and 2 was collected for between the years 1989 and 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 in this study is the number of years from the start year to the year of financial distress for distressed companies or to the last year observed for active companies. In this study, the start year is the first year when data are available. Each company is followed up to the year when it experienced an event in one of the multiple states of financial distress or until the end of the study period, whichever comes first.

The explanatory variables used in the model are financial ratios, market-based data and company-specific variables. The details of the variables used in this chapter are the same as the previous chapter that is shown in Table 4.1.

5.6 Empirical results

5.6.1 Descriptive statistics

Table 5.1 presents the descriptive statistics of the data employed in the study. Sample means, medians, minimum, maximum, inter-quartile range, standard deviations, skewness, kurtosis and the number of observations are presented for each financial distress state.

The Chi-square statistics for the median test and its p -value are the result of a non-parametric test for a significant difference between the group medians. Variables with significant differences within the group medians will be 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 percent level.

It is important to note that the financial ratios employed in this study behave in an inappropriate manner as the standard deviations before truncation are very large. This is due to there being a number of outliers that could influence the results. Unlike many previous studies, which do not account for this problem, this study uses the truncation technique to minimize the effect of the outliers. All observations with variable values higher than the ninety-ninth percentile of each variable are set to that value; in the same way, all variable values lower than the first percentile of each variable are truncated. This method is consistent with Shumway (2001). However, it is important to note that the ninety-ninth percentile and the first percentile, which have been used in the study, are just arbitrary values. An alternative way to handle asymmetric shape is using the logarithmic transformed variable as the predictor variables that can be considered in a future research.

To avoid the extreme values, median and inter-quartile range are used as summary statistics in this study instead of mean and standard deviation which are very sensitive to outliers.

Table 5.1 reports the calculated figures after truncation. The descriptive statistics results before truncation are reported in Table B.3 in the appendix. According to Table 5.1, the EBT and ROA medians of active and distressed external administration companies are negative while it is positive for distressed takeover, merger or acquisition companies. In addition, the median of ROE is negative positive active companies while it is positive for both distressed external administration companies and distressed takeover, merger or acquisition companies. Furthermore, the ROE median of distressed takeover, merger or acquisition companies is higher than for distressed external administration companies. This implies that distressed takeover, merger or acquisition companies in this study have a higher ability to generate earnings than have both active and distressed external administration companies.

For liquidity ratios, CUR and QUK, financially distressed companies have lower medians of both CUR and QUK than have active ones. This shows that distressed companies are less able to meet their current obligations as they become due than are active companies. However, the WCA medians of distressed takeover, merger or acquisition companies is higher than for both active and distressed external administration companies.

Considering the medians of DET, it is found that the ability of financially distressed companies in all states to pay long term liabilities is less than it is for active companies.

For activity ratios, CPT and TAT, the median values of both ratios show a mixed interpretation. For variable CPT, the median value for active companies is higher than

for distressed external administration companies but lower than for distressed takeover, merger or acquisition companies. However, the medians of TAT for financially distressed companies in all states are higher than for the active ones.

The SIZE median values imply that the size of financially distressed companies in all states is larger than that of active companies. Furthermore, the age median of distressed external administration in this study is greater than the age of active companies.

Finally, the median of EXR suggests the company's past excess returns for active companies is higher than that of distressed external administration companies but lower than that of distressed takeover, merger or acquisition companies.

5.6.2 Correlation coefficients

In order to investigate the relationships between the variables, an examination of the correlation coefficients across the variables has been conducted. The Pearson correlation coefficients are shown in Table 5.2.

According to the table, the Pearson correlation coefficients results found that most of the variables are significantly correlated but the magnitudes are small.

Table 5.1: Descriptive statistics of the data

	EBT	ROE	ROA	CUR	QUK	WCA	DET	CPT	TAT	SIZE	SIZE2	AGE	EXR
State 0 (n = 891)													
Mean	-39.1882	-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	-0.0200	-0.0081	-0.0085	1.7600	1.3000	0.0128	0.3433	0.9230	0.4394	15.9391	254.0548	14.0000	-0.0805
Min	-1110.0460	-4.2639	-2.3701	0.0500	0.0400	-1.0000	0.0047	0.0002	0.0002	6.7708	45.8436	1.0000	-2.2731
IQR	3.3639	0.3049	0.2225	3.4300	3.4400	0.1799	0.4479	2.4305	1.0491	5.4443	168.8465	14.0000	0.7598
Max	1.9072	2.5722	0.3884	155.0900	155.0900	0.6999	3.5587	82.7817	5.7367	22.5982	510.6794	90.0000	2.0433
Std Dev.	163.2580	0.7526	0.4061	18.6848	18.7216	0.2201	0.4282	9.9278	0.9912	3.7188	111.9211	18.4983	0.7280
Skewness	-5.4568	-2.4059	-3.3643	5.4057	5.3990	-0.9343	3.9324	6.3372	2.3255	-0.3126	0.1798	2.0393	-0.0737
Kurtosis	30.4554	13.9761	13.5418	33.4315	33.3725	5.8129	23.7046	44.3049	6.9079	-0.5608	-0.6265	4.1816	1.1784
State 1 (n = 50)													
Mean	-10.3121	-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	-0.0214	0.0025	-0.0062	1.3200	1.0400	0.0106	0.4556	0.8820	0.4533	16.4390	270.2389	17.0000	-0.2096
Min	-318.6193	-4.2639	-2.3701	0.0500	0.0400	-1.0000	0.0047	0.0004	0.0002	7.4396	55.3470	1.0000	-2.2731
IQR	1.2552	0.2360	0.1733	1.9100	1.9800	0.2134	0.4491	2.2523	1.0574	3.5043	113.5213	23.0000	0.8338
Max	1.9072	2.5722	0.3884	155.0900	155.0900	0.6999	3.5587	51.4800	5.7367	21.5449	464.1840	90.0000	2.0433
Std Dev.	45.5966	0.7766	0.5007	17.3525	17.3967	0.2756	0.7348	6.9209	1.1424	3.0109	89.6430	16.6491	0.8061
Skewness	-5.8346	-1.5362	-3.2754	7.2412	7.2240	-1.4149	2.9279	4.8427	2.6287	-0.6863	-0.2302	1.3985	-0.0785
Kurtosis	34.5908	10.7583	10.7957	55.7535	55.5423	5.0272	8.6108	26.4602	7.9975	-0.0097	-0.3737	2.6935	1.0194
State 2 (n = 140)													
Mean	-2.5188	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	0.0742	0.0825	0.0538	1.5000	1.0100	0.0460	0.4663	1.5115	0.8167	18.1779	330.4352	14.0000	-0.0556
Min	-847.0480	-4.2639	-2.3701	0.0500	0.0400	-1.0000	0.0047	0.0003	0.0002	6.9078	47.7171	1.0000	-2.2731
IQR	0.1384	0.1297	0.0664	1.2100	0.8500	0.2117	0.2407	2.2310	1.0833	2.9449	107.4156	24.0000	0.5509
Max	1.9072	2.5722	0.3884	155.0900	155.0900	0.6999	3.5587	82.7817	5.7367	22.4284	503.0313	90.0000	2.0433
Std Dev.	26.8813	0.5037	0.2137	11.7242	11.7859	0.1951	0.4269	9.1551	0.9212	2.6052	86.8882	20.6510	0.5769
Skewness	-24.3415	-3.8848	-6.4543	8.5974	8.5643	-0.3701	4.9554	5.8140	2.1054	-1.0868	-0.5215	1.4579	0.1276
Kurtosis	729.9061	38.0125	57.7766	87.2817	86.6035	4.7533	32.1249	39.5832	6.7491	1.7751	0.2680	1.4020	2.9682
Chi-square	450.5755**	358.9656**	423.0064**	110.6478**	153.4642**	61.9947**	229.6430**	89.0355**	178.8191**	547.7139**	547.8080**	23.0860**	23.2753**
p-value	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001

Note: State 0: Active companies, State 1: Distressed external administration companies and State 2: Distressed takeover, merger or acquisition companies.

Descriptive statistics grouped by company status. Chi-square from a non-parametric test of equality of group medians using median tests.

*** Significant at the 5 percent level.*

Table 5.2: Pearson correlation coefficients

Variable	EBT	ROE	ROA	CUR	QUK	WCA	DET	CPT	TAT	SIZE	SIZE2	AGE	EXR
EBT	1.0000	0.1027 ^a <.0001 ^b	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: a. Pearson correlation coefficients.

b. The p-value under the null hypothesis of zero correlation.

5.6.3 The model estimation results

In order to examine the determinants of multiple states of financial distress and to compare a pooled model with a competing risks model, nine financial ratios, a market-based variable and three company-specific variables are entered into the competing risks Cox proportional hazards model. The variables used are time-dependent variables covering 1989 to 2005. The estimation results of the competing risks model are presented in Table 5.3. Table 5.3 reports the model estimation results after truncation. For the results before truncation, see Table B.4 in the appendix.

In order to highlight the effect of allowing for multiple states of financial distress, the estimation results from the single risk model or pooled model (where all states of financial distress are pooled together) and the competing risks model are presented. The competing risk model applied to each three states collectively. Panel (A) provides the results for the single risk model while Panel (B) contains the competing risks model estimation results. The three columns in each panel report the coefficients estimation with the relative p -value for testing the null hypothesis that the coefficient of each variable is equal to zero and 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. If the hazard ratio is greater (less) than 1, this indicates the more rapid (slower) hazard timing. The empirical results reported in Table 5.3 are discussed below.

1) Competing risks model estimation

According to the competing risks model estimation results, it was found that WCA and EXR significantly affect the risk of filing for external administration process but do not drive the risk of takeover, merger or acquisition.

The coefficient of WCA has a positive sign, which means that an increase in the working capital to total assets ratio increases the hazard of facing external administration process. The ratio is used for measuring company liquidity and, as mentioned in Altman (1968a), a firm experiencing consistent operating losses will have shrinking current assets in relation to total assets. This result is in contrast to what was expected, as a company with high liquidity should have a lower likelihood of facing financial difficulties. This perverse finding should be held out for future research until the issue can be revisited and an attempt made to explain the inconsistency.

For EXR, the coefficient sign is negative, which means that an increase in a company's past excess returns decreases the hazard of entering financial distress. The hazard ratio for EXR is 0.4710, which means that an increase of one unit in a company's past excess returns implies a 52.90 percent decrease in the risk of financial distress. The result suggests the potential of market data in predicting corporate financial distress. Shumway (2001) and Partington et al. (2006) also reported similar 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, the coefficient of DET is positive while in the distressed takeover, merger or acquisition model, DET has a negative coefficient. These results imply that the company with the lower debt to total assets ratio is less likely to file for external administration process but is more likely to be subject to a takeover, merger or acquisition. Consistently, Schary (1991) also found the 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 debts to enable them to purchase the company (Dickerson, Gibson and Tsakalotos, 1999).

The coefficient sign of SIZE is positive in both models. The positive sign of SIZE means that the larger the size of a company, the higher the likelihood of that company entering financial distress both through external administration process and through takeover, merger or acquisition. The reasonable explanation for this result is that a large company might have inflexible organizations and have problems monitoring managers and employees, which leads to inefficient communication (Rommer, 2004). Furthermore, Perez, Llopis and Llopis (2002) also reported similar results, that is, that the risk of acquisition increases with company size, and suggested that large firms tend to be involved in mergers.

The variable CPT and SIZE2 were found to have a significant effect on the risk of being subject to takeover, merger or acquisition, but are not significantly related to the probability of entering external administration process.

The coefficient sign of CPT is positive, which implies that an increase in the operating revenue to operating invested capital ratio increases the hazard of a company being subject to takeover, merger or acquisition. A reasonable explanation is that a company that uses its assets efficiently will increase its income and liquidity and so the company is more attractive for being subject to takeover, merger or acquisition. Wheelock and Wilson (2000) also found consistent results when 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, as the cost of reorganizing an inefficient bank could be high.

The estimated coefficients for SIZE2 of distressed takeover, merger or acquisition is negative. The result suggests that the effect of company size on distressed takeover, merger or acquisition is an inverted U-shape or bell-shape. This finding is consistent with Bhattacharjee et al. (2004), which also found a bell-shaped relationship between firm size and the likelihood of the firm being acquired. In particular, the finding supports the evidence from the acquisition literature that listed firms in the middle range of the size are more likely to be acquired.

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

2) Single risk model estimation

When pooling all the different states of financial distress, three variables are highly significant at the five percent level. These variables are TAT, SIZE and SIZE2 with the coefficient -0.1825, 1.2398 and -0.0302 respectively. The variables ROA and DET are also significant at the 10 percent level with the estimated coefficient -0.4461 and 0.3275 respectively.

The coefficient of TAT has a negative sign, which means that an increase in a firm's ability to utilize assets decreases the hazard of entering into financial distress. The hazard ratio for TAT is 0.8330; this means that for each unit increase in the total assets turnover ratio, the risk of becoming financially distressed decreases by 16.70 percent.

The positive sign of SIZE means that the larger the size of a company, the higher the likelihood of the company entering financial distress. This is because a large company might have inflexible organizations and have problems with monitoring managers and employees; consequently, the company will face problems of inefficient communication and then face financial difficulties (Rommer, 2004).

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

The possible explanation for this finding is that the companies in the sample used in this study are all publicly listed Australian companies excluding non-publicly listed companies. Therefore, the used sample with a relatively large size might capture only the effect of size for those company samples on the likelihood of financial distress. In other words, the results do not capture the effect of company size on financial distress for non-publicly listed companies, which have a relatively small size.

In addition, the coefficient of ROA has a negative sign, which means that an increase in a firm's ability to generate earnings decreases the hazard of entering into financial distress. The hazard ratio for ROA is 0.6400, which means that for each unit increase in ROA, the risk of becoming financially distressed decreases by 36.00 percent. This is consistent with the expectation that companies with a high ability to generate earnings are less likely to face financial difficulties.

Furthermore, the estimated sign of the variable DET is positive, which means the company with a low debt ratio is less likely to file for financial distress. The hazard ratio for DET is 1.3880, which means that for every unit increase in debt ratio, the risk of becoming financially distressed increases 38.80 percent.

3) A comparison between the models

Comparing the estimation results between the single risk and the competing risks model, the results suggest that DET and SIZE are common significant variables in the single risk model and the competing risks model.

The coefficient sign of DET in single risk and distressed external administration in the competing risks model are both positive, which implies that the company with a lower debt to total assets ratio is less likely to file for financial distress. However, the sign of the parameter for DET is negative for distressed takeover, merger or acquisition in the competing risks model. The result indicates that the company with a higher debt has a lower probability of being subject to a distressed takeover, merger or acquisition.

The coefficient sign of SIZE is positive; this is for values in the single risk model and the two specifications in the competing risks model. This result implies that they have the same effect on the hazard for financial distress in the single risk model and the hazard for filing for external administration process and the hazard for distressed takeover, merger or acquisition in the competing risks model. In particular, the results suggested that the larger the size of the company, the greater the likelihood of the company entering financial distress.

There are some variables that significantly affect the hazard of financial distress in the single risk model but do not significantly affect the hazard of distressed external administration and distressed takeover, merger or acquisition in the competing risks model. Those variables include ROA and TAT.

The estimation of the competing risks model shows that the sign of the variable ROA is negative, which implies that a company with high profitability has a lower probability of facing financial difficulties. Additionally, it is found that the variable

TAT has a negative estimated sign, which suggests that companies with a higher ability to utilize assets are less likely to fail.

Furthermore, the variable AGE was never found to be a significant variable 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, active companies, distressed external administration companies and distressed takeover, merger or acquisition companies within the framework of a competing risks model, it was found that each state of financial distress is caused by different factors. Furthermore, by comparing the empirical estimation results between a single risk and a competing risks model, the results indicate that both models' specifications result in different significant variables explaining financial distress. Therefore, the conclusion is that it is important to distinguish between the financial distress states.

This finding is consistent with Harhoff, Stahl and Woywode (1998), Perez, Llopis and Llopis (2002) and Rommer (2004). Harhoff, Stahl and Woywode (1998) concluded that a separate consideration of the modes of corporate exit is highly desirable and revealed that pooling exit types is a major source of misspecification and the econometric results may be misleading if the distinction between exits is not made.

Table 5.3: Single and competing risks Cox proportional hazards model estimation

Variable	(A) Single Risk Model			(B) Competing Risks Model					
				Distressed External Administration Companies			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	-0.2706	0.1745	0.7630	-0.6151	0.1712	0.5410	-0.1782	0.4427	0.8370
QUK	0.2641	0.1842	1.3020	0.6216	0.1660	1.8620	0.0916	0.6951	1.0960
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 percent level.

** Significant at the 5 percent level.

5.6.4 Corporate survival probability evaluation

The survival function of typical active, distressed external administration and distressed takeover, merger or acquisition companies is presented in Figure 5.1. The survival function defines the probability that a company will survive longer than t time units.

The survival function shown in Figure 5.1 does not show monotonic relationship because it is produced by averaging the estimated survival probability of companies by different states of financial distress, for example, state 0: active companies, state 1: distressed external administration companies and state 2: distressed takeover, merger or acquisition companies.

According to Figure 5.1, the survival probability of the typical financially distressed external administration companies is lower than that of the typical active companies and distressed takeover, merger or acquisition companies. The noticeable decrease in corporate survival for distressed external administration companies occurs nine years after the companies are entered into the analysis.

The survival probability that the companies will survive beyond 17 years for active and distressed takeover, merger or acquisition companies is approximately 88.61 and 90.18 percent respectively, while that for distressed external administration companies is about 76.77 percent.

It should be noted that the survival profiles of active companies and distressed takeover, merger or acquisition companies are very similar. Additionally, the probability that distressed takeover, merger or acquisition companies will survive beyond year 12 to year 14 and year 16 to year 17 is slightly higher than that of active ones. The detail of the survival probability of a company within a given time stratified by company status is shown in Table 5.4.

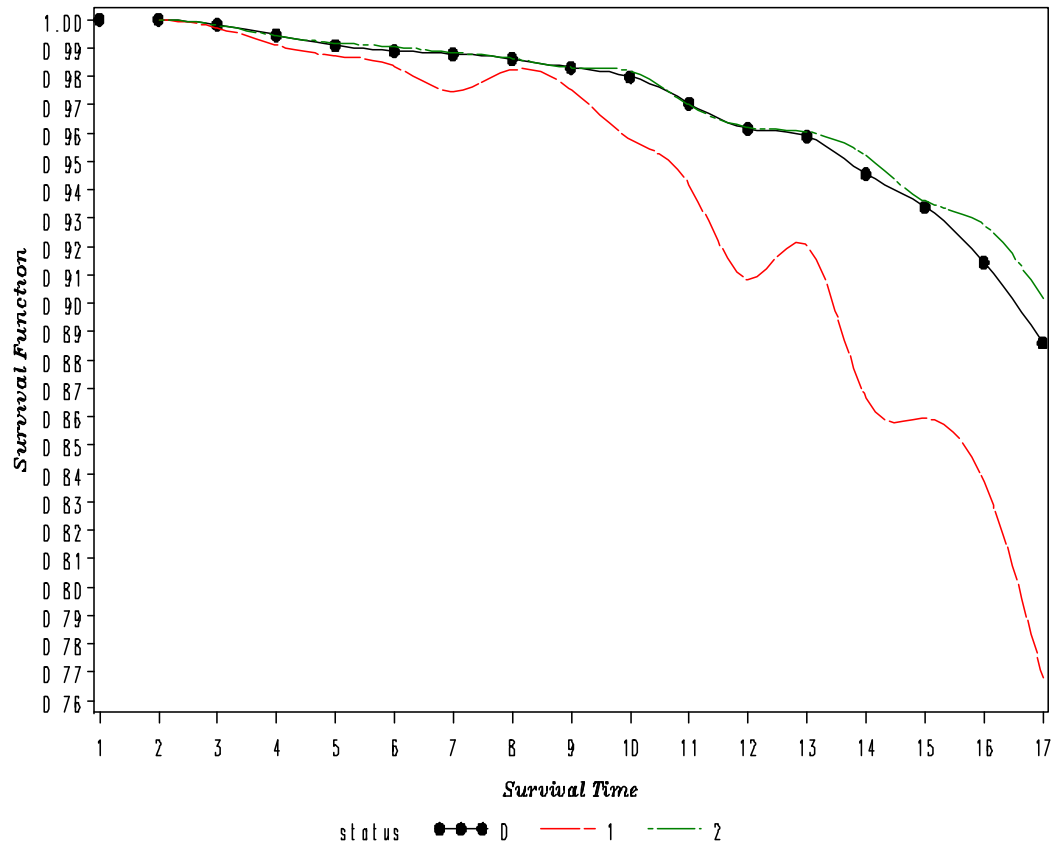


Figure 5.1: Graph of survival function and survival time by financial distress states

Table 5.4: Survival probabilities of companies by company status

Survival Time	Survival Probability		
	State 0	State 1	State 2
1	1.0000	1.0000	1.0000
2	1.0000	1.0000	1.0000
3	0.9982	0.9971	0.9980
4	0.9946	0.9910	0.9942
5	0.9910	0.9871	0.9917
6	0.9889	0.9836	0.9904
7	0.9879	0.9747	0.9883
8	0.9862	0.9823	0.9863
9	0.9831	0.9752	0.9830
10	0.9798	0.9578	0.9817
11	0.9704	0.9418	0.9699
12	0.9616	0.9082	0.9620
13	0.9589	0.9203	0.9604
14	0.9456	0.8667	0.9519
15	0.9339	0.8594	0.9360
16	0.9144	0.8371	0.9278
17	0.8861	0.7677	0.9018

Note: State 0: Active companies, State 1: Distressed external administration companies and State 2: Distressed takeover, merger or acquisition companies.

5.7 Conclusion

Companies might face a range of financial health states and might exit the market in several ways such as through merger, acquisition, voluntary liquidation and bankruptcy and each form of exit is likely to be caused by different factors. The multiple state of financial distress model would provide a wider range of distress scenarios than public companies typically face in reality. This study, therefore, focuses on examining the determinants of multiple states of financial distress using a competing risks model and comparing the empirical results to the pooled model.

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

The sample consists of 891 active companies, 50 distressed external administration companies and 140 distressed takeover, merger or acquisition companies covering the period 1989 to 2005. The competing risks Cox proportional hazards model is estimated based on the proposed variables. Four main categories of financial ratios are used as indicators of financial distress: profitability, liquidity, leverage and activity. Additionally, the company's past excess returns are used as a proxy for market-based data. The relationship between company-specific variables, that is, age, size and squared size and corporate endurance are also examined.

The results show that there are differences in the factors determining whether companies enter different states of financial distress. Specifically, distressed external administration companies have higher leverage, lower past excess returns and a larger size compared to active companies, while distressed takeover, merger or acquisition companies have lower leverage, higher capital utilization efficiency and a bigger size compared to active companies. The conclusion from the comparison of the results from the single risk model and the competing risks model is that it is important to distinguish between the financial distress states. The study results do not support the importance of the company age factor in explaining financial distress.

Further implications of this study relate to further research on potential factors for predicting corporate failure that need to be considered, for example, corporate governance variables and macroeconomic variables.

CHAPTER 6

CORPORATE GOVERNANCE MECHANISMS AND NEW ECONOMY AUSTRALIAN IPO COMPANIES' SURVIVAL

6.1 Introduction

This chapter explores corporate governance structures in explaining the new economy IPO companies' survival in the Australian context. Corporate governance has become a prominent topic over the last two decades. One of the reasons for this prominence is a series of recent USA scandals and corporate failures during the late 1990s (Becht, Bolton and Roell, 2002). Since the boom period of dot-com companies between late 1998 and early 2000, initial public offerings (IPOs) for internet-based or new economy companies dramatically increased during this period. There existed a speculation in increasing stock values and growth in the new internet sector called the 'tech-bubble' (Chan-Lau and Ivaschenko, 2003). During these 'bubble years', entrepreneurs rapidly implemented new business models and developed new products. Unfortunately, it quickly became clear that many of these new businesses were unprofitable and the 'bubble years' were quickly followed by a dramatic period of collapsing stock prices, exits and bankruptcies (Cockburn and Wagner, 2007).

One major Australian corporate collapse in the new economy sector was the collapse of One.Tel, Australia's fourth largest telecommunications company in 2001, shortly after its listing on the Australian Stock Exchange in 1997. One.Tel's 1,400 workers were laid off after the collapse. Furthermore, the company owed more than 600 million dollars to over 3,000 creditors. The collapse also caused the bankruptcy of many minor creditors who were owed thousands of dollars for goods and services (Cook, 2001). It can be seen that the failure of companies entails significant direct and indirect

costs to many stakeholders. Many of these costs could be avoided if it were possible to identify the factors and the survival probability of companies after their IPOs.

The literature examining the impact of corporate governance attributes on the survival of IPO companies suggests that many corporate governance structures are associated with corporate survival. For example, Parker, Peters and Turetsky (2002a) have reported that auditors are less likely to issue going concern modifications to companies in the presence of employee audit committee members, or with greater insider ownership and blockholder ownership. By investigating 176 financially distressed firms, Parker, Peters and Turetsky (2002b) suggested that firms that replaced their CEOs with outsiders were more than twice as likely to experience bankruptcy. Furthermore, the results suggested a positive relationship between firm survival and larger levels of blockholder and insider ownership.

Recent literature investigating the survival of new economy IPO companies utilizes corporate governance attributes; for example, Audretsch and Lehmann (2004) explored the influence of ownership and induced incentives on the survival of young and high-tech firms confirming that the governance structure needed for firms in the new economy industries is different to that needed by traditional firms. Additionally, Dowell, Shackell and Stuart (2007) examined the effects of board independence and board size on internet firms' survival. The authors found that the expected survival time of firms is influenced by the interaction between founder-CEOs and the degree of board independence. The study also found a nonlinear relationship between board size and expected corporate survival time. Furthermore, Van der Goot, Van Giersbergen and Botman (2008) found a positive relationship between insider ownership retention and the survival of internet firms. In Australia, however, there is a lack of studies that focus on survival analysis using extensive corporate governance attributes.

The purpose of this chapter is to explore extensively the corporate governance attributes that influence the likelihood of the survival of new economy IPO companies. Three areas of corporate governance structures, that is, board size, board independence and ownership concentration, are employed in this analysis. Furthermore, offering characteristics, financial ratios and company-specific variables are also included as control variables. To achieve this objective, the 127 new economy companies of the sample that were listed on the ASX between 1994 and 2002 were tracked until 31 December 2007 so companies' status could be identified including trading, delisted and suspended. The Cox proportional hazards model was then employed to identify the likelihood of survival of a company after IPOs.

To the best of the author's knowledge, this is the first study that investigates the survival of Australian IPO companies and that focuses on the new economy sector. Although studies by both Woo, Jeffrey and Lange (1995) and by Lamberto and Rath (2008) investigated the survival of IPO companies in Australia, neither study focused on the new economy sector.

Furthermore, unlike some previous studies, this study allows time-varying variables in the Cox proportional hazards model rather than merely using time-invariant variables as in Woo, Jeffrey and Lange (1995), Audretsch and Lehmann (2004), Lamberto and Rath (2008) and Van der Goot, Van Giersbergen and Botman (2008). This features allows for the deterioration in the variables of financial ratios and company-specific variables over time, since it is unlikely that their values or effects would remain constant with the progression of the corporate failure process (Luoma and Laitinen, 1991). LeClere (2005) suggested that the potential proportional hazards model with time-varying variables outperforms proportional hazards models with time-

invariant variables since it allows the sensitivity of the proportional hazards model to the choice of variable time-dependence in financial distress applications to be tested.

In this study, the results show that new economy IPO companies' survival time is negatively related to the percentage of the largest top 20 shareholders of the companies, which suggests that a lower ownership concentration in new economy IPO companies should be encouraged. In addition, offering size and company size are found to be negatively related to new economy IPO companies' survival, which is contrary to expectations. Furthermore, the results found that board size and board independence are insignificantly associated with new economy IPO companies' survival.

The remainder of the chapter is organized as follows. Section 6.2 reviews previous studies relating to corporate governance structure and IPO companies' survival. The hypotheses development is then specified in Section 6.3. Section 6.4 presents the details of the methodology used in this study, that is, the Cox proportional hazards model. Section 6.5 discusses the data and sample employed in the analysis. The empirical results are then presented and discussed in Section 6.6. Finally, the conclusion and possible future extensions are discussed in the last section.

6.2 Literature review

Corporate governance has become a prominent topic over the last decade. The reason for this prominence has been a number of events such as the 1998 East Asia crisis, which put the spotlight on corporate governance in emerging markets and a series of recent scandals in the USA and corporate failures during the late 1990s (Becht, Bolton and Roell, 2002). The corporate collapses of the late 1990s highlighted the need for good corporate governance and high quality financial reporting. Various studies explore corporate governance aspects in relation to corporate performance in various countries. For example, in Australia, Balatbat, Taylor and Walter (2004) found that board

composition measured by outsider ownership is not related to Australian IPO companies' operating performance while independent board leadership structure is associated with better company performance.

The consistent finding about the influence of CEO duality on corporate performance is also found in Bai et al. (2004) and Li and Naughton (2007), who focused their studies on Chinese firms. In the context of Chinese companies, Hovey, Li and Naughton (2003) confirmed that ownership concentration has little explanatory power, but ownership structure has a significant relationship to firm performance. However, Xu and Wang (1999) argued that the mix and concentration of stock ownership significantly affects a company's performance. Lehmann and Weigand (2000) also found that ownership concentration negatively affected corporate profitability in German corporations. Furthermore, investigating ownership structure and corporate performance in the Czech Republic, Claessens and Djankov (1999) also found that the more concentrated the ownership, the higher the firm's profitability and labour productivity.

However, Weir and Laing (2001) investigated the relationship of corporate governance structure with corporate performance in the UK and suggested that there is no clear relationship between corporate governance and corporate performance.

If corporate governance factors influence the performance of the company, then the governance attributes are expected to impact on the likelihood of company survival (Goktan, Kieschnick and Moussawi, 2006). Previous literature suggests that many corporate governance structures are associated with financial distress or the likelihood of firm survival. For example, Lee, Yeh and Liu (2003) employed accounting, corporate governance and macroeconomic variables to construct a binary logistic regression model for the prediction of financially distressed firms. The percentage of directors

controlled by the largest shareholder, management participation, and the percentage of shares pledged for loans by large shareholders are found to have a positive relationship with the probability of financial distress.

Lee and Yeh (2004) utilized three corporate governance variables, namely, 1) the percentage of directors occupied by the controlling shareholder, 2) the percentage the controlling shareholders shareholding pledged for bank loans and 3) the deviation in control away from the cash flow rights to fit the dichotomous prediction models. The results suggested that the three variables mentioned above are positively related to the risk of financial distress in Taiwanese companies.

Goktan, Kieschnick and Moussawi (2006) examined the relation between corporate governance structures and the likelihood of a company going private, being acquired or going bankrupt. They found evidence that corporate governance primarily influences whether a corporation is acquired or whether it goes private, but not whether it goes bankrupt.

In order to reduce the agency costs, Yang and Sheu (2006) suggested that the equity stake owned by management, especially by top officers of an IPO firm, should be encouraged. Furthermore, they observed the U-shaped relationship between insider ownership and the survival time of Taiwanese IPO companies.

The recent literature on the impact of corporate governance on the survival of new economy IPO companies started to focus on the dot-com boom period; for example, Audretsch and Lehmann (2004) explored the relationship between ownership and induced incentives and the survival of young and high-tech firms listed on the German stock market from 1997 to 2002. They found that CEO ownership was negatively related to the likelihood of company failure, but became insignificant when measurements of human capital and intellectual rights were introduced. The results

confirmed that the governance structure needed for firms in the new economy industries was different to that of traditional firms.

Additionally, Dowell, Shackell and Stuart (2007) investigated whether corporate governance affected the survival of internet US firms that went public during 1996 to 1999. The results found that the expected survival time of firms with founder-CEOs decreased with the degree of independence of the board while the expected survival time of firms with non-founder CEOs increased with the degree of board independence. The study also found a nonlinear relationship between board size and the expected survival time of a firm.

Van der Goot, Van Giersbergen and Botman (2008) analysed the determinants of the survival of internet firms listed on the NASDAQ between 1996 and 2001. Their results showed that surviving firms were associated with lower risk indications in the IPO prospectus, higher underwriter reputation, higher investor demand for the shares issued at the IPO, lower valuation uncertainty, higher insider ownership retention, a lower NASDAQ market level, and a higher operating cash flow to liabilities ratio compared to non-survivors.

In Australia, Woo, Jeffrey and Lange (1995) used survival analysis techniques, namely, Weibull and log-normal models, to investigate whether firm characteristics observed at the time of listing are capable of indicating Australian IPO firms' survival. They used ownership concentration as one potential variable in explaining the survival rate of newly listed firms in Australia. They found a negative relationship between ownership concentration and firm survival, which is inconsistent with agency theory. Lamberto and Rath (2008) employed the Cox proportional hazards model to examine the likelihood of survival for IPO firms in Australia by utilising three ownership structure variables: 1) non-executive chairman, 2) number of directors and 3) percentage

of independent directors. Their study focused on testing the value of information publicly available from IPO prospectuses in explaining IPO firms' survival. However, both Woo, Jeffrey and Lange (1995) and Lamberto and Rath (2008) focused only on the period before the tech stock boom towards the end of the 1990s. Furthermore, neither study focused on the new economy sector.

By focusing on a particular sector, namely, the new economy sector, this study provides an opportunity to restrict the analysis to a relatively homogenous sample of firms. Existing empirical evidence shows that the performance of IPO firms varies widely in different industries (Ritter, 1991; Levis, 1993). Audretsch and Lehmann (2004) further pointed out that firms in the new economy or knowledge-based industries differ in their governance structure from traditional firms. Hensler, Rutherford and Springer (1997) and Lamberto and Rath (2008) also found that the survival likelihood of IPO companies varies between industries. Therefore, it is justified to focus the survival analysis of Australian IPO firms within one particular sector, namely, the new economy sector.

6.3 Hypotheses development

In this chapter, the influences of four factors on the survival of new economy IPO companies are explored. These factors include 1) corporate governance attributes, 2) offering characteristics, 3) financial ratios and 4) company-specific variables.

6.3.1 Corporate governance attributes

Corporate governance mechanisms have received extensive attention in corporate financial distress prediction researches since the occurrence of a series of corporate collapses in the late 1990s, for example, the Enron and WorldCom collapse in the USA

in 2001 and 2002 respectively and the collapse of the Maxwell media empire in the UK in 1992 (Becht, Bolton and Roell, 2002).

The reason why firms succeed or fail is perhaps the central question of strategy (Porter, 1991). Since corporate governance is the system by which companies are directed and controlled and boards of directors are responsible for the governance of the companies and developing a firm's strategy (Pass, 2004), then it is expected that corporate performance and survival is affected by corporate governance attributes.

This study explores the influence of corporate governance on new economy IPO companies' survival. Three areas of corporate governance including board size, board independence and ownership concentration are examined based on the Cox proportion hazards model.

To develop the research hypotheses corresponding to the research questions discussed in Chapter 1, this section provides the theoretical and empirical literature relating to corporate governance mechanisms in association with corporate performance and survival likelihood. In this section, reference is made to research question #6 in Chapter 1; the research hypotheses are discussed as follows.

1) Board size

The hypothesis relating to board size is specified as follows.

Research hypothesis #6.1: Board size significantly affects the survival likelihood of new economy IPO companies.

Each board of directors is appointed by the shareholders of a company to satisfy the shareholders that an appropriate governance structure is in place (Pass, 2004). The major responsibility of the board of directors is to minimize costs arising from the

separation of ownership and decision control of the modern operation (Fama and Jensen, 1983).

The empirical results regarding the relationship of board size and firm survival are inconclusive. Some studies suggest that a company with a larger board size is less likely to fail because of the greater accountability of its directors (Lamberto and Rath, 2008) and the wider range of views and external connections (Pfeffer and Salancik, 1978). Similar results were found in Chaganti, Mahajan and Sharma (1985), Adams and Mehran (2003) and Li and Naughton (2007).

In contrast, some researchers argue that small boards can improve corporate performance while large boards are ineffective in terms of the communication, coordination and decision-making process since there are too many people involved on the boards (Lipton and Lorsch, 1992; Jensen, 1993). Empirical evidence supports this argument, which is found in Beasley (1996), Yermack (1996), Eisenberg, Sundgren and Wells (1998) and Bohren and Strom (2007). As a result, the relationship between board size and firm performance and survival remains inconclusive.

Accordingly, this study hypothesises that board size is significantly related to new economy IPO firms' survival. To test this hypothesis, the total number of directors on the boards is used to measure board size. The effect of board size on IPO firms' survival is tested utilizing the Cox proportional hazards model.

2) Board independence

Another aspect of corporate structure suggested by the previous literature as being a significant factor of corporate survival is board independence. This study utilizes three measures of the level of board independence, namely, the proportion of non-executive directors on the board, the presence of a non-executive chairman and the usage of an independent leadership structure.

To examine the linkage between board independence and IPO companies' survival, the research hypothesis relating the proportion of non-executive directors on the board is set as follows.

2.1) Percentage of independent directors

Research hypothesis #6.2: A new economy IPO company with a high proportion of independent directors on the board is more likely to survive than those with a low proportion of independent directors on the board.

According to the Principle of Good Corporate Governance and Best Practice Recommendations, which was published by the ASX Corporate Governance Council in March 2003, an independent director is defined as a director who is independent of the management and free of any business or other relationship that could reasonably be perceived to interfere materially with the exercise of their unfettered and independent judgment (ASX, March 2003).

There is only limited information regarding the disclosures a company's directors make to the external stakeholders. Thus, the studies exploring director independence face difficulties in comparing definitions of director independence from one company to another (Kang, Cheng and Gray, 2007). Some previous studies use the word 'outside directors' instead of 'independent' to describe directors who are presumed to be independent from management (Ajinkya, Bhojraj and Sengupta, 2005). Some existing studies simply consider the differences between 'executive' and 'non-executive' directors (Kang, Cheng and Gray, 2007; Lamberto and Rath, 2008).

For the purpose of this study, all non-executive directors are classified as 'independent directors'. This is consistent with the definition used in Lamberto and Rath (2008).

Based on the agency perspective, Fama and Jensen (1983) argued that if the majority of the directors on the board were independent, then it would be less likely that the CEO and inside directors would exercise behaviours that were self-serving at the expense of shareholders.

Similarly, Pass (2004) pointed out that since non-executive directors can provide independent judgment, thus, the interests of shareholders will be protected by the presence of independent directors. Furthermore, the company could benefit from non-executive directors since these directors can contribute valuable external business expertise to the company, and can often see risks and opportunities for the company that might have been overlooked by the company's executive directors who are typically immersed in the day-to-day running of the business.

The results from the literature relating the effects of the proportion of non-executive directors on corporate performance and survival are mixed.

Some of the literature found evidence supporting the expectation that a higher proportion of non-executive directors in the board would lead to better corporate performance and consequently, a higher probability of corporate survival., for example, Rosenstein and Wyatt (1990), Daily and Dalton (1994) and Beasley (1996). In contrast, Hermalin and Weisbach (1991), Yermack (1996) and Klein (1998) found a negative relationship between the proportion of outside directors and corporate performance. Furthermore, some studies found there to be no relationship between the proportion of non-executive directors and corporate performance, for example, Vafeas and Theodorou (1998), Laing and Weir (1999), Bhagat and Black (2001) and Balatbat, Taylor and Walter (2004).

Following Recommendation 2.1 of the Principle of Good Corporate Governance and Best Practice Recommendations published by the ASX Corporate Governance

Council in March 2003, which states that a majority of the board should be independent directors (ASX, March 2003), this study hypothesises that new economy IPO companies with a high level of board independence are more likely to survive.

To test this hypothesis, the percentage of non-executive directors on the board is employed as a proxy of board independence in the model.

2.2) Non-executive chairman

The second measurement of the level of board independence is the presence of a non-executive chairman. The research hypothesis testing the association between the presence of a non-executive chairman and corporate survival is described as follows.

Research hypothesis #6.3: New economy IPO companies with the presence of an independent chairman of the board are more likely to survive.

The chairman is responsible for leadership of the board, for the efficient organization and conduct of the board's function and for briefing all directors in relation to issues arising at board meetings (ASX, March 2003).

It is expected that a company with an independent chairman is more likely to pursue the interests of the shareholders and effectively monitor the management (Weir and Laing, 2001). This implies that a non-executive chairman enhances the corporate performance and survival likelihood.

However, an executive chairman is expected to have greater knowledge of a firm and its industry and have a greater commitment to the organization than would an external or non-executive chairman (Boyd, 1995). Therefore, this argument expects there to be a negative relationship between the presence of a non-executive chairman and firm performance and survival.

It can be seen that there are conflicting arguments about the effect of a non-executive chairman on corporate performance and survival. However, since this study investigates the survival of the companies in the Australian context, the study follows Recommendation 2.2 of Good Corporate Governance and Best Practice Recommendations by the ASX Governance Council in March 2003. Recommendation 2.2 points out the chairperson should be an independent director; therefore, it is hypothesised that new economy IPO companies with a non-executive chairman are more likely to survive.

To test this hypothesis, a dummy variable for the presence of a non-executive chairman is used in the Cox proportional hazards model. In particular, if the chairman listed in the company prospectus is a non-executive director then a value of 1 is recorded, 0 otherwise.

2.3) Dual leadership structure

The research hypothesis to test the effect of an independent leadership structure or, in contrast, a CEO duality structure on IPO companies' survival is set as follows.

Research hypothesis #6.4: New economy IPO companies that adopt a CEO duality leadership structure are less likely to survive.

A CEO duality leadership structure exists when the same person serves as a firm's CEO and as the chairman of the board of directors, while an independent leadership structure could be described as the case in which different individuals serve in these positions.

There are conflicting opinions about the benefits and costs of using these leadership structures. Proponents of the independent structure argue that a CEO duality structure might constitute a clear conflict of interests and so systematically reduce the

board's ability to fulfil its governance function (Rechner and Dalton, 1991; Brickley, Coles and Jarrell, 1997).

Given that one of the board's central functions is to monitor the performance of top management, allowing the CEO to play both roles might lead to a compromise in the desired system of check and balance (Levy, 1981; Dayton, 1984; Rechner and Dalton, 1991). The inappropriate governance structures might contribute to firm crisis and eventual bankruptcy (Daily and Dalton, 1994).

In contrast, advocates of the CEO duality structure argue that the CEO duality structure provides a single focal point for company leadership and provides a clear focus for objectives and operations (Rechner and Dalton, 1991). Additionally, the independent leadership structure might lead to a potential for rivalry between the CEO and the chairperson and make it difficult to pinpoint the blame for poor performance (Brickley, Coles and Jarrell, 1997).

The empirical results regarding the association between CEO duality structure and corporate performance survival are mixed. For example, Fama and Jensen (1983), Rechner and Dalton (1991), Jensen (1993) and Daily and Dalton (1994) suggested that CEO duality leadership is ineffective. However, some studies found CEO duality has no impact on corporate failure (Chaganti, Mahajan and Sharma, 1985) and corporate performance (Elsayed, 2007).

In Australia, Recommendation 2.3, suggested by the ASX Governance Council in March 2003, is that the roles of chairperson and chief executive officer should not be exercised by the same individual; therefore, this study expects that those new economy IPO companies that adopt a CEO duality leadership structure are likely to survive.

A dummy variable is used to measure the independent leadership structure. Specifically, if the chairman and CEO are different people then a value of 1 is recorded, 0 otherwise.

3) Ownership concentration

The third area of corporate governance mechanisms examined in this study is that of ownership concentration. Particular attention in the corporate governance literature has been paid to ownership concentration as a key to more effective corporate governance and the maximization of shareholder wealth.

The research hypothesis testing the relationship of ownership concentration and new economy IPO companies' survival is identified as follows.

Research hypothesis #6.5: The ownership concentration attribute significantly affects the survival likelihood of new economy IPO companies.

Over three hundred years ago, Adam Smith raised the issue of separation of ownership and control in a corporation. The classical problem lies in the separation of ownership structure and control, for example, the conflicts of interest or agency costs resulting from a divergence of interests between the owners and the managers of the company (Jensen and Meckling, 1976).

Agency theory is concerned with which set of governance rules will enhance efficiency and thus maximize wealth (Arthur et al., 1993). The main concern is whether managers pursue their own interests rather than maximizing shareholder wealth.

Based on the monitoring and convergence of agency theory, when shareholders are too diffuse to monitor managers, corporate assets can be used for the benefit of managers rather than for maximizing shareholder wealth (Himmelberg, Hubbard and Palia, 1999). In addition, it is argued that a firm is more likely to survive if ownership

concentration is high. This is because shareholders are more likely to have an influence on management's decisions and shareholders will want to expend funds on monitoring costs, as their stake in the firm is relatively high (Jensen and Meckling, 1976).

Based on information asymmetry theory, when stockholdings are concentrated, information asymmetries are low, so the ability of stockholders to remove a management team is high and managers are more likely to pursue strategies that are in stockholders' interests. Conversely, when stockholdings are diffused, significant information asymmetries are likely to exist and management is then more likely to pursue strategies inconsistent with stockholders' interests (Hill and Snell, 1989).

The effect of ownership concentration on corporate performance has been the subject of many theoretical and empirical researches. However, the empirical results about the effects of ownership concentration on firm performance are mixed. For example, Claessens and Djankov (1999) suggested that the more concentrated the ownership, the higher the profitability and labour productivity. Similarly, Bai et al. (2004) confirmed the positive relationship between ownership concentration and corporate values.

In contrast, some studies suggested that ownership concentration was negatively related to corporate survival, for example, Woo, Jeffrey and Lange (1995) and Kang, Cheng and Gray (2007). Furthermore, Demsetz and Lehn (1985) found that corporate ownership concentration is not related to the accounting profit rates of a company. Like Demsetz and Lehn (1985) and Hovey, Li and Naughton (2003) indicated that ownership concentration does not explain firm performance.

Because of the mixed results regarding the effect of ownership concentration on corporate survival, this study hypothesises that the ownership concentration attribute is significantly related to new economy IPO companies' survival. To test this hypothesis,

the proportion of common stock held by the top largest 20 shareholders of a company is used as a proxy of ownership concentration based on the Cox proportional hazards model.

6.3.2 Offering characteristics

This study further examines the relationship between control variables and the likelihood of survival of IPO companies in addition to corporate governance as the core variables in the analysis. The control variables include offering characteristics, financial ratios and company-specific variables.

The literature employed offering characteristics of IPO firms in examining IPO firms' post listing performance (Bhabra and Pettway, 2003), explaining initial return, long run return and the relationship between initial and seasoned offerings (Murgulov, 2006). Consequently, the research hypotheses are set as follows.

1) Offering price

Research hypothesis #6.6: Offering price at IPO firms is positively related to new economy IPO companies' survival.

Ho et al. (2001) indicated that IPOs are typically underpriced, that is, an investor who purchases new issues at the offering price can, on average, make relatively large returns. To compensate investors for the greater uncertainty, higher risk IPOs have higher initial returns. Therefore, IPOs with a higher *ex-ante* uncertainty are more underpriced than are those with a lower *ex-ante* uncertainty. This hypothesis is consistent with the views of Lamberto and Rath (2008). Thus, a positive relationship between offer price and IPO firm survival is expected.

2) Offering size

Research hypothesis #6.7: Offering size at IPOs is positively related to new economy IPO companies' survival.

It is argued that larger offerings signal market confidence, more stringent monitoring (Lamberto and Rath, 2008) and good prospects (Jain and Kini, 2000). Ritter (1991) suggested that smaller offerings tend to have the worst aftermarket performance. Furthermore, previous studies of American IPO firms; for example, Hensler, Rutherford and Springer (1997) and Jain and Kini (1999) found that the offering size is positively related to firm survival.

3) Offering age

Research hypothesis #6.8: Offering age at IPOs is positively related to new economy IPO companies' survival.

Firm age has been used as a proxy for risk (Ritter, 1991; Ho et al., 2001). Ritter (1991) found that older firms performed better in the after-market than did younger ones. Established firms are expected to have a more stable source of business, be less speculative and also be more likely to survive than are young firms (Lamberto and Rath, 2008). Therefore, it is expected that the company age at offering should be positively related to its likelihood of survival.

4) Retained ownership

Research hypothesis #6.9: The percentage of stock retained by pre-IPO shareholders is positively related to new economy IPO companies' survival.

Leland and Pyle (1977) argued that firm owners can signal quality in equity markets by retaining equity. Consistent with signal theory, a high percentage of insider ownership

retention at IPOs serves as a certification that managerial decisions will coincide with the outside shareholders' interests, which results in reduced agency costs and better firm performance after the offering (Jensen and Meckling, 1976).

However, the empirical results are mixed. While Hensler, Rutherford and Springer (1997) suggested that IPO firms with a higher percentage of retained ownership have a longer survival period, Lamberto and Rath (2008) found that ownership retention is not significantly related to IPO firms' survival.

5) Underwriter backing

Research hypothesis #6.10: New economy IPO companies with underwriter backing are more likely to survive.

It is in the best interest of the underwriter to endorse companies with sound prospects and it is a fact that most underwriters invest in the offers they underwrite (Lamberto and Rath, 2008). Therefore, it is expected that companies with underwriter backing will be more likely to survive than will those without.

6) Auditor reputation

Research hypothesis #6.11: New economy IPO companies with an auditor from one of the Big 5 are more likely to survive.

Auditor reputation is included as an indicator variable with a value of 1 if the auditor is from one of the Big 5 accounting firms and 0 otherwise. The Big 5 companies include PricewaterhouseCoopers, KPMG, Arthur Anderson, Deloitte Touche Tohmatsu and Ernst and Young (How, Izan and Monroe, 1995; Dimovski and Brooks, 2003; Lamberto and Rath, 2008). The literature suggests that reputable auditors tend to lessen the amount of underpricing achieved by an IPO candidate since they are construed as

providing a signal of the quality of the information to potential investors (How and Yeo, 2000).

Therefore, it is expected that companies with an auditor from one of the Big 5 companies will have a higher likelihood of survival than will those with an auditor from a smaller auditor firm.

7) Number of risk factors in the prospectus

Research hypothesis #6.12: The number of risk factors listed in the prospectus is negatively related to new economy IPO companies' survival.

Risk can be proxied directly using the number of risk factors listed in the prospectus (Bhabra and Pettway, 2003). Assuming full disclosure, the number of risk factors listed in the prospectus should be negatively related to survival (Lamberto and Rath, 2008). A high number of risk factors listed in the prospectus suggests a risky firm and hence an increased likelihood of failure. The informational value of the number of risk factors was found to be significant and negatively related to the likelihood of survival of American IPO firms by Hensler, Rutherford and Springer (1997) and Bhabra and Pettway (2003). However, it should be noted that since the number of risk factors in the prospectus is a voluntary disclosure by an IPO company, the interpretation of the number of risk factors on survival probability and hazard rate may be biased.

6.3.3 Financial ratios

Another group of control variables included in the model is financial ratios. Four categories of financial ratios are used in this study. The relevant research hypotheses are as follows.

1) Profitability ratio

Research hypothesis #6.13: New economy IPO companies with a high profitability are more likely to survive.

It is expected that companies with a high profitability ratio will have more likelihood of survival. This study utilizes return on asset (ROA) as a measure of the profitability ratio. The profitability ratio measures the firm's ability to generate earnings. Many firms face financial distress when their earnings are negative. Therefore, profit is often used as a predictor of financial distress events.

2) Liquidity ratio

Research hypothesis #6.14: New economy IPO companies with a high liquidity are more likely to survive.

The liquidity ratios measure a firm's ability to meet its current obligations as they become due. Liquidity ratios also have been used to measure short term solvency. Higher levels of liquidity provide a strong barrier against financial failure. In this study, the current ratio is a measure of a firm's liquidity.

3) Leverage ratio

Research hypothesis #6.15: New economy IPO companies with a high level of financial leverage are less likely to survive.

Financial risk shows the firm's ability to find the sources of external funds provided for the benefit of their shareholders. The degree of financial risk is related to the likelihood of financial distress (Lee and Yeh, 2004). It is expected that companies with a higher leverage are more likely to fail. Debt ratio is used as a measure of leverage in this study.

4) Activity ratio

Research hypothesis #6.16: New economy IPO companies with high activity ratios are more likely to survive.

The activity ratios measure the efficiency of a firm's asset utilization. They measure the ability of a firm to use assets to generate revenue or returns. If firms can use assets efficiently, they will earn more revenue and increase liquidity. Total asset turnover ratio is employed in this study.

6.3.4 Company-specific variables

Finally, two variables measuring company-specific characteristics, for example, company size and IPO timing, are employed in the analysis as the control variables. Consequently, the research hypotheses associated with company-specific variables are as follows:

1) Company size

Research hypothesis #6.17: Larger new economy IPO companies survive longer than do smaller companies.

The previous literature has shown that firm survival is negatively correlated with firm size. The rationale for this relationship is that larger firms have a greater ability to avoid financial distress by using public equity markets (Goktan, Kieschnick and Moussawi, 2006). Schultz (1993) found an inverse relationship between the probability of delisting and firm size. Smaller firms have a higher probability of delisting and larger firms have a higher probability of survival. Therefore, it is expected that larger IPO firms will survive longer than will smaller ones. To test this hypothesis, the logarithm of total

assets of the firm according to the first available full year's results after listing is used as a proxy of IPO company size.

2) IPO_9900

Research hypothesis #6.18: New economy IPO companies that went public between January 1999 and April 2000 are more likely to fail than are other companies.

To examine the effect of IPO timing, a dummy variable is used to indicate whether a company has issued stock between January 1999 and April 2000. The definition of a variable is adapted from Ho et al. (2001) and Kauffman and Wang (2007). It is expected that companies that went public between January 1999 and April 2000 are more likely to fail because April 2000 is the date generally recognized by Australian financial market participants as coinciding with the 'bursting of the dot come bubble' (Ho et al., 2001).

Table 6.1 provides the details of variables used in this study.

Table 6.1: The variables used in the study

Variable Code	Variable Name	Definition of Variable
	<i>Corporate Governance Attributes:</i>	
BD_SIZE	Board Size	Number of directors on the board including chairman.
	Board Independence	
BD_INDP	Percentage of Independent Directors	The ratio of the number of non-executive directors to the number of directors, as listed in the prospectus.
CM_NEXC	Non-Executive Chairman	If the chairman listed in the prospectus is a non-executive director then a value of 1 is recorded, 0 otherwise.
CM_DUAL	Dual Leadership Structure	If the chairman and CEO are different people then a value of 1 is recorded, 0 otherwise.
	Ownership Concentration	
TOP20	Top 20 Shareholders	The proportion of common stock held by the top 20 shareholders.
	<i>Offering Characteristics:</i>	
OF_PRICE	Offering Price	The offer price listed in the prospectus, or the midpoint of the price range.
OF_SIZE	Offering Size	The size of the offering listed in the prospectus, or the minimum subscription amount.
OF_AGE	Offering Age	The difference between the year in which the prospectus was lodged and the year in which the company was founded.
RETAIN	Retained Ownership	The difference between the market capitalization of the company after listing and the size of the offering, divided by the market capitalization of the company after listing.
BACK	Underwriter Backing	Initial public offerings that had an underwriter recorded a value of 1, 0 otherwise.
BIG5	Auditor Reputation	Initial public offerings that had an auditor belonging to one of the Big 5 accounting firms recorded a value of 1, 0 otherwise. The Big 5 accounting firms include PricewaterhouseCoopers, KPMG, Arthur Anderson, Deloitte Touche Tohmatsu and Ernst and Young.
NUM_RISK	Number of Risk Factors in the Prospectus	The number of risk factors listed in the prospectus. If there is no specific risk factor section, the number is 0.
	<i>Financial Ratios:</i>	
ROA	Profitability	Return on Asset (ROA): Earnings before interest/(total assets-outside equity interests).
CUR	Liquidity Ratio	Current Ratio (CUR): Current assets/current liabilities.
DET	Leverage Ratio	Debt Ratio (DET): Total debt/ total assets.
TAT	Activity Ratio	Total Asset Turnover (TAT): Operating revenue/total assets.
	<i>Company-Specific Variables:</i>	
C_SIZE	Company Size	The logarithm of total assets of the firm.
IPO_9900	IPO_9900	A dummy variable recorded a value of 1 if a company issued stock between 1999 and April 2000, 0 otherwise.

6.4 Methodology

In order to analyse the factors influencing the survival of new economy Australian IPO companies, a Cox proportional hazards model is employed. The model is a semi-parametric model and the sub-discipline of survival analysis techniques.

Previous literature has employed a Cox proportional hazards model in IPO survival analysis, for example, Kauffman and Wang (2001; 2007), Cockburn and Wagner (2007) and Lamberto and Rath (2008).

Kauffman and Wang (2001; 2007) found that market, firm and e-commerce-related variables such as the entry of additional internet firms via IPOs, a smaller firm size, good IPO timing, being a late entrant and the selling of digital products and services can reduce an internet firm's likelihood of exit. In addition, the study also reported that internet firms that operate in breakthrough markets are more likely to survive than those that operate in re-formed markets.

Other IPO survival studies used other techniques in survival analysis, for example, the Weibull model (Woo, Jeffrey and Lange, 1995; Audretsch and Lehmann, 2004), log-normal model (Woo, Jeffrey and Lange, 1995), log-logistic model (Hensler, Rutherford and Springer, 1997) and piecewise exponential model (Yang and Sheu, 2006).

Survival analysis has two advantages over the traditional methods, for example, MDA, logit and probit models. These advantages are the ability to handle time-varying variables and censored observations. Time-varying variables are the explanatory variables that change with time. The financial ratios used in this study are similar to time-varying variables, as their values change over time. Censored observations are the observations that have never experienced the event during the observation time. Censoring occurs when the duration of the study is limited in time. In this study,

censored observations are the IPO companies that are still trading on the ASX at the end of the observation period, that is, 31 December 2007.

Survival analysis contains two key functions: the survivor 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 . Given that T is a random variable that defines the event time for some particular observation, then the survival function is defined as:

$$S(t) = \Pr(T > t) \quad (6.1)$$

The hazard function defines the instantaneous risk of an event occurring at time t given 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 form of number of events per interval of time. The hazard function is defined as:

$$h(t) = \lim_{\Delta t \rightarrow 0} \frac{\Pr(t \leq T < t + \Delta t | X, T \geq t)}{\Delta t} \quad (6.2)$$

The Cox proportional hazards model is the most widely used semi-parametric model for survival analysis. In Cox’s (1972) study, there were two significant innovations, namely, the proportional hazards model and maximum partial likelihood. The proportional hazards model is represented as:

$$h_i(t) = h_0(t) \exp(X_i \beta) \quad (6.3)$$

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 all have values of zero. 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:

$$\log h_i(t) = \alpha(t) + \beta_1 X_{i1} + \beta_2 X_{i2} + \dots + \beta_k X_{ik} \quad (6.4)$$

Where $\alpha(t) = \log h_0(t)$ and $h_0(t)$ is an arbitrary unspecified baseline hazard rate (LeClere, 2000).

The model does not require the particular probability distribution specification of the survival times, but it possesses the property that different individuals have hazard functions that are proportional, that is,

$$\frac{h_i(t)}{h_j(t)} = \exp[\beta_1(X_{i1} - X_{j1}) + \beta_2(X_{i2} - X_{j2}) + \dots + \beta_k(X_{ik} - X_{jk})] \quad (6.5)$$

The ratio of the hazard functions for two individuals does not vary with time t . These special properties make the Cox proportional hazards model robust and popular amongst researchers.

To estimate the coefficients of β , Cox (1972) proposed a partial likelihood function based on a conditional probability of failure by assuming that there are no tied values in the survival times. The function was later modified to handle ties (Efron, 1977). This study uses SAS PROC PHREG to complete the estimation.

6.5 Data and sample

In this study, a new economy company is defined as an entity with business activities in any high technology production or service. In particular, IPO firms in four industry sectors based on GICS², that is, information technology, media³, telecommunication services and health care, are examined. This definition of a new economy company is consistent with that of Murgulov (2006).

The new economy IPO companies listed in Australia between 1994 and 2002 are included in estimating the Cox proportional hazards model. The year 2002 is chosen as

² GICS is an enhanced industry classification system jointly developed by Standard & Poor's and Morgan Stanley Capital International (MSCI) in 1991 to meet the needs of the investment community for a classification system that reflects a company's financial performance and financial analysis (Standard and Poor's, 2002).

³ According to GICS, media is an industry group rather than an industry sector. It belongs to the consumer discretionary industry sector.

the cut off year because it allows five years of post-listing accounting information to be considered at the time of data collection. Each IPO company is tracked from its listing on the ASX until 31 December 2007 or until delisting or suspension.

The sample of IPO firms and their prospectuses was collected mainly from the *Annual Reports Online Database*. Some IPO firms with their prospectus were not available on the *Annual Reports Online Database*, in which case, the prospectus was obtained from the *Connect 4 Company Prospectuses Database*. In the industry sector, financial information of the companies was obtained from the *FinAnalysis Database*.

In this study, non-survival or failed companies are simply defined as companies that have been delisted or suspended from the ASX. Survivors are companies that remain trading on the ASX. This definition is consistent with Welbourne and Andrews (1996) and Lamberto and Rath (2008). Correspondingly, survival time is measured as the number of years between the year of listing and the year the company is delisted or suspended from the ASX for non-survival IPO companies or the year end of observation period for survival IPO companies. The final sample consists of 127 new economy Australian IPO companies. Among these companies, 93 companies are survivors and 34 companies are non-survivors. The distribution of new economy IPO companies between 1994 and 2002 by industry sector and by company status is presented in Table 6.2 and Table 6.3 respectively.

Table 6.2: New economy IPO companies stratified by GICS industry sector

GICS Industry Sector	N	Percent
Information Technology	55	43.31
Media	13	10.24
Telecommunication Services	14	11.02
Health Care	45	35.43
Total	127	100.00

Note: N is the number of companies. Percent is the number of companies in a particular industry group as a proportion of total number of companies.

Table 6.3: New economy IPO companies stratified by company status

Trading Status	N	Percent
Trading	93	73.23
Delisted	32	25.20
Suspended	2	1.57
Total	127	100.00

Note: N is the number of companies. Percent is the number of companies in a particular industry group as a proportion of total number of companies.

6.6 Empirical results

6.6.1 Descriptive statistics

Due to there being a number of extreme values among the observations, which might have a significant effect on the statistical results, the observations were truncated at the specified thresholds. All observations with variable values higher than the ninety-ninth percentile of each variable were set to that value. In the same way, all variable values lower than the first percentile of each variable were truncated. This method is consistent with Shumway (2001).

Table 6.4 presents the descriptive statistics of the data employed in the study after truncation stratified by company status. The descriptive statistics results before truncation are reported in Table B.5 in the appendix. Table 6.4 presents the number of observations, means, medians, min, max, standard deviations, skewness and kurtosis for each company status. It should be noted that because of the binary or dummy variables that have been used for some factors, the mean for these variables should be interpreted as the percentage of companies in the sample. The binary variables employed in this study include CM_NEXC, CM_DUAL, BACK, BIG5 and IPO_9900.

The Kruskal-Wallis test and its p -value are the result of a non-parametric test for a significant difference between the group means. Variables with significant differences within their group means will be expected to add information to a regression analysis. The variables TOP20, OF_PRICE, BACK and C_SIZE display a significant difference.

According to Table 6.4, the mean number of directors for both survival and non-survival new economy IPO companies is five, which is consistent with Lamberto and Rath (2008) and Rosa, Izan and Lin (2004); this suggests the majority of IPO companies have fewer than six directors on the board, which is the minimum number of directors recommended by the ASX for good governance. The mean percentage of non-executive directors on the board was 53.41 and 61.96 for active and non-survival IPO companies respectively. This figure implies that the majority of directors on the board of new economy Australian IPO companies are independent directors. In addition, 64.42 and 69.59 percent of active and non-survival new economy IPO companies respectively have a non-executive chairman, and 85.51 and 84.80 percent of these companies have the title of CEO and chairperson held by different people. These results suggest that the majority of new economy Australian IPO companies have boards that can be considered independent. Furthermore, the mean percentages of the top largest 20 shareholders for active and non-survival companies are 65.98 and 76.77 percent respectively.

Regarding the offering characteristics, the median offering price was A\$0.50 and A\$1.00. The median offer size was A\$8 and A\$12 million and the medians of offering age were 3.04 and 4.51 years for survival and non-survival companies respectively. These results suggest that the new economy Australian IPO companies are relatively young and small, which is consistent with the results reported by Lamberto (2008).

Additionally, 73.98 and 90.06 percent of the offering by active and non-survival companies respectively are underwritten while 53.16 and 70.18 percent of the offering by active and non-survival companies respectively have an auditor from one of the Big Five accounting firms. These findings contradict to the expectation as underwritten companies or the companies that have an auditor from one of the Big Five accounting

firms are expected to survive longer than those that have not. Furthermore, on average, the number of risk factors identified in the prospectus was 13 and 14 for active and non-survival companies respectively.

The means of retained ownership by pre-IPO owners were 62.16 and 70.48 percent for active and non-survival IPO companies respectively, which implies that control of the new economy IPO companies was retained by the original owners. It is also interesting to note that 39.52 and 35.67 percent of active and non-survival IPO companies respectively are listed for the period January 1999 to April 2000.

The profitability ratios, which show the low ability of a company to generate profit, are both negative. The means of ROA for active and non-survival companies are -0.29 and -0.35 respectively. This result suggests that non-survival IPO companies have lost fewer earnings than have active companies. For liquidity ratios, CUR, non-survival companies have the higher means of CUR than have active ones. The means of DET values show that the ability of non-survival companies to pay long term liabilities is less than that of active companies. For activity ratios, the mean of TAT of non-survival companies is higher than that of survival companies. However, the Kruskal-Wallis test suggests that there is no difference in means of these ratios between active and non-survival new economy IPO companies.

Finally, the mean SIZE of active and non-survival companies is 7.27 and 7.41 respectively and the Kruskal-Wallis test shows that, on average, the size of active and non-survival new economy IPO companies in the study has a statistically significant difference at the 10 percent level.

6.6.2 Correlation coefficients

The relationships across the variables are investigated using Pearson correlation coefficients. The Pearson correlation coefficients are shown as in Table 6.5.

The results suggest that most of the variables are significantly correlated but the magnitudes are small.

Table 6.4: Descriptive statistics of the data

	BD_SIZE	BD_INDP	CM_NEXC	CM_DUAL	TOP20	OF_PRICE	OF_SIZE	OF_AGE	RETAIN	BACK	BIG5	NUM_RISK
Survival IPOs (n=93)												
Mean	5.1885	53.4149	0.6442	0.8551	65.9798	0.8857	32.9512	5.7981	62.1626	0.7398	0.5316	12.7173
Median	5.0000	60.0000	1.0000	1.0000	70.0000	0.5000	8.0000	3.0493	70.0000	1.0000	1.0000	12.0000
Min	3.0000	0.0000	0.0000	0.0000	14.4000	0.2000	1.5000	0.0027	0.0000	0.0000	0.0000	0.0000
Max	10.0000	83.0000	1.0000	1.0000	94.1400	4.6000	421.0940	38.4603	96.3400	1.0000	1.0000	31.0000
Std Dev.	1.3198	19.5939	0.4791	0.3522	18.6702	0.8525	73.9985	7.1613	23.6733	0.4391	0.4994	5.3226
Skewness	0.6119	-0.6757	-0.6035	-2.0223	-0.8569	2.4452	3.7922	1.9579	-1.1423	-1.0955	-0.1271	0.8013
Kurtosis	0.9508	-0.1034	-1.6404	2.0955	0.0362	7.2115	14.4321	4.7397	0.6540	-0.8022	-1.9894	2.0205
Non-Survival IPOs (n=34)												
Mean	5.1345	61.9591	0.6959	0.8480	76.7651	0.9282	135.0988	6.2423	70.4801	0.9006	0.7018	14.2456
Median	5.0000	67.0000	1.0000	1.0000	78.4100	1.0000	12.0000	4.5068	74.3400	1.0000	1.0000	13.0000
Min	3.0000	0.0000	0.0000	0.0000	19.9900	0.2000	1.0000	0.0082	0.0000	0.0000	0.0000	7.0000
Max	9.0000	89.0000	1.0000	1.0000	98.2800	2.0000	6652.7300	18.8301	99.5200	1.0000	1.0000	25.0000
Std Dev.	1.1270	20.0849	0.4614	0.3601	14.5248	0.4959	873.7467	5.4964	20.0611	0.3001	0.4588	3.7555
Skewness	0.8544	-0.8914	-0.8593	-1.9553	-0.6455	0.2855	7.4087	0.5869	-1.0167	-2.7013	-0.8898	0.9136
Kurtosis	1.7554	0.2530	-1.2767	1.8446	0.3556	-0.6623	53.5469	-0.9495	1.2692	5.3595	-1.2226	0.8229
Kruskal-Wallis Test	0.0864	2.5854	0.1069	0.2197	7.2061**	3.6893*	0.6289	0.2592	0.9395	2.8339*	2.2513	1.9929
p-value	0.7688	0.1079	0.7437	0.6393	0.0073	0.0548	0.4277	0.6107	0.3324	0.0923	0.1335	0.1580

Table 6.4: Descriptive statistics of the data (Continued)

	ROA	CUR	TAT	DET	C_SIZE	IPO_9900
Survival IPOs (n=93)						
Mean	-0.2895	7.1661	0.8726	0.4290	7.2674	0.3952
Median	-0.0590	2.0000	0.6130	0.3106	7.2258	0.0000
Min	-6.0955	0.0200	0.0000	0.0008	5.6139	0.0000
Max	0.5770	331.5200	4.8237	4.1984	9.4247	1.0000
Std Dev.	0.7464	20.6795	0.9768	0.5321	0.7685	0.4892
Skewness	-3.9595	9.1896	1.8291	4.4175	0.5033	0.4296
Kurtosis	21.5622	116.2732	3.6165	25.5749	0.3938	-1.8206
Non-Survival IPOs (n=34)						
Mean	-0.3533	7.0450	0.9472	0.5034	7.4054	0.3567
Median	-0.0132	1.8100	0.6198	0.3418	7.3498	0.0000
Min	-6.0955	0.0200	0.0000	0.0009	5.6139	0.0000
Max	0.5770	567.0300	4.8237	4.1984	9.4247	1.0000
Std Dev.	1.1682	43.3931	0.9932	0.6012	0.7292	0.4804
Skewness	-4.2630	12.7933	1.6825	3.5528	0.1647	0.6035
Kurtosis	18.3912	165.9545	3.4190	16.4266	0.3321	-1.6553
Kruskal-Wallis Test	1.0930	0.2092	0.5770	1.4612	3.3274*	0.1226
p-value	0.2958	0.6474	0.4475	0.2267	0.0681	0.7263

Note: Descriptive statistics grouped by company status. n is the number of companies. Kruskal-Wallis Test from a non-parametric test of equality of group means.

* Significant at the 10 percent level, ** Significant at the 5 percent level.

Table 6.5: Pearson correlation coefficients

Variable	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18
1. BD_SIZE	1.0000	0.0845 ^a 0.0121 ^b	0.0340 0.3136	0.1849 <.0001	0.0377 0.2637	0.4475 <.0001	0.2551 <.0001	-0.0901 0.0074	-0.0458 0.1738	-0.0842 0.0124	0.1681 <.0001	0.0399 0.2364	0.0601 0.0745	-0.0246 0.4657	-0.0200 0.5527	0.0062 0.8534	0.5228 <.0001	-0.1358 <.0001
2. BD_INDP		1.0000	0.3518 <.0001	0.1849 <.0001	0.1305 0.0001	-0.0186 0.5808	0.0857 0.0109	0.0139 0.6798	-0.0101 0.7645	0.1239 0.0002	0.1466 <.0001	0.1447 <.0001	-0.0919 0.0063	0.0172 0.6096	-0.0447 0.1849	0.0672 0.0460	-0.0944 0.0050	0.0601 0.0743
3. CM_NEXC			1.0000	0.3332 <.0001	-0.1602 <.0001	0.0152 0.6514	0.0132 0.6958	-0.0109 0.7457	0.0043 0.8988	0.0235 0.4853	-0.0951 0.0047	0.0825 0.0142	-0.0834 0.0132	0.0125 0.7119	-0.0108 0.7478	-0.0432 0.2002	-0.1006 0.0028	0.0355 0.2917
4. CM_DUAL				1.0000	-0.0459 0.1731	0.1038 0.0020	0.0464 0.1687	-0.1522 <.0001	0.0041 0.9036	0.0951 0.0047	0.0248 0.4615	0.1096 0.0011	-0.0270 0.4237	-0.0985 0.0034	0.0937 0.0054	0.0716 0.0336	0.0803 0.0171	0.0792 0.0187
5. TOP20					1.0000	0.0996 0.0031	0.0414 0.2192	0.1746 <.0001	0.3515 <.0001	0.1389 <.0001	-0.0610 0.0704	0.1277 0.0001	0.0414 0.2198	-0.0546 0.1053	0.0874 0.0094	0.0816 0.0153	0.0661 0.0497	-0.1725 <.0001
6. OF_PRICE						1.0000	0.1790 <.0001	-0.0404 0.2311	-0.0186 0.5807	-0.1787 <.0001	0.0875 0.0093	0.0254 0.4513	0.1528 <.0001	-0.0890 0.0082	0.0651 0.0534	0.0803 0.0170	0.5380 <.0001	-0.0215 0.5231
7. OF_SIZE							1.0000	-0.0079 0.8154	-0.1949 <.0001	-0.1522 <.0001	0.0643 0.0565	0.0093 0.7838	0.0444 0.1876	-0.0241 0.4740	0.0514 0.1269	0.0945 0.0050	0.2401 <.0001	-0.0423 0.2091
8. OF_AGE								1.0000	0.0815 0.0154	0.1514 <.0001	-0.0394 0.2428	-0.1600 <.0001	0.1266 0.0002	-0.1096 0.0011	0.0980 0.0036	0.0172 0.6093	0.0377 0.2639	0.0641 0.0569
9. RETAIN									1.0000	0.1507 <.0001	0.0103 0.7606	0.2281 <.0001	-0.0800 0.0174	-0.1107 0.0010	0.0251 0.4573	0.0637 0.0587	-0.0913 0.0066	-0.1025 0.0023
10. BACK										1.0000	0.0166 0.6220	-0.1184 0.0004	0.0187 0.5783	-0.0494 0.1425	0.1657 <.0001	0.0778 0.0209	-0.0472 0.1611	0.0406 0.2287
11. BIG5											1.0000	0.0868 0.0099	0.0119 0.7246	-0.0179 0.5947	-0.1083 0.0013	0.0486 0.1496	0.1275 0.0001	-0.0005 0.9887
12. NUM_RISK												1.0000	-0.0494 0.1429	-0.0172 0.6109	0.0048 0.8864	0.0355 0.2921	-0.0032 0.9233	0.0784 0.0199
13. ROA													1.0000	0.0442 0.1894	-0.0158 0.6402	-0.4817 <.0001	0.4663 <.0001	-0.0040 0.9052
14. CUR														1.0000	-0.1493 <.0001	-0.1634 <.0001	-0.0814 0.0157	-0.0492 0.1446
15. TAT															1.0000	0.4016 <.0001	0.0274 0.4171	0.0686 0.0416
16. DET																1.0000	-0.1472 <.0001	0.0544 0.1064
17. C_SIZE																	1.0000	-0.0797 0.0179
18. IPO9900																		1.0000

Note: a. Pearson correlation coefficients.

b. The p-value under the null hypothesis of zero correlation

6.6.3 Cox proportional hazards model estimation results

To investigate the influence of corporate governance on new economy IPO companies and identify the survival probability of new economy IPO companies after going public, the Cox proportional hazards model is estimated.

After the Cox proportional hazards model with corporate governance variables, offering characteristic variables, financial ratios and company-specific variables is applied, the Cox proportional hazards model estimation results are presented in Table 6.6. Table 6.6 reports the model estimation results after truncation. For the results before truncation, see Table B.6 in the appendix.

The variable selection method used in this study is the simplest method and the default in PROC PHREG in SAS. The SAS PROC PHREG fits the complete model as specified in the MODEL statement. The variables are selected from the full model (all variables were included in the model), instead of backward, forward or stepwise selection procedures being used⁴. The results in Table 6.6 report only significant variables⁵.

⁴ The models using backward, forward and stepwise procedure have also been estimated but they gave different results. The full model is chosen in this study because it is consistent to the economic intuitive.

⁵ This study also investigated the effect of interactive variable of BD_SIZE and BD_INDP as the number of directors and the proportional of non-executive directors may be correlated. However, the result found that BD*SIZE*BD_INDP is not significant variable.

Table 6.6: Cox proportional hazards model estimation

Variable	Coefficient	Standard Error	χ^2 Statistic	<i>p</i> -Value	Hazard Ratio
TOP20	0.0329**	0.0142	5.4006	0.0201	1.0330
OF_SIZE	0.0004*	0.0002	3.1200	0.0773	1.0004
BACK	1.1579*	0.6686	2.9992	0.0833	3.1830
DET	0.5294*	0.3147	2.8310	0.0925	1.6980
C_SIZE	0.7321**	0.3326	4.8458	0.0277	2.0790

Note: *Significant at the 10 percent level.

** Significant at the 5 percent level.

Table 6.6 presents the coefficient estimation, the standard error of this estimate, and the Wald chi-square tests with the relative *p*-value for testing the null hypothesis where the coefficient of each variable is equal to zero and the hazard ratio, which 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. If the hazard ratio is greater (less) than 1, then this indicates a more rapid (slower) hazard timing.

Considering the *p*-value, two variables are highly significant at the 5 percent level. These ratios are TOP20 and C_SIZE with the coefficients 0.0329 and 0.7321 respectively. The variables OF_SIZE, BACK and DET are statistically significant at the 10 percent level with the estimated coefficients 0.0004, 1.1579 and 0.5294 respectively.

The estimated coefficient of TOP20 is positive, which suggests a positive relationship between the percentage of the largest top 20 shareholders of the company and failure risk. The estimated hazard ratio of TOP20 is 1.0330, which means that the financial distress risk of IPO companies increases by 3.30 percent for each percentage increase in the largest top 20

shareholders. This result is consistent with the findings of Woo, Jeffrey and Lange (1995), who suggested that low ownership concentration is related to corporate longevity.

The offering characteristics that are significant variables in explaining IPO firms' survival are offering size and underwriter backing. The positive sign of the estimated coefficient of the OF_SIZE suggests that IPO companies that offer a larger size are less likely to survive than are those that offer a smaller size. This result is contrary to expectations and is inconsistent with the findings of Hensler, Rutherford and Springer (1997), Jain and Kini (1999) and Lamberto (2008). However, the estimated hazard ratio of OF_SIZE is 1.0004, which means that for each A\$1 million increase in offering size, the hazard of financial distress increases by only 0.04 percent. This implies that there is a minimal effect of offering size on IPO firms' survival in an economic sense.

The estimated hazard ratio for BACK is 3.1830, which means that the hazard of financial distress for the company whose offer is underwritten is about 318.30 percent of the hazard for those whose offer is not underwritten. This result is not what was expected, as companies with underwriter backing should be more likely to survive than are companies without such backing. However, Lamberto (2008) also found similar results and suggested that this unexpected result might be explained by the extreme difficulty in differentiating between a reputable underwriter and a not so reputable underwriter. Hence, the distinction between underwriters based on reputation might further explain this result.

Considering financial ratio factors, a financial ratio that is statistically significant in explaining IPO firms' survival is DET. The sign of the parameter for DET is positive, which means that the IPO companies with a low debt ratio are less likely to fail. The estimated hazard ratio for DET is 1.6980, which indicates that for every unit increase in debt ratio, the risk of failing increases by 69.80 percent.

For C_SIZE, the estimated coefficient is 0.7321. The positive sign of SIZE means that the larger the size of IPO companies, the higher the likelihood of companies entering into financial distress. This result is consistent with the findings in Lamberto (2008) but contradict with the hypothesis. A reasonable explanation for this result is that large companies might have inflexible organizations and have problems with monitoring managers and employees, which leads to inefficient communication (Rommer, 2004).

From the sample in this study, the results suggest that new economy IPO companies with low ownership concentration, small offering size, low leverage and small company size are more likely to survive. However, this result does not comply with the Principle of Good Corporate Governance and Best Practice Recommendations published by the ASX Corporate Governance Council in March 2003, which states that a majority of the board should be independent directors (Recommendation 2.1), the chairperson should be an independent director (Recommendation 2.2) and the roles of chairperson and chief executive officer should not be exercised by the same individual (Recommendation 2.3).

The expected effect and the estimated effect are summarized in Table 6.7. The table shows that DET has the expected sign while OF_SIZE, BACK and C_SIZE do not have the expected sign when the model is estimated.

Table 6.7: Summary of estimated effects of variables on financial distress

Variable	Expected effect	Estimated effect
TOP20	Unclear	+
OF_SIZE	-	+
BACK	-	+
DET	+	+
C_SIZE	-	+

According to Table 6.7, it should be noted that the variables OF_SIZE, BACK and C_SIZE are unexpected results and should be held out for future research.

6.6.4 IPO companies' survival probability evaluation

The survival function, shown in Equation (6.1), which defines the survival probability, can be estimated from the model to identify the probability that a company will survive longer than t time units. The survival profiles of typical non-survival and survival new economy IPO companies by survival time and by calendar year are presented in Figure 6.1 and Figure 6.2 respectively.

The survival function shown in both figures is produced by averaging the estimated survival probability of companies by company status, non-survival and survival companies. It can be inferred that the survival probabilities of typical failed IPO companies are lower than those of typical active IPO companies. Since the survival function denotes a company's probability of surviving past time t , it starts with 1.00 and declines as more companies fail.

The graph shows that the survival probability of non-survival companies is lower than that of the active companies and as time goes by, the survival probabilities for both start to decrease.

According to Figure 6.1, the dramatic decrease in survival probability for new economy non-survival companies occurs at seven years after IPOs with a probability of 65.77 percent, then the survival probability increases slightly after year eight and continuously drops after year nine. The non-survival new economy IPO companies in this study had traded on the ASX for no longer than ten years. For active or survival companies, the noticeable decrease of survival probability occurs ten years after the companies have gone public with the probability of survival being around 68.42 percent. For non-survival companies, the probability that the companies will survive beyond ten years after IPOs is around 54.22

percent. The detail of survival probability of company within a given time stratified by company status is shown in Table 6.8.

As can be seen in Figure 6.2, the probability of new economy non-survival companies started to drop rigorously from 1998 until 2000, which coincides with the crash of the new economy sector in April 2000. After this, the survival probability of these companies continuously increases throughout 2001 and 2002. The dramatic reduction of survival probability before 2000 could be interpreted cautiously in two ways: First, it could be because the significant market diminished at the end of March 2000 (Johnston and Madura, 2002), which influenced the low survival probability of typical new economy IPO companies. The survival probability of IPO companies could have been affected by the abrupt weakening of the market. Secondly, as these companies are those that had been listed for the few years before 2000, their survival probability declined over time. Consequently, the survival probability of average non-survival companies before 2000 decreased.

In addition, new economy active IPO companies experience a low survival probability before a period of a diminished new economy sector. The survival probability at 1999 was approximately 95.91 percent. However, companies that were able withstand the market decline were able to recover, and their survival probability slightly increased throughout 2000 to 97.61 percent.

It should be noted that the results between the years 2003 and 2007 are not comparable to those of the years 1994 to 2002 because there were no IPO companies that fitted into the analysis after 2002. During the period 2003 to 2007, the survival probability of non-survival IPO firms continuously dropped to 55.06 percent in 2007 as a result of these companies being relatively well established since their listing between 1994 and 2002. The actual previously

listed IPO companies' data did not reflect the results. The detail of survival probability of companies within a calendar year stratified by company status is shown in Table 6.9.

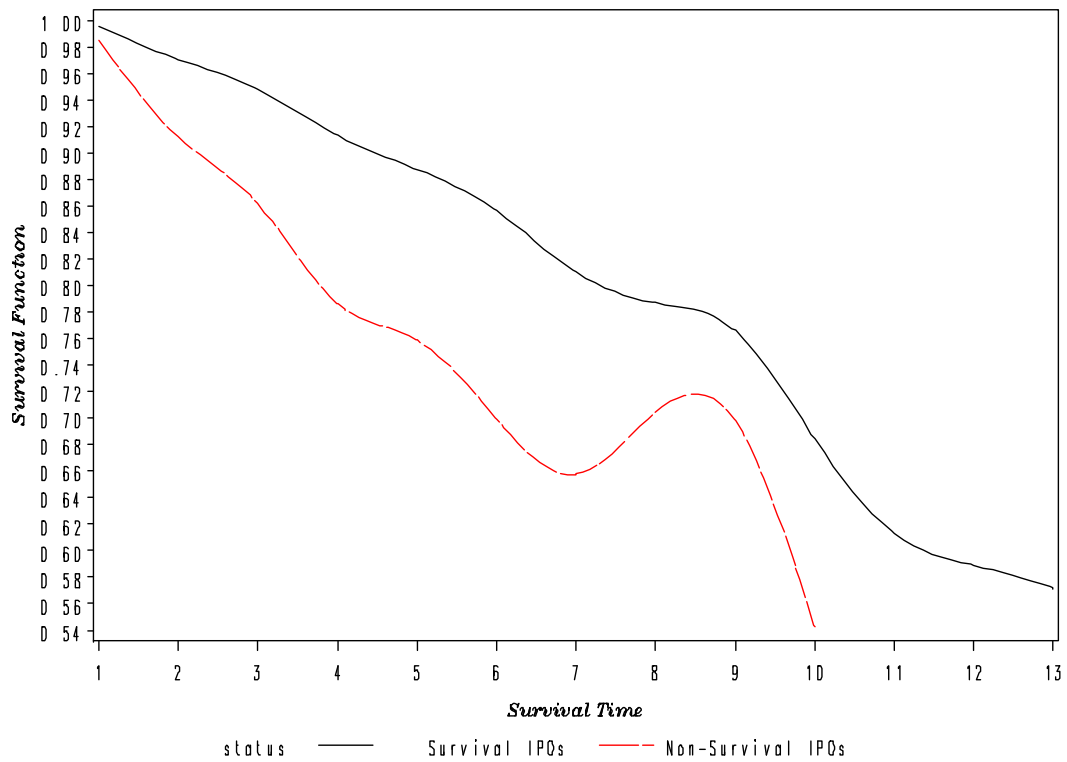


Figure 6.1: Graph of survival function and survival time by company status

Table 6.8: Survival probabilities of companies by company status

Survival Time	Survival Probability	
	Survival IPO Companies	Non-Survival IPO Companies
1	0.9951	0.9846
2	0.9705	0.9120
3	0.9481	0.8615
4	0.9129	0.7861
5	0.8876	0.7589
6	0.8562	0.6994
7	0.8100	0.6577
8	0.7869	0.7046
9	0.7659	0.6980
10	0.6842	0.5422
11	0.6130	-
12	0.5890	-
13	0.5722	-

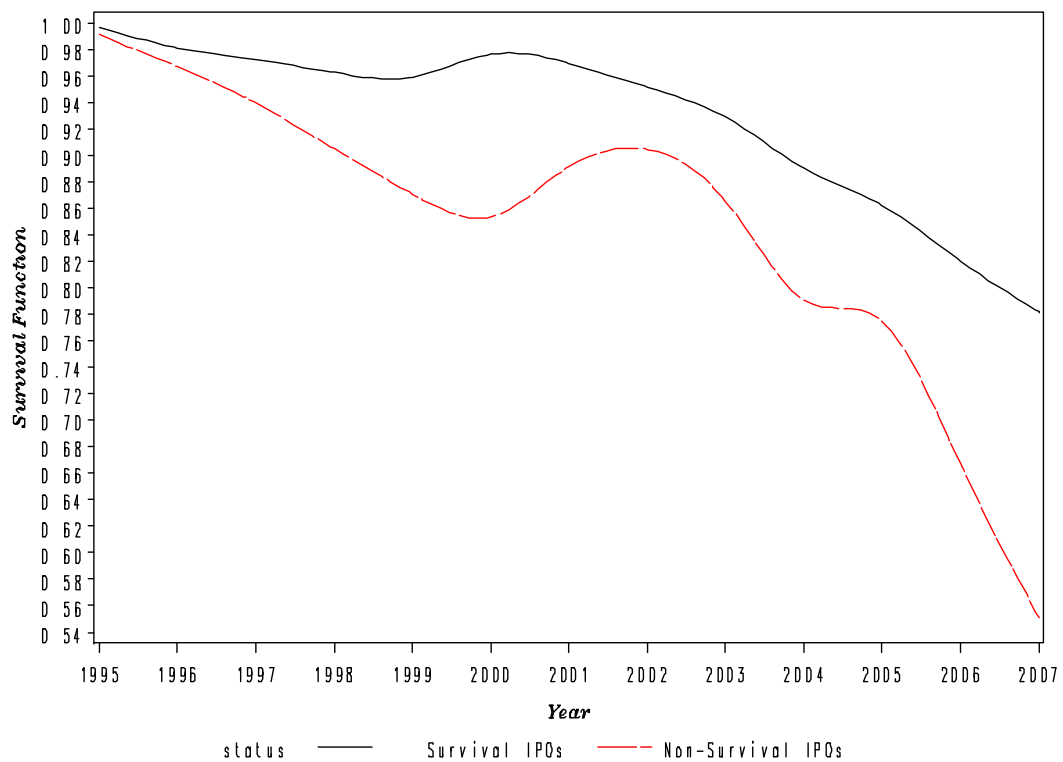


Figure 6.2: Graph of survival function and calendar year by company status

Table 6.9: Survival probabilities within calendar year by company status

Calendar Year	Survival Probability	
	Survival IPO Companies	Non-Survival IPO Companies
1995	0.9968	0.9908
1996	0.9809	0.9668
1997	0.9719	0.9395
1998	0.9625	0.9048
1999	0.9591	0.8707
2000	0.9761	0.8534
2001	0.9694	0.8914
2002	0.9512	0.9042
2003	0.9289	0.8654
2004	0.8901	0.7907
2005	0.8624	0.7746
2006	0.8202	0.6671
2007	0.7819	0.5506

6.7 Conclusion

This study explores the relationship between corporate governance attributes and new economy Australian IPO companies' survival using the Cox proportional hazards model. The survival probability of new economy IPO firms after listing on the ASX is also examined. Three main areas of corporate governance mechanisms are board size, board independence and ownership concentration along with control variables; for example, offering characteristics, financial ratios and company-specific variables are incorporated in the model.

The findings reveal that ownership concentration is negatively related to new economy IPO firms' survival. This result is consistent with Woo, Jeffrey and Lange (1995). Agency theory suggests that a firm is more likely to survive if ownership concentration is high. This is because 1) shareholders are more likely to have an influence on management's decisions and 2) shareholders will want to expend money on monitoring, as their stake in the firm is relatively high (Jensen and Meckling, 1976). However, Woo, Jeffrey and Lange (1995) argued that lower ownership concentration, where the stock of the firm is more widely held, could facilitate more effective capital raisings from a wider investment group, which makes the company less likely to fail.

The results also suggest that new economy IPO companies with a small offering size, low leverage and small company size are more likely to survive.

However, the empirical results do not support the good governance related Recommendations 2.1, 2.2 and 2.3 published by the ASX Corporate Governance Council. The results found that board size, board independence and CEO duality have an insignificant impact on new economy IPO firms' survival. Lamberto (2008) also found consistent results to show that board size and board independence have an insignificant impact on Australian IPO firms' survival.

This study has a number of implications for managerial practice. First, board size and board independence have no impact on new economy IPO firms' survival, which suggests that there is no optimal number of directors on the board, or percentage of non-executive directors in the board to ensure new economy IPO firms' survival; nor does the use of a non executive chairman and the usage of a dual leadership structure guarantee survival.

Secondly, management should focus on the ownership concentration structure in order to improve company survivability after listing in the market. Specifically, low percentages of the largest top 20 shareholders should be encouraged in order to enhance the likelihood of new economy IPO firms' survival.

Finally, as the debt ratio is the only significant financial ratio influencing IPO firms' survival, management needs to consider carefully the optimal financial structure of the company in order to prevent possible failure of new economy IPO firms.

Further research should explore the IPO companies' survival analysis in more depth regarding corporate governance attributes by investigating the characteristics of the board in more detail, for example, the experience of the director in a particular industry sector, the number of meetings of the board, and the board's remuneration. In addition, research could explore Principle 4 in ASX Corporate Governance Council, which focuses on safeguarding integrity in the financial reporting of the company by exploring the audit committee structure. Finally, as stated in Principle 9 in the ASX, companies need to adopt remuneration policies that attract and maintain talented and motivated directors and employees to encourage enhanced company performance. Therefore, investigating the company's remuneration policy, for example, the disclosure of the remuneration policy, the existence of remuneration committee and the remuneration committee structure in relation to IPO firms' survival could be another interesting aspect for further study.

CHAPTER 7

SUMMARY AND CONCLUSION

7.1 Introduction

This chapter presents the summary and conclusion of this thesis. The chapter begins with a summary of the study, which will provide the overall picture of this thesis, and a discussion of the empirical results and major findings will be given in the next section. Then, Section 7.3 will discuss the policy implications, which will provide information regarding how the study's findings could be applied in practice. The limitations of the study will be presented in Section 7.4 followed by the suggestions for future research in Section 7.5. This chapter ends with the conclusion.

7.2 Summary and discussion

This thesis focuses on examining financially distressed companies in Australia using survival analysis techniques. The motivation behind this thesis is the considerable financial and social costs related to a diverse group of stakeholders as a result of a firm entering a state of financial distress. A financial distress model that can identify the factors influencing the impending financial difficulties of a company will enable the company's management to mitigate or reduce the failure-induced costs.

Three main essays are developed and presented in Chapters 4, 5 and 6 of this thesis. The details of these chapters can be summarized as follows.

Chapter 4 explores the effect of financial ratios and other variables on corporate financial distress and identifies the probability of corporate survival in a given time frame based on the state of the financial health of a company. The core variables in this study are four main categories of financial ratios, namely, profitability, liquidity, leverage and activity

ratios, while control variables include a market-based variable and company-specific variables, for example, company age, company size and squared size. Specifically, a survival analysis technique, that is, a Cox proportional hazards model, was estimated using time-varying variables based on a sample of 1,117 publicly listed Australian companies over the period 1989 to 2005.

The ability to incorporate failure time in the model is the major advantage of survival analysis techniques compared to other techniques, for example, MDA, logit and probit analysis, which cannot provide any estimation of the failure rate as a function of time. Furthermore, the financial data used in this study are time-varying variables, which can be included in the analysis by extending the Cox proportional hazards model.

There is no previous literature in Australia regarding the adaptation of the Cox proportional hazards model with a time-varying variable. By allowing time-varying variables based on the Cox proportional hazards model, this study will make a contribution to the corporate financial distress literature based on survival analysis techniques in the Australian context.

Empirical results from the analysis support the usefulness of financial ratios, a market-based variable and company size as predictors of financial distress. In particular, financially distressed companies have higher leverage measured by debt ratio, lower past excess returns and a larger size compared to active companies.

The finding about debt ratio is consistent with the expectation that a high financial leverage company is more likely to face financial distress. Previous studies also found similar results, for example, Beaver (1966; 1968a), Damolena and Khoury (1980), Flagg, Giroux and Wiggins (1991), Charalambous, Charitou and Kaourou (2000), Laitinen and Laitinen

(2000), Zapranis and Ginoglou (2000), Charitou, Neophytou and Charalambous (2004) and Beaver, McNichols and Rhie (2005).

Additionally, the results about a market-based variable indicate a negative relationship between a company's past excess returns and the hazard of the company entering into financial distress. In particular, past excess returns or market adjusted returns turn downward as the probability of financial distress increases. The results show the potential usefulness of market data for the prediction of corporate financial distress; this is consistent with the results found in Shumway (2001) and Partington et al.(2006).

The finding regarding company size is consistent with those of previous studies, for example, Laitinen (1992), Parker, Peters and Turetsky (2002b), Lamberto and Rath (2008), which found that corporate size is positively related to the likelihood of financial distress.

Similarly, investigating the influence of governance mechanisms and the market valuation of publicly listed firms in China, Bai et al. (2004) pointed out that smaller firms have a higher market valuation. The possible explanation for this finding is that larger firms may have inflexible organizations and have problems with monitoring managers and employees, which leads to inefficient communication (Rommer, 2004).

However, the results found company age lacks significance in explaining financial distress. This is consistent with Shumway (2001), which also found that the logarithm of firm age is not statistically significant in the hazard model. In addition, Shumway pointed out that the estimated coefficient of company age is quite small, which implies that there appears to be little evidence in bankruptcy probability.

Chapter 4 focuses on the conventional failing vs. non-failing dichotomy and defines a financially distressed company as in a single risk model while some studies suggest that researchers should distinguish between the different types of exit or financial distress. There

is criticism that a single risk specification might provide limited empirical estimation results compared to a multiple risks financial distress model since companies might face the continuum of financial health in practice.

Furthermore, researchers argue that a company could 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. These arguments motivated the further investigation conducted in Chapter 5.

Chapter 5 investigates the determinants of multiple states of financial distress by applying a competing risks Cox proportional hazards model. An unordered three-state financial distress model is defined as state 0: active companies, state 1: distressed external administration companies and state 2: distressed takeover, merger or acquisition companies. The effect of financial ratios, a market-based variable and company-specific variables, including company age, size and squared size, on three different states of corporate financial distress are investigated. A sample of 1,081 publicly listed Australian companies is examined over the period 1989 to 2005 using a competing risks model.

In the Australian context, the literature examines multiple states of financial distress, for example, Jones and Hensher (2004), which was then extended by Hensher, Jones and Greene (2007) and Jones and Hensher (2007b). However, the methods used by these studies are advanced logit models, which are different from the method employed in this thesis.

As far as is known, this is the first study to utilize a competing risks Cox proportional hazards model to examine a multiple states of financial distress model in the Australian context. Compared to other methods, the Cox proportional hazards model allows the failure rate to be estimated as a function of time and allows time-varying variables to be

incorporated. The latter feature is important because it is expected that the value of financial ratios would deteriorate as failure approaches.

The results from the comparison of the results from the single risk model and the competing risks model indicate that a multi-state of financial distress should be defined when modelling failure prediction rather than the company status being classified simply into a binary classification of failure vs. non-failure. Additionally, comparing the determinants driving each state of financial distress within the competing risks framework, the results confirmed that the significant factors determining each state of corporate financial distress are different.

Specifically, distressed external administration companies have higher leverage, lower past excess returns and a larger size, while distressed takeover, merger or acquisition companies have lower leverage, higher capital utilization efficiency and a bigger size compared to active companies.

The results indicate that a company with a lower debt to total assets ratio is less likely to file for external administration process but is more likely to be subject to a takeover, merger or acquisition. Similarly, Schary (1991) also found debt ratio is negatively related to the probability of 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 and Tsakalotos, 1999).

The empirical results confirm that a market-based variable is useful in explaining outright financial distress but not for a distressed takeover, merger or acquisition event.

In addition, the results imply that the larger the size of a company, the higher the likelihood of a company entering financial distress both through external administration process and through takeover, merger or acquisition. The reasonable explanation for this

result is that the large company might have inflexible organization and have problems with monitoring managers and employees, which leads to inefficient communication (Rommer, 2004). Furthermore, Perez, Llopis and Llopis (2002) also reported consistent results, that is, that the risk of acquisition increases with company size; this suggests that large firms tend to be involved in mergers. Similarly, Hensher, Jones and Greene (2007) reported that larger firms have a higher probability of entering a distressed merger in a four-state failure model.

The fact that larger firms are more likely to enter a distressed merger is consistent with the view that such mergers are motivated by an attempt to salvage residual value in the assets of distressed businesses, which is more likely for larger businesses, which also tend to be more established and therefore have higher residual assets, than for smaller entities (Altman, Resti and Sironi, 2005).

Furthermore, the results found that the effect of company size on distressed takeover, merger or acquisition is the inverted U-shaped or bell-shaped. This finding is consistent with Bhattacharjee et al. (2004), who also found a bell-shaped relationship between firm size and the likelihood of a firm being acquired. In particular, the finding supports the evidence from the acquisition literature, which indicated that firms in the middle range for size are more likely to be acquired.

Additionally, the results suggest that an increase in the operating revenue to operating invested capital ratio increases the hazard of a company being subject to a takeover, merger or acquisition. The reasonable explanation is that a company that uses its assets efficiently will increase its income and liquidity; thus, the company is more attractive to bids for a 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 plants or labour, are less likely to be acquired as the cost of reorganizing an inefficient bank could be high.

Chapters 4 and 5 focus on the sample of established publicly listed companies on the ASX using financial ratios as the main variables. In Chapter 6, other categories of variable, namely, corporate governance attributes, are examined in the context of new economy IPO companies. The motivation for focusing on corporate governance variables is that this became a very important issue after a series of corporate collapse since the late 1990s.

Furthermore, during the boom or tech-bubble period of dot-com companies between late 1998 and early 2000, the number of IPOs for new economy companies dramatically increased because of high speculation in increasing stock values and growth in the sector. However, there was the collapse of new economy companies due to the end of tech-bubble period in March 2000 (Johnston and Madura, 2002).

Researchers argue that good corporate governance mechanisms enhance corporate performance and long-term survival. Accordingly, whether corporate governance influences the survival of these new economy IPO companies remains questionable. To answer this question, the third essay is then developed and the details presented in Chapter 6.

Chapter 6 examines the influences of corporate governance mechanisms on new economy IPO companies' survival. A sample of 127 new economy IPO companies listed on the ASX between 1994 and 2002 is tracked until 31 December 2007. A non-survival IPO company is defined as a company that is delisted or suspended from the ASX after going public. Otherwise, the company is categorized as a survival company.

By focusing on a particular sector, namely, the new economy sector, this study has been able to restrict the analysis within a relatively homogenous sample of firms. Audretsch and Lehmann (2004) further pointed out that firms in the new economy or knowledge-based

industries differ in their governance structure from traditional firms. Hensler, Rutherford and Springer (1997) and Lamberto and Rath (2008) also found that the survival likelihood of IPO companies varies between the industries. Therefore, focusing the survival analysis of Australian IPO firms within one particular sector is justifiable.

A survival analysis technique in the form of the Cox proportional hazards model is utilized with three main categories of corporate governance attribute, specifically, board size, board independence and ownership concentration after controlling for relevant variables, for example, offering characteristics, financial ratios and company-specific variables.

Unlike some previous studies, the financial ratios and company size are treated as time-varying covariates in the Cox proportional hazards model rather than the study using merely time-invariant covariates as in Woo, Jeffrey and Lange (1995), Audretsch and Lehmann (2004), Lamberto and Rath (2008) and Van der Goot, Van Giersbergen and Botman (2008). This feature is consistent with the fact that a firm changes through time and the financial ratios tend to deteriorate when the firm is approaching failure.

The Cox proportional hazards model estimation results suggest that ownership concentration measured by the largest top 20 shareholders is the only corporate governance attribute that is found to be significantly negative related to the survival of new economy IPO companies. This result is consistent with the findings of Woo, Jeffrey and Lange (1995), which suggested that low ownership concentration is related to corporate longevity. Woo, Jeffrey and Lange (1995) argued that lower ownership concentration, where stock of the firm is more widely held, could facilitate more effective capital raisings from a wider investment group, which makes the company less likely to fail.

Similarly, Alba, Claessens and Djankov (1998) also found a negative relationship between ownership concentration and performance in Thai listed companies and discussed the

view that high concentrated ownership companies may be less flexible over time in changing the corporate governance. Controlling ownership may also lead to increased risk taking behaviour since other stakeholders, for example, creditors and employees share in the downside risks but not to the same degree in the benefits. These behaviours consequently lead to a deterioration in financial performance.

In contrast, agency theory suggests that a firm is more likely to survive if ownership concentration is high. This is because 1) shareholders are more likely to have an influence on management's decisions and 2) shareholders will want to expend funds on monitoring costs as their stake in the firm is relatively high (Jensen and Meckling, 1976).

The results additionally found that, for offering characteristics variables, the offering size and the underwriter backing are significant variables in explaining new economy IPO firms' survival. Particularly, new economy IPO companies with a larger offering size are less likely to survive than are those that offer a smaller size. This result is contradictory to expectations and is inconsistent with Hensler, Rutherford and Springer (1997), Jain and Kini (1999) and Lamberto (2008). However, the estimated hazard ratio magnitude implies that there is a minimal effect of offering size on new economy IPO firms' survival in an economic sense.

Furthermore, the results found that the hazard of financial distress for companies with an offer that is underwritten is more than the hazard for those for which the offer is not underwritten. This result is not what was expected, as companies with underwriter backing should be more likely to survive than companies without such backing. However, the result is consistent with Lamberto (2008).

Considering the relationship between financial ratios and new economy IPO companies' survival, the results indicate that debt ratio is statistically significant in explaining IPO firms'

survival. In particular, the new economy IPO companies with a low total debts to total assets ratio are less likely to fail.

The results do not support the influence of independent directors of the board on new economy IPO companies' survival. This finding is consistent with Chaganti, Mahajan and Sharma (1985), which suggested that there is no significant difference in the proportion of non-executive directors on the boards of failed and non-failed retailing companies. Similarly, Vafeas and Theodorou (1998) and Laing and Weir (1999) also found there is no relationship between the proportion of non-executive directors and corporate performance.

The reason why the expected positive relationship between independent directors and corporate performance or survival is not supported could be that non-executive directors are employed only on a part-time basis and are likely to have other work commitments. Based on the part time basis, therefore, the time devoted by these directors might be insufficient, the expertise to understand highly technical and complex business issues might be lacking and there might be insufficient information on which to make key decisions (Weir and Laing, 2001; Pass, 2004).

Putting the empirical results of the three assays together, this thesis provides some support for the idea that leverage ratio and company size are the common significant indicators of financial distress in the context of both established and new economy IPO firms. In particular, companies with higher leverage and a larger size are more likely to face financial distress.

Similarly, leverage ratios and company size also play important roles in determining different types of financially distressed states, namely, distressed external administration and distressed takeover, merger or acquisition. However, it should be noted that the effects of leverage ratio on the likelihood of entering both states of financial distress are different.

Specifically, companies with higher financial leverage are more likely to face financial distress through external administration process, but less likely to face distressed takeover, merger or acquisition. For company size, both distressed external administration and distressed takeover, merger or acquisition companies have a larger size compared to active companies.

In addition, some variables affect one specific state of financial distress but not another. Specifically, market-based data is an important factor for detecting the possibility of financial distress through external administration process while the capital utilization ratio is significant in driving the likelihood of the company being subject to takeover, merger or acquisition.

Finally, this thesis found that ownership concentration is the only significant corporate governance attribute that is related to new economy IPO firms' survival. The results indicate that new economy IPO companies with less concentrated ownership are more likely to survive. Two offering characteristics variables, that is, offering size and underwriter backing are significantly related to IPO companies' survival likelihood; however, the estimated signs are the opposite to those expected.

7.3 Policy implications

This section provides the policy implications that are derived from the empirical results and findings in the three essays. The policy implications will be discussed within two contexts, namely, established companies and new economy IPO companies. In the context of established companies, there are a number of practical implications as follows.

First, management needs to consider carefully the capital structure of the company in order to prevent possible financial difficulties arising. An important part of the literature focuses on financial fragility especially that arising from debt. The level, maturity and structure of debt are considered to be important variables affecting the credit-worthiness of

companies (Haksar and Kongsamut, 2003). This implies the importance of the financial leverage ratio in explaining the financial risk of companies.

Secondly, market-based data is valuable information for detecting the possibility of financial distress. Management and investors might use market data in addition to financial ratios in examining corporate financial distress to enable them to make better decisions in relation to predicting corporate failure, which consequently, might reduce losses.

Finally, the findings show that there are differences in the factors determining which companies enter different states of financial distress. Therefore, management should distinguish between the different types of financial distress, namely, outright failure or distressed external administration and distressed takeover, merger or acquisition companies. Management could consider financial ratios, market-based variables and company-specific variables when detecting the likelihood of financial distress within a multi-state of financial distress framework. Particularly, the financial leverage ratio and company size could be useful when considering the indicators of financial distress in both states. In addition, market-based variables could be useful when detecting the possibility of outright failure while the capital utilization ratio is an important determinant of the likelihood of the company being subject to takeover, merger or acquisition.

In addition, considering the context of new economy IPO firms, this study has a number of implications for managerial practice as follows.

First, board size and board independence have no impact on the survival of new economy IPO firms, which suggests that there is no optimum for the number of directors on the board, or for the percentage of non-executive directors on the board to ensure the survival of new economy IPO firms; nor does the use of a non executive chairman and the usage of an independent leadership structure guarantee the IPO firms' survival.

Secondly, management should focus on the ownership concentration structure in order to improve the company's survivability after listing in the market. Specifically, a lower ownership concentration in new economy IPO companies should be encouraged in order to enhance company survivability.

Concentrated ownership has been a method used to solve the agency problem; however, ownership concentration can also cause problems (Haksar and Kongsamut, 2003), for example, if a majority shareholders try to expropriate resources for their own interests, which can be to the detriment of the firm (Grossman and Hart, 1988).

Finally, the results suggest that larger new economy IPO companies appear to be more exposed to financial distress risks than smaller ones. This finding suggests that financial managers should slow down the process of acquiring external funds. As a company's growth in terms of total assets accelerates, its need for funds to finance this growth also accelerates. It is more than likely such funds will come from external sources. This rapid growth might raise the concerns of creditors and investors about the firm's financial risk. Such perceptions can lead to a higher cost of capital and therefore a decline in shareholders' wealth (Elkhal, 2002).

7.4 Limitations of the study

The interpretation of empirical results in this study should be made with the acknowledgment of a number of limitations. The limitations of this study can be summarized into three board areas as follows.

7.4.1 Sample restricted to publicly listed companies only

The sample of companies included in this thesis is restricted to publicly listed companies on the ASX only. Accordingly, private and other smaller non-listed companies are excluded from the analysis. This bias is important because small companies are prone to financial distress

(Ryan, 1994). Therefore, this limitation might restrict the generalization of the empirical results.

7.4.2 Small sample size of financially distressed companies

A financially distressed company in this study is defined as a company that has entered into external administration process. Since there was a limited number of companies that had actually entered into external administration process and those were additionally filtered by the criteria that it had to be a public company, the sample size of financially distressed companies is relatively small. In particular, only 50 out of 1,117 companies had entered into external administration process during the 1989 to 2005 period.

This is an unfortunate feature of research into corporate failure prediction since very few firms actually face financial failure during the observation period; however, this limited sample size might affect the model estimation results and a larger sample size would generally be preferred.

7.4.3 The accuracy of the database

The financial data employed in this thesis are all obtained from *FinAnalysis Database*, except for the S&P/ASX200 monthly index data, which are obtained from *Dx Database*.

The initial list of new economy IPO companies listed on the ASX from 1994 to 2002 was manually tracked mainly from *Annual Reports Online Database* and additionally from the *Connect 4 Company Prospectuses Database*. Then, the IPO companies' prospectuses were downloaded from these two databases. The corporate governance data and offering characteristics were then manually collected from these prospectuses.

Although these databases belong to major leading database companies in Australia⁶, it should be noted that the results of this study remain dependent upon the accuracy of the database.

7.5 Suggestions for future research

Future research could improve upon this current research in the following aspects.

1) Improvement on explanatory variables

The corporate governance variables employed in this study could be further explored in other aspects since corporate governance mechanisms relate to various aspects of corporation. For example, the number of meetings by the boards, the board's remuneration, the structure of the audit committee and the company's remuneration policy, the disclosure of the remuneration policy, the existence of a remuneration committee and the structure of the remuneration committee in relation to corporate survival could be another interesting aspect for further study.

Furthermore, this thesis incorporates various explanatory variables in the model, including financial ratios, a market-based variable, company-specific variables, corporate governance attributes and IPO companies' offering characteristics variables. These variables could be categorized as the internal factors of financial distress. In addition to internal factors, however, future research could further explore the external factor of financial distress.

⁶ *FinAnalysis Database* and *Annual Reports Online Database* are two leading Australian financial database sources which contains up to 15 years of historical data on all listed companies in Australia. These databases belong to AspectHuntley Pty Ltd which was created in 2003 from a merger of two leading data providers in Australia: Aspect Financial Pty Ltd and Huntley's Financial Services. *Connect 4 Company Prospectuses Database* provides companies prospectus data since 1994. CONNECT 4, founded in 1992, is a wholly owned Australian Company which specialises in providing information on companies which are listed on the ASX.

Particularly, macroeconomic variables, for instance, GNP, interest rates and unemployment rates could be added to the financial distress model.

2) Improvement on survival analysis methods

There are three different techniques in survival analysis for constructing survival analysis models, namely, non-parametric, semi-parametric and parametric techniques. Although the most widely used semi-parametric regression model for survival data is the Cox proportional hazards model, which is adopted in this thesis, future research could further explore other techniques of survival analysis in explaining the financial distress issue to obtain an added dimension to the analysis.

Non-parametric models are useful for conducting a preliminary analysis of survival data and for estimating and comparing the survivor function. The two main methods are the Kaplan-Meier method and the Life-Table method.

Parametric models or accelerated failure time (AFT) models would be appropriate if the data suggested a suitable distribution. The key issue is to specify a probability distribution for the time of event. Common distributions include the exponential, Weibull, log-normal, log-logistic and gamma distribution (Allison, 1995). These models would be applicable if the proportional hazards assumption does not hold (Stepanova, 2001).

3) Improvement on the sample

As mentioned in the previous section, this study is limited to publicly listed companies on the ASX only. Private and other smaller non-listed companies are excluded from the analysis. This might result in a limited generalisation of the empirical results.

Accordingly, further study incorporating smaller and private companies is required to eliminate the limitation. Although it is difficult to gather data on non-public companies, the

findings of such an extended study could be generalized to cover the profiles of all companies.

7.6 Conclusion

This thesis focuses on examining financially distressed companies both in the context of established and new economy IPO companies using survival analysis techniques. Consequently, three mains assays are conducted for this thesis based on the sample of publicly listed Australian companies.

Overall, the empirical results suggest that leverage ratio and company size are the common significant indicators of financial distress in the context of both established companies and new economy IPO companies. In particular, companies with higher leverage and a larger size are more likely to face financial distress.

In addition to being significant indicators of outright failure, leverage ratio and company size are also are significant determinants of distressed takeover, merger or acquisition. However, the directions of the effects of leverage ratio on the likelihood of entering both states of financial distress are different while the effects of company size on both specifications are the same.

Furthermore, market-based data is an important factor for detecting the possibility of financial distress through external administration process while the capital utilization ratio is significant in driving the likelihood of a company being subject to takeover, merger or acquisition.

Finally, this thesis found that ownership concentration is the only significant corporate governance attribute that is related to the survival of new economy IPO firms. The results indicate that new economy IPO companies with a less concentrated ownership are more likely to survive.

Given that various studies suggest the significant influence of corporate governance mechanisms on the survival likelihood of companies, further in-depth examination of corporate governance variables in relation to corporate survival would be required.

A number of policy implications are discussed based on major findings. First, management needs to consider carefully the financial structure of the company in order to avoid possible financial difficulties. Secondly, management and investors can use market data in addition to financial ratios in examining corporate financial distress to obtain better decisions in relation to predicting corporate failure. Finally, management should distinguish between the different types of financial distress, namely, outright failure or distressed external administration and distressed takeover, merger or acquisition companies. Particularly, the financial leverage ratio and company size could be useful when considering the indicators of financial distress in both states. In addition, market-based variables could be useful when detecting the possibility of outright failure while the capital utilization ratio is an important determinant of the likelihood of a company being subject to takeover, merger or acquisition.

In addition, the implications for managerial practice relating to the context of new economy IPO firms are concluded as follows. First, there is no optimal number for directors on the board, or for the percentage of non-executive directors on the board to ensure new economy IPO firms' survival, and the use of a non executive chairman and the usage of an independent leadership structure do not guarantee survival. Secondly, management should encourage a lower ownership concentration in new economy IPO companies to enhance company survivability. Finally, financial managers should slow down the process of acquiring external funds. The rapid growth in terms of total assets may give rise to concerns of creditors and investors about the financial risk of the firm, which can lead to a higher cost of capital and a decline in shareholders' wealth.

However, any implications should be considered taking into account the limitations of this research. Such limitations include the restriction of the sample to publicly listed companies only, the small sample size of financially distressed companies and the accuracy of the database.

Future research could further improve on the study in three areas: improvement on explanatory variables, improvement on survival analysis methods and improvement on the sample.

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LIST OF CANDIDATE'S PUBLICATIONS

CONFERENCE PRESENTATIONS

Chancharat, N., Davy, P. and McCrae, M. 2007, 'Examining financially distressed company in Australia: The application of survival analysis', *Proceedings of the 2007 European Applied Business Research (EABR) Conference*, 4-7 June, Clute Institute for Academic Research, Padova, Italy.

Chancharat, N., Davy, P., McCrae, M. and Tian G. 2007, 'How do Australian financially distressed firms survive?', *Proceedings of the 12th Finsia-Melbourne Centre for Financial Studies Banking and Finance Conference*, 24-25 September, Melbourne, Australia.

Chancharat, N., Davy, P., McCrae, M. and Tian G. 2007, 'Firms in financial distress, a survival model analysis', *Proceedings of the 20th Australasian Finance & Banking Conference 2007*, 12-14 December, Sydney, Australia.

ARTICLES UNDER REVIEW

Chancharat, N., Davy, P., McCrae, M., Tian G. and Liu, P. 'Predicting financially distressed Australian firms using survival model', *Australian Economic Papers*.

Chancharat, N. Davy, P., McCrae, M. and Tian G. 'Multiple states of financially distressed Australian companies: A competing risks model', *Journal of Business Finance and Accounting*.

APPENDIX A

INSOLVENCY ARRANGEMENT IN AUSTRALIA

This section briefly describes the Corporations Law in Australia under the Corporations Act 2001 in order to explain the insolvency arrangement system in Australia. The Corporations Law sets the legal framework for incorporated businesses (The Office of Legislative Drafting and Publishing, 2005).

According to Bickerdyke, Lattimore and Madge (2000), insolvency is defined as the situation where an individual or a business is unable to pay debts as and when they fall due for payment. Australia's insolvency regime rests on two laws: the Corporations Act 2001, which is for incorporated enterprises, and the Bankruptcy Act 1966, which is for unincorporated enterprises. Figure A.1 provides an outline of the relevant provisions of the Corporations Law.

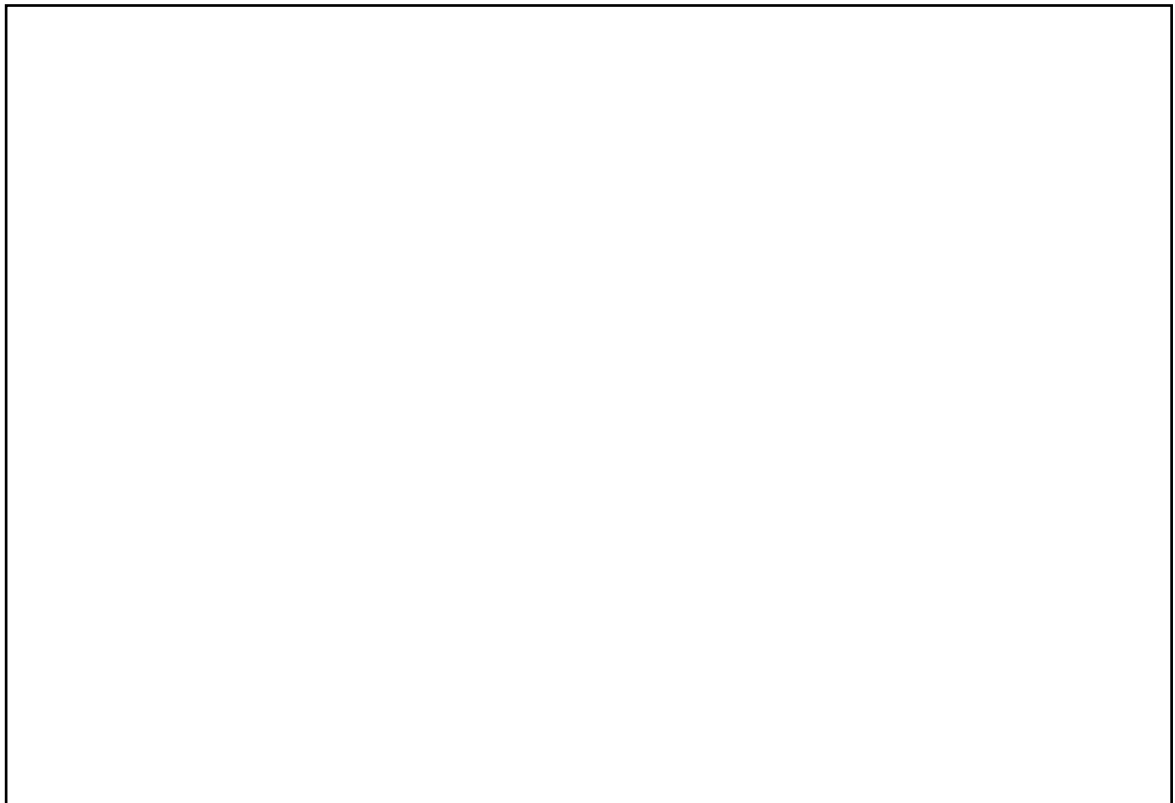


Figure A.1: The Corporations Law in Australia

Source: Adapted from Bickerdyke, I., Lattimore, R. and Madge, A. 2000, Business failure and change: An Australian perspective, Working Paper, Productivity Commission, AusInfo, Canberra.

1. Reorganization

Reorganization is an alternative to liquidation for insolvent companies. There are two ways that insolvent companies can reorganize under the Corporations Law: Voluntary Administration (followed by a Deed of Company Arrangement) and a Scheme of Arrangement.

1.1 Voluntary Administration

Voluntary Administration was introduced in 1992 and replaced earlier arrangements that were considered to offer too little scope for companies to trade their way out of difficulties.

Definition:

Voluntary Administration involves the appointment of a professional practitioner, the administrator, to take control of the company's affairs from its directors. It can be initiated by the directors (the usual case), corporate liquidators if the company is in liquidation, or by the holder of a property charge over the whole, or at least a substantial portion, of the company's assets.

Process:

Administrators essentially take over the duties and responsibilities of the company's directors. However, their primary task is to prepare a report on the company's financial position for a meeting of its creditors. This meeting will generally be held within 28 days of the appointment being made. The notice of the meeting will include the administrator's assessment as to whether it would be in the interests of the company's creditors to execute a Deed of Company Arrangement, end the administration (which would restore control to the directors), or wind up the company. Consequently, the creditors decide at the meeting which of these options are preferred. In practice, they usually agree to allow a Deed of Company Arrangement. A Deed of Company

Arrangement is an agreement between a company and its creditors, the details of which vary with the particular circumstances involved.

1.2 A Scheme of Arrangement

A Scheme of Arrangement is available under Part 5.1 of the Corporations Law. The procedures are cumbersome and costly compared to Voluntary Administration and a Deeds of Company Arrangement. Schemes of Arrangement have been seldom used since the introduction of Voluntary Administration and Deeds of Company Arrangements in 1992.

Definition:

A Scheme of Arrangement is a restructuring of a company's capital structure or rescheduling of its debts. The arrangement is binding on all its creditors/members (either or both), or classes of either or both. A scheme may be proposed by the company, the liquidator or a creditor or member and is approved by special resolution.

Process:

A Scheme of Arrangement begins with a decision by the company's board or its liquidator to seek a Scheme of Arrangement. Consequently, preparation of an explanatory statement and other documents required under the Corporations Law has to be made. The company must seek the court's approval to call a meeting of creditors to consider the scheme. The meetings of creditors and shareholders will be held to consider the proposed scheme and the majorities prescribed by law will be obtained. After that, the company has to seek the approval of the court for the scheme document approved by creditors and shareholders and lodge a copy of the court order with the ASIC.

2. Receivership

Definition:

This is the process in which a receiver is appointed to a company to collect or protect property for the benefit either of the appointor or the persons ultimately held to be entitled to that property.

Process:

Under the Corporations Law, a receiver, that is, a person appointed by a secured creditor to take control of the secured assets for the benefit of the secured creditor (in addition, a person can be appointed receiver by the Court to take charge of assets) can be appointed by the court or as an agent of individuals having a property charge over all, or a substantial part, of a company's assets. In either case, the receiver has substantial powers over the business concerned, including day-to-day control over its activities. The appointment of a receiver outside of the courts in many ways parallels the process of liquidation. A particular class of creditors, namely, secured debenture holders, has the power to place the company in receivership. Receivers normally have the authority to take proceedings in the name of the company, to collect and sell its property and most importantly, to carry on its business. Only registered liquidators may be appointed as receivers under the Corporations Law (Section 418(1)). Unlike liquidators, a receiver's primary duty is to deal with the payment of debts secured by the relevant charge. They have to obtain the best price for the sale of any of the corporation's assets and, with the approval of the corporation's liquidator or of the court, have the power to continue the corporation's business. However, they are under no obligation to do so. Nor are they obliged to attempt to revive the business or restore its profitability, even if this is in the interests of creditors as a whole. Their responsibility is to the relevant debenture holders or to the court (if court appointed) and

not to the business' owners, unsecured debtors or to any other business stakeholders. Liquidation may follow or occur simultaneously with receivership, in which case the receiver, as representative of the mortgagees, has prior claim over unsecured creditors to possession of the secured assets. In many cases, this will amount to virtually all of the company's assets.

3. Liquidation

Definition:

Liquidation or winding up is the process of ending a company's business operations.

Process:

This involves selling the company's assets and discharging its liabilities, settling any questions of account or contribution between its members and dividing the surplus (if any) between those members. Winding up does not preclude the sale of the business as a going concern. There are two ways of winding up a corporation: insolvency, that is, winding up via creditors, which involves voluntary administration, and compulsory (court ordered) liquidation.

3.1 Winding up via creditors voluntary administration

If the compulsory creditors' meeting held after the appointment of the administrator votes to wind up the company, a registered liquidator must be appointed. There are two types of registered liquidators, namely, official liquidators who are appointed by ASIC, and others (mainly lawyers and accountants). The creditors' meeting, or a committee appointed at the meeting, decides whether to approach ASIC to nominate an official liquidator or to choose a non-official liquidator.

Where a company is to be wound up, the role of the liquidator is to investigate its affairs and take legal action against company personnel if appropriate. The liquidator

may also take action to recover assets under certain circumstances. In more detail, the main tasks of a liquidator where the corporation has clearly failed are to:

- Collect, preserve and sell the company's assets including any surplus arising from receivership.
- Investigate and report to creditors any preferential payments that might be recoverable.
- Arrange for the distribution of proceeds to creditors according to their priority.
- Complete the liquidation and apply for deregistration of the company.

The relative priority of creditors is set out in the Corporations Law.

3.2 Compulsory liquidation

Compulsory winding up requires a court order. It most often arises when creditors petition the court following the failure of a corporation to meet debt repayments. If the petition is successful, the court appoints an official liquidator.

Instead of a final winding up order, the court may grant a provisional liquidation order. The objective of provisional liquidation is to remove control of the company from its directors while further investigation is undertaken. It is most commonly granted when there are concerns that the company's assets may be dissipated. Provisional winding up often precedes full liquidation.

APPENDIX B

THE EMPIRICAL RESULTS BEFORE TRUNCATION

Table B.1: Descriptive statistics of the data before truncation (Chapter 4)

	EBT	ROE	ROA	CUR	QUK	WCA	DET	CPT	TAT	SIZE	SIZE2	AGE	EXR
Active (n=1067)													
Min	-269433.2667	-122.3413	-805.0400	0.0100	0.0100	-2501.5000	0.0007	-0.1751	-1.2585	1.3900	1.9220	1.0000	-3.8080
Mean	-189.9519	-0.1379	-0.3091	7.9075	7.5878	-0.3063	0.9518	6.5482	1.0962	15.8328	264.61212	20.1142	-0.1142
Median	0.0150	0.0137	0.0092	1.7100	1.2300	0.0186	0.3701	1.0023	0.4924	16.3499	67.3185	14.0000	-0.0777
IQR	2.1593	0.2819	0.2032	2.8100	2.8000	0.1865	0.4322	2.3921	1.0719	5.2371	166.3267	16.0000	0.7319
Max	1171.5671	216.0961	21.1001	1773.0600	1773.0600	0.9900	2816.1700	15999.0000	1367.1111	25.9000	670.5000	123.0000	4.1780
Std Dev.	4000.3407	4.2778	9.7370	36.9202	36.9461	24.4976	28.5408	156.3487	13.5428	3.7237	113.1512	19.5590	0.7414
Skewness	-43.9270	11.1857	-70.3142	21.1189	21.0948	-94.7161	86.5241	94.1245	90.7056	-0.4333	0.1206	2.1505	0.0501
Kurtosis	2397.7085	1026.1623	5304.1674	706.6495	705.3569	9509.9139	8304.5518	9547.1498	9035.3128	-0.2721	-0.4596	5.1587	2.7380
Distressed (n=50)													
Min	-318.6193	-6.9456	-35.9132	0.0100	0.0100	-1173.1100	0.0006	0.0004	-2.1020	7.4400	55.0000	1.0000	-3.1700
Mean	-2.8237	0.1781	-0.3909	5.6716	5.4426	-5.0741	6.8735	2.9237	1.4010	15.8297	259.8330	22.0473	-0.2529
Median	-0.0214	0.0025	-0.0062	1.3200	1.0400	0.0106	0.4556	0.8820	0.4533	16.4390	270.2389	17.0000	-0.2096
IQR	1.2552	0.2360	0.1733	1.9100	1.9800	0.2134	0.4491	2.2523	1.0574	3.5043	113.5213	23.0000	0.8338
Max	358.0000	52.7059	0.4981	275.0300	275.0300	0.9760	1459.560	51.4800	52.0378	21.5000	460.0000	91.0000	3.1000
Std Dev.	69.6318	3.4298	2.4245	22.7840	22.8230	68.5709	85.2836	6.9209	5.0967	3.0109	89.6430	16.6568	0.8523
Skewness	1.1315	10.7222	-10.0981	8.9678	8.9511	-14.5041	14.5059	4.8427	8.4766	-0.6863	-0.2302	1.4019	-0.1260
Kurtosis	19.8310	134.4389	116.9295	90.3050	90.0309	218.9222	218.9423	26.4602	77.7171	-0.0097	-0.3737	2.7141	1.9990
Chi-square	16.3737**	0.7138	5.9812**	45.0747 **	11.7515 **	0.7138	11.1221 **	0.5715	1.2358	1.0463	1.2358	19.9972**	17.8448 **
p-value	<.0001	0.3982	0.0145	<.0001	0.0006	0.3982	0.0009	0.4497	0.2663	0.3064	0.2663	<.0001	<.0001

Note: Descriptive statistics grouped by company status. Chi-square from a non-parametric test of equality of group medians using median tests.

*** Significant at the 5 percent level*

Table B.2: Cox proportional hazards model estimation before truncation (Chapter 4)

Covariate	Coefficient	Standard Error	χ^2 Statistic	p-Value	Hazard Ratio
SIZE	0.6653*	0.3985	2.7882	0.0950	1.9450
EXR	-0.8220**	0.1691	23.6241	<.0001	0.4400

*Note: *Significant at the 10 percent level, ** Significant at the 5 percent level.*

Table B.3: Descriptive statistics of the data before truncation (Chapter 5)

	EBT	ROE	ROA	CUR	QUK	WCA	DET	CPT	TAT	SIZE	SIZE2	AGE	EXR
State 0 (n = 891)													
Mean	-222.9160	-0.1539	-0.3635	8.6304	8.3302	-0.3722	1.0275	7.0097	1.1073	15.4864	254.1814	19.6904	-0.1195
Median	-0.0190	-0.0081	-0.0085	1.7600	1.3000	0.0128	0.3433	0.9230	0.4394	15.9391	254.0548	14.0000	-0.0805
Min	-269433.2667	-113.4359	-805.0400	0.0100	0.0100	-2501.5000	0.0007	-0.1751	-1.2590	1.3900	1.9220	1.0000	-3.8080
IQR	3.3639	0.3049	0.2225	3.4300	3.4400	0.1799	0.4479	2.4305	1.0491	5.4443	168.8465	14.0000	0.7598
Max	1171.5671	216.0961	21.1001	1773.0600	1773.0600	0.9840	2816.1700	15999.0000	1367.0000	25.9000	670.5000	123.0000	4.1780
Std Dev.	4336.6624	4.4631	10.5560	39.5934	39.6158	26.5614	30.9439	169.3725	14.6744	3.7789	113.8856	19.3796	0.7593
Skewness	-40.5147	13.6923	-64.8660	20.0057	19.9892	-87.3580	79.8119	87.0359	83.8237	-0.3135	0.2603	2.3037	0.0315
Kurtosis	2039.5382	960.8441	4513.0999	626.0327	625.1861	8089.4670	7065.2559	8149.5189	7706.0037	-0.3538	-0.3480	6.0457	2.5460
State 1 (n = 50)													
Mean	-2.8237	0.1781	-0.3909	5.6716	5.4426	-5.0741	6.8735	2.9237	1.4010	15.8297	259.8330	22.0473	-0.2529
Median	-0.0214	0.0025	-0.0062	1.3200	1.0400	0.0106	0.4556	0.8820	0.4533	16.4390	270.2389	17.0000	-0.2096
Min	-318.6193	-6.9456	-35.9132	0.0100	0.0100	-1173.0011	0.0007	0.0004	-2.1000	7.4400	55.0000	1.0000	-3.1700
IQR	1.2552	0.2360	0.1733	1.9100	1.9800	0.2134	0.4491	2.2523	1.0574	3.5043	113.5213	23.0000	0.8338
Max	358.0000	52.7059	0.4981	275.0300	275.0300	0.9759	1459.5600	51.0000	52.0000	21.5000	460.0000	91.0000	3.1000
Std Dev.	69.6318	3.4298	2.4245	22.7840	22.8230	68.5709	85.2836	6.9209	5.0967	3.0109	89.6430	16.6568	0.8523
Skewness	1.1315	10.7222	-10.0981	8.9678	8.9511	-14.5041	14.5059	4.8427	8.4766	-0.6863	-0.2302	1.4019	-0.1260
Kurtosis	19.8310	134.4389	116.9295	90.3050	90.0309	218.9222	218.9423	26.4602	77.7171	-0.0097	-0.3737	2.7141	1.9990
State 2 (n = 140)													
Mean	-2.5094	-0.0551	0.0160	3.8489	3.4357	0.0719	0.5340	4.3603	1.0577	17.9684	329.6880	22.2459	-0.0655
Median	0.0742	0.0825	0.0538	1.5000	1.0100	0.0460	0.4663	1.5115	0.8167	18.1779	330.4352	14.0000	-0.0556
Min	-847.0480	-122.3413	-5.6567	0.0100	0.0100	-5.6010	0.0002	0.0003	0.0001	6.9100	47.7000	1.0000	-2.4230
IQR	0.1384	0.1297	0.0664	1.2100	0.8500	0.2117	0.2407	2.2310	1.0833	2.9449	107.4156	24.0000	0.5509
Max	4.9407	4.6935	2.2246	243.8000	243.8000	0.9902	11.2588	532.0000	21.7000	22.4000	503.0000	94.0000	3.2670
Std Dev.	26.8833	3.3811	0.2847	14.2955	14.3512	0.3378	0.8362	19.0255	1.3295	2.6052	86.8882	20.6832	0.5940
Skewness	-24.3370	-35.1317	-7.3551	11.4221	11.3737	-10.8624	9.5215	19.2516	8.9266	-1.0868	-0.5215	1.4653	0.4327
Kurtosis	729.7166	1271.1167	142.8397	161.8494	160.6155	178.3127	105.2614	477.9148	128.1303	1.7751	0.2680	1.4417	4.4416
Chi-square	450.5755**	358.9656**	423.0064**	110.6478**	153.4642**	61.9947**	229.6430**	89.0355**	178.8191**	547.7139**	547.8080**	23.0860**	23.2753**
p-value	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001

Note: State 0: Active companies, State 1: Distressed external administration companies and State 2: Distressed takeover, merger or acquisition companies.

Descriptive statistics grouped by company status. Chi-square from a non-parametric test of equality of group medians using median tests.

*** Significant at the 5 percent level*

Table B.4: Single and competing risks Cox proportional hazards model estimation before truncation (Chapter 5)

Variable	(A) Single Risk Model			(B) Competing Risks Model					
				Distressed External Administration Companies			Distressed Takeover, Merger or Acquisition Companies		
	Coefficient	p-Value	Hazard Ratio	Coefficient	p-Value	Hazard Ratio	Coefficient	p-Value	Hazard Ratio
EBT	0.00001	0.9963	1.0000	0.0002	0.8740	1.0000	-0.00002	0.9462	1.0000
ROE	0.0117	0.4603	1.0120	0.0066	0.6773	1.0070	0.0054	0.8795	1.0050
ROA	0.0005	0.9615	1.0000	0.0004	0.9659	1.0000	-0.0196	0.6751	0.9810
CUR	-0.3288*	0.0686	0.7200	-0.6210	0.1396	0.5370	-0.2021	0.3584	0.8170
QUK	0.3270*	0.0700	1.3870	0.6217	0.1391	1.8620	0.1230	0.5832	1.1310
WCA	-0.0002	0.9873	1.0000	0.0018	0.7668	1.0020	-0.5768	0.2429	0.5620
DET	0.0015	0.8742	1.0010	0.0037	0.4729	1.0040	-0.6803*	0.0930	0.5060
CPT	-0.0006	0.7883	0.9990	-0.0047	0.6765	0.9950	-0.0002	0.8854	1.0000
TAT	-0.0047	0.8019	0.9950	-0.0013	0.8253	0.9990	-0.0740	0.3769	0.9290
SIZE	1.0049**	<.0001	2.7310	0.6754*	0.0903	1.9650	1.5711**	0.0001	4.8120
SIZE2	-0.0245**	0.0008	0.9760	-0.0186	0.1315	0.9820	-0.0384**	0.0007	0.9620
AGE	-0.0040	0.2957	0.9960	-0.0027	0.7427	0.9970	-0.0035	0.4074	0.9960
EXR	-0.2048*	0.0574	0.8150	-0.8183**	<.0001	0.4410	0.0812	0.5336	1.0850
Number of events	190			50			140		

Note: * Significant at the 10 percent level.

** Significant at the 5 percent level.

Table B.5: Descriptive statistics of the data before truncation (Chapter 6)

	BD_SIZE	BD_INDP	CM_NEXC	CM_DUAL	TOP20	OF_PRICE	OF_SIZE	OF_AGE	RETAIN	BACK	BIG5	NUM_RISK
Survival IPOs (n=93)												
Mean	5.1885	53.4149	0.6442	0.8551	65.9798	0.8857	32.9512	5.7981	62.1626	0.7398	0.5316	12.7173
Median	5.0000	60.0000	1.0000	1.0000	70.0000	0.5000	8.0000	3.0493	70.0000	1.0000	1.0000	12.0000
Min	3.0000	0.0000	0.0000	0.0000	14.4000	0.2000	1.5000	0.0027	0.0000	0.0000	0.0000	0.0000
Max	10.0000	83.0000	1.0000	1.0000	94.1400	4.6000	421.0940	38.4603	96.3400	1.0000	1.0000	31.0000
Std Dev.	1.3198	19.5939	0.4791	0.3522	18.6702	0.8525	73.9985	7.1613	23.6733	0.4391	0.4994	5.3226
Skewness	0.6119	-0.6757	-0.6035	-2.0223	-0.8569	2.4452	3.7922	1.9579	-1.1423	-1.0955	-0.1271	0.8013
Kurtosis	0.9508	-0.1034	-1.6404	2.0955	0.0362	7.2115	14.4321	4.7397	0.6540	-0.8022	-1.9894	2.0205
Non-Survival IPOs (n=34)												
Mean	5.1345	61.9591	0.6959	0.8480	76.7651	0.9282	135.0988	6.2423	70.4801	0.9006	0.7018	14.2456
Median	5.0000	67.0000	1.0000	1.0000	78.4100	1.0000	12.0000	4.5068	74.3400	1.0000	1.0000	13.0000
Min	3.0000	0.0000	0.0000	0.0000	19.9900	0.2000	1.0000	0.0082	0.0000	0.0000	0.0000	7.0000
Max	9.0000	89.0000	1.0000	1.0000	98.2800	2.0000	6652.7300	18.8301	99.5200	1.0000	1.0000	25.0000
Std Dev.	1.1270	20.0849	0.4614	0.3601	14.5248	0.4959	873.7467	5.4964	20.0611	0.3001	0.4588	3.7555
Skewness	0.8544	-0.8914	-0.8593	-1.9553	-0.6455	0.2855	7.4087	0.5869	-1.0167	-2.7013	-0.8898	0.9136
Kurtosis	1.7554	0.2530	-1.2767	1.8446	0.3556	-0.6623	53.5469	-0.9495	1.2692	5.3595	-1.2226	0.8229
Kruskal-Wallis Test	0.0864	2.5854	0.1069	0.2197	7.2061**	3.6893*	0.6289	0.2592	0.9395	2.8339*	2.2513	1.9929
p-value	0.7688	0.1079	0.7437	0.6393	0.0073	0.0548	0.4277	0.6107	0.3324	0.0923	0.1335	0.1580

Table B.5: Descriptive statistics of the data before truncation (Chapter 6): Continued

	ROA	CUR	TAT	DET	C_SIZE	IPO_9900
Survival IPOs (n=93)						
Mean	-0.2969	7.1660	0.9023	0.4585	7.2659	0.3952
Median	-0.0590	2.0000	0.6130	0.3106	7.2258	0.0000
Min	-15.4217	0.0000	-0.0058	0.0008	5.0000	0.0000
Max	10.1470	331.5200	17.4242	14.0791	9.7000	1.0000
Std Dev.	1.0641	20.6795	1.1974	0.8563	0.7805	0.4892
Skewness	-5.4100	9.1896	5.1073	10.1437	0.4673	0.4296
Kurtosis	90.3834	116.2730	53.9945	134.0131	0.6128	-1.8206
Non-Survival IPOs (n=34)						
Mean	-0.7461	8.9613	1.0098	0.7166	7.4053	0.3567
Median	-0.0132	1.8100	0.6198	0.3418	7.3498	0.0000
Min	-35.9132	0.0000	0.0000	0.0009	4.7000	0.0000
Max	1.0449	894.7300	15.0340	40.6610	9.9000	1.0000
Std Dev.	3.6683	68.3364	1.4442	3.1179	0.7617	0.4804
Skewness	-7.0966	12.9614	5.8747	12.5240	0.1373	0.6035
Kurtosis	57.0133	168.9561	52.3817	161.1057	1.3460	-1.6553
Kruskal-Wallis Test	0.7781	0.2092	0.5205	1.4877	3.3075*	0.1226
p-value	0.3777	0.6474	0.4706	0.2226	0.0690	0.7263

Note: Descriptive statistics grouped by company status. n is the number of companies. Kruskal-Wallis Test from a non-parametric test of equality of group means.

** Significant at the 10 percent level, ** Significant at the 5 percent level.*

Table B.6: Cox proportional hazards model estimation before truncation (Chapter 6)

Variable	Coefficient	Standard Error	χ^2 Statistic	<i>p</i> -Value	Hazard Ratio
TOP20	0.0321**	0.0141	5.1633	0.0231	1.0330
OF_SIZE	0.0004*	0.0002	2.7304	0.0985	1.0004
TAT	0.1969**	0.0918	4.6032	0.0319	1.2180
C_SIZE	0.6798**	0.3330	4.1667	0.0412	1.9730

Note: *Significant at the 10 percent level.

** Significant at the 5 percent level.