A COMPARATIVE ANALYSIS OF THE APPLICATION OF ALTMAN (1968) Z-SCORE AND OHLSON (1980) O-SCORE PREDCITION MODELS TO HONG KONG PUBLIC-LISTED COMPANIES, AND THE IMPACT OF CASH CONVERSION CYCLE AND NON-FINANCIAL VARIABLES ON PREDICTING BUSINESS FAILURE

by

KAM-WING LAU

MBA, Hong Kong Baptist University, 1999

BBA, University of Hawaii at Manoa, 1992

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

DOCTOR OF BUSINESS ADMINISTRATION

Macquarie Graduate School of Management
Macquarie University
Sydney, Australia

January 2014

CERTIFICATION STATEMENT

I hereby certify that this dissertation constitutes my own product, and that appropriate credit is given where I have used the ideas, expressions, or writings of another person.

Signed___________________

Kam-wing Lau

ACKNOWLEDGEMENTS

I would like to thank Professor Richard Petty, my thesis supervisor, for his guidance and quick response to my requests for assistance. I am always amazed by his generosity with his time in giving me comments on the various drafts of this dissertation. He has been so supportive and has made my experience at Macquarie University rewarding.

I would like to express my appreciation to Brenda Lee of SPSS Hong Kong, for giving me invaluable advices on the statistical analyses in this research. I would also like to thank the librarians at the Hong Kong Central Library, who have provided tremendous support to my library search and have made my time spent in the library much more enjoyable.

I am indebted to my family for their love and support. I am thankful to my respectful mother, Rebecca, who has been waiting for me during this honorable journey. Without her giving the confidence of my ability to explore new frontiers, and her teaching of integrity during my childhood, I could not have completed this dissertation.

Last but not least, special thanks must go to my wife Selina and family cat Meow Chu for their patience, support, and the freedom given to me while pursuing this goal. I am extremely grateful to Selina her encouragement that has helped me overcome all hardships and stayed steadfast to the finish line. She is always by my side, no matter whether I am happy or unhappy.

This thesis was edited by Dr Alison Basden in accordance with the IPEd/DDOGS thesis editing policy (2010).

ABSTRACT

The bankruptcy prediction models most frequently used in empirical research of business failure are the Altman (1968) and Ohlson (1980) models. The predictive accuracy of both models, developed using US data, has been repeatedly tested and compared using data of different countries. However, no published studies have compared these models using Hong Kong data, nor have they explored how cash conversion cycle and HIBOR rate are connected with business failure, despite evidence that liquidity and non-financial variables affect failure prediction.

This study examined the applicability of the Altman (1968) and Ohlson (1980) models in predicting business failure using data from Hong Kong public listed companies. It also tested whether adjusting the cutoff points (points determined by scorings that classified companies as failed or non-failed) improved the models' accuracy, and compared the accuracy of the two models. Finally, it examined the effects of cash conversion cycle and some non-financial variables including change of auditor and change of HIBOR interest rate, on predicting business failure.

The sample comprised 234 Hong Kong public-listed companies: 39 failed companies that had been delisted from the Hong Kong Stock Exchange between 1998 and 2011, and 195 non-failed public listed companies that were not delisted during the same time period. Financial data were obtained from the Standard and Poor (S&P) Capital IQ and the Hong Kong Stock Exchange (HKEx) database.

Both the Altman and Ohlson models achieved an overall predictive accuracy significantly greater than 50 per cent of the total sample for each of the three years prior to delisting. The Ohlson (1980) model was relatively superior to the Altman model in making overall correct classifications of the non-failed companies publicly listed in the HKEx. This study is the first to find that cash conversion cycle and HIBOR interest rate are significantly correlated to business failure when data of Hong Kong public-listed companies are applied.

CONTENTS

LIST OF FIGURES

LIST OF TABLES

LIST OF APPENDICES

CHAPTER ONE

INTRODUCTION

The important topic of how business failure can be predicted has been studied since the late 20th century (Wilson & Sharda, 1994). Stakeholders such as investors and lenders seek an accurate model that can identify potential failures and provide early warning signals that enable them to take precautionary measures and avoid losses (Udo, 1993). Researchers have developed many bankruptcy prediction models, including multiple discriminant analysis (MDA), logistic regression (logit), recursive partitioning, hazard model, and neural networks (Beaver, 1966; Altman, 1968; Wilcox, 1973; Deakin, 1972; Olson, 1980; Taffler, 1983; Boritz et al., 2007).

Most empirical research into predicting business failure has emanated from Western countries, especially the US and the UK, with relatively few studies conducted elsewhere. Some researchers (Altman, 1984; Swanson & Tybout, 1988) have recognized that financial data from developing countries such as Brazil and Argentina provide an important context for studying business failure, while others (Boritz et al., 2007) have questioned whether models developed in the West can accurately predict business failure in Asian countries that have different business environments and operations.

Some recent studies have focused on predicting business failure outside the US. Examples include the comparison of MDA and logit models by Mohamed et al. (2001) for distressed Malaysian companies; the study of collapsed public companies in Taiwan by Wu (2004) using non-financial data; the study of bankrupt public listed companies in China by Wang and Campbell (2010) using the Altman Z-score and Ohlson models; and the study of failed Korean firms by Han et al. (2012) using logit regression.

To date, however, studies of business failure using company data from Hong Kong are scarce. Listed companies in Hong Kong rarely declare bankruptcy and, while bankruptcy is more common for non-listed companies, the financial records of those companies are virtually impossible to retrieve. Researchers are often unable to obtain sufficient financial data. As a result, small sample sizes and limited data sources from Hong Kong have hindered researchers, and most studies of failed businesses have concentrated on other developed countries.

This research addresses this gap in knowledge by investigating whether the models developed in a Western context can reliably predict business outcomes when applied to companies in Hong Kong.

1.1. Background to the study

This section provides background information about Hong Kong, its economic structure, government policy towards foreign investment, and stock markets as a financial centre for overseas foreign direct investments. It also outlines the Hong Kong economy's vulnerability to global economic and financial instability.

Hong Kong's population was 7.3 million in 2012, with an annual GDP growth rate in 2011 and 2012 of 1.2 per cent and 1.3 per cent, respectively, and per capita GDP in 2012 was approximately HK$285,146 (Census & Statistics Report, HKSAR, 2012). As outlined in the Global Financial Centre Index 1 Executive Summary, the GDP of Hong Kong had grown 180 times (Preston & Haacke, 2003) and per capita GDP had increased more than 87 times between 1961 and 1997 (Yeung, 2008).

Hong Kong is known as one of the Four Asian Tigers because of its high growth rate and rapid development between the 1960s and the 1990s. Its economy is dominated by the service sector, which contributes over 90 per cent of its GDP, with only 9 per cent produced by the industrial sector (United Nations, 2009). Imports and exports account for a large proportion of the service sector. As noted in the Census & Statistics Report, HKSAR (2006), the total value of Hong Kong's imports and exports had exceeded its GDP to make it the world's 11th largest trading entity. Hong Kong is the world's largest re-export centre (Dhungana, 2006); most of its exports are re-exported products made in mainland China. Hong Kong's largest export markets are mainland China, the US and Japan (Triennial Central Bank Survey, 2010).

Hong Kong holds a high international ranking in a number of areas. It is an important centre for international finance and trade, with one of the greatest concentrations of corporate headquarters in the Asia-Pacific region (Bromma, 2007). Its currency, the Hong Kong dollar, is the eighth most traded currency in the world (Triennial Central Bank Survey, 2010). Its government was once described as the world's greatest experiment in laissez-faire capitalism (Economist, 2010), and its economy has been ranked as the world's freest developed capitalist economy by the Index of Economic Freedom every year since 1995. Hong Kong was ranked highly for its economic freedom, financial and economic competitiveness, quality of life, perception of corruption and human development index by the World Competitive Yearbook (2012, 2013).

The Hong Kong Stock Exchange (HKEx) lists and trades the stocks of Hong Kong public companies. The HKEx has several functions: it serves as the market regulator and operates the stock exchange, and it is also responsible for regulating listed companies, promulgating listing, trading and clearing rules, clearing the futures exchange and securities, and serving as an intermediary between listed companies and investment banks, custodian banks, information vendors, securities and derivatives brokers.

The HKEx is composed of two trading markets: the Main Board and the Growth Enterprise Market (GEM). In 2006 the trading volume of the Main Board was HK$8,332.6 billion. Seven years later, in 2013, it had increased by 82 per cent to HK$15,185.8 billion. The total market capitalization and the numbers of foreign company listed in the HKEx from 2006 to 2013 are shown in Table 1.1. In this seven-year period, the number of listed domestic companies increased 50 per cent and the amount of market capitalization increased 51 per cent.

Year	No. of listed companies		Total market capitalization (HK$ billion)
	Domestic	Foreign	
2006	967	10	$132.5
2007	1,039	11	$205.4
2008	1,077	11	$102.5
2009	1,145	12	$177.7
2010	1,244	21	$209.4
2011	1,326	29	$174.5
2012	1,368	30	$218.7
2013	1,451	30	$239.1

Table 1.1: Foreign direct investment in HKEx, 2006–2013

The second market of the HKEx, the GEM, provides emerging growth companies (such as SMEs) an alternative fundraising channel. In 2013, 192 SMEs were listed in the GEM, with a total market capitalization of HK$134.6 billion. The market capitalization of the GEM from 2006 to 2013 is shown in Table 1.2.

Year	Market capitalization (HK$ billion)	Percentage change from previous year
2006	$88.89	N/A
2007	$161.08	+81%
2008	$45.16	–72%
2009	$105.04	+133%
2010	$134.67	+28%
2011	$84.59	–37%
2012	$78.40	-7%
2013	$134.0	+71%

Table 1.2: Market capitalization of the GEM, 2006–2013

Source: HKEx (2013)

In 2012 the HKEx was ranked seventh in the world in terms of market capitalization (World Federation of Exchanges, 2012), as shown in Table 1.3. In 2012 the Shanghai Stock Exchange had surpassed the HKEx to become Asia’s second-largest stock exchange; the HKEx currently ranks third behind the Tokyo Stock Exchange and the Shanghai Stock Exchange in term of market capitalization.

Stock exchange	Country	World ranking	Asia ranking	Market capitalization (US$ billion)
New York Stock Exchange	US	1		13,027.88
NASDAQ	US	2		4,474.77
Tokyo Stock Exchange	Japan	3	1	3,384.87
London Stock Exchange	UK	4		3,332.23
NYSE Euronext	Europe	5		2,460.42
Shanghai Stock Exchange	China	6	2	2,410.87
Hong Kong Stock Exchange	Hong Kong	7	3	2,375.85
Toronto Stock Exchange	Canada	8		1,860.19
Australian Stock Exchange	Australia	9	4	1,215.60
Frankfurt Stock Exchange	Germany	10		1,212.47
Shenzhen Stock Exchange	China	11	5	1,149.18
BM & FBOVESPA	Brazil	12		1,127.25
Bombay Stock Exchange	India	13	6	1,101.87
Swiss Stock Exchange	Switzerland	14		1,077.96
Korean Stock Exchange	Korea	15	7	1,024.63

Table 1.3: Market capitalization of the world's top-ranked stock exchanges (June 2012)

Remarks:
(1) ranking is based on market capitalization, excludes investment funds
(2) all World Federation of Exchanges (WFE) member stock exchanges are included in the ranking, not only the main exchange for each country

Ranked seventh in the world and second in Asia, with a market capitalized amount of US$60.8 billion, the HKEx successfully raised 22 per cent of worldwide initial public offering (IPO) capital in 2009, making it the world's largest centre of IPO (Bloomberg, 2009) and the easiest place to raise capital (Thomaswhite.com, 2009). The HKEx continued to raise nearly US$53 billion through IPO in 2010, compared with only US$42 billion in the US and US$16 billion (£10 billion) in the UK. Analysts reported (MoneyBeat, 2013) that Hong Kong remained sixth place in 2013, continued to raise US$ 14 billion in 2012 and US$ 6 billion in 2013.

The capitalized amounts of the HKEx from 1999 to 2013 are shown in Figure 1.1. The sharp jump from US$1,047 million in 2005 to US$2,650 million in 2007 represented an increase of 153 per cent. Although the amount had dropped 50 per cent to US$1,323 million the following year, the capitalized amount climbed to a peak of US$3,085 million in 2013.

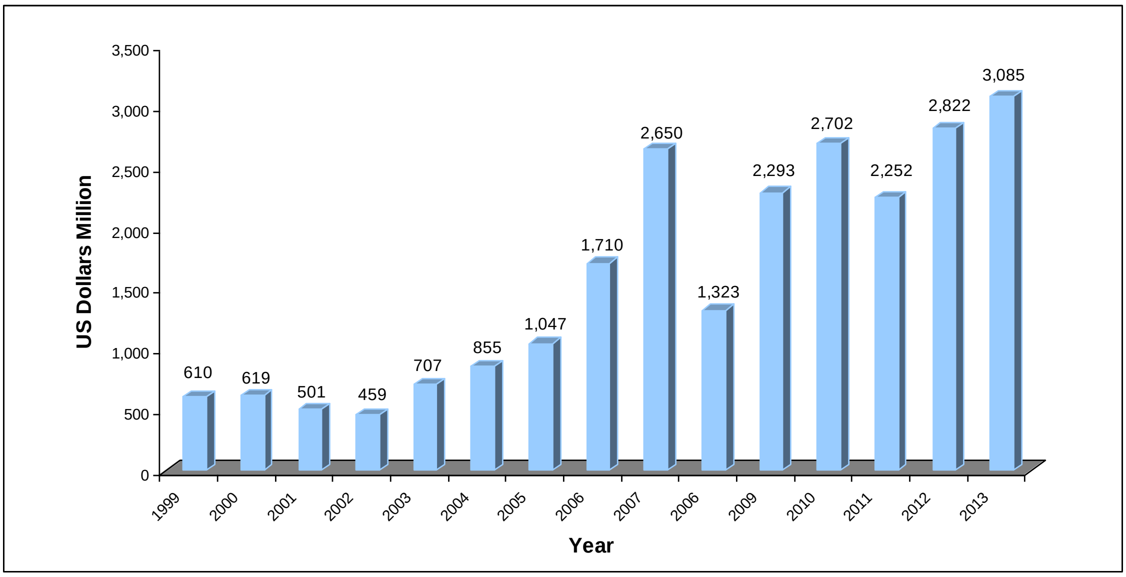

Figure 1.1: Market capitalization of the HKEx (1999–2013)

Source: HKEx (2013)

Foreign direct investments in Hong Kong come under the jurisdiction of the Hong Kong Special Administration Government (HKSAR), which emphasizes the rule of law and promotes a fair market, no access barriers to foreign businesses and no restrictions on flow of capital into and out of Hong Kong. Such an open policy with minimum government intervention in the market, and low and simple taxation system that maximizes business initiatives and innovation, has attracted investment from overseas. In 2012 Hong Kong was ranked third in the Asia-Pacific region as a destination for foreign direct investment (FDI) (World Investment Report, 2013). Hong Kong was also ranked highest in FDI stock in Asia, with US$ 407 billion in 2012, with FDI inflows of US$ 96 billion and US$ 75 billion in 2011 and 2012, respectively. Simon Galpin, Director-General of Investment Promotion at InvestHK and the agent for FDI of the Hong Kong Special Administrative Region (HKSAR), said, "Hong Kong has surpassed major economies such as the United Kingdom as the hub of global foreign direct investment".

Hong Kong's Company Registry is responsible for incorporating local companies and registering foreign companies that operate in Hong Kong. It ensures companies and their officers fully comply with their obligations under the Hong Kong Company Ordinances, and it enables the public to inspect and obtain information, including current registered company data. In June 2011, 912,242 companies were registered, 8,342 of which, or nearly 1 per cent, were foreign companies from 79 overseas countries. The number of foreign companies listed in the HKEx Main Board had doubled in the preceding five years (HKEx, 2006, 2007, 2008, 2009, 2010).

Although foreign companies represent just 1 per cent of the total number of companies registered, overseas investors' participation in the HKEx securities market reached a record high in 2010, according to the 2013 Cash Market Transaction Survey (CMTS) conducted by Hong Kong Exchanges & Clearing Ltd (2014). For the first time, overseas investors surpassed local investors in trading on HKEx's securities market. Overseas investors' contribution climbed from 38 per cent in 2008 to 42 per cent in 2009, and further to 46 per cent in 2010. In Table 1.4, the number one overseas investor in 2013 was Europe (including the UK), contributing more than 39 per cent (25.6% plus 13.62%) of the total, followed by US investors with over 28 per cent. The aggregate contribution of the Asian investors in 2013 was 23.8 per cent of the overseas investor trading, with mainland China and Singapore the two major Asian investors. Table 1.4 summarizes the overseas investor trading values in cash markets by origin from 2009 to 2013.

Overseas Origin	**2009**	**2010**	**2011**	**2012**	**2013**
United States	36.3%	24.37%	27.75%	32.27%	28.07%
United Kingdom	23.35%	28.68%	27.32%	25.35%	25.60%
Europe	10.49%	16.13%	13.91%	12.05%	13.62%
Mainland China	11.86%	10.55%	9.92%	8.49%	11.12%
Singapore	7.69%	9.28%	6.63%	6.97%	6.40%
Japan	1.92%	2.58%	1.90%	1.74%	1.12%
Rest of Asia	3.0%	3.11%	2.73%	2.95%	4.09%
Others	2.46%	2.66%	3.28%	2.95%	3.54%
Taiwan	1.11%	1.03%	1.09%	1.08%	1.10%
Australia	1.81%	1.60%	5.47%	6.15%	5.35%
Total	100%	100%	100%	100%	100%

Table 1.4: Distribution of overseas investor trading value in cash market (2009–2013)

Source: Cash Market Transaction Survey (CMTS) (Hong Kong Exchanges & Clearing, 2013)

The above discussion highlights that Hong Kong is a major capitalist service economy characterized by low taxation and free trade. Hong Kong is ranked top in Asia and fourth in the Asia-Pacific region as a destination for FDI, and the HKEx is ranked seventh in the world and third in Asia in raising market capital. Hong Kong has undoubtedly become one of the world's leading financial centres, attracting foreign investments from around the globe.

Globalization has led to financial centres, such as Hong Kong, being more vulnerable to financial and economic turbulence in other regions. Since Great Britain returned Hong Kong to Communist China in 1997, the Hong Kong economy has been hit hard by several economic blows. These include the Asian financial crisis that broke out in Korea in 1998 and the SARS (severe acute respiratory syndrome) epidemic in 2003, which caused 299 deaths, infected 1,755 people (WHO, 2003) and gravely affected the Hong Kong economy with huge loss in contracts (BBC News, 2003).

The sub-prime mortgage crisis in the US that spread worldwide in 2008 and the sovereign debt crisis in Greece, Ireland, Portugal and Spain that brought about the European economic recession in late 2009 resulted in unexpected economic changes. Many financially strong companies, unable to either face the challenges and the unexpected economic changes or fulfil their financial obligations due to inadequate cash flows, were thrown out of business or were forced into bankruptcy. The collapse of Lehman Brothers in 2008 during the global financial crisis was one example.

The ripple effects of these global events on Hong Kong's economy are no exception. Hong Kong's GDP growth dipped down into negative growth of 2.5 per cent during the 2008 financial crisis (Census & Statistics Report, HKSAR, 2009). Confronting what the HKSAR Government called "once-in-a-century financial turmoil", it was probably the worst performance of Hong Kong's economy since the 1999 Asian financial crisis.

Each year a significant number of Hong Kong businesses are compulsorily wound up. Between 1998 and 2013 the total number of compulsory winding-up orders granted by the Official Receiver's Office (OR) was 11,435, an average of 715 cases per year (see Table 1.5). The table shows an increase in the number of compulsory winding-up of companies as a result of the 1998 Asian financial crisis and the 2003 SARS incident (1999, 9 per cent; 2000, 14 per cent; 2001, 17 per cent; 2002, 21 per cent), while the number of compulsory winding-up of companies declined as the economy recovered from the SARS incident in 2004 (2005, –25 per cent; 2006, –35 per cent; 2007, –18 per cent). The number picked up again when the US sub-prime mortgage crisis broke out in 2008, to 22 per cent in 2009. Obviously, the economy of Hong Kong and the performance of its companies are negatively affected by financial crises in other regions.

Year	No. of winding-up orders by OR	% change from previous year
1998	723	N/A
1999	795	+9%
2000	910	+14%
2001	1,066	+17%
2002	1,292	+21%
2003	1,248	+3%
2004	1,147	–8%
2005	849	–25%
2006	552	–35%
2007	455	–18%
2008	468	+3%
2009	573	+22%
2010	438	–24%
2011	333	-24%
2012	312	-6%
2013	274	–12%
Total	11,435	

Table 1.5: Compulsory winding-up of HK companies, 1998–2013

Source: Official Receiver's Office, HKSAR (2013)

The number of company bankruptcies in different countries is displayed in Table 1.6. Hong Kong ranked second behind the US for average number of company bankruptcies in 2012. The average annual number of business bankruptcies in Hong Kong between 1994 and 2012 was 3,421.62 cases. This average number, when compared with neighbouring Asian countries, was 14 times greater than Singapore, six times greater than South Korea and four times greater than Japan. Hong Kong's average was also seven times greater than Canada and France and five times greater than

Australia. Recent numbers of bankruptcy in Hong Kong were 5,458 cases in 2011 and 4,051 cases in 2012 (Census & Statistics Report, HKSAR, 2012).

Country	2012	2011	Highest	Lowest	Average
United States	42,008	44,435	82,446	19,695	49,279
Hong Kong	4,051	5,458	8,297	409	3,422
United Kingdom	3,971	4,115	6,509	924	3,312
Taiwan	1,892	1,871	7,810	1,256	2,998
Germany	2,390	2,580	3,755	416	1,671
Malaysia	1,717	1,693	1,864	503	1,157
Japan	1,035	931	1,965	6	927
Finland	703	734	2,038	493	875
Sweden	687	570	2,148	276	722
Belgium	1,163	1,118	1,163	262	655
Australia	881	996	1,123	217	634
South Korea	102	117	3,377	90	573
Turkey	1,176	932	2,449	11	542
Luxembourg	978	918	978	102	493
Canada	263	244	872	219	478
France	224	359	964	119	427
Netherlands	1,064	878	1,074	72	400
Switzerland	661	508	661	232	388
Spain	1,646	2,272	2,272	11	324
Norway	393	330	595	43	279
South Africa	235	236	511	63	244
Singapore	175	128	507	78	240
Denmark	470	415	698	69	221

Table 1.6: Number of company bankruptcies in various countries

Highest = highest number of company bankruptcies between 1994 and 2012
Lowest = lowest number of company bankruptcies between 1994 and 2012
Average = average number of company bankruptcies between 1994 and 2012
Source: Census & Statistics Report, HKSAR (2012)

In summary, Hong Kong ranks second in the world for average number of company bankruptcies. Domestic and foreign investors doing business in Hong Kong are exposed to a high risk of company bankruptcy. Business failure has proved painful for many, and the economic cost of business failures has severe effects on stakeholders, capital owners, investors, creditors, management and society overall. Studies have shown that the market value of distressed firms declined substantially prior to their ultimate collapse (Warner, 1977; Charalambous et al., 2000), and it is therefore important for researchers to find ways of providing early warning signs to avoid substantial economic loss.

1.2. Purpose of the study

The purposes of this study were to examine the financial characteristics of failing firms in Hong Kong, to test the applicability of the Altman (1968) and Ohlson (1980) models, and to investigate whether the parameters of the two models have changed from when they were originally developed.

Management can monitor the financial performance of firms using financial ratios (Wilson & Sharda, 1994). These ratios also permit creditors and investors to identify borrowers' problems, auditors to assess firm's performance, and researchers to predict business failure. This study aimed to use financial ratios to determine which model, the MDA-based Altman model or the logistic-based Ohlson model, is more applicable to the Hong Kong situation. Some researchers (Deakin, 1976; Eisenbeis, 1977; Pinches & Trieschmann, 1977; Jones, 1987) have claimed that MDA has serious shortfalls, such as making assumptions that independent variables must have similar variance covariance matrices and linear distributions, and that these assumptions could lead to invalid prediction results. This study was motivated by such arguments to examine whether or not the Ohlson model (logistic regression based) is superior to the Altman model (MDA based) in predicting corporate failure when applied to Hong Kong data, and to determine which independent variables appear significant in the two models studied.

This study, therefore, addressed the research question: How do the Altman (1968) and Ohlson (1980) models differ in predicting business failure of Hong Kong companies when the cutoff values are revised?

1.3. Significance of the study

This research into Hong Kong's business failures was motivated by several considerations. First, the market of Hong Kong is clearly independent of the US and the UK markets, and so this study will provide a valuable out-of-sample test of the current literature which focuses on these Western markets. Second, the HKEx has experienced rapid expansion and is the third largest in Asia, after Japan and Shanghai. The HKEx is surely assuming importance in the global financial system and deserves serious study. Third, the number of business failures serves as an index of the health of Hong Kong's economy (see Table 1.5). Many large and small Hong Kong companies have experienced business failure in recent decades. Such failures can produce substantial and widespread losses to numerous stakeholders, and can have a negative spill over effect on other companies (Altman & Brenner, 1981), potentially damaging the efficient operation of a market economy (Storey et al., 1990).

Some recent studies have provided a foundation for this current research. Wu's (2004) study of business failures in Taiwan found that non-financial variables can influence the predictive accuracy of the logistic regression model. Charalambous et al. (2000) found that distressed companies' market value substantially declines prior to collapse, confirming the earlier findings of Beaver (1966) that changes in stock market prices are indicative of financial distress. This research follows the suggestion of Boritz et al. (2007), who noted the need to test the predictive power of the Altman (1968) and Ohlson (1980) models using samples other than developed countries. This study is the first to apply the Altman (1968) and Ohlson (1980) models using Hong Kong company data, and therefore it makes a valuable contribution to the finance literature of business failure prediction.

Research into predicting a company's fate is important because of the high cost of business failure to shareholders, investors and communities (Van Auken et al., 2009). Early prediction of potential failures can ameliorate the associated losses (Deakin, 1972). Foster (1986) argued that a successful business failure prediction model can assist investors in debt securities when they assess the likelihood of a company experiencing problems when making interest and principal repayments, and it has relevance to lending institutions, both in deciding whether to grant a loan and in devising policies to monitor existing loans:

> *… bankruptcy can mean that a firm incurs both direct and indirect costs. Direct costs include fees to professional such as accountants and lawyers. Indirect costs include the lost sales or profits due to the constraints imposed by the court-appointed trustee … It may well be that if early warning signals of bankruptcy were observed, these costs could be reduced by management arranging a merger with another firm or adopting a corporate reorganization plan at a more propitious time* (Foster, 1986, p.534).

Accurate business failure prediction models can aid auditors in making going-concern judgments (Altman & McGough, 1974) that can benefit not only the company itself, but their suppliers, researchers and policymakers (Dennis & Fernald, 2001). Indeed, some government and academic institutions have devoted efforts and resources to investigate ways of reducing the incidence of business failure (Carter & van Auken, 2006), although Rogoff et al. (2004) queried which factors or practices leading to business failure still require further research.

Research into corporate failure using Hong Kong data is very limited, and to date no empirical research into the business failure of Hong Kong companies has been published. Lussier and Pfeifer (2001) highlighted the need to replicate results cross-nationally, Oviatt and McDougall (2005) suggested a comparison of domestic and international companies, while Benzing et al. (2009) concluded that classifications can vary in different countries.

One recent study (Wang & Campbell, 2010) used data from Chinese public-listed companies to test the accuracy of Altman model; however, China’s one-country-two-system administrative structure, the nature of business there and the environment in which it is conducted, its style of management and legal system are all substantially different from the situation in Hong Kong. For example, Chinese companies’ unique two-tier model consists of a management board of directors with independent outside directors and a board of supervisors comprising both employees and other members. The state is typically the controlling shareholder of listed companies in China. In contrast, Hong Kong companies are family-based, with a mixture of Anglo-American and Asian ideas and a single board that consists of both executive and non-executive directors. The board plays a supportive role through relationships between the dominant head of the family and other family members in key top management positions.

Some researchers have noted the importance of financial data from developing countries such as Brazil and Argentina when investigating business failure (Altman, 1984; Swanson & Tybout, 1988), while others have questioned the suitability of the Altman-Ohlson models for predicting business failures companies outside the US, such as Canada (Boritz et al., 2007) or the UK; in this latter case Charitou et al. (2004) noted that the Altman model did not outperform other models when UK data were applied.

The findings from this research add to those of previous studies that are characterized by a lack of theory and show wide discrepancy in reporting business failure prediction variables. If the Altman (1968) and Ohlson (1980) models are proven robust for Hong Kong companies, an empirical theoretical framework can be developed that applies to nations outside the US.

1.4. Justification for the study

The Altman and Ohlson models were selected as the focus of this study because they are considered more accurate in predicting business failure than the traditional method of ratio analysis. Financial analysts often use the Altman model to forecast financial distress, while academic researchers tend to favour the Ohlson model to estimate the probability of business failure. Both models are based on data from the 1940s to the 1970s; whether they are still applicable is questionable because the model parameters could have changed in the four decades since these models were developed. This study has extended existing research, first, by testing these models using contemporary data and, second, by breaking new ground in examining the ability of the models to predict business failure for Hong Kong public-listed companies.

The data used in this study were drawn from the 1990s and 2000s, with a sample size of 39 failed public-listed companies that were delisted from the HKEx between 1998 and 2011. Many published studies of business failure used similar or smaller sample sizes, as listed in Table 1.7, probably because bankruptcy is not common. Perhaps Altman's (1968) study is the most notable; it sampled only 33 failed companies.

Study	Country	No. of failed companies	Remarks
Altman (1968)	USA	33	Manufacturing firms that filed for bankruptcy 1946–1965
Deakin (1972)	USA	32	Bankrupted companies 1964–1970
Hamer (1983)	USA	44	Bankrupted firms 1966–1975
Mensah (1983)	USA	30	Bankrupted firms 1975–1978
Zavgren (1985)	USA	45	Manufacturing companies failed 1972–1978
Nam, Jinn (2000)	South Korea	46	Non-financial listed firms bankrupted in 1997 & 1998
Lin & Piesse (2004)	UK	32	Failed UK industrial firms 1985–1994
Sandin (2007)	Argentina	11	Bankrupted companies traded on the Buenos Aires Stock Exchange 1990–1998
Zeitun et al. (2007)	Jordan	29	Failed industrial & services public firms on the Amman Stock Exchange 1989–2003
Hiau et al. (2008)	Malaysia	26	Distressed firms listed in the Bursa Malaysia Berhad 1990–2000
Hauser & Booth (2011)	USA	24	US corporations that filed for bankruptcy in 2008 and 2009

Table 1.7: Previous business failure prediction studies with small sample size

1.5. Organization of the thesis

This chapter has outlined the background of the study and discussed its purpose, significance and justification.

Chapter 2 reports the review of previous literature of corporate failure prediction models, with special focus on the Altman (1968) multiple-discriminant-based Z-score prediction model and the Ohlson (1980) logistic-regression-based O-score prediction model.

Chapter 3 discusses the research design, the methodology of sample selection and data collection, and the statistical analysis.

Chapter 4 reports the findings from the hypothesis testing and the predictive power of the Altman and Ohlson models using original and revised cutoff values. This chapter discusses the further testing of the models for significant association with the variables cash conversion cycle, and two non-financial variables: change of auditor and change of HIBOR.

Chapter 5, the final chapter, presents the study's conclusions and limitations, and recommends possible areas for future research.

CHAPTER TWO

LITERATURE REVIEW

2.1 Introduction

This chapter reviews the relevant literature in business failure prediction, concentrating on five main aspects. Section 2.2 presents definitions of business failure, often called “bankruptcy”, and reviews bankruptcy theory, thereby providing a background for the theories that have been used to support research into business failure. Section 2.3 discusses the prediction of business failure, focusing on the development of prediction models. Section 2.4 narrows the discussion to the models of Altman (1968) and Ohlson (1980). Section 2.5 presents comparisons in the literature of a number of traditional and non-traditional business failure prediction models. Section 2.6 describes the cash conversion cycle in the context of bankruptcy, while Section 2.7 reviews the use of financial and non-financial information as independent variables to predict business failure. The chapter concludes with a summary in Section 2.8

2.2 Definition of business failure

2.2.1 Overview

Business failure, or bankruptcy, has no widely accepted definition. For decades researchers have described it quite differently, such as a firm that enters into a bankruptcy proceeding or agreement with creditors to reduce the company’s debt (Blum, 1974); a company that cannot make scheduled payments (Altman, 1983); or a firm with negative net worth, non-payment to creditors, bond defaults, inability to pay debts or overdrawn bank accounts (Karels & Prakash, 1987). Dimitras et al. (1996) suggested that a general description of “business failure” is when a company cannot pay its lenders, preferred stock shareholders, suppliers, or overdrawn a bill, or is bankrupted according to law. Table 2.1 provides a more comprehensive list of definitions proposed by previous researchers.

Researcher	Definition of “bankruptcy”
Ulmer & Neilsen (1947)	Firms that are disposed of with loss, to avoid further loss.
Beaver (1966)	Default on interest payments on its debt, overdraw its bank account or declare bankruptcy
Altman (1968)	Firm has filed a bankruptcy petition under Chapter X of the National Bankruptcy Act, or has failed if its return on capital is significantly and consistently lower than that obtainable on similar investments
Blum (1974	Enter into a bankruptcy proceeding or an explicit agreement with creditors which reduced the debts of the company
Deakin (1972)	Firms experience insolvency or are liquidated for the benefit of creditors
Taffler & Tisshaw (1977)	Enter into receivership, creditor's voluntary liquidation, compulsory winding up by court order, or government action
Hamer (1983)	File a petition under the national bankruptcy act
Storey et al. (1990)	Business cease trading and has no likelihood to restart
Kwansa & Parsa (1990)	File for bankruptcy under Chapter XI of the Bankruptcy Code
Laitinen (1991)	Firm unable to pay its financial obligations when they come due
Cho (1994)	Firms with negative net income for three or more years consecutively
Dun & Bradstreet (1993)	Cease operations following assignment or bankruptcy; cease with loss to creditors after such actions as execution, foreclosure, or attachment; voluntarily withdrew, leaving unpaid obligations; court actions such as receivership, reorganization, or arrangement
Dimitras et al. (1996)	Firm cannot pay lenders, preferred stock shareholders, suppliers etc. or a bill is overdrawn, is bankrupted according to law

Table 2.1: Definitions of business failure by previous researchers

Authorities in the US (Altman, 1968; Kwansa & Parsa, 1990) tend to describe bankruptcy in terms of the Bankruptcy Code, and filing for bankruptcy protection under chapters VII, X or XI of the US Federal Bankruptcy Code is the most common definition in the literature for business failure (Altman, 1968; Zavgren, 1985; Platt & Platt, 1991; McGurr, 1996). The Bankruptcy Act was established in 1898, and was replaced in 1938 by the Chandler Act. Under the Chandler Act, corporations may opt to either liquidate themselves under Chapter VII or reorganize themselves under chapters X or XI.

Chapter X gives creditors preferential treatment relative to shareholders. An independent trustee appointed by the court has investigative powers and can propose a reorganized payment plan, whereby senior creditors are paid before junior creditors.

Chapter XI in the US Bankruptcy Code protects a firm who cannot pay its creditors from being filed as bankrupt by the creditors. The court empowers an independent trustee to take over the business, to manage the corporate property and to restructure the firm. The court places the firm's assets strictly in the custody of the court, free from any prior pending court proceeding.

In contrast, Hong Kong has no equivalent protection for debtors. When a company in Hong Kong cannot repay its debts, the Labor Department and the Official Receiver's Office are responsible for handling the case. Creditors may opt to seek a court order for a compulsory winding-up petition, with the intention of liquidating the debtor's assets, converting those assets to cash and repaying the debts through legal proceedings.

This variation in bankruptcy proceedings in different jurisdictions makes it particularly difficult to define business failure. This study, applies the term "business failure" where (1) public companies in the HKEx are being compulsorily wound up or (2) public companies are being suspended from trading in the HKEx due to financial problems.

2.2.2 Bankruptcy theory

Researchers have long been seeking a single theory that can support business failure prediction. For example, Wilcox (1971) presented a theoretical model based on the classic gambler's ruin probability theory. He assumed that a firm is like a gambler, competing with other firms (or gamblers), and with the opportunity to make gains or losses until the other firm's net worth becomes zero, or it is bankrupt. Under this model, a company could probably go bankrupt when its net liquidation value (NLV) becomes negative. NLV is calculated by total asset liquidation value less total liabilities (Jones, 2002). However, Wilcox (1971) did not use a holdout sample to test this model.

Scott (1981) recognized that research that used Black-Scholes Option Pricing Model yields superior results in predicting business failure, and he therefore assumed that the Black-Scholes Option Pricing Model could support a bankruptcy theory. Although recent research using Black-Scholes Option Pricing Model has shown superior results in predicting business failure, Dichev (1998) has argued that the model fails to reflect theoretical results because it lacks data on earnings, market value and cash flow.

Booth (1983) predicted business failure based on the decomposition theory, using a sample of 42 companies delisted from the Sydney Stock Exchange Research Department from 1964 to 1979, with 35 non-failed companies matched by asset size and financial data. Five years of financial data were obtained for each company, and the four variables – total assets, total liabilities, total equities and total balance sheet – were tested by a multivariate model. Booth (1983) noted that "decomposition measures have different attributes for failed and non-failed companies" (p. 80) and suggested that future research should test the usefulness of the decomposition theory in predicting business failure.

D'Aveni (1989) tested a bankruptcy model based on Agency and Prospect theory, and found that a company has high probability of bankruptcy when financial and managerial assets fall below a minimum level. According to Prospect theory, creditors will withdraw their financial support to avoid significant loss. Agency theory, on the other hand, states that shareholders and creditors view bankruptcy as a legal resolution of conflicts.

Dhumale (1998) attempted to establish a bankruptcy theory using Jensen's (1986) Free Cash Flow theory, which states that business failure can occur when managers are tempted to utilize excessive cash flows for unprofitable investments. But Dhumale (1998) found that only healthy companies held excessive cash flow for investment opportunities, while unhealthy companies did not. The results did not support Jensen's theory.

However, no single theory adequately supports bankruptcy prediction (Jones, 1987). Current bankruptcy prediction research uses empirical models based on mathematical or statistical theories which are inconsistent in determining the predictor variables (Ball & Foster, 1982; Jones, 1987). Therefore bankruptcy prediction research continues to focus on predicting bankruptcy rather than developing a theoretical understanding of bankruptcy.

2.3 Evolution of failure prediction models

Early business failure studies developed different forms of prediction models based upon cash flow or accrual-based financial ratios. Empirical business failure prediction models have been developed in three major stages (Scott, 1981), from the estimation techniques that use only one dependent measure, such as univariate analysis, to the statistical techniques which analyse variables in one or multiple relationships, such as multiple discriminant analysis, logit and probit analysis, to the more complicated computerized analysis, such as recursive partitioning, hazard models, artificial neural network. Scott (1981) considers it rather difficult to determine which of these prediction models discriminate best.

Bellovary et al. (2007) reviewed bankruptcy prediction studies from 1930 to 2004 and confirmed that multivariate discriminant analysis (MDA), logit analysis, probit analysis and neural networks are the techniques most frequently used in business failure studies. MDA was among the most popular model in the 1960s, 1970s and 1980s; logit and probit analysis began to appear in the late 1970s and, together with neural network, overtook MDA in popularity in the 1990s.

These popular techniques are summarized in Table 2.2. The remainder of this section reviews the evolution of these business failure prediction models and discusses their strengths and weaknesses.

Period	MDA	Logit	Probit	ANN	Others
1960s	2	0	0	0	1
1970s	22	1	1	0	4
1980s	28	16	3	1	7
1990s	9	16	3	35	11
2000s	2	3	0	4	3
Total	63	36	7	40	26

Table 2.2: Techniques used in previous bankruptcy studies

Source: Bellovary et al. (2007)

2.3.1 Univariate analysis

Univariate analysis is a statistical technique based on one dependent measure (Hair et al., 1995). Historically, it was the first statistical method to be used to discriminate between healthy and unhealthy companies. The major studies of business failure prediction that used the univariate analysis approach from 1932 to 1985 are summarized in Table 2.3 and discussed below.

Study	Sample size (no. of bankrupt)	No. of independent variables
Fitzpatrick (1932)	20 (20)	13 ratios
Winakor & Smith (1935)	183 (183)	21 ratios
Foulke (1937)	47,980 (0)	14 ratios
Merwin (1942)	939 (558)	3 ratios
Beaver (1966)	158 (79)	30 ratios
Casey & Bartczak (1984)	290 (60)	9 ratios
Casey & Bartczak (1985)	290 (60)	7 ratios

Table 2.3: Previous studies of business failure prediction using univariate analysis

Fitzpatrick (1932) was probably the first to investigate whether financial ratios can predict business failure prior to actual failure. He utilized the published financial statement of 20 failed publicly traded companies from 16 manufacturing industries, and compared these companies with a sample of non-failed companies in each respective industry. By using 13 financial ratios that had been widely used in previous studies, he found that the ratios of the non-failed companies were more favorable than those of the failed companies. He also discovered that the predictive ability of these ratios deteriorated as the company approached actual failure. Fitzpatrick (1932) concluded that “financial ratios are important tools in ascertaining significant relationships of business facts, although absolute indicators of impending financial difficulties” (p. 731). However, some samples lacked the information to calculate each ratio, and some companies had different fiscal year-ends, so he highlighted that his study had two problems: the financial statements lacked uniformity and the financial ratios lacked standardization.

Winakor and Smith (1935) extended Fitzpatrick’s work by studying 183 companies that failed between 1923 and 1931. These companies included 125 manufacturing companies that came from four industries: machinery, steel-iron, sugar and textiles. Winakor and Smith (1935) reviewed the financial statements 10 years prior to failure, tracked 21 financial ratios for the industries and two distinct firm sizes, and found two characteristics: less than 1 per cent of the failed companies had capital of US$100,000 or more, and the current position of failed companies “greatly pressed for immediately available funds in the last two or three years in its operation” (Winakor & Smith, 1935, p. 13). Winakor and Smith also noted that “only nine percent of all 1931 failed companies in the United States were manufacturing concerns” (p.8). Furthermore, they concluded that, although financial ratios can act as “danger signals” of business failure, the ratio of net working capital to total assets was the most accurate and steady indicator of business failure. Drawbacks of the study were, first, that the sample was skewed towards manufacturing because as more data were available for manufacturing concerns and, second, the results could have been biased because of the larger number of sampled fail companies that occurred after the 1929 Great Depression.

Foulke (1937) studied companies from 60 different industries, including retail, wholesale and manufacturing, calculating 14 financial ratios from 47,980 annual reports between 1931 and 1935. This study was based upon two maxims: first, a company is healthy if tangible net worth is less than US$250,000 and its net fixed assets are greater than 67 per cent of it tangible net worth; second, a company is unhealthy if its tangible net worth is greater than US$250,000 and its net fixed assets are greater than 75 per cent of its tangible net worth. This study was the first to use ratio group for industry averages (Horrigan, 1968). But researchers criticized this study because the use of a specific dollar range for net worth may have changed over time and the financial information during the depression era could have biased the high business failure rate.

Merwin (1942) observed 939 companies from five industries over a six-year period from 1926 to 1936. By comparing the sample data means against the industry means, the study confirmed that the ratios of 558 failed companies for most of the industries were “below estimated normal ratios as early as the sixth year before failure” (Merwin, 1942, p. 99). The study also identified three sensitive indicators of business failure: current ratio, ratio of net worth to total assets and ratio of net working capital to total assets. Similar to the studies of Winakor and Smith (1935) and Foulke (1937), Merwin’s work was also criticised for using data from the Great Depression years that could have biased the results, and failing to account for Type I and Type II errors.

Hickman (1958) studied the predictive ability of ratios for bonds that were issued from 1900 to 1943. His study found that time-interest-earned ratio and net income were very sensitive to the cyclical business environment and were useful variables for predicting companies that might default on their debts. Hickman’s (1958) findings were later confirmed by Saulnier et al. (1958), who found similar characteristics in companies which submitted loan applications and defaulted on loan repayments between 1934 and 1951.

Beaver (1966) studied which financial ratio could classify the failed companies from the non-failed set using 79 companies that failed between 1954 and 1964. He defined failed companies as those that experienced bankruptcy, bond default or overdrawn bank accounts, or were incapable to pay preferred stock dividends. Unlike previous research, Beaver did not control for industry and size differences by matching each failed company with a non-failed firm from same industry and with similar asset size. He selected 79 non-failed companies with the closest asset size to the failed companies. The asset size ranged from US$0.6 million to US$45 million; the average asset size for the non-failed companies was approximately US$8.5 million and that for the failed companies was approximately US$6.3 million.

His study focused on comparing the mean values, testing the dichotomous classification, and analysing the likelihood ratios. Thirty ratios that were most commonly used in previous research and adhered to cash flow concepts were selected for testing; these included ratios of cash flow to total debt, net income to total assets, debt to total assets, working capital to total assets, liquid assets to current debt (i.e. current ratio) and no-credit interval (i.e. turnover).

The study yielded a high predictive rate of 87 per cent, 79 per cent, 77 per cent, 76 per cent, and 78 per cent, respectively, for the five years prior to failure. Type I errors in the first and second year before failure were four times greater than the Type II errors, and grew to ten times greater in the fourth and fifth years. Beaver found that failed companies generally had lower cash flow, liquid assets and net income, and higher debt than their non-failed counterpart over a five-year period. He also found that changes of stock market prices were indicative of financial distress.

Beaver (1966) made three conclusions: first, financial ratios have the ability to predict business failure for at least five years prior failure; second, the ratio cash flow to total debt is the overall best predictor; and third, financial ratios should be complemented by frequency distributions and likelihood ratios.

To extend Beaver's (1966) conclusion that failed companies generally have lower cash flow and net income, Casey and Bartczak (1984) compared the predictive accuracy of three operating cash flow ratios with six conventional accrual-based earning ratios. They tested 290 failed and non-failed companies, and found that accrual-based earning ratios had a higher predictive accuracy than operation cash flow ratios in all five years prior to failure. Casey and Bartczak (1985) conducted another study using the Altman (1968) and Ohlson (1980) multivariate models to compare operating cash flow ratios to earning ratios. Again, they found that the predictive accuracy of the accrual-based earning ratios still surpassed that of operation cash flow ratios in discriminating between fail and non-failed companies.

Strengths and weaknesses of Univariate Analysis

Although the univariate technique had been extensively used by researchers in early business failure prediction studies, Zavgren (1983) argued that a multivariate technique is better than a univariate technique in making the prediction because the latter is weak in explanatory power, and the statistical design of independent ratio has discriminatory power. This section discusses the pros and cons of the univariate technique.

The strength of the univariate failure prediction model is its simplicity. The application does not need any statistical knowledge to determine the classification, it simply compares each ratio value with a cutoff point. On the other hand, the classification of a failed company can occur for only one ratio at a time; both Altman (1968) and Zavgren (1983) criticized how classifying different ratios at the same time can lead to inconsistency and confusion, which they called the 'inconsistency problem'. Another weakness is that most variables in the univariate model are highly correlated, and so it is rather difficult to evaluate the significance of a single separate ratio (Cybinski, 2001).

This technique has the limitation of lacking a statistical relationship between the measures. Hossari and Rahman (2005), in a formal ranking of 48 financial ratios in 53 studies on business failure, found that in more than 25 per cent of studies only five ratios were useful: net income/total assets, current assets/current liabilities, total liabilities/total assets, working capital/total assets, and earnings before interests and taxes/total assets. This supported the argument by Beaver (1966) that one single ratio cannot predict a company's financial health, so that a more sophisticated multivariate analysis technique is more preferable than the univariate technique.

2.3.2 Multiple Discriminant Analysis (MDA)

Multiple discriminant analysis (MDA) is a statistical technique commonly used in biological and behavioural sciences (Fisher, 1950), most commonly for classifying plants in order to solve taxonomic problems. The technique was not applied in business research until the 1960s. It forms the second generation of business failure prediction techniques. Unlike univariate analysis, which analyses the predictive ability of a single ratio, MDA combines the information of several financial ratios into a single weighted index (Laitinen, 1991).

This technique makes several assumptions: first, the dataset is dichotomous and the observation groups must be discrete, non-overlapping and identifiable; second, the independent variables are multivariate and are normally distributed; third, the group dispersion matrices are equal across the failing and non-failing groups; and fourth, the prior probability of failure and the misclassification costs are specified (Edmister, 1972; Eisenbeis, 1977; Zavgren, 1983; Karels & Prakash, 1987; Joos et al., 1998).

Dimitras et al. (1996) reviewed 158 bankruptcy prediction articles from 1932 to 1994, limiting their analysis to articles related to the industrial and retail sectors. They concluded that the solvency ratios (working capital/total assets, total debt/total assets) were the most important financial ratios. They noted that MDA was the most frequently used method, followed by logit analysis. The major business failure prediction studies using multiple discriminant analysis from 1968 to 1975 are summarized in Table 2.4.

Study	**Sample size (no. of bankrupt)**	**No. of independent variables**
Altman (1968)	66 (33)	5 ratios
Deakin (1972)	64 (32)	14 ratios
Edmister (1972)	604 (42)	19 ratios
Altman (1973)	42 (21)	7 ratios
Blum (1974)	230 (115)	12 ratios
Libby (1975)	60 (30)	14 ratios
Casey & Bartczak (1985)	290 (60)	9 ratios
Dimitras et al. (1996)	158 (-)	ratios
Grice & Ingram (2001)	-	ratios

Table 2.4: Previous studies of business failure using MDA

Altman (1968) followed up Beaver's (1966) study by employing an MDA model to identify ratios that were strongly correlated to business failures. Altman's (1968) study was first to use linear MDA to predict business failure, and it is important because it set the quality of ratio analysis as an analytical technique using a multivariate statistical model. Altman's work is discussed more in detail below in Section 2.4.

Edmister (1972) conducted a test similar to that of Altman (1968). Small companies which applied for SBA loans from 1954 to 1969 were selected as test samples, including 42 failing and 42 profitable small companies with an average sales volume of US$400,000. Nineteen financial ratios that were significantly used in previous business failure studies were used as independent variables. Seven variable ratios were selected using stepwise linear multiple to eliminate multicollinearity, a problem caused by variables being highly correlated to each other. Edmister (1972) combined the industrial trend for each ratio as predictors of business failure and focused on examining the trend and the three-year average of the ratios.

Edmister's findings were quite similar to Altman's (1968), in that small groups of ratios had a better predictive ability than any individual ratio. The study correctly discriminated 93 per cent of the selected small companies. But Edmister (1972) admitted that companies drawn from SBA loans granted were expected to have healthier finance than those companies whose loan applications were rejected, and so the results were not generalizable to all small companies.

Blum (1974) developed the Failing Company Model (FCM) to examine 115 industrial companies that failed between 1954 and 1968. These failed companies were randomly selected from Standard & Poor's COMPUSTAT database and included only companies with liabilities of US$1 million or more at the time of failure. An equal number of non-failed companies were pair-matched by industry, sales, employee size and fiscal year. Eight years of financial data were collected and 12 variables were grouped into three specific classes: liquidity, profitability and variability. The liquidity ratio was subdivided into short-term and long-term liquidity. Short-term liquidity included two ratios: quick flow (cash and notes receivable plus marketable securities/cost of sales less depreciation plus administrative expenses plus interest) and net quick assets (cash plus accounts receivable and notes receivable less current liabilities). Long-term liquidity included three ratios: cash flow/total liabilities, net worth on market value/total liabilities and net worth on book values/total liabilities. The profitability ratio equalled the rate of return to shareholders that had been invested for at least six years. A multiple discriminant analysis model was used to assess the probability of business failure of this data set.

Blum's FCM model (1974) distinguished failed and non-failed companies with accuracy rates of 93 per cent, 80 per cent, and 70 per cent for one, two and three years, respectively, prior to failure. The accuracy rate declined over time and became statistically insignificant at the sixth year before failure. The results further confirmed that an MDA statistical model using financial ratios as independent variables could accurately predict failed and non-failed companies. Blum's study highlighted two points: first, failed companies' liabilities increasing more steadily indicated that failed companies used more debt to finance growth; second, failed companies' inventory declining rapidly had implied that excessive accumulation of inventory was not the reason for business failure (Blum, 1974).

Deakin (1977) examined frequency and nature as indicators of misclassifying non-failed companies by means of both linear discriminant analysis and quadratic discriminant analysis. He collected 63 failed companies from Moody's Industrial Manual and randomly selected 80 non-failed companies from the same year. He then classified the 143 sample companies by the Lachenbruch (1968) jackknife method. Financial data for two years prior to failure were collected. The linear classification model used five variables to classify the prediction of business failure: net income to total assets, current assets to total assets, cash to total assets, current assets to current liabilities and sales to current assets. The results showed that the linear model produced a comparatively higher overall classification rate but lower classification rate for failed companies than the quadratic model.

Deakin (1977) further validated the five-variable model by testing 1,780 companies obtained from the COMPUSTAT for the fiscal year 1971. The model classified 290 companies (16 per cent) as failed and 1,317 companies (74 per cent) as non-failed. Deakin further checked the 290 failed companies and 100 companies of the 1,317 non-failed companies for 1972 to 1975. Only 18 out of the 290 failed companies (6.2 per cent) filed for bankruptcy protection and none of the 100 non-failed companies failed. Deakin noted that the inaccurate defining "failed companies" could have caused the low correct classification rate of failed companies.

Moyer (1977) re-examined the predictive ability of Altman's model using companies with asset sizes between US$15 million and US$1 billion from 1965 to 1975. Moyer suggested that future developments of the prediction model should study the inclusion of other factors: "better explanatory power would be obtained from the model if the market value of equity/book value of debt, and sales/total assets variable are eliminated from the model" (Moyer, 1977, p.16).

Fulmer et al. (1984) used MDA statistical techniques to study 30 failed and non-failed small companies with total assets smaller than US$10 million. These 30 failed companies came from the manufacturing, retailing, and servicing industries that filed for federal bankruptcy protection. They used nine variable ratios: retained earnings/total assets, sales/total assets, earnings before taxes/equity, cash flow/total debt, debt/total assets, current liabilities/total assets, log of tangible assets, working capital/total debt, log of earnings before interest and taxes/interest. Failure was classified by an h-score less than zero. The model achieved an overall classification accuracy of 98 per cent and 81 per cent for one year and two years, respectively, prior to failure.

Casey and Bartczak (1985) used MDA to compare three operating cash flow ratios and six accrual-based earning ratios as independent variables. They found that operating cash flow ratios did not increase the predictive power over the conventional accrual-based ratios. The study pointed out that "the classification accuracy was not improved by the addition of the operating cash flow variables … the results in terms of the level and trend of accuracy across years are generally consistent with the findings of previous bankruptcy studies" (p. 392). Their findings supported Altman's exclusion of cash flow ratios in his 1968 model.

Rance (1999) studied the Altman revised four-variable model using 63 companies that failed during the period 1982 to 1996 and an equal number of non-failed companies. The sample was not controlled by asset size and half of the total population was randomly used to produce a holdout sample. The overall predictive accuracy were 92 per cent, 69 per cent and 62 per cent for one, two and three years, respectively, prior to failure, while the overall predictive accuracy of the holdout sample were 98 per cent, 84 per cent, and 77 per cent, respectively, for the same timeframes. Rance (1999) also evaluated how the Z-score is related to asset size and revenue growth by dividing the population into declining and growth companies for one, two, and three years prior to failure; however, the study was inconclusive regarding a relationship between Z-score and asset size and revenue growth.

Grice and Ingram (2001) studied Altman's original Z-score model using four sample sets from different times: Altman's 1968 samples; samples from 1988 to 1991; 972 bankrupted firms; and 547 manufacturing firms. The results indicated that the prediction accuracy rate significantly declined from 83.5 per cent to 57.8 per cent over time. This supported the findings of Begley et al. (1996) that time will affect the financial ratios when testing financial distress, and that the prediction accuracy for non-manufacturing companies was lower than that of manufacturing companies. Grice and Ingram (2001) suggested that the coefficients of the model in future business failure prediction research should be re-estimated.

To test the applicability of Altman's model outside the US, Wang and Campbell (2010) used Chinese publicly listed company data for the period 2000 to 2008. Three models were used to test the predictive accuracy: Altman's (1968) original model; a re-estimated model that re-calculated Altman's coefficients; and a revised model with different variables. Samples included 42 delisted companies (16 from the manufacturing industry) from the Shanghai Stock Exchange (SHSE) or the Shenzhen Stock Exchange (SZSE) and 42 matching non-failed companies (also 16 from the manufacturing industry). In addition, 12 out of the 42 delisted companies and their matching non-failed companies were randomly selected as hold-out samples. Wang and Campbell found that all three models had significant predictive power. The original Altman (1968) model predicted the highest accuracy in predicting failed companies; the re-estimated model had the highest accuracy in predicting non-failed companies; whereas the revised model had the highest overall prediction accuracy. Wang and Campbell (2010) confirmed that Altman's MDA models were a useful tool in predicting business failure of Chinese public listed companies. They further suggested testing Ohlson's (1980) logit model and comparing the efficacy of MDA and logit for Chinese listed companies with a larger sample size. Jackman (2011) concluded that the MDA models were the best two performing models in the holdout sample in predicting corporate bankruptcy, and logit models performed the worst in both the test and the holdout samples.

Strengths and weaknesses of MDA analysis

MDA is a multivariate method that can classify phenomena into incompatible groups based on their characteristics. As noted earlier, MDA has the advantage of considering all characteristics of ratios and noting their interactions, and it also has the advantage of understanding the group differences and predicting the likelihood a company that belongs to a specific group based on certain independent variables (Hair et al., 1995). With these advantages, MDA is particularly useful in classifying dependant variables that fall into one of several groups, such as good or bad, male or female, fail or not fail (Fulmer et al., 1984). In other words, MDA is powerful in distinguishing failed companies from non-failed companies by combining linear independent variables such as financial ratios. As Altman (2000) highlighted, the advantages of MDA over the univariate analysis technique are that:

> *MDA is a statistical technique used to classify an observation into one of several a priori grouping dependent upon the observation's individual characteristics. It is used primarily to classify and/or make predictions in problems where the dependent variable appears in qualitative form, for example, male or female, bankrupt or non-bankrupt ....The MDA techniques has the advantage of considering an entire profile of characteristics common to relevant firms, as well as the interaction of these properties. A univariate study, on the other hand, can only consider the measurement used for group assignments one at a time. (Altman, 2000, pp. 4–5)*

Given the above advantages, MDA has been used by many researchers in developing their business failure prediction models.

On the other hand, MDA has some weaknesses. First, MDA requires that the classifications between the fail and the non-fail companies are linearly separated, so that the discriminant scores above or below the cutoff point represent healthy or unhealthy companies. But most variables do not have such linear relationships. Second, multivariate normality is often violated (Deakin, 1976; Taffler & Tisshaw, 1977; Barnes, 1987) and may cause bias in the estimated error rates because ratio's signal cannot vacillate to another ratio or set of ratios (Coats & Fant, 1992). As noted by Ohlson, assuming that the covariance matrices of the two groups are equivalent creates problems in the business failure prediction context because the distribution of the financial ratio is not normal (Ohlson, 1980, p.112). Finally, Johnson (1970) and Joy and Tollefson (1975) pointed out that the pitfalls of the discriminatory power of MDA are normality, priori probability, assumption stationarity, multicollinearity, and interpretation of ex post discriminations as predictions. As Collins and Green (1982) had remarked, financial ratios of future failed companies are highly likely to differ from that of non-failed companies.

2.3.3 Logit regression analysis

Logistic regression analysis (logit) technique is a nonlinear probability model that has been commonly used for investigating the relationship between binary or ordinal probability and explaining variables by the method of maximum likelihood (Ohlson, 1980). Like the MDA model, the logit model weights the independent variables and assigns a score in a form of failure probability to each sample (Jones, 1987). But the logit model differs from MDA in that it does not require the independent variables to be multivariate normal, nor does it require the groups to have equal covariance matrices. In a logit model, the dependent variable can be non-metric and dichotomous, while the independent variable can either be metric or non-metric (Kmenta, 1971).

A number of significant studies have used the logit model to predict business failure. These are summarized in Table 2.5.

Study	**Sample size (no. of bankrupt)**	**No. of independent variables**
Ohlson (1980)	2,163 (105)	9 ratios
Zmijewski (1984)	1,681 (81)	3 ratios
Zavgren (1985)	228 (114)	7 ratios & factors
Dichev (1998)	n/a	16 ratios & macroeconomic
Grice (2002)	226 (113))	4 ratios
Darayseh et al. (2003)	220 (110)	9 ratios & macroeconomic
Hol (2007)	2,251 (18,952)	4 ratios & macroeconomic

Table 2.5: Previous studies of business failure using logit and probit

Martin (1977) was one of the first researchers to use logit analysis to predict the probability of failure for banks. His sample included 58 Federal Reserve member banks that failed between 1970 and 1976, and 5,575 randomly selected non-failed banks. Twenty-five financial ratios were used as independent variables that were classified into four groups: asset risk, liquidity, capital adequacy, and earnings. Six selected combinations of independent variables were applied to a logit model. The logit model managed to correctly classify between 87 and 95.7 per cent of failed banks and 88.6 to 89.2 per cent of non-failed banks.

Ohlson (1980) contributed to the bankruptcy literature by developing a logit model to predict business failure. Using 105 failed and 2,058 non-failed companies, with nine financial ratios as independent variables, he reported 12.4 per cent Type I error and 17.4 per cent Type II error one year prior to business failure. The Ohlson (1980) logit model became a benchmark for later business failure modelling attempts. The Ohlson (1980) model is discussed in more in detail in Section 2.4.3.

The logit model has maintained its high accuracy when applied to business failure in a variety of industries. Lynn and Wertheim (1993) studied 71 small and medium-sized hospitals that failed in 1986 and 1987, which they matched with an equal number of non-failed hospitals by bed size, geographical status and location. They used 21 financial ratios in four categories: leverage, liquidity, capital efficiency and resource availability. The logit model succeeded in predicting failure in 75 per cent and 74 per cent of cases one and two years, respectively, prior to failure.

Barniv et al. (1999) evaluated the default risk of 101 failed and 1,326 non-failed US listed manufacturing companies by a logit model using three years of financial data that were collected from the National Bureau of Economic Research between 1975 and 1988. The three ratios to estimate the logistic probability for each company's failure were return on assets, current assets to current liabilities and total debt to total assets. The logit model found that decreasing financial leverage, increasing profitability and reducing liquidity could control the probability of business failure. Barniv remarked that "the results of this study may apply to predicting takeovers, bond ratings, and commercial loan ratings" (Barniv et al., 1999, p. 563).

This remark reflects the findings from earlier work by Lau (1987), who used logit analysis and a five-financial-state classification to determine the financial health of companies. This was the first study that classified financial information five ways, instead of the traditional two states of failed versus non-failed. The five states were state of financial stability, state of reducing dividend payments, state of defaulting loan payments, state of protection under chapters X and XI of the Bankruptcy Act, and state of bankruptcy and liquidation. This method of categorizing companies “provides a better approximation to the continuum of alternative financial judgment and actions in realty” (Lau, 1987, p. 128). Samples consisted of 350 financially healthy companies (state of stability) and 50 financially unhealthy companies (state of reducing dividends payments through state of liquidity) from 1972 to 1976. Ten variables were used to measure the trends and financial status. The study gave an overall predictive accuracy of 96 per cent, 92 per cent and 90 per cent for one, two and three years, respectively, prior to business failure, with Lau noting that “the validation in this study provided at least some confirmation of the model’s predictive ability” (1987, p. 137).

Johnsen and Melicher (1994) built on the work of Lau (1987) and developed a logit analysis model with three states of financial health: non-failed, financially weak and failed. Financially weak was defined as having common stock ranked below average, lower and lowest by Standard & Poor. The sample consisted of 112 failed companies, 293 non-failed companies and 255 financially weak companies. Two constructed models, with one containing all seven variables used by Altman and Saunders (1997) and the other the six variables by Beaver (1966), concluded that the three states of financial health were independent, and including the financially weak classification helped improve the misclassification error.

Further attempts to improve the predictive power included adding different financial variables to the logit model (Dichev, 1998; Garlappi et al., 2008). Dichev hypothesized that “bankruptcy risk is negatively related to company size and positively related to book-to-value” (1998, p. 1132). He analysed how company size and book-to-market were associated with business failure using Ohlson’s (1980) and Altman’s (1968) models. The results found that neither variable was ideal for measuring business failure because a greater number of large companies had failed since the 1980s, and failed companies had lower book-to-market ratios. Garlappi et al. (2008) extended Dichev’s work and confirmed that higher expected stock returns were not associated with higher failure probabilities.

Including macroeconomic factors in the logit model gave positive results (Darayseh et al., 2003; Campbell et al., 2008; Fich & Slezak, 2008; Chava & Jarrow, 2004; Shumway, 2001; Lennox, 1999). Darayseh et al. (2003) made use of three macroeconomic variables (change in GNP, interest rates, stock price index) to predict the business failure of 220 matched companies. The coefficients of the financial ratios and the macroeconomic variables were not correlated. Two logit models were compared, one with six financial ratios and another with three macroeconomic variables, and the results indicated that the logit model with macroeconomic variables gave greater prediction accuracy five years prior to business failure.

Campbell et al. (2008), Fich and Slezak (2008), Chava and Jarrow (2004) and Shumway (2001) attempted to include governance and market-driven variables, and adjusted the industry effects to improve the results using binary logit analysis.

Lennox (1999) took into consideration the impact of industry sector, the economic cycle and company size on predicting the business failure of 949 listed companies between 1987 and 1994. The variables data, company size, profitability, cash flow and leverage were collected from Datastream. The logit analysis found that cash flow and leverage had non-linear effects on business failure probability and could improve greater prediction accuracy. Lennox (1999) added that "Probit and logit models were found to perform better than discriminant analysis. The test for misspecification found that probit and logit models were superior than the discriminant analysis for well-specified nonlinear probit and logit models" (p. 362).

Strengths and weaknesses of Logit prediction model

Based on a cumulative probability function, logit analysis uses financial ratios to measure the probability of a company belonging to one of the predetermined groups. The advantage of the logit analysis is that, unlike MDA, it does not assume multivariate normality and equal covariance matrices. It simply incorporates non-linear effects and uses the logistical cumulative function to predict business failure.

The downside of the logit analysis is that, again unlike MDA, it does not have a specific cutoff percentage, nor is there a guidance of the probability of business failure. The user of a logit model has to ascertain the level of failure risk (Martin, 1977). In sum, logit analysis is more complicated than univariate analysis and MDA to develop and understand.

2.3.4 Recursive Partitioning Algorithm (RPA)

Recursive partitioning, also known as Classification and Regression Tree (CART), is a computerized, non-parametric technique that can recognize patterns. It was first introduced in 1984 for classifying loan and predicting financial distress. Some significant studies of business failure have used the RPA model.

Marais et al. (1984) compared RPA with the probit model in classifying various commercial loans with 13 ratios and non-ratio variables, and found that RPA outperformed the nonfinancial statement indicators.

Frydman et al. (1985) collected 58 failed industrial and 142 non-failed manufacturing and retailing companies from COMPUSTAT during 1971 and 1981 to compare RPA against two MDA models. Ten variables (net income to total assets; current assets to current liabilities; log total assets; market value of equity to total capitalization; current assets to total assets; cash flow to total debt; quick assets to total assets; quick assets to current liabilities; earnings before interest and tax to total assets; and log interest coverage +15) were contained in one MDA model. Frydman et al. (1985) developed another model which contained only the four most important variables from the first model (net income to total assets; current assets to current liabilities; log total assets; and market value of equity to total capitalization). The study found that cash flow to total debt was the most important discriminator of the failed companies. The RPA trees achieved 90 per cent classification efficiency, so the study concluded that the RPA trees outperformed the MDA.

In contrast, McKee and Greenstein (2000) found the opposite when comparing the RPA ID 3 with a logit model and a neural network. Six variables (net income to total assets; current assets to total assets; current assets to current liabilities; cash to total assets; current assets to sales; and long-term debt to total assets) were used to analyse a sample of companies that filed for bankruptcy between 1981 and 1989. The ex-ante data of failed companies were collected from COMPUSTAT and the SEC List. Although the RPA model had a higher overall accuracy, the study found that the logit and the neural network were more accurate in predicting the failed companies, and could better minimize the Type I error (the misclassification of a failed company as non-failed) than the RPA ID 3 model.

Strengths and weaknesses of Recursive Partitioning Model

The advantage of RPA is that it need not make any assumption about the distributions of the independent variables and the dependent variables, and it does not suffer the drawbacks of MDA and logit (Jones, 1987). Other advantages are that it generates more intuitive models that do not require users to calculate, and it allows prioritizing of misclassifications in order to create a decision rule that has more sensitivity or specificity.

The primary weakness of RPA is that the same variable may reappear in the analysis and may have a different cutoff point (Zopounidis & Dimitras, 1998). In addition, it does not work well for continuous variables and it overfits the data. Consequently, RPA is not a popular tool for predicting business failure.

2.3.5 Artificial Neural Networks

Artificial Neural Network (ANN) is a mathematical model inspired by biological neural networks. It is a computer program that operates like a human brain that develop sets of rule through learning and experience (Haykin, 1999). The processing unit is composed of three hierarchically structured layers – an input layer, a hidden layer and an output layer – that process information using a connectionist approach for computation. An ANN consists of an interconnected group of artificial neurons. These neurons store the information and divide the data into groups called 'networks' (Turban et al., 2005). The neurons receive input data, transform the input data automatically and model any type of parametric or non-parametric process (Hiew and Green, 1992). The hidden layer is the learning area, which determines the output by trial and error. More than one hidden layer could exist for higher statistical needs. Finally, the neurons emit weighted output in mathematical value. The output can either be a final result or an input for another neuron.

When used in business failure prediction, the ANN analyses the ratios and the relevant data (the input) and looks for the patterns and the association between failed and non-failed companies (the output).

ANN was first used in bankruptcy prediction modelling in the 1980s. Table 2.6 summarizes the major studies that have used artificial neural networks to predict business failure.

Study	**Sample size (no. of bankrupt)**	**No. of independent variables**
Tam & Kiang (1992)	162 (81)	19 ratios
Coats & Fant (1992)	282 (94)	5 ratios
Wilson & Sharda (1994)	129 (64)	5 ratios
Altman et al. (1994)	1,108 (554)	10 ratios
Luther (1998)	104 (31)	13 ratios
Anandarajan et al. (2001)	522 (522)	5 finance & non-finance

Table 2.6: Previous studies of business failure using ANN

Nittayagasetwat (1994) used the ANN technique to predict bankruptcy for failed and non-failed companies from 1991 to 1993. Of the 173 failed companies that filed for chapters VII or XI of the US Bankruptcy code that were obtained from 10-K Compact Disclosure, and the 1,578 non-failed companies obtained by matching 9 to 1 of the failed ones, the study reported an overall 80 per cent classification accuracy. Nittayagasetwat (1994) concluded that an ANN model that uses financial ratios as predictors can be trained to accurately predict business failure, and noted that ANN outperformed the logit model and the recursive partitioning algorithm.

Luther (1998) tested the predictive accuracy of an ANN model against a logit model. He developed an ANN model using a genetic algorithm to predict companies identified by Chapter XI of the Bankruptcy Act. The sample comprised 73 reorganized companies and 31 liquidated companies from 1984 to 1989. Variables that served as the input nodes of the ANN input layer were 13 financial ratios grouped into five areas: size, profitability, liquidity, debt and activity, and growth from one year prior to filing for bankruptcy. Results indicated that the ANN had a smaller error rate and was less sensitive to changes than the logit model when examining the cutoff point. Luther (1998) therefore confirmed Nittayagasetwat's (1994) conclusion that the ANN surpassed the logit model and was more robust in predicting business failure.

Abid and Zouari (2002) applied the Black and Scholes (1973) formula to distinguish healthy and unhealthy companies in Tunisia. Fifteen financial ratios and nine different ANN were used to present different time periods. The study yielded an 86.67 per cent accuracy rate, further confirming the efficiency of ANN in studying business failure.

Neves and Vieira (2006) compared a free-forward multilayer perceptions ANN and a hidden layer vector quantization (HLVQ) ANN with MDA in predicting business failure in France. The study concluded that the HLVQ ANN model was accurate only when the number of variables was large.

Shah and Murtaza (2000) used an ANN model to investigate the financial strength of 54 financially healthy companies and six failed companies from 1992 to 1994. They selected eight ratios based on previous research results. The study reached a 73 per cent correct prediction rate. Shah and Murtaza concluded that the ANN model performed no better than other extant models.

Strengths and weaknesses of Artificial Neural Network model

ANN, one type of artificial intelligence techniques, is similar to the intelligence and logic of humans, in that it can learn and improve its problem-solving power based on experience. This technique has several advantages. First, it is nonlinear and can therefore deal with linear problems. Indeed, its capability in dealing with nonlinear problems has attracted interest from both practitioners and academics (de Gooijer & Kumar, 1992). Second, it can learn from the examples given and need not make prior assumptions, like most statistical models. Third, it can adjust new data and can analyse either financial or non-financial information. Fourth, it can tolerate errors of poor quality data or missing data (Haykin, 1999). Fifth, it can quickly handle large volumes of data. Other advantages of the technique include the ability to extract more signals from complex underlying functional forms by approximating the functional form that best characterizes the data (Hornik & Baldi, 1989); it can transform input data automatically (Connor, 1988; Donaldson & Kamstra, 1996); and it can extract residual elements from the data after removing the linear terms (Rumelhart & McClelland, 1986; Wasserman, 1989). Empirical studies (Altman et al., 1994; Coats & Fant, 1992; Wilson & Sharda, 1994; Yang et al., 1999) have shown that this technique outperformed some traditional statistical methods.

However, ANN does have disadvantages. The major criticism is the hidden correlations among the exploratory variables caused by the nature of its ad hoc foundation and fishing expedition (Altman and Saunders, 1997). Another drawback is that ANN requires a large diversity of training for real-world operation. Moreover, ANN is more difficult to interpret and to give physical meaning to than most other forecasting models, despite ANN containing more estimating parameters than most other models. Finally, development of commercial software for ANN often lags, whereas software for statistical techniques is available. The ANN modelling technique is changing rapidly but statistical modelling techniques are relatively stable and well-developed.

2.3.6 Survival Analysis

Prior methods mentioned (include MDA, logit analysis, ANN) assume that the time from classifying business failure to actual corporate bankruptcy occur within a single period. However bankruptcy does not occur immediately after classification. Instead it occurs over a number of years after the deterioration in company's health. Survival analysis, which identifies the degree of failure by symptom variables such as financial ratios, emerges to overcome such assumption, such as the Weibull and Cox proportional hazard models.

Cox proportional hazards model (Cox, 1972) assesses survival and failure probability that based on historical data of previously failed companies. The proportional hazards model, also called Cox model, is a class of survival model that relates time of an event to a number of explanatory variables known as covariates. The main assumption of the Cox Proportional Hazard model is that the effect of the independent variables is the same over time. The proportional hazard violates that covariate if the independent variable varies with time, which could result biased parameter values, incorrect standard errors, biased estimates of the true hazards rate. Lane et al. (1986) studied 334 non-failed and 130 failed banks was the pioneer paper in Survival Analysis with Cox proportional model. The Survival Analysis's prediction accuracy was found comparable with MDA and the Cox model produced lower Type I errors. Crapp and Stevenson (1987) examined the credit unions in Australia using Cox model generated same result. Laitinen and Luoma (1991) conducted study in Finland and found that Cox model was slightly less accurate than MDA and logit analysis.

Weibull model was named after Waloddi Weibull who first described this continuous probability distribution in 1951. Unlike Cox proportional hazard and multi-period logistic, Weibull model does not provide a reasonable parametric fit for modelling phenomenon with non-monotone failure rates, therefore it has been extensively used over the past decades for modelling data in reliability, engineering and biological studies (Cordeiro & Lemonte, 2013).

Strengths and weaknesses of Survival Analysis model

The weakness of the survival analysis model includes the form of time-dependent covariate that is more complex than fixed (non-time) dependent and the interrationship between the outcome and the variable over time can lead to bias (Fisher & Lin, 1999). As the underlying distribution is rarely normal, it cannot be usually applied. Even in the days of financial crisis, it is unfair to assume that all companies will file for bankruptcy in the future.

2.3.7 Summary

Numerous studies have constructed statistical models to predict probable business failure. Statistical methodologies such as linear discriminant analysis, quadratic discriminant analysis, logistic regression analysis and probit analysis have been widely used. Among all, the models of Altman (1968), Ohlson (1980) are probably the most commonly mentioned models in the literature and most widely recognized models in research into the prediction of business failure. These two models are discussed in detail in the next section.

2.4 The Altman Z-score and Ohlson O-score prediction models

The Altman (1968) and Ohlson (1980) models were used in this research for predicting business failure in Hong Kong. This section discusses the models in detail.

2.4.1 The Altman Z-score prediction model

Altman (1968) developed his business failure prediction model in the US using the multivariate discriminant analysis (MDA) technique. This technique is primarily used for classifying or predicting two or more groups with respect to qualitative variables, such as fail or non-fail. Altman pioneered using the MDA technique to predict business failure from financial ratios. Altman first selected 22 financial variables that were most popularly used in the literature and were relevant to his research, then categorized these variables into five financial ratios to develop his Z-score model to distinguish the likelihood of failure or non-failure. These five ratios were: (1) working capital to total assets; (2) retained earnings to total assets; (3) earnings before interests and taxes to total assets; (4) market value of equity to book value of total liabilities; and (5) net sales to total assets. The functions of each ratio are discussed briefly in turn.

Working capital to total assets (X_1 variable) measures a company’s ability to cover its short-term financial obligations (total current liabilities) by comparing its total current assets with its total assets. This ratio provides an insight into a company’s liquidity. Working capital is current assets less current liabilities, where current assets include cash, trade receivables, inventory, and current liabilities include short-term debt and trade payables. A positive working capital indicates the ability to meet short-term financial obligations, while a negative working capital indicates the opposite. Altman viewed this variable as the most valuable liquidity ratio because he expected a company's current assets to shrink in relation to total assets when operating losses persist. Other researchers (Altman, 2000; Chuvakhin & Gertmenian, 2003) agreed that working capital to total assets is more helpful than current ratio or quick ratio in explaining a company's liquidity.

Retained earnings to total assets (X_2 variable) measures how successfully a company can accumulate assets through retained earnings. This ratio weights comparatively heavier on older companies, as they have had more time than younger companies to build up their retained earnings, and younger companies are more often to fail in their early years (Pompe & Bilderbeek, 2005). Low retained earnings may indicate poor business performance or reduce longevity.

Earnings before interest and taxes (EBIT) to total assets (X_3 variable) measures the productivity of the company's assets, that is, the efficiency of making use of the assets in generating cash available for allocating to creditors, tax bureau and shareholders. This ratio represents general profitability of the company's assets. Whereas Return on Assets (ROA) uses net income, EBIT to total assets uses earnings before interest and tax. Altman viewed this ratio the most important contributor in the discriminant function; it is a better measure of profitability than cash flow, because a company's final year of existence depends on the earning power of its assets.

Market value of equity to book value of total liabilities (X_4 variable) measures a company's market stock price to its total debt. It shows the company owners and investors how much the company's assets value can decline before the liabilities exceed the assets when the company fails. Market value of equity is the summation of preferred stock and common stock. Altman (2000) believed that this X_4 variable, which uses market value in the numerator, is a more effective predictor than the ratio net worth to total debt, which uses book value in the numerator. However, Altman (1993b) admitted that this X_4 variable is not applicable to private non-listed companies, "X_4 requires stock price data, the original Z-score model is applicable to public companies only" (Altman, 1993b, p. 202).

Net sales to total assets (X_5 variable) measures the ability of a company's assets to generate sales, in other words, how effectively the company uses its assets. Altman ranked this ratio second in contributing to the overall discriminating function of the model.

The final discriminant function selected five of these variables:

$$Z = 0.012X_1 + 0.014X_2 + 0.033X_3 + 0.006X_4 + 0.999X_5$$

where: X_1 = net working capital / total assets

X_2 = retained earnings / total assets

X_3 = earnings before interests and taxes / total assets

X_4 = market value of equity / book value of total liabilities

X_5 = net sales / total assets

The discriminating ability of the variables $X_{1,}$ X_5 was tested by an F-test and was found to be significant at the 0.001 level. Scaled vectors were used to test the discriminant function of each variable; X_3, X_5, and X_4 were found to have the largest contributions to group separation.

The model with a Z-score value smaller than 1.81 indicated a company has the characteristics of failure, while a Z-score value greater than 2.99 indicated a company is financially healthy. The cutoff point that minimized the total number of misclassified companies by the model was 2.675, which classified firms as bankrupt or non-bankrupt. Z-score values between 1.81 and 2.99 were defined as "zone of ignorance" (Altman, 1968, p. 75) where caution must be taken in classifying companies as failed or non-failed.

The test samples were 33 failed public companies and 33 healthy public companies matched by year, industry and asset size. Failed companies were those who filed for protection under the Bankruptcy Act chapters X and XI from 1946 to 1965. Non-failed companies were those companies that did not file for bankruptcy protection and remained in operation through to 1966. One good point about the matching technique was that variables not included in the model were controlled (Zavgren, 1983). The 66 sampled companies were all manufacturing companies. The asset variable was controlled to avoid the bias of rare failure in larger companies and high frequency of failure in small companies. Companies with asset size smaller than US$1 million were excluded. The asset size of the failed companies ranged from US$7 million to US$25.9 million, with a mean asset size of US$6.4 million, while that of the non-failed companies ranged from US$1 million to US$25 million.

Altman's model correctly classified 94 per cent of the total sample one year prior to failure and 72 per cent of the total sample two years prior to failure. The predictive accuracy diminished greatly to 48 per cent three years prior to failure and continued to deteriorate over time. The accuracy rate further dropped to 29 per cent and 36 per cent, respectively, four years and five years prior to failure. Altman concluded that the unreliability of the data had caused the accuracy to increase from year four to year five.

Type I error was 6 per cent and Type II error was 3 per cent one year prior to failure. Type II error for two years prior to failure increased to 6 per cent. Altman (1968) suggested that using "below-average performance" companies that had not yet declared bankruptcy could have caused the Type II error to increase. Altman (1968) defined Type I error as actual failure being misclassified as non-failure (or false positive error); this error type occurs when a true null hypothesis is rejected. Type II error is defined as actual non-failure being misclassified as failure (or false negative error), which occurs when the null hypothesis is false but fails to reject. Altman et al. (1977) remarked that Type I error is more expensive for investors and creditors for it misinterprets a company as healthy when it is actually unhealthy or will fail soon, whereas Type II error is just a cost for the investors and the creditors who lose the opportunity of making a good investment or borrowing to an actual healthy company that is being misclassified as unhealthy. In sum, the Altman (1968) model correctly classified 31 of the 33 failed companies (93.9%), with 6 per cent Type I error and 3 per cent Type II error.

In 1983 Altman revised his original Z-score model (Altman, 1993b, p. 202) for predicting failure of private companies. As Altman had admitted that the X_4 variable of his 1968 model could not apply to private non-listed companies, all variables in the 1968 model were kept except variable X_4. The market value of equity of variable X_4 was replaced by book value of equity. The revised Altman (1983) Z^1-score function became:

$$Z^1 = 0.717X_1 + 0.84X_2 + 3.107X_3 + 0.42X_4 + 0.998X_5$$

A Z^1-score value less than 1.23 indicated failure, a value larger than 2.9 indicated healthy, and values between 1.23 and 2.9 were defined as a grey area (zone of ignorance) where caution must be taken in classifying companies as failed or non-failed. The revised 1983 model yielded slightly weaker prediction accuracy than the 1968 model. The accuracy of the two models is compared in Table 2.7.

	Predicted fail		**Predicted non-fail**	
	Altman 1968 model	Altman 1983 model	Altman 1968 model	Altman 1983 model
Actual fail	93.9%	91%	3%	3%
Actual non-fail	6.1%	9%	97%	97%

Table 2.7: Comparison of Altman (1968) and Altman (1983) models

In 1993, Altman further revised his 1983 Z^1-score model by substituting the book value of market value equity in X_4 and taking out the variable sales to total assets (variable X_5). This move was intended to reduce the potential industry effect by excluding asset turnover. In addition, all variables' coefficients and cutoff points were re-calculated. The revised Altman Z^{II} (1993) function was:

$$Z^{II} = 6.56X_1 + 3.26X_2 + 6.72X_3 +1.05X_4$$

X_4 variable (book value of equity/book value of total liabilities) measures the net worth to both the current and long-term debt. Altman considered this ratio the third contributor to the discriminant function.

A Z^{II}-score value below 1.1 indicates failure, a value above 2.6 indicates healthy, and values between 1.1 and 2.6 are defined as a grey area (zone of ignorance) where caution must be taken in classifying companies as failed or non-failed. Table 2.8 summarizes the comparison of Altman's Z-score model, Z^I-score model and Z^{II}-score model.

	Original 1968 model	Revised 1983 model	Revised 4-variable 1993 model
Coefficients			
X_1	0.012	0.717	6.56
X_2	0.014	0.847	3.26
X_3	0.033	3.107	6.72
X_4	0.006	0.42	1.05
X_5	0.999	0.998	/
Classification accuracy			
Actual fail	93.9%	91%	91%
Type I error	6.1%	9%	9%
Actual not fail	97%	97%	97%
Type II error	3%	3%	3%
Cutoff point			
Fail	<1.81	<1.23	<1.1
Not fail	>2.67	>2.9	>2.6
Zone of ignorance	1.81–2.67	1.23–2.9	1.1–2.6

Table 2.8: Comparison of Altman's three generations of prediction model

2.4.2 Study of Altman's model outside the US

Benzing et al. (2009) found that classification accuracy varies in different countries, while Lussier and Pfeifer (2001) suggested replicating the results cross-nationally, and Oviatt and McDougall (2005) recommended an empirical study comparing domestic and international companies.

Altman's model has influenced the research of bankruptcy prediction in countries outside the US. Examples include studies of business failure in South Korea by Altman and Kim (1995), Lee (1998) and Nam and Jinn (2000); the comparison of the MDA model with the logit regression model by Ugurlu and Aksoy (2006) using Turkish data; and the use of modified Altman's model to predict bankrupt firms in Argentina by Sandin and Porporato (2007). The following discussion focuses on research in foreign countries that used Altman's MDA model.

In Canada, Boritz et al. (2007) refined Altman's model using Canadian company data with a cutoff point at .27 for bankrupt versus non-bankrupt business. The same sample as the original study was used to measure the models' performance. The Canada-based Z-score model was:

$$Z = 2.149X_1 + 0.624X_2 + 1.354X_3 + 0.018X_4 + 0.463X_5$$

Their findings indicated that the model's predictive accuracy was lower than when Altman's original coefficients were re-estimated, with much greater Type I error and lower Type II error. Boritz et al. (2007) explained that the use of same sample to estimate the model coefficients and to measure the model's performance could have led to an upward bias in the performance measure. For that reason, the current study measured the model's performance by different sample without changing the model's coefficients. Instead, the model's cutoff point was adjusted.

In China, Wang and Campbell (2010) compared three models for predicting company failure. They developed a re-estimated model, recalculated the coefficients of the five financial ratios of Altman's Z-score model, and created a revised model using three ratios that included a variable X_6 (total asset one year prior to delisting less total assets two years prior to delisting to total asset two years prior to delisting). Results showed that all three models effectively predicted company failure in China. The results also indicated that Altman's Z-score model (1968) had higher prediction accuracy for the delisted group, and the revised model had greater overall prediction accuracy than the re-estimated model and Altman's 1968 model.

Other Chinese researchers also investigated the business failure classification problem. Zhang (2000) developed a four-variable discriminant model and found that the model had a predictive ability of up to four years prior to ST. ST stands for "special treatment' that is defined by China's Securities Regulatory Commission (CSRS) as companies in financial difficulties. This "ST" aimed at differentiating those unhealthy companies to alert the investor's awareness of the default risk. The "ST" companies were forced by the CSRS to improve their financial condition through reorganization or mergers, and if their financial position could not be improved in the following year, they received a "particular transfer" (PT) warning from the CSRS. Wu and Lu (2001) conducted a similar study of ST companies using MDA, LPM and logit and found 72 per cent predictive accuracy four years prior to ST.

Xu & Zhang (2005) examined listed companies in Japan that failed between 1992 and 2003 and found that the Altman model's accounting variables were useful in predicting bankruptcy. The study further concluded that the model's predictability improved substantially when traditional accounting variables and stock market variables were used together.

In Argentina, Sandin and Porporato (2007) investigated 22 public companies listed in the Buenos Aires Stock Exchange that traded from 1990 to 1998. The sample included 11 failed and 11 healthy companies, with asset sizes ranging from US$8 million to US$77 million. They selected as variables 13 ratios that had high-predictive potential in previous empirical studies, and used book value instead of market value of shareholder's equity. Using a stepwise method based on Altman's MDA, Sandin and Porporato's (2007) MDA function identified that operative income to net sales and shareholder's equity to total assets had high predictive value. The latter variable also appeared in Altman (1993a) model.

In Israel, Lifschutz and Jacobi (2010) empirically tested the reliability of two Altman models: the Altman Survival Model and the Altman (1983) model for private companies converted by Ingbar (1994). The samples were 40 public companies traded on the Tel-Aviv Stock Exchange between 2000 and 2007, which included 20 failed companies that were either suspended or liquidated, and 20 non-failed companies with stable finances. The study found that the Ingbar converted Altman (1983) model could predict with an accuracy 95 per cent one year prior to failure and an 85 per cent accuracy rate two years prior failure.

Alkhatib and Al Bzour (2011) used the Altman Z-score model and the Kida Z-score model to predict failed companies that were listed in the Jordanian Stock Exchange. The sample included 16 non-financial and industrial companies that failed in Jordan between 1990 and 2006. They used the formula for the Altman Z score model given above in Section 2.4.1. The formula for the Kida Z-score model was:

$$Z = 1.042X_1 + 0.42X_2 + 0.461X_3 + 0.463X_4 + 0.271X_5$$

where X_1 = net profit/total assets

X_2 = interest expenses discounted for short-term and long-term obligations

X_3 = (accounts and notes payable/total assets)*12

X_4 = sales/total assets

X_5 = cash/total assets

A Z-score greater than .38 was considered non-failed, while a Z-score less than .38 was considered failed. The study found that the Altman Z-score model outperformed the Kida Z-score model, with 93.8 per cent predictive ability against 70.2 per cent for the Kida Z-score model. The Altman model still performed strongly in predicting business failure in Jordan.

An empirical study of business failure in Hong Kong is found in Chan's (1985) MBA thesis. Chan applied an MDA model to study 15 liquidated companies that had been suspended from the Hong Kong Stock Exchange (HKEx) between 1975 and 1984, with 15 existing companies as best-paired sample included. Chan (1985) concluded that MDA is generally useful and applicable in Hong Kong. The overall correct classification rate one year prior failure was 90 per cent, Type I error was 6.7 per cent, and Type II error was 13.3 per cent. But he further pointed out that "the peculiar feature of H.K. economy to frequent sharp turns has made prediction of bankruptcy at earlier stages difficult" and "the small number of samples available thus prohibiting cross validation, the reliability of the data, and the insufficiency in contributing to a total theory of financial distress" (Chan, 1985, p. 51).

2.4.3 The Ohlson O-score prediction model

Ohlson (1980) used a logit regression model to examine the effect of four factors on the probability of business failure: size, financial structure, performance and the current liquidity of the company. The logit model was based on a cumulative probability function and the maximum likelihood method to predict failure. A logit model is a conditional probability model which assumes that companies face two possible outcomes. The outcome is the dependent variable, which is generally qualitative and is expressed as fail or not fail. The value of the independent variable is 0 or 1. A logit model takes the form:

$$\ln [P/ (1-P)] = Z = \beta X$$

P is the probability that an event will occur, given at X, while X is a vector of attributes; and β is an unknown parameter vector to be estimated. The logit probability model derives the probability of a dependent variable by assigning coefficients to the independent variables. According to Ohlson (1980), the coefficients can be interpreted as an effect of a unit change in an independent variable on the index Z. The Ohlson's (1980) P model is as follows:

P = (–1.32 – 0.0407 SIZE + 6.03 TLTA – 1.43 WCTA + 0.0757 CLCA – 2.37 NITA – 1.83 FUTL + 0.285 INTWO – 1.72 OENEG – 0.521 CHIN)

where P = overall probability of business failure

SIZE = log (Total assets to GNP price – level index)

TLTA = Total liabilities to total assets

WCTA = Working capital to total assets

WCTA = Working capital to total assets

CLCA = Current liabilities to current assets

NITA = Net income to total assets

FUTL = Operating cash flow to total liabilities

INTWO = 1 if net income is negative for the last two years, 0 otherwise

OENEG = 1 if total liabilities are greater than total assets, 0 otherwise

CHIN = (Nit – Nit-1)/(| Nit | + Nit-1), Nit is net income for the most current period

Ohlson selected 105 failed publicly traded industrial companies from the Wall Street Journal Index which filed for bankruptcy under chapters X or XI between 1970 and 1976. Three years of financial data prior to business failure were obtained from 10-K financial statements for analysis. Ohlson also randomly selected 2,058 non-failed companies from COMPUSTAT file. Only one year's financial data were gathered for the non-failed companies, due to limited memory capacity of the statistical analysis. Companies with missing data were excluded from the sample.

Ohlson (1980) developed three models with different time periods under review before failure. Model One predicted business failure within one year of failure; Model Two predicted business failure within two years; Model Three predicted business failure within one or two years. The independent variables were weighted to create a score that identified each company's health (Jones, 1987, 146). The signs of all predictors in Model One were within the expectation of Ohlson, except the OENEG variable. Ohlson expected OENEG to be an indeterminate sign but it turned out negative. The coefficients of the variables were estimated without base choice of variables. Most coefficients appeared to have significant t-statistics, except the coefficients of WCTA, CLCA and INTWO, which were less than 2. The models classified 87.6 per cent and 82.6 per cent, respectively, for failed and non-failed companies, for one year preceding failure, with 12.4 per cent Type I error rate and 17.4 per cent Type II error rate. The overall classification accuracy rate was 85 per cent. Ohlson concluded that company size, total liabilities to total assets, net income to total assets and working capital to total assets were the four statistically significant factors. Ohlson reported that the mean probability was 0.39 for the failed companies one year prior to failure, and 0.2 for the failed companies two years prior to failure. According to the likelihood ratio index which measured the goodness-of-fit, Model One had an accuracy rate of 84 per cent, and Model Two decreased to 79 per cent. Ohlson explained that the accuracy decreased when the lead time increased. The cutoff point which minimized the Type I and Type II errors was 0.38. This cutoff point is determined based on the assumption that the costs of Type I and Type II error were equal. Ohlson defined Type I and Type II errors quite differently from Altman, in that Type I error was when P was less than the cutoff point and the company was failed. Similarly, Type II error was when P was larger than the cutoff point and the company was non-failed.

Ohlson's (1980) model overcame several problems that MDA model could not, for example, the assumptions that financial ratios must be normally distributed and variance-covariance matrix for failed and non-failed companies must be same. The Ohlson logit O-score model therefore became a benchmark for many other prediction models when measuring business failure. For example, Beneda (2007) examined the relationship between returns and business failure for new public companies that issued IPOs in the US from 1995 to 2002, and found that Ohlson's model was effective in classifying companies that had a higher probability of financial distress with lower than average returns.

But the Ohlson O-score model did receive some criticisms. For example, the results of the models were difficult to compare due to different time periods, probability and data (Grice & Dugan, 2001). The model's weighted variables were determined by the combined probability of the sampled failed and non-failed companies, and the results of a given model were inapplicable to new data, so that the probability of new samples needed recalculation (Laitinen, 1991). Although MDA could have same technical drawback, the cutoff point of the MDA, which was based upon prior probabilities, had been adjusted (Jones, 1987). Because the Ohlson model did not validate the results by holdout sample, the over-fitting problem could be misleading (Stone & Rasp, 1993). Finally, the Ohlson model lacked a specific cutoff percentage to guide the probability of business failure, and so users had to ascertain the level of failure risk themselves (Martin, 1977).

2.4.4 Study of Ohlson's model outside the US

In Korea, Nam and Jinn (2000) employed a logit maximum likelihood estimator to study business failure of Korean listed companies during the recession period of the IMF crisis (foreign exchange crisis) from 1997 to 1998. The sample consisted of 46 non-financial listed companies that were drawn from a variety of industries with asset size ranged between 39 million won and 6,945 billion won. Equal numbers of non-failed companies from same industries with similar asset size were matched. Thirty-three financial ratios were used and only 10 variables were found to be significant predictors at the 5 per cent significant level using t-test. Only three variables – interest expense to sales, receivables turnover and debt coverage – were significant predictors in the logit maximum likelihood estimator using stepwise procedure to finalize the variables. The model demonstrated decent predictive accuracy and robustness, with 80.4 per cent accuracy in predicting failed companies and 73.9 per cent in predicting non-failed companies. Holdout sample results were similar to the predictive accuracy. The predictive accuracy remained constant when the model was applied to data from 1991 to 1996, the time before the IMF crisis broke out. This finding was interpreted by Nam and Jinn (2000) that those failed companies in Korea had poor performance long before the crisis and that the IMF crisis was not a temporary crisis.

In Canada, Boritz et al. (2007) compared three Canadian bankruptcy prediction models of Springate (1978), Altman and Lavallee (1980) and Legault and Veronneau

(1986) against the Altman and Ohlson models. The study indicated that all models performed better with original coefficients than with re-estimated coefficients. The Altman (1968) and Altman and Lavallee (1980) models were less accurate than the other models, while the Springate (1978) and Legault and Veronneau (1986) models yielded similar results to Ohlson’s (1980) model. The Legault and Veronneau model had higher Type I error and lower Type II error, while the Ohlson and Springate models had similar Type I and Type II errors. Boritz et al. (2007) concluded that the Ohlson model is superior to the Altman model and is robust over time. Begley et al. (1996) made a similar finding.

In China, Wang and Campbell (2010) re-examined the Ohlson (1980) model by re-estimating and revising the model to better fit the specific situation in China. They collected company data for 1,336 companies, which included 76 failed companies that were delisted from the Shanghai Stock Exchange (SHSE) or the Shenzhen Stock Exchange (SZSE) for 11 years from 1998 to 2008. The study followed the strategy of Ohlson (1980), using nine variables and three sets of models to predict business failure: Model One predicted failure within one year; Model Two predicted failure within two years; Model Three predicted failure within one or two years. The nine variables were SIZE (company size), TLTA (total liabilities/total assets), WCTA (working capital/total assets), CLCA (current liabilities/current assets), NITA (net income/total assets), FUTL (operating cash flow/total liabilities), INTWO (one if net income was negative for the last two years, zero otherwise), OENEG (one if total liabilities exceeds total assets, zero otherwise), CHIN (change of income). Model One and Model Three selected TLA, WCTA, CLCA, OENEG, and INTWO as the five independent variables; Model Two selected CLCA, OENEG, INTWO, CHIN as the four independent variables. Wang and Campbell (2010) found that the Ohlson (1980) models achieved 95 per cent accuracy using data from Chinese publicly listed companies. In addition, INTWO and OENEG were the two most influential variables in predicting failure, significant at $p<0.1$. Wang and Campbell noted that when the backward stepwise method was used in Model One and Model Three using the five variables (TLTA, WCTA, CLCA, OENEG, INTWO), the prediction accuracy was quite similar to that when all nine variables were employed . Therefore Wang and Campbell suggested comparing the Ohlson (1980) and Altman (1968) models using China ex-ante data.

2.4.5 Summary

Review of the literature shows that Altman's Z-score model has stood the test of time and is still widely used in recent academic research for predicting business failure outside the US. Examples include the work of Chen and Merville (1999), Zhang (2000), and Wang and Campbell (2010) in China; Xu and Zhang (2009) in Japan, Sandin and Porporato (2007) in Argentina; Lifschutz and Jacobi (2010) and Alkhatib and Al Bzour (2011) in the Middle East; and Boritz et al. (2007) in Canada. Yet no recent empirical research has applied the company data of Hong Kong to Altman's model to study the prediction of business failure, despite the fact that Hong Kong was ranked as the world's seventh-largest capitalized market in 2011 (World Federation of Exchanges, 2012). The single study of Hong Kong companies was the work by Chan in 1985, some 28 years ago.

The Ohlson O-score model has been widely used in many countries, but no published studies have examined their use in Hong Kong. A review of the literature indicates that the Altman and Ohlson models are the two most influential models in the finance literature. Both have been tested in the US and other countries but, with one exception 28 years ago, they have not been tested using Hong Kong company data. This study fills this gap by studying the models when they are applied to the companies listed in the HKEx between 1998 and 2011.

2.5 Comparison of business failure prediction models

With the development of ever more business failure prediction models, researchers were keen to evaluate their accuracy by making different comparisons. This section reviews previous studies comparing business failure prediction models: first, comparison of traditional statistical models, for example, univariate model versus MDA model, MDA model versus logit regression model; second, comparison of traditional statistical models and non-traditional statistical models, for example, the survival model versus MDA model, artificial neural network versus MDA and the like.

2.5.1 Comparison of traditional statistical models

This section focuses on previous empirical studies comparing traditional statistical models.

Holmen (1988) tried to compare Beaver's (1966) univariate model and Altman's (1968) multivariate model using 84 failed companies for the years 1977 to 1984, matched with 84 non-failed firms controlled by year, total assets and industry that were drawn from the Wall Street Journal Index. Financial data were obtained from Moody's industrial, transportation or over-the-counter manuals. Holmen (1988) found that the Altman model correctly predicted 56.2–72 per cent of failures with an average 30.4 per cent error rate. The Beaver model correctly predicted 70.8–91.7 per cent of failures, with an average 20.2 per cent error rate when the cutoff point was set at .07. When the cutoff point was moved to .03, the Beaver model correctly predicted 56.2–83.3 per cent of failures, with an average 26.2 per cent error rate. Furthermore, the Altman model yielded an average 29.8 per cent and 31 per cent for Type I and Type II errors, respectively, whilst the Beaver model yielded an average 21.4 per cent and 10 per cent for Type I and Type II errors, respectively. Holmen (1988) therefore concluded that the univariate model outperformed the multivariate model by making less error when the cash flow to total debt ratio was used.

Collins and Green (1992) compared the predictive power, robustness and applicability of MDA, linear probability model (LPM), and logit regression. They found that results from the MDA were as good as from the LPM, and although the logit model produced fewer Type I errors, the logit model was not significantly better at classifying failure.

Begley et al. (1996) compared the superiority of the Altman (1968) MDA model and the Ohlson (1980) logit model. Samples were 99 failed and 99 non-failed companies matched by size and industry. They first examined the two models using the original coefficients; they then tested the updated models of re-estimated coefficients. They found that Ohlson's (1980) original and re-estimated models outperformed Altman's (1968) original and re-estimated models, and concluded that the change of the coefficients also changed the structure and the relative contribution of each parameter.

Researchers in many empirical studies have found that the MDA and logit had equivalent accuracy in predicting business failure. For example, Ginoglou et al. (2002) compared 40 Greek firms using both logit and MDA models but did not find either one performed significantly better than the other. More examples are discussed below.

Hamer (1983) compared the predictive ability of linear discriminant analysis, quadratic discriminant analysis and logit analysis that used 44 failed companies and 44 non-failed companies from the manufacturing industry for 1972 to 1975. He used four sets of variables that were employed by Altman (1968), Deakin (1972), Blum (1974) and Ohlson (1980), and financial statements were obtained from Moody's Industrial Manual and Standard & Poor's COMPUSTAT database. Hamer (1983) found that the three models had a similar predictive ability in each of the three years prior to failure, and the four variable sets had comparable accuracy in predicting failure.

Lo (1986) found similar results to those of Hamer (1983). He compared MDA and logit analysis techniques by making an assumption that the MDA was asymptotically more efficient than the logit analysis. To test this, Lo (1986) collected a sample of 38 failed companies that filed for chapters X or XI between 1973 and 1983, with 38 non-failed companies matched by year, industry and total assets. Lo (1986) concluded that the explanatory variables were conditionally normal and the discriminant and logit models were equivalent in predicting business failure (Lo, 1986).

However, Aziz et al. (1988) made different conclusions when comparing the MDA and the logit analysis using cash flow data. Aziz et al. (1988) developed five models, each with five cash flow variables for the five years prior to business failure. The logit model predicted an accuracy rate of 79–92 per cent, while the MDA model achieved accuracy of 73–89 per cent. Unlike the findings of Hamer (1983) and Lo (1986), Aziz et al. (1988) concluded that the MDA model based on cash flow data was more likely to provide early warning three or more years prior to failure.

Hillegeist et al. (2004) compared the Altman and Ohlson models against a Black-Scholes-Merton probability of bankruptcy model (BSM-PB). The large sample size consisted of 516 failed companies from 1979 to 1997, and 65,960 company-year observations were made. The study found that the BSM-PB was inadequate in predicting the probability of failure because it contained no significant incremental information that reflected market-based information about business failure, such as excess returns and market size. Merton's (1974) distance to default (DD) model has been widely adopted in academic research. The model measures the difference between a company's asset value and the face value of its debt scaled by the standard deviation of the company's asset value away from default, hence the smaller the value of DD, the larger the probability of default. The DD model is expressed as:

$$DD = (In(V/F) + (\mu - 0.5 * {}^{\sigma}V \text{^}2) T) / ({}^{\sigma}V \sqrt{T}))$$

where:

V = total value of the company

μ = expected continuously compounded return on V

F = face value of company's debt

${}^{\sigma}V$ = volatility of underlying company

T = time of maturity

This model assumed that an event of default is determined by the market value of the company's assets in conjunction with the company's liability structure. The company is deemed to be in default when the asset value falls below its debt payable at a fixed future date. The DD model has been extensively applied to bank and highly leveraged companies for its advantage of being insensitive to the leverage ratio. Bharath & Shumway (2008) found that the model can classify 65 per cent of defaulting companies in the highest probability decide at the beginning of the quarter in which they default.

The downside of the model is that the likelihood of default that a company has insufficient buffer to absorb losses in its asset value is determined by the movements (trend and volatility) of the company's asset value, but asset value's trend and volatility are difficult to estimate and the market values of a company's asset as postulated in Merton model are not directly observable (Duan, 1994). Bharath and Shumway (2008) further found that a "naive" application of the DD model with leverage ratio outperformed the complex DD model, the DD model did not provide a sufficient statistic for default probability. Campbell et. al (2008) found that Merton model probabilities have relatively little contribution to the predictive power. Duan (2000) suggested that the model be calibrated by a reduced-form model, e.g. logistic regression, to yield better performance.

Mossman et al. (1998) compared Altman's (1968) Z-score model, the Aziz et al. (1988) cash flow model, the Clark and Weinstein (1983) market return model, and the Aharony et al. (1980) market return variation model. The four models were based on financial ratios, cash flows, stock return, and standard deviations, respectively. Samples consisted of 190 failed companies that filed for chapters VII and XI of the US bankruptcy code between 1980 and 1991. In addition, 190 non-failed companies were obtained from COMPUSTAT or Wall Street Journal Index. The non-failed companies were matched by controlling for size and industry. Financial institutions were excluded from the sample. The study found that the financial ratios model (Altman model) was more effective in explaining the probability of occurrence one year prior to failure, while the cash flow model (Aziz et al. model) was more consistent in discriminating failed and non-failed two or three years prior to failure. Mossman et al. (1998) drew four conclusions: first, no single model could satisfactorily classify between fail and non-fail; second, neither model was particularly reliable in discriminating more than three years prior to failure; third, financial ratios plus cash flow variables were more useful than using market returns alone in predicting failure; fourth, different types of models should be applied for different purposes.

Nunthaphad (2000) compared the Altman (1993a) and McGurr (1996) models in classifying small retail companies. Their sample included 67 failed publicly traded retail firms from 1986 to 2000, with a matched sample of 67 non-failed retail companies. Nunthaphad (2000) found that the two models had no statistically significant difference in classifying failed and non-failed companies.

In summary, MDA and logit are the two highly rated traditional statistical models in the literatures of business failure prediction (Collins & Green, 1992; Hamer, 1983; Lo, 1986; Mossman et al., 1998; Nunthaphad, 2000; Hillegeist et al., 2004), but neither model can be rated better than the other.

2.5.2 Comparison of traditional and non-traditional statistical models

In the 1990s, more researchers were interested in comparing the effectiveness of traditional and non-traditional prediction models in a variety of combinations, either one-to-one (e.g. MDA vs. ANN, logit vs. ANN) or one-to-multiple (e.g. ANN vs. logit and MDA, recursive partitioning and hazard vs. logit). This section discusses some of those studies: first, simple one-to-one comparisons, and later in the section more complicated one-to-multiple comparisons.

Coats and Fant (1993) compared an ANN with the Altman (1968) model by including auditors' going concern as a non-financial variable to uncover the inconsistency between the known pattern and the recurring patterns in the financial data. The study built four Cascor models, each with a different lead time to test the predictability. The sample included 94 failed companies from 1970 to 1989, and 188 randomly selected viable companies obtained from the Standard & Poor's COMPUSTAT database. The two sample groups were then randomized and recombined to form eight non-overlapping sets with 47 failed and 94 viable companies in each group. One group was trained by auditor's going-concern opinion to recognize the pattern; another group tested the network's predictive power. The results indicated that ANN had a higher misclassification rate in the third year prior to auditor issued going-concern. Type I error of the ANN model was 10.6–19.1 per cent, while that of the Altman's MDA model was 29.8–36.2 per cent. Coats and Fant (1993) concluded that the ANN model was more robust and gave better predictive value and a higher accuracy rate than the MDA in classifying business failure.

Yang et al. (1999) compared a probabilistic ANN with an MDA model and a back-propagation ANN for companies of the oil and gas industry and found the opposite results: the MDA model outperformed the ANN models in correctly classifying failed companies. Moreover the MDA model and the probabilistic ANN model had the best overall predictability.

A similar conclusion was made by Boritz and Kennedy (1995), who had conducted test similar to those by Coats and Fant (1993). Boritz and Kennedy compared an ANN against the Altman (1968) and Ohlson (1980) models and found that the predictive ability of the ANN varied across different techniques and was highly sensitive to the set of predictors used and the sampling error. They also found that the Ohlson model had lower Type I error than the Altman model, but the reverse was true for Type II error. The classification accuracy of the ANN model was affected by the proportion of failed companies in the testing and training dataset, the selection of variables, and the assumptions of the relative costs of Type I and Type II errors, and Boritz and Kennedy (1995) concluded that the ANN was not superior to the Altman and Ohlson models.

Earlier work by Altman et al. (1994) also supported Yang's conclusion. They compared the linear discriminant analysis and the neural networks for predicting 1,000 healthy and unhealthy Italian industrial companies for the period 1982 to 1992. Although both the discriminant analysis and neural networks resulted 90 per cent accuracy rate, Altman et al. (1994) found that the neural networks technique had illogically weighted the indicators and over-fitted in the training stage, which could have negatively influenced the predictive accuracy. They concluded that the discriminant technique was more effective than the neural networks. This criticism about ANN's illogical behavior was further confirmed by Wilson and Sharda (1994), who compared the Altman (1968) model and an ANN model utilizing 65 companies that failed from 1975 to 1982. Wilson and Sharda established three training sample sets: Set One included equal numbers of matched non-failed and failed companies; Set Two composed 80 per cent non-failed companies and 20 per cent failed companies; Set Three consisted of 90 per cent non-failed companies and 10 per cent failed companies. A back-propagation training algorithm was used, with five input neurons and a 10-neuron hidden layer, and two output neurons. The ANN model outperformed the MDA model in every case. For Set One, the ANN correctly predicted 95.68 per cent and the MDA, 93.32 per cent; for Set Two, the ANN correctly predicted 95.68 per cent and the MDA, 91.59 per cent; the ANN of training for Set Three, the ANN correctly predicted 94.55 per cent and the MDA, 91.81 per cent. However, Wilson and Sharda cautioned that the ANN models were used in an illogical behaviour and concluded that, although the MDA model performed lower than the ANN, future studies should integrate the use of both models.

Non-traditional statistical models have also been compared with logit regression. Charitou et al. (2004) compared neural networks with logit regression and argued that both models could be viable alternatives for predicting business failure. Using 25 failed and 25 matched healthy UK public industrial companies for the period 1988 to 1997, and an out-of-sample ex-ante test with 26 matched failed and healthy companies to validate the models, the study employed a logit regression model that was built with three financial ratios (leverage, profitability, operating cash flow), a feed forward artificial neural network with a conjugate gradient training algorithm, and a second logit model that was constructed using the entire sample and was validated by the Lachenbruch jackknife technique. The study yielded high classification results for all three models for one, two and three years prior to business failure. The logit model achieved an overall 76 per cent accuracy rate, while the neural network yielded 78 per cent. The average Type I error rates for the logit model and neural network were 16 per cent and 17 per cent, respectively. Charitou et al. (2004) concluded that operating cash flow variables were useful in predicting business failure using the UK sample.

As an example of a more complicated one-to-multiple comparison, Becerra et al. (2005) compared MDA, ANN and wavelet network models using British samples. Both the ANN and the wavelet ANN models were found to perform better than the MDA model in predicting business failure.

Neves and Vieira (2006) compared the predictability of MDA, ANN and a hidden layer learning vector quantization (HLVQ) ANN for 1,000 French industrial companies. The study concluded that the HLVQ ANN had the best predictive power when a large number of variables were used.

Tam (1991) compared the predictive accuracy of recursive partitioning, multiple discriminant analysis, logit regression and cluster analysis models with a decision tree (ID3) developed by Messier and Hansen (1988). The test sample included 59 Texas banks that failed from 1985 to 1987 and an equal number of healthy banks. Nineteen variables of capital, asset, management, equity and liquidity were selected. These ratios were applied to two ANNs, one with three layers and 10 hidden units (ANN-10) and another without hidden layer (ANN-0). Results showed that for one year prior business failure, the Type I and Type II errors of the ANN were 8.6 per cent and 12.3 per cent, respectively. The errors of the MDA were 17.3 per cent and 11.1 per cent, respectively, and the errors of the logit regression were 12.3 per cent and 17.3 per cent, respectively.

Dwyer (1992) evaluated the traditional statistical models and the back-propagation network model by comparing discriminant analysis and the logit regression against the artificial neural networks model. Again, the study adopted a matched sample controlled by industry and total asset for the period 1979 to 1988. Financial data were obtained from COMPUSTAT data files. The study found that the logit regression model achieved 76.3 per cent accuracy rate in classifying failed companies, while the back-propagation network model achieved 78.9 per cent accuracy rate. Dwyer (1992) concluded that both the logit model and the back-propagation network models were accurate prediction techniques.

Yim and Mitchell (2004) compared the prediction accuracy of MDA, logit and probit, ANN and hybrid ANNA models for Japanese financial and nonfinancial firms and found that the MDA model performed the best in classifying failed firms.

Chen et al. (2006) conducted a test to compare linear discriminant analysis, logit regression, decision tree and neural networks using 39 “ST” Chinese listed companies and 517 Chinese “non-ST” companies for 1999 to 2003. In addition, 17 “ST’ Chinese companies and 222 “non-ST” companies were used as holdout sample for validating the accuracy of the parameters of the sample. The study indicated that EBIT to total assets, earning per shares, total debt to total assets, price to book ratio, and current assets to current liabilities were the five most significant predictors. The predictors suggested that the probability of business failure was highly associated to illiquidity, low operating efficiency and high financial leverage. The logit model resulted in 12.36 per cent and 12.66 per cent Type I and Type II errors, respectively, while the neural network yielded 6.74 per cent and 23.62 per cent Type I and Type II errors, respectively. The linear discriminant analysis produced the highest Type I error, 41.57 per cent. Chen et al. (2006) concluded that the logit regression and neural network models were the best prediction models which yielded the lowest misclassification.

Ding (2007) compared a decision-tree algorithm model with an MDA model and a probit model using variables of operating earnings and interest payment for debt. The decision-tree algorithm model was able to predict business failure accurately two and five years prior to failure.

Muller et al. (2009) evaluated the effectiveness of four failure prediction models using data of South African companies listed on the Johannesburg Stock Exchange. The study found that logit analysis and neural networks had the highest overall predictive accuracy, but MDA and recursive partitioning were more accurate in predicting failed companies. Since Muller et al. considered Type I errors (misclassifying non-failed companies that were failed) more costly than Type II errors (misclassifying failed companies that were non-failed), they rated MDA and recursive partitioning as more robust.

Abdullah et al. (2008) compared multiple discriminant analysis, logit regression and hazard model in identifying financially distressed companies in Malaysia. The sample comprised 26 failed and 26 non-failed companies matched by industry and size. Ten ratios were used. The accurate prediction of the hazard model was 94.9 per cent, while the MDA was 85 per cent and the logit model was 82.7 per cent in the estimation sample. The hazard model seemed to provide an overall better accuracy rate than the MDA and logit models. But the MDA model gave a higher accuracy rate when the estimation equation was applied to the holdout sample. Abdullah et al. (2008) also found that leverage ratio (debt to total assets) was a significant predictor in all three models, net income growth was another significant predictor in the MDA model, and return on asset (ROA) was significant in the logit and hazard models. But the coefficients of the ROA had opposite sign in the logit and hazard model. Abdullah et al. (2008) therefore suggested that future research should investigate these contradictory results.

In summary, recent studies comparing the predictive power of various models have produced mixed results, with no single model clearly predicting more accurately than the others. As stated by Altman (1993b) "a generalized model can be modified to better suit the specific needs and characteristics either of the user or for the types of firms being analysed" (p. 245). The demand for a consistent business failure prediction model that is developed for specific a country or region remains unsatisfied, and provides opportunities for future academic research.

2.6 Cash Conversion Cycle

Working capital management has important effects on a company's value and risk (Smith, 1980). Soenen (1993) noted that a company's reliance on external financing is determined by the length of cash conversion cycle (CCC); he even suspected that a longer CCC might cause companies to go bankrupt. But much less attention has been paid on studying how CCC is related to business failure. This section reviews past empirical studies of CCC.

CCC was first introduced by Gitman (1974) and was later refined by Gitman and Sachdeva (1981). It is a key measurement of liquidity that measures how fast a company can convert its products into cash, how long a company's fund are tied up in the cycle, and how long between paying for raw materials and receiving cash from sales. CCC combines several activity ratios that involve accounts receivable (AR), accounts payable (AP) and inventory turnover, according to the following formula:

$$CCC = DIO + DSO - DPO$$

DIO denotes number of day inventory turnover, and is calculated by average inventory over purchase per day, purchase is cost of goods sold (COGS) less opening inventory add closing inventory; DSO denotes number of day sales turnover that is calculated by average AR over sales per day; DPO denotes number of day purchase turnover that is calculated by average AP over purchase per day.

To calculate a CCC, several items from the financial statements are needed:

- sales and purchase from the income statement
- opening and closing inventory from the balance sheet
- opening and closing account receivable from the balance sheet
- opening and closing account payable from the balance sheet
- number of days in the period (year = 365 days, quarter = 90 days).

CCC is predicated on four factors: the number of days it takes customers to pay what they owe; the number of days it takes the company to make its product; the number of days the product sits in inventory before it is sold; and the length of time that the company has to pay its vendors.

Economists and business consultants consider that CCC, unlike other often-used ratios such as current ratio and quick ratio which may not provide advance notice of the cash flow position, is one of the truest measures of company's health and provides a more accurate reading of work capital pressure on cash flow. Current ratio and quick ratio do not work well for companies going through a period of dynamic change. For example, when collection of accounts receivable slows down and the company is actually in substantial need of capital, or the asset becomes sluggish, current ratio would still look good while quick ratio may even show improvement or remain steady.

There are usually two approaches in working capital management policy: aggressive and conservative. Jose et al. (1996) examined the relationship between profitability measures and liquidity management for firms over a 20-year period. They found strong evidence that aggressive working capital management policies enhance corporate profitability. An aggressive approach will result in a lower CCC by reducing the inventory and the accounts receivable period while increasing the accounts payable period; a conservative approach will result in a higher CCC by increasing the inventory and the accounts receivable period, while reducing the accounts payable period. There exists a trade-off between liquidity and profitability for CCC management because the longer the CCC, the longer the company has to wait to be paid, the longer that money is unavailable for investment elsewhere, the fewer working capital a company can generate, and more debt has to be borrowed to finance the working capital. Previous studies of CCC mostly examined how liquidity management is related to corporate profitability.

In an earlier study, Kamath (1989) had reported that net trade cycle was inversely related to profitability. Net trade cycle is a measurement closely correlated with the CCC. Soenen (1993) reported that net trade cycle was inconsistently related to the total rate of return on assets. His study identified the industry effects that the net trade cycle and returns varied from positive to negative from industry to industry.

In summary, Soenen (1993) suggested that a long CCC might be a primary reason why firms go bankrupt. The rationale is that firms have to forgo opportunity cost of other productive investments to keep the cash to maintain a long CCC. A search of the literature identified only one previous study by Back (2001) that examined CCC as bankruptcy prediction variables. Much less attention has been given to studying how

CCC and business failure are related. This study intends to examine this relationship based on Soenen's (1993) suggestion that long CCC might cause bankruptcy.

2.7 Predictor variables in business failure prediction models

The use of financial ratios in the accounting literature dates back to the 1890s, when the US banks used current ratio for making credit decisions, and profitability ratios for both credit and managerial analysis later. "Around 1919 the Du Pont Company began to use its famous ratio triangle system for managerial decision making, providing the foundation for the modern intercompany comparison scheme in accounting" (Barnes, 1987, p. 449).

The most commonly used ratios in predicting business failure can be grouped into five categories: financial ratios, measures of cash flow and funds flow, measures of financial decomposition, market prices, and qualitative managerial or behavioral characteristics. Numerous studies have tried to explore the ability of financial ratios in predicting business failure. Table 2.9 displays various financial ratios employed in major empirical studies. This section reviews the financial ratios used by researchers in previous business failure studies.

Financial ratios	**Beaver (1966)**	**Altman (1968)**	**Ohlson (1980)**
Working capital / total assets	√	√	√
Current assets / current liabilities	√		√
Cash flow / total assets	√		√
Total debt / total assets	√		√
Market value of equity / total assets		√	
Sales / total assets		√	
EBIT / total assets		√	
Net income / total assets	√		√
Retained earnings / total assets		√	
Company size			√

Table 2.9: Financial ratios used in major empirical studies of business failure

2.7.1 Financial information as independent variables

Financial information has long been recognized as useful in understanding business failure, as explained by Karels and Prakash (1987, p. 575):

> *The causes of business failure have been attributed to internal and external factors. Internal factors stem from poor management which is manifested through lack of responsiveness to change, inadequate communication, over expansion, mishandling of major projects and fraud. External factors may include labor problems, governmental regulation and natural causes such as weather disasters. Researchers have used financial ratios to account for these factors ...*

Smith and Winakor (1930) were the first researchers to use ratios to predict company financial distress. They used 21 ratios to analyse a sample of distressed companies in a 10-year trend and found that net working capital to total assets was the most reliable predictor. Fitzpatrick (1932) and Ramser and Foster (1931) also concluded that financial ratios were the predominant choice of variables and were reliable predictors for studying business failure. Beaver (1966) noted in his study that financial ratios could predict failure at least five years prior failure occurred. Watts and Zimmerman (1986) agreed that accounting data is useful in predicting business failure, and Nittayagasetwat (1994) confirmed that financial ratios could train an ANN model to predict business failure more accurately.

There seems no doubt that financial ratios can give indicators to predict business failure. Bellovary et al. (2007) noted that the bankruptcy studies from 1930 to 2004 had used 752 different variables; over the last 40 years the common variables used were return on assets (54 studies), current ratio (51 studies), working capital/total assets (45 studies), retained earnings/total assets (42 studies), EBIT/total assets (35 studies), sales/total assets (32 studies), quick ratio (30 studies), total debt/total assets (27 studies), current assets/total assets (26 studies) and net income/net worth (23 studies). But which ratios are most suitable as independent variables remains questionable. Several researchers have sought an answer.

Hossari and Rahman (2005) studied 53 business failure studies and found 48 useful financial ratios, the five most useful being net income/total assets, current assets/current liabilities, total liabilities/total assets, working capital/total assets, and earnings before interest and taxes/total assets.

Casey and Bartczak (1984) compared the predictive accuracy of accrual-based earning ratios and operating cash flow ratios and found that conventional ratios surpassed operating cash flow ratios in all five years prior to business failure. Adding another operating cash flow variable did not improve the model's predictive power.

Gentry et al. (1985) studied cash flow variables and business failure using a cash-based fund flow logit model to examine 33 companies that failed from 1970 to 1981. They used eight independent variables based on Helfert's (1982) study. The model reported an overall 83 per cent accuracy one year prior to failure and 77 per cent three years prior to failure. Gentry et al. (1985) concluded that cash-based fund flow improved the ability to predict business failure. This finding was later confirmed by Mossman et al. (1998), who found that financial ratios were more effective in explaining the occurrence of business failure one year prior to failure, while a cash flow model was more consistent in classifying failed and non-failed two or three years preceding failure.

Zavgren (1985) studied failed companies that filed for chapters X or XI from 1972 to 1978. Her sample included only manufacturing companies, and excluded companies from the wholesale and retail industries, with 45 non-failed manufacturing companies matched on industry and asset size. Five-year financial statements were obtained from the COMPUSTAT files, and ratios based on the study of Pinches et al. (1973) were used. These ratios were inventory to sales, accounts receivable to inventory, cash to total assets, quick assets to current liabilities, total income to total capital, debt to total capital and sales to net plant. For each of the five years prior to actual failure, the model showed a prediction accuracy of 82, 83, 72, 73 and 80 per cent, respectively.

Similar to Zavgren's (1985) study, Harlan Platt and Marjorie Platt (1990) used seven categories of financial ratios from the Pinches et al. (1973) study to investigate 60 failed companies that filed for Chapter XI bankruptcy and had been liquidated under Chapter VII bankruptcy rules from 1972 until the first quarter of 1986. The ratios included profitability, capital intensiveness, financial leverage, inventory intensiveness, receivable intensiveness, short-term liquidity and cash position (Platt & Platt, 1990).

Sampled companies came from the transportation, wholesale, retail and manufacturing industries and were drawn from COMPUSTAT tapes, with 60 non-failed companies matched by year, asset size and industry. Industry averages were collected from the Internal Revenue Service to compare with the ratios. The overall results were 93 per cent for the failed companies and 86 per cent for the non-failed companies. Platt and Platt (1990) considered that the industry-relative ratios provided stable forecasts.

Hol (2007) analysed the impact of adjusting the accounting treatment using the Ohlson (1980) model to classify failed companies. Peat (2007) used expected earnings and earning dispersion as variables in a business failure prediction model. Both studies indicated that adjusted financial ratio data can improve the predictive power.

In summary, theoretical models do not provide guidance as to which financial ratios are most important for prediction business failure. Most studies have been inconsistent in determining what predictor variables to use in bankruptcy prediction research (Ball & Foster, 1982; Jones, 1987) and they have failed to indicate how financial variables were selected (Scott, 1981). Due to a lack of theoretical support, researchers had to look for other procedures when selecting independent variables (Jones, 1987). For example, Beaver (1966) and Altman (1968) selected financial ratios based on their popularity and predictive success in earlier studies. As stated by Ohlson (1980, p. 118), "the first six predictors were partially selected simply because they appear to be the ones most frequently mentioned in the literature". Earlier researchers (Johnson, 1970) had already argued that financial ratios contained insufficient information about the economic conditions confronting the management and the investors. Consequently, Mensah (1984) suggested the inclusion of non-financial variables such as macroeconomic indicators to possibly improve failure assessment.

2.7.2 Non-financial information as independent variables

Non-financial firm characteristics can be an important business failure predictor (Dimitras et al., 1996; Loong & Hughes, 2007). Previous research by Rose et al. (1982), Mensah (1984) and Liu (2004) has suggested that adding macroeconomic variables can increase a prediction model's predictive accuracy.

For example, Shumway (2001) found that some market-driven ratios such as company size and stock returns had strong correlation with business failure. His study compared a hazard model against Altman's model for 300 companies that failed between 1962 and 1992, obtaining data from the Wall Street Journal Index, the Capital Changes Reporter, the Compustat Research file, the Directory of Obsolete Securities (1993) and Nexis. The model incorporated the independent variables of the Altman (1968) and Zmijewski (1984) models, which included working capital to total assets, retained earnings to total assets, earnings before interests and taxes to total assets, market equity to total liabilities, and sales to total assets (from Altman model), net income to total assets, total liabilities to total assets, current assets to current liabilities (from Zmijewski model). However, he found that half of the accounting ratios were poor predictors.

Keasey and Watson (1987) employed 73 failed companies and 73 non-failed companies from 1970 to 1983 in a logistic regression to construct three prediction models: Model 1 contained financial ratios only, Model 2 non-financial data only, and Model 3 a mixture of financial ratios and non-financial data. The models included 28 financial variables and eight non-financial variables. Keasey and Watson found that the accurate classification rates of the three models were 78.7 per cent, 75.3 per cent, and 82.2 per cent, respectively. Model 3 with non-financial variables was able to predict more accurately than Model 1.

Wu (2004) studied whether non-financial data alone, or in conjunction with financial ratios, can predict failed companies in the Taiwan Stock Exchange (TSE). The study included 31 companies that failed between 1995 and 2000, and 31 non-failed companies matched by industry, size and similar products. Factor analysis selected 18 ratios, with the highest loading in each factor obtained from the database of Taiwan Economic Journal. The prediction model included three non-financial variables: board holding ratio, stock price trend and change of auditor. Board holding ratio was represented by board holding divided by capital issued; change of auditor was denoted by 0 = no change and 1 = change; stock price trend was calculated using the formula: $(H_t - H_{t-1}) + (L_t - L_{t-1})/(H_t + H_{t-1} + L_t + L_{t-1})$ where H_t and L_t represented the high and low values of the stock price in year t. The financial and non-financial variables were added into a logistic regression model to see if they could increase the rate of accuracy. The study found that the financial model correctly predicted failure of 79.03, 77.42 and

66.13 per cent one, two and three years, respectively, prior to failure. When the three non-financial variables were added, the models' correct prediction improved to 87.1, 77.42 and 72.58 per cent, respectively. Wu (2004) therefore concluded that the non-financial information contained in the prediction models increased the correct prediction percentage.

Sun and Li (2009) analysed the predictability of business failure in China using MDA, logit and ANN models and found that qualitative attributes of multiple experts' experiential knowledge effectively improved the predictability. Sun and Li's findings supported Wu's (2004) argument that qualitative information would somehow increase the predictive ability.

The current research included two non-financial variables: change of auditor from Wu (2004)'s study and interest rates, as discussed below.

It is expected that companies suffering deteriorating financial conditions would be more likely to change auditor than companies whose finances are healthy. But previous empirical research has found mixed evidence that auditor switch and prediction of business failure are related.

Some studies have found that business failure is more strongly associated with a qualified auditor's opinion than it is with auditor change. Chow and Rice (1982), Dodd et al. (1984), Dopuch et al. (1986) and Elliot (1982) examined the information of qualified opinions, and found that the market inevitably reacted to audit opinion.

Chow and Rice (1982) analysed auditor changes for a sample of 9,460 firms in 1973 and 1974, and concluded that "firms tend to switch auditors after receiving qualified opinions" (p. 334). A more recent study by Geiger et al. (2005) pointed out that qualified opinions could serve as an early warning signal for financial distress, for some audit going-concern opinions issued were not related to differences in client characteristics but to changes in auditor reporting decision.

However, Citron and Taffler (1992) and Barnes and Huan (1993) argued the importance of strategic considerations in an auditor's decision of issuing going-concern qualified opinion. Chow and Rice (1982) noted that auditor change associated with qualified auditor opinions is marginal. Schwartz and Menon (1985) found that modifying the auditor's opinion was not the underlying force that motivated changes in auditor; rather, it was smaller audit firms with presumably less conservative accounting principles that attracted failing firms to switch auditor. Schwartz and Menon found that auditor changes among financially deteriorating firms are more frequent than in financially sound firms.

Lennox's (2000) study supported Schwartz and Menon's finding by noting that some companies replaced their auditor in the hope of receiving an unqualified opinion, while some companies switched auditor to increase the probability of receiving a modified audit report.

An earlier study by Kida (1980) examined whether the issuing of a going-concern qualified opinion is a function of the auditor's ability to predict a client's eventual bankruptcy. Kida found that auditors sometimes choose not to issue a going-concern qualified opinion due to fear of losing the client, even if their clients have a high possibility of going bankrupt. Kida's argument received support from Blay (2005), who found that auditors tend not to issue a modified audit report when facing a high possibility of losing the client.

In sum, previous studies have provided mixed findings regarding the relevance of auditor switch to the prediction of business failure. This research examined the link between changing auditors and business failure, an area requiring further study, as explained by Chen et al. (2004, p. 423):

> *Although the existing empirical evidence indicates that the association between auditor change and subsequent firm failure is not as strong as the association between auditor qualified opinion and subsequent firm bankruptcy it is none the less significant and may provide additional important source of information about clients more aggressive preference for application of accounting principles beyond that conveyed by the qualified auditor opinion which is useful in explaining and anticipating firm bankruptcy. The usefulness of auditor changes in predicting firm failure and its incremental explanatory ability beyond the information conveyed by auditor qualified opinions alone remains to an open empirical question in the existing relevant research literature.*

Furthermore interest rates could be crucial for high-geared companies and may impact on business failure (Turner et al., 1992; Graves & Smith, 2002). Mensah (1984) remarked that liquidity ratio, long-term leverage ratio and interest coverage helped predicting bankruptcy. Rose et al. (1982) noted that interest rates influence a company's long-term capital spending, adaptability and flexibility. Argenti (1976) considered high debt/equity ratio one crucial reason for business failure. Darayseh et al. (2003) used change in GNP, interest rates and stock price index to predict the business failure of 220 companies, with results indicating that the logit model with macroeconomic variables gave greater prediction accuracy five years prior to business failure.

HIBOR (Hong Kong Interbank Offering Rate) is an interest rate stated in Hong Kong dollars on the lending and borrowing between banks in the Hong Kong interbank market. It refers to the middle closing rates quoted by the Standard Chartered Bank in the interbank money market. HIBOR is the official rate traded in the Asian economy, similar to London Interbank Offering Rate (LIBOR), the UK version. Both LIBOR and HIBOR reflect the funding cost for banks which lend money to one another at tenors ranging from overnight to one year. The HIBOR market rate is set by 20 authorized banks by referencing the market rate and sending their quotations to the Hong Kong Association of Banks. The Association, after receiving these 20 quotations, takes 14 middle quotations, takes out the average rate from them, rounds off to five decimal places, and announces the HIBOR rate to be used in the open market.

Given that prices for derivatives, other personal loans such as mortgage loans and Hong Kong currency loans to small and medium-sized enterprises are set by the HIBOR rates, HIBOR can be viewed as the borrowing cost for most Hong Kong companies raising loans in Hong Kong currency. Andrew Fung, executive director of Hang Seng Bank, stated that Hong Kong listed companies and many corporate loans and bonds are based on an interest rate benchmarked on LIBOR and HIBOR. As HIBOR rate fluctuates depending on the situation of market liquidity, a soar in the HIBOR would impose extra debt burden on corporations and could increase their default risk.

Prior study of HIBOR by Yu & Fung (2005) who used the 12-month HIBOR as risk-free interest rate in a study to examine if the Merton approach can effectively monitor default probability for Hong Kong non-financial companies listed in the Heng Sang Index (HSI) during 1991 to 2005.

The historical three-month HIBOR rates between 1998 and 2012 are listed in Table 2.10.

Recent three-month HIBOR rates have remained at low level since the financial crisis of 2009. The average three-month HIBOR rate dropped from 2.273 per cent in 2008 to 0.38 per cent in 2009, and further to 0.25 per cent in 2010. In fact the three-month HIBOR rate remained constant at 0.33 per cent for 17 months from August 2010 to December 2011.

Year	**Highest**	**Lowest**	**12-month average**
1998	11.78	5.48	8.08
1999	6.40	5.14	5.84
2000	6.85	5.68	6.12
2001	3.58	1.81	3.58
2002	2.12	1.48	1.79
2003	1.41	0.15	0.97
2004	0.93	0.07	0.39
2005	4.22	0.65	3.00
2006	4.56	3.91	4.20
2007	5.0	3.56	4.25
2008	3.72	1.43	2.27
2009	0.82	0.13	0.38
2010	0.48	0.13	0.25
2011	0.33	0.33	0.33
2012	0.55	0.43	0.48

Table 2.10: Highest and lowest three-month HIBOR rates, 1998–2012

The three-month HIBOR rate was at its highest, 11.78 per cent, in August 1998 when the Asian financial crisis broke out in South Korea. When the economic bubble burst in 1998, the HIBOR rate declined 56 per cent from its high of 11.78 per cent to reach 5.17 per cent in May 1999. The HIBOR continued to fall: to 1.81 per cent in 2001 and, after SARS broke out in Hong Kong in March 2003, to 0.15 per cent by the end of 2003, and 0.07 per cent in February 2004. The Hong Kong economy started to pick up later in 2004, and the HIBOR responded, soaring to 2.25 per cent in early 2005, reaching 4.15 per cent at the end of 2005, and staying constant at 4–5 per cent in subsequent years. Interestingly, during 2005 to 2007 when the HIBOR rate climbed back to a higher level, the number of companies delisted from the HKEx also increased.

HIBOR rates from 1990 are displayed in Appendix 1.

In summary, no previous empirical studies have examined the relationship between business failure and HIBOR rate. This research is the first to do so.

2.8 Chapter summary

This chapter has summarized the development of business failure prediction models, described previous studies of business failure prediction and discussed comparisons of the more common prediction models. Most of these comparisons were based in developed countries, mainly the US and the UK, with very few studies conducted in Asia, including Hong Kong.

Empirical evidence indicates that financial ratios are useful in discriminating between failed and non-failed companies. On the other hand, non-financial data can also be useful in predicting business failure. However, few business failure prediction studies have applied theoretical models or provided economic guidelines in selecting variables (Jones, 1987), and no consensus has been reached as to which variables are the most effective predictors. Most business failure studies have used the statistical techniques of multiple discriminant analysis and logistic regression to develop prediction models.

Keen to ascertain the most accurate prediction models, researchers have compared different models, including multiple discriminant analysis versus logit regression, artificial neural network versus logistic regression, and multiple discriminant analysis versus artificial neural network. However, the findings have been mixed. Each model has its advantages and disadvantages and no single model is superior to the other in making accurate predictions.

This study extends previous work on business failure prediction by comparing two models, the Altman (1968) model and the Ohlson (1980) probabilistic model, to determine which model is more accurate in predicting business failure using a Hong Kong data set. It used reported data from HKEx database, including three years of financial data, to study companies which failed between 1998 and 2011.

This study is the most comprehensive research of corporate failure prediction in 14 years using contemporary Hong Kong company data. In addition, it included two variables, cash conversion cycle and HIBOR rate, that have never been tested in previous business failure research.

The next chapter describes the methodology and research design, including the procedures of sample selection and data collection, and how the hypotheses were tested.

CHAPTER THREE

METHODOLOGY

3.1 Chapter overview

This study examined the accuracy of the Altman Z-scores prediction model and the Ohlson O-scores model, using a sample of companies publicly listed in the Hong Kong Stock Exchange (HKEx). The accuracy of the two models was determined by how well they classified failed and non-failed companies. The study also tested the differences in Ohlson O-scores resulting from cash conversion cycle and non-financial variables (namely change of auditor and the effect of the HIBOR rates) on predicting business failure.

To meet the research objectives, samples of public companies were drawn from the HKEx between 1998 and 2011. The hypotheses were tested at the .05 significance level.

This chapter describes the research method, presents the hypotheses, and outlines the sample selection and data collection procedures. It discusses in detail the methodology used to test and statistically analyse each hypothesis.

3.2 Research design

This research adopted a longitudinal approach by observing the sample of Hong Kong public-listed companies for between one and three years prior to delisting. The financial analysis used company information collected from the public domain. The models being tested – the Altman (1968) and Ohlson (1980) models – are the two most popular prediction models; in this study they were used to analyse characteristics and the significant difference in financial data between the failed and non-failed public companies. The models were compared to determine which model is more robust in predicting business failure in Hong Kong.

3.3 Basis for analysis

As described in the previous chapter, both the Altman (1968) and the Ohlson (1980) models identify business failure by considering financial ratios, and both were developed from studies of US companies: Altman (1968) used 33 failed and 33 non-failed manufacturing companies, while Ohlson used 105 failed and 2,058 non-failed companies of various types. It is therefore of interest to investigate how well these two models can predict business failure for Hong Kong public-listed companies, one to three years prior to the failure occurring.

This study tested the effects of two non-financial variables on the Ohlson O-scores model in predicting business failure. The variables were auditor change and change of HIBOR interest rate. Auditor change is a non-financial variable that assumes that, when failed companies engage in manipulating accounting principles to make their financial reporting sound, their auditors will probably either qualify their audit reports and resign or refuse to go along with the manipulation and be fired. Hence, failed companies are more likely to switch auditors. A company's financial costs will increase when interest rates go up, leading to a fall in profit and an increased risk of default.

3.4 Statement of hypotheses

This study addressed four research questions:

(1) Can the Altman (1968) Z-scores and Ohlson (1980) O-scores models accurately predict business failure for Hong Kong public companies without having to modify the variables or coefficients?

(2) Will revising the cutoff values improve the predictive power of the Altman (1968) Z-scores and Ohlson (1980) O-scores models?

(3) Which prediction model, the Altman (1968) Z-scores or Ohlson (1980) O-scores model, is more accurate in classifying business failure for Hong Kong public companies?

(4) Are cash conversion cycle and non-financial variables, including change of auditor, and HIBOR interest rates, associated with the accuracy of predicting business failure for Hong Kong public-listed companies?

Nine hypotheses were developed to address these questions and guide the research.

Research Hypothesis 1:

The first hypothesis stated in null form is:

H_0: *The predictive accuracy of the Altman (1968) 5-variable prediction model is less than 50 per cent when predicting business failure for Hong Kong public-listed companies.*

The first hypothesis stated in alternative form is:

Ha: *The predictive accuracy of the Altman (1968) 5-variable prediction model is greater than 50 per cent when predicting business failure for Hong Kong public-listed companies.*

Hypothesis 1 was tested on a sample of 78 companies, comprising 39 failed companies and 39 non-failed companies matched by asset size and industry. Chi Square and Z tests were used, with 95 per cent confidence level.

Research Hypothesis 2:

The second hypothesis stated in null form is:

H_0: *There is no significant difference at the .05 level for the strength of predicting business failure using the Altman (1968) 5-variable prediction model and the strength of the Altman (1968) model using revised cutoff value, when the two models are applied to company data from Hong Kong listed companies.*

The second hypothesis stated in alternative form is:

Ha: *There is a significant difference at the .05 level for the strength of predicting business failure using the Altman (1968) 5-variable prediction model and the strength of the Altman (1968) model using revised cutoff value, when the two models are applied to company data from Hong Kong listed companies.*

This hypothesis was tested on the same 78 companies as for Hypothesis 1, using a Z-test with a 95 per cent confidence level.

Research Hypothesis 3:

The third hypothesis stated in null form is:

H_0: The predictive accuracy of the Ohlson (1980) O-scores model is less than 50 per cent when predicting business failure for Hong Kong public-listed companies.

The third hypothesis stated in alternative form is:

Ha: *The predictive accuracy of the Ohlson (1980) O-scores model is greater than 50 per cent when predicting business failure for Hong Kong public-listed companies.*

This hypothesis was tested on the same 39 failed companies and 39 non-failed companies as for Hypothesis 1, plus 195 randomly selected non-failed companies, giving a total sample size of 234 companies. This hypothesis was tested using Chi Square and Z-tests with 95 per cent confidence level.

Research Hypothesis 4:

The fourth hypothesis stated in null form is:

H_0: There is no significant difference at the .05 level for the strength of predicting business failure using the Ohlson (1980) O-scores model and the strength of the Ohlson (1980) model using revised cutoff values, when the two models are applied to company data from Hong Kong listed companies.

The fourth hypothesis stated in alternative form is:

Ha: There is a significant difference at the .05 level for the strength of predicting business failure using the Ohlson (1980) O-scores model and the strength of the Ohlson (1980) model using revised cutoff values, when the two models are applied to company data from Hong Kong listed companies.

Hypothesis 4 was tested on the same sample of 234 companies as for Hypothesis 3, using a Z-test with a 95 per cent confidence level to test the correlation of the two variables.

Research Hypothesis 5:

The fifth hypothesis stated in null form is:

H_0: There is no significant difference between the levels of predictive accuracy of the Altman revised cutoff model and the Ohlson revised cutoff model in predicting business failure for Hong Kong public-listed companies.

The fifth hypothesis stated in alternative form is:

Ha: There is a significant difference between the levels of predictive accuracy of the Altman revised cutoff model and the Ohlson revised cutoff model in predicting business failure for Hong Kong public-listed companies.

Hypothesis 5 was tested on a sample of 39 failed and 195 non-failed companies, using a Z test with a 95 per cent confidence level to test the correlation of the predictive difference of the two models.

Research Hypothesis 6:

The sixth hypothesis stated in null form is:

> *H_0: There is a negative or no significant relationship between the Ohlson O-scores and the total liabilities of the companies.*

The sixth hypothesis stated in alternative form is:

> *Ha: There is a significant positive relationship between the Ohlson O-scores and the total liabilities of the companies.*

Hypothesis 6 was tested on the full sample of 234 companies (39 failed and 195 non-failed companies), using a parametric Pearson Correlation Test at the .05 significance level.

Research Hypothesis 7

The seventh hypothesis stated in null form is:

> *H_0: There is a negative or no significant relationship at the .05 level between the Ohlson O-scores and cash conversion cycle of the failed companies.*

The seventh hypothesis stated in alternative form is:

> *Ha: There is a significant positive relationship at the .05 level between the Ohlson O-scores and cash conversion cycle of the failed companies.*

Hypothesis 7 was tested on the same full sample of 234 companies, using the Pearson Correlation Analysis with a .05 significance level to test the correlation of the two variables.

Research Hypothesis 8:

The eighth hypothesis stated in null form is:

H_0: *There is no significant difference at the .05 level between failed and non-failed companies experience change of auditor.*

The eighth hypothesis stated in alternative form is:

Ha: *There are significant differences at the .05 level between failed and non-failed companies experience change of auditor.*

Hypothesis 8 was tested on the same sample of 234 companies, using Chi-square test with a .05 significance level.

Research Hypothesis 9

The ninth hypothesis stated in null form is:

H_0: *The population distribution of the average HIBOR rate of the failed companies is not significantly different from that of the non-failed companies.*

The ninth hypothesis stated in alternative form is:

Ha: *The population distribution of the average HIBOR rate of the failed companies is significantly different from that of the non-failed companies.*

This final hypothesis was tested on the same sample of 234 companies, using an equality of means t test with a .05 significance level.

	Hypothesis	Test method
H_1	The predictive accuracy of the Altman (1968) 5-variable prediction model is greater than 50 per cent when predicting business failure for Hong Kong public-listed companies.	Chi-square test & Z-test
H_2	There is a significant difference at the 0.05 level for the strength of predicting business failure using the Altman (1968) prediction model and the strength of the Altman (1968) model using revised cutoff value, when the two models are applied to company data from the Hong Kong listed companies.	Z-test
H_3	The predictive accuracy of the Ohlson (1980) O-scores model is greater than 50 per cent when predicting business failure for Hong Kong public-listed companies.	Chi-square test & Z-test
H_4	There is a significant difference at the 0.05 level for the strength of predicting business failure using the Ohlson (1980) O-scores model and the strength of the Ohlson (1980) model using revised cutoff value, when the two models are applied to company data from the Hong Kong listed companies.	Z-test
H_5	There is a significant difference between the levels of predictive accuracy of the Altman revised cutoff model and the Ohlson revised cutoff model in predicting failure for Hong Kong public-listed companies.	Z-test
H_6	There is a significant positive relationship between the Ohlson O-scores and the total liabilities of the companies.	Pearson Correlation Analysis
H_7	There is a significant positive relationship at the 0.05 level between the Ohlson O-scores and cash conversion cycle of the failed companies.	Pearson Correlation Analysis
H_8	There are significant differences at the 0.05 level between failed and non-failed companies experience change of auditor.	Chi-square
H_9	The population distribution of the average HIBOR rate of the failed companies is significantly different from that of the non-failed companies.	Equality of means t-test

Table 3.1: Summary of hypotheses and test methods

The next section explains how the test samples were selected.

3.5 Sample selection

Two possible approaches to sampling are the matched-paired technique and uneven sample size procedure; however, previous research offers no guidance as to which technique is preferable for studying business failure. The matched-paired technique has been used by many failure prediction models (Beaver, 1966; Altman, 1968; Edmister, 1972; Zavgren, 1985; Platt & Platt, 1990). Pinches (1980) suggested that unequal sample sizes will influence the results, while Mutchler (1985) studied the effect of unequal sample sizes and concluded that multiple discriminant and logit studies should use samples of equal size. Zavgren (1983) found that matching samples was a more appropriate technique for prediction studies. However, Ohlson (1980) argued that matching samples according to size or industry tends to be arbitrary. The matching-selection technique has been used by majority of the business failure studies (Beaver, 1966; Altman, 1968; Edmister, 1972; Blum, 1974; Norton and Smith, 1979; Gentry et al., 1985; Zavgren, 1985; Platt & Platt, 1990; Bukovinsky, 1993; Nittayagasetwat, 1994; McGurr, 1996). Furthermore, Neves and Vieira (2006) found that balanced data sets (that is, the same number of failed and non-failed companies) resulted in better predictability.

This research utilized two sample sets. The first was a sub-set sample that contained 39 failed and 39 non-failed companies controlled by industry, asset size and calendar year selection. This pair-matched sub-set sample of 78 companies was used for testing the Altman (1968) Z-score model. The second sample set consisted of 156 randomly selected companies plus the 78 companies in the sub-set; this second set therefore contained 234 unequal numbers of failed and non-failed companies. This full sample was used for testing the Ohlson (1980) O-score model.

The remainder of this section describes how the two samples were selected.

3.5.1 The pair-matched samples

The pair-matched sample was achieved by first identifying a group of failed companies and then matching them with an equal number of non-failed companies controlled by industry, size and calendar year.

Failed companies

The first step was to select the failed companies. In this research, companies were defined as "failed" if they were unable to pay their financial obligations when these fell due (Beaver, 1966). This study looked at business failure from investor's standpoint. That is, once a company is delisted, even though the delisted company will continue to operate, the stock value become worthless and shareholders lose their investment as the shares are no longer available to exchange publicly.

This study focused on Hong Kong corporations after 1997, when the former British colony was handed back to China. The failed corporations are publicly listed in the HKEx. Appendix 3 shows the entire data set of the delisted companies during this period. Conditions for inclusion in the failed category were (a) companies listed in the HKEx for at least three consecutive years, (b) delisted between 1998 and 2011 due to financial problems, and (c) industries other than financial and property industries. The first criterion was to ensure that at least three years of financial data were available for calculating the prediction scores; the second was to ensure that no similar study published after 1997 had used the same data; and the third was to ensure that the financial data were comparable.

The delisted companies are searched through the HKEx website http://hkex.com.hk/eng/stat/statrpt/statrpt.htm. Appendix 3 lists the 220 possible delisted companies. To be included in the study, each failed company had to have financial data available for at least three consecutive years prior to the delisting date. Financial data included the balance sheet, the profit and loss income statement, the cash flow statement and the equity statement.

The delisting of a public-listed company commonly results from any of five situations: (a) privatization, acquisition or mergers, takeover, and voluntary windup or withdrawal; (b) compulsory windup by creditors; (c) failure to disclose financial information as required by HKEx or fraudulent accounting; (d) illegal activities that violate the HKEx listing rules; and (e) transfer from the GEM (growth enterprises market) to the Main Board. This study included only companies delisted because of situations (b) and (c) (companies being wound up by creditors and companies that failed to disclose financial information according to HKEx requirements).

Companies delisted under situation (a) were not included in this study because they could be companies which decided to go private, to merge with another company or to go public overseas, and so they did not necessarily have financial problems. Similarly, companies delisted under situation (d) were involved in illegal activities, such as bribe activities against ICAC's (Independent Commission Against Corruption) Bribery Protection Ordinance, and did not necessarily have financial problems. These companies could still be financially sound, even though they had committed illegal activities, and thus their financial condition could not be predicted with financial ratios. Companies delisted under situation (e) were companies that had transferred from GEM to the Main Board for larger fundraising opportunities, and so they had no financial problems at all.

After eliminating delisted companies due to criteria (a) (109 voluntary windup and privatized companies), (d) (2 ICAC investigation companies) and (e) (65 companies transferred from GEM to the Main Board), the number had reduced from the initial 220 companies to 44 companies. Two companies without sufficient financial information and three financial and property companies were subsequently removed, making the final sample size of 39 failed companies that spanned many industries including communications, logistics, transportation, wholesalers, pharmaceuticals and garment manufacturing. The selection process is summarized in Table 3.2.

Number of firms delisted from the HKEx Main Board or GEM (1998 to 2011)		220
Less:	Companies that do not have at least three consecutive years of financial data	(2)
	Companies belong to the financial and property industries	(3)
	Companies delisted from the GEM market and transfer to Main Board	(65)
	Companies delisted for reasons of privatization or merger and acquisition	(93)
	Companies delisted for reason of ICAC investigation	(2)
	Companies delisted for reason of listing overseas	(6)
	Companies delisted for reason of voluntary windup	(9)
	Companies delisted due to convert nature	(1)
Final sample of failed companies		39

Table 3.2: Selection process for 39 failed companies

The failed sample size of 39 of this study was comparable to samples used in other business failure prediction research using pair-matched samples, including Altman's (1968) 33 companies, Deakin's (1972) 32 and Mensah's (1983) 30 (see Table 1.7).

The size of each of these 39 companies was determined by looking up their total asset value for the previous three fiscal years. Each failed company's standardized industrial classification code (SIC code) was searched with the help of Dun & Bradstreet (1993) to determine to which industry they belonged. The study did not include companies from the financial, real estate, investment, mortgage and banking, or insurance industries. The sampled 39 failed companies are listed in Table 3.3.

Count	**Symbol**	**Company name**	**SIC**	**Year delisted**	**Asset size (HK$000)**
1	ENGL	Englong International Ltd	2311	1999	684,000
2	GILB	Gilbert Holdings Ltd	5131	2001	468,000
3	SIUF	Siu Fung Ceramics Holdings	3567	2001	75,000
4	BEST	Best Wide Group	5131	2001	186,000
5	YAOH	Yaohan Int'l Holdings Ltd	7389	2002	2,784,000
6	TOPS	Chengdu Top Sci-Tech	8135	2003	337,000
7	AKAI	Akai Holdings	5065	2003	10,857,600
8	GOWO	Gold Wo Int'l Holdings Ltd	5199	2004	171,000
9	KING	King Pacific Int'l Holdings	6531	2004	690,000
10	LDSP	Leading Spirit High-Tech	5065	2004	3,812,000
11	SCAN	Sinocan Holding Ltd	3411	2004	550,000
12	CDIG	China DigiContent	3639	2004	3,156,000
13	DAXI	Changchun Da Xing Pharma	8067	2004	319,000
14	401H	401 Holdings Ltd	4731	2005	39,000
15	AKUP	AKuP Int'l Holdings Ltd	7371	2005	64,000
16	ARCT	Arcontech Corporation	7373	2005	22,000
17	LCT	Luen Cheong Tai	1542	2005	344,000
18	CSPE	China Specialised Fibre	5169	2005	1,430,000
19	GPNA	GP Nano Technology Group	5199	2005	151,000
20	INFO	Infoserve Technology Corp	4813	2005	178,000
21	RIVH	Riverhill Holdings Ltd	5045	2005	27,000
22	RNAH	RNA Holdings Ltd	5094	2005	1,681,000
23	SHXI	Shanxi Central Pharma	2899	2005	326,000
24	YUEF	Yue Fung Int'l Group	5044	2005	733,000
25	DIGI	DigiTel Group Ltd	7373	2006	19,000
26	GOFC	Gold-Face Holdings Ltd	7389	2006	316,000

(Table 3.3 continued overleaf)

(continued)

Count	Symbol	Company name	SIC	Year delisted	Asset size (HK$000)
27	KINE	Kinetana Int'l Biotech	8731	2006	37,000
28	WANA	Wanasports Holdings Ltd	5136	2006	6,000
29	EZCM	Ezcom Holdings Ltd	5065	2007	1,214,000
30	GREE	Greencool Technology	5169	2007	1,471,000
31	MOUL	Moulin Global Eyecare	5049	2007	3,716,000
32	DATA	Datasys Technology Holdings	7371	2008	109,000
33	GOWZ	Goldwiz Holdings Ltd	5065	2008	739,000
34	ORPW	Orient Power Holdings Ltd	5064	2008	1,371,000
35	LOUL	Loulan Holdings	5122	2008	86,000
36	SANY	Sanyuan Group	5122	2009	117,000
37	PCMK	Peace Mark (Holdings) Ltd	5094	2011	10,678,000
38	PANS	Pan Sino Int'l Holding Ltd	5149	2011	626,000
39	EGAN	Eganagoldpfeil Holdings	5094	2011	4,790,000

Table 3.3: Final sample of 39 failed companies

The years when the 39 failed companies were delisted are shown in Table 3.4.

Year delisted	No of companies
1998	0
1999	1
2000	0
2001	3
2002	1
2003	2
2004	6
2005	11
2006	4
2007	3
2008	4
2009	1
2010	0
2011	3
Total	39

Table 3.4: Year of delisting for 39 failed companies

The 39 failed companies were distributed among the production industry (SIC 23XX, 28XX, 34XX, 35XX, 36XX; five companies), the service industry (15XX, 47XX, 48XX, 65XX, 73XX, 80XX, 81XX, 87XX; 13 companies) and the wholesale industry (50XX, 51XX; 20 companies). Over half (54 per cent) of the sampled companies came from the wholesale industry. The industry type of the 39 failed companies is shown in Table 3.5.

SIC	Industry title	Count
15XX	Building contractor services	1
23XX	Garments & apparels products	1
28XX	Plastics & pharmaceutical products	1
34XX	Metal product	1
35XX	Machinery & equipments products	1
36XX	Household & electronic products	1
47XX	Transportation services	1
48XX	Communications services	1
50XX	Wholesale of durable goods	11
51XX	Wholesale of non-durable goods	10
65XX	Building services	1
73XX	Business services	6
80XX	Health care services	1
81XX	Legal services	1
87XX	Engineering services	1
	Total	39

Table 3.5: Industry type of the 39 failed companies

Non-failed companies

After the 39 failed companies were identified, and each company's asset size and SIC ascertained, the next step was to match the non-failed companies. For each failed company, a non-failed company was matched by a four-digit SIC code and asset size was selected. The asset size was based on the asset value reported in each company's last annual report and the asset size of the matching company reported for that same year. If the exact asset size could not be matched, the company with the closest asset size was chosen.

The process of matching the non-failed companies involved randomly picking the first batch of 100 public-listed companies drawn from the HKEx Main Board and GEM market. To qualify as "non-failed" candidates, each company's history of listing year and delisting year were checked from the Webb database (http://webb-site.com) to ensure that they were continuously listed in the HKEx between 1997 and the present. Those companies delisted in any year during this period were disqualified and were eliminated from the first batch. Next, the SIC codes for the potential candidates were searched with the help of Dun & Bradstreet (1993). Non-failed companies with same SIC code as the failed companies became possible match-pair candidates. Then the asset size of these non-failed companies was searched from the HKEx database, and was also based on the asset value reported in the annual report of the year corresponding to that of their possible pairing partner.

The first batch succeeded in matching about half of the required non-failed companies. A second batch of 100 public-listed companies was drawn, and the matching process was repeated until all 39 non-failed companies were successfully matched. Table 3.6 lists the 39 matching non-failed companies.

3.5.2 The randomly selected samples

The randomly selected samples were used for studying the Ohlson (1980) O-score model, and the selection method replicated that used for Ohlson's (1980) study. Ohlson included in his sample 105 failed and 2,058 non-failed companies that were collected from the COMPUSTAT file. The proportion of the failed and non-failed was based on a 1:20 ratio. Since the size of the HKEx database is much smaller than that of the COMPUSTAT database, this study used a smaller 1:5 ratio instead. Therefore the required size for the non-failed companies was 195 (39*5=195). Deducting the 39 pair-matched non-delisted companies already on hand, an additional 156 (195 less 39) randomly selected non-failed companies were required.

These 156 non-failed companies were randomly collected from the HKEx database without controlling their asset size, industry or calendar year. The only selection criterion was that the companies were not from the financial or property industries. Details of the 156 randomly selected non-failed companies are given in Appendix 4.

Count	Symbol	Company name	SIC	Asset size (HK$000)
1	PROS	Prosten Technology	4812	257,000
2	DECA	Decca Holdings	7371	355,000
3	CTEC	Computech Holdings	7379	21,000
4	CHEV	Chevalier iTech Holdings	1522	549,000
5	KEES	Kee Shing (Holdings)	5169	827,000
6	ABCC	ABC Communications	7371	259,000
7	EXCL	Excel Technology Int'l	7373	217,000
8	ALCO	Alco Holding	5065	2,018,000
9	YTKG	Yangtzekiang Garment	5136	804,000
10	STAR	Starlite Holding	5199	417,000
11	CULC	Culturecom Holdings	7389	324,000
12	SUNC	Suncorp Technologies	5065	860,000
13	NGAI	Ngai Hing Hong	5162	381,000
14	KARR	Karrie International	5162	984,000
15	DVNH	DVN	4833	290,000
16	IMER	iMerchants	8731	221,000
17	YGMT	YGM Trading	6531	1,092,000
18	GOPK	Gold Peak Industries	5065	3,308,000
19	ELEG	Elegance International	5049	559,000
20	SNWY	Sunway International	5064	1,113,000
21	MOBI	Mobicon Group	5065	182,000
22	TONI	Tonic Industries	5065	913,000
23	GRAN	Graneagle Holdings	5136	86,000
24	SKYW	Skyworth Digital	5064	13,070,000
25	HAEC	HAECO	7699	2,997,000
26	CECI	CEC International	3679	589,000
27	ASMP	ASM Pacific Technology	3674	2,898,000
28	UNPC	United Pacific	3524	1,054,000
29	YIPS	Yip' Hang Cheung	2911	761,000
30	MANS	Man Sang International	5094	655,000
31	HUNG	Hung Hing Printing Group	2652	779,000
32	IDTI	IDT International	5065	1,804,000
33	NESP	New Spring Holdings	5122	183,000
34	PAKF	Pak Fah Yeow Int’l	5122	389,000
35	STYL	Styland Holdings	5141	240,000
36	MING	Mingyuan Medicare	2835	473,000
37	VTEC	Vtech Holdings	5065	3,531,060
38	TIME	Timeless Software	8028	281,000
39	HERA	Herald Holding	5045	557,000

Table 3.6: The 39 sampled non-failed companies

3.6 The division of samples

The full sample of 234 companies was divided into three groups: Group 1 consisted of 39 failed companies; Group 2, 39 pair-matched non-failed companies controlled by asset size and industry; and Group 3, 156 non-failed companies randomly selected from the HKEx without control criteria (except that they were not from the financial or property industries). Table 3.7 illustrates the classification and function of the three groups.

The 78 pair-matched sample in Group 1 (39 failed companies) and Group 2 (39 non-failed companies) formed the samples used to test hypotheses 1 and 2 using the Altman (1968) model. The full sample of 234 companies (39 failed companies in Group 1 and 195 non-failed random companies in groups 2 and 3) formed the samples to test hypotheses 3, 4 and 5 using the Ohlson (1980) model, and also for testing the remaining hypotheses 6–9.

Failed companies	Non-failed companies	
(39 failed companies) **Group 1**	(39 non-failed companies) **Group 2**	Pair-matched
	(156 non-failed companies) **Group 3**	Random

Group 1: Sample set of 39 failed companies for all hypothesis testing
Group 2: Sample set of 39 pair-matched non-failed companies for all hypothesis testing
Group 3: Sample set of 156 random non-failed companies for all hypothesis testing (except hypotheses 1 and 2)

Table 3.7: Division of the sample sets for hypothesis tests

3.7 Data collection

This study examined companies that had been delisted from the HKEx between 1998 and 2011, using both financial and non-financial data. The financial data were used to analyse the Altman and Ohlson models in hypotheses 1–7, while the non-financial data such as change of auditor and HIBOR interest rates were applied to test hypotheses 8–9. This section describes how the data were collected from the 234 sampled companies.

3.7.1 Collecting the financial data

Examining a company's financial status three years prior to delisting required obtaining financial data as early as 1995. Financial statements were available from two sources: electronic data from the Standard & Poor CapitalIQ database (http://spcapitaliq.com) or the HKEx database (http://hkex.org) from 2001 onwards, and microfiche annual reports at the public libraries, such as the Hong Kong Central Research Library (Causeway Bay) or the City Hall Library (Central), for years prior to 2001.

The financial data needed to satisfy four conditions:

1. the data must be available for at least three consecutive years during the period 1995 to 2011, thereby meeting the requirements of the Altman and Ohlson models for at least two years of data;

2. the data must contain date of delisting from the HKEx, in order to avoid ex post bias (*"financial statement data for the failed companies must be selected carefully to ensure that it is available prior to the date of bankruptcy filing, otherwise, 'back-casting' for many of the bankrupt firms may occur":* Ohlson, 1980, p. 110);

3. company's stock price must be available for the end of fiscal year from the HKEx or Quamnet database, to satisfy the Altman (1968) model's requirement of calculating the equity at market value;

4. companies are not to be from the financial or property/land development industries, in order to exclude companies such as banks, insurance companies and land developers, whose financial statements are structured differently from those of commercial and industrial companies.

3.7.2 Collecting the non-financial data

This study also examined the relationship between non-financial variables and business failure. These variables included HIBOR interest rate and auditor change. This section describes how these non-financial data were collected.

Movement of HIBOR rate

HIBOR interest rates are obtainable online from the Bloomberg database. The HIBOR rate of all tenures (1-week, 6-month, 9-month etc.) at any given time generally moves in the same direction but at different degrees. For example, 3-month HIBOR and 9-month HIBOR in February 2007 both moved up, and in June 2009 both decreased. For simplicity, this study opted to use 3-month HIBOR rates. More historical HIBOR rates for overnight, 1-week, 1-month, 3-month, 6-month, 9-month and 12-month between 1991 and 2012 are displayed in Appendix 2.

Auditor change

Auditor information is available in each annual report. For the purpose of this study, ‘No change’ was denoted by ‘0’, meaning that the same auditor audited all three years financial statements; ‘Change’ was denoted by ‘1’, meaning that a different auditor audited at least one year of the financial statements.

This study purposely adjusted for companies who switched auditor from Arthur Andersen (AA) in 2002 and 2003. AA, founded in 1913, was a Big Five CPA firm prior to the Enron scandal in 2002. During the Enron incident, AA was found to have reported fraud accounting with its client, Enron, and was forced to surrender its CPA licence in 2002. Knowing that companies who hired AA as auditor were forced to switch auditor in 2002 or 2003, these companies were adjusted to ‘No change’.

A complete list of auditor change is provided in Appendix 7.

3.8 Recording and calculating methods

The three years of financial data for the 234 sampled companies were extracted and entered into a Microsoft Excel spreadsheet that had been programmed to calculate the financial ratios of each of the three years prior to the delisting year. Financial data were extracted from three types of financial statement: balance sheets, profit and loss accounts, and cash flow statements, and these were converted into various financial ratios. The data entry format and the financial ratios are presented in appendices 5 and 6, respectively.

To avoid confusion, it is necessary to define several terms when interpreting the three-year financial data for the failed and non-failed companies throughout this dissertation. These include “1 year prior to delisting”, “2 years prior to delisting”, “3 years prior to delisting” for failed companies and “first year of observation”, “second year of observation” and “third year of observation”. Table 3.8 illustrates each term.

For the failed group, if 2009 was the delisting year, then 2008 is “1 year prior to delisting”, 2007 is “2 years prior to delisting” and so on.

For the pair-matched non-failed group, if 2009 was the delisting year of their matched failed partner, then 2008 is “third year of observation”, 2007 is “second year of observation” and 2006 is “first year of observation”.

For the randomly selected non-failed group that do not have a matched failed partner, if 2007, 2008 and 2009 were the three randomly selected years, then 2009 is “third year of observation”, 2008 is “second year of observation” and 2007 is “first year of observation”.

Sample Group	2009	2008	2007	2006
Failed	Year of delisting	1 year prior to delisting	2 years prior to delisting	3 years prior to delisting
Non-failed (pair-matched)	N/A	third year of observation	second year of observation	first year of observation
Non-failed (random)	third year of observation	second year of observation	first year of observation	N/A

Table 3.8: Definition of years for failed and non-failed groups

3.9 Research methodology

This section describes the method and the sample group used to test each hypothesis.

3.9.1 Hypothesis 1

Hypothesis 1 referred to the predictive accuracy of the Altman (1968) model in classifying failed and non-failed companies in Hong Kong. The test of the hypothesis used a sample of 39 failed companies delisted from the HKEx between 1998 and 2011, and 39 matched non-failed public companies controlled by industry and asset size. Financial data for the three years prior to delisting were obtained from the HKEx database.

The financial data were input into a Microsoft Excel spreadsheet to generate the five variables necessary for calculating the Z-scores for each of the failed and non-failed companies. The five variables were: working capital to total assets; retained earnings to total assets; earnings before interests and taxes to total assets; market value of equity to book value of total liabilities; and sales to total assets. The predictive accuracy of the Altman (1968) model was analysed using the Statistical Packages for Social Sciences (SPSS GradPack version 19) by determining the financial data one year, two years and three years prior to delisting.

The equation for the Altman (1968) 5-variable prediction model was used:

$$Z = 0.012X_1 + 0.014X_2 + 0.033X_3 + 0.006X_4 + 0.999X_5$$

The Z-scores were calculated to classify all 78 sampled companies, both failed and non-failed. A Z-score value 1.81 or below indicated a company had the characteristics of failure, while a Z-score value greater than 2.99 indicated a company was financially healthy.

The predicted result of each company was then compared with its actual result and the numbers of correct and incorrect classification were accumulated into a 4-quadrant matrix table (Figure 3.1).

	Predict failed	Predict non-failed
Actual failed	fPf	fPnf
Actual non-failed	nfPf	nfPnf

Figure 3.1: Matrix for recording the model classifications

The data in this matrix are expressed as percentages. The upper left-hand cell is the percentage of failed companies correctly predicted failed (fPf); the lower right-hand cell is the percentage of non-failed companies correctly predicted non-failed (nfPnf); the other two cells are 1 minus the adjacent cell, where fPnf in the upper right-hand cell corresponds to a Type I error (mistakenly predict failed companies as non-failed) and nfPf in the lower left-hand cell corresponds to a Type II error (mistakenly predict non-failed companies as failed).

Hypothesis 1 was tested by a statistical technique z-test at the 95 per cent level of confidence. The equation by Nunthaphad (2000, p. 121) was used to compute the Z-test:

$$Z = (p - 0.5)/\sqrt{0.5 * 0.5/n}$$

where p = proportion of correct classified companies in the sample

n = total number of companies in the sample.

The null hypothesis was rejected if it was significant at the 5 per cent level, which would imply that the level of predictive accuracy of the Altman (1968) five-variable prediction model can predict business failure when applied to companies listed in the HKEx.

3.9.2 Hypothesis 2

Hypothesis 2 referred to the improved accuracy of the Altman (1968) 5-variable prediction model in predicting business failure when the cutoff value is revised. The model used the same 39 failed and 39 non-failed public companies as for Hypothesis 1.

The sample company was identified in HKEx and financial data were downloaded to a Microsoft Excel spreadsheet to calculate the Z-scores using financial ratios, and statistical calculations were performed in SPSS. Samples were tested at the 95 per cent confidence level.

The financial data obtained were used to calculate each failed and non-failed company's ratios and the total Z-scores for one year, two years and three years prior to delisting. Through observation (see Table 4.13), a company with revised Z-score larger than .95 was classified as 'non-failed', while a company having a revised Z-score smaller than .95 was classified as 'failed'. The null hypothesis was tested at the 95 per cent confidence level, and the null hypothesis was rejected if significant at the 5 per cent level.

3.9.3 Hypothesis 3

Hypothesis 3 referred to the accuracy of the Ohlson (1980) O-score prediction model in predicting failed and non-failed companies in Hong Kong.

The hypothesis was tested using a sample of 39 failed delisted from the HKEx between 1998 and 2011, and 195 (39 matched and 156 random) non-failed public companies during the same period. Financial data for three years prior to delisting were obtained from the HKEx database. The financial data were input into a Microsoft Excel spreadsheet to calculate the nine financial variables and the O-scores of each of the failed and non-failed companies. The equation used for the Ohlson (1980) prediction model (see Section 2.4) was:

$$P = -1.32 - 0.0407 \text{ SIZE} + 6.03 \text{ TLA} - 1.43 \text{ WCTA} + 0.0757 \text{ CLCA} - 2.37 \text{ NITA} - 1.83 \text{ FUTL} + 0.285 \text{ INTWO} - 1.72 \text{ OENEG} - 0.521 \text{ CHIN}$$

The nine variables were: log Size (Total assets to GNP price – level index); total liabilities to total assets; working capital to total assets; working capital to total assets; current liabilities to current assets; net income to total assets; operating cash flow to total liabilities; INTWO = 1 if net income was negative for the last two years, otherwise 0; OENEG = 1 if total liabilities were greater than total assets, otherwise 0; CHIN = (Nit – Nit-1)/(| Nit | + Nit-1), where Nit was net income for the most current period.

O-scores were calculated to classify the 234 sampled companies into failed or non-failed. An O-score larger than .38 indicated a company had the characteristics of failure, while an O-score value smaller than .38 indicated a company that was financially healthy. The predictive accuracy of the Ohlson (1980) model was analysed using the SSPS software by determining the financial data one year, two years and three years prior to delisting. The predicted result of each company was then compared with its actual result and the numbers of correct and incorrect classification.

Hypothesis 3 was tested by a statistical technique z-test at the 95 per cent level of confidence. The following equation (Nunthaphad, 2000, p. 121) was used to compute the Z-test:

$$Z = (p - 0.5)/\sqrt{0.5 * 0.5}/n$$

where p = proportion of correct classified companies in the sample

n = total number of companies in the sample.

The null hypothesis was rejected if significant at the 5 percent level, and it was inferred that the level of predictive accuracy of the Ohlson (1980) prediction model can predict business failure when applied to public companies in the HKEx.

3.9.4 Hypothesis 4

Hypothesis 4 addressed the improved accuracy of the Ohlson (1980) prediction model in predicting business failure when the cutoff value is revised. To test the hypothesis, the model was applied to the same 39 failed and 195 non-failed public companies as for Hypothesis 3.

Financial data were downloaded to a Microsoft Excel spreadsheet to calculate the O-scores using financial ratios, and SPSS was used to perform the statistical calculations.

The financial data obtained were used to calculate each failed and non-failed company's ratios and the total O-score for one year, two years and three years prior to failure. By observation (Table 4.20), an O-score greater than 1.3 was associated with a higher probability of failure, while the companies having the O-scores smaller than 1.3 were classified as healthy. The null hypothesis was tested at the 95 per cent confidence level.

3.9.5 Hypothesis 5

This hypothesis compared the predictive accuracy of the revised cutoff values of the Altman (1968) and Ohlson (1980) models in predicting business failure of the Hong Kong public-traded companies. According to Bruning and Kintz (1996), the significant differences of two groups with dichotomous data can be tested whether or not there is any difference between the groups.

The classification accuracy of the Altman's revised cutoff value in Hypothesis 2 and that of the Ohlson's revised cutoff value in Hypothesis 4 were compared to determine if significant differences of the two models in predicting business failure of the Hong Kong public traded companies. The predictive accuracy of the two models was compared for one year, two years and three years prior to delisting.

The following formula (Nunthaphad, 2000, p. 126) was used to calculate the significance of the difference between the proportions of the Altman revised cutoff value model and the Ohlson revised cutoff value model:

$$Z = (p1 - p2) / \sqrt{\{\frac{p1(1-p1)}{n1} + \frac{p2(1-p2)}{n2}\}}$$

where p1 = proportion of correct classification by the revised Altman's model

p2 = proportion of correct classification by revised Ohlson model

n1 = sample size of revised Altman model

n2 = sample size of revised Ohlson model.

A Z-test was conducted to test the significance of the difference between the two revised models by comparing their classification accuracy in predicting business failure of the Hong Kong public traded companies. The Z-test was conducted at the 95 per cent level of confidence. If it was significant at the 5 percent level, the null hypothesis was rejected and it was inferred that there is a significant difference between the levels of predictive accuracy of the two models in predicting business failure of the Hong Kong public traded companies.

3.9.6 Hypothesis 6

Hypothesis 6 referred to the correlation between total liabilities and Ohlson O-scores. The sample consisted of all 39 failed and 195 non-failed companies in each of the three years prior to business failure. Financial data were obtained from the HKEx database.

Pearson Correlation tested correlation at the 95 per cent level of confidence. If the results were significant at the 5 per cent level, the null hypothesis was rejected and it was concluded that total liabilities were significantly correlated to Ohlson O-scores in predicting business failure of the Hong Kong public-listed companies.

3.9.7 Hypothesis 7

Hypothesis 7 referred to the correlation between the Ohlson O-scores and the cash conversion cycle. The full sample of 234 companies was used, that is, all 39 failed and 195 non-failed companies in each of the three years prior to business failure.

Pearson Correlation was conducted to test their correlation at the 95 per cent level of confidence. If the results were significant at the 5 percent level, the null hypothesis was rejected and it was concluded that cash conversion cycle is significantly correlated to the Ohlson O-scores positively in predicting business failure of the Hong Kong public-listed companies.

3.9.8 Hypothesis 8

Hypothesis 8 referred to the differences between failed and non-failed companies that changed their auditor.

Chi-square test in SPSS was used to test the full sample of 234 companies, at the 95 per cent level of confidence. The null hypothesis was rejected if the results were significant at the 5 percent level, which implied that there are significant differences between failed and non-failed companies who change their auditor.

3.9.9 Hypothesis 9

Hypothesis 9 referred to the distribution of the average HIBOR interest rate for failed and non-failed companies. Again, the full sample of 234 companies – 39 failed and 195 non-failed companies – was used and tested by an equality of means t-test in SPSS at the 95 per cent confidence level.

The null hypothesis was rejected if the results were significant at the 5 per cent level, which would imply that the population distributions of average HIBOR rate for failed and non-failed companies are significantly different.

3.10 Chapter summary

This chapter has provided an overview of the research methodology, presented the hypothesis of each business failure prediction model tested, and explained how the financial and non-financial data of the selected companies were collected

This study used a total sample of 234 public companies listed in the HKEx. Of these, 39 were failed companies who had been suspended and delisted from the HKEx between 1998 and 2011. These companies needed to fulfil one of two criteria: they were delisted due to compulsory wind up by creditors for financial reasons, or they failed to disclose financial information as required by the HKEx. Another 39 companies that had not been suspended or delisted from the HKEx were matched by industry and size to form a group of 39 non-failed companies. In addition, the sample included 156 randomly selected companies that had not been delisted from the HKEx. All 234 companies were required to have at least three years of complete financial data.

Financial data for the years 1995 to 2011 were used for calculating the necessary financial ratios of the Altman (1968) and Ohlson (1980) models. All financial data used for analysis were on a consolidated basis, that is, consolidated income statement, consolidated balance sheet and consolidated cash flow statement. The most recent three years of financial data prior to delisting of the failed firms were gathered from either the Standard & Poor CapitalIQ database or the HKEx database. Non-failed companies' financial data were collected for the reporting period same as their paired failed partners.

Statistical techniques for testing the nine hypotheses included Z-test, Pearson Correlation, Equity of means t-test, and Chi-square test (see Table 3.1). All tests were conducted using SPSS software.

The accuracy of the Altman (1968) 5-variable Z-score and the Ohlson (1980) O-score models in predicting business failure was compared. Both models' predictive accuracy was determined by the correct prediction of the sampled companies' actual financial status. The cutoff values of the two models were then revised and the two models were compared with actual business failure to determine which model has higher predictive power in discriminating between failed and non-failed companies. Finally, the relationship of business failure with cash conversion cycle (CCC) and two non-financial variables (namely change of auditor and HIBOR rate movement) were examined using the Ohlson revised cutoff value model.

The next chapter presents the analysis and results of the hypothesis testing.

CHAPTER FOUR

ANALYSIS AND FINDINGS

4.1 Chapter overview

The aim of this research was to examine the applicability of the Altman (1968) and Ohlson (1980) prediction models in Hong Kong, and whether or not cash conversion cycle and non-financial variables have impact on Ohlson model's predictive accuracy of business failure.

Section 4.2 discusses the characteristics of the sampled companies relevant to this research – assets, revenue and profit – and their descriptive statistics. Section 4.3 presents the test and statistical analysis for all nine hypotheses, and Section 4.4 summarizes the chapter.

4.2 Descriptive statistics

Descriptive statistics, such as the mean, median, standard deviation, minimum and maximum, were calculated to highlight the characteristics of the selected variables. Profile analysis helped to identify any possible differences between the sampled failed and non-failed companies.

The distribution over time of the 234 sampled companies – the failed companies, the pair-matched non-failed companies and the randomly selected non-failed companies – is demonstrated in Table 4.1.

Year	No. of failed companies	No. of non-failed companies (pair-matched)	No. of non-failed companies (random)
1998	0	0	0
1999	1	1	0
2000	0	0	0
2001	3	3	0
2002	1	1	6
2003	1	1	12
2004	5	5	11
2005	11	11	16
2006	4	4	30
2007	4	4	20
2008	5	5	26
2009	1	1	21
2010	0	0	13
2011	3	3	1
n	39	39	156

Table 4.1: Distribution of 39 failed and 195 non-failed companies (1998–2011)

Table 4.1 shows that the numbers of failed companies were unevenly distributed across the period 1998 to 2011. The largest number of companies were delisted (i.e. failed) from the Hong Kong Stock Exchange (HKEx) in 2005. A possible reason is that Hong Kong's economy was badly hit by the outbreak of the SARS epidemic in 2003, with a comparatively large number of companies failed during 2004 and 2005. Surprisingly, the numbers of company failed did not increase in 1999 following the bursting of Hong Kong's economic bubble as a result of the Asian financial crisis, nor did the number increase in 2009 or 2010 shortly after the US sub-prime mortgage crisis that led to the global financial crisis.

The 156 non-delisted (i.e. non-failed) companies in Table 4.1 were randomly selected from the HKEx between 2002 and 2011. Of these 156 non-failed companies, 113 (72 per cent) were randomly drawn for the period 2006 to 2009. The only selection criteria were that they did not belong to the financial or property industries, as explained in Chapter 3.

The following sections discuss the characteristics of the failed and non-failed companies in terms of asset size, revenue and net profit. Table 4.2 summarizes the mean total assets, revenue and net profits for one, two and three years prior to delisting.

Year(s) prior to delisting	**Mean total assets**		**Mean revenues**		**Mean net profit**	
	Failed	**Non-failed**	**Failed**	**Non-failed**	**Failed**	**Non-failed**
1	$1,394	$1,332	$1,256	$1,259	–$203	$69
2	$1,430	$1,124	$1,235	$1,186	–$18	$37
3	$1,418	$1,021	$1,195	$1,050	–$43	$44

Table 4.2: Mean total assets, revenues, net profit of failed and non-failed companies (HK$ million)

4.2.1 Asset size

The asset size of the failed group ranged from HK$5.54 million to HK$10,857 million for one year prior failure (Table 4.3), while that of the non-failed companies ranged from HK$6.4 million to HK$21,320 million (Table 4.4). Small asset sizes in both group resulted from including SMEs (small-medium enterprises) that had been delisted or were listed in the GEM (Growth Enterprise Market of the HKEx; see Chapter 1). Thirteen GEM companies were included in the failed group, which accounted for 33.3 per cent (13 of 39) of the total sample size of the failed group; 19 GEM companies were included in the non-failed group, which accounted for 9.7 per cent (19 of 195) of the total sample size of the non-failed group.

Year(s) prior to delisting	Total assets (HK$ million) Min	Max	Mean
One year	5.54	10,857	1,394
Two years	1.98	14,509	1,430
Three years	23.73	16,472	1,418

Table 4.3: Descriptive statistics of total assets for the failed group

Year of observation	Total assets (HK$ million) Min	Max	Mean
Third year	6.43	21,320	1,332
Second year	5.40	20,375	1,124
First year	22	13,903	1,021

Table 4.4: Descriptive statistics of total assets for the non-failed group

The mean total assets of the failed companies decreased 1.7 per cent (from $1,418 to $1,394; see Table 4.3) when moving closer to the delisting year, while the non-failed group increased 30.5 per cent (from $1,021 to $1,332; see Table 4.4) over the same three-year period. Previous studies of business failure have noted similar characteristics (Rance, 1999), and so the failed Hong Kong companies in the sample can be said to possess similar asset characteristics as failed companies in other countries.

4.2.2 Revenue

Descriptive statistical figures showed no wide spread of revenue in either the failed or non-failed groups. The low level of revenue of the failed group (HK$1.13 million; Table 4.5) and non-failed group (HK$3.8 million; Table 4.6) resulted from the inclusion of the GEM companies. The mean revenues of the failed companies one year prior delisting and the non-failed companies in the third year of observation were similar (HK$1,255 million and HK$1,259 million, respectively; tables 4.5 and 4.6). The high level of maximum revenues could result from including some gigantic corporations, such as Peace Mark, Yaohan International, Leading Spirit High-tech and Moulin Global Eyecare in the failed group, and Sinopec Kentons, Asia Aluminium, South China Industries, Vtech Holdings and HAECO in the non-failed group. Notably, the failed group's revenue did not shrink when approaching the delisting year, which indicated that failed corporation's business volume in its final stage could look normal and not indicate any sign of danger.

Year(s) prior to delisting	Revenue (HK$ million) Min	Max	Mean
One year	1.13	8,571	1,255
Two years	0.72	11,243	1,235
Three years	1.13	11,297	1,195

Table 4.5: Descriptive statistics of revenue for the failed group

Year of observation	Revenue (HK$ million) Min	Max	Mean
Third year	3.8	21,823	1,259
Second year	6	22,358	1,186
First year	2	16,304	1,050

Table 4.6: Descriptive statistics of revenue for the non-failed group

4.2.3 Net profit

The net profit of the failed group had a narrower range and was lower (Table 4.7) than that of the non-failed group (Table 4.8). As expected, the non-failed group's mean net profits were greater than that of the failed group in the three-year period. In addition, the failed group's net profits shrank when moving close to the delisting year, while the non-failed group's net profits grew progressively over the years of observation.

Year(s) prior to delisting	Net profit (HK$ million)		
	Min	Max	Mean
One year	–1,940	471	–203
Two years	–808	450	–18
Three years	–1,231	483	–43

Table 4.7: Descriptive statistics of net profit for the failed group

Year of observation	Net profit (HK$ million)		
	Min	Max	Mean
Third year	–734	2,167	69
Second year	–1,390	1,345	37
First year	–596	10,090	44

Table 4.8: Descriptive statistics of net profit for the non-failed group

4.2.4 Summary

In summary, the mean total assets and mean revenue of the failed companies one year prior to failure (HK$1,394 million in Table 4.3 and HK$1,255 million in Table 4.5, respectively) are similar to those of the matched non-failed companies in the third year of observation (HK$1,332 million in Table 4.4 and HK$1,259 million in Table 4.6, respectively), indicating that the failed and non-failed companies were reasonably matched in terms of size. As expected, the mean profit of the failed companies one year prior to failure (–HK$203 million loss; Table 4.7) was significantly lower than that of the non-failed companies (HK$69 million; Table 4.8). Over the three years prior to delisting, the mean net loss of the failed companies increased almost four-fold, from -HK$43 million three years prior to –HK$203 million one year prior to delisting (Table 4.7). In contrast, the mean net profit of the non-failed companies increased from HK$44 million to HK$69 million during the same period (Table 4.8).

The Altman (1968) and Ohlson (1980) models used 13 variables, and their descriptive statistics are compared and displayed in Table 4.9.

	Non-failed companies				Failed companies			
Variables	**Min**	**Max**	**Mean**	**SD**	**Min**	**Max**	**Mean**	**SD**
SIZE	3.81	7.33	5.80	0.53	3.74	7.04	5.58	0.79
TLTA	0.01	51.66	0.71	3.72	0.02	22.88	1.64	3.89
WCTA	–50.66	0.85	–0.03	3.66	–22.56	0.74	–1.0	3.92
CLCA	0.01	51.77	0.98	3.76	0.03	70.09	3.62	11.25
NWNEG	0	1	0.04	0.19	0	1	0.31	0.47
ROA	–3.2	0.57	–0.04	0.31	–8.4	0.24	–0.74	1.70
CFOTL	–37.98	3.34	0.035	2.81	–9.45	8.31	–0.14	2.10
NPCHG	–1	1	-0.003	0.60	–1	1	–0.22	0.70
NPNEG	0	1	0.23	0.42	0	1	0.36	0.49
RETA	–73.75	0.94	–0.74	5.87	–32.99	0.71	–3.01	7.54
EBITTA	–2.11	0.41	–0.01	0.24	–3.82	0.32	–0.50	1.02
MVETL	0.05	815.22	8.82	59.016	0.06	96.47	6.05	16.84
NSTA	0.02	6.22	1.04	0.86	0.03	5.1	0.92	1.02
n	195				39			

Table 4.9: Descriptive statistics of variables using the financial report one year prior to delisting (failed group) and third year of observation (non-failed group) (full sample: 234 companies)

SIZE = asset size of the company
TLTA = total liabilities/total assets
WCTA = working capital/total assets (working capital = (current assets – current liabilities))
CLCA = current liabilities/current assets
NWNEG = 1 if total liabilities > total assets, 0 otherwise
ROA = return on asset or net income/total assets
CFOTL = cash from operating activities/total liabilities
NINEG = 1 if negative net profit in two consecutive years, 0 otherwise
NPCHG = change of net profit
RETA = retained earnings/total assets
EBITTA = earnings before interests & taxes/total assets
MVETL = market value of equity/total liabilities
NSTA = net sales/total assets

Comparing the means, the failed group had lower means than the non-failed group in five variables: working capital/total assets (WCTA), asset size of the company (SIZE), return on assets (ROA), cash flow from operating activities/total liabilities (CFOTL) and net profit change (NPCHG); and higher means for total liabilities/total assets (TLTA), current liabilities/current assets (CLCA), negative net worth (NWNEG) and negative net profit (NPNEG). Variables related to the failed companies' debt were obviously higher than those of the non-failed companies, including total liabilities to total assets (TLTA) and current liabilities to current assets (CLCA). The statistical characteristics of the debt formed the foundation for Hypothesis 6, which examined the correlation between total liabilities and business failure.

4.3 Hypothesis tests

Having understood the sample characteristics, the next step was to test the hypotheses. The tests were divided into two parts. The first used hypotheses 1–4 to test the predictive accuracy of the Altman and Ohlson models, in relation to failed and non-failed Hong Kong public companies. The predictive power of the two models was further compared when testing Hypothesis 5. The second part of the test examined the impact of the cash conversion cycle and several non-financial variables on business failure prediction in hypotheses 6–9. The procedures used for testing each hypothesis were described in the previous chapter. The remainder of this chapter presents the test results for each research hypothesis.

4.3.1 Hypothesis 1

Hypothesis 1 tested the predictive accuracy of Altman's (1968) 5-variable prediction model as it pertains to delisted (failed) and non-delisted (non-failed) public companies in Hong Kong. Table 4.10 presents the descriptive statistics of the Altman (1968) Z-scores for the sampled failed companies at one, two and three years prior to delisting and for non-failed companies at first, second and third year of observation.

	n	Min	Max	Mean	SD
Failed companies					
One year prior to delisting	39	-.61	5.08	.89	1.04
Two years prior to delisting	39	.02	4.21	.94	.88
Three years prior to delisting	39	.04	2.94	.97	.75
Non-failed companies					
Third year of observation	39	.04	3.95	1.24	.88
Second year of observation	39	.04	3.53	1.27	.88
First year of observation	39	.09	7.12	1.41	1.26

Table 4.10: Descriptive statistics of the Z-scores from Altman's (1968) model

The failed companies' mean Z-scores dropped from .94 to .89 in the year prior to delisting. These Z-scores are smaller than 1.81, a characteristic that indicates failure, as discussed in Chapter 2, Section 2.3.

Table 4.11 gives the classifications of the failed and non-failed data from one year to three years prior to delisting.

Group	Predicted failed	Predicted non-failed	n	Accuracy (%)
One year prior to delisting / Third year of observation				
Failed	33	6 △	39	84.6
Non-failed	30 ∞	9	39	23
Overall	63	15	78	54
Two years prior to delisting / Second year of observation				
Failed	34	5 △	39	87.2
Non-failed	29 ∞	10	39	25.6
Overall	63	15	78	56
Three years prior to delisting / First year of observation				
Failed	34	5 △	39	87.2
Non-failed	30 ∞	9	39	23
Overall	64	14	78	55

Table 4.11: Predictive accuracy of Altman (1968) model

△ Type I error
∞ Type II error

Unlike previous studies of business failure, the accuracy of predicting failure of the sample group did not increase when moving closer towards the delisting date. The accuracy remained constant at 85–87 per cent for predicting failure in the three years prior to delisting, and 23–25 per cent for predicting non-failure, an overall accuracy of 54–56 per cent. Altman's original test using the US company data had accuracy rates of 94, 72 and 48 per cent for one, two and three years, respectively, prior to business failure; the model was less accurate when applied to Hong Kong data.

Moreover, the Type I error rate (mistakenly predicting failed companies as non-failed) increased from 12.8 per cent at two years prior to delisting to 15.4 per cent at one year prior to delisting. However, the Type II error rate (mistakenly predicting non-failed companies as failed) stayed at approximately 77 per cent. A high Type II error for the model when applied to Hong Kong companies been supported by previous studies (by Barnes, 1987) that also found the Altman or MDA model tended to understate non-failed companies (i.e. Type II error).

Hypothesis 1 was further tested by calculating the Z-values, as described in Chapter 3, Section 3.9.1, for the levels of accuracy displayed in Table 4.12. The significance level of the Z-value was obtained from the cumulative standard normal distribution table. The Z-value was computed using the formula:

$$Z = (p - 0.5) / \sqrt{0.5 * 0.5/n}$$

where p represents the proportion of correct prediction and n the sample size. The Z-test results for Hypothesis 1 are displayed in Table 4.12.

The overall accuracy of predicting failure one year prior to delisting for the failed group (Panel A in Table 4.12) was 84.6 per cent, at two years prior (Panel B) was 87.2 per cent and at three years prior (Panel C) was 87.2 per cent. The failed companies in all years of data had a significance level (.000 for all three years) smaller than .05. Although the Altman (1968) model accurately classified failed companies in all years of data when applied to Hong Kong public listed companies, its extremely low accuracy in predicting non-failed companies decreased the overall accuracy to 54, 56 and 55 per cent for one, two and three years, respectively, prior to delisting. The Z-values of .707, 1.06 and .883 and the significance levels of .240, .1446 and 1.876 for all three years were greater than.05. From these levels, it could be inferred that the Altman model's overall classification accuracy level was little more than 50 per cent when predicting Hong Kong public listed companies for each of the three years prior to business failure. Consequently, the null hypothesis is rejected, meaning that the predictive accuracy of the Altman (1968) model is greater than 50 per cent when predicting business failure for the Hong Kong listed companies.

	Accuracy of prediction (%)	**Z-value**	**Sig. level**
A. One year prior to delisting / Third year of observation			
Failed companies	84.6	4.322	.0000*
Non-failed companies	23	–3.372	.9996
Overall accuracy	54	.707	0.240
B. Two years prior to delisting / Second year of observation			
Failed companies	87.2	4.646	.0000*
Non-failed companies	25.6	–3.048	.9988
Overall accuracy	56	1.06	.1446
C. Three years prior to delisting / First year of observation			
Failed companies	87.2	4.646	.0000*
Non-failed companies	23	–3.372	.9996
Overall accuracy	55	.883	1.876

Table 4.12: Results of Z-test statistics for Hypothesis 1

* Significant at .05 level

In summary, the Altman (1968) prediction model achieved greater than 50 per cent accuracy in classifying Hong Kong public listed companies for each of the three years prior to delisting. The alternative Hypothesis 1 is therefore accepted.

4.3.2 Hypothesis 2

Hypothesis 2 examined the predictive accuracy of Altman's (1968) model when the cutoff value was revised to fit the Hong Kong data. The cutoff value was revised by observation, and Table 4.13 gives the observed results. Moving the cutoff value down resulted in more Type I errors but fewer Type II errors until a cutoff value of .95, where the number of Type I and Type II errors was optimal, at an overall error of 71.8 per cent.

Cutoff value	Type I error (%)	Type II error (%)	Overall error (%)
.8	39.3	31.6	70.9
.9	35.9	37.6	73.5
.935	32.5	40.2	72.7
▷ .95	31.6	40.2	71.8
.98	30.8	41.9	72.7
1.0	30.8	41.9	72.7
1.05	29.1	45.3	74.4
1.1	29.1	50.4	79.5
1.15	26.5	53	79.5
1.2	25.6	53.8	79.5
1.25	25.6	56.4	82
1.5	17.9	69.2	87.1
2.0	12.8	82.1	94.9

Table 4.13: Observation of revised cutoff values for Altman's (1968) model

When testing Hypothesis 2, sampled companies with a Z-score less than .95 were considered as failed, and those with a Z-score greater than .95 were considered as non-failed. The classifications of the failed and non-failed data using the revised Altman model from one year to three years prior to delisting are summarized in Table 4.14.

The revised model produced 28.2 per cent Type I error and 41 per cent Type II error for one year prior to delisting. Compared with the prediction results from Hypothesis 1, which used the original cutoff value, the revised cutoff value largely reduced the Type II error from 77 per cent to 41 per cent, although this was at the expense of Type I error, which increased to 28 per cent. The correct classifications for failed companies were still high with 28 (71.8 per cent), 26 (66.7 per cent) and 26 (66.7 per cent) correct predictions for one, two and three years, respectively, prior to delisting.

Group	Predicted failed	Predicted non-failed	n	Accuracy (%)
One year prior to delisting / Third year of observation				
Failed	28	11 △	39	71.8
Non-failed	16 ∞	23	39	59
Overall	44	34	78	65.4
Two years prior to delisting / Second year of observation				
Failed	26	13 △	39	66.7
Non-failed	17 ∞	22	39	56.4
Overall	43	35	78	61.5
Three years prior to delisting / First year of observation				
Failed	26	13 △	39	66.7
Non-failed	14 ∞	25	39	64.1
Overall	40	38	78	65.4

Table 4.14: Predictive accuracy of Altman (1968) model with revised cutoff value

△ Type I error
∞ Type II error

The Z test was used to test whether the strength of the Altman (1968) model in predicting business failure using the revised cutoff value was significantly different from that of the original Altman (1968) model. In other words, the Z-test determined whether there was a significant difference between the two models in predicting business failure for failed and non-failed companies. The difference between the two proportion of Altman (1968) model and Altman (1968) revised model was tested using a Z-test at 95 per cent level of confidence. The two proportions took the following form:

H_0 : pf, Altman – pf, Altman revised = 0 and

pnf, Altman – pnf, Altman revised = 0

Ha: pf, Altman – pf, Altman revised ≠ 0 and

pnf, Altman – pnf, Altman revised ≠ 0

where: pf = predictive accuracy for failed

pnf = predictive accuracy for non-failed

The predictive accuracy of the Altman (1968) model and the revised Altman (1968) model for each of the three years is displayed in Table 4.15.

The Z-value was calculated using the formula:

$$Z = (p1 - p2) / \sqrt{\{\frac{p1(1-p1)}{n1} + \frac{p2(1-p2)}{n2}\}}$$

Group	Accuracy of prediction (%) Altman	Revised Altman	Z-value	Sig. level
One year prior to delisting / Third year of observation				
Failed	84.6	71.8	1.386	.162
Non-failed	23	59	–3.473	.001*
Overall	54	65.4	–1.461	.144
Two years prior to delisting / Second year of observation				
Failed	87.2	66.7	2.216	.027*
Non-failed	25.6	56.4	–2.912	.004*
Overall	56	61.5	–.763	.445
Three years prior to delisting / First year of observation				
Failed	87.2	66.7	2.216	.027*
Non-failed	23	64.1	–4.011	.000*
Overall	55	65.4	–1.281	.201

Table 4.15: Comparison of predictive accuracy of Altman (1968) model and revised Altman (1968) model and Z-test statistics

* Significant at .05 level

The Z-values and the related significance levels show that the differences between the two models in predicting failed companies two and three years prior to delisting are significant at the .05 level. The significance levels of predicting failed companies were .027 for two years and .027 for three years prior to delisting. Levels of both two and three years were smaller than the .05 level. The positive Z-values imply that the Altman model used to test Hypothesis 1 outperformed the Altman revised cutoff model in predicting failed companies in two and three years of data. Moving the cutoff point improves the prediction accuracy confirms that replicating Altman's original cutoff point does not work well nor optimizes the prediction accuracy when it is applied to the samples used in this study.

The Z-test for the differences between the models in predicting non-failed companies was also significant at the .05 level, in that the significant levels were <.05 for all three years. These results and the negative Z-values indicate that, for non-failed company prediction, the Altman revised cutoff model was significantly better than the original model at predicting non-failed companies.

In terms of overall prediction, the negative Z-values (–.1461, –.763, –1.281) show that the Altman revised cutoff model performed better than the original model for all three years prior to delisting; however, the accuracy of the two models was not statistically different in that the significance levels (.144, .445 and .201) are greater than .05. Consequently there is insufficient evidence to reject the null hypothesis.

To validate the level of agreement between the predictions of the original and revised model, a Cohen's Kappa Test was performed using SPSS. Kappa measures the agreement between two raters, where k=1 if the raters are in complete agreement and k=0 if there is no agreement. Results of the Kappa Test are shown in Table 4.16.

	Altman revised cutoff model			
Altman Z model	**Non-failed**	**Failed**	**k value**	**Sig. level**
One year prior to delisting / Third year of observation				
Failed	18	45	.49	0.000*
Non-failed	15	0		
Two years prior to delisting / Second year of observation				
Failed	20	43	.453	0.000*
Non-failed	15	0		
Three years prior to delisting / First year of observation				
Failed	24	40	.374	0.000*
Non-failed	14	0		

Table 4.16: Kappa Test results for Altman (1968) model and Altman (1968) revised model

* Significant at .05 level

As a rule of thumb, k values from .21 to .40 indicate fair agreement, while values of .41 to .60 represent moderate agreement (Landis & Koch, 1977). The k values obtained from the interrater analysis (.49, .453 and .374 for one, two and three years, respectively, prior to delisting) indicate only fair to moderate agreement between the predictions of the Altman (1968) Z-score and Altman (1968) revised cutoff models.

In summary, the differences in the two model's predictive accuracy are statistically significant. The accuracy of the two models in predicting failed and non-failed Hong Kong public listed companies is significantly different. The null hypothesis is therefore rejected at the .05 level, meaning that revising the cutoff value does improve the accuracy rate of the Altman models in predicting business failure for Hong Kong public listed companies.

The test found that the Altman revised cutoff model is more accurate in predicting failed companies in all three years of data, while the Altman model more is accurate in predicting non-failed companies in all three years. Given that Type I error is more expensive than Type II error (Altman, 1983), the Altman revised cutoff model is therefore preferable. This study therefore used the Altman revised cutoff model to compare with the Ohlson model when testing Hypothesis 5.

4.3.3 Hypothesis 3

Hypothesis 3 examined the predictive accuracy of Ohlson (1980) O-score model for Hong Kong public companies. The descriptive statistics of Ohlson (1980) O-scores of classifying failed and non-failed Hong Kong public companies for one, two and three years prior to delisting are provided in Table 4.17.

	n	Min	Max	Mean	SD
Failed					
One year prior to delisting	39	–18.29	175.55	11.8	31.55
Two years prior to delisting	39	–16.57	44.82	4.57	10.20
Three years prior to delisting	39	–12.83	26.21	2.54	6.49
Non-failed					
Third year of observation	195	–8.76	384.93	2.90	28.40
Second year of observation	195	–6.52	539.01	3.62	38.76
First year of observation	195	–11.94	27.22	.35	4.0

Table 4.17: Descriptive statistics of the O-score from Ohlson's (1980) model of failed and non-failed companies in the HKEx

As discussed in Chapter 2, Section 2.4, an O-score larger than .38 indicates the characteristic of failure. The sampled failed companies' mean O-scores in all three years (11.8, 4.57 and 2.54) lie above this value.

The predictive accuracy of the Ohlson (1980) model in classifying failed and non-failed for Hong Kong public companies is presented in Table 4.18.

Group	Predicted failed	Predicted non-failed	n	Accuracy (%)
One year prior to delisting / Third year of observation				
Failed	23	16△	39	59
Non-failed	28 ∞	167	195	85
Total	51	183	234	81
Two years prior to delisting / Second year of observation				
Failed	17	22△	39	43
Non-failed	36 ∞	159	195	81
Total	53	181	234	75
Three years prior to delisting / First year of observation				
Failed	14	25△	39	35
Non-failed	26 ∞	169	195	86
Total	40	194	234	78

Table 4.18: Predictive accuracy of Ohlson (1980) model

△ Type I error
∞ Type II error

The results in Table 4.18 show that the model's predicative accuracy for both failed and non-failed companies combined were on a slight upward trend as time progressed: up from 78 per cent to 81 per cent when entering the delisting year for the failed group or in the third year of observation for the non-failed group. The same was true for predicting failed companies. These figures differed from those of the Altman (1968) model tested in Hypothesis 1, where the model's predictive accuracy showed a slight downward trend with time. In particular, the Altman model's predictive power for the failed companies declined. The two models moved in opposite directions when predicting the failed and the overall results.

The Ohlson (1980) model's Type I error rate also improved from 64.1 per cent at three years, to 56.4 per cent at two years and further down to 41 per cent at one year prior to delisting. In contrast, the Type II error for all three time periods was between 14 and 19 per cent.

A Z-test, similar to that used for Hypothesis 1, was conducted to determine the significance of the accuracy of the Ohlson (1980) model for Hong Kong public companies. The null hypothesis was rejected if the model results showed a difference in prediction accuracy between failed and non-failed companies, and it could then be inferred that the Ohlson (1980) predictive model is useful in predicting business failure for Hong Kong public companies. The Z-test results for testing Hypothesis 3 are summarized in Table 4.19.

	Accuracy of prediction (%)	**Z-value**	**Sig. level**
One year prior to delisting / Third year of observation			
Failed companies	58	.999	.160
Non-failed companies	85	9.775	.000*
Overall accuracy	81	9.484	.000*
Two years prior to delisting / Second year of observation			
Failed companies	43	–.874	.808
Non-failed companies	81	8.658	.000*
Overall accuracy	75	7.649	.000*
Three years prior to delisting / First year of observation			
Failed companies	35	–1.873	.970
Non-failed companies	86	10.054	.000*
Overall accuracy	78	8.566	.000*

Table 4.19: Results of Z-test statistics for Hypothesis 3

* Significant at .05 level

The model did not accurately predict failed companies (58, 43 and 35 per cent for one, two and three years prior to delisting) but had a higher accuracy predicting non-failed companies (85, 81 and 86 per cent) and companies overall (81, 75 and 78 per cent). Z values of .000 for non-failed and overall companies for all three years infer that the model has significantly greater than 50 per cent accuracy when predicting public listed companies that were non-delisted (non-failed) from the HKEx.

In conclusion, the model's predictive accuracy was sufficient to reject the null hypothesis at the .05 level of significance for failed companies one, two and three years prior to delisting. The results suggest that the Ohlson (1980) model is capable of classifying only non-failed companies and predicting overall accuracy in all years of data when applied to Hong Kong public listed companies, but that it cannot accurately classify failed companies.

4.3.4 Hypothesis 4

Hypothesis 4 examined the predictive accuracy of the Ohlson (1980) model when the cutoff value was revised to fit the Hong Kong data. The observed results are presented in Table 4.20.

Cutoff value	Type I error (%)	Type II error (%)	Overall error (%)
1.7	41	25	66
1.5	38.5	27.5	66
1.4	37.6	29.4	67
1.38	35.9	29.9	65.8
1.35	35.9	30	66
1.32	35	30.4	65.4
▷ 1.3	35	30.4	65.4
1.28	35	30.6	65.6
1.25	35	31.1	66.1
1.1	34.2	33	67.2
.8	29.9	39.7	69.6
.5	26.5	43.6	70
.38	23.1	47.7	70.8
.19	22.2	49.9	72.1
.15	22.2	50.9	73.1
.1	21.4	52.1	73.5
.05	20.5	52.8	73.3

Table 4.20: Observations when revising Ohlson's cutoff value

By observation, the levels of Type I error and Type II errors were optimized at the cutoff value at 1.3, with total error of 65.4 per cent. When testing Hypothesis 4, therefore, companies with an O-score less than 1.3 were classified as non-failed, and those with an O-score greater than 1.3 as failed. The classification of results using the Ohlson (1980) revised cutoff model are demonstrated in Table 4.21.

Group	Predicted failed	Predicted non-failed	n	Accuracy (%)
One year prior to delisting / Third year of observation				
Failed	25	14 △	39	64.1
Non-failed	35 ∞	160	195	82.1
Overall	60	174	234	79
Two years prior to delisting / Second year of observation				
Failed	22	17 △	39	56
Non-failed	39 ∞	156	195	80
Overall	61	173	234	76
Three years prior to delisting / First year of observation				
Failed	24	15 △	39	61
Non-failed	31 ∞	164	195	84
Overall	55	179	234	80

Table 4.21: Predictive accuracy of Ohlson's (1980) model with revised cutoff value

△ Type I error
∞ Type II error

By revising the cutoff value, the model's accuracy in predicting failed companies increased closer to the delisting year (61 per cent for three years prior to delisting; 64.1 per cent for one year). The accuracy for non-failed companies slightly increased over this period.

The difference in predictive accuracy for failed and non-failed companies between the Ohlson (1980) model and the Ohlson (1980) revised cutoff model was tested at the .05 confidence level using a Z-test. The two proportions took the following form:

H_0 : pf, Ohlson – pf, revised Ohlson = 0 and

pnf, Ohlson – pnf, revised Ohlson = 0

Ha: pf, Ohlson – pf, revised Ohlson ≠ 0 and

pnf, Ohlson – pnf, revised Ohlson ≠ 0

where: pf = predictive accuracy for failed companies

pnf = predictive accuracy for non-failed companies

The Z-test examined whether the strength of predicting business failure using Ohlson (1980) revised cutoff model was significantly different from that of the original Ohlson (1980) model, as reported in the previous section for Hypothesis 3.

The difference between the two proportions with a Z-value equal to or greater than ±1.96 was deemed significant at the .05 level for a two-tailed significance test. The null hypothesis is rejected if there is a significant difference between the two models. Failure to reject the null may mean that the predictive accuracy of the two models has no significant difference.

The predictive accuracy of the Ohlson (1980) model and the Ohlson (1980) revised model was compared for each of the three years:

$$Z = (p1 - p2) / \sqrt{\left\{\frac{p1(1-p1)}{n1} + \frac{p2(1-p2)}{n2}\right\}}$$

The classifications of the failed and non-failed data by Ohlson revised cutoff model from one year to three years prior to delisting are summarized in Table 4.22.

The negative sign for Z indicates that revising the cutoff value improved the predictive accuracy for failed companies, but significance levels greater than .05 indicate that the improvement in predicting failed companies was not significant. Similarly, the significance levels for the non-failed groups were greater than .05 in all three years (.430, .803 and .578 for one, two and three years, respectively, prior to delisting), indicating that the improvement in predicting non-failed companies was not significant. Indeed, the positive sign for Z implies that the revised cutoff values made the prediction for the non-failed groups less accurate than the original cutoff value in all three years. Finally, the overall predictions were also larger than .05 for all three years (.589, .802 and .596), indicating that the overall accuracy of both models' predictive power for all three years did not differ significantly.

Group	% Correct prediction Ohlson	Revised Ohlson	Z-value	Sig. level
One year prior to delisting / Third year of observation				
Failed	58	64	–.544	.586
Non-failed	85	82	.799	.430
Overall	81	79	.541	.589
Two years prior to delisting / Second year of observation				
Failed	43	56	–1.158	.247
Non-failed	81	80	.249	.803
Overall	75	76	–.252	.802
Three years prior to delisting / First year of observation				
Failed	35	61	–2.38	.017*
Non-failed	86	84	.553	.578
Overall	78	80	–.531	.596

Table 4.22: Predictive accuracy of Ohlson (1980) model and Ohlson (1980) revised model and Z-test statistics

* Significant at .05 level

In summary, revising the cutoff value marginally improved the accuracy rate of the Ohlson model. Specifically, the negative Z-values indicate that the predictive accuracy for non-failed companies improved in all three years, although the improvement was not significant. Again, a Cohen's Kappa Test was run to validate the level of agreement of the predictive accuracy between the original and revised cutoff Ohlson models. Results of the interrater analysis (Table 4.23), with k=.894, k=.964, k=.915 and significance values smaller than .05, indicate a high level of agreement. Landis and Koch (1977) described k values between .60 and .79 as substantial and .80 as outstanding. The Ohlson (1980) and Ohlson revised cutoff models predicted very similar results.

	Group	Ohlson revised cutoff model Non-failed	Failed	K value	Sig. level
One year prior to delisting / Third year of observation					
Ohlson P model	Failed	0	51	.894	0.000*
	Non-failed	174	9		
Two years prior delisting / Second year of observation					
Ohlson P model	Failed	0	53	.964	0.000*
	Non-failed	178	3		
Three years prior delisting / First year of observation					
Ohlson P model	Failed	0	40	.915	0.000*
	Non-failed	188	6		

Table 4.23: Kappa Test results of Ohlson (1980) and Ohlson (1980) revised model

* Significant at .05 level

This test failed to find sufficient evidence to reject the null hypothesis at the .05 level. Failure to reject the null hypothesis may mean that revising the cutoff value does not significantly improve the accuracy rate of the Ohlson p model.

The testing of this hypothesis concluded that the Ohlson revised cutoff model better predicted failed companies for all three years of data, while retaining its predictive accuracy for non-failed companies. Given the higher cost of Type I errors, the Ohlson revised cutoff model was therefore used in the comparison with the Altman revised cutoff model when testing Hypothesis 5.

4.3.5 Hypothesis 5

Hypothesis 5 examined which model, the Altman (1968) revised cutoff model or the Ohlson (1980) revised cutoff model, was more accurate in predicting business failure for Hong Kong public listed companies. The differences between the two models were tested by Z-test at 95 per cent level of confidence. The two proportions took the following form:

H_0 : pf, revised Altman (1968) model – pf, revised Ohlson (1980) model = 0 and

pnf, revised Altman (1968) model – pnf, revised Ohlson (1980) model = 0

Ha: pf, revised Altman (1968) model – pf, revised Ohlson (1980) model ≠ 0 and

pnf, revised Altman (1968) model – revised Ohlson (1980) model ≠ 0

where: pf = predictive accuracy for failed companies

pnf = predictive accuracy for non-failed companies

Table 4.24 summarizes the classification of the failed and non-failed data by the two models. A Z-test was performed to examine whether the overall predictive power of the two models was significantly different. Again, the Z-value was calculated using the formula:

$$Z = (p1 - p2) / \sqrt{\{\frac{p1(1-p1)}{n1} + \frac{p2(1-p2)}{n2}\}}$$

Difference of the predictive accuracy for failed and non-failed of the two models with a Z-value equal to or greater than ±1.96 would be significant at the .05 level. Rejecting the null hypothesis may mean there is a significant difference between the Altman (1968) revised cutoff model and the Ohlson (1980) revised cutoff model in predicting business failure of Hong Kong public companies. On the contrary, failure to reject may mean that there is no significant difference between the predictive accuracy of the two models. The results of comparing the predictive accuracy of the two models for each of the three years are also shown in Table 4.24.

The differences between the two models when predicting non-failed companies increased during the progressing years, indicated by Z-values of –2.462, –2.796, –2.757 for first, second and third year of observation, respectively, with significance <.05. The negative Z-value means that the Ohlson revised cutoff model made a better prediction for non-failed companies. The Ohlson revised cutoff model also made a better overall prediction, with Z-values of –2.50, –2.271, –2.264 and significance <.05. This comparison supports the hypothesis that predictions by the two models are significantly different for non-failed companies and overall prediction. The null is therefore rejected and it is concluded that a significant difference in predicting business failure in Hong Kong exists between the two models.

	% Correct prediction			
Group	**Revised Altman**	**Revised Ohlson**	**Z-value**	**Sig. level**
One year prior to delisting / Third year of observation				
Failed	71.8	64	.74	.459
Non-failed	59.0	82	–2.757	.006*
Overall	65.4	79	–2.264	.024*
Two years prior to delisting / Second year of observation				
Failed	66.7	56	.976	.330
Non-failed	56.4	80	–2.796	.005*
Overall	62.0	76	–2.271	.023*
Three years prior to delisting / First year of observation				
Failed	66.7	61	.525	.60
Non-failed	64.0	84	–2.462	.014*
Overall	65.0	80	–2.50	.012*

Table 4.24: Comparison of predictive accuracy of revised Altman (1968) model and revised Ohlson (1980) model and Z-test statistics

* Significant at .05 level

The Altman model was slightly better than the Ohlson model in classifying the failed group, and the opposite is true for Ohlson model in classifying the non-failed group. This suggests that neither model is clearly superior to the other. In summary, when testing Hypothesis 1 the Altman model was not reliable, with very high Type II error. When the cutoff value was revised to test Hypothesis 2, the model's predictive accuracy for non-failed companies improved, and its overall predictive accuracy when testing Hypothesis 5 was as good as that of the Ohlson revised cutoff model. Nevertheless, the Ohlson revised cutoff model had better overall predictive accuracy and classification accuracy for non-failed companies for all three years. It was therefore used as the model for testing hypotheses 6–10.

4.3.6 Hypothesis 6

Hypothesis 6 examined the relationship between total liabilities and revised O-scores, using the Parametric Pearson Correlation. The descriptive statistics are shown in Table 4.25.

	Revised Ohlson O-score		Total liabilities	
	Mean	**SD**	**Mean**	**SD**
Failed companies				
One year prior	–18.3	31.55	$1,015.8	$1,818
Two years prior	4.57	10.20	$936.8	$1,890
Three years prior	2.54	6.49	$93.1	$2,358
Non-failed companies				
First year of observation	2.90	28.41	$575.9	$1,415
Second year of observation	3.62	38.76	$470.4	$1,173
Third year of observation	–.35	4.0	$421.6	$930

Table 4.25: Descriptive statistics of the revised O-scores and the total liabilities of failed and non-failed companies (HK$ million)

The mean total liabilities of the failed group had largely increased when moving close to the year of delisting, whereas those of the non-failed group did not change very much. At this point, the findings seemed to agree with the hypothesis that the failed companies' total liabilities are positively correlated with business failure. Therefore, a Pearson Correlation Analysis was run to confirm this. The results from the Pearson Correlation Analysis are displayed in Table 4.26.

	Year prior to delisting		
	One year	**Two years**	**Three years**
Failed companies			
n	39	39	39
Total liabilities	$1,015.8	$936.8	$93.1
Pearson Correlation (r value)	.018	-.003	.079
Significance	.914	.987	.632
	Year of observation		
	Third year	**Second year**	**First year**
Non-failed companies			
n	195	195	195
Total liabilities	$575.9	$470.4	$421.6
Pearson Correlation (r value)	-.012	-.008	.06
Significance	.868	.914	.406

Table 4.26: Results of Pearson Correlation Analysis for total liabilities (HK$ million)

* Significant at 0.05 level

The failed group's Pearson Correlation r values at one year and three years prior to delisting show a positive value, meaning that the O-scores and the total liabilities are positively correlated. In other words, the larger the total liabilities, the higher the O-scores and the higher the probability of failure. The opposite holds true for the non-failed group, in that the larger the total liabilities, the lower the O-scores and the lower the probability of failure.

Further inspection of the significance level revealed, however, that the values were >.05 for all three years. This may infer that the total liabilities and the O-scores are positively related, but not significantly. P-values greater than .05 provided insufficient evidence to reject the null hypothesis. The test concluded there was no significant positive relationship between the Ohlson O-scores and the total liabilities for the sample companies.

The implication of this result is that investors, creditors and stockholders in Hong Kong should not simply rely on total liabilities to predict or determine a company's level of risk. The non-failed group's negative relationship with total liabilities illustrates that high total liabilities do not necessarily result in a high risk of default. Instead, if debts are wisely utilized, such as investing the interest-borrowing loans in profitable projects, a company could generate revenues and profits and survive. That being said, companies with small total liabilities are just as vulnerable to failure as those with large total liabilities in term of failure prediction. Investors, creditors and stockholders should consider more than one variable in order to make a better judgment.

4.3.7 Hypothesis 7

Hypothesis 7 examined the relationship between Ohlson revised O-scores and the failed companies' cash conversion cycle (CCC), again by using the Pearson Correlation. The descriptive statistics of O-scores and CCC are outlined in Table 4.27.

The CCC of both failed and non-failed companies surged when approaching the year of delisting. For the non-failed companies, the mean CCC largely increased from -1,006.79 days in the first year of observation to 134.56 days in the third year of observation. For the failed companies the mean CCC was similar for two years and three years prior to delisting, but increased from 124.58 days to 204.07 days at one year prior to delisting.

	Ohlson revised O-score		Cash Conversion Cycle	
	Mean	**SD**	**Mean**	**SD**
Failed companies				
One year prior	–18.29	31.55	204.07	787.98
Two years prior	4.57	10.20	124.58	255.44
Three years prior	2.57	6.49	125.69	133.51
Non-failed companies				
Third year of observation	2.90	28.41	134.56	427.82
Second year of observation	3.62	38.76	–279.57	5946.3
First year of observation	.35	4.00	–1006.79	15869.38

Table 4.27: Descriptive statistics of the Cash Conversion Cycle of failed and non-failed companies

Failed and non-failed companies were tested separately using the Pearson Correlation Test. The overall correlation results are presented in Table 4.28.

	Year prior to delisting		
	One year	**Two years**	**Three years**
Failed companies			
n	39	39	39
CCC	204.07	124.58	125.69
Pearson Correlation	–.416	–.438	.086
Significance	.008*	.005*	.601
	Year of observation		
	Third year	**Second year**	**First year**
Non-failed companies			
n	195	195	195
CCC	134.56	–279.57	–1006.79
Pearson Correlation	0.715	0.055	–0.027
Significance	0.000*	0.448	0.703

Table 4.28: Results of Pearson Correlation Analysis for Cash Conversion Cycle

* Significant at .05 level

The P-value for both failed companies at one year prior to delisting and non-failed groups at the third year of observation (.008 and .000, respectively) was smaller than .05, which indicates that CCC was significantly correlated with Ohlson O-scores when moving from two years to one year prior to delisting or from the second to third year of observation. In fact, the two variables are negatively correlated, as stated in the null hypothesis. The failed group's mean CCC and mean O-scores are negatively correlated: the shorter the CCC the larger the O-score (higher probability of failure). On the other hand, the non-failed group's mean CCC and O-scores are also negatively correlated. This finding contradicts Soenen (1993)'s assumption that a long CCC might be a primary reason for bankruptcy. This study is the first to find this correlation between CCC and O-scores.

In summary, CCC is negatively correlated with O-scores of the failed companies, and the overall results using the Pearson Correlation Analysis at the .05 level supports not rejecting the null hypothesis that CCC is negatively correlated with the Ohlson revised O-scores for failed companies in Hong Kong. Not rejecting the null hypothesis may infer that companies in Hong Kong which attempt to enhance their profitability by using aggressive CCC to keep a shorter inventory and receivable and a longer payable period will have a high probability of business failure.

4.3.8 Hypothesis 8

Hypothesis 8 examined the effect of change of auditor on failed and non-failed companies, using the Ohlson revised O-score prediction model. The hypothesis took the following form:

H_0: canf = caf

Ha: canf < > caf

where canf = change of auditor for non-failed companies

caf = change of auditor for failed companies

A Chi-square test at the .05 level was used to examine the hypothesis. The Chi-square test measures the discrepancy between the observed counts of business failure and what is expected if the change of auditor is related. A small Chi-square (large P-value) would indicate agreement between the data and the null hypothesis, while a large Chi-square (small P-value) would indicate disagreement. Rejection of the null hypothesis would indicate that failed and non-failed companies experience change of auditor differently.

The descriptive statistics for the change of auditor for the three-year period prior to delisting are displayed in Table 4.29.

Group	n	Non-failed	%	Failed	%
No change of auditor	181	157	86.7	24	13.3
Change of auditor	53	38	71.7	15	28.3
Overall	234	195		39	

Table 4.29: Proportions analysis for Hypothesis 8

As shown in Table 4.29, 53 companies (22.6 per cent) of the total 234 sample companies had experienced auditor change. Of those 53 companies that had changed auditor, 28.3 per cent (15 companies) had been delisted (i.e. failed) from the HKEx, which accounted for 6.4 per cent of the total sample.

For the failed group, the number of companies that experienced auditor change (15 companies) accounted for 38.5 per cent of the failed sample size (39 companies). On the contrary, the number of companies in the non-failed group that experienced auditor change (38 companies) represented merely 19.5 per cent of the non-failed sample size (195 companies). Apparently, the failed group had a higher rate of auditor change than the non-failed group. To determine if the two groups experienced significant difference in auditor change, a Chi-square test was run.

The Chi-square analytical test results are summarized in Table 4.30.

Test	Distribution	Test value	Sig. (2 tail)	Sig. at .05?
Fisher's Exact	Hypergeometric		.019*	Yes
Chi-square Test	Chi-square	6.679	.010*	Yes
Chi-square Test (C.C.)	Chi-square	5.64	.018*	Yes
Mantel-Haenszel Test	Normal	6.679	.010*	Yes
Likelihood Ratio	Chi-square	6.062	.014*	Yes

Table 4.30: Chi Square test results for Hypothesis 8

* Significant at .05 level

As shown in Table 4.30, the Chi-square test found all observations of variance significant at the .05 level. Clearly, the P-value of the Chi-square is returned at .01. Other tests show similar level of the P-value by the Fisher's Exact Test, the Likelihood Ratio and the Chi-square contingency coefficient test. These results imply that if change of auditor has no effect on business failure, the probability of obtaining the large discrepancy in our sample would be about 5 per cent. In other words, it is highly unlikely that we would obtain this large difference between the failed and non-failed companies if there is no difference in the population. Given that there is strong evidence to prove that auditor change in the failed companies is significantly different from that of the non-failed companies, the null hypothesis is therefore rejected.

In summary, failed companies had a higher rate of auditor change. Rejecting the null and holding the alternative hypothesis may infer that the failed companies experienced significant difference in auditor change than the non-failed companies in Hong Kong. This test finds auditor change a useful predictor variable for business failure.

4.3.9 Hypothesis 9

Hypothesis 9 examined the population distributions of the average HIBOR rate for the failed and non-failed companies, using an equality of means t-test. The testing variable was HIBOR rate and the grouping variable was status, with 0 denoting "non-failed companies" and 1 denoting "failed companies".

The descriptive statistics of the average HIBOR rate for the three-year period are displayed in Table 4.31. The mean HIBOR rates for the non-failed companies remained fairly constant below 3 per cent over the three observation years, whereas the mean HIBOR rates for the failed companies decreased towards the delisting year.

The decreasing HIBOR rate for the failed group could imply that, at time the HIBOR rates were low, the failed companies tended to borrow more to fund their investments with the aim of turning around their fading business. This is consistent with the findings from Hypothesis 6 that the mean total liabilities of the failed group largely increased when approaching the delisting year.

	n	**Mean**	**SD**	**Std. error mean**
Non-failed companies				
Third year of observation	195	2.39	1.74	.12
Second year of observation	195	2.69	1.65	.12
First year of observation	195	2.97	1.91	.14
Failed companies				
One year prior	39	2.99	2.17	.35
Two years prior	39	3.42	2.21	.35
Three years prior	39	4.31	2.31	.37

Table 4.31: Descriptive statistics of the three-year average HIBOR rate

T-tests were run in SPSS and the results are shown in Table 4.32. Results of the Equality of means t-test in the table show strong evidence that the population distributions of HIBOR rate for the failed and non-failed companies are significantly different: t-values were –1.85, –2.38 and –3.86 for the three-year period, and the corresponding P-values were .066, .02 and .00. The significance levels for two and three years prior to delisting were less than .05, providing strong evidence to reject the null hypothesis and support the alternative hypothesis that the population distributions of average HIBOR rate for failed and non-failed companies are significantly different.

Independent samples test: Levene's test for Equality of Variances		f	Sig.
One year prior to delisting	Equal variances assumed:	2.85	.09
Two years prior to delisting	Equal variances assumed:	4.91	.03
Three years prior to delisting	Equal variances assumed:	5.63	.02

Equality of Means t-test

	Std. Error Diff.	Mean Diff.	95% Confidence Interval		t	df	Sig. 2-tail
			Lower	Upper			
One year prior to delisting							
Equal variances	.32	–.59	–1.22	.04	–1.85	232	.066
Unequal variances	.37	–.59	–1.33	.15	–1.60	48.3	.12
Two years prior to delisting							
Equal variances	.31	–.73	–1.34	–.13	–2.38	232	.02*
Unequal variances	.37	–.73	–1.48	.02	–1.96	46.8	.06
Three years prior to delisting							
Equal variances	0.35	–1.34	–2.02	–.65	–3.86	232	.000*
Unequal variances	0.39	–1.34	–2.13	–.54	–3.39	48.9	.001*

Table 4.32: Results of Equality of Means t-test for Hypothesis 9

* Significant at 0.05 level

4.4 Chapter summary

This chapter has provided an overview of the hypothesis testing. The study examined nine hypotheses using several statistical tools in SPSS: Chi-square test, equity of means t-test, Pearson Correlation Analysis and Z-test.

Hypothesis 1 examined whether the predictive accuracy of the Altman (1968) model is greater than 50 per cent when predicting business failure for Hong Kong public-listed companies; the null hypothesis was rejected and the alternative hypothesis held, that the predictive accuracy of the Altman (1968) model is greater than 50 per cent when predicting business failure for the Hong Kong public-listed companies.

Hypothesis 2 further investigated whether there is a significant difference at the .05 level for the strength of predicting business failure using the Altman (1968) model and the strength of the Altman (1968) model using the revised cutoff value, when the two models are applied to company data from the Hong Kong listed companies; the null hypothesis was rejected and the alternative hypothesis held, that using revised cutoff value improved the strength of the Altman (1968) model.

Hypotheses 3 and 4 repeated the investigations conducted for hypotheses 1 and 2, using the Ohlson (1980) model; null Hypothesis 3 was rejected, the hypothesis that the predictive accuracy of the Ohlson (1980) model is greater than 50 per cent when predicting business failure for the Hong Kong public-listed companies holds. But null Hypothesis 4 was not rejected; revising the cutoff value did not improve the strength of the Ohlson (1980) O-scores model.

Hypothesis 5 tested the difference between the accuracy of the Altman revised cutoff model and the Ohlson revised cutoff model in predicting failure for Hong Kong public-listed companies; null Hypothesis 5 was rejected, in that the Ohlson revised cutoff model outperformed the Altman revised cutoff model in accuracy for non-failed and overall prediction.

Hypothesis 6 investigated the significant positive relationship between the Ohlson O-scores and the total liabilities; null Hypothesis 6 was not rejected. Although the total liabilities and Ohlson O-scores were positively correlated, the correlation was not statistically significant.

Hypothesis 7 examined the significant positive relationship between the Ohlson O-scores of the failed companies and cash conversion cycle; null Hypothesis 7 was not rejected and the alternative hypothesis did not hold, that cash conversion cycle was negatively associated with failed companies as classified by the Ohlson O-scores.

Hypotheses 8 and 9 analysed how auditor change and HIBOR interest rates differ between the failed and non-failed companies, classified by Ohlson's O-scores. Hypothesis 8 analysed the significant difference between the failed and non-failed companies experience auditor change; null Hypotheses 8 was rejected, which indicated that failed and non-failed companies had significantly different experiences during auditor change. Indeed, failed companies had a higher rate of auditor change. Finally, Hypothesis 9 tested whether the population distribution of the average HIBOR rate of the failed companies is significantly different from that of the non-failed companies; null Hypothesis 9 was rejected and the alternative hypothesis held. The distribution of the HIBOR interest rate for the failed companies was significantly different from that for the non-failed companies.

In summary, both the Altman (1968) and Ohlson (1980) models are capable of classifying failed and non-failed companies using Hong Kong company data. The predictive accuracy of both models can be slightly improved by revising the cutoff values, although the improvements are not significantly large, and the Ohlson revised cutoff model outperforms the Altman revised model because it makes a better overall prediction. Cash conversion cycle (CCC) and O-scores of the failed group are found to be negatively correlated with each other. This research is the first business failure study to identify that CCC is significantly correlated with business failure as classified by the Ohlson revised O-scores. Finally, the non-financial variables change of auditor and HIBOR interest rates are significantly different between the failed and non-failed sample group.

The next chapter summarizes the findings, discusses the research limitations and makes suggestions for future research.

	Hypothetical Results	
H_1	Reject null	The predictive accuracy of the Altman (1968) 5-variable prediction model is greater than 50 per cent, the Altman model is capable in predicting business failure for Hong Kong public-listed companies.
H_2	Reject null	There is a significant difference at the 0.05 level for the strength of predicting business failure using the Altman (1968) prediction model and the strength of the Altman (1968) model using revised cutoff value, revising the cutoff value does improve the predictive accuracy of the Altman model in predicting business failure for Hong Kong public listed companies.
H_3	Reject null	The predictive accuracy of the Ohlson (1980) O-scores model is greater than 50 per cent, the Ohlson model is capable in predicting business failure for Hong Kong public-listed companies.
H_4	Can't reject null	There is no significant difference at the 0.05 level for the strength of predicting business failure using the Ohlson (1980) O-scores model and the strength of the Ohlson (1980) model using revised cutoff value, revising the cutoff value does not improve the predictive accuracy of the Ohlson model in predicting business failure for the Hong Kong listed companies.
H_5	Reject null	There is a significant difference between the levels of predictive accuracy of the Altman revised cutoff model and the Ohlson revised cutoff model in predicting failure for Hong Kong public-listed companies.
H_6	Can't reject null	There is no significant positive relationship between the Ohlson O-scores and the total liabilities of the companies.
H_7	Can't reject null	There is a significant negative relationship at the 0.05 level between the Ohlson O-scores and cash conversion cycle of the failed companies.
H_8	Reject null	There are significant differences at the 0.05 level between failed and non-failed companies experience change of auditor.
H_9	Reject null	The population distribution of the average HIBOR rate of the failed companies is significantly different from that of the non-failed companies.

Table 4.33: Summary of the hypothetical results

CHAPTER FIVE

SUMMARY AND CONCLUSIONS

5.1 Introduction

This research study had four research objectives: to investigate the predictability of the Altman (1968) and Ohlson (1980) models in Hong Kong using the models' original variables and coefficients; to test the predictive accuracy of the two models using revised cutoff values; to compare the models' accuracy in classifying business failure for Hong Kong public companies; and to examine whether cash conversion cycle, auditor switch or interest rates change are associated with the Ohlson model's predictability. This research contributes to the finance literature by finding that the two models can predict and identify business failure in Hong Kong companies, and it aims to stimulate further research interest in exploring new variables.

The following section summarizes the findings of the nine hypotheses. Section 5.3 outlines the study's limitations, and Section 5.4 recommends areas of future research. Section 5.5 contains concluding remarks.

5.2 Summary and results

This research made several findings. First, although the Altman (1968) Z-score and Ohlson (1980) O-score models were developed in the US more than 30 years ago, this study provides strong evidence that the two models can reliably classify failed and non-failed public companies in Hong Kong with a predictive accuracy of over 50 per cent. Revising the cutoff values produced only marginal improvement in the models' accuracy, indicating that the models' original variables and coefficients have stood the test of time and still provide relatively precise predictions. This study also found that the two revised cutoff models performed differently in predicting Hong Kong business failures, in that the Ohlson model better classified non-failed companies and had higher overall predictability. From the perspective of creditors and investors, this strength of prediction (better classifying non-failed companies, or lower Type II error) is being viewed as less costly than a Type I error. With this characteristic, this dissertation weights the Ohlson model's prediction power relatively superior than that of the Altman model in giving a more robust result.

Second, the propensity of business failure in Hong Kong was found to have no relationship with the size of a company's total liabilities. In other words, public-listed companies in Hong Kong with small total liabilities are just as vulnerable to business failure as companies with large total liabilities. Furthermore, because the variable "total liabilities" is not responsible a company's financial health, investors and creditors of Hong Kong public-listed companies should not simply assume that the size of a company's liabilities gives any indication of its financial health. It is highly recommended that investors should evaluate a company's financial condition using a cluster of financial variables instead.

Third, cash conversion cycle (CCC) was found to be negatively correlated with the Ohlson O-scores in predicting business failure. The failed group's inverse relationship with CCC infers that the shorter the CCC, the higher the probability that a company is financially unhealthy (larger O-score). This study is the first to provide empirical evidence that CCC and business failure in Hong Kong companies are associated. A shorter CCC indicates aggressive management of working capital (Soenen, 1993). This finding does not support the findings of Jose et al. (1996) that aggressive (lower) CCC policy enhances profitability. Instead, the findings of this study are consistent with those of Nazir and Afza (2009), who also identified a negative relationship between an aggressive working capital policy and profitability. To keep a shorter CCC, a company has to implement a stringent credit control policy to reduce the accounts receivable (AR). Rigid AR and inflexible credit control policies could have a negative impact on the business relationship with buyers, which in turn affect revenue and profits. To keep inventory (INV) low and lengthen the accounts payable (AP), a company has to achieve just-in-time (JIT) inventory management and rely heavily on good relationships with suppliers. Although JIT helps reduce the stock holding cost, a company has to bear the risks of market fluctuations. Under low INV, a company has to stock-in under unfavourable market situations when the market price is high, causing higher cost of sales (COGS) which negatively impacts the gross profit (GP).

Lengthening the AP may mean that suppliers, which offer a credit payment term to the buyer (i.e. the company) with finance cost, will mark up the selling price for the finance cost, which will push up the company's COGS and lower the GP. This reasoning probably explains why a shorter CCC (an aggressive approach) has a higher probability of business failure, because an aggressive working capital policy has been shown to negatively impact the profitability.

Fourth, auditor switch was found to correlate with business failure in Hong Kong companies. This finding is consistent with the study by Wu (2004), who also found that corporate bankruptcy in Taiwan was associated with auditor change. Although it is beyond the scope of this thesis to explain the rationale of shifting auditors, stakeholders should pay special attention to companies that change auditors frequently. Perhaps a switch in auditor reveals a warning sign that the company is dissatisfied with an auditor's professional advice, or that the company switches auditor in exchange for an unqualified opinion, or that the auditor refuses to compromise their professional integrity by agreeing to issue a modified report. Whatever the reason for changing auditors, this non-financial variable has important implications for the study of business failure prediction.

Finally, decreasing HIBOR interest rates are found to relate to business failure in Hong Kong. This finding contradicts the assumption that increased financial costs will reduce a company's profit and generally cause more defaults and failures. This study found that the failed sample group's total liabilities tended to increase when moving closer to the final year before delisting, at the time when HIBOR rates were decreasing. This may imply that the failed sample companies were inclined to raise more interest-bearing loans to finance their investment projects, since the costs of finance (e.g. HIBOR rates) were getting cheaper. Obviously, their investment projects were unsuccessful and failed to turn around the fading business, and the companies ended up bankrupt.

The findings of the nine hypotheses are summarized in Table 5.1.

Hypothesis	Confirm?	Research Findings
H_1	✓	The predictive accuracy of the Altman (1968) prediction model is greater than 50 per cent, the model is capable to accurately predict business failure for Hong Kong listed companies.
H_2	✓	There is significant difference for the strength of predicting business failure using Altman (1968) prediction model and the strength of the Altman (1968) model using revised cutoff values, revising the cutoff value improves the model's prediction accuracy.
H_3	✓	The predictive accuracy of the Ohlson (1980) O-scores model is greater than 50 per cent, the model is capable to accurately predict business failure for Hong Kong listed companies.
H_4	X	There is no significant difference for the strength of predicting business failure using the Ohlson (1980) O-scores model and the Ohlson (1980) model using revised cutoff values, revising the cutoff value does not improve the model's prediction accuracy.
H_5	✓	There is significant difference between the levels of predictive accuracy of the Altman revised cutoff Z-score model and the Ohlson revised cutoff model in predicting failure for Hong Kong public-listed companies.
H_6	X	The Ohlson O-scores are not significantly related to the total liabilities of the companies.
H_7	X	The Ohlson O-scores are negatively correlated to cash conversion cycle of the failed companies. The shorter the cycle, the higher the probability that the Hong Kong companies will fail.
H_8	✓	There are significant differences between the failed and non-failed companies that experience change of auditor, the high frequency of auditor switch has important implications for studying business failure in Hong Kong.
H_9	✓	The population distributions of the average HIBOR rate for the failed are significantly different from that of the non-failed companies, decrease of HIBOR interest rates is found to relate to business failure in Hong Kong.

Table 5.1: Summary of the research findings

5.3 Research limitations

The first limitation of this study was the small failed sample group. Due to the inaccessibility of financial data for private companies, this research excluded private companies and focused on public companies that were delisted from the HKEx. The failure or bankruptcy of a public company is rare (Appendix 3), although hundreds of private companies are wound up in Hong Kong each year (Table 1.5).

Because of the small size of the failed sample group, this research was unable to separate the failed companies of the Growth Enterprise Market (GEM) and those of the Main Board. As discussed in Chapter One, GEM listed companies are mostly emerging small-medium companies that are comparatively newer and smaller. Their financial structures are certainly different from those of the Main Board listed companies, especially gigantic corporations like the Cheung Kong Group, the Hutchison Whampoa Group and the Li & Fung Group. The results of this study, therefore, cannot be generalized to all Hong Kong companies. However, this limitation does not diminish the importance of observing those younger and smaller companies in future investigations.

Another limitation is the absence of an industrial indicator for the cash conversion cycle. The 234 sampled companies represented a large variety of industries. Each industry has its unique characteristics in managing their AR and AP and controlling their INV levels, and so the average length of the CCC could vary across industries. The results of directly comparing the CCC for companies from different industries, therefore, cannot be generalized.

5.4 Recommendation for future research

This study's sampling data were restricted to public companies that traded in a stock exchange platform. Future research could extend the findings of this study by developing models for private SMEs, which could provide different results that may or may not confirm the comparative accuracy of the Altman and Ohlson models. Private SMEs in Hong Kong have always been reluctant to disclose their financial information to the public, although financial data from bank lenders could facilitate future research to test private SMEs. Developing failure prediction models with reasonably high accuracy for private SMEs would be challenging for researchers interested in studying business failure in Hong Kong.

While the business failure prediction models were applied to public listed companies in the HKEx, no research has investigated GEM companies alone. It is widely believed that younger companies are more vulnerable to business failure (Dun & Bradstreet, 1993), and it would be interesting to compare the models' predictive accuracy in correctly classifying small and young companies that trade within the GEM.

This research explored the links between CCC and business failure in Hypothesis 7. Despite finding a negative relationship, it is likely that the average length of the CCC varies across industries, and future research could strive to identify an average length of CCC that addresses the industry standard in order to develop a better measurement.

This research has highlighted that total liabilities, just like total assets, do not necessarily result in high probability of business failure, as tested by Hypothesis 6. Most failure prediction research (including this thesis) adopting the pair-matched selection method has used total asset size as a criterion for selecting the non-failed group. Future research may consider using total liabilities as a selection criterion; this has not been done before.

Finally, it should be noted that this research focused on how HIBOR rate is related to business failure, as tested with Hypothesis 9. Most Hong Kong companies raise loan in currencies other than Hong Kong dollars, which include US dollars, Euros, British pounds, Japanese Yen and Renminbi. Therefore future research should consider the impact of other types of interest rate variables on business failure, such as the LIBOR rates that may possibly affect prediction accuracy. Especially when sustainable recovery of the US economy becomes more clear-cut, the US Federal will cut bond purchase and raise interest rates to tackle inflation. It is important to understand more how corporate's borrowing costs impact company's fade.

5.5 Concluding remarks

This research investigated the applicability of the Altman and Ohlson models on predicting 234 Hong Kong public listed companies for the period 1998–2011. The impact of CCC and two non-financial variables – auditor change and HIBOR rate change – were examined using the Ohlson revised cutoff model. The findings confirm that both the Altman and Ohlson models are capable of correctly predicting business failure in Hong Kong. The Ohlson model better predicts non-failed companies and makes better overall prediction results. Users can rely on both models, depending on their purpose for studying Hong Kong companies. Creditors who wish to predict failed companies with low Type I errors (mis-predicting unhealthy companies as healthy) may consider the use of the Altman model; investors who prefer low Type II errors (mis-predicting healthy companies as unhealthy) may find the Ohlson model provides more meaningful implications.

The findings of this research make significant contributions to the finance literature. First, this is the most comprehensive study of failure prediction in Hong Kong since that of Chan (1985). This research is a more contemporary study of business failure in Hong Kong using data from 234 companies between 1998 and 2011. Second, this research further confirms that auditor switch is a good predictor of business failure. This finding provides strong support for the reliability of this non-financial variable, as reported in previous studies. Third, this research has found a negative relationship between business failure and cash conversion cycle, which has not been tested before. This finding opens up a new path of investigation for researchers to further test this variable in the bankruptcy prediction arena.

This research also suggests some policy implications for creditors and prospective investors. Companies with shorter CCC may face a higher probability of business failure, since aggressive capital management may not generate more profit. However, various other factors like industrial average may play a pivotal role, and so those factors should be further explored in future studies.

REFERENCES

Abdullah, N., Halim, A., Ahmad A., & Rus, R. (2008). Predicting corporate failure of Malaysian listed companies: Comparing multiple discriminant analysis, logistic regression and the hazard model. International *Research Journal of Finance and Economics,* 15, 201-217.

Abid, F., & Zouari, A. (2002). Predicting corporate financial distress: A new neural networks approach. *Finance India*, 16(2), 601-612.

Aharony J., Jones C., & Swary, I. (1980). An analysis of risk and return characteristics of corporate bankruptcy using capital market data. *Journal of Finance,* 35(4), 1001-1016.

Alkhatib, K., & Al Bzour, A.E. (2011). Predicting corporate bankruptcy of Jordanian listed companies: Using Altman and Kida models. *International Journal of Business,* 6(3), 208-215.

Altman, E.I. (1968). Financial ratios, discriminant analysis and the prediction of corporate bankruptcy. *Journal of Finance*, 23(4), 589-609.

Altman, E.I. (1973). Predicting railroad bankruptcies in America. *Bell Journal of Economics and Management Science*, 4(1), 184-211.

Altman, E.I. (1982). Accounting implications of failure prediction models. *Journal of Accounting, Auditing and Finance,* 6(1), 4-19.

Altman, E.I. (1983). The behavior of firms in financial distress: Discussion. *Journal of Finance*, 38(2), 517-522.

Altman, E.I. (1984). A further empirical investigation of the bankruptcy cost question. *Journal of Finance*, 39(4), 1067-1089.

Altman, E.I. (1993a). *Corporate financial distress and bankruptcy: A complete guide to predicting & avoiding distress and profiting from bankruptcy* (2nd ed.). New York: John Wiley & Sons, Inc.

Altman, E.I. (1993b). *Corporate financial distress and bankruptcy* (3rd ed.). New York: John Wiley & Sons, Inc.

Altman, E.I. (2000). Predicting financial distress of companies: Revisiting the Z-score and zeta models. http://www.pages.stern.nyu.edu/~ealtman/. Retrieved 13 June 2011.

Altman, E.I., & Brenner, M. (1981). Information effects and stock market response to signs of firm deterioration. *Journal of Financial & Quantitative Analysis*, 16(1), 35-51.

Altman, E.I., Haldeman, R.G., & Narayanan, P. (1977). Zeta analysis, a new model to identify bankruptcy risk of corporations. *Journal of Banking & Finance,* 1(1), 29-54.

Altman, E.I., & Kim, D.W. (1995). Failure prediction: Evidence from Korea. *Journal of International Financial Management and Accounting*, 6(3), 230-249.

Altman, E.I., & Lavallee, M.Y. (1980). Business failure classification in Canada. *Journal of Business Administration*, 12(1), 147-164.

Altman, E.I., & McGough, T.P. (1974). Evaluation of a company as a going concern. *Journal of Accountancy*, 136(6), 50.

Altman, E.I., Marco, G., & Varetto, F. (1994). Corporate distress diagnosis: Comparisons using linear discriminant analysis and neural networks. *Journal of Banking & Finance*, 18(3), 505-529.

Altman, E.I., & Saunders, A. (1997). Credit risk measurement: Development over the last 20 years. *Journal of Banking and Finance*, 21, 1721-1742.

Anandarajan, M., Lee, P.C., & Anandarajan, A. (2001). Bankruptcy prediction of financially stressed firms: an examination of the predictive accuracy of artificial neural networks. *Intelligent Systems in Accounting, Finance and Management*, 10(2), 69-81.

Argenti, J. (1976). *Corporate collapse: the causes and symptoms*. London: McGraw-Hill.

Aziz, A., Emanual, D., & Lawson, G. (1988). Bankruptcy prediction – An analysis of cash flow based models. *Journal of Management Studies*, 25(5), 419-437.

Back, P. (2001). Testing liquidity measures as bankruptcy prediction variables. *LTA*, 3, 309-327.

Ball, R., & Foster, G. (1982). Corporate financial reporting: A methodological review of empirical research. *Journal of Accounting Research*, 20, 161-234.

Barnes, P. (1987). The analysis and use of financial ratios: A review article. *Journal of Business Finance and Accounting*, 449-461.

Barnes, P., & Huan, H.D. (1993). The auditor's going concern decision: Some UK evidence concerning independence and competence. *Journal of Business Finance and Accounting*, 20, 213-228.

Barniv, R., Hathorn, J., Mehrez, A., & Kline, D. (1999). Confidence intervals for the probability of insolvency in the insurance industry. *Journal of Risk and Insurance*, 66(1), 125-137.

BBC News (2003). The impact of economic losses in the great epidemic. 28 May 2003. http://news.bbc.co.uk/hi/chinese/news/newid_2944000/29441642.stm. Retrieved 18 February 2012.

Beaver, W.H. (1966). Financial ratios as predictors of failure. Empirical Research in Accounting: selected studies. *Journal of Accounting Research*, 4, 71-111.

Becerra, V.M., Galvao, R.K.H., & Abou-Seada, M. (2005). Neural and wavelet network models for financial distress classification. *Data Mining and Knowledge Discovery*, 11(1), 35-55.

Begley, J., Ming, J., & Watts, S. (1996). Bankruptcy classification errors in the 1980s: An empirical analysis of Altman's and Ohlson's models. *Review of Accounting Studies*, 1(4), 267-284.

Beneda, N. (2007). Performance and distress indicators of new public companies. *Journal of Asset Management*, 8(1), 24-33.

Benzing, C., Chu, H.M, & Kara, O. (2009). Entrepreneurs in Turkey: A factor analysis of motivations, success factors, and problems. *Journal of Small Business Management*, 47(1), 58-91.

Bellovary, J., Giacominao, D., & Akers, M. (2007). A review of bankruptcy prediction studies: 1930 to present. *Journal of Financial Education*, 33, 1-42.

Bharath, S.T. & Shumway, T. (2008). Forecasting default with the Merton distance to default model. *The Review of Financial Studies*, 21(3), 1339-1369.

Black, F., & Scholes, M. (1973). The pricing of options and corporate liabilities. *Journal of Political Economy*, 81(3), 637-654.

Blay, A.D. (2005). Independence threats, litigation risk, and the auditor's decision process. *Contemporary Accounting Research*, 22, 759-789.

Bloomberg (2009). Hong Kong IPOs may raise record $48 billion in 2010. Ernst & Young. http://bloomberg.com/app/news?pid=newsarchive&sid=aI3U6ahtflyo. Retrieved 15 April 2010.

Blum, M. (1974). Failing company discriminant analysis. *Journal of Accounting Research*, 12 (1), 1-25.

Booth, P.J. (1983). Decomposition measures and the prediction of financial failure. *Journal of Business Finance and Accounting*, 10(1), 67-82.

Boritz, J., & Kennedy, B. (1995). Effectiveness of neural network types for prediction of business failure. *Expert System with Applications*, 9(4), 503-512.

Boritz, J., Kennedy, B., & Albuquerque, A.M. (1994). Predicting corporate failure using a neural network approach. *Intelligent Systems in Accounting, Finance and Management*, 2, 1-18.

Boritz, J., Kennedy, B., & Sun, J.Y. (2007). Predicting business failure in Canada. *Accounting Perspectives*, 6(2), 141-165.

Bromma, H. (2007). How to invest in offshore real estate and pay little or no taxes. *McGraw-Hill Profession*, 161.

Bruning, J.L., & Kintz, B.L. (1996). *Computational handbook of statistics* (4^{th} ed.). New York, NY: Addison Wesley Longman, Inc.

Bukovinsky, D.M. (1993). Cash flow and cash position measures in the prediction of business failure: An empirical study. Doctoral Dissertation, University of Kentucky.

Campbell, J.Y., Hilscher, J., & Szilagyi, J. (2008). In search of distress risk. *Journal of Finance*, 63(6), 2899-2939.

Carter, R., & Van Auken, H. (2006). Small firm bankruptcy. *Journal of Small Business Management*, 44(4), 493-512.

Casey, C.J., & Bartczak, N.J. (1984). Cash flow – it's not the bottom line. *Harvard Business Review*, 61-66.

Casey, C.J., & Bartczak, N.J. (1985). Using operating cash flow data to predict financial distress. *Journal of Accounting Research*, 23(1), 384-401.

Census & Statistics Report, HKSAR (2006). About Hong Kong. http://www.info.gov.hk/info/hkbrief/eng/ahk.htm. Retrieved 4 October 2012.

Census & Statistics Report, HKSAR (2009). About Hong Kong. http://www.info.gov.hk/info/hkbrief/eng/ahk.htm. Retrieved 18 September 2012.

Census & Statistics Report, HKSAR (2012). About Hong Kong. http://www.info.gov.hk/info/hkbrief/eng/ahk.htm. Retrieved 4 December 2012.

Chan, H.C. (1985). Financial ratios, discriminant analysis and the prediction of corporate financial distress in Hong Kong. MBA dissertation, University of Hong Kong.

Charalambous, C., Charitou, A., & Kaourou, F. (2000). Comparative analysis of Artificial Neural Network Models: Application in bankruptcy prediction. *Annals of Operations Research*, 99(1), 403-425.

Charitou, A., Neophytou, E., & Charalambour, C. (2004). Predicting corporate failure: Empirical evidence for the UK. *European Accounting Review*, 13(3), 465-497.

Chava, S., & Jarrow, R. (2004). Bankruptcy prediction with industry effects. *Review of Finance,* 8(4), 537-569.

Chen, Y., Gupta, A., & Senteney, D.L. (2004). Predicting impending bankruptcy using audit firm changes. *Journal of American Academy of Business*, 4(1/2), 423-433.

Chen, J., Marshall, B., Zhang, J., & Ganesh, S. (2006). Financial distress prediction in China. *Review of Pacific Basin Financial Markets and Policies*, 9(2), 317-336.

Chen, G.M., & Merville, L.J. (1999). An analysis of the underreported magnitude of the total indirect costs of financial distress. *Review of Quantitative Finance and Accounting*, 13(3), 277-293.

Cho, M. (1994). Predicting business failure in the hospitality industry: An application of logit model. PhD dissertation, Virginia Polytechnic Institute and State University.

Chow, M.S., & Rice, S. J. (1982). Qualified auditor opinions and auditor switching. *Accounting Review*, 57, 326-335.

Chuvakhin, N., & Gertmenian, L. (2003). Predicting bankruptcy in the WorldCom age. *Graziadio Business Report*, 6(1).

Citron, D., & Taffler, R. (1992). The audit report under going concern uncertainties: An analysis. *Accounting and Business Research,* 22, 337-345.

Clark, T.A., & Weinstein, M.I. (1983). The behavior of the common stock of bankrupt firms. *Journal of Finance*, 38(2), 489-504.

Coats, P.K., & Fant, L.F. (1992). A neural network approach to forecasting financial distress. *Journal of Business Forecasting*, 10(4), 9-12.

Coats, P.K., & Fant, L.F. (1993). Recognizing financial distress patterns using a Neural Network tool. *Financial Management,* 22(3), 142-155.

Collins, R.A., & Green, R.D. (1982). Statistical methods for bankruptcy forecasting. *Journal of Economics and Business,* 34, 349-354.

Connor, D. (1988). Data transformation explains the basics of neural networks. *EDN*, May 12, 138-144.

Cordeiro, G.M., & Lemonte, A.J. (2013). On the Marshall-Olkin extended Weibull distribution. Statistical papers, 54(2), 333-353.

Cox, D. (1972). Regression models and life-tables. *Journal of the Royal Statistical Society, Series B (Methodological)*, 34(2), 187-220.

Crapp, H., & Stevenson, M. (1987). Development of a method to access the relevant variable and the probability of financial distress. *Australian Journal of Management*, 12(2), 221-236.

Cybinski, P. (2001). Description, explanation, prediction – the evolution of bankruptcy studies? *Managerial Finance*, 27(4), 29-44.

Darayseh, M., Waples, E., & Tsoukalas, D. (2003). Corporate failure for manufacturing industries using firms specifics and economic environment with logit analysis. *Managerial Finance*, 29(8), 23-36.

d'Aveni, R.A. (1989). Dependability and organizational bankruptcy: An application of agency and prospect theory. *Management Science*, 35(9), 1120-1138.

de Gooijer, J., & Kumar, K. (1992). Some recent developments in non-linear time series modelling, testing, and forecasting. *International Journal of Forecasting*, 8(2), 135-156.

Deakin, E.B. (1972). A discriminant analysis of predictors of business failure. *Journal of Accounting Research*, 10(1), 167-179.

Deakin, E.B. (1976). Distributions of financial accounting ratios: Some empirical evidence. *The Accounting Review*, 51(1), 90-96.

Deakin, E.B. (1977). *Business failure prediction: An empirical analysis*. In E. Altman (Ed.), Financial crisis: Institutions and Markets in Fragile Environment, 72-88.

Dennis, W., & Fernald, L. (2001). The chances of financial success (and loss) from small business ownership. *Entrepreneurship: Theory & Practice*, 26(1), 75-83.

Dhumale, R. (1998). Earnings retention as a specification mechanism in logistic bankruptcy models: A test of the free cash flow theory. *Journal of Business Finance & Accounting*, 25, 1005-1023.

Dhungana, G. (2006). Growth in exports defies predictions. *The Standard*, 29 December 2006. http:/www.thestandard.com.hk/news_detail.sap?pp_cat=1&art_id=34998&sid=1152347&con_type=1. Retrieved 4 May 2011.

Dichev, I.D. (1998). Is the risk of bankruptcy a systematic risk? *Journal of Finance*, 53(3), 1131-1147.

Ding, A. (2007). Early discovery of individual firm insolvency. *IMA Journal of Management Mathematics*, 18, 269-295.

Dimitras, A.I., Zanakis, S.H., & Zopounidis, C. (1996). A survey of business failure with an emphasis on prediction methods and industrial applications. *European Journal of Operational Research*, 90(3), 487-513.

Dodd, P., Dopuch, N., Holthausen, W., & Leftwich, R. (1984). Qualified audit opinions and stock prices: Information content, announcement dates, and concurrent disclosures. *Journal of Accounting and Economics*, 6, 3-39.

Donaldson, R.G., & Kamstra, M. (1996). Forecast combining with neural networks. *Journal of Forecasting*, 15(1), 49-61.

Dopuch, N., Holthausen, W., & Leftwich, R. (1986). Abnormal stock returns associated with media disclosures of ‘subject to’ qualified audit opinions. *Journal of Accounting and Economics,* 8, 93-117.

Duan, J.C., (1994). Maximum likelihood estimation using price data of the derivative contract. Mathematical Finance, 4, 155-167.

Duan, J.C. (2000). Correction: Maximum likelihood estimation using price data of the derivative contract. Mathematical Finance, 10(4), 461-462.

Dun & Bradstreet (1993). *Business failure record: A statistical analysis of geographic and industry trends in business failure in the United States*. New York.

Dwyer, M.D. (1992). A comparison of statistical techniques and artificial neural network models in corporate bankruptcy prediction. Unpublished doctoral dissertation, University of Wisconsin-Madison.

Edmister, R.O. (1972). An empirical test of financial ratio analysis for small business failure prediction. *Journal of Financial and Quantitative Analysis*, 7(2), 1477-1493.

Eisenbeis, R.A. (1977). Pitfalls in the application of discriminant analysis in business, finance, and economics. *Journal of Finance*, 32(3), 875-900.

Elliot, J.A. (1982). Subject to audit opinions and abnormal security returns: Outcomes and ambiguities. *Journal of Accounting Research*, 20, 617-638.

Economist (2010). End of an experiment. *The Economist,* 15 July 2010. http://www. Economist.com/node/16591088.

Fich, E.M., & Slezak, S.L. (2008). Can corporate governance save distressed firms from bankruptcy? An empirical analysis. *Review of Quantitative Finance and Accounting*, 30(20), 225-251.

Fisher, R.A. (1950). *The use of multiple measurements in taxonomic problems*. In J. Tukey (Ed.) Contributions to Mathematical Statistics, pp. 465-475. New York: John Wiley & Sons, Inc.

Fisher, L., & Lin, D.Y. (1999). Time-dependent covariates in the Cox proportional-Harzards regression model. *Annual Review of Public Health,* 20, 145-157.

Fitzpatrick, P.J. (1932). A comparison of the ratios of successful industrial enterprises with those of failed companies. *The Certified Public Accountant*, 598-731.

Foster, G. (1986). *Financial Statement Analysis* (2nd ed.). Engelwood Cliffs, New Jersey: Prentice-Hall, Inc.

Foulke, R.A. (1937). Financial ratios become of age. *Journal of Accountancy*, 64(3), 203-213.

Frydman, H., Altman, E.I., & Kao, D. (1985). Introducing recursive partitioning for financial classifications: The case of financial distress. *Journal of Finance,* 40(1), 269-291.

Fulmer, J.G., Moon, J.E., Gavin, T.A., & Erwin, J.M. (1984). A bankruptcy classification model for small firms. *Journal of Commercial Bank Lending*, 66(11), 25-37.

Garlappi, L., Shu, T., & Yan, H. (2008). Default risk, shareholder advantage, and stock returns. *Review of Financial Studies*, 21(6), 2743-2778.

Geiger, M.A., Raghunanda, K., & Rama, D.V. (2005). Recent changes in the association between bankruptcies and prior audit opinions. *A Journal of Practice and Theory*, 24, 21-35.

Gentry, J.A., Newbold, P., & Whitford, D.T. (1985). Classifying bankrupt firms with funds flow components. *Journal of Accounting Research*, 23(1), 146-160.

Gentry, J.A., Newbold, P., & Whitford, D.T. (1987). Funds flow components, financial ratios and bankruptcy. *Journal of Business Finance and Accounting*, 14(4), 595-606.

Ginoglou, D., Agorastos, K., & Hatzigagios, T. (2002). Predicting corporate failure of problematic firms in Greece with LPM logit probit and discriminant analysis models. *Journal of Financial Management and Analysis*, 15(1), 1-15.

Gitman, L.J. (1974). Corporate liquidity requirements: A simplified approach. *The Financial Review*, 9, 79-88.

Gitman, L.J., & Sachdeva, K.S. (1981). Accounts receivable decisions in a capital budgeting framework. *Financial Management*, 10(5), 45-49.

Graves, C., & Smith, M. (2002). Identifying recovery candidates, BAA Conference Paper, 1-24.

Grice, J.S., Sr. (2002). Bankruptcy prediction models: sensitivity to statistical methodologies. *Southern Business & Economic Journal*, 25(3), 174-181.

Grice, J.S., & Dugan, M.T. (2001). The limitations of bankruptcy prediction models: Some cautions for the researcher. *Review of Quantitative Finance and Accounting*, 17(2), 151-166.

Grice, J., & Ingram, R. (2001). Tests of the generalizability of Altman's Bankruptcy prediction model. *Journal of Business Research*, 54(13), 53-61.

Hair, J., Anderson, R., Tatham, R., & Black, W. (1995). *Multivariate data analysis with readings* (4th ed.). Englewood Cliffs, New Jersey: Prentice Hall.

Hamer, M.M. (1983). Failure prediction: Sensitivity of classification accuracy to alternative statistical methods and variable sets. *Journal of Accounting and Public Policy*, 2(4), 289-307.

Han, C.W., Kang, H.M., Kim, G.M., & Yi, J. (2012). Logit regression based bankruptcy prediction of Korean firms. *Asia-Pacific Journal of Risk and Insurance*, 7(1), 1-28.

Hauser, R., & Booth, D. (2011). Predicting bankruptcy with robust logistic regression. *Journal of Data Science*, 9, 565-584.

Haykin, S. (1999). *Neural networks: A comprehensive foundation* (2nd ed.). Upper Saddle River, New Jersey: Prentice-Hall, Inc.

Helfert, E.A. (1982). *Techniques in financial analysis* (5th ed). Homewood, Illinois: Irwin.

Hiau, N.R., Halim, A., Hamilton, A., & Rus, R.M. (2008). Predicting corporate failure of Malaysia's listed companies: Comparing discriminant analysis, logistic regression and hazard model. *International Research Journal of Finance & Economics*, 15, 201-217.

Hickman, W.B. (1958). *Corporate bond quality and investor experience*. Princeton, New Jersey: Princeton University Press.

Hiew, M., & Green, G. (1992). Beyond statistics, a forecasting system that learns. *The Forum*, 5, 63-71.

Hillegeist, S.A., Keating, E.K., Cram, D.P., & Lundstedt, K.G. (2004). Assessing the Probability of Bankruptcy. *Review of Accounting Studies*, 9(1), 5-34.

Hol, S. (2007). The influence of the business cycle on bankruptcy probability. *International Transactions in Operational Research*, 14, 75-90.

Holmen, J.S. (1988). Using financial ratios to predict bankruptcy: An evaluation of classic models using recent evidence. *Akron Business and Economic Review*, 19(1), 52-63.

Hong Kong. The World Factbook. CIA. 23 August 2010. http;//cia.gov/library/publications/the-world-factbook/geos/hk.html. Retrieved 17 December 2011.

HKEx (2006). The Year 2006 in Review. Hong Kong Exchanges & Clearing Limited.

HKEx (2007). The Year 2007 in Review. Hong Kong Exchanges & Clearing Limited.

HKEx (2008). The Year 2008 in Review. Hong Kong Exchanges & Clearing Limited.

HKEx (2009). The Year 2009 in Review. Hong Kong Exchanges & Clearing Limited.

HKEx (2010). The Year 2010 in Review. Hong Kong Exchanges & Clearing Limited.

HKEx (2011). The Year 2011 in Review. Hong Kong Exchanges & Clearing Limited.

HKEx (2012). The Year 2012 in Review. Hong Kong Exchanges & Clearing Limited.

HKEx (2013). The Year 2013 in Review. Hong Kong Exchanges & Clearing Limited.

Hong Kong Exchanges & Clearing Limited (2011). Overseas investor participation in HKEx's securities market reaches new record high. April 2011.

Hong Kong Exchanges & Clearing Limited (2013). Cash market transaction survey 2013. February 2014.

Hornik, K., & Baldi, P. (1989). Neural networks and principal component analysis: Learning from examples without local minima. *Neural Networks*, 2(1), 53-58.

Horrigan, J. (1968). A short history of financial ratio analysis. *Accounting Review*, 12, 284-294.

Hossari, G., & Rahman, S. (2005). A comprehensive formal ranking of the popularity of financial ratios in multivariate modelling of corporate collapse. *Journal of American Academy of Business*, 3, 321-327.

Ingbar, Y. (1994). *Analysis of financial statements*. Israel Institute of Productivity. Chapter 13.

Jackman, T. (2011). Corporate bankruptcy and prediction: an analysis of multi-discriminant, logit and survival models using the statement of cash flow. Doctoral dissertation, University of Nebraska-Lincoln.

Jensen, M. (1986). Agency cost of free cash flow, corporate finance, and takeovers. *American Economic Review*, 76(2), 323-329.

Johnsen, T., & Melicher, R.W. (1994). Predicting corporate bankruptcy and financial distress: Information value added by multinomial logit models. *Journal of Economics and Business*, 46(4), 269-286.

Johnson, C.G. (1970). Ratio analysis and the prediction of firm failure. *Journal of Finance*, 5, 1166-1168.

Jones, F. (1987). Current techniques in bankruptcy prediction. *Journal of Accounting Literature*, 6(3), 131-164.

Jones, K.E. (2002). Corporate insolvency. http://www.solvency.com/bankpred.htm. Retrieved 1 September 2002.

Joos, P., Vanhoof, K., Ooghe H., & Sierens, N. (1998). Credit classification: A comparison of logit models and decision trees. Proceedings notes of the workshop on application of machine learning and data mining in finance. 10th European Conference on Machine Learning, April, 24, Chemnitz (Germany), 59-72.

Jose, M.L., Lancaster, C., Stevens, J.L. (1996). Corporate returns and cash conversion cycles. *Journal of Economics and Finance*, 20(1), 33-46.

Joy, O.M., & Tollefson, J.O. (1975). On the financial application of discriminant analysis. *Journal of Financial and Quantitative Analysis*, 10(5), 723-739.

Kamath, R., (1989). How useful are common liquidity measures? *Journal of Cash Management*, 9(1), 24-28.

Karels, G.V., & Prakash, A.J. (1987). Multivariate normality and forecasting of business bankruptcy. *Journal of Business Finance and Accounting*, 14(4), 573-593.

Keasey, K., & Watson, R. (1987). Non-financial symptoms and the prediction of small company failure: A test of Argenti's hypotheses. *Journal of Business Finance and Accounting*, 14(4), 335-355.

Kida, T. (1980). An investigation into auditor's continuity and related qualification judgments. *Journal of Accounting Research*, 18, 505-523.

Kmenta, J. (1971). *Elements of econometrics*. New York: MacMillan Publishing Company.

Kwansa, F.A., & Parsa, H.G. (1990). Business failure analysis: An event approach. *Journal of Hospitality and Tourism Research*, 14(2), 23-34.

Lachenbruch, P.A. (1968). On expected probabilities of misclassification in discriminant analysis, necessary sample size, and a relation with the multiple correlation coefficient. *Biometrics*, 24(4), 823-834.

Laitinen, E.K. (1991). Financial ratios and different failure processes. *Journal of Business Finance and Accounting*, 18(5), 649-673.

Laitinen, E., & Luoma, M. (1991). Survival analysis as a tool for company failure prediction. *Omega*, 19(6), 673-678.

Landis, J.R., & Koch, G.G. (1977). Measurement of observer agreement for categorical data. *Biometrics*, 33(1), 159-174.

Lane, W., Looney, S., & Wansley, J. (1986). An application of the Cox proportional hazards model to bank failure. *Journal of Banking and Finance*, 10(4), 511-531.

Lau, H.L. (1987). A five-state financial distress prediction model. *Journal of Accounting Research*, 25(1), 127-138.

Lee, J.S. (1998). Causes for business failure: Understanding the 1997 Korean crisis. *Journal of Asian Economics*, 9(4), 637-651.

Legault, J., & Veronneau, P. (1986). CA-score, un modele de prevision de faillite. Research report for Ordre des comptables agrees du Quebec.

Lennox, C. (1999). Identifying failing companies: A re-evaluation of the logit, probit, and DA approaches. *Journal of Economics and Business*, 51, 347-364.

Lennox, C. (2000). Do companies successfully engage in opinion-shopping? Evidence from the UK. *Journal of Accounting and Economics*, 29, 321-337.

Libby, R. (1975). Accounting ratios and the prediction of failure: Some behavioral evidence. *Journal of Accounting Research*, 13(1), 150-161.

Lifschutz, S., & Jacobi, A. (2010). Predicting bankruptcy: Evidence from Israel. *International Journal of Business and Management*, 5(4), 133-141.

Liu, J. (2004). Macroeconomic determinants of corporate failures: evidence from UK. *Applied Economics*, 36, 939-945.

Lo, A.W. (1986). Logit versus discriminant analysis: A specification test and application to corporate bankruptcies. *Journal of Econometrics*, 31, 151-178.

Loong, S., & Hughes, H. (2007). *Explorative investigation into the drives of firm failure*. UK: Nottingham University Business School.

Lussier, R., & Pfeifer, S. (2001). A cross-national prediction model for business success. *Journal of Small Business Management*, 39(3), 228-239.

Luther, R.K. (1998). An artificial neural network approach to predicting the outcome of Chapter XI bankruptcy. *Journal of Business and Economic Studies*, 4(1), 51-73.

Lynn, M.L., & Wertheim, P. (1993). Key financial ratios can foretell hospital closures. *Healthcare Financial Management*, 66-70.

Marais, M.L., Patell, J.M., & Wolfson, M.A. (1984). The experimental design of classification models: An application of recursive partitioning and bootstrapping to commercial bank loan classifications. *Journal of Accounting Research*, 22, 87-114.

Martin, D. (1977). Early warning of bank failure: A logit regression approach. *Journal of Banking and Finance*, 1, 249-276.

McKee, T.E., & Greenstein, M. (2000). Predicting bankruptcy using recursive partitioning and a realistically proportioned data set. *Journal of Forecasting*, 19(3), 219-230.

McGurr, P.T. (1996). Failure prediction of retail firms through use of financial ratios. Doctoral Dissertation, Purdue University.

Mensah, Y.M. (1984). An examination of the stationarity of multivariate bankruptcy prediction models: a methodological study. *Journal of Accounting Research*, 22(1), 380-395.

Merton, R. (1974). On the pricing of corporate debt: The risk structure of interest rates. *The Journal of Finance*, 29, 449-470.

Merwin, C. (1942). *Financing small corporations: In five manufacturing industries, 1926-1936*. Cambridge, MA: National Bureau of Economic Research.

Messier, W.F. Jr., & Hansen, J.V. (1988). Inducing rules for expert system development: An example using default and bankruptcy data. *Management Science*, 34(12), 1403-1415.

Mohamed, S., Li, A.J., & Sanda, A.U. (2001). Predicting corporate failure in Malaysia: An application of the logit model to financial ratio analysis. *Asian Academy of Management Journal*, 6(1), 99-118.

MoneyBeat. The Wall Street Journal. 16 September 2013. Retrieved on 23 May 2014.

http://blogs.wsj-com/moneybeat/2013/09/16/hong-kongs-ipo-market-perks-up/

Morris, R. (1997). *Early warning indicators of corporate failure*. Aldershot: Ashgate.

Mossman, C.E., Bell, G.G., Swartz, L.M., & Turtle, H. (1998). An empirical comparison of bankruptcy models. *The Financial Review*, 33, 35-54.

Moyer, R.C. (1977). Forecasting financial failure: A re-examination. *Financial Management*, 11-17.

Muller, G.J., Steyn-Bruwer, B.W., & Hamman, W.D. (2009). Predicting financial distress of companies listed on the JSE-A comparison of techniques. *South African Journal of Business Management*, 40(1), 21-32.

Mutchler, J.F. (1985). A multivariate analysis of the auditor's going-concern opinion decision. *Journal of Accounting Research*, 23(2), 668-682.

Nam, J.H., & Jinn, T.H. (2000). Bankruptcy prediction: Evidence from Korean listed companies during the IMF crisis. *Journal of International Financial Management and Accounting*, 11(3), 178-197.

Nazir, M.S., & Afza, T. (2009). Impact of aggressive working capital management policy on firm's profitability. *Journal of Applied Finance*, 15(8), 19-30.

Neves, J.C., & Vieira, A. (2006). Improving bankruptcy prediction with hidden layer learning vector quantization. *European Accounting Review*, 15(2), 253-271.

Nittayagasetwat, A. (1994). A test of financial ratios and untransformed financial accounts for predicting bankruptcy. Unpublished Doctoral Dissertation, University of Mississippi.

Norton, C.L., & Smith, R.E. (1979). A comparison of general price level and historical cost financial statements in the prediction of bankruptcy. *Accounting Review*, 54(1), 79-87.

Nunthaphad, P. (2000). The application of Altman's and McGurr's bankruptcy prediction models to small retail firms: A comparative analysis. Unpublished Doctoral Dissertation, Nova South-eastern University.

Official Receiver's Office, HKSAR (2013). www.oro.gov.hk/cgi-bin/stat.cgi

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

Oviatt, B.M., & McDougall, P. (2005). Defining international entrepreneurship and modelling the speed of internationalization. *Entrepreneurship Theory & Practice*, 29(5), 537-554.

Peat, M. (2007). Factors affecting the probability of bankruptcy: A managerial decision-based approach. *ABACUS*, 43(3), 303-324.

Pinches, G.E. (1980). Factors influencing classification results from multiple discriminant analysis. *Journal of Business Research*, 8(4), 429-456.

Pinches, G.E., Mingo, K.A., & Caruthers, J.K. (1973). The stability of financial patterns in industrial organizations. *Journal of Finance*, 28, 389-396.

Pinches, G.E., & Trieschmann, J.S. (1977). Discriminant analysis, classification results, and financially distressed P-L insurers. *Journal of Risk and Insurance*, 44(2), 289-298.

Platt, H.D., & Platt, M.B. (1990). Development of a class of stable predictive variables: The case bankruptcy prediction. *Journal of Business Finance and Accounting*, 17(1), 31-51.

Platt, H.D., & Platt, M.B. (1991). A note in the use of industry-relative ratios in bankruptcy prediction. *Journal of Banking and Finance*, 15(6), 1183-1194.

Pompe, P.P.M., & Bilderbeek, J. (2005). The prediction of bankruptcy of small and medium sized industrial firms. *Journal of Business Venturing*, 20, 847-868.

Preston, P.W., Haacke, J. (2003). Contemporary China: The dynamic of change at the start of the new millennium. *Psychology Press*, 80-107.

Ramser, J.R., & Foster, L.O. (1931). *A demonstration of ration analysis*. Bulletin no. 40. Bureau of Business Research. University of Illinois: Urbana.

Rance, R. (1999). The application of Altman's revised four-variable Z-score bankruptcy prediction model for retail firms and the influence of asset size and sales growth on their future. Doctoral dissertation, Nova South-eastern University.

Rogoff, E.G., Lee, M., & Sub, D. (2004). "Who Done It" Attributions by entrepreneurs & experts of the factors that cause and impede small business success. *Journal of Small Business Management*, 42(4), 364-376.

Rose, P., Andrews, W., Giroux, G. (1982). Predicting business failure: A macroeconomic perspective. *Journal of Accounting, Auditing and Finance*, 6(1), 20-31.

Rumelhart, D.E., & McClelland, J.L. (1986). *Parallel distributed processing: Explorations in the microstructure of cognition*, Volume 1. Cambridge, MA: MIT.

Sandin, A.R., & Porporato, M. (2007). Corporate bankruptcy prediction models applied to emerging economies. Evidence from Argentina in the years 1991-1998. *International Journal of Commerce and Management*, 17(4), 295-311.

Saulnier, R., Halcrow, H., & Jacoby, N. (1958). *Federal lending and loan insurance*. Princeton University Press, pp. 286-362.

Schwartz, K.B., & Menon, K. (1985). Auditor switches by failing firms. *Accounting Review*, 60, 248-261.

Scott, J. (1981). The probability of bankruptcy: A comparison of empirical predictions and theoretical models. *Journal of Banking & Finance*, 5, 318-344.

Shah, J.R., & Murtaza, M.B. (2000). A neural network based clustering procedure for bankruptcy prediction. *American Business Review*, 18(2), 80-86.

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

Smith, K. (1980). *Profitability versus liquidity trade-offs in working capital management*. Reading on the management of working capital. St Paul, MN: West Publishing Company, pp. 549-562.

Smith, R.F., & Winakor, A.H. (1930). *Test analysis of unsuccessful industrial companies*. Bulletin 31. Bureau of Business Research. University of Illinois: Urbana.

Soenen, L. (1993). Cash conversion cycle and corporate profitability. *Journal of Cash Management*, 13(4), 53-57.

Springate, G. (1978). Predicting the possibility of failure in a Canadian firm. Unpublished MBA Research Project, Simon Fraser University.

Stone, M., & Rasp, J. (1993). The assessment of predictive accuracy and model overfitting: an alternative approach. *Journal of Business Finance & Accounting*, 20(1), 125-131.

Storey, D., Keasy, K., Watson, R., & Wynarczyk, P. (1990). *The performance of small firms: profits, jobs, and failures*. London: Routledge Small Business Series.

Sun, J., & Lee, H. (2009). Financial distress early warning based on group decision making. *Computer & Operations Research*, 36, 885-906.

Swanson, E., & Tybout, J. (1988). Industrial bankruptcy determinants in Argentina. *Journal of Banking and Finance*, 7, 1-25.

Taffler, R.J. (1983). The assessment of company solvency and performance using a statistical model: a comparative UK based study. *Accounting and Business Research*, 15(52), 295-308.

Taffler, R.J., & Tisshaw, H. (1977). Going, going, gone – Four factors which predict. *Accountancy*, 88(1003), 50-54.

Tam, K. (1991). Neural network models and the prediction of bank bankruptcy. *Omega*, 19(5), 429-445.

Tam, K.Y., & Kiang, M. Y. (1992). Managerial applications of neural networks: The case of bank failure predictions. *Management Science*, 38(7), 926-947.

Thomaswhite.com (2009). Hong Kong: A symphony of lights. 16 October 2009. http://thomaswhite.com/explore-the-world/hongkong.aspx. Retrieved 19 July 2010.

Triennial Central Bank Survey (2010). Report on global foreign exchange market activity in 2010. Monetary and Economic Department (Bank for International Settlements): 12 December 2010.

Turban, E., Aronson, J.E., & Liang, T.P. (2005). *Decision support systems and intelligent systems* (7th ed.). Upper Saddle River, NJ: Prentice-Hall, Inc.

Turner, P., Coutts, A., & Bowden, S. (1992). The effect of the Thatcher government on company liquidations: An econometric study. *Journal of Applied Economics*, 24, 935-943.

Udo, G. (1993). Neural network performance on the bankruptcy classification problem. *Computers & Industrial Engineering*, 25(1), 37-80.

Ugurlu, M., & Aksoy, H. (2006). Prediction of corporate financial distress in an emerging market: The case of Turkey. *Cross Cultural Management*, 13(4), 277-295.

Ulmer, M.J., & Nielsen, A. (1947). Business turn-over and causes of failure. *Survey of Current Business*, 27(4), 10-16.

United Nations. (2009). *Economic and Social Survey of Asia and the Pacific 2009: Addressing triple threats to development*. United Nations Publications, pp. 94-99.

Van Auken, H., Kaufmann, J., & Herrmann, P. (2009). An empirical analysis of the relationship between capital acquisition and bankruptcy law. *Journal of Small Business Management*, 47(1), 23-37.

Wang, Y., & Campbell, M. (2010). Business failure prediction for publicly listed companies in China. *Journal of Business & Management*, 16(1), 75-88.

Warner, J. (1977). Bankruptcy costs: Some evidence. *Journal of Finance*, 32, 337-347.

Wasserman, P.D. (1989). *Neural Computing: Theory and Practice*. New York: Van Nistrand Reinhold Co.

Watts, R.L., & Zimmerman, J.L. (1986). *Positive Accounting Theory*. Prentice-Hall Inc.

Wilcox, J.W. (1971). A simple theory of financial ratios as predictors of failure. *Journal of Accounting Research*, 2, 389-395.

Wilcox, J.W. (1973). A prediction of business failure using accounting data. *Journal of Accounting Research*, 163-190.

Wilson, R.L., & Sharda, R. (1994). Bankruptcy prediction using neural networks. *Decision Support Systems*, 11(5), 547-557.

Winakor, A.H., & Smith, R.F. (1935). *Changes in the financial structure of unsuccessful industrial corporations*. Bureau of Business Research, Bulletin No. 51. Urbana: University of Illinois Press.

World Competitiveness Yearbook 2012.

http://www.statiques.public.lu/fr/actualites/economic-finances/competitive/2015/05/20120531/PressReleaseIMD.pdf. Retrieved 22 May 2014.

World Competiveness Yearbook 2013.

www.imd.org/uupload/IMD.website/wcc/WCYResults/1/scoreboard.pdf. Retrieved 22 May 2014.

World Fact Book. CIA. 23 August 2010. http://cia.gov/library/publications/the-world-factbook/goes/hk.html. Retrieved 17 September 2011.

World Federation of Exchanges (2012). http://web.archive.org/web/20130123006036/en/world-federation-exchange-publishes-2012-global –market-highlights. Retrieved 29 December 2012.

WHO (2003). Summary of probable SARS cases with onset of illness from 1 November 2002 to 31 July 2003. World Health Organization. http://www.who.int/csr/sars/table2004_4_21/en/index.html. Retrieved 9 August 2012.

World Investment Report (2013). unctad.org/en/publicationslibrary/wir2013_en.pdf. Retrieved 22 May 2014.

Wu, C.Y. (2004) Using non-financial information to predict bankruptcy: A study of public companies in Taiwan. *International Journal of Management*, 21(2), 194-201.

Wu, Shilong & Lu, Xianyi (2001). Financial distress prediction model for Chinese trading firms. *Economic Research Journal*, 6, 46-55.

Xu, M., & Zhang, C. (2009). Bankruptcy prediction: the case of Japanese listed companies. Review of accounting studies, 14(4), 534-558.

Yang, Z.R., Platt, M.B., & Platt, H.D. (1999). Probabilistic neural networks in bankruptcy prediction. *Journal of Business Research*, 44, 67-74.

Yeung, R. (2008). *Moving millions: The commercial success and political controversies of Hong Kong's railways*. Hong Kong University Press, 16.

Yim, J., & Mitchell, H. (2004). A comparison of Japanese failure models: Hybrid neural networks, logit models, and discriminant analysis. *International Journal of Asian Management*, 3(1), 103-20.

Yu, I.W., & Fung, L. (2005). A structural approach to assessing the credit risk of Hong Kong's corporate sector. Hong Kong Monetary Authority Research Memorandum 24/2005.

Zavgren, C.V. (1983). The prediction of corporate failure: The state of the art. *Journal of Accounting Literature*, 2, 1-38.

Zavgren, C.V. (1985). Assessing the vulnerability to failure of American industrial firms: A logistic analysis. *Journal of Business Finance & Accounting*, 12(1), 19-45.

Zeitun, R., Tian, G., & Keen, K. (2007). Default probability for the Jordanian companies: A test of cash flow theory. *International Research Journal of Finance and Economics*, 8, 147-164.

Zhang, L. (2000). Financial distress early warning model. *Quantitative and Technical Economics*, 3, 49-51.

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

Zopounidis, C., & Dimitras, A.I. (1998). *Multicriteria decision aid methods for the prediction of business*. Boston, MA: Kluwer Academic Publisher.

APPENDICES

Appendix 1. Thirty-nine failed companies delisted from the Hong Kong Stock Exchange (1998 to 2011) and 39 matched non-failed companies

Sample	Company Name	SIC	Latest data Year	Total assets (HK$ mil)
F - 1	401 Holdings	4731	2002	39
NF - 1	Prosten Tech Holdings	4812	2002	257
F - 2	AKuP Int'L Holdings	7371	2002	64
NF -2	Decca Holdings	7371	2002	355
F - 3	Arcontech Corp	7373	2005	22
NF - 3	Computech Holdings	7379	2005	21
F - 4	Luen Cheong Tai	1542	2001	344
NF -4	Chevalier iTech	1522	2001	549
F - 5	China Specialized Fibre Holdings	5169	2002	1,430
NF - 5	Kee Shing Holdings	5169	2002	827
F - 6	Datasys Tech Holdings	7371	2003	109
NF -6	ABC Communications	7371	2003	259
F - 7	DigiTel Group	7373	2002	19
NF - 7	Excel Tech Int'l Holdings	7373	2002	217
F - 8	Ezcom Holdings	5065	2004	1,214
NF -8	Alco Holding	5065	2004	2,018
F - 9	Gilbert Holdings	5131	1998	468
NF - 9	Yangtzekiang Garment	5136	1998	618
F - 10	Gold Wo Int'l Holdings	5199	2002	171
NF - 10	Starlite Holding	5199	2002	417
F - 11	Gold-Face Holdings	7389	2005	316
NF - 11	Culturecom Holdings	7389	2005	324
F - 12	Goldwiz Holdings	5065	2005	739
NF - 12	Suncorp Technologies	5065	2005	860
F - 13	GP Nano Tech Group	5199	2002	151
NF - 13	Ngai Hing Hong	5162	2002	381
F - 14	Greencool Tech Holdings	5169	2004	1,471
NF - 14	Karrie Int'l Holdings	5162	2004	984
F - 15	Infoserve Tech Corp	4813	2002	178
NF - 15	DVN Holdings	4833	2002	290
F - 16	Kinetana Int'l Biotech	8731	2004	37
NF -16	iMerchants	8731	2004	221
F - 17	King Pacific Int'l	6531	2000	690
NF - 17	YGM Trading	6531	2000	1,092
F - 18	Leading Spirit High-tech	5065	2000	3,812
NF - 18	Gold Peak Industries	5065	2000	3,308
F - 19	Moulin Global Eyecare	5049	2003	3,716
NF - 19	Elegance Int'l Holdings	5049	2003	559

Sample	Company Name	SIC	Latest data Year	Total assets (HK$ mil)
F - 20	Orient Power Holdings	5064	2005	1,371
NF - 20	Sunway Int’l	5064	2005	1,123
F - 21	Riverhill Holdings	5045	2003	50
NF- 21	Mobicon Group	5065	2003	140
F - 22	RNA Holdings	5094	2002	1,681
NF - 22	Tonic Industries Holdings	5065	2002	913
F - 23	Wanasports Holdings	5136	2004	6
NF - 23	Graneagle Holdings	5136	2004	86
F - 24	Peace Mark Holdings	5094	2008	10,678
NF - 24	Skyworth Digital Holdings	5064	2008	13,070
F - 25	Yaohan Int’l Holdings	7389	1997	2,784
NF - 25	HAECO	7699	1997	2,494
F - 26	Sinocan Holding	3411	2001	550
NF - 26	CEC Int’l Holdings	3679	2001	589
F - 27	China DigiContent	3639	2000	3,156
NF - 27	ASM Pacific Tech	3674	2000	2,898
F - 28	Siu Fung Ceramics Holdings	3567	1999	75
NF - 28	United Pacific	3524	1999	402
F - 29	Shanxi Central Pharmaceutical	2899	2002	326
NF - 29	Yip’s Hang Cheung	2911	2002	761
F - 30	Pan Sino Int’l Holdings	5149	2006	626
NF - 30	Man Sang Int’l	5094	2006	655
F - 31	Englong Int’l	2311	1995	684
NF - 31	Hung Hing Printing	2652	1995	779
F - 32	Loulan Holdings	5122	2005	85
NF - 32	New Spring Holdings	5122	2005	183
F - 33	Sanyuan Group	5122	2008	117
NF - 33	Pak Fah Yeow Int’l	5122	2008	356
F - 34	Best Wide Group	5131	1995	271
NF - 34	Styland Holdings	5141	1995	313
F - 35	Changchun Da Xing	2834	2004	319
NF - 35	Mingyuan Medicare	2835	2004	473
F - 36	Chengdu Top Sci-tech	7372	2003	337
NF - 36	Timeless Software	7372	2003	257
F - 37	Yue Fung Int’l Group Holdings	5044	2002	733
NF - 37	Herald Holding	5045	2002	557
F - 38	Eganagoldpheil Holdings	5094	2007	4,790
NF - 38	IDT Int’l	5065	2007	1,804
F - 39	Akai Holdings	5049	1999	10,858
NF - 39	Vtech Holdings	5065	1999	3,531

F = failed, NF = non-failed

Appendix 2. Hong Kong Interbank Offered Rates (HIBOR), 1991 to 2012 (% per annum)

Year	Month	Overnight	1 week	1 month	3 months	6 months	9 months	12 months
1991	Jan	6.87	6.99	7.40	7.47	7.47	n/a	7.81
	Feb	6.18	6.30	6.36	6.51	6.61	n/a	7.26
	Mar	8.21	7.91	7.48	7.22	7.18	n/a	7.48
	Apr	6.06	6.16	6.36	6.68	6.95	n/a	7.28
	May	6.52	6.65	6.71	6.84	7.01	n/a	7.32
	Jun	8.03	8.06	8.13	7.99	7.93	n/a	8.22
	Jul	6.26	6.28	6.43	6.71	7.04	n/a	7.39
	Aug	5.07	5.19	5.46	5.95	6.33	n/a	6.92
	Sep	4.81	4.88	5.05	5.45	5.91	n/a	6.61
	Oct	4.58	4.64	4.82	5.17	5.38	n/a	6.22
	Nov	3.57	3.65	3.90	4.46	4.91	n/a	5.77
	Dec	3.93	4.03	4.18	4.19	4.46	n/a	5.27
1992	Jan	4.73	4.53	4.49	4.39	4.43	4.60	4.93
	Feb	4.02	4.14	4.25	4.39	4.59	4.78	5.04
	Mar	4.51	4.58	4.66	4.76	4.99	5.15	5.41
	Apr	4.54	4.57	4.51	4.58	4.82	5.04	5.31
	May	3.31	3.41	3.56	3.80	4.12	4.54	4.89
	Jun	3.33	3.51	3.51	3.62	3.99	4.25	4.58
	Jul	2.87	2.95	3.02	3.11	3.42	3.69	4.18
	Aug	2.87	3.12	3.13	3.23	3.43	3.64	4.06
	Sep	2.93	3.16	3.21	3.21	3.39	3.60	4.00
	Oct	2.86	3.30	3.30	3.38	3.53	3.65	3.96
	Nov	3.18	3.45	3.64	3.92	4.10	4.12	4.32
	Dec	3.56	3.85	4.31	4.39	4.56	4.69	4.90
1993	Jan	3.24	3.48	3.58	3.81	4.05	4.45	4.74
	Feb	3.17	3.42	3.43	3.50	3.67	4.03	4.48
	Mar	2.56	2.70	3.02	3.24	3.47	3.71	4.03
	Apr	2.98	3.00	3.06	3.18	3.39	3.54	3.85
	May	2.93	2.99	3.10	3.24	3.40	3.48	3.73
	Jun	3.00	3.20	3.36	3.46	3.61	3.66	3.96
	Jul	2.64	2.94	3.28	3.52	3.75	3.89	4.14
	Aug	3.21	3.15	3.19	3.34	3.62	3.88	4.13
	Sep	3.13	3.14	3.18	3.24	3.46	3.76	4.01
	Oct	2.97	2.98	3.05	3.20	3.34	3.47	3.72
	Nov	3.09	3.22	3.21	3.41	3.50	3.50	3.69
	Dec	3.48	3.66	3.63	3.61	3.68	3.74	3.98
1994	Jan	3.05	3.41	3.40	3.48	3.59	3.75	4.00
	Feb	2.84	3.21	3.51	3.74	3.94	3.96	4.16
	Mar	3.59	3.85	3.98	4.21	4.52	4.55	4.75
	Apr	2.99	3.34	3.78	4.31	4.71	4.84	5.11
	May	3.68	3.81	4.09	4.64	5.07	5.30	5.63
	Jun	3.94	4.10	4.28	4.64	5.02	5.28	5.69

Year	Month	Overnight	1 week	1 month	3 months	6 months	9 months	12 months
1994	Jul	4.24	4.35	4.53	4.88	5.29	5.63	6.00
	Aug	4.10	4.27	4.52	4.84	5.25	5.57	5.99
	Sep	4.44	4.54	4.67	4.93	5.37	5.59	6.05
	Oct	4.43	4.60	4.87	5.44	5.82	5.97	6.34
	Nov	4.44	4.70	5.11	5.66	6.07	6.24	6.55
	Dec	5.08	5.36	5.78	6.22	6.79	6.96	7.32
1995	Jan	6.11	6.68	7.00	7.21	7.59	7.78	8.13
	Feb	5.68	6.01	6.44	6.83	7.23	7.45	7.74
	Mar	5.27	5.42	5.76	6.29	6.70	6.87	7.19
	Apr	5.50	5.70	5.84	6.14	6.43	6.54	6.92
	May	5.72	6.00	6.12	6.23	6.39	6.45	6.76
	Jun	5.36	5.53	5.69	5.82	5.93	5.97	6.23
	Jul	5.28	5.43	5.57	5.72	5.82	5.86	6.01
	Aug	5.65	5.76	5.86	5.96	6.04	6.07	6.24
	Sep	5.95	6.04	6.06	6.14	6.19	6.18	6.43
	Oct	5.48	5.65	5.80	5.95	6.06	6.02	6.16
	Nov	5.52	5.56	5.71	5.88	6.01	5.96	6.01
	Dec	5.88	5.92	5.93	5.93	5.93	5.91	6.00
1996	Jan	5.55	5.56	5.62	5.66	5.67	5.71	5.87
	Feb	4.81	4.93	5.12	5.24	5.25	5.34	5.47
	Mar	4.82	4.93	5.13	5.33	5.44	5.46	5.67
	Apr	5.00	5.06	5.12	5.28	5.48	5.55	5.80
	May	5.06	5.12	5.16	5.31	5.50	5.61	5.85
	Jun	5.22	5.34	5.36	5.49	5.66	5.78	6.04
	Jul	5.21	5.29	5.40	5.61	5.83	5.91	6.16
	Aug	5.09	5.16	5.27	5.50	5.76	5.77	5.96
	Sep	5.21	5.26	5.35	5.58	5.84	5.94	6.07
	Oct	5.14	5.19	5.23	5.46	5.65	5.65	5.90
	Nov	5.23	5.29	5.31	5.49	5.59	5.63	5.84
	Dec	4.83	5.18	5.47	5.54	5.63	5.63	5.87
1997	Jan	4.87	4.96	5.17	5.41	5.56	5.74	5.94
	Feb	5.28	5.36	5.38	5.48	5.60	5.69	5.97
	Mar	5.27	5.46	5.54	5.67	5.81	5.93	6.21
	Apr	5.65	5.66	5.69	5.85	6.11	6.21	6.44
	May	5.57	5.99	5.97	6.03	6.18	6.32	6.50
	Jun	5.65	6.04	6.31	6.37	6.45	6.53	6.64
	Jul	5.79	6.07	6.31	6.40	6.47	6.56	6.65
	Aug	6.50	6.99	7.22	7.18	7.18	7.16	7.20
	Sep	6.76	7.20	7.49	7.49	7.48	7.34	7.39
	Oct	11.23	16.75	10.24	9.90	9.65	9.49	9.56
	Nov	5.43	7.48	9.66	10.49	10.65	10.61	10.61
	Dec	4.53	5.18	7.29	9.25	10.35	10.50	10.50
1998	Jan	7.06	8.81	10.72	11.51	12.01	12.09	12.09
	Feb	4.68	5.01	6.57	8.37	9.38	9.83	10.10
	Mar	4.43	4.64	5.63	6.72	7.71	8.41	8.87
	Apr	4.47	4.78	5.47	6.22	7.07	7.58	7.96

Year	Month	Overnight	1 week	1 month	3 months	6 months	9 months	12 months
1998	May	5.13	6.13	6.94	7.22	7.94	8.26	8.72
	Jun	6.72	8.74	9.44	9.61	9.94	9.94	10.28
	Jul	5.78	6.74	7.81	8.49	9.46	9.70	10.06
	Aug	9.84	12.13	12.03	11.78	12.02	11.63	11.71
	Sep	5.83	7.01	8.29	9.19	9.93	10.02	10.33
	Oct	4.52	5.00	5.67	6.44	7.03	7.32	7.74
	Nov	4.61	5.05	5.43	5.99	6.54	6.79	7.31
	Dec	4.23	4.55	5.25	5.48	5.97	6.36	6.73
1999	Jan	3.96	4.80	5.39	5.87	6.33	6.53	6.92
	Feb	4.96	5.23	5.59	5.99	6.62	6.98	7.27
	Mar	4.50	4.76	5.16	5.55	6.17	6.69	7.17
	Apr	4.44	4.56	4.86	5.14	5.48	5.95	6.30
	May	4.47	4.63	4.86	5.17	5.63	6.14	6.43
	Jun	5.21	5.36	5.36	5.53	5.93	6.47	6.80
	Jul	5.51	5.67	5.86	5.95	6.39	6.63	6.90
	Aug	5.55	5.93	6.17	6.40	7.01	7.17	7.35
	Sep	5.12	5.43	5.76	6.00	6.69	6.88	7.03
	Oct	5.37	5.44	5.56	6.29	6.43	6.70	6.92
	Nov	5.01	5.24	5.49	6.20	6.30	6.53	6.73
	Dec	3.58	4.59	6.01	5.97	6.13	6.44	6.68
2000	Jan	3.33	4.37	5.10	5.68	6.08	6.47	6.74
	Feb	5.37	5.67	5.80	5.88	6.21	6.44	6.75
	Mar	5.41	5.59	5.78	5.93	6.19	6.41	6.69
	Apr	6.32	6.45	6.29	6.27	6.39	6.55	6.73
	May	6.04	6.38	6.70	6.85	7.03	7.15	7.30
	Jun	5.95	6.08	6.32	6.58	6.76	6.91	7.07
	Jul	5.86	5.91	6.03	6.21	6.50	6.63	6.77
	Aug	5.33	5.65	5.79	5.92	6.21	6.33	6.46
	Sep	6.73	6.44	6.24	6.23	6.32	6.39	6.49
	Oct	5.11	5.47	5.78	6.06	6.19	6.26	6.33
	Nov	5.03	5.28	5.50	5.86	6.08	6.15	6.26
	Dec	6.26	6.23	6.13	5.94	5.93	5.90	5.92
2001	Jan	5.41	5.49	5.46	5.32	5.20	5.13	5.14
	Feb	5.08	5.09	5.14	5.08	4.99	4.93	4.94
	Mar	4.94	4.93	4.92	4.83	4.78	4.72	4.74
	Apr	4.37	4.50	4.61	4.57	4.58	4.60	4.69
	May	3.72	3.78	3.80	3.84	3.91	4.01	4.16
	Jun	3.82	3.84	3.71	3.67	3.69	3.76	3.92
	Jul	3.57	3.57	3.63	3.63	3.66	3.71	3.86
	Aug	3.38	3.37	3.38	3.36	3.39	3.40	3.51
	Sep	2.96	2.95	2.89	2.84	2.85	2.90	2.93
	Oct	2.00	2.12	2.14	2.12	2.14	2.23	2.35
	Nov	2.06	1.97	1.84	1.84	1.89	2.06	2.29
	Dec	1.75	1.80	1.83	1.81	1.87	2.11	2.44
2002	Jan	1.74	1.73	1.73	1.76	1.85	2.07	2.36
	Feb	1.81	1.81	1.84	1.90	2.03	2.19	2.47

Year	Month	Overnight	1 week	1 month	3 months	6 months	9 months	12 months
2002	Mar	1.86	1.93	2.03	2.12	2.34	2.57	2.93
	Apr	1.73	1.73	1.83	1.95	2.24	2.49	2.80
	May	1.60	1.61	1.71	1.81	2.02	2.23	2.54
	Jun	1.41	1.45	1.65	1.75	1.93	2.09	2.34
	Jul	1.52	1.58	1.70	1.75	1.81	1.88	2.04
	Aug	1.53	1.54	1.63	1.65	1.68	1.67	1.78
	Sep	1.67	1.70	1.78	1.77	1.75	1.75	1.82
	Oct	1.90	1.95	2.00	1.97	1.94	1.91	1.99
	Nov	1.37	1.40	1.51	1.56	1.63	1.66	1.79
	Dec	1.16	1.24	1.46	1.48	1.51	1.55	1.68
2003	Jan	1.18	1.22	1.34	1.36	1.41	1.44	1.54
	Feb	1.20	1.22	1.32	1.34	1.39	1.41	1.50
	Mar	1.17	1.19	1.28	1.28	1.29	1.30	1.37
	Apr	1.29	1.34	1.41	1.41	1.41	1.40	1.50
	May	1.14	1.20	1.29	1.30	1.30	1.26	1.33
	Jun	1.06	1.06	1.08	1.06	1.09	1.08	1.13
	Jul	0.96	0.99	1.06	1.08	1.14	1.14	1.21
	Aug	0.88	0.92	1.04	1.08	1.16	1.22	1.38
	Sep	0.64	0.73	0.87	0.94	1.06	1.10	1.21
	Oct	0.08	0.09	0.14	0.37	0.64	0.81	1.02
	Nov	0.07	0.07	0.08	0.21	0.50	0.71	0.99
	Dec	0.23	0.25	0.15	0.15	0.33	0.50	0.76
2004	Jan	0.07	0.07	0.07	0.07	0.14	0.24	0.42
	Feb	0.07	0.07	0.07	0.07	0.13	0.21	0.41
	Mar	0.08	0.07	0.07	0.09	0.23	0.32	0.48
	Apr	0.07	0.07	0.08	0.11	0.33	0.48	0.73
	May	0.07	0.07	0.09	0.36	0.75	1.02	1.32
	Jun	0.07	0.07	0.13	0.44	0.83	1.12	1.45
	Jul	0.07	0.07	0.13	0.42	0.81	1.08	1.43
	Aug	0.11	0.16	0.38	0.73	1.08	1.28	1.59
	Sep	0.39	0.57	0.74	0.93	1.18	1.32	1.58
	Oct	0.39	0.56	0.63	0.81	1.00	1.12	1.34
	Nov	0.07	0.11	0.16	0.27	0.52	0.72	0.98
	Dec	0.32	0.53	0.44	0.37	0.59	0.74	0.95
2005	Jan	0.07	0.14	0.40	0.65	0.92	1.07	1.27
	Feb	0.83	1.16	1.27	1.45	1.64	1.77	1.92
	Mar	1.36	1.68	2.00	2.25	2.49	2.61	2.74
	Apr	1.80	2.08	2.28	2.40	2.56	2.63	2.73
	May	1.95	2.25	2.48	2.58	2.74	2.80	2.89
	Jun	2.94	3.17	3.23	3.22	3.27	3.25	3.29
	Jul	2.99	3.12	3.26	3.40	3.51	3.52	3.57
	Aug	3.14	3.25	3.44	3.64	3.80	3.82	3.87
	Sep	3.36	3.46	3.69	3.83	3.90	3.90	3.93
	Oct	3.55	3.83	4.16	4.22	4.30	4.31	4.37
	Nov	3.10	3.44	3.89	4.17	4.37	4.44	4.52
	Dec	3.66	3.83	4.03	4.15	4.33	4.34	4.39

Year	Month	Overnight	1 week	1 month	3 months	6 months	9 months	12 months
2006	Jan	3.43	3.62	3.78	3.95	4.11	4.12	4.17
	Feb	3.64	3.75	3.80	4.00	4.20	4.24	4.32
	Mar	3.83	4.05	4.14	4.31	4.43	4.46	4.51
	Apr	3.83	4.06	4.27	4.52	4.60	4.60	4.64
	May	3.76	4.18	4.46	4.50	4.60	4.59	4.63
	Jun	3.82	3.93	4.28	4.56	4.74	4.78	4.84
	Jul	3.72	3.80	4.02	4.36	4.62	4.70	4.79
	Aug	3.61	3.67	3.89	4.17	4.33	4.39	4.48
	Sep	3.72	3.86	4.00	4.10	4.18	4.20	4.26
	Oct	3.81	3.92	4.07	4.08	4.15	4.16	4.22
	Nov	3.76	3.82	3.88	3.93	4.00	4.00	4.04
	Dec	3.70	3.97	3.94	3.91	3.93	3.88	3.90
2007	Jan	3.59	3.72	3.88	3.96	4.03	4.04	4.08
	Feb	3.87	4.00	4.07	4.14	4.25	4.31	4.40
	Mar	3.84	3.99	4.10	4.14	4.19	4.20	4.25
	Apr	4.65	4.55	4.26	4.17	4.19	4.19	4.24
	May	3.99	4.43	4.42	4.37	4.37	4.36	4.41
	Jun	3.54	4.14	4.35	4.41	4.49	4.55	4.64
	Jul	3.93	4.15	4.25	4.34	4.42	4.45	4.54
	Aug	3.99	4.41	4.46	4.53	4.55	4.53	4.56
	Sep	4.46	4.99	4.89	4.78	4.71	4.59	4.59
	Oct	4.50	5.06	5.14	5.00	4.81	4.66	4.60
	Nov	1.34	2.80	3.18	3.56	3.65	3.64	3.67
	Dec	2.31	2.78	3.59	3.64	3.64	3.58	3.58
2008	Jan	1.69	2.16	2.65	2.88	2.92	2.82	2.80
	Feb	1.52	1.79	2.16	2.23	2.24	2.18	2.17
	Mar	1.49	1.85	1.94	1.99	1.97	1.90	1.89
	Apr	0.77	1.05	1.50	1.90	2.01	2.04	2.12
	May	0.81	1.06	1.39	1.81	2.03	2.22	2.38
	Jun	0.87	1.27	1.72	2.15	2.46	2.71	2.99
	Jul	1.14	1.40	1.76	2.19	2.52	2.68	2.90
	Aug	1.29	1.42	1.74	2.17	2.46	2.59	2.80
	Sep	1.66	2.17	2.60	2.64	2.73	2.77	2.88
	Oct	1.36	2.13	3.64	3.72	3.60	3.57	3.57
	Nov	0.21	0.31	1.03	2.17	2.42	2.44	2.44
	Dec	0.18	0.28	0.87	1.43	1.93	2.10	2.15
2009	Jan	0.13	0.15	0.27	0.82	1.22	1.49	1.67
	Feb	0.13	0.15	0.16	0.73	1.08	1.34	1.58
	Mar	0.14	0.13	0.19	0.78	1.10	1.33	1.55
	Apr	0.13	0.13	0.17	0.76	1.04	1.22	1.42
	May	0.13	0.13	0.13	0.44	0.75	0.94	1.11
	Jun	0.13	0.13	0.13	0.23	0.56	0.80	1.02
	Jul	0.13	0.13	0.13	0.16	0.45	0.65	0.86
	Aug	0.13	0.13	0.13	0.13	0.39	0.59	0.79
	Sep	0.13	0.13	0.13	0.13	0.37	0.54	0.72
	Oct	0.13	0.13	0.13	0.13	0.38	0.53	0.69

Year	Month	Overnight	1 week	1 month	3 months	6 months	9 months	12 months
2009	Nov	0.13	0.13	0.13	0.13	0.26	0.40	0.54
	Dec	0.13	0.13	0.13	0.13	0.14	0.28	0.43
2010	Jan	0.13	0.13	0.13	0.13	0.13	0.28	0.45
	Feb	0.13	0.13	0.13	0.13	0.13	0.28	0.46
	Mar	0.13	0.13	0.13	0.13	0.13	0.28	0.46
	Apr	0.13	0.13	0.13	0.13	0.13	0.28	0.46
	May	0.13	0.13	0.13	0.13	0.13	0.28	0.46
	Jun	0.13	0.13	0.17	0.21	0.22	0.37	0.55
	Jul	0.13	0.13	0.29	0.48	0.55	0.70	0.92
	Aug	0.13	0.13	0.23	0.33	0.43	0.58	0.81
	Sep	0.13	0.13	0.23	0.33	0.43	0.58	0.78
	Oct	0.13	0.13	0.23	0.33	0.43	0.58	0.78
	Nov	0.13	0.13	0.23	0.33	0.43	0.58	0.78
	Dec	0.13	0.13	0.23	0.33	0.43	0.58	0.78
2011	Jan	0.13	0.13	0.23	0.33	0.43	0.58	0.80
	Feb	0.13	0.13	0.23	0.33	0.43	0.58	0.80
	Mar	0.13	0.13	0.23	0.33	0.43	0.58	0.80
	Apr	0.13	0.13	0.23	0.33	0.43	0.58	0.80
	May	0.13	0.13	0.23	0.33	0.43	0.58	0.80
	Jun	0.13	0.13	0.23	0.33	0.43	0.58	0.78
	Jul	0.13	0.13	0.23	0.33	0.43	0.58	0.75
	Aug	0.13	0.13	0.23	0.33	0.43	0.58	0.75
	Sep	0.13	0.13	0.23	0.33	0.43	0.58	0.75
	Oct	0.13	0.13	0.23	0.33	0.43	0.58	0.75
	Nov	0.13	0.13	0.23	0.33	0.43	0.58	0.75
	Dec	0.13	0.13	0.23	0.33	0.43	0.58	0.75
2012	Jan	0.13	0.17	0.40	0.50	0.60	0.67	0.94
	Feb	0.13	0.18	0.45	0.55	0.65	0.70	1.00
	Mar	0.13	0.18	0.45	0.55	0.65	0.70	1.00
	Apr	0.09	0.12	0.38	0.48	0.63	0.68	0.91
	May	0.06	0.08	0.33	0.43	0.63	0.68	0.85
	Jun	0.06	0.09	0.33	0.45	0.63	0.70	0.85
	Jul	0.06	0.10	0.33	0.45	0.63	0.70	0.85
	Aug	0.06	0.10	0.33	0.45	0.63	0.70	0.85
	Sep	0.06	0.10	0.33	0.45	0.63	0.70	0.85
	Oct	0.06	0.10	0.33	0.45	0.63	0.69	0.85

Source: Bloomberg online download

Appendix 3: Full list of companies delisted from the Hong Kong Stock Exchange (1998 to 2011)

Year Delisted	Company Name	Reason for Delist	Selected Sample?
1998	Cathay Investment Fund	Listed overseas	
	Haw Par Corporation	Listed overseas	
	Laws International	Privatization	
	Manhattan Card	Privatization	
	Orient Telecom & Tech	Privatization	
	Pakistan Fund	Voluntary withdraw	
	United Overseas Bank	Listed overseas	
1999	FAI Insurance	Privatization	
	Peregrine Investments	Compulsory windup	
	Kwong On Bank	Privatization	
	Citybus Group	Acquisition	
	Lane Crawford Int'l	Privatization	
	Englong International	Compulsory windup	Y
	Thornton Taiwan Fund	Convert to open end	
	AXA China	Acquisition	
	Chevalier Development	Privatization	
	New Taipei Fund	Listed overseas	
2000	Wing On International	Acquisition	
	Peninsula & Oriental Steam Navigation	Withdraw for 2^{nd} listing	
	JF Indonesia Fund	Restructure	
	Wah Kwong Shipping	Acquisition	
	Cable & Wireless HKT	Acquisition	
	Jardine Int'l Motor	Privatization	
	The Taiwan Index Fund	Acquisition	
	GKC Holdings	Voluntary windup	
2001	Ng Fung Hong Ltd	Acquisition	
	FPB Bank	Acquisition	
	The Mingly Corporation	Acquisition	
	Concord Land Dev	Offering	
	Guangdong Dev Fund	Withdraw for 2^{nd} listing	
	Sime Darby HK	Privatization	
	Dao Heng Bank	Acquisition	
	Gilbert Holdings	Compulsory windup	Y
	Best Wide Group	Compulsory windup	Y
	Evergo China	Privatization	
	Siu Fung Ceramic	Compulsory windup	Y
2002	Yaohan International	Compulsory windup	Y
	IMC Holdings	Privatization	
	Lam Soon Food	Privatization	
	Ryoden Development	Privatization	
	China Argotech	Transfer to Main Board	

Year Delisted	Company Name	Reason for Delist	Selected Sample?
2002	Xinao Gas	Transfer to Main Board	
2003	JP Japan OTC Fund	Voluntary liquidation	
	Grand Hotel A Shares	Acquisition	
	Grand Hotel B Shares	Acquisition	
	Realty Development	Privatization	
	Winton Holdings	Privatization	
	Top Glory International	Privatization	
	Pacific Concord	Privatization	
	Sinotronics Holdings	Transfer to Main Board	
	Techwayson Holdings	Transfer to Main Board	
	Vitop Bioenergy	Transfer to Main Board	
	Vital Bio Tech	Transfer to Main Board	
	SIIC Medical Science	Privatization	
	Akai Holdings	Reorganization	Y
	Goldigit Atom Tech	Transfer to Main Board	
	iLink Holdings	Transfer to Main Board	
	Sino Biopharma	Transfer to Main Board	
2004	Leading Spirit	Compulsory windup	Y
	China DigiContent	Compulsory windup	Y
	Chevalier Construction	Privatization	
	King Pacific Int’l	Compulsory windup	Y
	Euro-Asia Agriculture	Compulsory windup	
	Oxford Properties	Privatization	
	Gold Wo International	Compulsory windup	Y
	Harbin Brewery	Acquisition	
	Sinocan Holdings	Compulsory windup	Y
	Fortune Telecom	Transfer to Main Board	
	TOM Group	Transer to Main Board	
2005	Alpha General	Privatization	
	Yue Fung International	Compulsory windup	Y
	Kwong Sang Hong	Privatization	
	Global Trend Intelligent Tech	ICAC investigation	
	Luen Cheong Tai	Compulsory windup	Y
	Elec & Eltek Int’l	Acquisition	
	Shanxi Central Pharma	Compulsory windup	Y
	HSBC China Fund	Voluntary liquidation	
	Sinopec Beijing Yanhua Petrochem	Privatization	
	401 Holdings	Compulsory windup	Y
	Hutchison Global	Privatization	
	Henderson China	Privatization	
	RNA Holdings	Compulsory windup	Y
	Shanghai Land Holdings	Voluntary windup	
	China Special Fibre	Compulsory windup	Y
	Codebank Ltd	Windup & restructure	
	Infoserve Technology	Compulsory windup	Y
	GP Nano Technology	Compulsory windup	Y

Year Delisted	Company Name	Reason for Delist	Selected Sample?
2005	Kingdee Int'l Software	Transfer to Main Board	
contd	Akup Int'l	Strike off	Y
	Int'l Capital Network	Compulsory windup	(Y)❖
	MediaNation Inc	Acquisition	
	Lai Fai Int'l	Privatization	
	Riverhill Holdings	Strike off	Y
	Arcontech Corporation	Compulsory windup	Y
	Far Eastern Polychem	Privatization	
	Panva Gas	Transfer to Main Board	
	Henderson Cyber	Privatization	
2006	Jilin Chemical	Acquisition	
	Thai Asset Fund	Voluntary windup	
	New World TMT	Privatization	
	Thai-Asia Fund	Voluntary windup	
	Sinopec Zhenhai Refining & Chemcial	Privatization	
	China Resources People Telephone	Acquisition	
	Asai Aluminum	Privatization	
	Fu Cheong International	ICAC investigation	
	China Resources Cement	Privatization	
	People's Food Holdings	Voluntary withdraw	
	Gold-Face Holdings	Compulsory windup	Y
	SNP Leefung	Privatization	
	Egana Jewellery & Pearls	Privatization	
	SUNDAY Communications	Sales of business	
	Winsor Industrial Corp	Privatization	
	Pan Sino International	Transfer to Main Board	
	Wanasports Holdings	3rd party dispute	Y
	DigiTel Group	Compulsory windup	Y
	Media Partners Int'l	Acquisition	
	Superdata Software	Acquisition	
	Enric Energy	Transfer to Main Board	
	M Channel Corporation	Voluntary windup	
	Kinetana International	Strike off	Y
	Sino Stride Tech	Take over	
2007	China National Aviation	Privatization	
	China Paradise Electronic	Acquisition	
	Senyuan International	Acquisition	
	Saint Honore Holdings	Take over	
	Value Partners China	Conversion of Corporate nature	
	Moulin Global Eyecare	Compulsory windup	Y
	Shimao International	Privatization	
	Ezcom Holdings	Debt structure	Y
	Pacific Century Insurance	Acquisition	
	Shandong Molong	Transfer to Main Board	
	Greencool Technology	Strike off	Y

Year Delisted	Company Name	Reason for Delist	Selected Sample?
2007	Chengdu Top Sci-Tech	Strike off	Y
contd	Zhengzhou Gas	Transfer to Main Board	
	Recruit Holdings	Transfer to Main Board	
	TOM Online	Privatization	
	Anhui Tianda Oil Pipe	Transfer to Main Board	
2008	Chia Hsin Cement	Acquisition	
	Orient Power Holdings	Compulsory windup	Y
	Lei Shing Hong	Privatization	
	BALtrans Holdings	Takeover & merger	
	Goldwiz Holdings	Compulsory windup	Y
	Mirabell International	Takeover & merger	
	China Netcom Group	Takeover & merger	
	CITIC Int’l Financial	Privatization	
	Xinjiang Tianye Water Saving	Transfer to Main Board	
	Beijing Jingkelong	Transfer to Main Board	
	CASH Financial Service	Transfer to Main Board	
	Loulan Holdings	Strike off	Y
	Datasys Technology	Compulsory windup	Y
	Netdragon Websoft	Transfer to Main Board	
	Centure Sunshine Ecological Tech	Transfer to Main Board	
	Town Health Int’l	Transfer to Main Board	
	Value Convergence	Transfer to Main Board	
	Midland IC & I	Transfer to Main Board	
	Ko Yo Ecological Argotech	Transfer to Main Board	
	Inspur International	Transfer to Main Board	
	CK Life Science Int’l	Transfer to Main Board	
	JF Household Furnishing	Transfer to Main Board	
	China Fire Safety Group	Transfer to Main Board	
	Changchun Da Xing	Strike off	Y
	First Mobile Group	Transfer to Main Board	
	Jinheng Automotive Safety	Transfer to Main Board	
	Phoenix Satellite TV	Transfer to Main Board	
	Prosperity International	Transfer to Main Board	
	Chinasoft International	Transfer to Main Board	
2009	Wing Lung Bank	Privatization	
	Shaw Brothers	Privatization	
	O2Micro International	Privatization	
	Delta Networks	Privatization	
	Ming An Holdings	Privatization	
	Stone Group Holdings	Privatization	
	Nam Tai Electronics	Privatization	
	Sino Gold Mining	Take over & merger	
	GST Holdings	Take over & merger	
	Sanyuan Group	Strike off	Y
	International Elite	Transfer to Main Board	
	TSC Offshore Group	Transfer to Main Board	

Year Delisted	Company Name	Reason for Delist	Selected Sample?
2009	Golden Meditech	Transfer to Main Board	
contd	DeTeam Company	Transfer to Main Board	
	A-S China Plumbing Products	Acquisition	
2010	Meadville Holdings	Take over & merger	
	Hutchison Telecom Int'l	Privatization	
	Times Ltd	Take over & merger	
	Wheelock Properties	Privatization	
	Denway Motors	Privatization	
	Integrated Distribution Service Group	Privatization	
	Industrial & Commercial Bank of China	Privatization	
	Lee's Pharmaceutical	Transfer to Main Board	
	Universal Technologies	Transfer to Main Board	
	Tong Ren Tang Tech	Transfer to Main Board	
	EVOC Intelligent Tech	Transfer to Main Board	
	Shandong Weigao Group	Transfer to Main Board	
	Int'l Entertainment	Transfer to Main Board	
	Shenzhen Dongjiang Envir-onmental	Transfer to Main Board	
	Pine Technology	Transfer to Main Board	
	Nanjing Sample Tech	Transfer to Main Board	
	Richfield Group	Transfer to Main Board	
	Yusei Holdings	Transfer to Main Board	
	Enviro Energy Int'l	Transfer to Main Board	
2011	Shanghai Forte Land	Acquisition	
	Fubon Bank	Acquisition	
	Peace Mark Holdings	Compulsory windup	Y
	Pan Sino International	Compulsory liquidation	Y
	Hannstar Board Int'l	Privatization	
	Yantai North Andre Juice	Transfer to Main Board	
	Capinfo Company	Transfer to Main Board	
	China Resources Micro-electronics	Privatization	
	Zhejiang Shibao	Transfer to Main Board	
	Launch Tech	Transfer to Main Board	
	Sino Haijing Holdings	Transfer to Main Board	
	Jiangchen International	Transfer to Main Board	
	Perception Digital	Transfer to Main Board	
	Convenience Retail Asia	Transfer to Main Board	
	Essex Bio-Tech	Transfer to Main Board	
	Wumark Store	Transfer to Main Board	
	Qianlong Technology Int'l	Transfer to Main Board	
	Tianjin Tianlian Public Utilities	Transfer to Main Board	
	Eganagoldfeil Holdings	Compulsory windup	Y

❖(Y) = dropped out due to 3 years financial statement unavailable

Appendix 4. List of 156 randomly selected non-failed companies

Company Name	Symbol	Total assets (HK$ million)
Allan International	ALAN	1,036
Alltronics Holdings	ALTR	343
Anex International	ANEX	240
Argos Enterprise	ARGO	173
Artel Solutions Group	ATEL	6
Artini China	ARTI	546
Arts Optical International	ARTS	810
Asia Aluminum	ASIA	9,421
Asia Resources Holdings	ASRE	570
Asia Telenet	ATNT	519
Aupu Group	AUPU	633
Automated Systems	AUTO	773
BEL Global Resources	BELG	996
Bright International	BRIG	740
Brightoil Petroleum	BRIT	7,177
Bun Kee	BUNK	523
Burwill Holdings	BURW	2,454
Carico Holdings	CARI	79
Carry Wealth	CARY	507
CCT Technology	CCTT	2,330
Chen Hsong Holdings	CHEN	2,478
Cheung Tai Hong Holdings	CTHH	362
China Agrotech	CARO	1,438
China Chengtong	CCDG	1,922
China Ground Source Energy	CGSE	1,477
China Rare Earth Holdings	CREH	1,594
China Seven Star	SEVE	371
China-HK Photo	FOTO	1,238
Ching Hing Group	CGHG	170
Chuang's Consortium	CHUS	7,356
CIL Holdings	CILH	57
CITIC 21 CN	CITI	944
Climax International	CLIM	236
Continental Mariner	CMIC	3,470
Crocodile Garments	CROC	761
Dah Hwa International	DAWA	247
Daido Group	DAID	230
Daisho Microline Holdings	DASH	263
Datronix Holdings	DATX	288
Dynasty Wines	DYNA	2,341
E Bon Holding	EBON	157
EC Founder	ECFO	458
Eco-Tek Holdings	ETEK	169

Company Name	Symbol	Total assets (HK$ million)
eForce Holdings	EFOR	71
FAVA International	FAVA	99
FlexSystem Holdings	FLEX	145
Fortuna International	FONA	476
Four Seas Mercantile	FSMH	1,530
Frankie Dominion	FRAN	437
Fujikon Industrial	FUJI	482
Golden Dragon	GODR	380
Golden Resources	GRDI	920
Goldlion Holdings	GOLD	1,745
Grande Holdings	GRAN	4,064
Greater China Holdings	GCHL	417
Group Sense International	GSIL	859
Guangdong Tannery	GDTL	413
Heng Tai Consumables	HTAI	689
Hengan International	HENG	8,374
Hi Sun Technology	HSUN	847
HK Economic Times	HKET	812
HK Pharmaceutical	HKPH	250
Honbridge Holdings	HONB	42
Hua Yi Copper	HUAY	771
JIC Technology	JICT	326
JLF Investment	JFLI	215
Joyce Boutique	JOYC	712
K & P International	KNPI	289
Kingmaker Footwear	KGFW	920
Kith Holdings	KITH	973
KPI Company	KPIC	1,822
Kwong Hing Internatinal	KWHI	500
Kwoon Chung Bus	KWOO	2,158
Le Saunda Holdings	LESA	664
Lee & Man Holdings	LNMH	515
Leeport Holdings	LEEP	329
Lerado Group	LERA	1,006
Lifetec Group	LTEC	257
Linefan Tech	LFAN	48
Linmark Group	LINM	803
Lung Cheong International	LUNG	793
Lung Kee Holdings	LKMH	2,311
M Dream Inworld	MDRM	37
MAE Holdings	MAEH	38
Magician Industries	MAGI	310
Mainland Headwear	MAIN	611
Man Yue Holdings	MYUE	1,879
Mayer Holdings	MYER	905
Mei Ah Entertainment	MEIA	356

Company Name	Symbol	Total assets (HK$ million)
Midas International	MIDA	861
Ming Fung Jewellery	MFJW	511
Morning Star Resources	MORN	456
New Century Group	NUCE	180
New Island Printing	NEWI	649
New Times Group	NEWT	221
Nority International	NORI	315
One Media Group	ONEM	196
ONFEM Holdings	OFEM	777
Peaktop International	PKTP	718
Perfectech International	PERF	352
Pico Far East	PICO	1,092
Playmates	PLAY	2,377
Plus Holdings	PLUS	71
Ports Design	PORT	2,986
QPL International	QPLI	365
Qualipak International	QUAL	539
Raymond Industrial	RAYM	580
RBI Holdings	RBIH	647
Rising Development	RISI	1,930
Rojam Entertainment	RJAM	470
Sa Sa International	SASA	1,094
Same Time Holdings	SAME	461
Shell Electric	SHEL	4,667
Shun Ho Technology	SHHO	2,026
Sincere Company	SINC	1,589
Sinopec Kentons	KENT	2,844
SIS International	SISI	1,406
SMI Publishing	SMIP	33
Sonavox International	SONA	416
South China Industries	SCHI	1,618
Sparkle Roll Group	SPAR	879
Starlight International	STAR	1,219
SuneVision	SVIS	3,471
Swank International	SWAN	241
Symponthy Holdings	SYMP	2,024
Syscan Technology	SYSC	298
Tai Ping Carpet	TAIP	1,048
Takson Holdings	TSON	137
Techtronics Industries	TTIC	21,320
Termbray Industries	TERM	1,405
Tomorrow International	TOMO	915
Tongda Group	TONG	552
Tristate Holdings	TRIS	1,638
Truly International	TRUL	1,253
Tungtex Holdings	TUNG	892

Company Name	Symbol	Total assets (HK$ million)
USI Holdings	USIH	14,836
V.S. International	VSIG	1,448
Van Shung Chong	VANS	1,444
Varitronix International	VATX	1,880
Veeko International	VEKO	491
Vitasoy International	VITA	1,799
Vitop Bioenergy Holdings	VTOP	75
Vodatel	VODA	308
VST Holdings	VSTH	508
Wai Yuen Tong Medicine	WYTM	828
Wang On Group	WANG	782
Wanji Pharmaceutical	WANJ	29
Warderly International	WARD	423
Water Oasis Group	OASI	522
Winbox International	WBOX	198
Wing Lee Holdings	WLEE	415
Wing Sang Int'l	WGSG	611
Wing Shing International	WSHG	274
Wo kee Hong	WOKE	616
World Houseware	WORH	1,362
Yunnan Entrprises	YUNN	220

Appendix 5. Data input entry format

Basic information:
- Identity no
- Company name
- Symbol
- Status
- Data year
- Sample type
- Auditor

Balance sheet items:
- Cash on hand
- Inventory
- Inventory of previous ago
- Accounts receivable
- Accounts receivable of previous year
- Current assets
- Total assets
- Total assets of previous year
- Accounts payable
- Accounts payable of previous year
- Interest-bearing debt
- Current liabilities
- Total liabilities
- Working capital
- Retained earnings
- Net worth
- Net sales
- Net sales of previous year
- Book value of equity
- Number of shares
- Stock market price
- Market value of equity

Profit & loss items:
- Cost of sales
- Cost of sales of previous year
- Interest expenses
- Earnings before interests & taxes
- Net profit
- Net profit of previous year

Cash flow statement item:
- Cash flow from operations

Appendix 6. List of financial ratios for hypothetical tests

Size
Interest coverage
Debt/Total assets
Total liabilities/Total assets
Debt/Equity
Current assets/Current liabilities
Quick ratio
Current liabilities/Total assets
Cash/Total assets
Cash/Current liabilities
Working capital/Total assets
Cash conversion cycle
Cash conversion cycle of previous year
Net income/Total assets
Retained earnings/Total assets
EBIT/Total assets
Net profit margin
Return on assets
Return on equity
Earnings per share
Market value of equity/Total liabilities
Book value of equity/Total liabilities
Net profit growth
Net sales growth
Cash flow from operating/Total assets
Cash flow from operating/Total liabilities
Cash flow from operating/Net income

Appendix 7. Auditors of 234 sampled companies

Sample	Company SYMBOL	Auditor 1 year	Auditor 2 years	Auditor 3 years	Status (1=fail, 0=nonfail)	Auditor change (0=no, 1=yes)
NF-01	ELEG	Ernst & Young	Ernst & Young	Ernst & Young	0	0
NF-02	TONI	Ernst & Young	Ernst & Young	Ernst & Young	0	0
NF-03	YTKG	KPMG	KPMG	KPGM	0	0
NF-04	ABCC	PWC	PWC	PWC	0	0
NF-05	CHEV	Deloitte	Deloitte	Deloitte	0	0
NF-06	KEES	Deloitte	Deloitte	Deloitte	0	0
NF-07	CULT	Deloitte	Deloitte	Deloitte	0	0
NF-08	SUNC	Deloitte	Deloitte	Deloitte	0	0
NF-09	KARR	PWC	PWC	PWC	0	0
NF-10	CTEC	PKF	PKF	PKF	0	0
NF-11	HERA	KPMG	KPMG	KPGM	0	0
NF-12	ALCO	PWC	PWC	PWC	0	0
NF-13	PROS	Ernst & Young	Ernst & Young	Ernst & Young	0	0
NF-14	SNWY	Ernst & Young	Ernst & Young	Ernst & Young	0	0
NF-15	NHHL	PWC	PWC	PWC	0	0
NF-16	GREG	Deloitte	Deloitte	Deloitte	0	0
NF-17	STAL	PWC	Arthur Andersen	Arthur Andersen	0	0 *
NF-18	YGMT	KPMG	KPMG	KPGM	0	0
NF-19	GOPK	Deloitte	Deloitte	Deloitte	0	0
NF-20	MOBI	PWC	Arthur Andersen	Arthur Andersen	0	0 *
NF-21	SKYW	Deloitte	Deloitte	Deloitte	0	0
NF-22	MANS	Mazars	Mazars	Deliotte	0	1
NF-23	DVNH	PWC	PWC	Ernst & Young	0	1
NF-24	EXCL	KPMG	KPMG	KPGM	0	0
NF-25	HAEC	PWC	PWC	PWC	0	0
NF-26	ASMP	Deloitte	Deloitte	Deloitte	0	0
NF-27	HHPR	Ernst & Young	Ernst & Young	Ernst & Young	0	0
NF-28	CECI	Aurthur Andersen	Aurthur Andersen	N/A	0	0
NF-29	UNPC	Deloitte	Deloitte	Deloitte	0	0
NF-30	YIPS	Deloitte	Deliotte	Deliotte	0	0
NF-31	DECA	Deloitte	KPMG	KPMG	0	1
NF-32	STYL	Ernst & Young	Ernst & Young	Ernst & Young	0	0
NF-33	IDTI	Deloitte	Deloitte	Deloitte	0	0
NF-34	iMER	Deloitte	Deloitte	Deloitte	0	0

Sample	Company SYMBOL	Auditor 1 year	Auditor 2 years	Auditor 3 years	Status (1=fail, 0=nonfail)	Auditor change (0=no, 1=yes)
NF-35	PFYI	Mazars	Mazars	Mazars	0	0
NF-36	TIME	Deloitte	PWC	PWC	0	1
NF-37	MING	Deloitte	Deloitte	Deloitte	0	0
NF-38	VTEC	PWC	PWC	PWC	0	0
NF-39	KPIC	CCIF	CCIF	CCIF	0	0
NF-40	ECFO	Ernst & Young	Ernst & Young	Ernst & Young	0	0
NF-41	SYSC	CCIF	CCIF	Andersen	0	0 *
NF-42	DAID	Deloitte	Deloitte	Deloitte	0	0
NF-43	USIH	PWC	PWC	PWC	0	0
NF-44	ASIA	Ernst & Young	Ernst & Young	Ernst & Young	0	0
NF-45	SCHI	Deloitte	Andersen	Andersen	0	0 *
NF-46	SHEL	Grant Thornton	Deloitte	Deloitte	0	1
NF-47	KWOO	Ernst & Young	Ernst & Young	Ernst & Young	0	0
NF-48	QUAL	Deloitte	Deloitte	Deloitte	0	0
NF-49	GODR	Deloitte	Deloitte	Deloitte	0	0
NF-50	HENG	PWC	PWC	PWC	0	0
NF-51	GRAN	Moore Stephens	Moore Stephens	Moore Stephens	0	0
NF-52	FLEX	Hodgson Impey Cheng	PWC	PWC	0	1
NF-53	HKPH	Ernst & Young	Ernst & Young	Ernst & Young	0	0
NF-54	RBIH	Deloitte	Deloitte	Deloitte	0	0
NF-55	SINC	Ernst & Young	Ernst & Young	Ernst & Young	0	0
NF-56	FRAN	Deloitte	Deloitte	Deloitte	0	0
NF-57	BRIT	Deloitte	Deloitte	Deloitte	0	0
NF-58	DAWA	Moores Rowland	Moores Rowland	Deloitte	0	1
NF-59	CROC	Horwath	Horwath	Ernst & Young	0	1
NF-60	NEWT	CCIF	CCIF	CCIF	0	0
NF-61	NEWI	KPMG	KPMG	KPMG	0	0
NF-62	CTHH	Deloitte	Deloitte	Deloitte	0	0
NF-63	CMIC	Deloitte	Deloitte	Deloitte	0	0
NF-64	CCDG	Moore Stephens	Moore Stephens	PPWC	0	1
NF-65	ATNT	Deloitte	Deloitte	Deloitte	0	0
NF-66	WGSG	KPMG	KPMG	KPMG	0	0
NF-67	WSHG	Lau & Au Yeung	Lau & Au Yeung	Lau & Au Yeung	0	0
NF-68	MEIA	PWC	PWC	PWC	0	0

Sample	Company SYMBOL	Auditor 1 year	Auditor 2 years	Auditor 3 years	Status (1=fail, 0=nonfail)	Auditor change (0=no, 1=yes)
NF-69	TOMO	Ernst & Young	Ernst & Young	Ernst & Young	0	0
NF-70	LKMH	Deloitte	Deloitte	Deloitte	0	0
NF-71	CARO	CCIF	CCIF	CCIF	0	0
NF-72	KENT	KPMG	KPMG	KPMG	0	0
NF-73	TRIS	PWC	PWC	PWC	0	0
NF-74	ANEX	CCIF	Ernst & Young	Ernst & Young	0	1
NF-75	VANS	PWC	PWC	PWC	0	0
NF-76	WANG	Ernst & Young	Ernst & Young	Ernst & Young	0	0
NF-77	DYNA	PWC	PWC	PWC	0	0
NF-78	MYER	CCIF	CCIF	CCIF	0	0
NF-79	MORN	Nelson Wheeler	Nelson Wheeler	Nelson Wheeler	0	0
NF-80	VSTH	PWC	PWC	PWC	0	0
NF-81	ALAN	Deloitte	Deloitte	Deloitte	0	0
NF-82	LEEP	PWC	PWC	PWC	0	0
NF-83	WORH	Deloitte	Deloitte	Deloitte	0	0
NF-84	WYTM	Deloitte	Deloitte	Deloitte	0	0
NF-85	CARY	PWC	PWC	PWC	0	0
NF-86	PICO	Nelson Wheeler	Deloitte	Deloitte	0	1
NF-87	CARI	CCIF	CCIF	Moore Stephens	0	1
NF-88	YUNN	Deliotte	Deliotte	Deliotte	0	0
NF-89	NORI	PWC	PWC	PWC	0	0
NF-90	MDRM	Baker Tilly	Baker Tilly	Baker Tilly	0	0
NF-91	LFAN	Horwath	Deloitte	Deloitte	0	1
NF-92	SVIS	Deloitte	Deloitte	Deloitte	0	0
NF-93	RJAM	PWC	PWC	PWC	0	0
NF-94	ARGO	CCIF	Ting Ho Kwan & Chan	Ting Ho Kwan & Chan	0	1
NF-95	ETEK	Grant Thornton	Grant Thornton	Grant Thornton	0	0
NF-96	TSON	PWC	PWC	PWC	0	0
NF-97	ARTI	KPMG	KPMG	KPMG	0	0
NF-98	SEVE	Nelson Wheeler	Nelson Wheeler	Nelson Wheeler	0	0
NF-99	PORT	KPMG	KPMG	KPMG	0	0
NF-100	HONB	Grant Thornton	Grant Thornton	Grant Thornton	0	0
NF-101	VODA	PWC	PWC	PWC	0	0
NF-102	SAME	PWC	PWC	PWC	0	0
NF-103	TERM	Deloitte	Deloitte	Deloitte	0	0

Sample	Company SYMBOL	Auditor 1 year	Auditor 2 years	Auditor 3 years	Status (1=fail, 0=nonfail)	Auditor change (0=no, 1=yes)
NF-104	FAVA	Hodgson Impey Cheng	Hodgson Impey Cheng	Hodgson Impey Cheng	0	0
NF-105	PERF	HLM	Deliotte	Deliotte	0	1
NF-106	LERA	Deloitte	Deloitte	Deloitte	0	0
NF-107	PKTP	Ernst & Young	Ernst & Young	Ernst & Young	0	0
NF-108	WLEE	Deliotte	Deliotte	Ernst & Young	0	1
NF-109	SISI	Deloitte	Deloitte	Deloitte	0	0
NF-110	TRUL	Deloitte	Deloitte	Deloitte	0	0
NF-111	WOKE	Hodgson Impey Cheng	Nelson Wheeler	Deloitte	0	1
NF-112	TAIP	BDO McCabe	BDO McCabe	BDO McCabe	0	0
NF-113	JOYC	PWC	PWC	PWC	0	0
NF-114	BUNK	PWC	PWC	PWC	0	0
NF-115	CHUS	PWC	PWC	PWC	0	0
NF-116	SASA	PWC	PWC	PWC	0	0
NF-117	BURW	Hodgson Impey Cheng	PWC	PWC	0	1
NF-118	VITA	KPMG	KPMG	KPMG	0	0
NF-119	MAEH	CCIF	Deloitte	Deloitte	0	1
NF-120	SWAN	CCIF	CCIF	CCIF	0	0
NF-121	SYMP	Deloitte	Deloitte	Deloitte	0	0
NF-122	NUCE	Ernst & Young	Ernst & Young	Ernst & Young	0	0
NF-123	MIDA	Deloitte	Deloitte	Deloitte	0	0
NF-124	FUJI	PWC	PWC	PWC	0	0
NF-125	HKET	PWC	PWC	PWC	0	0
NF-126	AUPU	Deloitte	Deloitte	Deloitte	0	0
NF-127	ALTR	PWC	PWC	PWC	0	0
NF-128	ASRE	Hodgson Impey Cheng	Hodgson Impey Cheng	Deloitte	0	1
NF-129	SPAR	Grant Thornton	Grant Thornton	Grant Thornton	0	0
NF-130	VEKO	Deloitte	Deloitte	Deloitte	0	0
NF-131	CGSE	Hodgson Impey Cheng	Hodgson Impey Cheng	Hodgson Impey Cheng	0	0
NF-132	SONA	BDO	Shinewing	Shinewin g	0	1
NF-133	TTIC	Deloitte	Deloitte	Deloitte	0	0
NF-134	LUNG	PWC	PWC	PWC	0	0
NF-135	MAIN	PWC	Grant Thornton	Grant Thornton	0	1
NF-136	PLUS	Lee Ka Leung	Deloitte	Arthur	0	1

Sample	Company SYMBOL	Auditor 1 year	Auditor 2 years	Auditor 3 years	Status (1=fail, 0=nonfail)	Auditor change (0=no, 1=yes)
NF-137	RISI	Li, Tang, Chen	Li, Tang, Chen	Andersen Li, Tang, Chen	0	0
NF-138	LTEC	Nelson Wheeler	Nelson Wheeler	Deloitte	0	1
NF-139	PLAY	Moores Rowland	Moores Rowland	PWC	0	1
NF-140	GOLD	PWC	PWC	PWC	0	0
NF-141	ARTS	Deloitte	Deloitte	Deloitte	0	0
NF-142	QPLI	Deloitte	Deloitte	Deloitte	0	0
NF-143	TONG	Ernst & Young	Ernst & Young	Ernst & Young	0	0
NF-144	KWHI	Deloitte	Deloitte	Deloitte	0	0
NF-145	OASI	Deloitte	Deloitte	Deloitte	0	0
NF-146	LINM	Ernst & Young	Ernst & Young	PWC	0	1
NF-147	WBOX	Deloitte	Deloitte	Deloitte	0	0
NF-148	EBON	Moores Rowland	Moores Rowland	Moores Rowland	0	0
NF-149	RAYM	Baker Tilly	Baker Tilly	Baker Tilly	0	0
NF-150	VSIG	KPMG	KPMG	KPMG	0	0
NF-151	HSUN	PWC	PWC	PWC	0	0
NF-152	ONEM	PWC	PWC	PWC	0	0
NF-153	CGHG	Horwath	Horwath	Horwath	0	0
NF-154	JICT	Deloitte	Deloitte	Deloitte	0	0
NF-155	CITI	Deloitte	Deloitte	Deloitte	0	0
NF-156	DATX	CCIF	CCIF	CCIF	0	0
NF-157	BELG	Ernst & Young	Ernst & Young	Ernst & Young	0	0
NF-158	VATX	KPMG	KPMG	KPMG	0	0
NF-159	ATEL	PKF	PKF	Deloitte	0	1
NF-160	DASH	Ernst & Young	Ernst & Young	Ernst & Young	0	0
NF-161	FONA	Ernst & Young	Ernst & Young	Ernst & Young	0	0
NF-162	HTAI	Nelson Wheeler	Nelson Wheeler	Nelson Wheeler	0	0
NF-163	AUTO	Deloitte	Deloitte	Ernst & Young	0	1
NF-164	OFEM	PWC	PWC	PWC	0	0
NF-165	MAGI	Moores Rowland	Moores Rowland	Moores Rowland	0	0
NF-166	WARD	Deloitte	Deloitte	Deloitte	0	0
NF-167	EFOR	Nelson Wheeler	Nelson Wheeler	Nelson Wheeler	0	0
NF-168	CILH	Graham HY Chan	Graham HY Chan	Graham HY Chan	0	0

Sample	Company SYMBOL	Auditor 1 year	Auditor 2 years	Auditor 3 years	Status (1=fail, 0=nonfail)	Auditor change (0=no, 1=yes)
Nf-169	WANJ	PWC	PWC	PWC	0	0
NF-170	KITH	Deloitte	Deloitte	Deloitte	0	0
NF-171	MYUE	Ernst & Young	Ernst & Young	Ernst & Young	0	0
NF-172	BRIG	Elite Partners	Grant Thornton	Grant Thornton	0	1
NF-173	CCTT	Ernst & Young	Ernst & Young	Ernst & Young	0	0
NF-174	CHEN	Ernst & Young	Ernst & Young	Ernst & Young	0	0
NF-175	SMIP	CCIF	CCIF	Deloitte	0	1
NF-176	STAR	Deloitte	Deloitte	Deloitte	0	0
NF-177	HUAY	BDO	BDO	Horwath	0	1
NF-178	CREH	Shinewing	Shinewing	Shinewin g	0	0
NF-179	GDTL	Ernst & Young	Ernst & Young	Ernst & Young	0	0
NF-180	VTOP	Pan-China	NCN	Grant Thornton	0	1
NF-181	GRDI	HLM	HLM	HLM	0	0
NF-182	KGFW	Ernst & Young	Ernst & Young	Ernst & Young	0	0
NF-183	CLIM	Shinewing	Shinewing	Deloitte	0	1
NF-184	FOTO	Ernst & Young	Ernst & Young	Ernst & Young	0	0
NF-185	LESA	PWC	PWC	PWC	0	0
NF-186	LNMH	Deloitte	Deloitte	Deloitte	0	0
NF-187	MFJW	Hopkins	Hopkins	Hopkins	0	0
NF-188	GSIL	Ernst & Young	Deloitte	Deloitte	0	1
NF-189	KNPI	Ernst & Young	Ernst & Young	Ernst & Young	0	0
NF-190	FSMH	Ernst & Young	Ernst & Young	Ernst & Young	0	0
NF-191	JFLI	Hodgson Impey Cheng	Hodgson Impey Cheng	Hodgson Impey Cheng	0	0
NF-192	TUNG	Deloitte	Deloitte	Deloitte	0	0
NF-193	SHHO	Deloitte	Deloitte	Deloitte	0	0
NF-194	GCHL	Deloitte	Deloitte	Deloitte	0	0
NF-195	NESP	Albert Lam	Albert Lam	PWC	0	1
F-01	401H	Graham HY Chan	Graham HY Chan	Graham HY Chan	1	0
F-02	AKUP	Morison Heng	KPMG	N/A	1	1
F-03	SANY	Charles Chan, Ip & Fung	Charles Chan, Ip & Fung	Charles Chan, Ip & Fung	1	0
F-04	ARCT	Graham HY Chan	Graham HY Chan	Graham HY Chan	1	0

Sample	Company SYMBOL	Auditor 1 year	Auditor 2 years	Auditor 3 years	Status (1=fail, 0=nonfail)	Auditor change (0=no, 1=yes)
F-05	LCT	Nelson Wheeler	PWC	PWC	1	1
F-06	CSPE	Charles Chan, IP & Fung	Charles Chan, IP & Fung	Arthur Andersen	1	0 *
F-07	DATA	Ernst & Young	Ernst & Young	N/A	1	0
F-08	DIGI	Graham HY Chan	Nelson Wheeler	Graham HY Chan	1	1
F-09	EZCM	Deloitte	PWC	PWC	1	1
F-10	GILB	Arthur Andersen	Arthur Andersen	Arthur Andersen	1	0
F-11	GOWO	Ernst & Young	Ernst & Young	N/A	1	0
F-12	GOFC	Li, Tang, Chen	Li, Tang, Chen	Deloitte	1	1
F-13	GOWZ	Charles Chan, Ip & Fung	Charles Chan, Ip & Fung	Charles Chan, Ip & Fung	1	0
F-14	GPNA	KL Lee	KL Lee	N/A	1	0
F-15	GREC	Deloitte	Deloitte	Deloitte	1	0
F-16	INFO	Deloitte	Andersen	N/A	1	0 *
F-17	KINE	Ernst & Young	Ernst & Young	N/A	1	0
F-18	KING	Ernst & Young	Ernst & Young	Ernst & Young	1	0
F-19	LDSP	Charles Chan, Ip & Fung	Charles Chan, Ip & Fung	Ernst & Young	1	1
F-20	MOUL	Ernst & Young	Ernst & Young	KPMG	1	1
F-21	ORPW	Ernst & Young	Ernst & Young	Ernst & Young	1	0
F-22	RIVH	Albert Lam	Ernst & Young	Ernst & Young	1	1
F-23	RNAH	Ernst & Young	Ernst & Young	PWC	1	1
F-24	WANA	Graham HY Chan	Graham HY Chan	Graham HY Chan	1	0
F-25	PCMK	Chu & Chu	Chu & Chu	Chu & Chu	1	0
F-26	PANS	Li, Tang, Chen	PKF	PKF	1	1
F-27	YAOH	PWC	PWC	PWC	1	0
F-28	YUEF	Ernst & Young	Ernst & Young	Ernst & Young	1	0
F-29	SIUF	Deloitte	Deloitte	Deloitte	1	0
F-30	CDIG	Charles, Chan, IP & Fung	Charles, Chan, IP & Fung	Ernst & Young	1	1
F-31	SCAN	Horwath	Nelson Wheeler	Ernst & Young	1	1
F-32	SHXI	Ernst & Young	Ernst & Young	Ernst & Young	1	0
F-33	ENGL	Deloitte	Deloitte	Kwan, Wong, Tan & Wong	1	1
F-34	EGAN	Baker Tilly	Baker Tilly	Baker	1	0

Sample	**Company SYMBOL**	**Auditor 1 year**	**Auditor 2 years**	**Auditor 3 years**	**Status (1=fail, 0=nonfail)**	**Auditor change (0=no, 1=yes)**
F-35	BEST	Deloitte	Deloitte	Tilly KPMG	1	1
F-36	LOUL	Cheng & Cheng	Wong Brother	BDO McCube Lo	1	1
F-37	TOPS	PWC	PWC	Arthur Andersen	1	0 *
F-38	DAXI	Horwath	Horwath	Horwath	1	0
F-39	AKAI	Ernst & Young	Ernst & Young	Ernst & Young	1	0

* adjust to “0=no” due to Enron-Arthur Andersen incident

F = failed, NF = non-failed