A Study of Financial Distress Prediction of Chinese Growth Enterprises

Thesis submitted for the degree of
Doctor of Business Administration (DBA) of the University of Canberra

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August 2011

Abstract

In the past three decades, China has made enormous progress in its economic development. With the development of Chinese economy, growth enterprises, particularly those enterprises that either have high technology or use good business ideas and growth potential, have become important in the industrialization process in China. Furthermore, the continued health of growth enterprises is essential to China's global economic competitiveness (CSRC, 2008).

In order to provide a fund raising venue and an exit ground for high-growth and high-risk enterprises in all industries, the Hong Kong Exchanges and Clearing Limited (HKEx) established the Hong Kong Growth Enterprise Market (GEM) in 1999. The GEM has lowered the entry barriers to attract an increasing number of growth enterprises to capitalize on this market.

There is no doubt that the GEMs with a lower entry threshold enable growth enterprises with growth potential but without a proven track record of performance to capitalize on the growth opportunities of China by raising expansion capital on a well-established market (Vong and Zhao, 2008). Nevertheless, the future performance of growth companies, particularly those without a profit track record, is susceptible to great uncertainty.

Because of the high financial risk and imperfections in the financial constitution of growth enterprises, the investors are cautious about investing in GEM in Hong Kong and in the newly established GEM in mainland China (Chen, Sun and Zhang, 2005). Therefore, it has become very

important to develop a reliable financial distress prediction model which covers appropriate predictors to predict the financial distress of growth enterprises on the GEM. The present study, using the data of growth enterprises on Hong Kong GEM, made the first attempt to construct a financial distress prediction model for Chinese growth enterprises. The methods including Mann-Whitney-Wilcoxon (MWW), factor analysis and logistic regression, were then applied to analyse the data. One financial distress model which included financial factors and another financial distress model which included non-financial and macroeconomic factors were constructed in the method section. Based on these two models, the present study developed a financial distress prediction model, which used not only financial factors but also non-financial and macroeconomic factors.

In the existing literature, financial variables (ratios or factors) were the most frequently used predictors in the models that forecast corporate financial distress. Some important research studies suggested they were the most important predictors for forecasting the financial distress (Altman, 1968; Altman, Haldeman and Narayanan, 1977; Ohlson, 1980). In contrast, the present study's findings are different and significant: the logistic regression model that included firm-specific non-financial and macroeconomic factors was better in predicting growth enterprises' financial distress than the model which included firm-specific financial factors. Furthermore, the model incorporating firm-specific financial, firm-specific non-financial and macroeconomic factors was better than the model which included firm-specific financial factors in financial distress prediction. The investors or potential investors can benefit from these findings on financial distress prediction because these findings would enable them to better assess the probability of the growth enterprises experiencing financial distress in the near future.

Acknowledgements

I would like to express my sincere thanks to Prof. Milind Sathye, my Primary Supervisor, for providing specialist knowledge, guidance and assistance during the course of my candidacy. I am also grateful to members of my supervisory panel – Dr. Craig Applegate and Dr. Shuangzhe Liu – for their invaluable advice and encouragement.

Many other people who have been a part of this journey with me and each have carried me along my path in some way. I would like to thank my parents, Prof. Shengshui Hu and Jiahui Luo, for their eternal patience and unconditional support; my sister Rong Hu for always believing in me; Prof. Justin Lin for his new ideas; and especially Mr. Chris Gardner for his moving story which has been inspiring me to believe I can achieve my dreams.

BRIEF CONTENTS

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List of Abbreviations

AIES	artificial intelligent expert system
AIM	Alternative Investment Market
ANN	Artificial Neural Networks
ASX	Australian Stock Exchange
CSRC	China Securities Regulatory Commission
EIU	Economist Intelligence Unit
FDI	foreign direct investment
GDP	gross domestic product
GEM	Growth Enterprise Market
GNP	gross national product
GPL	general price level
HKEx	Hong Kong Exchanges and Clearing Limited
HKSE	Hong Kong Stock Exchange
IPO	Initial Public Offering
ITDRS	Information Transparency and Disclosure Ranking System
LA	logistic analysis
MDA	multiple discriminant analysis
MNL	multinomial logistic
MWW	Mann-Whitney-Wilcoxon
NBSC	National Bureau of Statistics of China
NCF	Normalised Cost of Failure

NN	neural networks
OECD	Organization for Economic Cooperation and Development
PPP	purchasing power parity
ROA	return on assets ratio
ROE	return on ordinary shareholders' equity ratio
RP	recursive partitioning
RPA	Recursive Partitioning Algorithm
SEC	Securities and Exchange Commission
SFI	Securities and Futures Institute
SME	small and medium-sized enterprise
SSE	Shanghai Stock Exchange
SZSE	Shenzhen Stock Exchange
TSE	Taiwan Stocks Exchange
TSEC	Taiwan Stock Exchange Corporation
WTO	World Trade Organization

Chapter 1 Introduction

1.1 Overview of the Chinese economy

For hundreds of years, China stood as a leading country, outpacing the rest of the world not only in arts, technology and science but also in economic growth (Maddison, 1998). However, from 1840 to 1949, this country was beset by foreign occupation, civil wars, civil unrest and great famines. After the Chinese Civil War ended in 1949, the Communist Party of China started to be in control of mainland China and the Chinese Nationalist Party retreated to Taiwan. From the People's Republic of China's founding in 1949, China began to establish a Soviet-style centrally planned economy to promote the economic recovery and growth.

Following the Soviet economic model, China started to establish state-owned enterprises without private investment and concentrated state investments mainly on heavy industrial facilities.

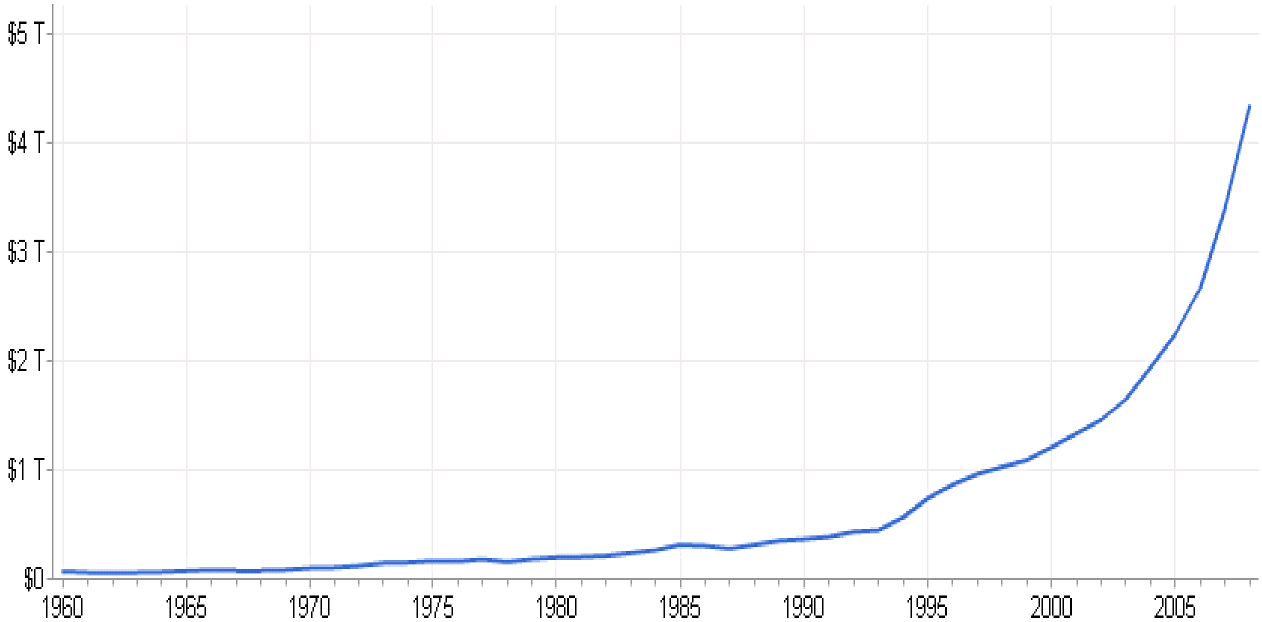
Between 1952 and 1957, 156 major facilities with thousands of mining and industrial firms were established. During the same period, China's industrial production increased at an average annual growth rate of above 19 per cent while national income grew at an average annual rate of 9 per cent (He and Zhou, 2007). Despite the lack of state investment in agriculture, agricultural output still increased on average by approximately 4 per cent a year because over 90 per cent of farm households in China had joined the advanced producers' cooperatives by 1957. At the beginning, this reorganization and cooperation with voluntary collectivization achieved in the rural area increased agricultural efficiency to some extent (Lin, 1990).

In the late 1950s and early 1960s, Chinese economy experienced the Great Leap Forward movement. During the Great Leap Forward, the Chinese government adopted an approach of inspiring people's spontaneous heroic efforts to produce a dramatic leap in production for all sectors of economy especially the heavy industry within a short time. At the beginning, the political zeal can be the motive force but obviously the growth of agricultural output depending on the political inspiration is unsustainable. Meanwhile, the compulsory collectivization, namely the people's commune, was created and most of the farm population was organized into the communes. Subsequently, this communal movement resulted in a terminal agricultural crisis between 1959 and 1961 because the compulsory collectivization discouraged the agricultural production. In 1959, the agricultural gross output of China dropped by 14 per cent. Following that, the gross output of agriculture fell 12 per cent and 2.5 per cent in 1960 and 1961 respectively (Lin, 1990).

Between 1966 and 1976, the Cultural Revolution happened as a series of fierce power struggles between several groups of top leaders. The impact of the Cultural Revolution on Chinese economy became conspicuous as the struggles were extended into production units in late 1966 (Cheng, 1967). At the beginning of the Cultural Revolution, because of the national political activities of students, workers and even the army, production was reduced in most sectors of the economy. Later on, the effects of the power struggles and policy disputes further slowed down the economic growth. Finally, by the end of the Cultural Revolution, China had been in a complete shambles economically, socially and politically.

After the Cultural Revolution ended towards the end of 1976, the new leadership reaffirmed the importance of the economic growth. So the political struggle finally ended and economic reform with opening-up policy was initiated. Since the reforms and economic opening-up policy started from 1978, China has experienced a remarkable transformation from a centrally planned economy to a market-oriented economy with private and foreign businesses in China growing rapidly. In the past three decades, the Chinese economy has grown at an unprecedented rate with an average annual gross domestic product (GDP) growth rate above 9 per cent (see Figure 1.1). This growth rate has not been observed at any time in the past economic history of China and very few economies in the world today can parallel this (Gordon and Li, 1991; Fung, Pei and Zhang, 2006). According to the National Bureau of Statistics of China (NBSC), China's GDP reached US$5.88 trillion in 2010 (NBSC, 2011). China has become the world's second largest economy since 2010, just behind that of the U.S. (CIA, 2011). With regard to purchasing power parity (PPP) GDP, China has been the second largest economy since 2001. Therefore, many economists expect that China's GDP in PPP terms may surpass that of the United States in the first quarter of this century (Zhang, 2009).

Figure 1.1 China's Gross Domestic Product (GDP) between 1960 and 2008*



Data source: World Bank, World Development Indicators – Last updated March 2, 2010.
* GDP in trillions of U.S. dollars

Furthermore, China has accumulated the world's largest foreign exchange reserves which have surpassed US$2 trillion by 2009 because of its rapid growth in trade surplus and capital inflows. In terms of foreign direct investment (FDI), the Chinese government has removed the restrictions on the geographical location of foreign-invested enterprises and the restrictions on the legal form and type of foreign-invested firms. Moreover, China becoming a member of World Trade Organization (WTO) and increasing administrative incentives to investors attract more FDI flowing into China. Hence, all these policies led to an increase in annual inward FDI in China from 30 billion U.S. dollars in the period during 1990- 2000 to US$108 billion in 2008 (Williams, 2009).

In terms of international trade, China's international trade has expanded steadily since 1979 when the opening-up of economy policy started. Chinese international trade has grown much faster than average growth rate of world trade for nearly 30 years (Rumbaugh and Blancher, 2004). By the end of 2009, China has also become the second largest trading nation, the second largest importer and the largest exporter globally (WTO, 2010). As a result of booming Chinese economy, China created 19.2 per cent of world economic growth in 2007 and has topped the world in contribution to the global economic growth since that year (NBSC, 2011).

As a developing country, China also has achieved tremendous success in poverty reduction. Since the late 1970s, several hundred million people have been helped to lift out of absolute poverty in China. In other words, China alone accounted for more than 75 per cent of poverty reduction in the third world countries over the last 20 years (World Bank, 2010b).

With 1.3 billion population and over 300 million farmers, Chinese people regard agriculture as one of the most important economic sectors. Beginning in 1978, as part of the economic reform, the household-based farming responsibility system was created. This new system dismantled people's communes and gave agricultural production responsibility back to individual households. Households, which lease land from the state, are free to use their farmland for farming without the communes' supervision. This freedom has given more incentives to individual families to produce (OECD, 2005). As a result of adopting this system and other related policies, China's agricultural production has greatly increased and China has become the world's largest consumer and producer of agricultural products (NBSC, 2011).

Besides the reforms mentioned above, the reforms, starting from late 1970s, included increasing autonomy for state-owned enterprises, gradual liberalization of prices, fiscal decentralization, reforming the banking system, establishing the securities markets, etc. In the rapid progress of constructing the securities markets, the GEM is introduced. Introducing the GEM is an important step towards promoting the development of high-growth, high-tech independent innovation enterprises and also an important step towards improving the securities markets.

1.2 Overview of Chinese stock exchanges

Prior to the introduction of reform and opening-up policies, capital or funds in China were typically centrally administered and allocated to enterprises under planning economic system and there were no real capital markets existing (CSRC, 2008). After the reforming policies were applied in 1978, China's economic reform paved the way for the emergence of real capital markets. Along with the dramatic development of economy and the rapid development of non-state businesses, enterprises needed to diversify their funding channels and called for the emergence of real capital markets (Fama, 1970). Hence, mainland China has launched its large-scale reform in the capital markets.

In late 1980s, the Chinese government started to allow several big cities to establish stock exchange. As a consequence, mainland China established two stock exchanges in early 1990s, the Shanghai Stock Exchange (SSE) and Shenzhen Stock Exchange (SZSE). When SZSE launched the Shenzhen Composite Index on April 4, 1991, its base of 100 points was set equivalent to the stocks' total value as of the market close on the previous day. After that, SSE also launched the Shanghai Composite Index and took December 19, 1990, as its base of 100 points. From then on, these two exchanges have provided many Chinese companies with more capital raising opportunities (CSRC, 2008).

After that, the China Securities Regulatory Commission (CSRC) was established by the Chinese government in 1992. The establishment of CSRC means that the Chinese authorities have started to consolidate the supervision of mainland China's capital markets. In addition, the CSRC has driven the formulation of a series of regulations, rules and laws for the securities markets since its inception. For instance, the Company Law, which was implemented in 1994, sets out specific provisions for the conditions of setting up and organizing a company, issuing and transferring securities, legal liabilities and liquidation procedures. Moreover, the Company Law sets standards of corporate governance for different enterprises and in turn lays legal foundation for the securities markets (CSRC, 2008).

Furthermore, with the enaction of Securities Law in 1999, the issuance and trading of securities in mainland China have been regulated legally for the first time. Admittedly, the introduction of the CSRC with related regulations, rules and laws had a profound impact on the development of the Chinese securities markets (CSRC, 2008). In sum, along with the establishment of a centralized regulatory organization (CSRC) and the national stock exchanges (SSE and SZSE), there has been rapid growth in the number of listed enterprises, total trading volume and total market capitalization. It follows that these two stock exchanges of mainland China have experienced rapid growth in the past two decades and SSE has become one of the largest capital exchanges in the world with significant influence on the world capital markets and the global economy (see Table 1.1).

Table 1.1 Largest domestic equity market capitalizations at year-end, 2009 and 2008

	Exchange	USD bn. end-2009	USD bn. end-2008	% change in USD	% change in local currency
1	NYSE Euronext (US)	11 838	9 209	28.5%	28.5%
2	Tokyo Stock Exchange Group	3 306	3 116	6.1%	8.6%
3	NASDAQ OMX (US)	3 239	2 249	44.0%	44.0%
4	NYSE Euronext (Europe)	2 869	2 102	36.5%	32.6%
5	London Stock Exchange	2 796	1 868	49.7%	34.4%
6	Shanghai Stock Exchange	2 705	1 425	89.8%	89.9%
7	Hong Kong Exchanges	2 305	1 329	73.5%	73.6%
8	TMX Group	1 608	1 033	55.6%	34.2%
9	BMandFBOVESPA	1 337	592	125.9%	69.7%
10	Bombay SE	1 306	647	101.9%	93.3%

Source: World Federation of Exchanges, 2010. 2009 World Federation Exchanges Market Highlights.

1.3 The emerging of Growth Enterprise Markets and growth enterprises in China

As discussed previously, China's securities markets have made great progress. However, there were still some structural problems restricting the effective functioning of the markets in the process of their development. One of the most serious issues of mainland China's securities markets was that many growth enterprises in mainland China may not always be able to take advantage of fund-raising opportunities. Mainland China's capital markets have long been dominated by the exchanges in Shanghai and Shenzhen without much diversification (CSRC, 2008). Although growth enterprises, particularly those emerging ones- i.e. enterprises that either use high technology or have good business ideas and growth potential, are considered important in the economic development and industrialization process in many developed and developing countries (Keizo, 1998), the stringent listing requirements on size, profitability and industry focus exclude these companies. A great number of them did not fulfil the profitability or track record requirements of the major stock exchanges in mainland China and were therefore unable to obtain a listing.

In order to provide a fund raising venue and an exit ground for high-growth and high-risk enterprises in all industries, the HKEx established the Hong Kong GEM in 1999. The GEM has lowered the entry barrier to attract increasingly number of small or medium growth enterprises to capitalize on this market. Hence, the Hong Kong GEM has become an alternative securities market for Chinese growth enterprises.

1.3.1 The Growth Enterprise Market with its listed growth enterprises in mainland China

However, given Hong Kong's independent judicial, monetary and financial systems, most growth enterprises from mainland China prefer to be listed on the mainland's securities market. Hence, to expand the securities market of mainland China, the proposal of establishing a secondary securities market like Hong Kong GEM was first put forth by the CSRC in late 1990s. The SZSE has begun to explore the possibility of developing a GEM since 2001 and set up a mini secondary market for small and medium-sized enterprises (SMEs) on a trial basis.

In order to cope with international financial crises and promote Chinese economic development, the CSRC accelerated the proceeding of building GEM in late 2000s. According to the CSRC's report (2008), establishing GEM is a vital step to carry out the strategy of building multi-level capital market system. The launch of the GEM can provide a direct financing option for start-ups that engage in emerging industries and support these firms at their growth stage.

Before the establishment of GEM in mainland China, for the future GEM's stability and healthy development, the CSRC orderly promulgated GEM rules and stipulated related regulations in

2009. On March 31, 2009, the Tentative Administrative Measures for Initial Public Offerings (IPO) and Listing on the GEM was promulgated. The issuance of these tentative administrative measures is a milestone in establishing a GEM in mainland China after Hong Kong GEM was founded. The tentative administrative measures are like Hong Kong GEM rules and composed of six chapters and 58 articles. On the one hand, according to these measures, the GEM is similar to the SSE and SZSE to a certain extent requiring that issuer should satisfy the requirements on independence, qualifications, formalized accounting and financial operation (Shao, 2009).

On the other hand, since the GEM targets growth enterprises which are defined as those enterprises having self-innovation, high technology, growth potential or good business ideas, the GEM rules for these enterprises are much different from the rules of SSE and SZSE especially in some certain requirements and offering conditions. Because of the higher financial and operational risk, the CSRC strengthen the growth enterprises' public supervision and information disclosure. For example, the issuer should disclose its application prospectus prior to the examination by the Public Offering Review Committee (CSRC, 2010).

Furthermore, the entry threshold set by the GEM rules is much lower than SSE and SZSE's entry thresholds. Even if growth enterprises cannot fulfil the profitability and track record requirement for the IPO and listing on the SSE and SZSE(Shao, 2009), the GEM still can offer an avenue for those growth enterprises to capitalize on their growth opportunities. The core threshold of entering GEM include two sets of criteria: first, the issuer should make its accumulated net profits of at least RMB 10 million (approximately US$1.5 million) for the recent two consecutive years which is only one third of the profit requirement under the SZSE's rules; second, the GEM issuer's revenue in the most recent year should be no less than RMB50 million (approximately

US$7.3 million) and it is undoubtedly lower than the requirement of issuer on the SSE or SZSE which is the revenues in the recent three consecutive years being no less than RMB 300 million (approximately US$43.9 million). In addition, the GEM do not have any requirements on cash flow, nor do they require the maximum 20% of intangible assets to net assets in the most recent financial statement (Shao, 2009).

Other than the differences in offering requirements, the following regulations especially stipulated in the GEM but not in the SSE and SZSE also deserve attention. With respect to operational stability, the GEM rules require that the issuer should focus on one main business. On business operation, the GEM issuer's profit is required to be in continuous growth and the annual revenue growth should not be less than 30 per cent in the recent two consecutive years, while the rules of SSE and SZSE do not have such requirements (Shao, 2009).

After the GEM rules were issued, the GEM Public Offering Review Committee was established to inspect the quality and credibility of the listed firms and maintain the GEM credibility. The committee should be responsible for reviewing and approving the applications for the IPO and listing on the GEM. Besides that, the committee must be in charge of protecting the economic interests and legitimate rights of all investors (CSRC, 2010).

Finally, CSRC announced the launch of a long-awaited GEM in Shenzhen, which is similar to the GEM in Hong Kong, as a new direct financing platform for growth companies to bridge the financing gap on October 30, 2009. The first batch of 28 enterprises listed on the GEM debuted on the same day at the SZSE. By the end of February 2010, 58 growth enterprises had been listed on the GEM with a combined market capitalization of more than RMB 232.4 billion (approximately US$34 billion). In other words, the GEM in mainland China is a very young market but grows quite rapidly.

In sum, the GEM in mainland China is a newly founded secondary market of the SZSE which offers an avenue for Chinese growth enterprises to raise funds on their growth opportunities, if they are unable to fulfil the profitability and track record requirements for the IPO and listing on SSE and SZSE (CSRC, 2010). The GEM listing threshold for growth enterprise is much lower than that for SSE and SZSE in mainland China. According to the Tentative Administrative Measures, the GEM is reserved for growth enterprises whose operations fall under Chinese government-specified categories of high-tech research and development (EIU, 2008). The growth enterprises on the GEM are defined as those enterprises having self-innovation, high technology, growth potential or good business ideas. However, this study cannot examine the GEM in mainland China and the growth enterprises on this GEM because this GEM is an emerging secondary stock exchange without enough data available for doing research. Hence, this study focuses on Hong Kong GEM and the growth enterprises on it instead.

1.3.2 The GEM with its listed growth enterprises in Hong Kong

Since Hong Kong was handed over to China in 1997, Hong Kong has become more integrated with the economy of mainland China. As an international financial centre, Hong Kong has also become an important capital raising centre for mainland Chinese enterprises. However, in order to obtain a listing on the Hong Kong Stock Exchange (HKSE), both Chinese and international enterprises are required to achieve a record of at least three years' trading history. The enterprise should have a profit of HK$50 million (approximately US$6.4 million) in the last three years and its market capitalization has to exceed HK$200 million (approximately US$25.6 million). By the end of 2009, there were 1145 companies listed on the HKSE with a market capitalization of HK$17,769.3 billion (approximately US$2305 billion). It is Asia's third largest stock exchange in terms of market capitalisation, behind the Tokyo Stock Exchange and the SSE (World Federation of Exchanges, 2010). Although the HKSE provides an avenue for new enterprises to raise capital, only the big companies or conglomerates can fulfil the HKSE's requirements (Vong and Zhao, 2008).

Since most growth enterprises are not allowed to take advantage of the HKSE, the Hong Kong GEM was officially established on November 25, 1999 to bridge this gap. From November 1999, the GEM has offered an independent and recognized market for growth enterprises particularly those smaller and emerging technology companies to issue their new shares. With the lower entry threshold, the GEM enables enterprises with growth potential but without a proven track record of performance to gain access to equity capital (Vong and Zhao, 2008). In that case, the Hong Kong GEM has become a beneficial complement of HKSE. Hong Kong GEM operates on a base of strong disclosure regime and self-compliance by listed issuers and sponsors in the discharge of their respective responsibilities. There are three features to support this principle. First, a listing applicant should disclose its detailed business history and future business plans. From the time of listing, the GEM issuer has to compare its business result with their business plan every half year in its first two financial years. Additionally, annual accounts, quarterly accounts and an even shorter period accounts are allowed to be published publicly. The GEM is taking responsibility of providing comprehensive information including trading prices, company announcements, market statistics and other related information of listed issuers to the market participants (GEM, 2010b).

Second, having been successfully listed, a GEM issuer is required to establish a set of corporate governance principles. All these principles can make the issuer adhere to proper business practices and comply with the listing rules of the GEM. These principles include designating a qualified accountant to supervise the issuers' finance and accounting functions, appointment of two independent directors, appointing an executive director as the compliance officer and establishing an audit committee. Moreover, the issuer is also required to retain a sponsor. Generally, this sponsor has one major responsibility which is advising and assisting the enterprise and its directors in the discharge of their listing obligations (GEM, 2010b).

Third, the main responsibility of the GEM itself is to ensure the listing documents of an applicant comply with the requirements of the Companies Ordinance and the GEM listing rules but not to assess the commercial viability of the applicants. Similarly, the GEM is only in charge of reviewing all issuers' public announcements and the issuer and its directors have to be responsible for the sufficiency, correctness and quality of their disclosed information. Additionally, the GEM has to monitor the securities trading on the GEM and issuers and sponsors complying with the GEM listing rules (GEM, 2010b).

Since the inception of Hong Kong's GEM in 1999, the GEM has made considerable progress. By the end of 2009, there have been 174 enterprises listed on the GEM with the total market capitalization of HK$105 billion (approximately US$13.5 billion). However, companies listed on HKSE are still much larger than those listed on the GEM on average. For instance, the average market capitalization of a HKSE listed company is approximate HK$15,519 million (approximately US$1989.6 million) whereas that of a GEM company is approximate HK$ 603.7 million (approximately US$77.4 million). Along with the development of the GEM and the GEM companies, some GEM companies have transferred their listings from the GEM to the HKSE because they have become able to fulfil the requirements stipulated by the HKSE. By the end of 2009, 40 GEM enterprises had switched their listings to the HKSE (GEM, 2010a).

In sum, the Hong Kong GEM was established by the HKSE as a secondary market of securities market which offers growth enterprises, especially those cannot meet the profitability or track record requirements of HKSE, an exit ground and an avenue for raising capital. The lower entry threshold enables growth enterprises to capitalize on the growth opportunities of Hong Kong and even the whole China by raising expansion capital under a well-established market and regulatory infrastructure. No doubt, investing in those growth enterprises without profit record means great uncertainty. Furthermore, due to the increasing globalization of world economy, some growth enterprises, particularly those export-oriented enterprises, are seriously affected by the global financial crisis in 2009 (Liu, 2009). Because of the higher risks involved, Hong Kong GEM operates on a philosophy of strong disclosure regime and self- compliance by listed issuers and sponsors being in the discharge of their respective responsibilities. Meanwhile, the GEM is also in charge of supervising issuers' compliance with the listing rules. So the GEM works on the principle of investors beware (GEM, 2010a).

Comparing the GEM in Hong Kong and the GEM in mainland China, several points can be concluded. First of all, according to the listing rules of Hong Kong GEM, the enterprises that have innovation, high technology, good business ideas or growth potential are defined as growth enterprises. So the growth enterprises on the Hong Kong GEM are similar to the enterprises listed on mainland China's GEM. Next, these two GEMs are secondary markets of major securities markets and quite similar because the GEM in mainland China was established in the same way as the GEM in Hong Kong. Compared to the newly established GEM in mainland China, the Hong Kong GEM has more than ten years' trading history which has enough data available for research. Hence, in the present study, Hong Kong GEM is used as target market and the growth enterprises are defined as those enterprises on the GEM currently or in the past. For looking at the financial risks of growth enterprises on Hong Kong GEM, this study examines their corporate financial distress.

1.4 Defining financial distress in Chinese growth enterprises

In the past four decades, one of the major concerns in the field of predicting whether enterprises will enter into financial distress is the lack of consensus on the definition of situations of enterprises facing financial difficulty. Thus, properly defining the situations of enterprises facing financial difficulty has attracted considerable attention and can be regarded as a precondition to predict corporate distress. In the past literature there have been continuous attempts to define situations of enterprises facing financial difficulty.

To date, bankruptcy is one of the most common terms used as a synonym for enterprises being confronted with financial difficulty. Most early studies on predicting corporate failure focused on the firms which were filed for bankruptcy (Beaver, 1966; 1968; Altman, 1968; Altman, Haldeman and Narayanan, 1977; Ohlson, 1980). Foster (1986) indicated that filing for bankruptcy is a legal event which is heavily influenced by the actions of bankers and/ or other creditors. In Wruck's (1990) study, bankruptcy referred to the court-supervised process for breaking and rewriting contracts. Similarly, Altman and Hotchkiss (2006) defined bankruptcy as a legal event that a corporate bankruptcy petition is filed under the National Bankruptcy Act.

Further, insolvency is also commonly used as a proxy for confronting financial difficulties which includes liquidity and performance problems (Altman and Hotchkiss, 2006). Therefore, the insolvent firm can be defined as a firm with negative economic net worth or the present value of the firm's cash flows is less than its total obligations (Altman, 1983; Keating et al., 2005).

Liquidation is the process by which a firm selling its assets or property and redistributing the proceeds to claimants (Wruck, 1990). When a limited company becomes insolvent, it goes into liquidation. Otherwise, bankruptcy is another option which can be considered when a company is insolvent.

Apart from bankruptcy, insolvency and liquidation, default is another situation seen as a firm encountering financial difficulties. According to Altman and Hotchkiss (2006), default happens when an enterprise has not met its legal obligations and legal action has been taken.

Last but not least, the final proxy which is commonly used for corporate financial difficulty from the financial viewpoint is corporate failure. In the earlier research, the corporate failure was defined as a combined concept which includes the following alternative items: stock market delisting, large losses disproportionate to assets, firms in the process of liquidation, negative share returns, and an arrangement with creditors. Balcaen and Ooghe (2006, p. 72) mentioned that 'corporate failure is not a well defined dichotomy'. It appears from most research that the criterion for failure is chosen arbitrarily and could either mean judicial bankruptcy or financial distress. A more recent definition given by Altman and Hotchkiss (2006) define 'corporate failure' as the situation where the realized rate of return on invested capital with allowances for risk consideration is continually and significantly lower than the prevailing rates of similar investments.

Since the definitions of these five terms (bankruptcy, insolvency, liquidation, default and corporate failure) are similar, it is necessary to distinguish one from another. The definitions of these four terms are summarized as follows:

1. *Bankruptcy* is a legal process in which insolvent enterprises or enterprises in default declare inability to pay debts.
2. *Insolvency* is a legal term that refers to an enterprise being unable to pay its debt.
3. *Liquidation* is a process of assets sale and redistributing the proceeds when the firms become insolvent.
4. *Default* is a situation when a firm has not paid the debt which it is required to have paid.
5. *Corporate failure* occurs when the realized rate of return on invested capital with allowances is lower than the prevailing rates of similar investments.

In sum, all these five terms are different stages in the process of experiencing financial difficulty. For this reason, all of these five terms have close relationships between one another.

In earlier studies, researchers like using single proxy for financial distress. For instance, filing for bankruptcy is the most commonly used criterion for financial distress (Foster, 1986). However, being a legal event, bankruptcy can be heavily influenced by creditors like bankers (Foster, 1986). Accordingly, Foster (1986) continues to define financial distress to refer to 'severe liquidity problems that cannot be resolved without a sizable rescaling of the entities' operations or structure'. In that case, liquidation also becomes a synonym for financial distress (Wruck, 1990; Kuruppu, Laswad and Oyelere, 2003). In Wruck's (1990) study, liquidation, which is closely connected with the process of insolvency and bankruptcy, means selling firm's assets and distributing the proceeds to claimants. Furthermore, in earlier studies, insolvency was often used as a synonym for financial distress besides bankruptcy and liquidation (Wruck, 1990). Given the diverse nature of financial distress, some confusion and complexity may arise. The reason is a single term or situation cannot represent the various nature of financial distress.

For the purpose of resolving this confusion, recent research usually use the term 'financial distress' to describe all the situations of firms encountering financial difficulties. So the definition of financial distress in these researches should be diverse and covers a range of situations or terms. For example, Steyn-Bruwer and Hamman (2006) defined financial distress as the situation when a firm experiences filing for bankruptcy, delisting or a major organisational restructuring. Basing on the mode of payment of the recorded enterprises, Kaiser (2001) divided financial distress into two main categories: The 'Medium Problem', where companies cannot meet their obligations before the agreed deadline; The 'Severe Problem', where debt-collecting agencies have been authorized to collect the outstanding debt, bankruptcy proceedings have been started or the entrepreneur declares an affirmation in lieu of an oath.

In a similar manner, according to Jones and Hensher (2004), two states of firms listed on the Australian Stock Exchange (ASX) were defined as financially distressed. The firms in the first state were insolvent firms which were in the situations like failure to pay ASX annual listing fees, a diminished capacity to make loan repayments and loan default. The firms in the second state were those firms that were filed for bankruptcy.

In the Chinese context, the financially distressed firms in mainland China is defined differently from those definitions used in the developed securities markets. For example, according to the regulations released by the CSRC, corporations listed on mainland China' s stock exchanges are given the label of 'ST' (an abbreviation for 'special treatment'), on the basis of any of the following four criteria (Wang and Li, 2007):

1. The external auditors express negative opinions or clearly state that they are unable to express opinions on a company's annual report.
2. The company's financial conditions are considered to be abnormal by the stock exchange or the CSRC.
3. The company shows that it has suffered losses for two consecutive years.
4. The audited report shows that the shareholder's equity is lower than the registered capital.

In Wang and Li's (2007) study, they defined distressed companies on mainland China's securities markets as those suffering ST under the criteria 2, 3 and 4.

In sum, there is currently an extensive and well-developed body of literature that defines corporate financial distress in stock-issued companies in many countries, but there is a lack of definition of growth enterprises' financial distress on Chinese GEMs owing to the limited studies on Chinese growth enterprises.

This paper extends previous work by considering Chinese growth enterprises listed on the Hong Kong GEM, which has unique legislation regarding the suspension and termination of listed loss-making companies. As such, this study adds a new dimension to the current financial distress prediction literature which comprises mainly the U.S. and other developed securities markets.

As discussed previously, the Hong Kong GEM has a much lower entry threshold and the growth enterprises on the GEM have higher financial risks than the enterprises on the HKSE. The definition of growth enterprises' corporate distress should be based on the reality of GEM operations in Hong Kong. With the introduction of the official delisting, long trading suspension and reports on corporate governance practices disclosures on the GEM, a unique opportunity is provided to investigate the financial performance of distressed Chinese growth enterprises and its determinants. Hence, the present study defines a distressed growth enterprise as an enterprise which has experienced being filed for bankruptcy, cancellation of listing pursuant to delisting procedures under the GEM Listing Rules (excluding being transferred to other stock markets) or securities trading being suspended by the GEM for at least three months due to disobeying the GEM Listing Rules. On the contrary, those growth enterprises on the Hong Kong GEM, which have not experienced these situations, are defined as non-distressed enterprises.

1.5 Overview of financial distress prediction models

As corporate financial distress has been a worldwide economic and social issue, its prediction has become a hot topic in the corporate finance research (Cheng, Yeh and Chiu, 2007). Aziz and Humayon (2006) summarized three main types of financial distress predictive models: The first category of predictive models is the statistical models which mainly comprise the multiple discriminant analysis (MDA) model and logistic analysis model. Second, the artificial intelligent expert system models are another important type of financial distress prediction models. This category of models mainly includes neural networks analysis and recursive partitioning model (or decision trees model). The final type of predictive models is named theoretical models which consist primarily of entropy theory.

In addition, Aziz and Humayon (2006) compiled an extensive literature review of 46 papers which included 89 previous empirical studies of predicting corporate financial distress. According to their statistics, 64 per cent of total previous studies used the statistical predictive models, about a quarter of all previous studies applied artificial intelligent expert system models and only 11 per cent of the previous studies used the theoretical models. However, the overall average predictive accuracy of these three model categories is quite close. The range of these three models' predictive accuracy was from 84 per cent to 88 per cent. Therefore, in this study, the most frequently used predictive models, namely the statistical models, are discussed. The overviews of MDA model and logistic analysis model are stated respectively as follows.

1.5.1 Multivariate discriminant analysis

Altman's pioneering work (1968) used multivariate discriminant analysis with a set of five financial ratios for distinguishing failed firms from non-failed firms. The multivariate discriminant analysis is based on the development of a linear equation. This equation provides an overall score used to predict whether the subject lies in either of the groups which should be no less than two (Muller, Steyn-Bruwer and Hamman, 2009). In addition, this resulting equation firstly combines all the variables and weighs the variables in such a way as to maximise its ability to discriminate between different groups (Rees, 1995). Therefore, the discriminant function of this equation could transforms individual variables' values with their corresponding coefficients to a single discriminant score (Altman, 1968). In terms of predicting financial distress, enterprises are classified as ‘distressed’ or ‘non-distressed’ based on whether the overall score of the discriminant function is less than or greater than the predetermined cut-off value.

1.5.2 Logistic analysis

In 1980, Ohlson carried out a research into the probabilistic prediction of financial distress using logistic analysis. The application of logistic analysis requires four steps: (1) calculate a series of financial ratios; (2) multiply each ratio with its corresponding coefficient; (3) sum the result of each coefficient to form a new variable *y* and (4) calculate the probability of financial distress for a company as $1/(1+e^{-y})$. Here the independent variables with a negative coefficient increase the probability of financial distress due to the fact that they reduce e^{-y} toward zero, with the result that the financial distress (probability function) approaches 100 per cent or 1. Likewise, the independent variables with a positive coefficient decrease the probability of financial distress (Ohlson, 1980).

Compared to the multivariate discriminant analysis, the logistic analysis has its own advantages: First, logistic analysis does not rely on the assumption of normality for the sample data; second, logistic analysis does not require an equal dispersion matrix (Balcaen and Ooghe, 2006). In other words, logistic analysis is far less demanding than multivariate discriminant analysis.

Moreover, in terms of predictive accuracy, Ohlson (1980) predicted financial distress of companies based on the probability of financial distress for one year and two years prior to financial distress and got accuracy of 96.1 per cent and 95.5 per cent respectively. Collins and

Green (1982) compared forecasting results by using a logistic model, a discriminate analysis and a linear probability model, respectively. Their results show that the logistic model performs better. Hall (1994) set up a logistic model with non-financial variables and the model could distinguish distressed firms from non-distressed firms with as high as 95 per cent of accuracy. In summary, because of the advantages of the logistic analysis, this thesis constructs a financial distress model for growth enterprises based on employing the logistic model.

1.6 What this study is about?

This study is about the growth enterprises' distress prediction in China. However, the GEM in mainland China, which was established in 2009, is a newly established market offering growth enterprises an avenue to raise capital. Owing to the short history of this GEM, data of the listed companies is limited for research. Thus, the present study focuses on the growth enterprises listed on the GEM in Hong Kong instead because of the availability of more than 10 years' data from the Hong Kong GEM and the particularly strong economic relationship between Hong Kong and mainland China.

1.6.1 Identifying the gaps from previous research

From the review of existing literature, two gaps were identified. First, prior research has not considered the combined effect of financial variables, non-financial variables and macroeconomic variables on distress prediction. Second, although considerable research has been done on listed companies on the major stock exchanges and SMEs because of availability of sufficient financial data, much less is known about the importance of growth enterprises in developing economies (Keizo 1998). Based on all the literature and available data, the model of financial distress prediction needs to be developed in this study. In the previous literature, many researchers examined the firm-specific financial variables, non-financial variables and macroeconomic variables separately or formulated their research by combining two out of the three kinds of variables, but only several recent studies covered all three kinds. Furthermore, there is a lack of studies on growth enterprises on the secondary markets of major stock exchanges, namely the GEM, in China owing to the limitation of the data and company population. Hence, the improved model must consider three groups of variables, including firm-specific financial variables, non-financial variables and macroeconomic variables. It can be believed that incorporating all these three kinds of variables into the financial distress prediction model would advance the theory of financial distress prediction.

1.6.2 The importance of this study

The establishment of the GEM is regarded as an important measure to develop a multi-level capital market in China and expand the market's depth and width (CRSC, 2008). Lowering the GEM's entry threshold enables growth enterprises to capitalize on the growth opportunities of China by raising expansion capital under a well-established market and regulatory infrastructure. Nevertheless, the future performance of growth companies, particularly those without a profit track record, is susceptible to great uncertainty. Because of the higher risks involved, the GEM is designed for professional and informed investors. It works on the basis of *caveat emptor* or 'buyers beware' (GEM, 2010a).

Accumulating evidence suggests that growth enterprises are precisely these businesses which are responsible for much of an economy's dynamism. Chinese growth enterprises have also played a vital role in promoting economic growth during economic reforms and transition. Furthermore, growth enterprises' continued health is essential to China's global economic competition (CSRC, 2008). However, the GEMs in China have escaped attention of researchers.

A healthy GEM is conducive to meet the direct financing needs from growth enterprises, especially high-tech companies, as well as providing investment opportunities for venture capital firms (CSRC, 2008). Financing from the capital market could be an important way for growth enterprises to survive and develop. In some countries and regions, special stock exchanges or markets are established to assist enterprises that have potentiality for growth and development with the objective of raising capital, like the NASDAQ in the U.S., Jasdaq Securities Exchange in Japan, Alternative Investment Market (AIM) in the U.K., etc (Wang and She, 2008). Unfortunately, imperfections in the financial constitution of growth enterprises and high financial risk make the investors more cautious in investing money in GEM in Hong Kong (Chen, Sun and Zhang, 2005) and in the newly established GEM in mainland China. Chan et al. (2007) also found that most of newly listed stocks on the Hong Kong GEM were under-performing. Therefore, it has become very important to develop a reliable financial distress prediction model which can apply appropriate predictors to predict the financial distress of growth enterprises on the GEM. The present study is the first attempt to construct a financial distress prediction model for growth enterprises on the GEM. The model took not only firm-specific financial ratios into account, but also non-financial and macroeconomic variables.

1.7 Research objectives

This thesis focuses on identifying financial distress of growth enterprises on the Hong Kong GEM within the theory framework of financial distress prediction. This study includes the following research objectives:

1. *To identify whether there are significant differences in financial, non-financial and macroeconomic variables between distressed and non-distressed growth enterprises.*

In order to achieve this objective, the present study used the Mann-Whitney-Wilcoxon (MWW) test to identify whether there are significant differences in ten financial, four non-financial variables and four macroeconomic variables between distressed and non-distressed growth enterprises.

2. *To examine the relationship between financial factors and the occurrence of financial distress in the growth enterprise.*
3. *To examine the relationship between non-financial factors and the occurrence of financial distress in the growth enterprise.*
4. *To examine the relationship between macroeconomic factors and the occurrence of financial distress in the growth enterprise.*

To accomplish objective 2, 3 and 4, the present study firstly uses factor analysis to reduce the large number of financial variables to several financial factors. In the same way, the essential non-financial and macroeconomic factors are extracted from a set of non-financial and macroeconomic variables. The extracted key financial, non-financial and macroeconomic factors were then served as inputted independent variables for logistic regression. Finally, the present study used logistic regression analyses to examine the relationship between financial, non-financial and macroeconomic factors and the occurrence of financial distress in the growth enterprises.

5. *To examine whether the model that uses financial factors to predict financial distress of growth enterprise performs better in predicting financial distress than the model that uses non-financial and macroeconomic factors to predict financial distress.*

To achieve objective 5, the output of logistic regression model which incorporates firm-specific financial factors is compared with the output of logistic regression model which includes firm-specific non-financial and macroeconomic factors.

6. *To examine whether the model that uses all three kinds of factors (financial, non-financial and macroeconomic factors) to predict financial distress of growth enterprise performs better in predicting financial distress than the model that only uses financial factors to predict financial distress.*

To accomplish this objective, the output of logistic regression model which incorporates firm-specific financial, firm-specific non-financial and macroeconomic factors is compared with the output of logistic regression model which only includes firm-specific financial factors.

1.8 Research questions

According to the literature to date, the symptoms of financial distress are observable from the deterioration of firm- specific financial, firm- specific non-financial and macroeconomic variables. Various previous studies, for example, Altman (1968; 1984), Altman, Haldeman and Narayanan (1977), Ohlson (1980), Wruck (1990), Kuo et al. (2003), Jones and Hensher (2004), Smith and Liou (2007), incorporated firm-specific financial variables, firm-specific non-financial variables or macroeconomic variables in predicting financial distress. Their studies confirmed that one kind or even a combination of two kinds of these three variables were significant indicators of financial distress. There have been only several recent studies examining all these three kinds of variables together, but these studies did not relate to growth enterprises. As there have been few research studies on listed Chinese growth enterprises' financial distress, the research questions addressed in this study are as follows.

1. *Are there significant differences in firm-specific financial ratios between distressed and non-distressed growth enterprises?*

To answer this question, the present study incorporates ten financial ratios from three main categories which are profitability, liquidity and solvency ratios. The MWW test is then used to identify whether there are differences in firm-specific financial ratios between distressed and non-distressed growth enterprises.

In the present study, the firm-specific non-financial variables are also examined. The relevant research question is as follows.

2. *Are there significant differences in firm-specific non-financial variables between distressed and non-distressed growth enterprises?*

To answer this question, the present study incorporates four firm-specific non-financial variables which include ‘changing auditors’, ‘delay in releasing financial statements’, ‘auditors’ report with qualified opinion and/ or explanatory paragraph’ and ‘profit warning’. The MWW test is then used to identify whether there are differences in firm-specific non-financial variables between distressed and non-distressed growth enterprises.

Besides firm-specific financial and non-financial variables, the present study examines the macroeconomic variables. The relevant research question is as follows.

3. *Are there significant differences in macroeconomic variables between distressed and non-distressed growth enterprises?*

To answer this question, the present study incorporates four macroeconomic variables which include real GDP growth rate, average interest rate on loans, Business Climate Index and Entrepreneur Confidence Index. The MWW test is then used to identify whether there are differences in macroeconomic variables between distressed and non-distressed growth enterprises.

4. *Do firm-specific financial factors significantly predict whether growth enterprises have experienced financial distress?*

To answer this question, the firm-specific financial factors which are extracted from the firm-specific financial variables are firstly used as independent variables for logistic regression analyses. The dependent variable is whether the growth enterprise has experienced financial distress or not. The present study then used logistic regression analysis to identify whether the firm-specific financial factors can significantly predict financial distress of growth enterprises.

5. *Do firm-specific non-financial factors significantly predict whether growth enterprises have experienced financial distress?*

To answer this question, the firm-specific non-financial factors which are extracted from the firm-specific non-financial variables are used as independent variables for logistic regression analyses. The dependent variable is whether the growth enterprise has experienced financial distress or not. The present study then used logistic regression analysis to identify whether the firm-specific non-financial factors can significantly predict financial distress of growth enterprises.

6. *Does macroeconomic factor significantly predict whether growth enterprises have experienced financial distress?*

To answer this question, the macroeconomic factor which is extracted from the macroeconomic variables is used as an independent variable for logistic regression analyses. The dependent variable is whether the growth enterprise has experienced financial distress or not. The present study then used logistic regression analysis to identify whether the macroeconomic factors can significantly predict financial distress of growth enterprises.

7. *Does the model that considers firm-specific financial factors perform better than the model that considers firm-specific non-financial and macroeconomic factors in financial distress prediction?*

To answer this question, the study compares the classification accuracy of the logistic regression model which considers firm-specific financial factors with that of the model which considers firm-specific non-financial and macroeconomic factors.

8. *Does the model based on firm-specific financial, firm-specific non-financial and macroeconomic factors perform better than the model that only includes firm-specific financial factors in financial distress prediction?*

To answer this question, the study compares the classification accuracy of the logistic regression model which considers firm-specific financial, firm-specific non-financial and macroeconomic factors with that of the model which only considers firm-specific financial factors.

1.9 Implications of the present research

The aim of this study is to propose a financial distress prediction model to predict the distress of growth enterprises. Recently there has been growing interest in the importance of growth enterprises because they have some special characteristics including both as listed companies' and as enterprises with growth potential and uncertainty. In other words, the growth enterprises have high financial risk and are easily influenced by macroeconomic factors, like SMEs; while they have public information and financial data available to let investors assess this uncertainty themselves, like other listed companies. As a result, this study constructs a financial distress prediction model for growth enterprises, which should take not only firm-specific financial ratios into account, but also non-financial and macroeconomic variables.

The common firm-specific financial factors are extracted by using factor analysis. These factors are proxies for a firm's solvency ratios, assets turnover, managerial performance ratios, profitability ratios, financial leverages and cash flow. Moreover, several firm’s non-financial variables can enhance the accuracy of predicting growth enterprises’ financial distress. Financial distress prediction logistic regression model shows that firm-specific financial ratios combining non-financial variables and macroeconomic variables are useful in discriminating between distressed and non-distressed firms. Generally, the non-distressed growth enterprises outperform the distressed enterprises in some firm-specific financial and non-financial variables. Besides that, there is close relationship between firm’s distress and some macroeconomic variables.

Based on the logistic regression model, the proposed financial distress prediction model for growth enterprises makes it easier to classify distressed and non-distressed growth enterprises. Investors can use this model against losses of granting credit when making a decision to invest in growth enterprises. In addition, a comparison between distressed and non-distressed growth enterprises is valuable in providing growth enterprises with forecasting, diagnostic and evaluation tools to assess financing, investing and operating activities during the stage of the enterprises' growth. In particular, because of the establishing GEM in mainland China, a constructed financial distress prediction model based on growth enterprises in Hong Kong GEM can provide a lot of references for newly established GEM of mainland China in predicting financial distress of growth enterprises.

1.10 Thesis outline

This thesis is organized into six chapters and organised as follows. The first chapter has presented an introduction to this study, starting with an overview of the Chinese economy. Next, the development of the Chinese stock exchanges and the background of the Chinese GEMs have also been described. The chapter also has included a discussion of the definitions of corporate distress and financial distress predicting models from previous studies. The research objectives and research questions have been specified and they can improve the understanding of the research topic. Finally, this chapter has indicated the implications of the present study.

The following chapters proceed as follows:

Chapter 2 reviews the research studies in the area of predicting financial distress. The chronology of the key research studies in a chronological time sequence is then presented in Chapter 2. Finally, two gaps in the literature on predicting corporate financial distress are identified.

Chapter 3 develops eight hypotheses. The first two hypotheses are related to financial ratios and financial factors. Chapter 3 develops the second two hypotheses which are related to non-financial variables and non-financial factors. Chapter 3 then develops another two hypotheses which are related to macroeconomic variables and macroeconomic factors. Next, Chapter 3 develops the hypothesis regarding comparing the model incorporating firm-specific financial factors with the model which includes firm-specific non-financial and macroeconomic factors. Finally, the chapter develops the hypothesis relating to comparing the model incorporating firm-specific financial, firm-specific non-financial and macroeconomic factors with the model which only includes firm-specific financial factors.

Chapter 4 is regarding the data collection, variable measurements and the method in this study. The chapter firstly defines distressed growth enterprises and non-distressed growth enterprises. It then discusses the categories of financial distress predictors and selects the financial distress predictors for the present study. Next, Chapter 4 introduces the source of data and discusses the sample selection method in the present study. Finally, the methods, which include the MWW test, factor analysis and logistic regression, are present in the chapter.

In Chapter 5, the MWW test was firstly run to distinguish the difference between distressed and non-distressed growth enterprises in financial and non-financial performance and their respective macroeconomic situations. The chapter then used factor analysis to reduce the large number of ratios and variables to several factors. After the MWW test and factor analysis, the extracted financial, non-financial and macroeconomic factors were used as independent variables for logistic regression analyses. Finally, three types of financial distress models are established and relevant hypotheses are tested.

Besides concluding the whole thesis, Chapter 6 addresses not only the contribution of this research but also the limitations of this thesis and the proposing suggestions for future research. These contributions include the contributions to original academic research, the benefits to the investors, the managements and the independent auditors of growth enterprises and suggestions for the authorities of GEMs. The two limitations are missing values of financial ratios and the small sample size of growth enterprises. Chapter 6 finally proposes two suggestions for future research which including incorporating more growth enterprises and consider more non-financial variables in the future.

Chapter 2 Literature Review

2.1 Introduction

Corporate financial distress, including bankruptcy, delisting and suspension of securities trade, has been considered as a serious economic and social issue (Cheng, Yeh and Chiu, 2007). From the financial viewpoint, it usually brings about economic losses to investors, stockholders, employees and customers, together with a substantial social and economical cost to the nation. Therefore, a model of predicting corporate distress would serve to reduce such losses by providing a pre-warning to stakeholders of firms. Such a model could provide an early warning signal of probable distress which could help both management and investors to take preventive actions and shorten the length of time whereby losses are incurred (Jaikengkit, 2004). Hence, an accurate prediction of firms' financial distress has become an important issue in finance (Cybinski, 2001). As noted in the introduction chapter, this thesis integrates predictive variables from three disparate fields in order to enhance the predictive accuracy of financial distress prediction model. The objective of this research is to develop a better corporate distress prediction model which can make it easier to classify distressed and non-distressed growth enterprises.

The literature on corporate financial distress is extensive. The present chapter reviews the similar research studies in the area of predicting financial distress. The generally recognized pioneers in this area are Beaver (1966) and Altman (1968). The following sections of this chapter are as follows.

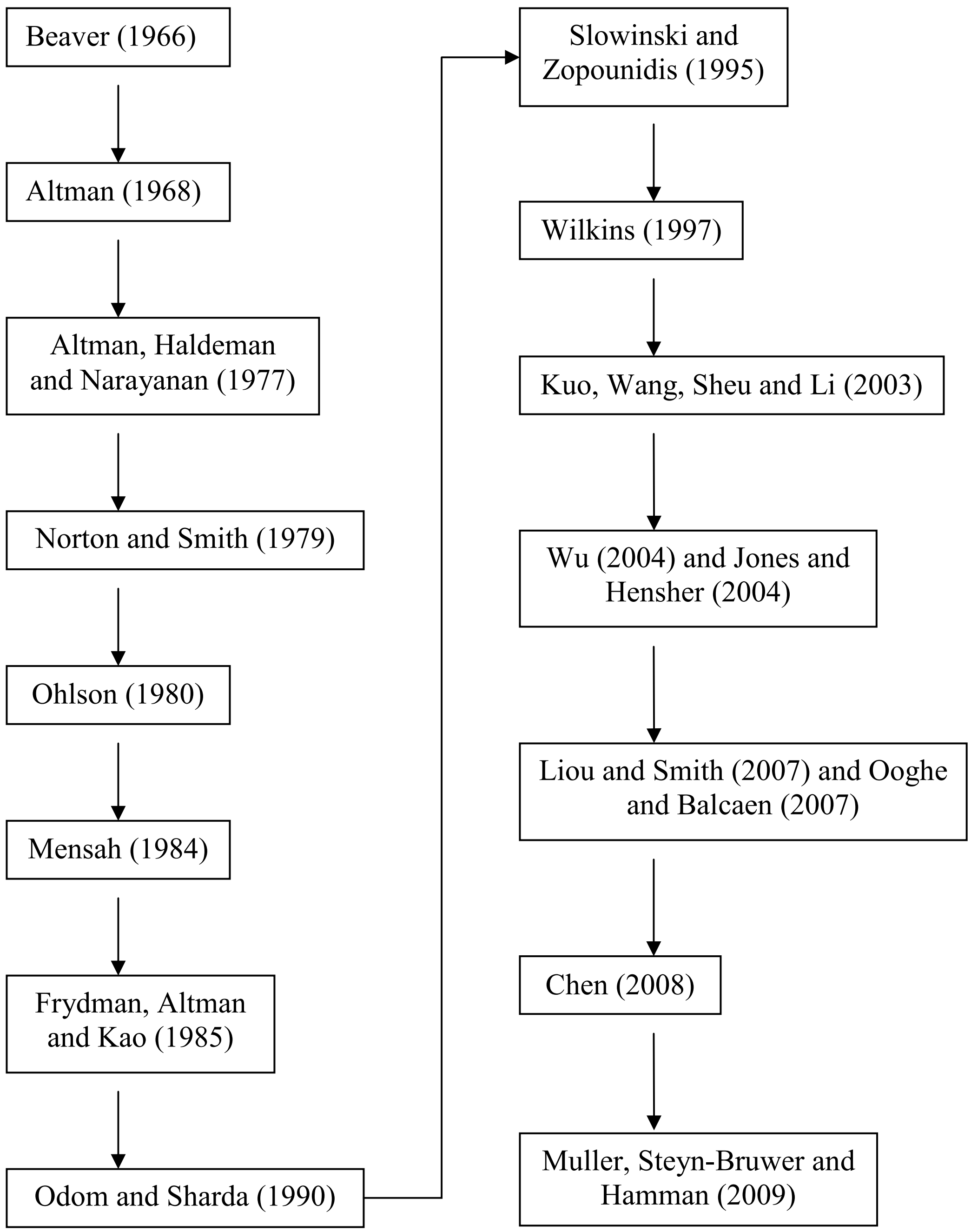
Section 2.2 presents the chronology of the key research studies.

Section 2.3 provides a summary of the literature review and thereafter identifies the gaps in the literature.

2.2 Chronology of key research in financial distress

In this section, 17 important research studies in the area of corporate financial distress prediction are reviewed (see Figure 2.1).

Figure 2.1 Chronology of important research studies in financial distress



2.2.1 Beaver (1966)

Beaver's (1966) study was one of the first studies using financial ratios, which were based on the data from financial statements, to predict failure. It was designed to provide an empirical verification of the predictive ability of financial statements. In Beaver's study, the term 'failure' was defined as a firm having no ability to pay its financial obligations when they mature. Thus, a firm is classified as a failed firm when it is involved in any one of the following situations: bond default, bankruptcy, non-payment of a preferred stock dividend or an overdrawn bank account.

79 failed firms, which had failed during a time period from 1954 to 1964 inclusively, were identified in Moody's *Industrial Manual*. The selected failed firms' financial-statement data were also obtained from Moody's *Industrial Manual* for five years prior to failure of firms. As the firms in Moody's were industrial, publicly owned corporations, the firms in this study were larger in terms of total assets. Hence, the probability of failure among these firms was much lower than smaller firms. In addition, the failed firms were categorized by total asset and industry. The 79 failed firms operated in 38 different industries with average total asset of US$6 million. Accordingly, for each failed firm in the sample, a non-failed firm with similar total asset and the same industry was selected.

In terms of ratios, Beaver selected 30 ratios and computed them according to the available data in financial statements. In the process of ratios selecting, three criteria were used. The first criterion was the ratios' frequent appearance in 19 previous financial-statement analysis studies. The second criterion was that the ratios performed well in one of the studies in the existing literature. The third criterion was the ratio being defined in terms of a cash-flow concept. Beaver's study included the ratios which fulfilled at least one of the three criteria and excluded the ratios which had similar meanings. Accordingly, all these 30 ratios were divided into six groups which were named cash-flow ratios, net-income ratios, debt to total-asset ratios, liquid-asset to total-asset ratios, liquid-asset to current debt ratios and turnover ratios.

In the analysis section of this study, one ratio from each group was selected as a focus. The six ratios were current ratios, cash flow to total debt, total debt to total assets, net income to total assets, no-credit interval and working capital to total assets. The data analysis was divided into three sections, including comparing the mean of the ratios (profile analysis), doing a dichotomous classification test and analysing likelihood ratios. Firstly, the profile analysis was used to outline the general difference between the failed and non-failed enterprises. However, profile analysis cannot answer how large the difference is. Secondly, based upon the financial ratios, dichotomous classification test was used to predict the enterprise's failure status. Although this test is a predictive test, it cannot provide as much information as likelihood ratios. Finally, financial ratios were viewed as a way of assessing the likelihood of failure and the likelihood ratios were computed from the financial ratios.

In sum, the predictive ability of financial ratios was investigated and ratio analysis was found useful in the predicting failure for at least five years before failure. However, the ratios predicted failed and non-failed firms with different degree of success and not all ratios predicted equally well. In addition, the analysis of Beaver's study was a univariate analysis and it could only examine one ratio's predictive ability at one time.

2.2.2 Altman (1968)

After Beaver's study (1966), instead of ratio analysis, using rigorous statistical techniques to assess the performance of the enterprises had gradually become more popular. Thus, Altman (1968) attempted to create a link between the rigorous statistical techniques and the traditional ratio analysis. This study aimed at assessing the quality of ratio analysis and predicting corporate bankruptcy was used as an illustrative case.

First, based on Beaver's study and other related studies, the shortcomings of traditional ratio analysis as a technique for investigating corporate performance were discussed. In most cases of using ratio analysis, this methodology was univariate in nature. These studies focused on individual signals of impending problems. In that case, ratio analysis was susceptible to faulty interpretation. Additionally, according to Beaver's study, a univariate study can only consider one measurement for assigning groups at a time.

In order to solve the problems of Beaver's study, Altman used a MDA as the statistical technique. MDA is usually used to classify an observation into one of several groups based on the observation's individual characteristics (Rettig, 1964). This statistical technique is mainly used to predicting or classifying issues with qualitative dependent variables. One advantage of MDA is that it considers the interaction and entire profile of characteristics common to the related enterprises. Furthermore, rather than sequentially examining the individual characteristics of the object, the primary advantage of MDA in dealing with classification problems is simultaneously analysing its entire variable profile (Altman, 1968).

In terms of sample selection, 66 corporations with 33 enterprises in the bankrupt group and the non-bankrupt group respectively were selected as initial sample firms. The firms in the bankrupt group were manufacturers which had filed a bankruptcy petition under the Chapter X of the *National Bankruptcy Act* between 1946 and 1965. The mean asset size of these firms was US$6.4 million approximately. The non-bankrupt group consisted of paired sample manufacturing firms which had been chosen on a stratified random basis. The data of the non-bankrupt firms were also from the years as compiled for the bankrupt group (Altman, 1968).

After two groups of firms were chosen, a list of 22 potentially helpful ratios was compiled from the firms' statements and reports for evaluation. These ratios were categorized into five ratio types which consist of activity ratio, leverage, liquidity, profitability and solvency. Five variables were then chosen as achieving the best overall prediction of corporate bankruptcy. The final discriminant function was used to predict bankruptcy in Altman's (1968) study is as follows:

$$Z = 0.12 \bullet X_1 + 0.14 \bullet X_2 + 0.033 \bullet X_3 + 0.006 \bullet X_4 + 0.999 \bullet X_5 \qquad (2.1)$$

where each coefficient is defined as:

X_1 is working capital / total assets ratio

X_2 is retained earnings / total assets ratio

X_3 is earnings before interest and taxes / total assets ratio

X_4 is market value of equity / book value of total debt ratio

X_5 is sales / total assets ratio

Z is overall index

In this model, the Z-score indicator provided a forecast of whether the company would enter into financial distress within a two-year period. The zones of Z score's discrimination were concluded as: enterprises with Z score greater than 2.99 are in the non-bankrupt sector; the Z score between 1.81 and 2.99 is the zone of ignorance because error classifications are observed in this area; the range of Z score below 1.81 is defined as the bankrupt zone.

2.2.3 Altman, Haldeman and Narayanan (1977)

Based on the model done by Altman in 1968, Altman, Haldeman and Narayanan (1977) developed a new model to identify bankruptcy risk of corporations. This new model incorporated comprehensive inputs and current refinements in using discriminant statistical techniques. A group of bankrupt firms during the period from 1969 to 1975 were chosen as sample firms. There were two samples of firms in this study. One sample consisted of 53 bankrupt firms and the matched sample had 58 non-bankrupt firms. The non-bankrupt entities were matched to the bankrupt group by year of the data and industry.

The main reason for creating a new model was that the new ZETA model could effectively classify bankrupt manufacturing and retailing firms up to five years before corporate failure. In addition, several other reasons for a new bankruptcy classification model improving previous statistical models were listed:

First, most studies before Altman, Haldeman and Narayanan's (1977) study used relatively small-sized firms in their samples. Their study utilized a group of bankrupt firms as samples with no firm having assets of less than US$20 million; the average asset size of these firms was US$100 million approximately. Further, 50 firms out of 53 firms in the sample failed in the previous seven years. Second, differing from the past studies, Altman, Haldeman and Narayanan analysed both retailing and manufacturing firms on an equal basis. Third, the data had been analysed and updated according to recent changes in accepted accounting practices and financial reporting standards. These operations make the model relevant to the data that would appear in the future. Finally, controversial aspects and advances were tested.

In terms of financial ratios and other measures, this study calculated the ratios or measures which had been found helpful in providing statistical evidence of impending failures in other studies. Additionally, this study added several new ratios which were believed to be helpful too. These 27 ratios and variables were classified as capitalization ratios, liquidity ratios, profitability ratios, leverage measures, coverage and other earnings relative to leverage measures and a few miscellaneous measures.

In Altman's (1968) study, a MDA was used as the statistical technique in bankruptcy classifying. Altman, Haldeman and Narayanan (1977) undertook bankruptcy classification by using the MDA as discriminant analysis and analysed both the quadratic and linear structures. As the results of the study shown, the quadratic and linear models yield equal overall accuracy results for the original sample classifications. In contrast, the holdout sample tests indicated superiority for the linear framework.

In addition, Altman Haldeman and Narayanan established a seven-variable model after an iterative process of reducing the number of variables. This model not only heightened the reliability of various validation procedures, but also classified its test sample effectively. In other words, the model with fewer variables could not perform as well and adding more variables could not significantly improve the results. The detailed descriptions of all variables are as follows:

X_1 is return on assets. This ratio was measured by the earnings before interest and taxes divided by total assets and had been proven helpful in assessing firm performance in studies by Altman (1968) and Beaver (1966).

X_2 is stability of earnings. This ratio was measured by a normalized measure of the standard error of estimate around a ten-year trend in X_1.

X_3 is debt service. This ratio was measured by the familiar interest coverage ratio, i.e. earnings before interest and taxes divided by total interest payments.

X_4 is cumulative profitability. This ratio was measured by the firm's retained earnings divided by total assets. Compared to Altman's (1968) results, the results of Altman, Haldeman and Narayanan's (1977) study revealed that the cumulative profitability measure was the most important variable.

X_5 is liquidity, measured by the familiar current ratio.

X_6 is capitalization, measured by common equity divided by total capital.

X_7 is size, measured by the firm's total assets.

According to this study, the most important ratio is the cumulative profitability ratio (X_4) and second in importance is the stability of earnings ratio (X_2). Capitalization variable(X_6) is the third in importance after X_2 and the least important variable is the overall profitability ratio (X_1).

Comparing the ZETA model (Altman, Haldeman and Narayanan, 1977) with the earlier model (Altman, 1968), the following results can be found: the ZETA model was far more accurate in bankruptcy classification in one year to five years prior to bankruptcy; the older model showed slightly more accurate non-bankruptcy classification when direct comparison was possible.

In summary, the ZETA model for predicting corporate bankruptcy risk developed in the study (Altman, Haldeman and Narayanan, 1977) demonstrated considerable improvement in promoting accuracy. This model's bankruptcy classification accuracy varied from 70 per cent in the fifth annual reporting period before bankruptcy to 96 per cent in the first period before bankruptcy.

2.2.4 Norton and Smith (1979)

A number of research studies had been conducted to examine whether ratios from enterprises' financial statements could be useful for predicting bankruptcy (Norton and Smith, 1979). In addition to financial ratios which were used in the previous studies, Norton and Smith (1979) used different accounting methods to forecast enterprises' financial distress. The purpose of this study was to compare the bankruptcy prediction based on the ratios calculated from traditional historical cost financial statements with the prediction based on ratios calculated from general price level (GPL) financial statements.

Firstly, the sample enterprises in this study were limited to the enterprises listed in Moody's *Industrial Manual*. They comprised 30 bankrupt enterprises and the same number of non-bankrupt enterprises. The bankrupt enterprises were those that had notified the US Securities and Exchange Commission (SEC) on Form 10-K or Form 8-K that legal bankruptcy proceedings had begun during the period from 1971 to 1975. This period was a high inflation period prior to 1979. All these 30 bankrupt enterprises had their financial statements available for four years before the year when bankruptcy notices were filled with the SEC. Further, a non-bankrupt enterprise was selected for each bankrupt enterprise according to two selection criteria: (a) the bankrupt enterprise and its matched enterprise were in the same industry and from the same year except one pair of enterprises; (b) the non-bankrupt enterprise should be similar to its matched enterprise in asset size (Norton and Smith, 1979).

Secondly, the GPL adjusted financial statements were constructed from the historical cost financial statements. After the GPL adjusted financial statements were developed, 32 financial ratios were calculated for each of the four years preceding bankruptcy from either GPL financial statements or historical cost financial statements. Then, Norton and Smith used linear MDA for bankruptcy predictions and bankruptcy or non-bankruptcy was regarded as dependent variables. The independent variables were those 32 financial ratios. Two discriminant functions, which were based on the GPL financial ratios and historical cost financial ratios respectively, were developed for each year preceding bankruptcy.

Finally, Norton and Smith found both GPL ratios and historical cost ratios having the ability to predict bankruptcy. There were many *a priori* arguments advanced that GPL financial statements should be more useful than traditional statements. However, the authors of this study could not find any evidence that implied GPL financial ratios were more accurate in predicting bankruptcy. The mixed results of this study illustrated that GPL ratios were slightly better in some years but slightly worse in others. In other words, for the sample firms selected in this study, historical cost and GPL data were equally useful for prediction of bankruptcy. In sum, if the ability of financial statements to predict bankruptcy was regarded as the criterion of usefulness, GPL financial statements cannot be recommended based on the results of Norton and Smith' s study.

The authors found that both GPL and traditional ratios exhibited the ability to predict bankruptcy. In spite of the sizable differences in magnitude that existed between GPL and historical cost financial statements, little difference was found in the bankruptcy predictions. GPL data were shown to be consistently neither more nor less accurate than historical data for predictions of bankruptcy.

2.2.5 Ohlson (1980)

Ohlson (1980) used the conditional logistic model as the methodology to research the probabilistic prediction of bankruptcy. The typical logistic model equation can be represented as follows (Muller, Steyn-Bruwer and Hamman, 2009):

$$P(x) = 1 / [\, 1 + e^{-(bo + b1 \bullet X1 + b2 \bullet X2 + \ldots + bn \bullet Xn)}] \qquad (2.2)$$

where:

$P(x)$ is the probability of failure for a firm

b_n is the coefficient for each independent variable

X_n is the actual value for each independent variable

The logistic model requires four steps:

- calculating a series of financial ratios;
- multiplying each ratio with its corresponding coefficient;
- adding the result of each coefficient to form a new variable y;
- calculating the probability of financial distress for a company as $1/\ (1+ e^{-y})$.

The conditional logistic analysis was selected to avoid some problems with respect to the MDA. Prior to Ohlson's (1980) study, the MDA, using vectors of predictors, was one of the most popular approaches for bankruptcy prediction (e.g. Altman, 1968; Altman, Haldeman and Narayanan, 1977). However, several problems of MDA are mentioned in Ohlson's (1980) study: first, certain statistical requirements are imposed on the distributional properties of the predictors; second, the output of applying a MDA model is a score which has little intuitive interpretation, since it is an ordinal discriminatory device; third, there are some problems related to the matching procedures that have been used in MDA frequently. Furthermore, the advantage of using logistic model is far less demanding than MDA analysis in general.

In Ohlson's (1980) study, the data set from the period 1970 to 1976 was chosen for corporate failure research. The study relied on observations from 2058 non-bankrupt enterprises and 105 bankrupt enterprises. Contrary to most of the studies conducted prior to Ohlson (1980), the data for the bankrupt enterprises were not derived from Moody's Manual and the data were obtained from 10-K financial statements instead.

Ohlson (1980) chose nine independent variables for the models.

1. SIZE equals log (total assets/GNP price-level index).
2. TLTA equals total liabilities divided by total assets.
3. WCTA equals working capital divided by total assets.
4. CLCA equals current liabilities divided by current assets.
5. OENEG equals one if total liabilities exceeds total assets, zero otherwise.
6. NITA equals net income divided by total assets.
7. FUTL equals funds provided by operations divided by total liabilities.
8. INTWO equals one if net income was negative for the last two years, zero otherwise.
9. CHIN equals $(NI_t - NI_{t-1})/(|NI_t| + |NI_{t-1}|)$, where NI_t is net income for the most recent period. The denominator acts as a level indicator. The variable is thus intended to measure change in net income.

Furthermore, Ohlson (1980) could predict firms' bankruptcy, based on the probability of financial distress, for one year and two years prior to bankruptcy to an accuracy of 96.1 per cent and 95.5 per cent respectively. First, this study identified four basic factors as being statistically significant in affecting the bankruptcy within one year: the size of the firms, a measure(s) of financial structure, a measure(s) of corporate performance and a measure(s) of current liquidity. Second, the predictive accuracy of all models depends on when the financial reports are available. Third, significant improvement of the model's predictive accuracy requires additional predictors.

2.2.6 Mensah (1984)

Prior to Mensah's (1984) research study, those studies using MDA of financial ratios showed inconsistency both in the relative importance of the various financial ratios and the values of the coefficients reported. This inconsistency can be partially attributed to the fact that different studies were using different sets of ratios. In addition, using a different functional form of the MDA model with different subsets of a given set of financial ratios could result in different coefficient values. In bankruptcy prediction studies, most methodological issues were associated with common practices, except for choosing different ratios in the final prediction models.

Thus, Mensah's (1984) study aimed to examine the relative importance of these issues in an empirical setting and tried to find the factors which might need to be considered in future bankruptcy studies.

First, according to some previous studies reviewed by Mensah (1984), external macroeconomic environments can be expected to affect the results of bankruptcy prediction models. Accordingly, Mensah (1984) investigated three external macroeconomic factors including inflation, business cycle (recession/expansion phases) and interest rates and credit availability in a sample period from January 1972 to June 1980 when sample companies failed. The examination divided the period into four sub-periods based on the movement of the three macroeconomic variables. These four sub-periods are steady growth phase, recessionary conditions, steady growth phase, stagflation and recession.

Second, Mensah (1984) used the *Wall Street Journal Index* and selected firms filing under Chapters X and XI of the Bankruptcy Act. Using assets and industry classification as matching criteria, 110 pairs of firms in the mining, manufacturing, retail and construction sectors were chosen as sample firms. These sample firms were divided into four groups whose bankrupt partners had failed in four sub-periods respectively.

Third, given the objective of Mensah's study, the MDA had some drawbacks. Accordingly, Mensah used the logistic model because this model permits the statistical significance of each of the variables in the model to be independently evaluated (Mensah, 1984). Additionally, factor analysis was used on a set of 38 ratios to distinguish the most important ratios. The factor coefficients were then applied to these ratios and factor scores were derived for all companies in the sample.

Fourth, since inadequate attention had been paid in the process of stationarity across different economic environments, Mensah merged the data for the four periods to examine whether different periods of aggregation affect the resultant model.

Fifth, in order to prove that the results were not due to using logistic model and factor scores, Mensah (1984) repeated using MDA on the original ratios. Furthermore, the recession/expansion theme was used in aggregating the data to generate adequate samples. To control for differences in the financial structure of firms in different industries, Mensah also analysed retail and manufacturing companies separately.

Finally, Mensah (1984) inferred three general conclusions from the study overall. First and foremost, the prediction models' structure and accuracy differed across different economic environments. Next, different predictive models were appropriate for firms in different industrial sectors even for similar economic environment. Lastly, considering multicollinearity might obtain more useful results in the intersectional and intertemporal development of the models, Mensah suggested that the general application of the prediction model might be improved by reducing collinearity.

2.2.7 Frydman, Altman and Kao (1985)

In the study by Frydman, Altman and Kao (1985), a new classification procedure called Recursive Partitioning Algorithm (RPA) was presented for financial analysis. RPA is a computerized and nonparametric classification technique based on pattern recognition. Moreover, RPA has attributes of both the multivariate procedures and classical univariate classification approach. Within the context of corporate financial distress, Frydman, Altman and Kao's study compared the RPA with discriminant analysis.

Frydman, Altman and Kao (1985) illustrated RPA by classifying the financial distress of firms. They showed that although both the classical discriminant analysis techniques and RPA achieved reasonably correct classification results on a data set of non-bankrupt and bankrupt firms, the RPA usually dominated the discriminant analysis (Frydman, Altman and Kao, 1985). The objective of this study was not to find the most efficient financial distress prediction model; it was concerned with the qualities and the potential of an alternative classification technique. Thus, this study mainly concentrated on RPA and its qualities. At the same time, since the discriminant analysis is a well known method of analysing the bankruptcy issue, this study contrasted discriminant analysis with RPA.

The 200 sample firms of this study included 58 bankrupt industrial firms which failed in the period between 1971 and 1981. Frydman, Altman and Kao (1985) randomly selected another 142 non-bankrupt retailing and manufacturing enterprises from the COMPUSTAT universe. The investigated financial years were also randomly selected from 1971 to 1981. However, the years of non-bankrupt enterprises did not match the exact years of the bankrupt enterprises.

20 financial variables used in this study had been found to be significant in predicting business distress by several previous researches (Altman, 1968; Deakin, 1972; Altman, Haldeman and Narayanan, 1977). These 20 financial variables are described as follows: Cash/ Total Assets, Cash/ Total Sales, Cash Flow/Total Debt, Current Assets/Current Liabilities, Current Assets/Total Assets, Current Assets/Total Sales, Earnings Before Interest and Taxes/Total Assets, Log (Interest Coverage + 15), Log (Total Assets), Market Value of Equity/Total Capitalization, Net income/Total Assets, Quick Assets/Current Liabilities, Quick Assets/Total Assets, Quick Assets/Total Sales, Retained Earnings/Total Assets, Standard Deviation of (Earnings Before Interest and Taxes/Total Assets), Total Debt/Total Assets, Total Sales/Total Assets, Working Capital/Total Assets and Working Capital/Total Sales. An adjustment for the capitalization of leases was applied to the 20 variables since companies had been required to capitalize financial leases from 1980 (Frydman, Altman and Kao, 1985).

This study selected two RPA models (RPA1 and RPA2) for comparison with discriminant analysis models. With respect to the discriminant functions, two discriminant analysis models were constructed and named DA1 and DA2 respectively. RPA models and discriminant analysis models were then compared with each other.

In Frydman, Altman and Kao's conclusion, the RPA's and discriminant analysis's ability to assess the performance of a firm relative to its prior condition or other firms was discussed. In the example of this study, the classification accuracy of RPA was actually superior to the traditional discriminant framework. However, Frydman, Altman and Kao did not claim RPA could always outperform the various other statistical classification techniques. The RPA does not have continuous scoring system qualities of discriminant analysis (Frydman, Altman and Kao, 1985).

2.2.8 Odom and Sharda (1990)

Artificial Neural Networks (ANN) is a popular research technique used in many fields of research such as business, medicine, politics and technology (Atiya, 2001). It has the most practical effect in event predicting, expert systems and signal processing (Lippmann, 1987). Along with MDA, logistic analysis and the recursive partitioning algorithm, ANN is also a technique applied in the area of business failure prediction. Odom and Sharda (1990) were the first to develop an ANN model for bankruptcy prediction.

The objective of Odom and Sharda's study was to compare the predictive ability of a neural network and a more traditional method (MDA) in predicting bankruptcy. In this study, Odom and Sharda then performed analysis on ratios applying a neural network and discriminant analysis. The study by Altman (1968) was used as the standard for comparison for subsequently classifying bankruptcy studies using discriminant analysis. Thus, the financial ratios used in Altman's study (1968) were also used in Odom and Sharda's study.

Similar to many previous studies, the ratios of sample firms were obtained from Moody's *Industrial Manual*. These sample firms consisted of 129 firms. 65 of these firms went bankrupt between 1975 and 1982 and the remaining 64 non-bankrupt firms were matched to the bankrupt group by year and industry. Two subsamples were developed from the 129 firms. The first subsample of 74 firms, which contained 38 bankrupt firms and 36 non-bankrupt firms, was used as the training set for ANN and MDA. The second subsample, which consisted of 27 bankrupt firms and 28 non-bankrupt firms, was used as the holdout sample. The data of bankrupt firms was from the last financial statements prior to the bankruptcy declaration.

With respect to models for bankruptcy prediction, using the training subsample, the discriminant analysis method predicted 86.8 per cent of bankrupt firms (33 out of 38 firms) as bankrupt firms correctly. Meanwhile, this model classified all the non-bankrupt firms correctly in the training subsample. On the other hand, the neural network classified all 38 bankrupt firms and all 36 non-bankrupt firms in the training subsample correctly. Similarly, the neural network performed better than the discriminant analysis in three separate groups for the holdout sample only. Thus, the neural networks might be more consistent than the discriminant analysis (Odom and Sharda, 1990).

In summary, the results of comparing multivariate discriminant analysis with the neural network showed promise in using neural network for bankruptcy prediction. The neural network performed better in predicting the bankrupt firms in the holdout sample and the training sample. In addition, the neural network was better than the discriminant analysis using a smaller sample.

2.2.9 Slowinski and Zopounidis (1995)

In 1995, Slowinski and Zopounidis presented a new method, which was based on the 'rough set', to analyse and evaluate corporate bankruptcy. The rough set theory introduced by Pawlak (1982) appeared to be effective for the analysis of financial information systems. In particular, in the case of corporate bankruptcy prediction, the concept of rough set could be used to describe a set of firms by a set of qualitative variables and financial variables or ratios (Ahn, Cho and Kim, 2000). In this study by Slowinski and Zopounidis (1995), the rough set approach was applied in order to explain and analysing financing decisions in a Greek industrial development bank called ETEVA.

ETEVA is a bank which mainly finances commercial and industrial enterprises in Greece. Besides the traditional financial activities like financing enterprises for example, the ETEVA bank is involved in some new financial activities such as acquiring and financial advisory services, bond issuing, merging, treasury services, securities underwriting and fund and syndicated loans management.

Undoubtedly, ETEVA is interested in investing its capital in commercial and industrial enterprises with lower financial risk. Thus, for ETEVA, the primary step of assessing an enterprise is to evaluate the financial risk of the enterprise. Slowinski and Zopounidis selected 39 enterprises for sample enterprises and the chosen firms were classified into three predefined categories of risk for the year 1988. The numbers of enterprises in these categories are as follows: 20 enterprises in the acceptable group (low-risk group), nine enterprises in the unacceptable group (failure group) and ten enterprises in the uncertain group. These enterprises were evaluated according to a total of 12 attributes which consisted of six qualitative variables and six quantitative financial ratios. The 12 attributes included: earnings before interests and taxes divided by total assets, net income divided by net worth, total liabilities divided by total assets, total liabilities divided by cash flow, interest expenses divided by sales, general and administrative expenses divided by sales, managers' work experience, firm's market niche divided by position, technical structure - facilities, organization - personnel, special competitive advantage of firms and market flexibility. The 39 enterprises were considered as a training sample. There were two sorting algorithms used in the study to evaluate the firms which sought to finance from the ETEVA bank for the first time (Slowinski and Zopounidis, 1995).

Slowinski and Zopounidis (1995) concluded that the concept of rough set is quite useful for discovering the preferential attitude of the decision maker in a multi-attribute evaluation of the firms' bankruptcy risk. The traditional models for forecasting bankruptcy risk, like MDA, only measure financial risk. These models ignore many other important risk measures such as management work experience, enterprises' special competitive advantages and market position of enterprises, whereas the constructed model of rules was closer to the real measure of potential bankruptcy risk. The results of the study showed that the global preference model in the form of rules, which were well formed by a set of examples, was better than a functional or relational model. In addition, the rough set analysis accorded a greater importance to qualitative attributes (interest expenses divided by sales, general and administrative expenses divided by sales, managers' work experience and organization - personnel) than to financial attributes.

2.2.10 Wilkins (1997)

Based on the positive accounting theory, debt covenant violation was assumed as a costly issue (Watts and Zimmerman, 1986). For this reason, an increasing number of studies had started to investigate the types of enterprises which were more likely to face technical default (Press and Weintrop, 1990). Following this research interest, several studies also evaluated how investors, lenders and managers responded to the incidents of debt covenant violations (Beneish and Press, 1993; 1995a; 1995b; Chen and Wei, 1993; Defond and Jiambalvo, 1994; Sweeney, 1994).

In order to complement previous research studies, Wilkins (1997) examined auditors' responses to first-time debt covenant violations. Unlike other financial distress predictive studies prior to 1997, the objective of Wilkins' study was to determine whether auditors' responses could be used to predict financial distress. The sample of enterprises used in Wilkins' study included 159 enterprises traded on the NYSE-AMEX or NASDAQ. The initial default dates of these enterprises ranged from 1978 to 1988. Each sample firm's annual report, or Form 10-K filings, was examined from two years before and two years after the initial identified year of default. This procedure was utilized to get data regarding the covenant violations and was used simultaneously to determine whether enterprises kept in violation after the initially identified years of default and whether covenants had been violated before the initially identified event years. In Wilkins' summary statistics section, the summary data suggested the incidents of default were associated with enterprises which were experiencing deterioration of financial health.

In terms of empirical analysis, univariate tests were firstly used to examine the association between lenders' and auditors' responses to initial debt covenant violations. The second set of univariate tests then examined the relationship between auditors' and lenders' decisions when the initial default occurred. It also examined the relationship at the time of financial distress encountered by violating firms in the following periods. Financial distress was defined as either debt service default or the incidence of bankruptcy. In addition, Wilkins further used three logistic models to re-examine the associations, which were discussed previously, in a multivariate setting.

The main results of Wilkins' study are as follows: firstly, consistent with Statements of Financial Accounting Standards No. 78, the evidence in Wilkins' study indicated the auditors were more likely to require debt reclassification if the corresponding violations were not waived. The results of Wilkins' study also revealed that the auditors' initial qualification decision could be used as a significant predictor of financial distress even though such distress may not occur in the subsequent years.

Moreover, Wilkins found that the actions of lenders partially influenced auditors' actions when enterprises experienced technical default and the waiver decisions could not significantly influence the auditors' qualification decisions. The results of empirical tests suggested that the auditors' opinion was an important determinant of future financial distress for the enterprises which encountered technical default. Even after controlling for the factors like Leverage Ratio, Current Ratio and Return on Assets etc., which are typically associated with bankruptcy, the defaulting enterprises that received qualified audit opinions also faced the likelihood of financial distress rising in subsequent periods.

2.2.11 Kuo, Wang, Sheu and Li (2003)

In the study done by Kuo, Wang, Sheu and Li (2003), a credit evaluation model for SMEs in Taiwan was formed based on financial and non-financial data. Unlike most financial distress prediction models only using financial ratios as predictive variables, Kuo et al.'s study also integrated non-financial variables as predictive variables. The main objectives of this study were to check whether introducing of non-financial variables could enhance the model's discrimination capability and to construct a more useful credit evaluation model to classify successful and failed SMEs.

In terms of data collection, the data was derived from the Taiwan Small Business Integrated Assistance Centre data file in the period from 1993 to 1995. According to the definition of SMEs from the Statutes for the Development of SMEs, an enterprise with no more than 200 staff or with paid-in capital between NT$5 million (US$143 thousand approximately) and NT$60 million (US$1.88 million approximately) is recognized as a SME. In this study (Kuo et al., 2003), the failed SMEs were defined as firms which had involved in any one of the following situations: having poor credit history, having net worth less than half of real assets, dishonouring bills or checks, delaying payment of bank loans and rejecting accounts in banking.

Based on the criteria and definitions stated above, 105 SMEs were chosen from the data file. Following that, these enterprises were divided into two groups to enhance the effectiveness of the empirical model. The first group was used as an original sample to construct the predicted model and the second group was a controlled sample used to verify this model.

With respect to variable measurements, 15 firm-specific financial ratios were analysed. The financial ratios included financial leverage ratios (Net Worth Ratio: Net Worth/Total Assets; Total Debt Ratio: Total Debt/Net Worth); interest coverage and assets insurance ratios (Interest Expenses Ratio: Interest Expenses/Net Sales; Fixed Assets Ratio: Fixed Assets/Total Assets; Fixed Ratio: Fixed Assets/Net Worth); profitability ratios (Net Operating Profit Margin: Operating Income/Operating Revenue; Net Profit Margin: Income Before Tax/Operating Revenue; Return on Net Worth: Income Before Tax/Net Worth; Return on Total Assets: Income Before Tax/Total Assets); assets turnover ratios (Inventory Turnover: Cost of Goods Sold/Inventories; Accounts Receivable Turnover: Operating Revenue/(Notes Receivable + Accounts Receivable); Fixed Assets Turnover: Operating Revenue/Fixed Assets; Total Assets Turnover: Operating Revenue/Total Assets); and short-term liquidity ratios (Current Ratio: Current Assets/Current Liabilities; Quick Ratio: (Current Assets | Inventories)/Current Liabilities) (Kuo et al., 2003).

In addition to firm-specific financial ratios, five non-financial variables, covering number of correspondent banks; magnitude of short-term debt; open credit line: the natural log of total credit line minus the total loans; foreign sales ratio and FDI, were examined (Kuo et al., 2003).

In the methodology section, the MWW test was first run to distinguish the difference in financial performance between successful and failed SMEs. Second, a factor analysis was used to extract common factors and to modify multicollinearity among variables. After that, the extracted financial ratios with five non-financial variables were inputted into a logistic regression analysis as independent variables to determine a final model. Finally, the T-test was employed to make a comparison of the model efficiency for both the original sample group and the controlled sample group based on correctly classification ratio of the model (Kuo, et al., 2003).

In summary, Kuo, et al. (2003) constructed a credit evaluation model for SMEs to overcome the unreliability or unavailability of SME's financial information. The results of this model showed that both firm-specific financial ratios and non-financial variables were useful in classifying failed and successful SMEs.

2.2.12 Wu (2004)

Similar to the study done by Kuo et al. (2003), Wu's (2004) study also used financial information together with some non- financial information to predict the failure of firms. The purpose of the study done by Wu was to examine whether it was possible to predict failure of listed firms by using non-financial variables in conjunction with financial variables.

Firstly, Wu defined the definition of a failed firm and non-failed firm based on the definition provided by the Taiwan Stocks Exchange (TSE). A failed firm on the TSE was defined as a listed firm which had experienced operation difficulties and been judicially declared a special stock arrangement firm by authorities. In contrast, a non-failed firm was defined as a listed firm on the TSE which had no special stock arrangement and had its stocks publicly tradable. According to the definition above, 31 failed firms and 31 non-failed firms on the TSE were chosen from the period between 1995 and 2000. The non-bankrupt entities were matched to the bankrupt group by some characters such as industry, sizes and/ or product.

Second, Wu listed the definitions of variables in the study as follows. The dependent variable was a dummy variable that indicated one as a failed firm and indicated zero as a non-failed firm. The independent variables included two groups of variables and they were the financial ratio related group and the non-financial group respectively. There were 18 financial ratios in the data of financial-related group which were collected from the database of the *Taiwan Economic Journal*.

These financial ratios consisted of debt ratio, long-term capital ratio to fixed assets, current ratio, quick ratio, times interest earned, account receivable turnover, inventory turnover, sales to fixed assets, total assets turnover, return on assets, return on total equity, operating profit to capital issued, net profit before taxes to capital issued, net profit margin, earnings per common share, cash flow ratio, cash flow adequacy ratio and cash reinvestment ratio. Besides financial ratios, the non-financial related group consisted of three variables: board holding ratio, changing external auditor and stock price trend.

Third, Wu chose only financial variables in factor analysis. The purpose of factor analysis was to filter out the best appropriate variables. The Kaiser – Meyer –Olkin measure was then used to decide the number of factor sets. According to the results of factor analysis, the variables having the highest loading in each factor were chosen. After that, the selected variables with non-financial variables were added into the logistic regression to check if the non-financial variables could increase the accuracy of the failure predictive models. At the same time, a financial failure prediction model was constructed.

In Wu's conclusion, the rate of correct classification for prediction model that based on both non-financial and financial variables was superior to the prediction model that was only based upon financial variables. Moreover, the superiority was evident, both in correctly classifying failed companies and in the overall correct classifications.

2.2.13 Jones and Hensher (2004)

While extensive research on the prediction of firm financial distress has emerged, modelling innovations have been slow to develop. Most research prior to 2004 relied on binary logistic, probit analysis, relatively simplistic MDA or rudimentary multinomial logistic (MNL) models. The main limitation of the financial distress literature before 2004 was that there was no recognition of major advances in discrete choice modelling. Thus, Jones and Hensher used an advanced discrete choice model, namely, mixed or random parameter ordered logistic which was the most advanced technique at that time. The study compared the predictive performance of mixed logistic with standard logistic in terms of accuracy.

First, Jones and Hensher explored the theoretical and econometric properties of the mixed logistic. Mixed logistic, which developed out of discrete choice theory, was a new breed of econometric models in the early 2000s and had supplanted some simpler models in many fields like management, economics, marketing health and science research, etc. (Train, 2003). In the case of firm failures prediction, the advantage of using mixed logistic models is that the model includes many additional parameters which capture observed and unobserved heterogeneity. For a mixed logistic model, the probability of failure of a firm is determined by the mean influence of each explanatory variable with a fixed parameter estimate in the sample and a random parameter from the distribution of individual firm parameters.

Second, in the study done by Jones and Hensher (2004), financial distress was modelled in three states. The State Zero firms were non-failed firms. The State One firms were insolvent firms and the State Two firms were those firms that had filed for bankruptcy. Jones and Hensher then developed two samples for the purpose of estimating and validating models. Based on firm financial distress data between 1996 and 2000, five annual reporting years' data of firms in States Zero, One and Two were collected for estimation sample. In the sample, there were 2838 firm years in State zero, 78 firm years in State One and 116 firm years in State Two. Using the same definitions and procedures, the validation sample was collected from the period between 2001 and 2003. In the validation sample, there were 4980, 119 and 100 firm years in State Zero, One and Two, respectively.

Third, in the methodology section, Jones and Hensher summarized the overall model system for both the mixed logistic model and MNL models. Following that, they investigated the overall predictive performance of the mixed logistic model and MNL and compared the predictive performance of mixed logistic and MNL.

In summary, the Jones and Hensher's study confirmed that the mixed logistic is superior to standard approaches such as MNL. Compared with MNL, mixed logistic produced a substantially improved model-fit after adjusting the number of parameters. Overall, the results of the study indicated that mixed logistic had substantially better predictive performance than MNL (Jones and Hensher, 2004).

2.2.14 Liou and Smith (2007)

The industrial sector was noted as a significant factor in designing and producing financial distress models in many studies. Most of the researchers prior to 2007 were content to amalgamate sub-sectors of manufacturing to construct a single manufacturing sector model. Unlike most other researchers, the purpose of the study done by Liou and Smith was to examine the differences, which exist across the manufacturing sector, to identify those sub-sectors for which such amalgamation was inadvisable (Liou and Smith, 2007).

First, with respect to variable selection, the following criteria were used: popularity of the variable in the previous literature, consistent and efficient performance in previous studies and commonly used by financial researchers in this field. According to these criteria and past studies, a five-category matrix was constructed and it comprised liquidity, profit margin, productivity, rates of return and turnover ratios. The financial ratio values for the U.K. companies listed on the London Stock Exchange were collected from Datastream in the period between 1973 and 2002. Furthermore, for the purpose of this study, Liou and Smith (2007) adopted the FTSE global classification system to compare firms in sectors and sub-sectors. Thus, the study matched the broad manufacturing sectors. In addition, five economic groups, which included basic industry, general industry, information technology, cyclical consumer goods and non- cyclical consumer goods, and the associated 17 specific industrial sectors were selected.

Second, in terms of research methods, this study sought anomalies in the distribution of correlations and patterns of failure that may be attributed to industrial sectors. Smith and Liou examined ratio means and correlations between the occurrence of failure and financial ratios and some correspondence between actual failure incidence and financial ratios across different groups could be anticipated. Besides that, in order to derive a sub-sample of firms which had been misclassified by commercial failure prediction models, this study computed Z-score measures of solvency for a large sample of manufacturing companies (Taffler, 1983).

Finally, Liou and Smith examined the correlation of traditional financial ratios with sector performance for a large sample of firms in the U.K. In order to determine the pattern of misclassification errors and their association with industrial sector, the study applied a proprietary Z-score failure prediction model to assess the solvency of 340 manufacturing firms. As a result, this study identified sub-sectors whose inclusion would make traditional models vulnerable to error and made suggestions regarding their continued inclusion for modeling. In sum, Liou and Smith's (2007) study made a significant contribution to knowledge of the explanatory factors associated with financial distress of firms.

2.2.15 Ooghe and Balcaen (2007)

In order to answer the question as to whether failure prediction models can be easily transferred and applied to other data setting, Ooghe and Balcaen (2007) examined the performance of seven models on the dataset of Belgian company failures. The purpose of the study by Ooghe and Balcaen (2007) was to identify some combinations of variables and models that had the best predictive performance on the dataset of Belgium over the period from 1995 to 1999. Additionally, this study used re-estimated coefficients of all model for the first time to avoid bad performance results caused by using the models' original coefficients.

A range of failure prediction models were chosen to compare the validity of these models formed in different periods and countries. Several criteria were taken into account in the selection procedure: first, Ooghe and Balcaen (2007) only concentrated on models estimated with logistic regression and linear discriminant analysis; second, the study focused on the models which were frequently applied in previous researches; third, only the models for developed countries were included in the study; fourth, this study only incorporated general models except for the models investigating the probability of failure of small-sized, high-tech or newly founded companies; finally, the coefficient and variable's availability was regarded as an important criterion and the models that required unavailable coefficient or variable were excluded.

Ooghe and Balcaen (2007) selected eight models from eight different research studies: Altman (1968) from the U.S., Bilderbeek (1979) from Holland, Zavgren (1985) from the US, Ooghe and Verbaere (1985) from Belgium, Gloubos and Grammatikos (1988) from Greece, Keasey and McGuinness (1990) from the UK and Ooghe, Joos and De Vos (1991) from Belgium.

Ooghe and Balcaen (2007) provided useful definitions of 'failed' and 'non-failed' companies. They defined a failed company as a company with an official approval of a judicial composition, with a request for a judicial composition or in the situation of bankruptcy. Their definition of non-failed company included non-distressed companies and all companies with associated doubts about the economic reasons for their juridical situation. Ooghe and Balcaen's (2007) data were obtained from the Bureau Van Dijk, information supplier Graydon and published annual accounts of non-financial firms during the period between 1994 and 1999.

Ooghe and Balcaen (2007) then calculated a range of ratios and variables (from X_1 to X_{40}) to re-estimate the models' coefficients on the basis of each annual account in the re-estimation samples. The study computed discriminant and logistic scores for each model to reveal the performance of model, based on each annual account in the validation samples

The validation results concluded that some failure prediction models were strongly predictive when they were applied to the new data set. When applied to the Belgian dataset, the Altman (1968) and Bilderbeek (1979) models indicated quite poor results. The models from Gloubos and Grammatikos (1988), Keasey and McGuinness (1990), however, performed the best for predicting failure within one year and three years prior to failure respectively. Additionally, the study also showed that a combination of some types of variables can lead to good predictive results. However, the number or complexity of variables and the estimation technique cannot explain the predictive performances.

2.2.16 Chen (2008)

Unlike previous studies related to financial distress prediction, the purpose of Chen's (2008) study was to investigate the timescale effects of the corporate governance measure on predicting corporate financial distress. Since Ohlson's (1980) study, logistic regression had been regarded as an effective method to predict financial distress of corporations. However, some researchers pointed out that the logistic regression did not perform well and its accuracy was usually low (Platt, 1995; Gestel et al., 2006). Therefore, Chen (2008) included the corporate governance measure in the logistic regression model to examine whether this measure could improve the accuracy of predicting.

In order to improve the disclosure of corporate information and make evaluating corporate governance possible, the Taiwan Stock Exchange Corporation (TSEC) entrusted the Securities and Futures Institute (SFI) to construct the Information Transparency and Disclosure Ranking System (ITDRS) in 2003. The ITDRS ranks all listed companies in Taiwan as A+, A, B, C and C-. This ranking was adopted in Chen's study to evaluate corporate governance; a lower value of the ranking indicated a worse status of corporate governance.

Chen (2008) collected data from a group of listed firms that encountered financial distress in 2006 and a matching group of healthy firms. The group of firms experiencing financial distress comprised 23 firms with complete financial data. The matching group consisted of 56 healthy firms having comparable size and in the same industry to each firm in the financial distress group.

In terms of independent variables, this study incorporated traditional financial ratios and corporate governance measures. After referring to some previous studies and excluding the financial ratios which were significantly correlated to others, this study selected four financial ratios (debt ratio, receivables turnover, net profit margin and earnings per share) as independent variables in the logistic model.

There were two distinguishing features of the study. The first feature was that this study evaluated the timescale effects of the corporate governance performance on corporate financial distress prediction. The analysis of the study was based on three different prediction horizons including one-year, two-year and three-year horizons to investigate the influence of corporate governance. The second feature was that an easier ranking system constructed by the SFI and the TSEC was used to measure the quality of corporate governance.

In addition to these two features, there were also two specifications which were estimated and compared in Chen's (2008) study. In the first specification, Chen used independent variables comprised traditional financial ratios alone. In contrast, the second specification adopted the corporate governance measure as the independent variable. From the results of the analysis, it can be concluded that incorporating the corporate governance measure into the analysis of logistic regression model can improve the accuracy of corporate financial distress prediction. Further, the accuracy of the prediction, which was promoted by including the corporate governance measure, improved as the prediction horizon was extended. To be specific, for the Year One model, the correct rate for financial distress classification was promoted from 94.2 per cent to 97.1 per cent by incorporating the corporate governance measure. For the Year Two and Year Three models, the accuracy of financial distress classification increased from 91.3 per cent to 95.7 per cent and from 89.9 per cent to 95.7 per cent respectively.

2.2.17 Muller, Steyn-Bruwer and Hamman (2009)

After the studies done by Beaver (1966) and Altman (1968), there had been numerous studies on corporate financial distress prediction prior to Muller, Steyn-Bruwer and Hamman's (2009) study, using many different techniques. However, there was little consensus on which technique could get the most accurate predictive results and what input ratios or variables could be used for prediction. Thus, the main purpose of the study completed by Muller, Steyn-Bruwer and

Hamman was to test whether particular techniques would produce better prediction accuracies than other techniques.

For the purposes of Muller Steyn-Bruwer and Hamman's (2009) study, a distressed firm was defined as a firm in at least one of the following situations: being delisted, experiencing a major organisational restructuring and going into bankruptcy. The terms 'failed' and 'non-failed' were used to classify the distressed and non-distressed firms.

Next, drawing on previous literature in the field of financial distress prediction, Muller Steyn-Bruwer and Hamman summarized three different types of predictive techniques (statistical models, artificial intelligent expert system (AIES) models and theoretical models). They refer to Aziz and Humayon's (2006) extensive literature review which found 64 per cent of all researches used statistical models; 25 per cent and 11 per cent of all previous researches used AIES and theoretical models respectively. The statistical models mainly comprised the logistic analysis (LA) and MDA and the AIES models consisted of neural networks (NN) and recursive partitioning (RP). Given that the statistical models and AIES models were employed by nearly 90 per cent of total researches, the four main techniques (LA, MDA, NN and RP) were examined in the study.

Consequently, the objectives of Muller, Steyn-Bruwer and Hamman's (2009) study were stated as follows: the primary purpose was to compare the predictive correct rates of the LA, NN, MDA and RP techniques; the secondary purpose of the study was to compare the difference in accuracy of prediction when the data was subdivided into economic phases. Since the literature did not readily consider the number of Type I and Type II errors made when evaluating each predictive technique, a term called the Normalised Cost of Failure (NCF) was defined in the study. The

NCF indicates that a Type I error costs 20 to 38 times that of a Type II error. Besides the NCF, some other ratios or variables were included in this study, such as cash flow variables, profit ratios, and the ratio incorporating the size and the structure of the company.

To meet the objectives of Muller, Steyn-Bruwer and Hamman's (2009) study, the *mnrfit* and *mnval* function within Matlab™ was applied to develop the LA model; the *classregtree* function in Mstlab™ was used to develop the RP model and the *classify* function in Matlab™ was used to model, the MDA equation. Finally, the log-sigmoid transfer function, namely the *logsig* function in Matlab™ was applied in the NN model.

The results of this study illustrated that different predictive techniques had different correct rates of prediction. To be specific, the RP and MDA techniques correctly predicted most failed firms and consequently had the lowest NCF. Muller, Steyn-Bruwer and Hamman (2009) also found that the NN and LA techniques produced high overall predictive accuracy; however, they had the highest NCF. Moreover, this research revealed that choosing the year before distress as a subdivision, instead of using the economic period as a subdivision, could produce better predictive accuracy.

2.3 Summary

This chapter reviewed all the major studies on financial distress prediction and established a chronology of research studies on financial distress. In terms of ratios, variables or factors used in predicting financial distress, the literature has developed in three stages. In the first stage, the firm-specific financial variables were solely used as predictors of financial distress. Beaver (1966) used financial ratios to predict the failure of firms and found that financial ratios were useful in predicting firms' failure. Beaver (1966), however, found that cash flow to total debt ratio had greater predictive ability than liquid assets ratios. Altman (1968) improved Beaver's (1966) work by doing a rigorous multiple discriminant analysis and found that only five ratios− working capital to total assets ratio, retained earnings to total assets ratio, earnings before interest and taxes to total assets ratio, market value of equity to book value of total debt ratio and sales to total assets ratio− were significant in predicting financial distress. Altman, Haldeman and Narayanan (1977) improved Altaman's (1968) model and developed a new ZETA model using seven financial variables to predict corporate bankruptcy. Ohlson (1980) identified four basic financial factors which can significantly affect bankruptcy within one year.

In the second stage, studies included macroeconomic variables in addition to firm-specific financial variables for financial distress prediction. Mensah (1984) suggested that the structure and accuracy of prediction models differed across different macroeconomic environments and different predictive models were appropriate for enterprises in different industrial sectors. Dionne et al. (2008) established a hybrid model by including a macroeconomic variable with some firm-specific financial variables. According to their study, a macroeconomic variable (real GDP growth) was negatively correlated to the likelihood of the firm facing financial difficulties.

In the third stage, studies examined the impact of firm-specific non-financial variables on distress prediction. These included studies by Slowinski and Zopounidis (1995) and Dimitras, et al. (1999) who accorded great importance to qualitative attributes than to financial attributes. In addition, the results of Wilkins's (1997) study suggested that the auditors' opinion is an important predictor of future financial distress for the technically distressed firms. Chen (2008) also found that incorporating the corporate governance measure into the analysis of logistic regression can improve the predictive accuracy of corporate financial distress. For the SMEs, Kuo et al. (2003) found both firm-specific financial variables and firm-specific non-financial variables were useful in classifying distressed and successful SMEs.

In terms of models or methodologies used in financial distress prediction, Beaver (1966) was also recognized as one of pioneers in this area. The study found ratio analysis was useful in the predicting financial failure. However, the analysis of Beaver's study was a univariate analysis and this analysis only examined one ratio's predictive ability at a time. In 1968, Altman created a Z-score model to link the traditional ratio analysis and the rigorous statistical techniques by using MDA. The Z-score indicator provided a forecast of whether a firm would enter into financial distress within two years. Based on the model done by Altman (1968), Altman, Haldeman and Narayanan (1977) developed a new model to identify bankruptcy risk of corporations. The new ZETA model can effectively classify bankrupt manufacturing and retailing firms up to five years before corporate failure.

In order to avoid some problems with regard to the MDA, Ohlson (1980) used the conditional logistic model as the methodology to research the probabilistic prediction of bankruptcy. In a similar manner, Mensah (1984) used the logistic model to avoid some drawbacks of the MDA. In the study of Frydman, Altman and Kao (1985), a new classification procedure RPA was presented for financial analysis. In the example of their study, the classification accuracy of RPA was actually superior to the traditional discriminant framework. However, Frydman, Altman and Kao (1985) did not claim RPA could always outperform the various other statistical classification techniques.

Along with MDA, logistic analysis and the recursive partitioning algorithm, ANN is also a technique applied in the area of business failure prediction. Odom and Sharda (1990) firstly developed an ANN model for bankruptcy prediction. According to the results of their study, the neural network performed better on predicting the bankrupt firms in the holdout sample and the training sample.

In 1995, Slowinski and Zopounidis presented a new method, which was based on the concept of rough set, to analyse and evaluate corporate bankruptcy. The results of the study showed that the rough set is quite useful for discovering the preferential attitude of the decision maker in multi-attribute evaluation of the bankruptcy risk of firms, and that the traditional models for forecasting bankruptcy risk, like MDA, only give a financial measure of risk. In addition to Slowinski and Zopounidis's study, a Chinese study by Wang and Li (2007) also used rough set model and found that the financial distress prediction model considering both financial ratios and non- financial variables outperforms the model only containing financial ratios.

As for models for classifying failed and successful SMEs, Kuo et al. (2003) used logistic regression and created a credit evaluation model for SMEs to overcome the unreliability or unavailability of SME's financial information. Instead of using standard logistic, Jones and Hensher (2004) used advanced mixed or random parameter ordered logistic to predict firms' financial distress. They confirmed that the mixed logistic was superior to standard approaches such as MNL and the mixed logistic had better predictive performance than the MNL.

In recent years, there have been several researches examining the performance of several models. For example, Ooghe and Balcaen (2007) examined the performance of seven models on the dataset of Belgian company failures. The results concluded that some failure prediction models were strongly predictive when they were applied to the new data set. In a more recent study (Muller, Steyn-Bruwer and Hamman, 2009), the results illustrated that different predictive techniques (RP, MDA, NN and LA) had different correct rates of prediction and different NCF. Moreover, this research revealed that choosing the year before distress as a subdivision, instead of using the economic period as a subdivision, could produce better predictive accuracy.

To sum up, two gaps in the literature on predicting corporate financial distress can be identified.

The first gap is that the prior research has not considered the combined effect of financial ratios, non-financial variables and macroeconomic variables in predicting financial distress of growth enterprises. In the previous literature, most of research studies on financial distress focused their attention on the predictive ability of firm-specific financial ratios. Besides that, many other financial distress predictive research studies examined the firm-specific financial ratios, non-financial variables and macroeconomic variables separately or formulated their research by combining two out of the three kinds of variables. Until recently, only several studies covered all these three kinds of variables (Lu and Chang, 2009 and Pranowo et al., 2010). Hence, the improved model consider three groups of variables, including firm-specific financial ratios, non-financial variables and macroeconomic variables. The improved model, which is especially for the growth enterprise, should be used to examine the connections between the distress of growth enterprises and these three kinds of variables.

The second gap is that there is currently an extensive and well-developed body of literature that examines the financial distress predicting in stock-issued companies and there are even some research studies on financial distress predicting of SMEs. However, there is a lack of research on growth enterprises in emerging countries, owing to the limitation of growth enterprises' financial data and company population. Accumulating evidence suggests that growth enterprises are precisely those businesses that are responsible for much of an emerging economy's dynamism (CSRC, 2008). Chinese growth enterprises, for example, have played a vital role in promoting rapid growth during Hong Kong or mainland China's economic transition and it follows that their continued health is essential to China's further economic growth.

The present study extends previous work by considering the case of Chinese growth enterprises on Hong Kong GEM, which has unique legislation regarding the suspension and termination of listed loss-making companies. As such, this study adds a new dimension to the current financial distress prediction literature which focuses mainly on the U.S. and other developed countries. In addition, this study aims to establish an appropriate model, which applies firms' financial, non-financial and macroeconomic variables, to identify the factors that have a high correlation with the occurrence of growth enterprises' financial distress.

Chapter 3 Hypotheses Development

Based on the literature reviewed previously, firm-specific financial ratios are regarded as the most important explanatory variables for corporate financial distress. Besides firm-specific financial ratios, firm-specific non-financial variables and macroeconomic variables are also regarded as explanatory variables for corporate financial distress. Three financial distress prediction models are then established. The first type of model considered firm-specific financial factors only, whereas the second type of model considered firm-specific non-financial factors and macroeconomic factors. The third type of model considered not only firm-specific financial factors but also firm-specific non-financial factors and macroeconomic factors. These three models were referred to as Model 1, Model 2 and Model 3 respectively. One purpose of the present study is to demonstrate that including firm-specific non-financial variables and macroeconomic variables can significantly enhance the ability of the financial distress prediction model to classify distressed and non-distressed growth enterprises. The present study also aims to identify the significant predictors of forecasting financial distress of growth enterprises. The sections of this chapter are listed as follows:

Section 3.1 develops the hypotheses relating to financial ratios and financial factors.

Section 3.2 develops the hypotheses relating to non-financial variables and non-financial factors.

Section 3.3 develops the hypotheses relating to macroeconomic variables and macroeconomic factors.

Section 3.4 develops the hypothesis relating to comparing the model incorporating firm-specific financial factors with the model which includes firm-specific non-financial and macroeconomic factors.

Section 3.5 develops the hypothesis relating to comparing the model incorporating firm-specific financial, firm-specific non-financial and macroeconomic factors with the model which only includes firm-specific financial factors.

All the research questions and their related hypotheses are shown in Table 3.1 below:

Table 3.1 Research questions and related hypotheses

Research question	Related hypothesis
Research question 1: Are there significant differences in firm-specific financial ratios between distressed and non-distressed growth enterprises?	Hypothesis 1: Null Hypothesis 1: There are no significant differences in financial ratios between distressed and non-distressed growth enterprises. Alternative Hypothesis 1: There are significant differences in financial ratios between distressed and non-distressed growth enterprises.
Research Question 2: Are there significant differences in firm-specific non-financial variables between distressed and non-distressed growth enterprises?	Hypothesis 3: Null Hypothesis 3: There are no significant differences in non-financial variables between distressed and non-distressed growth enterprises. Alternative Hypothesis 3: There are significant differences in non-financial variables between distressed and non-distressed growth enterprises.
Research Question 3： Are there significant differences in macroeconomic variables between distressed and non-distressed growth enterprises?	Hypothesis 5: Null Hypothesis 5: There are no significant differences in macroeconomic variables between distressed and non-distressed growth enterprises. Alternative Hypothesis 5: There are significant differences in macroeconomic variables between distressed and non-distressed growth enterprises.
Research Question 4: Do firm-specific financial factors significantly predict whether growth enterprises have experienced financial distress?	Hypothesis 2: Null Hypothesis 2: The extracted financial factors are not significant predictors of growth enterprises' financial distress. Alternative Hypothesis 2: The extracted

	financial factors are significant predictors of growth enterprises' financial distress.
Research Question 5: Do firm-specific non-financial factors significantly predict whether growth enterprises have experienced financial distress?	Hypothesis 4: Null Hypothesis 4: The extracted firm-specific non-financial factors are not significant predictors of growth enterprises' financial distress. Alternative Hypothesis 4: The extracted firm-specific non-financial factors are not significant predictors of growth enterprises' financial distress.
Research Question 6： Does macroeconomic factor significantly predict whether growth enterprises have experienced financial distress?	Hypothesis 6: Null Hypothesis 6: The extracted macroeconomic factors are not significant predictors of growth enterprises' financial distress. Alternative Hypothesis 6: The extracted macroeconomic factors are significant predictors of growth enterprises' financial distress.
Research Question 7： Does the model that considers firm-specific financial factors perform better than the model that considers firm-specific non-financial and macroeconomic factors in financial distress prediction?	Hypothesis 7: Null Hypothesis 7: The model incorporating firm-specific financial factors is not better than the model which includes firm-specific non-financial and macroeconomic factors in financial distress prediction. Alternative Hypothesis 7: The model incorporating firm-specific financial factors is better than the model which includes firm-specific non-financial and macroeconomic factors in financial distress prediction.
Research Question 8： Does the model based on firm-specific financial, firm-specific non-financial and macroeconomic factors perform better than the	Hypothesis 8： Null Hypothesis 8: The proposed model incorporating firm-specific financial, firm-specific non-financial and macroeconomic

model that includes firm-specific financial factors in financial distress prediction?	factors is not better than the model which only includes firm-specific financial factors in financial distress prediction. Alternative Hypothesis 8: The proposed model incorporating firm-specific financial, firm-specific non-financial and macroeconomic factors is better than the model which only includes firm-specific financial factors in financial distress prediction.

3.1 Hypotheses relating to financial ratios and financial factors

Firm-specific financial ratios have been widely used as predictor variables in models that forecast business distress and failure and a large number of financial ratios have been proposed in previous literature (Altman, 1968; Altman, Haldeman and Narayanan, 1977; Barnes, 1987; Kuo et al., 2003; Wu, 2004; Jones and Hensher, 2004; Smith, 2005; Chen, 2008). According to Kimmel et al. (2006), financial ratios can be classified into types including profitability ratios, solvency ratios and liquidity ratios. The present study extracts profitability factors, solvency factors and liquidity factors from these three types of financial ratios and variables. This study then examines the three types of financial factors in predicting financial distress of growth enterprises.

First, profitability ratios have been commonly used to identify or predict the enterprise's distress or failure in prior studies, for example, Altman (1968), Altman, Haldeman and Narayanan (1977), Kuo et al. (2003), Wu (2004), Liou and Smith (2007), Cheng, Yeh and Chiu (2007), Wang and Li (2007), Chen (2008)and Muller, Steyn-Bruwer and Hamman (2009).

Profitability factors, which are extracted from profitability ratios, measure the enterprise's ability to generate profit or operating success for a given period of time. Hence, an enterprise's profit or lack of profit can influence enterprise's liquidity position and enterprise's ability to obtain equity and debt financing (Kimmel et al., 2006, p. 616). In other words, the profit of a firm affects the firm's ability to grow. Likewise, Kuo et al. (2003) asserted that firm's profitability is negatively correlated with probability of firm facing financial distress. Additionally, in their study, they found the profitability was the most important factor to classify or predict successful and distressed SMEs. There is an expectation that growth enterprises' profitability could be a predictor of the enterprises' facing financial distress.

Second, liquidity ratios measure the short-term ability of the enterprise to pay off its maturing debt obligations and to meet unexpected needs for cash (Kimmel et al., 2006). Like profitability ratios, liquidity ratios have also been frequently used to identify or predict the enterprise's distress in prior studies, for example, Beaver (1966), Altman (1968), Altman, Haldeman and Narayanan (1977), Ohlson (1980), Kuo et al. (2003), Wu (2004), Cheng, Yeh and Chiu (2007) and Liou and Smith (2007).

Liquidity ratios compare liquid assets of an enterprise to its short-term liabilities. On the one hand, an enterprise having high proportion of liquid assets to short term liabilities is expected to be a clear signal that this enterprise has the ability to meet its obligations and run its operations in the near future. On the other hand, an enterprise having a low proportion of liquid assets to short term liabilities is expected to be a signal that this enterprise will have financial difficulties or financial distress (Chancharat, 2008). Hence, liquidity ratios have a high correlation with the probability of firm facing financial distress. The liquidity factor extracted from liquidity ratios has a higher likelihood of being a predictor of growth enterprises' financial distress.

Third, solvency ratios, according to Kimmel et al. (2006), are the third main category of financial ratios. Solvency ratios measure the firm's ability to repay the face value of the debt at maturity and pay the interest when it comes due. In other words, solvency ratios measure the ability of a firm to survive over a long period of time (Kimmel et al., 2006, p.614). The most widely used solvency ratios include cash debt coverage, debt to total assets ratio and times interest earned (Kimmel et al., 2006).

In the literature on corporate financial distress prediction, many researchers have used at least one of the three main ratios. For instance, Ohlson (1980) used debt to total assets ratio as one of nine independent variables for the bankruptcy predicting model. Similarly, Slowinski and Zopounidis (1995) employed debt to total assets ratio as one of 12 attributes to evaluate the bankruptcy risk of enterprise. Besides Ohlson (1980) and Slowinski and Zopounidis (1995), many other studies applied solvency ratios to predict corporate financial distress. These relevant studies include Beaver (1966), Altman, Haldeman and Narayanan (1977), Frydman, Altman and Kao (1985), Kaiser (2001), Pompe and Bilderbeek (2005) and Chen (2008) et al.

Based on the literature, it can be expected that there are differences between distressed and non-distressed growth enterprises in the three main kinds of financial ratios. In addition, the financial factors extracted from growth enterprises' financial ratios could also be expected to be effective predictors of the growth enterprises' facing financial distress. This leads to Hypothesis 1 which is related to Research Question 1(*Are there significant differences in firm-specific financial ratios between distressed and non-distressed growth enterprises?*):

Hypothesis 1:

Null Hypothesis 1: There are no significant differences in financial ratios between distressed and non-distressed growth enterprises.

Alternative Hypothesis 1: There are significant differences in financial ratios between distressed and non-distressed growth enterprises.

The Hypothesis 2 relating to Research Question 4 (*Do firm-specific financial factors significantly predict whether growth enterprises have experienced financial distress?*) is:

Hypothesis 2:

Null Hypothesis 2: The extracted financial factors are not significant predictors of growth enterprises' financial distress.

Alternative Hypothesis 2: The extracted financial factors are significant predictors of growth enterprises' financial distress.

In order to test Hypothesis 1, ten commonly used financial ratios, which include profitability ratios, liquidity ratios and solvency ratios, are employed and the MWW test is used. Chapter 4 will specify the selection of these ten financial ratios. To test Hypothesis 2, the extracted financial factors are applied and factor analysis and logistic regression analysis are used.

3.2 Hypotheses relating to non-financial variables and non-financial factors

In addition to financial ratios, different non-financial variables, which consist of, for example, management measures, corporate governance variables, audit variables, ownership, can also be used to forecast a firm's distress. In the last decade, an increasing number of researchers have started to consider a wider range of non-financial variables in their corporate distress studies. For instance, Haw et al. (2000) found that good firms which had better financial results released their financial reports earlier than other firms. In the same way, Graham, Harvey and Rajgopal (2005) suggested that the frequency of a firm delaying issuing its financial statements had a negative correlation with the performance of the firm, because a poorly performing firm is prone to delay releasing its bad financial results.

In Cheng, Yeh and Chiu's (2007) study, besides 14 financial variables perceived, the only non-financial variable considered was the status of auditor switching, which was used to indicate whether or not a firm had changed its auditor in the past one, two or three years before corporate distress. In the conclusion of Cheng, Yeh and Chiu's study, as exemplified in the empirical study, the non-financial variable (auditor switching) was found the most significant attribute of corporate distress and played an essential role in enhancing the performance of their models.

Thus, based on the literature, it can be expected that there are differences in non-financial variables between distressed and non-distressed growth enterprises. Furthermore, the firm-specific non-financial factor extracted from non-financial variables is expected to be an effective predictor of the growth enterprises facing financial distress. This leads to Hypothesis 3 which is related to Research Question 2 (*Are there significant differences in firm-specific non-financial variables between distressed and non-distressed growth enterprises?*).

Hypothesis 3:

Null Hypothesis 3: There are no significant differences in non-financial variables between distressed and non-distressed growth enterprises.

Alternative Hypothesis 3: There are significant differences in non-financial variables between distressed and non-distressed growth enterprises.

The Hypothesis 4 relating to Research Question 5 (*Do firm-specific non-financial factors significantly predict whether growth enterprises have experienced financial distress?*) is as follows:

Hypothesis 4:

Null Hypothesis 4: The extracted firm-specific non-financial factors are not significant predictors of growth enterprises' financial distress.

Alternative Hypothesis 4: The extracted firm-specific non-financial factors are not significant predictors of growth enterprises' financial distress.

In the present study, four firm-specific non-financial variables incorporating the frequency of the firm delaying in releasing its financial statements, the firm changing its auditor(s), the firm's auditors' reports with 'qualified opinion' and/ or explanatory paragraph and the firm getting profit warning are considered and the MWW test is used to test Hypothesis 3. Chapter 4 will specify the selection of the four non-financial variables. To test Hypothesis 4, the extracted non-financial factors are employed and factor analysis and logistic regression analysis are used.

3.3 Hypotheses relating to macroeconomic variables and macroeconomic factors

Besides firm-specific financial ratios and firm-specific non-financial variables, some research studies equally noted that the performance of a firm is usually affected by several macroeconomic factors. For example, three external macroeconomic ratios, which cover inflation, business cycle (recession/expansion phases) and interest rates and credit availability are investigated in Mensah's (1984) study. This study concluded that these three variables could influence corporate performance and survival. Likewise, Georgine's research in 2001 showed that small business development in Central and Eastern Europe countries has been influenced to a great extent by a group of macroeconomic factors

Moreover, Dionne et al.'s (2008) hybrid model combined the two sets of explanatory variables to predict the probabilities of facing financial difficulties for Canadian firms. In their study, they considered only one macroeconomic variable which was the real GDP growth rate and they found the real GDP growth was negatively related to the likelihood of firm facing financial difficulties.

According to the literature, distressed and non-distressed growth enterprises might experience different macroeconomic conditions. Macroeconomic factors are expected to be predictors for financial distress prediction or corporate performance assessment. This leads to the Hypothesis 5 which is related to Research Question 3 (*Are there significant differences in macroeconomic variables between distressed and non-distressed growth enterprises?*).

Hypothesis 5:

Null Hypothesis 5: There are no significant differences in macroeconomic variables between distressed and non-distressed growth enterprises.

Alternative Hypothesis 5: There are significant differences in macroeconomic variables between distressed and non-distressed growth enterprises.

The Hypothesis 6 relating to Research Question 6 (*Does macroeconomic factor significantly predict whether growth enterprises have experienced financial distress?*) is as follows:

Hypothesis 6:

Null Hypothesis 6: The extracted macroeconomic factors are not significant predictors of growth enterprises' financial distress.

Alternative Hypothesis 6: The extracted macroeconomic factors are significant predictors of growth enterprises' financial distress.

To test Hypothesis 5, four macroeconomic variables, which are real GDP growth rate, average interest rate on loans, Business Climate Index and Entrepreneur Confidence Index, are adopted and the MWW test is used. Chapter 4 will specify the selection of these four macroeconomic variables. To test Hypothesis 6, the extracted macroeconomic factors are adopted and factor analysis and logistic regression analysis are used.

3.4 Hypothesis relating to comparative predictability of Model 1 vis-a-vis Model 2

As discussed previously, in the present study, Model 1 considers firm-specific financial factors whereas Model 2 considers firm-specific non-financial factors and macroeconomic factors. Firm-specific financial ratios are the most frequently used predictors in models that forecast business distress and failure. All the core research studies used firm-specific financial ratios as the major predictors (Altman 1968; Altman, Haldeman and Narayanan 1977; Barnes 1987; Kuo et al., 2003; Wu, 2004; Jones and Hensher, 2004; Smith, 2005; Chen, 2008). Some important research studies suggested they were the most important predictors for forecasting the financial distress (Altman, 1968; Altman, Haldeman and Narayanan, 1977; Ohlson, 1980).

In the last decade, some studies have started to consider the increasing number of non-financial variables in their corporate distress studies. Besides firm-specific financial ratios and firm-specific non-financial variables, some researchers equally noted that the performance of a firm is usually affected by several macroeconomic factors (Georgine, 2001; Liou and Smith, 2007; Dionne et al., 2008).

Since financial ratios or factors are the more frequently used compared with non-financial factors and macroeconomic factors, financial factors are expected to be more significant than firm-specific non-financial factors and macroeconomic factors in predicting growth enterprises' financial distress. This leads to the Hypothesis 7 which is related to Research Question 7 (*Does the model that considers firm-specific financial factors perform better than the model that considers firm-specific non-financial and macroeconomic factors in financial distress prediction?*).

Hypothesis 7:

Null Hypothesis 7: The model incorporating firm-specific financial factors is not better than the model which includes firm-specific non-financial and macroeconomic factors in financial distress prediction.

Alternative Hypothesis 7: The model incorporating firm-specific financial factors is better than the model which includes firm-specific non-financial and macroeconomic factors in financial distress prediction.

To test Hypothesis 7, the present study uses factor analysis and logistic regression to determine two types of models. One type of model considers firm-specific financial factors and the other type of model considers firm-specific non-financial and macroeconomic factors. Lastly, the study compares prediction ability of Model 1 with that of Model 2 to test Hypothesis 7.

3.5 Hypothesis relating to comparative predictability of Model 1 vis-a-vis Model 3

As discussed previously, in the present study, Model 1 only considers firm-specific financial factors whereas Model 3 considers not only firm-specific financial factors but also firm-specific non-financial factors and macroeconomic factors. In terms of non-financial factors, Kuo et al. (2003) analysed five firm-specific non-financial variables which play vital role in the economy of Taiwan. They concluded that adding two variables out of the five firm-specific non-financial variables to the model that only included financial factors could enhance the ability to classify distressed and successful SMEs in Taiwan. In addition, from the results of Chen's (2008) study, it can also be concluded that incorporating the corporate governance measure into the analysis of logistic regression model can improve the accuracy of corporate financial distress prediction.

In terms of macroeconomic factors, Foster (1986, p.549) suggests that multivariate models incorporating forecasts of macroeconomic aggregates could increase the predictive ability of corporate distress models. In a Canadian study, Dionne et al. (2008) established a hybrid model by including a macroeconomic variable with some financial variables. According to their study, this macroeconomic variable (real GDP growth) was negatively correlated to the likelihood of the firm facing financial difficulties. Therefore, a corporate financial distress model covering financial factors, non-financial factors and macroeconomic factors is expected to have higher accuracy to predict financial distress than a model only considering financial factors. Accordingly, this leads to Hypothesis 8 which is related to Research Question 8 (*Does the model based on* *firm-specific financial, firm-specific non-financial and macroeconomic factors perform better than the model that includes firm-specific financial factors in financial distress prediction?*).

Hypothesis 8:

Null Hypothesis 8: The proposed model incorporating firm-specific financial, firm-specific non-financial and macroeconomic factors is not better than the model which only includes firm-specific financial factors in financial distress prediction.

Alternative Hypothesis 8: The proposed model incorporating firm-specific financial, firm-specific non-financial and macroeconomic factors is better than the model which only includes firm-specific financial factors in financial distress prediction.

In order to test Hypothesis 8, the present study uses factor analysis and logistic regression to determine two types of models. One type of model only considers firm-specific financial factors and the other type of model considers firm-specific financial, firm-specific non-financial and macroeconomic factors. Lastly, the study compares the prediction ability of Model 1 with that of Model 3 to test Hypothesis 8.

Chapter 4 Method

4.1 Introduction

In order to test the hypotheses and establish an appropriate model to identify the factors which have a high correlation with the occurrence of growth enterprises' financial distress, it is necessary to use the growth enterprises' data and the proper methods to organize the financial distress predictive model. In the present study, all the data was derived from the official portal of Hong Kong GEM and the methods include MWW test, factor analysis and logistic regression. This chapter presents and discusses the process of data collection, sample selection and the methods used in the present study. The following sections of this chapter are listed as follows:

Section 4.2 defines distressed growth enterprises and non-distressed growth enterprises. It then discusses the categories of financial distress predictors and selects the financial distress predictors for the present study.

Section 4.3 introduces the source of growth enterprise's data and confirms the reliability of the data source.

Section 4.4 discusses the sample selection methods in social research and literature. It then selects the sample for the present study using the appropriate sampling method.

Section 4.5 presents techniques and methods, which include the MWW test, factor analysis and logistic regression, employed in the present study.

Section 4.6 finally concludes the whole chapter.

4.2 Financial distress

4.2.1 Definitions of distressed and non-distressed growth enterprises

In terms of identifying distressed growth enterprises, the literature on the definition of corporate financial distress is extensive. From the financial angle, a financial distressed enterprise is commonly defined as an enterprise which files for bankruptcy (Beaver, 1966; 1968;Altman, 1968; Altman, Haldeman and Narayanan, 1977; Ohlson, 1980). However, unlike researches that have relied on a single definition of corporate financial distress, some later studies have used many extended or hybrid definitions (Trussel and Greenlee, 2004). For instance, Kuo et al. (2003) defined the distressed firm as a firm involved in dishonouring bills or checks, delaying repayment of banks' loans, having a poor credit history, having bank accounts rejected or having a net worth less than half of real assets. In addition, Steyn-Bruwer and Hamman (2006) defined a distressed firm as a firm which had experienced delisting, bankruptcy or a major organisational restructuring.

Moreover, in Wu's (2004) study, a distressed firm on the Taiwan Stock Exchange was defined as a listed firm which had experienced operational difficulties or had been judicially declared a special stock arrangement firm by authorities. For a research study on predicting financial distress of companies listed on the Johannesburg Stock Exchange in South Africa, financial distress was defined (Steyn-Bruwer and Hamman, 2006) as the situation when a firm could not continue to exist in its current form and had found itself in any of the three situations which included bankruptcy, delisting or a major organisational restructuring. Similarly, in Cheng, Yeh and Chiu's (2007) empirical study, a firm is identified as distressed if it is involved in any one of the following situations: filing for bankruptcy, being placed on a suspension of trading list, experiencing an altered trading method, or being involved in unusual actions such as a cease trading order or delisting.

According to the status report on delisting proceedings and suspensions (HKEx, 2010b) and the GEM Listing Rules (GEM, 2010b), the present study defined a distressed growth enterprise as an enterprise which has experienced being filed for bankruptcy, cancellation of listing pursuant to delisting procedures under the GEM Listing Rules (excluding being transferred to other stock markets) or securities trading being suspended by the GEM for at least three months due to disobeying the GEM Listing Rules. With respect to non-distressed growth enterprises, the present study regards an enterprise, which was transferred from the GEM to the HKSE, as a non-distressed firm. Besides this kind of enterprises, an enterprise on the GEM, which has not experienced being filed for bankruptcy, cancellation of listing or long suspension of securities trading (more than three months), can also be regarded as a non-distressed growth enterprise.

4.2.2 Selection of financial distress predictors

Firm-specific financial ratios have been widely used as predictor variables in models that forecast business distress and failure (Altman 1968; Altman, Haldeman and Narayanan 1977; Barnes 1987; Kuo et al., 2003; Wu, 2004; Jones and Hensher, 2004; Smith, 2005; Chen, 2008). So a large number of financial ratios have thus been proposed in previous literature. For example, Smith (2005, p. 23) indicated that the influence of four key categories of financial ratios, incorporating gearing variables, liquidity ratios, profitability ratios and working capital ratios, could be combined to be a measure of financial performance and an excellent indication of financial distress. Similarly, in a mainland China's study, Wang and Li (2007) found that some categories of financial ratios (activity ratios, growth ratios, interest coverage ratios and profitability ratios) have strong classification capability in financial distress prediction of listed companies on SSE and SZSE in mainland China.

In addition to firm-specific financial ratios, different firm-specific non-financial variables, such as management measures, corporate governance variables, audit variables, ownership, can also be used to forecast a firm's distress. For instance, Keasey and Watson (1987) employed several firm-specific non-financial variables on management structure, accounting information system, auditing delay and delay of issuing financial statements to construct a distress-forecasting model in their study. In Kuo et al.'s (2003) study, since the degree of internationalization has played a vital role in Taiwan's economic development and the Taiwanese financial institutions have their own special infrastructure, five firm-specific non-financial variables were analysed, which covered the number of firm's correspondent banks, the magnitude of firm's short-term debt, the open credit line of the firm, the foreign sales ratio of the firm and foreign direct investment of the firm. Their study concluded that the number of correspondent banks and foreign sales ratio of SMEs can enhance the ability of the model to classify the distressed and non-distressed SMEs.

A major factor affecting company failure rate would be the overall economic circumstances within which companies are operating (Liou and Smith, 2007). Therefore, besides financial ratios and non-financial variables, some prior research studies equally noted that the performance of an enterprise could be affected by several macroeconomic factors (Mensah, 1984; Liou and Smith, 2007; Muller et al., 2009). For instance, Liou and Smith (2007) considered several macroeconomic variables (GDP, industrial production index, interest rate, price index and share index) as indicators in their model of financial distress prediction. The results of their study reveal that these macroeconomic variables have real value for financial distress prediction and have the potential to improve the classificatory ability of the distress prediction model.

Table 4.1 below shows the firm-specific financial ratios with their formulas, firm-specific non-financial variables and macroeconomic variables which are used in this study,

Table 4.1 Financial distress predictors used in the present study

Panel A Firm-specific financial ratios used in this study

Category	Firm-specific financial ratio	Formula
Profitability ratios	ROE	Profits available to ordinary shareholders/Average ordinary shareholder's equity
	ROA	Net income/Average total assets
	Gross profit rate	Gross profit/Net sales
	Expense ratio	Expenses(excluding tax)/Net sales
	Asset turnover	Net sales/Average assets
	Cash return on sales	Cash provided from operating activities/Net sales
Liquidity ratios	Current ratio	Current assets/Current liabilities
	Quick ratio	(Current assets- inventories)/Current liabilities
Solvency ratios	Cash debt coverage	Net cash provided in operating activities/Average liabilities
	Debt to total assets ratio	Total debt/ Total assets

Panel B Firm-specific non-financial variables used in this study

The frequency of the firm delaying its release of financial statements
The frequency of the firm changing its auditor(s)
The frequency of the firm's auditors' report with 'qualified opinion' and/ or explanatory paragraph
The frequency of the firm issuing a profit warning

Panel C Macroeconomic variables used in this study

Real GDP growth rate
Average interest rate on loans
Business Climate Index
Entrepreneur Confidence Index

4.2.2.1 Types of firm-specific financial ratios used in the present study

According to Kimmel et al. (2006) and Weygandt et al. (2007), financial ratios, which are designed for analysing main financial statements of the firm, can be classified into types including profitability ratios, solvency ratios and liquidity ratios. The present study uses these three types of financial ratios as financial distress predictors. In this study, two criteria are used to identify the appropriate financial ratios for each type of ratio. The first criterion is that the selected ratio should be commonly used as financial distress predictors in prior research studies. Second, these financial ratios can be calculated based on the 100 sample growth enterprises' available financial data.

4.2.2.1.1 Profitability ratios

Profitability ratios measure the firm's ability to generate profit or operating success for a given period of time. A firm's profit or lack of profit can influence a firm's liquidity position and a firm's ability to obtain equity and debt financing (Kimmel et al., 2006, p. 616). In other words, the profit of a firm affects the firm's ability to grow. As a consequence, profitability ratios were most frequently used as the financial distress predictors in the existing literature.

According to the two criteria of identifying financial ratios, six profitability ratios, namely, return on ordinary shareholders' equity ratio (ROE), return on assets ratio (ROA), gross profit rate, cash return on sales, expense ratio and asset turnover, are used in this study. The description and discussion of these six profitability ratios are as follows.

ROA is a ratio that measures the overall profitability of assets in terms of the rate earned on each dollar invested in assets (Kimmel et al., 2006, p.617). In the present study, ROA is calculated by dividing average total assets into profit. Many previous research studies found ROA is a significant factor in identifying financial distress. For example, Altman (1968) identified ROA as one of the useful factors in discriminating financially distressed firms. Consistent with Altman (1968), Wu (2004) revealed that ROA was one of the significant financial variables in predicting financial distress one year before the corporate distress occurred.

ROE measures how many dollars of profit were earned for each dollar invested by the owners of firm. There are two factors affecting ROE: ROA and debt to total assets ratio (Kimmel et al., 2006, p.616). From the viewpoint of ordinary shareholder, the ratio ROE is a widely used measure of profitability. For instance, in Cheng, Yeh and Chiu's (2007) study, they examined ROE and other 13 financial ratios and tried to find the most significant attributes of firm's distress. Wu (2004) extracted ROE as one of the significant financial variables in predicting financial distress two years before the occurrence of corporate distress. In the present study, ROE is determined by dividing profit available to ordinary shareholder by the average ordinary shareholder's equity.

Cash return on sales is a measure to assess cash from operating activities which result from each dollar of net sales (Weygandt et al., 2007, p.864). This ratio had been found to be significant in predicting business distress (Deakin, 1972). Frydman, Altman and Kao (1985) also used cash return on sales as one of the financial variables to classify corporate financial distress. Hence, the present study uses cash return on sales as one of the financial distress predictors. In the present study, this ratio is computed by dividing cash provided from operating activities by net sales.

The expense ratio is a measure of percentage of each dollar of net sales that generates expenses (Weygandt et al., 2007, p.865). In the literature, Slowinski and Zopounidis (1995) considered the expense ratio in their study to evaluate corporate bankruptcy. Kuo et al. (2003) used it as one of the financial ratios to predict corporate financial distress. Consequently, the present study uses expense ratio as one of the financial distress predictors. In the present study, this ratio is computed by dividing an entity's expenses (excluding tax) by net sales.

Asset turnover is a measure of the net sales incurred for each dollar of assets (Weygandt et al., 2007, p.865). This ratio is used to measure the efficiency of a firm using its assets to generate sales. In the literature, asset turnover was a useful ratio to predict the firm's financial distress (e.g.

Beaver, 1966; Altman, 1968; Kuo et al., 2003 and Wu, 2004). In the present study, this ratio is computed by dividing net sales by average assets.

Gross profit rate indicates a firm's ability to maintain an adequate selling price above its costs. Gross profit rate of an industrial will decline when the industry becomes more competitive (Kimmel et al., 2006, p.619). In many prior studies, gross profit rate was a useful ratio to show a firm's financial performance (e.g. Kuo et al., 2003; Wang and Li, 2007; Muller, Steyn-Bruwer and Hamman, 2009 and Hossein and Hamid, 2010). Thus, the present study selects gross profit rate as one of the financial distress predictors and the gross profit rate is calculated by dividing gross profit by net sales.

4.2.2.1.2 Liquidity ratios

Liquidity ratios measure the short-term ability of the firm to pay its maturing obligations and to meet unexpected needs for cash. Therefore, suppliers and bankers, which are the short-term creditors of the firms, are particularly interested in assessing the firm's liquidity (Kimmel et al., 2006, p.610). According to the two criteria of identifying financial ratios mentioned previously, current ratio and quick ratio, the two most commonly used liquidity ratios, have been selected for the present study. These two ratios are usually used to determine the firm's short-term debt-paying ability.

The current ratio expresses the relationship of current assets to current liabilities. It is widely used for evaluating the firm's short-term debt paying ability and liquidity (Kimmel et al., 2006, p. 610). In the present study, the current ratio is calculated by dividing current assets by current liabilities.

In several studies on corporate distress prediction in Taiwan, current ratio was applied as a predictor of financial distress (Kuo et al., 2003; Wu, 2004; Cheng, Yeh and Chiu, 2007). In Wu's (2004) study, the current ratio was extracted to construct two corporate distress models which are respectively for one year and two years before the occurrence of distress.

However, a disadvantage of the current ratio is that this ratio is only one measure of liquidity. It cannot take into account the composition of the current assets. For instance, a firm might have a relatively high current ratio because it has a lot of slow-moving inventory. Nevertheless, a dollar's worth of slow-moving inventory is less readily available to pay the bills than a dollar of cash. Hence, the present study uses a quick ratio that can resolve the weakness of the current ratio to some extent.

The quick ratio is a measure of the firm's immediate short-term liquidity (Kimmel et al., 2006, p. 611). In the present study, the quick ratio is calculated by dividing the sum of cash, net receivables and marketable securities by current liabilities. Therefore, the quick ratio does not include prepaid expenses and inventory which may not be readily saleable. Since cash, receivables and marketable securities are highly liquid compared with prepaid expenses and inventory, the quick ratio is an important complement to the current ratio (Kimmel et al., 2006, p. 611). In the previous literature, Kuo et al. (2003) and Wu (2004) used the quick ratio as a predictor of corporate distress in their studies. Kuo et al. (2003) extracted short-term liquidity ratios, which included the current ratio and the quick ratio, with several other categories of ratios to construct their model for corporate financial distress prediction. Similarly, Wu (2004) extracted the quick ratio with several other ratios to construct a corporate distress model of one year before the occurrence of distress.

4.2.2.1.3 Solvency ratios

Solvency ratios measure the firm's ability to repay the face value of the debt at maturity and pay the interest when it comes due. In other words, solvency ratios measure the ability of a firm to survive over a long period of time (Kimmel et al., 2006, p.614). Based on the two criteria of identifying financial ratios mentioned previously, two solvency ratios (cash debt coverage and debt to total assets ratio) are used in the present study. These two solvency ratios are then discussed as follows.

The debt to total assets ratio is an indicator of the firm's financial risk. It measures the proportion of the firm's assets financed by creditors to its total assets. Moreover this ratio indicates the firm's ability to withstand losses without impairing its creditors' interests. Hence, from the viewpoint of creditors, a low ratio of debt to total assets is usually desirable (Kimmel et al., 2006, p.614). In the prior research studies, the debt to total assets ratio was one of the first financial ratios which was frequently used for predicting distressed firms (Beaver, 1966). The lower the percentage of total liabilities to total assets, the more equity 'butter' is available to creditors if the firm is declared insolvent. Relatively, the higher the ratio, the less the financial risk that the firm may be unable to meet its maturing obligations (Kimmel et al., 2006, p.614). In a recent study, Chen (2008) used this ratio to examine the financial health of corporations.

The second solvency ratio used in the present study is cash debt coverage. Cash debt coverage is a cash-basis measure of solvency. This ratio indicates the firm's ability to repay its liabilities from cash which generated from operating activities without liquidating the assets used in its operations (Kimmel et al., 2006, p.615). In the present study, cash debt coverage is measured by dividing net cash provided by operating activities to average total liabilities. In the existing literature, cash debt coverage was one of the first financial ratios to be used for predicting corporate distress (e.g. Beaver, 1966 and Frydman, Altman and Kao, 1985). Furthermore, Pompe and Bilderbeek (2005) suggested that cash debt coverage was the strongest single ratio to predict corporate financial distress.

4.2.2.2 Firm-specific non-financial variables used in the present study

In addition to financial ratios, different non-financial variables, which consist of management measures, corporate governance variables, audit variables, ownership, et al., can also be used to forecast a firm's distress (Keasey and Watson, 1987; Whitaker, 1999). In the last decade, a growing number of researchers have started to consider the increasing number of non-financial variables in their corporate distress studies. In Kuo et al.'s (2003) study, five firm-specific non-financial variables were analysed, which covered the number of correspondent banks, magnitude of short-term debt, open credit line, foreign sales ratio and foreign direct investment. The reasons these five variables were chosen are that financial institutions in Taiwan have their special infrastructure and internationalization plays a vital role in Taiwan's economy. Finally, they demonstrated that adding two out of these five non-financial variables to the model which only included financial factors could enhance the ability of predicting and classifying distressed and successful SMEs. Cheng, Yeh and Chiu (2007) also strongly suggested that financial ratios alone might not form a complete set of significant variables for the analysis of corporate distress predication, as conventionally used in a lot of existing models. In order to effectively address the corporate distress prediction problem, both financial and non-financial factors have to be considered.

Based on the information of growth enterprises disclosed by the GEM and prior studies on prediction of corporate financial distress, the present study has selected four firm-specific non-financial variables. These four variables incorporate the frequency of the firm delaying its release of financial statements, the frequency of the firm changing its auditor(s), the frequency of the firm's auditors' report with 'qualified opinion' and/ or explanatory paragraph and the frequency of the firm issuing a profit warning.

In the present study, the first firm-specific non-financial variable used is the frequency of a firm delaying its release of financial statements which measures the time a firm delays issuing its financial statements in a financial year. This variable is used as a predictor to predict corporate financial distress. Some prior research studies have demonstrated that the incidence of a firm delaying issuing its financial statements had a negative correlation with the performance of the firm, because a poorly performing firm is prone to delay releasing its bad financial results (Graham, Harvey and Rajgopal, 2005). Similarly, Haw et al. (2000) found that good firms which had better financial results released their financial reports earlier than other firms. They also suggested that distressed firms tended to delay releasing their financial reports. Keasey and Watson (1987) employed delay of issuing financial statements with several other firm-specific non-financial variables to construct a corporate failure forecasting model.

The second firm-specific non-financial variable used in the present study, changing auditor, measures the frequency a firm changes its auditor in a financial year. Previous studies have suggested that distressed firms are more likely to switch their auditor up to three years before failure, mainly resulting from disputes between auditors and managers over accounting methods as well as disagreements on audit opinions and qualifications (Schwartz and Menon, 1985).

In Cheng, Yeh and Chiu's (2007) study, besides the 14 financial variables perceived, the only non-financial variable considered was the status of auditor switching, which was used to indicate whether or not a firm had changed its auditor in the past one, two or three years before corporate distress. In the conclusion of Cheng, Yeh and Chiu's study, as exemplified in the empirical study, the non-financial variable (auditor switching) was found to be the most significant attribute of corporate distress and played an essential role in enhancing the performance of their models. The performance of the model with the non-financial variable (auditor switching) was much better than the one only using financial variables.

The third firm-specific non-financial variable, the frequency of the firm's auditors' report with qualified opinion and/ or explanatory paragraph, is tested in the present study. Auditors' report with qualified opinion means that a material matter affects the financial statements. In addition, the auditor believes that this material matter precludes a statement that the financial statements fairly present the financial position of the firm (Leung, et al., 2009, p.204). In certain circumstances, an auditors' report with unqualified opinion may require the auditors to add an explanatory paragraph after their opinion paragraph. In this paragraph, the auditor may describe a change in accounting principles, a material uncertainty or express doubt as to the ability of the firm to continue (Gibson, 2009, p.52). Furthermore, unqualified opinion containing an explanatory paragraph is important for this analysis. For example, an explanatory paragraph for a material uncertainty is often regarded as a serious matter (Gibson, 2009, p.53). Therefore, given the great importance of the auditor's report, the auditor's report with the auditor's opinion can provide additional information to help in assessing the performance of the firm (Guiral-Contreras, Gonzalo-Angulo and Rodgers, 2007).

The final non-financial variable in the present study is the number of times a firm issuing a profit warning. On the GEM, the announcement of profit warning is made pursuant to Rule 17.10 of the GEM Listing Rules by firm. As a general obligation of a growth enterprise, the firms on the GEM have to publish an announcement of profit warning when they experience a significant decline or increase in profit as compared to the same period the previous year. The present study only counted the number of warning announcements of a profit decline. Obviously, frequent significant reductions in profit is an early warning indicator of the firm's financial distress (Altman, Haldeman and Narayanan 1977; Ohlson, 1980).

4.2.2.3 Macroeconomic variables used in the present study

Besides firm-specific financial ratios and firm-specific non-financial variables, Mensah (1984) equally notes that the performance of a firm is usually affected by several macroeconomic factors. In Mensah's research study, three external macroeconomic ratios, which cover inflation, business cycle recession/expansion phases) and interest rates and credit availability are investigated. Furthermore, many empirical studies have found that macroeconomic effects affect firm survival. For example, using Belgian data, Sleuwaegen and Dehandschutter (1991) found that GDP growth has a significantly negative effect on firm exit. In another study, in Japan, Honjo (2000) observed a marked increase in the likelihood of firm exit after the burst of the Japanese bubble economy in the early 1990s. Audretsch and Mahmood (1995) used U.S. credit rating data and presented evidence for significant business cycle effects on firm survival. To sum up, the effects of macroeconomic factors influence firms to move in or out of financial distress.

Based on availability of macroeconomic variables and prior studies on prediction of corporate financial distress, the present study has selected four macroeconomic variables to predict financial distress. These four variables include real GDP growth rate, average interest rate on loans, Business Climate Index and Entrepreneur Confidence Index.

Real GDP growth rate in China shows GDP growth on an annual basis and it is adjusted for inflation and expressed as a percentage. In early studies, growth in gross national product (GNP) is traditionally taken to be an overall indicator of a nation's economic health (Altman, 1971). However, one disadvantage of GNP is that GNP includes the corporate profits made in foreign countries. On the one hand, as the number of international conglomerates grows, this kind of profit may be enormous. On the other hand, if the movement of the profit is restricted by government legislation or if the profit is required for further overseas investment, it cannot actually add directly to the 'home' country's economic growth (Liou and Smith, 2007). Thus, in more recent studies, an increasingly used alternative is the growth of GDP. For instance, Dionne et al.'s (2008) hybrid model combined the two sets of explanatory variables to predict the probability of defaults for Canadian firms. In their study, they considered only one macroeconomic variable which is the real GDP growth rate and they found the real GDP growth was negatively related to the likelihood of a firm's default.

The interest rate on loans measures the cost of loan paid by the borrower for the use of the fund (Mishkin, 2004, p.4). In other words, the interest rate is the price for use of the borrowed money.

On a general level, interest rates have an impact on the overall health of a nation's economy because they influence not only consumers' willingness to save or spend, but also firms' investment decisions (Mishkin, 2004, p.4). In the present study, the average interest rate on loans is expressed as the average percentage rate over the period of one year. In prior research studies, some researchers regarded the interest rate as one of macroeconomic variables that can affect the performance of a firm. For example, Mensah (1984) investigated the interest rate with two other external macroeconomic ratios. Mensah's study revealed that a firm's performance was gradually affected by several macroeconomic factors and the signs of failure were apparent at least three years before the event for most distressed firms. Georgine's research in 2001 showed a similar result in a study of small business development in Central and Eastern Europe countries, which has been influenced to a great extent by a group of macroeconomic factors which included interest rates.

Business Climate Index is a major indicator of macroeconomy and is used to rate or rank the relative attractiveness of a nation or an area as a location for economic activity. This index is usually made up of several variables, for example, economic growth rates, unemployment rate and various tax rates (Steinnes and Syck, 1990). In the present study, the Business Climate Index has been obtained from the NBSC. In China, the NBSC has reported the Business Climate Index and the Entrepreneur Confidence Index quarterly only since the first quarter of 1998. Therefore, the limitation of data makes it challenging to assess relationships between the Business Climate Index and the performance of the firms. In a German study, Rosch (2003) used business climate indices as additional indicators for the state of the macroeconomy. This study found that the forecasts for corporate default could become more adequate when the business climate indices were taken into account.

In the same way, the data of the fourth macroeconomic indicator, the Entrepreneur Confidence Index, is provided by the NBSC. The Entrepreneur Confidence Index is issued on the industry level and this index mainly reflects firm managers' expectations based on macroeconomic conditions (Ye and Yuan, 2008). As discussed previously, the Entrepreneur Confidence Index has been used in China only since early 1998. Thus, only a few studies in China have used the Entrepreneur Confidence Index as a predictor for financial distress prediction or corporate performance assessment. Nevertheless, there are some studies in other regions which have included Entrepreneur Confidence Index as one of the predictors. For instance, in Europe, Bodo, Golinelli, and Parigi (2000) found that a conditional error correction model that incorporated the European Commission's Business Confidence Index, which is similar to the Entrepreneur Confidence Index, performed well in forecasting industrial production.

In summary, this study analyses three types of firm-specific financial ratios: profitability ratios, liquidity ratios and solvency ratios. These three firm-specific financial ratios include ten ratios, namely, ROE, ROA, gross profit rate, cash return on sales, expense ratio and asset turnover, current ratio, quick ratio, cash debt coverage and debt to total assets ratio. From the financial viewpoint, the present study uses these eight firm-specific financial ratios to do the corporate distress prediction analysis. Besides firm-specific financial ratios, the present study uses four firm-specific non-financial variables and four macroeconomic variables as predictors to assess the probabilities of firms' financial distress. These firm-specific non-financial variables consist of the firm delaying in releasing its financial statements, the firm changing its auditor(s), the firm's auditors' reports with 'qualified opinion' and/ or explanatory paragraph and the firm making an announcement(s) concerning profit warning. The macroeconomic variables used in the present study include real GDP growth rate, average interest rate on loans, Business Climate Index and Entrepreneur Confidence Index.

4.3 Data source and reliability of the data

In terms of the data source, all the data of growth enterprises used in the present study was derived from the official portal of Hong Kong GEM (www.hkgem.com) on September 2, 2010. As a 'buyers beware' market for informed investors, the Hong Kong GEM makes its market statistics, securities' trading information and information on listed and delisted companies available for the public (GEM, 2010a). Based on the GEM listing rules and requirements, the official portal of GEM has become the way to provide comprehensive and timely information on all aspects of the GEM.

In terms of reliability of data provided by GEM, the Hong Kong GEM is a wholly-owned subsidiary of the HKSE. According to the statement previously reported, the HKSE ranks seventh in the world and third in Asian Pacific region by market capitalization of listed companies. Furthermore, the Government of the Hong Kong Special Administrative Region of China (the Government of Hong Kong) is the single largest shareholder in HKEx which is the holding company of the HKSE. The government of Hong Kong also has the right to appoint six of the thirteen directors to the Board of HKEx. The HKEx endeavours to ensure the accuracy and reliability of the information provided (GEM, 2010a). Therefore, the data provided by HKSE should be reliable for the present study.

Moreover, the data of GEM provided by HKSE has been widely used in prior researches. For instance, in order to compare three special stock exchanges in Asia with the AIM of the London Stock Exchange, the information of the GEM provided by the HKSE was used in Mizuno and Tabner's (2008) study. Vong and Zhao (2008) used the GEM data in the period between 1999 and 2005 to examine the first-day returns of IPOs listed on the Hong Kong GEM. Chan et al. (2007) also used the financial data and annual reports provided by the Hong Kong GEM to examine the stock return performance. Their study covered 85 stocks on the Hong Kong GEM and the data of these stocks was selected from 1999 to 2001. Like the present study, Chan et al.'s (2007) study obtained most of its financial data from the official Hong Kong GEM portal.

To sum up, the financial data for Hong Kong GEM are provided by the HKSE. The HKEx, which is supervised by the Hong Kong government, is also responsible for the accuracy and reliability of the financial data. In addition, the data of GEM provided by HKSE has been widely used in prior researches. Hence, the financial data and information on the GEM official portal are reliable and suitable for the present study.

4.4 Sample selection

4.4.1 Sampling methods in social research

There are two main types of sampling methods in the practice of social research: probability sampling and non-probability sampling.

4.4.1.1 Probability sampling

Probability sampling, which is based on probability theory, is the primary method of selecting large and representative samples for social research (Babbie, 2007, p.183). This method involves selecting a random sample from the population being sampled. Unlike non-probability sampling, probability sampling can be representative of the whole population. Furthermore, researchers also turn to probability sampling, if they need a precise statistical description of the population.

The basic logic of probability sampling is quite easy to understand. Obviously, there is no need for careful sampling procedures if all members of population are identical in all respects. Therefore, in a case of extremely perfect homogeneity, any single case can become a sample to study the features of the whole population (Babbie, 2007, p.187).

However, the members of the real population are quite heterogeneous in most cases. Thus, the sample has to illustrate various aspects of the population. In that case, a sample should be representative of the population from which it is drawn. In other words, the aggregate characteristics of the sample have to approximate those same aggregate characteristics in the population (Babbie, 2007, p.189). For instance, a sample should be approximately 50 per cent male if the population is 50 per cent male.

Additionally, the probability sampling method has two special advantages. First, probability samples are more representative than other types of samples. Compared with a non-probability sample, a probability sample is more likely to be representative of the population from which it was selected. Second, the probability theory makes it possible to estimate the representativeness or accuracy of the sample (Babbie, 2007, p.189).

4.4.1.2 Non-probability sampling

In social research, there are many situations that do not permit using probability sampling. For example, if there is a large-scale social survey with no list of all members of the population, probability sampling would not be appropriate.

In the following part of this section, the present study examines four types of non-probability sampling: reliance on available subjects, quota sampling, snowball sampling and purposive or judgmental sampling.

First, relying on available subjects is a frequently used but extremely risky sampling method (Babbie, 2007). The most commonly used case of reliance on available subjects is stopping people on a street or at any other sampling point. Obviously, this method cannot control the representativeness of a sample. Hence, the method of relying on available subjects can be regarded as justified only if other less risky sampling methods are not feasible. In general, researchers should exercise great caution in using this method.

Second, quota sampling is a non-probability sampling method in which data are chosen into a sample based on the pre-specified categories or characteristics. Therefore, the total sample would have the same distribution of categories or characteristics existing in the population being studied (Babbie, 2007).

Third, snowball sampling is a form of accidental sampling. If the members of a population are quite difficult to locate, this method is appropriate. In the procedure of snowball sampling, the researchers begin with collecting data on the few members of the target population. Researchers then let these members provide other member's information to locate some other members. Snowball sampling is an accumulating process as each subject identifies other subjects (Babbie, 2007).

Fourth, purposive or judgmental sampling is a method of selecting samples on the basis of knowledge of populations and the purpose of the study. The selected units of the sample have to be the most useful and representative in the researcher's judgement (Babbie, 2007).

4.4.2 Sample selection in previous financial distress prediction literature

According to previous financial distress prediction literature, there were three techniques used for sample selection. First, some research studies adopted a matching pair technique as the sample selection criteria of distressed and non-distressed enterprises (Beaver, 1966; Altman, 1968; Altman, Haldeman and Narayanan, 1977; Wu, 2004). Based on this technique, each distressed enterprise should match its selected characteristics such as its industry section and size of the enterprise, with the characteristics of another non-distressed enterprise. For this reason, this technique matches distressed enterprises with the same number of non-distressed enterprises.

The second technique is another matching technique for sample selection. This technique matches a larger number of non-distressed enterprises with a smaller number of distressed enterprises. For instance, every two non-distressed enterprises were matched with one distressed enterprise in Coats and Fant's (1993) sample.

However, some researchers suggested that these two types of matching techniques have some problems in their matching procedures. For example, it is impossible to investigate the effects of enterprises' characteristics, including the size of the enterprise, industry section et al., on the probability of distress (Lennox, 1999).

The third technique, which is also a typical probability sampling technique, is the random sample selection. The sample selected by this method has its ratio of distressed enterprises to non-distressed enterprises representing the actual distressed rate of the whole population (Lennox, 1999).

4.4.3 Sample selection in the present study

In order to avoid the disadvantages of the matching technique for sample selection, the present study has used the method of random sample selection to choose the sample. In addition, the size of the sample enterprises should meet the requirement of factor analysis. So the sample should incorporate at least 100 enterprises in which the ratio of non-distressed enterprises to distressed enterprises should equal the actual distress rate of the whole population.

The number of listed and delisted growth enterprises of Hong Kong GEM was 174 and 71 respectively by the end of 2009. In 2009, the overall capitalization of Hong Kong GEM is over 105 billion Hong Kong dollars (over US$13.5 billion) (HKEx, 2010a). Based on the criteria for distressed and non-distressed growth enterprises, the total 245 growth enterprises are separated into two groups: distressed growth enterprises and non-distressed growth enterprises.

There are 67 growth enterprise defined as distressed enterprises which have experienced being filed for bankruptcy, cancellation of listing pursuant to delisting procedures under the GEM Listing Rules (excluding being transferred to other stock markets) or securities trading being suspended by the GEM for at least three months due to disobeying the GEM Listing Rules. Conversely, the remaining 178 growth enterprises are defined as non-distressed growth enterprises which have not experienced being filed for bankruptcy, cancellation of listing or long suspension of securities trading.

In the present study, 100 growth enterprises have been selected. These 100 growth enterprises incorporate 30 distressed enterprises and 70 non-distressed enterprises. The 30 distressed enterprises have been randomly selected from the identified distressed growth enterprises which have at least 3 years' financial results available. In a similar manner, the 70 non-distressed enterprises have been randomly selected from the identified non-distress growth enterprises which have at least 3 years' financial results available. In the sample, the ratio of distressed enterprises to non-distressed enterprises is 30 to 70, which is quite close to the actual distress rate of the whole population. Furthermore, given Hong Kong GEM had only 174 listed enterprises and has 71 delisted enterprises by end of December, 2009, 100 enterprises is a large enough sample size compared with the size of the whole growth enterprise population.

In terms of time period for data selection, the sample of 100 growth enterprise is examined over the period from 2000 to 2009. Many prior research studies have demonstrated that some firm-specific financial variables or non-financial variables in the last three years before financial distress are significant variables in predicting financial distress for the firms (Kuo et al., 2003; Wu, 2004; Ooghe and Balcaen, 2007). Thus, for the selected 30 distressed growth enterprises, the present study uses their data in the last three years prior to the occurrence of their financial distress. The present study codes the year of their financial distress happening as T. According to logic, the last three years prior to the occurrence of their financial distress are coded as T-3, T-2 and T-1 respectively. For the other selected 70 non-distressed growth enterprises, any three consecutive years during the period from 2000 to 2009 can be chosen for investigation in the present study. The three consecutive years are coded as T-3, T-2 and T-1 respectively from the furthest year to the latest year. All of the financial data are derived from announcements, reports and financial statements of the growth enterprises which are available on the official portal of GEM as of September, 2010.

4.5 Methodology

4.5.1 The purpose of using the Mann-Whitney test in the present study

The present study runs the MWW test to distinguish the difference in financial and non-financial performance and macroeconomic situation between distressed and non-distressed growth enterprises.

4.5.1.1 Introduction to Mann-Whitney-Wilcoxon test

The Mann-Whitney-Wilcoxon test is a nonparametric technique. The test was developed jointly by Mann, Whitney and Wilcoxon. It is also called the Mann-Whitney U test or the Wilcoxon rank sum test. In other words, both the Mann-Whitney U test and Wilcoxon rank sum test are equivalent (Anderson, Sweeney and Williams, 2008, p.825). Therefore, the present study refers these two tests as the Mann-Whitney-Wilcoxon (MWW) test.

The MWW test can be used to determine whether there is a difference between two populations. This test is not based on a matched sample and uses two independent samples which come from two populations respectively. Furthermore, the nonparametric MWW test does not require interval data (also called integer) or the assumption that the populations are normally distributed. There are only two requirements of the MWW test. The first requirement is that the measurement scale for the data is at least ordinal. The second requirement is that the two samples from two populations should be independent. Hence, the MWW test examines whether two populations are identical instead of testing for the difference between the two populations' means (Anderson, Sweeney and Williams, 2008, p.825). The null hypothesis and alternative hypothesis of the MWW test are as follows.

H_0: The two populations are identical.

H_a: The two populations are not identical.

4.5.1.2 Calculations of Mann-Whitney-Wilcoxon test

4.5.1.2.1 The small-sample case for the Mann-Whitney-Wilcoxon test

When both sample sizes are less than or equal to 10, the small sample case for the MWW can be used. In the procedure of the MWW test for a small sample, the first step is ranking the combined data of the two samples from lowest to highest. The second step is to sum the ranks for each of the two samples separately. The procedure of the MWW test then can be based on the sum of the ranks for either sample. The test denotes the sum of the ranks for the used sample by the symbol T.

In the next step, we provide the critical values of the MWW T statistic for small sample cases in which both samples sizes are no more than 10. These critical values with a 0.05 level of significance can be shown as follows.

Table 4.2: T_L values for the Mann-Whitney-Wilcoxon test

		n_2								
α= 0.05		2	3	4	5	6	7	8	9	10
n_1	2	3	3	3	4	4	4	5	5	5
	3	6	6	6	7	8	8	9	9	10
	4	10	10	11	12	13	14	15	15	16
	5	15	16	17	18	19	21	22	23	24
	6	21	23	24	25	27	28	30	32	33
	7	28	30	32	34	35	37	39	41	43
	8	37	39	41	43	45	47	50	52	54
	9	46	48	50	53	56	58	61	63	66
	10	56	59	61	64	67	70	73	76	79

Data source: Anderson, Sweeney and Williams, 2008. Statistics for Business and Economics, p.945.

In this table, n_1 refers to the sample size corresponding to the sample whose rank sum is being used in this test and n_2 refers to the size of the other sample. The value T_L can be read from Table 4.2 directly and value T_u is computed from the Equation 4.1.

$$T_u = n_1\ (n_1 + n_2 + 1) - T_L \qquad (4.1)$$

The MWW decision rule for a small-sample case indicates that the null hypothesis of identical populations can be rejected if the value of T is less than the value of T_L shown in Table 3.2 or if the value of T is greater than the value of T_u which is computed from the Equation 4.1 (Anderson, Sweeney and Williams, 2008, p.827). Hence, the rejection rule can be written as:

$$\text{Reject } H_0 \text{ if } T < T_L \text{ or if } T < T_u$$

4.5.1.2.2 The large-sample case for the Mann-Whitney-Wilcoxon test

If both sample sizes are no less than 10, a normal approximation of the distribution of T can be used to conduct the MWW test analysis (Anderson, Sweeney and Williams, 2008, p.827). Similar to the procedure of MWW test for a small sample, the first step of the MWW test for a large-sample case is to rank the combined data from the lowest values to the highest values. In the process of ranking the combined data, two or more data values might be the same and the tied values should be given (Anderson, Sweeney and Williams, 2008, p.828).

The next step is then summing the ranks for each of the two samples. The procedure of the MWW test can use the sum of the ranks for either sample. The test denotes the sum of the ranks for the used sample by the symbol T. In the test for a large-sample test, n_1 is the sample size corresponding to the sample whose rank sum is being used in this test and n_2 equals the size of the other sample. When the sample sizes n_1 and n_2 are given, the test can use the normal approximation to the sampling distribution of the rank sum T for identical populations. The appropriate sampling distribution is given by Equation 4.2 and Equation 4.3.

$$\text{Mean: } \mu_T = n_1\,(n_1 + n_2 + 1)\,/\,2 \qquad (4.2)$$

$$\text{Standard Deviation: } \sigma_T = [n_1\, n_2\, (n_1 + n_2 + 1)/12]^{1/2} \qquad (4.3)$$

(Distribution form: approximately normal provided $n_1 \geq 10$ and $n_2 \geq 10$.)

With T value, μ_T value and σ_T value, the Z value (standard value) can be calculated based on Equation 4.4.

$$Z = (T - \mu_T)/\,\sigma_T \qquad (4.4)$$

Finally, the test uses the Z value and the standard normal probability table to calculate the two-tailed p-value. If p-value $\leq \alpha = 0.05$, null hypothesis H_0 is rejected and the two populations are not identical; if p-value $> \alpha = 0.05$, null hypothesis H_0 cannot be rejected and two populations are identical (Anderson, Sweeney and Williams, 2008, p.830).

4.5.1.3 Summary for Mann-Whitney-Wilcoxon test

To sum up, the procedure of the MWW test can be summarized as three steps which are stated as follows: the first step is to rank the combined data of the two samples from low to high with tied values being assigned the average value of the tied values. The sum of the ranks for the used sample (T value) is then calculated. Finally, in the small-sample case, the test computes the T_L

and T_u and compares the T value with them to decide whether or not to reject the null hypothesis. In the large-sample case, the test compares the value of T to the sampling distribution of T for identical populations using Equation 4.2 and Equation 4.3. Lastly, according to Z value and p-value provided, the test can identify whether the two independent random samples have been selected from two identical populations.

4.5.2 Factor analysis

4.5.2.1 The purpose of using factor analysis in the present study

The present study uses factor analysis to reduce ten financial ratios to several financial factors. The principal non-financial and macroeconomic factors are then extracted from eight set of non-financial and macroeconomic variables. In that case, the manageable number of factors can be then used in logistic regression.

4.5.2.2 Introduction to factor analysis

Factor analysis is a data reduction technique. The 'factor' in factor analysis refers to the group or clump of related variables. Therefore, this technique is designed to take a number of variables and let the data be summarized using a smaller set of components or factors. In addition, factor analysis can reduce a large set of related variables to a smaller and more manageable number prior to using the data in other analyses (Pallant, 2007, p.179).

In the literature, there are two key approaches, confirmatory and exploratory, to factor analysis. In the early stages of research, exploratory factor analysis is usually used to explore the interrelationships among a set of variables (Pallant, 2007, p.179). Differing from exploratory factor analysis, confirmatory factor analysis is a more sophisticated technique and it is used in the research process to confirm-specific hypotheses or theories concerning the structure underlying a set of variables (Pallant, 2007, p.179).

The term ‘factor analysis’ includes two sets of related but different techniques which are termed as factor analysis and principal components analysis. Factor analysis and principal components analysis are two similar sets of techniques and can be used interchangeably in most cases. Both factor analysis and principal components analysis attempt to produce several linear combinations of the original variables in a way that can account for most of the variability. However, these two techniques also have some differences. On the one hand, principal components analysis transforms the original variables into a smaller set of linear combinations with all the variance in these variables. On the other hand, factor analysis uses a mathematical model to estimate factors and this set of technique only analyses shared variance (Pallant, 2007, p.180). Tabachnick and Fidell (2007) concluded that principal components analysis is for an empirical summary of the data set, whereas factor analysis is for a theoretical solution uncontaminated by unique and error variability (p.635). The present study uses a computer application (SPSS), which allows both principal components analysis and factor analysis, to do the factor analysis. Therefore, the present study uses factor analysis as a general term to indicate this family of techniques which encompass factor analysis and principal components analysis.

4.5.2.3 Assumptions for factor analysis

According to Pallant (2007), there are four assumptions underlying the application of factor analysis. The first assumption is the sample size. Although there is no agreement in the literature concerning how large the sample should be, the general recommendation for the data size is: the larger, the better (Pallant, 2007, p.185). Generally, the overall sample size of no less than 100 is acceptable and a minimum of five cases for each of the variables is required for factor analysis (Coak, 2005, p.154).

Secondly, factor analysis is sensitive to outlying cases or outliers. Thus, these cases should be either removed from the data set or recoded to a less extreme value (Pallant, 2007, p.186).

The third assumption is the factorability of the correlation matrix. In other words, the correlation matrix of all variables should have at least some correlations, with r being no less than 0.3. Moreover, the Kaiser-Meyer-Olkin value ranges from 0 to 1 and should be no less than 0.5 (Child, 2006, p.55). Bartlett's test of Sphericity should have a p value less than 0.05 (Pallant, 2007, p.185).

Finally, relationship between variables is assumed to be linear since factor analysis is based on correlation. Given checking scatter plots of all variables with all other variables is not practical, a spot check can be an appropriate method to examine some combination of variables (Tabachnick and Fidell, 2007). It is safe to do factor analysis if there is no clear evidence to suggest a curvilinear relationship between variables (Pallant, 2007, p.185).

4.5.2.4 Steps in factor analysis

Besides using the four assumptions to assess the suitability of the data for factor analysis, there are other two steps to conduct factor analysis. These two steps are extracting factors and interpreting factors.

4.5.2.4.1 Step 1: Extracting factors

This step determines the smallest number of factors which can best represent the interrelations among the group of variables. In the process of extracting factors, several approaches can be used to identify the underlying factors. According to Pallant (2007) and Coak (2005), the most commonly used techniques include principal components, principal axis factoring, maximum likelihood, unweighted least squares, generalized least squares, alpha factoring and image factoring. Principal components is the most frequently used approach out of these seven approaches. This technique determines the number of factors which can best describe the underlying relationship among variables. Additionally, this technique has to balance two conflicting needs. The first need of this technique is explaining as much variance in the original data set as possible. Nevertheless, the other need is getting a simple solution with as few factors as possible (Pallant, 2007).

Subsequently, in the process of deciding the number of factors to retain, three main techniques, which incorporate Kaiser's criterion, a scree test and a parallel analysis, can be used. The most frequently used technique is the Kaiser's criterion or the eigenvalue rule. A factor's eigenvalue measures the variance in all the variables which is explained by the factor. Based on this criterion, the factors with their eigenvalues being no less than 1 can be retained.

Catell's scree test is another commonly used technique. This technique plots and graphically displays the eigenvalues for each of the factors. It then inspects the plot to find the point at which the shape of the curve makes an elbow and becomes less steep. Finally, all the factors, which are after the factor starting the elbow, should be dropped and the remaining factors should be retained. These remaining factors explain most of the variance in the data set (Pallant, 2007, p.182).

In addition, Horn's parallel analysis is becoming more popular in social science research, particularly in the education and psychology fields (Pallant, 2007, p.183). Parallel analysis compares the size of the eigenvalues with those obtained from an uncorrelated random data set of the same size. It only keeps the eigenvalues which exceed the corresponding values from the randomly generated data set.

4.5.2.4.2 Step 2: Factor rotation and interpreting factors

After determining the number of factors, the second step is the factor interpretation. At the beginning of this process, the factors need to be rotated. Factor rotation can make the pattern of loadings easier to interpret.

There are two key approaches to rotation. These two approaches result in either orthogonal (uncorrelated) or oblique (correlated) factor solutions (Pallant, 2007, p.183). Tabachnick and

Fidell (2007) argue that orthogonal rotation makes the solutions easier to report and interpret, whereas the researchers have to assume that the underlying constructs are independent or not correlated. In contrast, oblique approaches require the factors to be correlated, whereas they are more difficult to report, describe and interpret (Tabachnick and Fidell, 2007, p.638).

In practice, SPSS provides several rotational methods within the two broad categories of rotational approaches (orthogonal and oblique) respectively. These methods encompass Varimax, Quartimax, Equamax, Promax and Oblimin. The most frequently used oblique method is Direct Oblimin and it can show the degree of correlation between the factors. With respect to orthogonal methods, the Varimax method is most commonly used and it can minimise the number of variables that have a high loading on each factor (Pallant, 2007).

In most cases, the two rotational approaches (orthogonal and oblique) result in similar solutions. Hence, many researches have conducted both orthogonal and oblique rotations and selected the simplest and clearest solutions to interpret (Pallant, 2007, p.183). The final step is to assign a label to each factor and interpret them based on the variables of each factor.

4.5.2.5 Summary for factor analysis

To sum up, factor analysis is a technique to reduce a group of variables to a smaller number of factors which can summarize the essential information in the variables. On the one hand, if the purpose of the study is to summarise the structure of a set of variables, exploratory factor analysis is appropriate. On the other hand, confirmatory factor analysis is more frequently used when the research is aim to confirm-specific hypotheses or theories concerning the structure underlying a set of variables. In the process of conducting factor analysis, four assumptions, which are referred to sample size, linearity, outliers and factorability of the correlation matrix, should be tested at the beginning. Meanwhile, the suitability of the data for factor analysis also has to be assessed. The factors, which can best represent the interrelations among the group of variables, then have to be extracted based on factors' eigenvalues. In the final step of conducting factor analysis, the extracted factors are rotated and interpreted.

4.5.3 Logistic regression

After the MWW test and factor analysis, the extracted financial, non-financial and macroeconomic factors are used as independent variables for logistic regression analyses. The dependent variable is whether the growth enterprise experienced distress or not (distressed = 1, non-distressed =0). The present study then uses binary logistic regression analyses to establish three types of financial distress models. The first type of model considered firm-specific financial factors only, whereas the second type of model considered firm-specific non-financial factors and macroeconomic factors. The third type of model considered not only firm-specific financial factors but also firm-specific non-financial factors and macroeconomic factors.

4.5.3.1 Introduction to logistic regression

Logistic regression, which includes binary and multinomial logistic regressions, is used for prediction of the categorical outcomes. The binary and multinomial logistic regressions are used for two and more categories of outcomes respectively. In most cases, the dependent variable for logistic regression only assumes two discrete values and the binary logistic regression is used

(Anderson, Sweeney and Williams, 2008, p.665). For example, the dependent variable can be code as $y = 1$ if an event occurs, and $y = 0$ if this event does not occur. In terms of independent variables, they can be either continuous or categorical or a mixture of both in one model (Pallant, 2007, p.166). Using logistic regression, researchers can estimate the probability of occurrence of the event.

4.5.3.2 Assumptions for logistic regression

According to Pallant (2007), there are three assumptions underpinning the use of logistic regression. The first assumption concerns the number of cases in the sample and the number of independent variables included in the model. If there is a small sample with a large number of independent variables, the research might have problems with the analysis. It becomes a real problem when the categorical independent variables have limited cases in each category.

The second assumption refers to checking for intercorrelations among independent variables or namely, multicollinearity. Ideally, independent variables have to be strongly related to dependent variables but not strongly related to each other. Therefore, the highly intercorrelating variable has to be removed (Pallant, 2007, p.167).

Finally, the third assumption is about checking for the presence of outliers, because outliers can influence the results of logistic regression. If there are some cases that are not well explained by the model, checking the outlying cases would become a particularly important step.

4.5.3.3 Logistic regression equation

Like ordinary regression, logistic regression requires one dependent variable (y) and at least one independent variable. In logistic regression, the relationship between the mean or expected value of y and the independent variables ($x_1, x_2, \ldots, x_p$) is described by the following nonlinear equation (Anderson, Sweeney and Williams, 2008, p.666).

$$E(y) = (e^{\beta 0+\beta 1x1+\beta 2x2+\ldots+\beta pxp}) / (1+ e^{\beta 0+\beta 1x1+\beta 2x2+\ldots+\beta pxp}) \qquad (4.5)$$

If the values of the dependent variable are coded as 1 or 0, the value of E(y) in Equation 4.5 provides the probability that y =1 given a particular set of values for the independent variables. According to logistic regression equation, the probability of an event happening can be computed.

4.5.3.4 Judging the logistic regression

The logistic regression equation is used to model the probability for the two values of dependent variable (y = 1 or 0). The method of judging how well the model does is to fit the logistic model to the data and compute the fitted probabilities. A low proportion of data is classified correctly always means the logistic model does not work well. Conversely, a high proportion of correct classification would indicate the good performance of the model. In most practical cases, 0.5 is a recommended cut-off value for overall correct classification rate (Chatterjee and Hadi, 2006, p.328).

4.5.3.5 Summary for logistic regression

Logistic regression is a technique to assess the impact of a set of independent variables on a categorical dependent variable with two or more categories. The assumptions for logistic regression encompass the size of the sample, multicollinearity of independent variables and the outlying cases. In terms of retaining independent variables, a logarithm of the likelihood is usually used as the criterion of determining the number of variables. Furthermore, the correct classification rate of logistic regression is used for judging the model's performance. Finally, the binary logistic regression equation is used to calculate the probability for the two values of dependent variable ($y = 1$ or 0).

4.6 Conclusion

In summary, this chapter began with defining the distressed and non-distressed growth enterprises and identifying three categories of financial distress predictors. It then explained the methods for the distress prediction model, the process of data collection and sample selection in the present study.

According to literature and GEM Listing Rules on the definition of corporate financial distress, the present study defined a distressed growth enterprise as an enterprise which has experienced being filed for bankruptcy, cancellation of listing pursuant to delisting procedures under the GEM Listing Rules or suspension of securities trading for at least three months. The present study then summarizes firm-specific financial ratios, firm-specific non-financial variables and macroeconomic variables as the financial distress predictors.

The financial data were derived from the official portal of Hong Kong GEM. These data are reliable and trustworthy for the present study and they have been used by several important researches in recent years.

This chapter then reviewed the key types of sampling methods in social research. Three sampling methods which are frequently used in financial distress literature are matching pairs technique, matching larger number of non-distressed enterprises to smaller number of distressed enterprises and random sampling. In order to avoid the problems of matching sampling, the random sample selection was used to choose the sample. Based on the theory of random sample selection and the criterion for a distressed growth enterprise, 30 distressed and 70 non-distressed growth enterprises' data in the period from 2000 to 2009 were collected for further analysis.

In terms of methodology, the model of financial distress prediction encompassed MWW test, factor analysis and logistic regression. The present study ran the MWW test to distinguish the difference in financial and non-financial performance and macroeconomic situation between distressed and non-distressed growth enterprises. Factor analysis then reduced a group of variables to a smaller number of factors. The extracted financial, non-financial and macroeconomic factors are used as independent variables for logistic regression analyses.

Chapter 5 Data Analysis and Results

5.1 Introduction

The purpose of data analysis and results chapter is to establish financial distress prediction models for growth enterprises and test eight hypotheses. As the previous chapter discussed, the data of growth enterprises are from three consecutive years (T-1, T-2 and T-3). Therefore, this chapter is divided into three sections for the Year T-1, Year T-2 and Year T-3. In each section, the present study uses three methods to analyse the data for the corresponding year and test the hypotheses.

The MWW test was firstly run to distinguish the difference between distressed and non-distressed growth enterprises in financial and non-financial performance and their respective macroeconomic situations. This method was used to test Hypothesis 1, Hypothesis 3 and Hypothesis 5.

The present study then used factor analysis to reduce ten financial ratios to several financial factors. The non-financial and macroeconomic factors were then extracted from eight non-financial and macroeconomic variables. This resulted in a manageable number of factors which could be used in logistic regression.

After the MWW test and factor analysis, the extracted financial, non-financial and macroeconomic factors were used as independent variables for logistic regression analyses. The dependent variable is whether the growth enterprise experienced distress or not (distressed = 1, non-distressed =0). This chapter then used logistic regression analyses to establish three types of financial distress models. The first type of model only considers firm-specific financial factors whereas the second type of model considers firm-specific non-financial factors and macroeconomic factors. The third type of model considers not only firm-specific financial factors but also firm-specific financial factors and macroeconomic factors. Lastly, the study deployed these three types of models to test Hypothesis 2, Hypothesis 4, Hypothesis 6, Hypothesis 7 and Hypothesis 8. The following sections of this chapter are listed as follows:

Section 5.2 analyses the data of Year T-1 and tests hypotheses.

Section 5.3 analyses the data of Year T-2 and tests hypotheses.

Section 5.4 analyses the data of Year T-3 and tests hypotheses.

Section 5.5 finally concludes the whole chapter and interprets the findings.

5.2 Data analysis for the data of Year T-1 and testing hypotheses

5.2.1 Using the Mann-Whitney-Wilcoxon test to test Hypothesis 1, 3 and 5 (Year T-1)

According to statistical theory, the MWW test is used to determine whether there is a difference between two populations. The present study used the MWW test to test Hypothesis 1, Hypothesis 3 and Hypothesis 5.

In order to test these three hypotheses, the present study firstly inputted the values of all ten corporate financial ratios, four non-financial variables and four macroeconomic variables into the SPSS. It then used the MWW test to identify the difference in financial ratios, non-financial variables and macroeconomic variables between distressed and non-distressed growth enterprises. Hypothesis 1, Hypothesis 3 and Hypothesis 5 were tested by using the MWW test as follows.

Hypothesis 1:

Null Hypothesis 1: There are no significant differences in financial ratios between distressed and non-distressed growth enterprises.

Alternative Hypothesis 1: There are significant differences in financial ratios between distressed and non-distressed growth enterprises.

Table 5.1 presents the MWW test statistics for the financial ratios. In this table, the Z means the Z-score and the Asymp. Sig. (2-tailed) refers to the two-tailed *p* value which has been corrected for ties. The output of the test indicates that all the financial ratios except for quick ratio have two-tailed *p* values less than 0.05. In addition, the two-tailed *p* value of quick ratio is 0.057 which is slightly greater than 0.05. In other words, nine financial ratios' results of MWW test, with correction for Z-score conversion and ties, are significant at five per cent level of significance. Only the quick ratio's result of MWW test is not significant at five per cent level of significance. The results of MWW test shows there is significant difference in the Year T-1's nine financial variables between the distressed growth enterprises and non-distressed growth enterprises. Therefore, for all the tested financial variables except for quick ratio, the Null Hypothesis 1 has to be rejected. For only one financial variable (quick ratio), however, the Null Hypothesis 1 cannot be rejected.

Table 5.1 Test statistics for financial ratios [a, b] (Year T-1)

	ROA	ROE	Cash return on sales	Expense ratio	Asset turnover
MWW	234.500	336.500	524.500	639.500	661.500
Wilcoxon W	699.500	801.500	989.500	3124.500	1126.500
Z	-6.134	-5.367	-3.953	-3.088	-2.922
Asymp. Sig. (2-tailed)	0.000	0.000	0.000	0.002	0.003
	Gross profit margin	Debt to total assets	Cash debt coverage	Current ratio	Quick ratio
MWW	663.500	731.500	494.500	740.500	797.000
Wilcoxon W	1128.500	3216.500	959.500	1205.500	1262.000
Z	-2.907	-2.396	-4.178	-2.328	-1.903
Asymp. Sig. (2-tailed)	0.004	0.017	0.000	0.020	0.057

a. Grouping variables: financial status of the growth enterprises
b. Number of observations: 100

Hypothsis 3:

Null Hypothesis 3: There are no significant differences in non-financial variables between distressed and non-distressed growth enterprises.

Alternative Hypothesis 3: There are significant differences in non-financial variables between distressed and non-distressed growth enterprises.

Table 5.2 displays MWW test statistics for the non-financial variables. The output of the test indicates that all the non-financial variables have two-tailed *p* values less than 0.05. Accordingly, all the four non-financial variables' results of MWW test, with correction for Z-score conversion and ties, are significant at five per cent level of significance. Thus, the results of MWW test reveals that there are significant differences in the Year T-1's four non-financial variables between the distressed growth enterprises and non-distressed growth enterprises.

All the findings presented that there are significant differences in non-financial variables between distressed and non-distressed growth enterprises. Therefore, the Null Hypothesis 3 can be rejected.

Table 5.2 Test statistics for non-financial variables of Year T-1[a, b]

	Delay in releasing financial statements	Change auditors	Auditors' report with qualified opinion and/ or explanatory paragraph	Profit warning
MWW	385.000	549.500	575.000	910.000
Wilcoxon W	2870.000	3034.500	3060.000	3395.000
Z	-7.313	-5.068	-5.777	-3.102
Asymp. Sig. (2-tailed)	0.000	0.000	0.000	0.002

a. Grouping variables: non-financial status of the growth enterprises
b. Number of observations: 100

Hypothesis 5:

Null Hypothesis 5: There are no significant differences in macroeconomic variables between distressed and non-distressed growth enterprises.

Alternative Hypothesis 5: There are significant differences in macroeconomic variables between distressed and non-distressed growth enterprises.

Table 5.3 displays the MWW test statistics for the macroeconomic variables of Year T-1. The two-tailed *p* values of three macroeconomic variables, which have been corrected for ties, are less than 0.05. Accordingly, the results of these three macroeconomic variables are significant at five per cent level of significance. There is only one macroeconomic variable (Entrepreneur Confidence Index) which has a two-tailed *p* value larger than 0.05. Hence, the MWW test demonstrates that there are significant differences in the Year T-1's three macroeconomic conditions for the distressed growth enterprises and non-distressed growth enterprises.

Therefore, for three macroeconomic variables (real GDP growth rate, average interest rate on loans and Business Climate Index), the Null Hypothesis 5 has to be rejected. For one macroeconomic variable (Entrepreneur Confidence Index), however, the Null Hypothesis 5 cannot be rejected.

Table 5.3 Test statistics for macroeconomic variables of Year T-1[a, b]

	Real GDP growth rate	Average interest rate on loans	Business Climate Index	Entrepreneur Confidence Index
MWW	679.500	740.000	687.500	851.500
Wilcoxon W	1144.500	1205.000	1152.500	1316.500
Z	-2.872	-2.404	-2.810	-1.539
Asymp. Sig. (2-tailed)	0.004	0.016	0.005	0.124

a. Grouping variables: macroeconomic variables
b. Number of observations: 100

To sum up, the results of hypotheses testing are as follows. First, for all the tested financial variables except for quick ratio, the Null Hypothesis 1 has to be rejected. For only one financial variable (quick ratio), however, the Null Hypothesis 1 cannot be rejected. Second, the Null Hypothesis 3 has to be rejected. Finally, for three macroeconomic variables (real GDP growth rate, average interest rate on loans and Business Climate Index), the Null Hypothesis 5 has to be rejected. On the other hand, for one macroeconomic variable (Entrepreneur Confidence Index), the Null Hypothesis 5 cannot be rejected.

5.2.2 Using factor analysis and logistic regression to analyse data and test hypotheses (Year T-1)

As was discussed in Chapter 4, the present study used factor analysis to reduce ten financial ratios to several financial factors. The essential non-financial and macroeconomic factors were then extracted from a set of non-financial and macroeconomic variables. In addition, using factor analysis to extract the common factors made possible the modification of multicollinearity among all the ratios and variables considered in the present study (Kuo et al., 2003). The extracted key financial, non-financial and macroeconomic factors could then serve as inputted independent variables for logistic regression. This led to a manageable number of factors which could be used in logistic regression.

The dependent variable is whether the growth enterprise experienced distress or not (distressed = 1, non-distressed =0). The present study then used logistic regression analyses to establish three types of financial distress prediction models and test Hypothesis 2, Hypothesis 4, Hypothesis 6 , Hypothesis 7 and Hypothesis 8.

5.2.2.1 Assumption testing for factor analysis

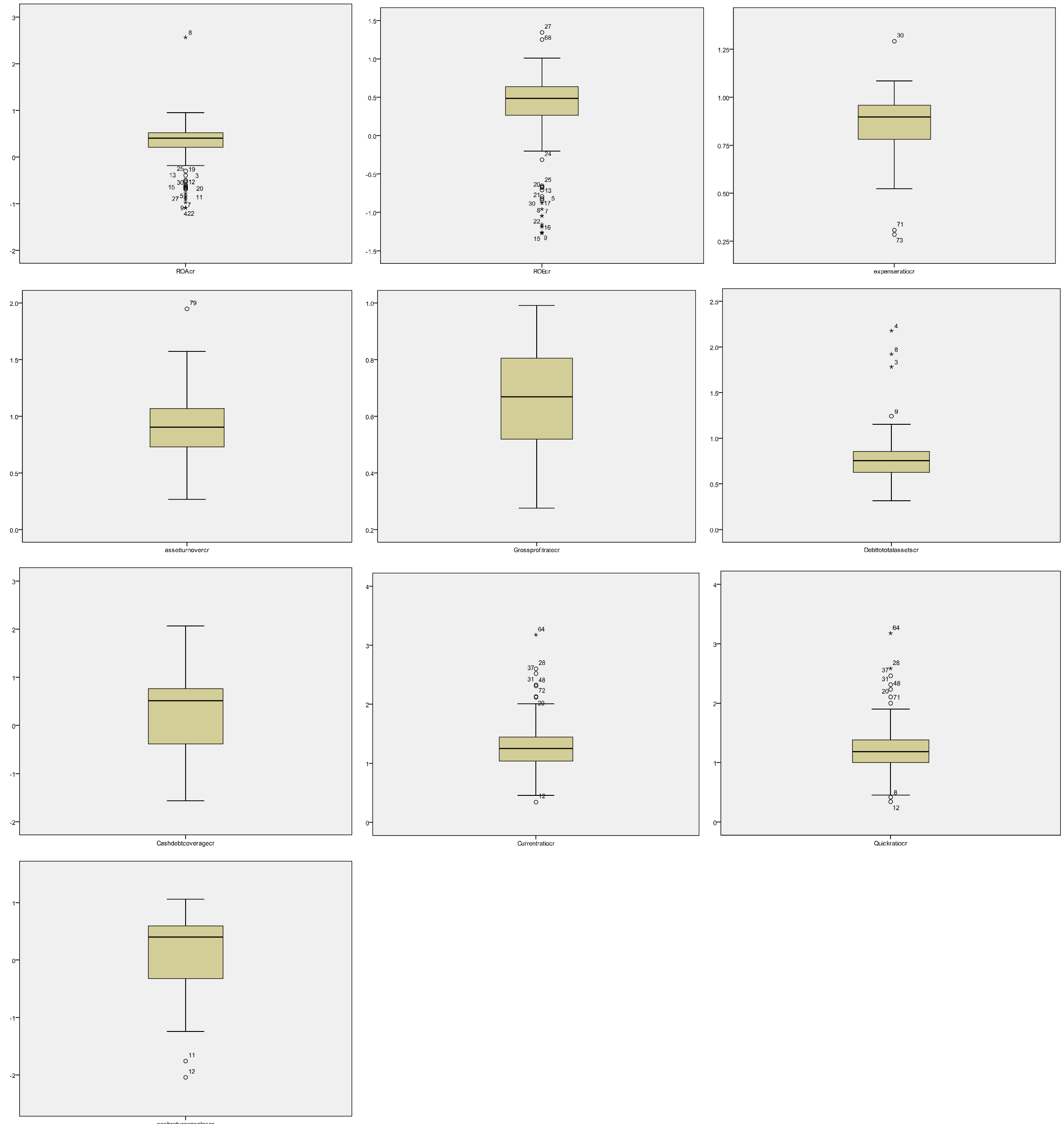
According to Pallant (2007), there are four assumptions underlying the application of factor analysis. The first assumption is the sample size. Although there is no common agreement in the literature concerning how large the sample should be, the overall sample size of 100 or more than 100 is acceptable and a minimum of five cases for each of the variables is required for factor analysis (Coak, 2005, p.154; Pallant, 2007, p.185). For the Year T-1, 100 growth enterprises' data are selected. These data incorporate the values of ten financial variables, four non-financial variables and four macroeconomic variables. Therefore, the sample size for the Year T-1 is suitable for factor analysis.

Second, since factor analysis is sensitive to outlying cases or outliers, these cases should be either removed from the data set or recoded to a less extreme value (Pallant, 2007, p.186). In SPSS, histogram, box plots and descriptive statistics of each variable or ratio are used to identify outliers (Pallant, 2007). The procedure of detecting outliers according to Pallant (2007) and Francis (2004) is as follows. First, the data points sitting on their own in the histogram are potential outliers. Second, in the box plots, any case, which extends more than 1.5 box-lengths from the edge of the box, is referred to as an outlier. The points indicated with a circle are those cases which extend more than 1.5 box-lengths from the edge of the box. The points indicated with an asterisk are those cases extend more than 3 box-lengths from the edge of the box.

Given that the values of all non-financial variables are discrete data, they are not suitable for detecting outliers. The present study only detected the outliers of financial ratios and macroeconomic variables. The first option for reducing the impact of outliers is to transform the variables (Tabachnick and Fidell, 2007, p. 77). The cube root is a commonly used transformation for both positive and negative data (Peck, Olsen and Devore, 2008, p. 249). The present study used cube root transformation and takes cube root of the values of the financial ratios and macroeconomic variables.

After data transformation, this study used SPSS to detect the outliers of the data. For the data of Year T-1, eight out of ten financial ratios' values have outliers (see Figure 5.1).

Figure 5.1 Box plots of all financial ratios (Year T-1)



In addition, two out of four macroeconomic variables' values have outliers (see Figure 5.2).

Figure 5.2 Box plots of all macroeconomic variables (Year T-1)

Given the limited cases deployed in the present study, deletion of the cases with outliers is not a reasonable strategy to reduce the influence of outliers. Besides deleting the cases with outliers, changing the score(s) on the outlying case(s) is an alternative method to reduce the influence of outliers. As Tabachnick and Fidell argued (2007, p. 77):

> A second option for univariate outliers is to change the score(s) on the variable(s) for the outlying case(s) so that they are deviant, but not as deviant as they were. For instance, assign the outlying case(s) a raw score on the offending variable that is one unit larger (or smaller) than the next most extreme score in the distribution. Because measurement of variables is sometimes rather arbitrary anyway, this is often an attractive alternative to reduce the impact of a univariate outlier.

Accordingly, the present study changed the value of outliers to the value of the next highest or lowest (non-outlier) case. As a result, the influence of all the outliers for Year T-1 was eliminated.

The third assumption is that the correlation matrix should have at least some correlations with *r* being no less than 0.3. Moreover, the Kaiser-Meyer-Olkin value ranges from 0 to 1 and should be no less than 0.5 (Child, 2006, p.55). The Bartlett's test of Sphericity should have a *p* value less than 0.05 (Pallant, 2007, p.185).

For the financial ratios of the Year T-1, the correlation matrix of all financial ratios is presented as Table 5.4. Table 5.4 shows that the correlation matrix of all financial variables for the Year T-1 has 12 correlations with *r* being greater than 0.3. With respect to non-financial variables and macroeconomic variables of the Year T-1, the correlation matrix of all non-financial variables and macroeconomic variables is presented as Table 5.5. This table provides that the correlation matrix of all non-financial variables and macroeconomic variables for the Year T-1 has eight correlations with *r* being greater than 0.3. Therefore, the matrix is suitable for factoring analysis.

Table 5.4 Correlation matrix of financial ratios for the Year T-1

	ROE	ROA	Cash return on sales	Expense ratio	Asset turnover	Gross profit rate	Debt to total assets	Cash debt coverage	Current ratio	Quick ratio
ROE	1.000	.648	.391	-.278	.316	.327	-.045	.393	.040	.038
ROA	.648	1.000	.533	-.337	.330	.325	-.216	.481	.204	.194
Cash return on sales	.391	.533	1.000	-.325	.127	.258	-.358	.854	.270	.287
Expense ratiocr	-.278	-.337	-.325	1.000	.170	-.692	.393	-.347	-.295	-.283
Asset turnover	.316	.330	.127	.170	1.000	-.060	.217	.076	-.182	-.222
Gross profit rate	.327	.325	.258	-.692	-.060	1.000	-.254	.317	.169	.148
Debt to total assets	-.045	-.216	-.358	.393	.217	-.254	1.000	-.353	-.860	-.835
Cash debt coverage	.393	.481	.854	-.347	.076	.317	-.353	1.000	.261	.290
Current ratio	.040	.204	.270	-.295	-.182	.169	-.860	.261	1.000	.974
Quick ratio	.038	.194	.287	-.283	-.222	.148	-.835	.290	.974	1.000

Table 5.5 Correlation matrix of non-financial and macroeconomic variables for the Year T-1

	Real GDP growth rate	Average interest rate on loans	Business Climate Index	Entrepreneur Confidence Index	Delay in releasing financial statements	Change auditors	Auditors' report with qualified opinion and/ or explanatory paragraph	Profit warning
Real GDP growth rate	1.000	.596	.945	.925	-.239	-.161	-.259	-.221
Average interest rate on loans	.596	1.000	.455	.395	-.187	-.222	-.175	.022
Business Climate Index	.945	.455	1.000	.996	-.221	-.107	-.185	-.229
Entrepreneur Confidence Index	.925	.395	.996	1.000	-.208	-.093	-.172	-.242
Delay in releasing financial statements	-.239	-.187	-.221	-.208	1.000	.377	.282	.255
Change auditors	-.161	-.222	-.107	-.093	.377	1.000	.329	.127
Auditors' report with qualified opinion and/ or explanatory paragraph	-.259	-.175	-.185	-.172	.282	.329	1.000	.242
Profit warning	-.221	.022	-.229	-.242	.255	.127	.242	1.000

The Kaiser-Meyer-Olkin measure of sampling adequacy and the results of the Bartlett's test of Sphericity are illustrated in Table 5.6 and Table 5.7. Table 5.6 indicates the Kaiser-Meyer-Olkin Measure and Bartlett's test for financial ratios in the Year T-1. The Kaiser-Meyer-Olkin Measure is 0.728 which is far greater than 0.5. It means that the financial ratios are adequate for factor analysis. Moreover, the Bartlett's test of Sphericity is significant with the *p* value less than 0.05. It suggests that there are significant correlations between the financial ratios.

Table 5.6 Kaiser-Meyer-Olkin Measure and Bartlett's Test for financial variables (Year T-1)

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		.728
Bartlett's Test of Sphericity	Approx. Chi-Square	771.652
	df	45
	Sig.	.000

Table 5.7 indicates the results of Kaiser-Meyer-Olkin Measure and Bartlett's test for non-financial and macroeconomic variables in the Year T-1. The Kaiser-Meyer-Olkin value is 0.669 which is greater than 0.5. This suggests that the non-financial and macroeconomic variables are adequate for factor analysis. Furthermore, the Bartlett's test of Sphericity is significant with the *p* value less than 0.05. It indicates that there are significant correlations between the variables.

Table 5.7 Kaiser-Meyer-Olkin Measure and Bartlett's Test for non-financial and macroeconomic variables (Year T-1)

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		.669
Bartlett's Test of Sphericity	Approx. Chi-Square	874.556
	df	28
	Sig.	.000

On the whole, according to the correlation matrix, Kaiser-Meyer-Olkin measure of sampling adequacy and Bartlett's Test of Sphericity, it can be concluded that the data of the present study is suitable for factor analysis.

To test the fourth assumption, the present study used scatter plots to check the linearity of the data. The scatter plots of financial ratios are presented in Appendix Figure A5.1 shows that there is no clear evidence of curvilinear relationship between any two financial ratios. The scatter plots of non-financial and macroeconomic variables are presented in Appendix Figure A5.2 shows that there is no clear evidence of curvilinear relationship between any two non-financial and macroeconomic variables. Therefore, the values of financial ratios, non-financial and macroeconomic variables are safe to do factor analysis (Pallant, 2007, p.185).

To sum up, all these four basic assumptions for factor analysis were used to assess the suitability of the data for factor analysis. They underlie the application of factor analysis. Based on the results of assumption testing, all these four basic assumptions for factor analysis are satisfied. Hence, the Year T-1's financial ratios, non-financial and macroeconomic variables for the present study are suitable for factor analysis.

5.2.2.2 Conducting factor analysis for financial ratios

5.2.2.2.1 Factor extraction

The present study used factor extraction to determine the smallest number of financial factors that could best represent the interrelations among a group of financial ratios. All the financial ratios for the Year T-1 were inputted into the SPSS. The most commonly used extraction technique (principal components) was then used to extract the underlying financial factors.

Firstly, Kaiser's criterion was used to assist in the decision concerning retaining the factors. As was discussed in Chapter 4, factors with eigenvalue greater than 1 could be retained for further investigation. In Table 5.8, there are three factors (Factor 1, 2 and 3) with their eigenvalues greater than 1. Overall, these three factors explain about 75 per cent of the original variance.

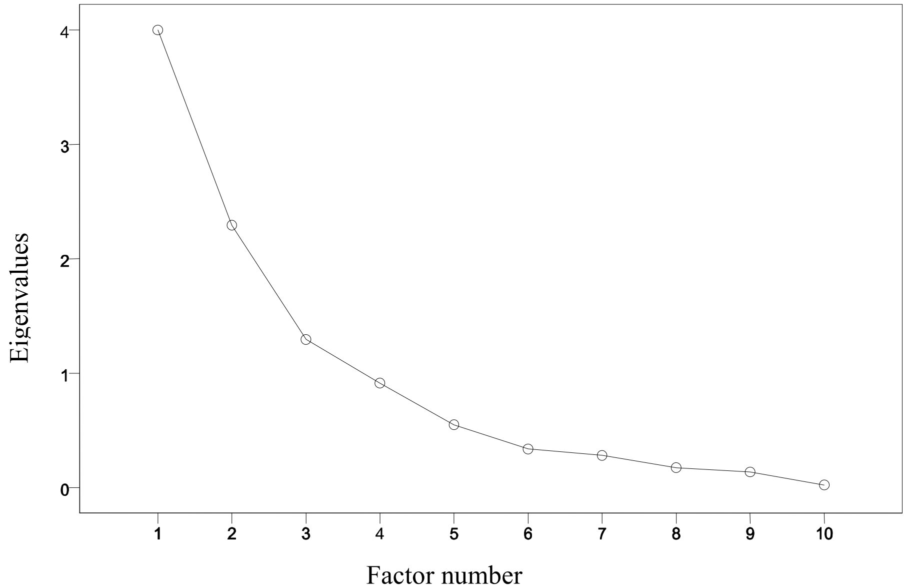
Table 5.8 Total variance explained for financial factors (Year T-1)

Factor	Initial Eigenvalues			Extraction Sums of Squared Loadings			Rotation Sums of Squared Loadings[a]
	Total	Percentage of Variance	Cumulative Percentage	Total	Percentage of Variance	Cumulative Percentage	Total
1	4.000	39.997	39.997	4.000	39.997	39.997	2.995
2	2.293	22.932	62.929	2.293	22.932	62.929	2.761
3	1.295	12.946	75.875	1.295	12.946	75.875	1.831
4	.913	9.130	85.005				
5	.549	5.487	90.492				
6	.337	3.369	93.861				
7	.281	2.813	96.674				
8	.174	1.742	98.417				
9	.137	1.365	99.782				
10	.022	.218	100.000				

Extraction Method: Principal Component Analysis.
a. When components are correlated, sums of squared loadings cannot be added to obtain a total variance.

Secondly, in Figure 5.3, the scree plot line begins to flatten out between the third and the fourth factor. As a result, according to theory of Catell's scree test discussed in Chapter 4, the scree plot also suggests that it is appropriate to retain three factors.

Figure 5.3 Scree plot for financial factors (Year T-1)



5.2.2.2.2 Factor rotation and interpreting factors

In order to interpret the factors, SPSS provides several methods for rotating the factors. As discussed in Chapter 4, there are two main approaches to rotation (the orthogonal approach and the oblique approach). The orthogonal approach produces factors which are uncorrelated. In contrast, the oblique approach allows the extracted factors to be highly correlated. In the present study, the extracted factors would be saved as the independent variables for logistic regression and these independent variables should be uncorrelated. Consequently, the orthogonal approach would be a more appropriate approach for the present study and the most commonly used orthogonal approach - Varimax method - was used in the study.

After the rotation, the number of complex variables among factors decrease and the factors become easier to be interpreted. The rotated factors are shown in the rotated factor matrix. Table

5.9 presents the items which constitute the three most important factors and these items' factor loadings. The cut off point for the absolute value of factor loading was set at 0.5.

Table 5.9 Rotated financial factor matrix[a] (Year T-1)

	Factor		
	1	2	3
Quick ratio	.959		
Current ratio	.957		
Debt to total assets	-.901		
ROA		.812	
Cash return on sales		.756	
ROE		.751	
Cash debt coverage		.718	
Asset turnover		.577	
Gross profit rate			.867
Expense ratio			-.859

Extraction Method: Principal Component Analysis.
Rotation Method: Varimax with Kaiser Normalization.
a. Rotation converged in 5 iterations.

The Table 5.9 indicates that Factor 1 comprises three items with factor loadings ranging from 0.959 to -0.901 and the most important item is quick ratio. The present study labels Factor 1 as Liquidity- Solvency Factor because Factor 1 consists of two liquidity ratios (current ratio and quick ratio) and one solvency ratio (debt to total assets ratio).

Factor 2 comprises five items with factor loadings ranging from 0.812 to 0.577 and the most important item is ROA. The present study labels Factor 2 as Profitability-Solvency Factor because Factor 2 consists of four profitability ratios (ROA, ROE, asset turnover ratio and cash return on sales) and one solvency ratio (cash debt coverage).

Factor 3 also includes two items: gross profit rate and expense ratio. The factor loadings of these two items are 0.867 and -0.859 respectively. The item which makes the most significant contribution to factor 3 is gross profit rate with factor loading of 0.867. The present study labels Factor 3 as Profitability Factor because Factor 3 consists of two profitability ratios (gross profit rate and expense ratio).

5.2.2.3 Conducting factor analysis for non-financial and macroeconomic variables

5.2.2.3.1 Factor extraction

The present study used factor extraction to determine the smallest number of non-financial and macroeconomic factors that can best represent the interrelations among non-financial and macroeconomic variables. All the non-financial and macroeconomic variables for the Year T-1 were inputted into the SPSS. The present study then applied the most commonly used extraction technique (principal components) to extract the underlying non-financial and macroeconomic factors.

Kaiser's criterion is used to decide the number of factors to retain and the factors with eigenvalue greater than 1 can be retained for further investigation. In Table 5.10, there are also three factors (Factor 1, 2 and 3) with their eigenvalues greater than 1. These three factors explain about 76 per cent of the totally original variance.

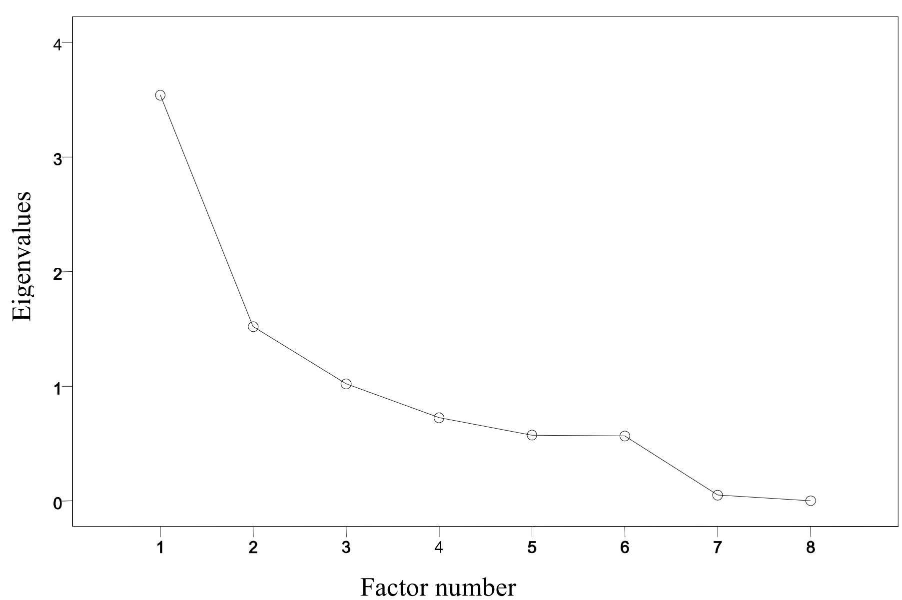
Table 5.10 Total variance explained for non-financial and macroeconomic factors (Year T-1)

Factor	Initial Eigenvalues			Extraction Sums of Squared Loadings			Rotation Sums of Squared Loadings
	Total	Percentage of Variance	Cumulative Percentage	Total	Percentage of Variance	Cumulative Percentage	Total
1	3.539	44.237	44.237	3.539	44.237	44.237	3.215
2	1.521	19.015	63.252	1.521	19.015	63.252	1.791
3	1.021	12.768	76.020	1.021	12.768	76.020	1.075
4	.725	9.065	85.085				
5	.575	7.184	92.269				
6	.567	7.083	99.352				
7	.050	.628	99.980				
8	.002	.020	100.000				

Extraction Method: Principal Component Analysis.

In Figure 5.4, the scree plot line begins to change in shape and flatten out between the third and the fourth factor. According to theory of Catell's scree test, only the factors above the fourth factor can be retained. Therefore, the scree plot also suggests that it is appropriate to retain three factors.

Figure 5.4 Scree plot for non-financial and macroeconomic factors (Year T-1)



5.2.2.3.2 Factor rotation and interpreting factors

In the present study, the rotation of financial factors is similar to the rotation of non-financial and macroeconomic factors. In addition, all of the extracted factors will be saved as independent variables for logistic regression and those independent variables should be uncorrelated. Hence, the orthogonal approach and the most commonly used orthogonal approach (Varimax method) were also used for extracting non-financial and macroeconomic factors in the present study.

After the rotation, the number of complex variables among factors decreased and the factors became easier to be interpreted. The rotated factors are shown in the rotated factor matrix. Table 5.11 presents the items which constitute the three extracted factors and these items' factor loadings. The cut off point for the absolute value of factor loading is 0.5.

Table 5.11 Rotated non-financial and macroeconomic factor matrix[a] (Year T-1)

	Factor		
	1	2	3
Business Climate Index	.975		
Real GDP growth rate	.965		
Entrepreneur Confidence Index	.961		
Average interest rate on loans	.585		
Changing auditors		.814	
Delay in releasing financial statements		.696	
Auditors' report with qualified opinion and/ or explanatory paragraph		.660	
Profit warning			.846

Extraction Method: Principal Component Analysis.
Rotation Method: Varimax with Kaiser Normalization.
a. Rotation converged in 5 iterations.

Table 5.11 indicates that Factor 1 comprises four items with factor loadings ranging from 0.975 to 0.585 and the most important item is the Business Climate Index. Furthermore, real GDP growth rate and Entrepreneur Confidence Index are other two important items, with their factor loadings quite close to the factor loading of Business Climate Index. The present study interpreted Factor 1 as Macroeconomic Factor because Factor 1 refers to four macroeconomic variables which include Business Climate Index, Entrepreneur Confidence Index, real GDP growth rate and average interest rate on loans.

Factor 2 consists of three items with factor loadings ranging from 0.814 to 0.66 and the most important item is ‘changing auditors’. Below this item, the items ‘delay in releasing financial statements’ and ‘auditors’ report with qualified opinion and/ or explanatory paragraph’ have factor loadings of 0.696 and 0.66 respectively. The present study labelled Factor 2 as Auditing-Disclosure Factor because Factor 2 consists of two non-financial variables concerning auditing (‘changing auditors’ and ‘auditors’ report with qualified opinion and/ or explanatory paragraph’) and one non-financial variable referring to corporate disclosure (‘delay in releasing financial statements’).

Factor 3 has only one item and the item is ‘profit warning’. This item with a factor loading of 0.846 contributes the most to Factor 3. As a result, the present study simply labelled Factor 3 as the Profit Warning Factor.

In summary, there are three financial factors extracted from financial ratios. Based on the items that constitute the factors, the present study labelled the three factors as Liquidity- Solvency Factor, Profitability- Solvency Factor and Profitability Factor respectively. Additionally, three non-financial and macroeconomic factors were generated from non-financial and macroeconomic variables. According to the items that constitute these factors, the present study labelled the three factors as Macroeconomic Factor, Auditing-Disclosure Factor and Profit Warning Factor. All of these six factors were used as independent variables for logistic regression analyses.

5.2.3 Logistic regression analysis (Year T-1)

After the MWW test and factor analysis, the extracted financial, non-financial and macroeconomic factors were used as independent variables for logistic regression analyses. The dependent variable is whether the growth enterprise experienced distress or not (distressed = 1, non-distressed = 0). The present study then used logistic regression analysis to establish three types of financial distress prediction models and test related hypotheses.

The first type of model considered firm-specific financial factors only, whereas the second type of model considered firm-specific non-financial factors and macroeconomic factors. The third type of model considered not only firm-specific financial factors but also firm-specific non-financial factors and macroeconomic factors. These three models were referred to as Model 1, Model 2 and Model 3 respectively. The study compared classification accuracy of Model 1 with that of Model 2. Subsequently, the study compared classification accuracy of Model 1 with that of Model 3. Finally, all the hypotheses in the present study were tested and the results were discussed.

5.2.3.1 Assumptions testing for logistic regression

As was discussed in Chapter 4, the first assumption refers to the number of cases in the sample and the number of independent variables included in the logistic regression model. The logistic regression might have problems, if there are a large number of independent variables with a small sample. In particular, it becomes a serious problem when the categorical independent variables have quite limited cases in each category.

The present study produced three logistic regression models. Model 1 considered three financial factors as independent variables; Model 2 considered three non-financial and macroeconomic factors as independent variables; Model 3 considered all the six factors as independent variables which included financial, non-financial and macroeconomic factors. Moreover, there were 100 growth enterprises considered in this study. In other words, there were a relatively small number of independent variables with a relatively large sample. Hence, the sample size of this study and its independent variables are suitable for logistic regression.

The second assumption is about checking for intercorrelations or multicollinearity among independent variables. Ideally, the independent variables should not be strongly related to each other and the highly intercorrelating variables have to be removed (Pallant, 2007, p.167). In the present study, given the orthogonal approach always results in uncorrelated factors, the three financial factors extracted by using the orthogonal approach (Varimax method) should be uncorrelated. In the same way, the three non-financial and macroeconomic factors also should be uncorrelated.

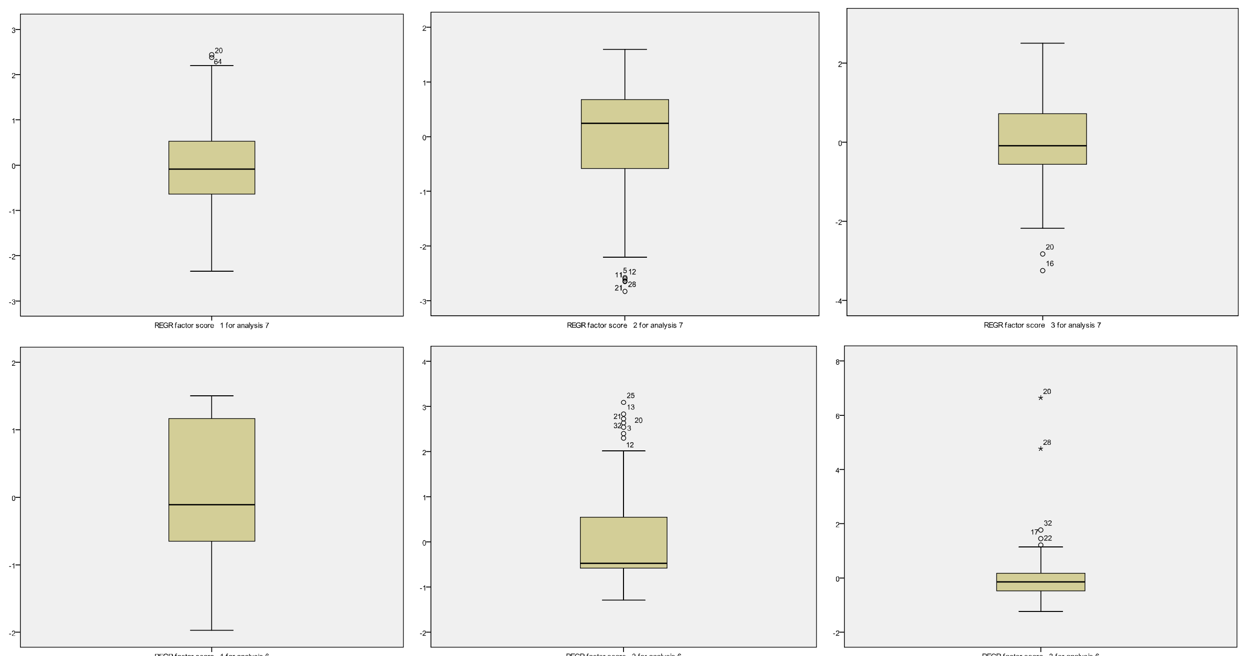
In order to check the multicollinearity of all these six factors, the present study checked the intercorrelation among these factors. Multicollinearity occurs when these factors are highly correlated with the value of *r* being no less than 0.9 (Tabachnick and Fidell, 2007, p. 88). The values of Pearson correlation in Table 5.12 show that the values of *r* are all less than 0.9. Therefore, there are no multicollinearities among these six factors and all these factors can be retained.

Table 5.12 Pearson Correlation of all factors (Year T-1)

	Liquidity-Solvency Factor	Profitability-Solvency Factor	Profitability Factor	Macroeconomic Factor	Auditing-Disclosure Factor	Profit Warning Factor
Liquidity-Solvency Factor	1.000	.170	-.133	.039	-.221	-.088
Profitability-Solvency Factor	.170	1.000	.055	.189	-.499	-.149
Profitability Factor	-.133	.055	1.000	-.305	.484	.532
Macroeconomic Factor	.039	.189	-.305	1.000	-.433	-.465
Auditing-Disclosure Factor	-.221	-.499	.484	-.433	1.000	.781
Profit Warning Factor	-.088	-.149	.532	-.465	.781	1.000

Finally, because of outliers influencing the results of logistic regression, the third assumption is about checking for the presence of outliers. If there are some cases that are not well explained by the model, these outlying cases would be removed or recoded to a lesser value (Tabachnick and Fidell, 2007, p. 77). In SPSS, histograms, box plots and descriptive statistics of each variable or ratio are used to identify outliers (Pallant, 2007). After checking the outliers, this study found five out of these six factors had outlying cases (see Figure 5.5).

Figure 5.5 Box plots of all factors (Year T-1)



As has been discussed previously, the present study changed the value of outliers to the value of the next highest or lowest (non-outlier) case. As a result, the influence of all the outliers for all the factors was eliminated.

5.2.3.2 Conducting logistic regression analysis for financial factors

As discussed previously, the three financial factors were used as independent variables and whether the growth enterprise having experienced distress was regarded as a dependent variable. The dependent variable was coded as follows: 0 was used to indicate the growth enterprise having not experienced financial distress and 1 was used to indicate the growth enterprise having experienced financial distress. The present study inputted these three independent variables and one dependent variable into SPSS and ran the logistic regression to analyse them. This logistic regression analysis was referred to as Model 1 for Year T-1 in this study.

The output of the logistic regression analysis (Model 1) and the interpretation of the output are as follows.

At the beginning, the Omnibus Tests of Model Coefficients provides an overall prediction of how well the model with three financial independent variables performs compared with the model without considering independent variables (Pallant, 2007, p.174). Panel A of Table 5.13 presents the significant value for Omnibus Tests of Model Coefficients as less than 0.05. Hence, the model with three financial factors used as independent variables is better than the model without using any financial factors as independent variables. The χ^2 (3, N = 100) = 66.006 with $p < 0.001$ also indicates that the model including three financial independent variables is able to distinguish between growth enterprises which have experienced financial distress and which have not experienced financial distress (Pallant, 2007, p.178).

The results shown in Panel B of Table 5.13 also provide some information about the usefulness of the model. The value of Cox and Snell R Square and the value of Nagelkerke R Square, which are from a minimum value of 0 to a maximum value of 1, indicate the amount of variation in the dependent variable explained by the model (Pallant, 2007, p.174). It can be seen from Table 5.13 (Panel B) that the value of Cox and Snell R Square and the value of Nagelkerke R Square are 0.483 and 0.685 respectively. In other words, between 48.3 per cent and 68.5 per cent of the variability in the dependent variable is explained by the independent variables.

Table 5.13 The performance and usefulness of Model 1

Panel A Omnibus Tests of Model Coefficients for Model 1

		Chi-square	Df	Sig.
Step 1	Step	66.006	3	.000
	Block	66.006	3	.000
	Model	66.006	3	.000

Panel B Model Summary for Model 1

-2 Log likelihood	Cox and Snell R Square	Nagelkerke R Square
56.167[a]	.483	.685

a. Estimation terminated at iteration number 6 because parameter estimates changed by less than .001.

Table 5.14 then shows the overall percentage of correctly classified cases without any independent variables deployed in this model. This is regarded as a baseline for comparing the model with another model which includes the independent variables. When the independent variables are not entered into the model, the overall percentage of correctly classified cases is 70 per cent (see Table 5.14).

Table 5.14 Classification for Model 1 [a,b] (without the independent variables)

Observed		Predicted		
		Status		Percentage Correct
		0	1	
Status	0	70	0	100.0
	1	30	0	.0
Overall Percentage				70.0

a. Constant is included in the model.
b. The cut value is .500

On the other hand, Table 5.15 shows the overall percentage of correctly classified cases when the model includes all independent variables. The present study compared this with the overall percentage of correctly classified case in Table 5.15 to see the improvement of including the independent variable in the model. Therefore, the model with the independent variable correctly classified 89 per cent of cases overall and has a great improvement over the 70 per cent of accuracy in classification for the model without using independent variables.

Table 5.15 Classification for Model 1[a] (with the independent variables)

Observed		Predicted		
		Status		Percentage Correct
		0	1	
Status	0	66	4	94.3
	1	7	23	76.7
Overall Percentage				89.0

a. The cut value is .500

As shown in Table 5.16, only one independent variable (Profitability-Solvency Factor) has a *Sig.* value less than 0.05. Therefore, Profitability-Solvency Factor made a statistically significant contribution to the model at the five per cent level. The other two financial independent variables (Liquidity- Solvency Factor and Profitability Factor) do not contribute significantly to the model.

The *B* values provided in Table 5.16 can be used in an equation to compute the probability of a case falling into a specific category (Pallant, 2007, p.175). Positive *B* value indicates that an increase in the independent variable causes an increase in the probability of the case that the dependent variable equals 1. In contrast, negative *B* value indicates that increasing the independent variable causes a decrease in probability of the case that the dependent variable equals 1 (Pallant, 2007, p.176). For the significant independent variable in Model 1, Profitability-Solvency Factor has a negative *B* value (-3.022). This suggests that: if a growth enterprise has higher Profitability-Solvency Factor, it is less likely to experience financial distress.

Table 5.16 Financial independent variables in the equation for Model 1

	B	S.E.	Wald	df	Sig.	Exp(B)
Liquidity-Solvency Factor	-.513	.369	1.930	1	.165	.599
Profitability-Solvency Factor	-3.022	.636	22.601	1	.000	.049
Profitability Factor	-.506	.399	1.607	1	.205	.603
Constant	-1.444	.382	14.315	1	.000	.236

5.2.3.3 Conducting logistic regression analysis for non-financial and macroeconomic factors

As discussed previously, the three non-financial and macroeconomic factors were used as independent variables and whether the growth enterprise having experienced distress was regarded as a dependent variable. The dependent variable was coded as follows: 0 was used to indicate the growth enterprise having not experienced financial distress and 1 was used to indicate the growth enterprise having experienced financial distress. The present study inputted these three independent variables and one dependent variable into SPSS and ran the logistic regression to analyse them. This logistic regression analysis was referred to as Model 2 for Year T-1 in this study.

The output of the logistic regression analysis (Model 2) and the interpretation of the output are as follows.

At the beginning, the Omnibus Tests of Model Coefficients provides an overall prediction of how well the model with three independent variables performs compared with the model without considering independent variables (Pallant, 2007, p.174). Panel A of Table 5.17 presents the significant value for Omnibus Tests of Model Coefficients as less than 0.05. Hence, the model with three factors used as independent variables is better than the model without using any factors as independent variables. The χ^2 (3, N = 100) = 78.165 with p < 0.001 also indicates that the model including three independent variables is able to distinguish between growth enterprises which have experienced financial distress and which have not experienced financial distress (Pallant, 2007, p.178).

It can be seen from Table 5.17 (Panel B) that the value of Cox and Snell R Square and the value of Nagelkerke R Square are 0.542 and 0.769 respectively. In other words, between 54.2 per cent and 76.9 per cent of the variability in the dependent variable is explained by the independent variables.

Table 5.17 The performance and usefulness of Model 2

Panel A Omnibus Tests of Model Coefficients for Model 2

		Chi-square	Df	Sig.
Step 1	Step	78.165	3	.000
	Block	78.165	3	.000
	Model	78.165	3	.000

Panel B Model Summary for Model 2

-2 Log likelihood	Cox and Snell R Square	Nagelkerke R Square
56.167[a]	.542	.769

a. Estimation terminated at iteration number 7 because parameter estimates changed by less than .001.

As discussed previously, when the independent variables are not entered into the model, the overall percentage of correctly classified cases is 70 per cent (see Table 5.14). On the other hand, Table 5.18 shows the overall percentage of correctly classified cases when the model includes all independent variables. The present study compared this with the overall percentage of correctly classified case in Table 5.18 to see the improvement of including the independent variable in the model. Therefore, the model with the independent variable correctly classified 94 per cent of cases overall and has a great improvement over the 70 per cent of accuracy in classification for the model without using independent variables.

Table 5.18 Classification for Model 2[a] (with the independent variables)

Observed		Predicted		
		Status		Percentage Correct
		0	1	
Status	0	69	1	98.6
	1	5	25	83.3
Overall Percentage				94.0

a. The cut value is .500

As shown in Table 5.19, three independent variables (Macroeconomic Factor, Auditing-Disclosure Factor and Profit Warning Factor) have their *Sig.* values less than 0.05. Therefore, Macroeconomic Factor, Auditing-Disclosure Factor and Profit Warning Factor make a statistically significant contribution to the model at the five per cent level.

The *B* values provided in Table 5.19 can be used in an equation to compute the probability of a case falling into a specific category (Pallant, 2007, p.175). For the significant independent variable in Model 2, Macroeconomic Factor has a negative *B* value (-1.123). This suggests that: if a growth enterprise has higher Macroeconomic Factor, it is less likely to experience financial distress. Auditing-Disclosure Factor and Profit Warning Factor have positive *B* values which are

4.742 and 3.357 respectively. This suggests that: if a growth enterprise has higher Auditing-Disclosure Factor and Profit Warning Factor, it is more likely to experience financial distress.

Table 5.19 Non-financial and macroeconomic independent variables in the equation for Model 2

	B	S.E.	Wald	df	Sig.	Exp(B)
Macroeconomic Factor	-1.123	.428	6.893	1	.009	.325
Auditing-Disclosure Factor	4.742	1.029	21.230	1	.000	114.690
Profit Warning Factor	3.357	1.030	10.614	1	.001	28.697
Constant	-.328	.445	.541	1	.462	.721

5.2.3.4 Testing Hypothesis 7

Hypothesis 7 is tested based on the outputs of Model 1 and Model 2 as follows.

Hypothesis 7:

Null Hypothesis 7: The model incorporating firm-specific financial factors is not better than the model which includes firm-specific non-financial and macroeconomic factors in financial distress prediction.

Alternative Hypothesis 7: The model incorporating firm-specific financial factors is better than the model which includes firm-specific non-financial and macroeconomic factors in financial distress prediction.

The findings presented in Table 5.15 indicate that the model 1 correctly classified 89 per cent of cases. The findings presented in Table 5.18 indicate that the model 2 correctly classified 94 per cent of cases. The classification accuracy of Model 2 (94 per cent) is higher than the classification accuracy of Model 1 (89 per cent). Therefore, Null Hypothesis 7 cannot be rejected.

5.2.3.5 Conducting logistic regression analysis for all factors

As discussed previously, the six factors, including financial, non-financial and macroeconomic factors, were used as independent variables and whether the growth enterprise had experienced distress was regarded as a dependent variable. The dependent variable was coded as 0, 1. 0 was used to indicate the growth enterprise having not experienced financial distress, and 1 was used to indicate the growth enterprise had experienced financial distress. The present study inputted these six independent variables and one dependent variable into SPSS and ran the logistic regression to analyse them. This logistic regression analysis was referred to as Model 3 for Year T-1 in this study.

The output of the logistic regression analysis (Model 3) and the interpretation of the output are as follows.

At the beginning, the Omnibus Tests of Model Coefficients provides an overall prediction of how well the model with six independent variables performs compared with the model, without considering independent variables (Pallant, 2007, p.174). It can be seen from Panel A of Table 5.20 that the significant value for Omnibus Tests of Model Coefficients is less than 0.05. Hence, the model with six factors used as independent variables is better than the model without using any factors as independent variables. The χ^2 (6, N = 100) = 100.951 with $p < 0.001$ also indicates that the model covering six independent variables is able to distinguish between growth enterprises which have experienced financial distress and which have not experienced financial distress (Pallant, 2007, p.178).

The results shown in Panel B of Table 5.20 also provide some information about the usefulness of the model. Table 5.20 (Panel B) presents that the values of Cox and Snell R Square and the value of Nagelkerke R Square are 0.636 and 0.901 respectively. In other words, between 63.6 per cent and 90.1 per cent of the variability in the dependent variable is explained by the independent variables.

Table 5.20 The performance and usefulness of Model 3

Panel A Omnibus Tests of Model Coefficients for Model 3

		Chi-square	df	Sig.
Step 1	Step	100.951	6	.000
	Block	100.951	6	.000
	Model	100.951	6	.000

Panel B Model summary for Model 3

-2 Log likelihood	Cox and Snell R Square	Nagelkerke R Square
21.222[a]	.636	.901

a. Estimation terminated at iteration number 9 because parameter estimates changed by less than .001.

As discussed previously, when the independent variables are not entered into the model, the overall percentage of correctly classified cases is 70 per cent (see Table 5.14). On the other hand, Table 5.21 shows the overall percentage of correctly classified cases when the model includes all independent variables. The present study compared this with the overall percentage of correctly classified cases in Table 5.21 to see the improvement of including the independent variable in the model. Therefore, the model with six independent variables correctly classified 98 per cent of cases overall and has a great improvement over the 70 per cent of accuracy in classification for the model without using independent variables.

Table 5.21 Classification for Model 3 [a] (with the independent variables)

Observed		Predicted		
		Status		Percentage Correct
		0	1	
Status	0	69	1	98.6
	1	1	29	96.7
Overall Percentage				98.0

a. The cut value is .500

As shown in Table 5.22, there are two independent variables (Profitability-Solvency Factor and Auditing-Disclosure Factor) with their *Sig.* values less than 0.05. Therefore, Profitability-Solvency Factor and Auditing-Disclosure Factor contribute significantly to the predictive ability of the model at the five per cent level. The other four independent variables (Liquidity-Solvency Factor, Profitability Factor Macroeconomic Factor and Profit Warning Factor) do not contribute significantly to the model.

As discussed previously, the *B* values provided in Table 5.22 can be used to compute the probability of a case falling into a specific category. For the two significant independent variables in this model, Profitability-Solvency Factor has a negative *B* value (-4.316), whereas Auditing-Disclosure Factor has a positive *B* values (4.796). The *B* value of Profitability-Solvency Factor indicates that if a growth enterprise has a higher value in Profitability-Solvency Factor, this growth enterprise was less likely to experience financial distress in one year. In contrast, the *B* value of Auditing-Disclosure Factor shows that if a growth enterprise more frequently had the problems in auditing and disclosure, this growth enterprise was more likely to experience financial distress in one year.

Table 5.22 Independent variables in the equation for Model 3

	B	S.E.	Wald	Df	Sig.	Exp(B)
Liquidity- Solvency Factor	-.326	.672	.235	1	.628	.722
Profitability-Solvency Factor	-4.316	1.606	7.219	1	.007	.013
Profitability Factor	.388	.766	.256	1	.613	1.474
Macroeconomic Factor	-.825	.759	1.181	1	.277	.438
Auditing-Disclosure Factor	4.796	1.629	8.671	1	.003	120.972
Profit Warning Factor	2.711	1.781	2.318	1	.128	15.047
Constant	-1.694	.908	3.483	1	.062	.184

5.2.3.6 Testing Hypothesis 2, 4, 6 and 8

Hypothesis 2, Hypothesis 4, Hypothesis 6 and Hypothesis 8 were tested based on the outputs of Model 3 as follows.

Hypothesis 2:

Null Hypothesis 2: For the proposed model incorporating firm-specific financial, firm-specific non-financial and macroeconomic factors, the firm-specific financial factors are not significant predictors of growth enterprises' financial distress.

Alternative Hypothesis 2: For the proposed model incorporating firm-specific financial, firm-specific non-financial and macroeconomic factors, the firm-specific financial factors are significant predictors of growth enterprises' financial distress.

As discussed previously, the findings presented in Table 5.22 indicate that only one of the financial factors (Profitability-Solvency Factor) has a *Sig.* value less than 0.05. In other words, the Profitability-Solvency Factor, which was extracted from financial ratios, is a significant predictor of growth enterprises' financial distress at the five per cent level. Therefore, for Model 3, the Null Hypothesis 2 has to be rejected.

Hypothesis 4:

Null Hypothesis 4: For the proposed model incorporating firm-specific financial, firm-specific non-financial and macroeconomic factors, the firm-specific non-financial factors are not significant predictors of growth enterprises' financial distress.

Alternative Hypothesis 4: For the proposed model incorporating firm-specific financial, firm-specific non-financial and macroeconomic factors, the firm-specific non-financial factors are significant predictors of growth enterprises' financial distress.

The findings presented in Table 5.22 also indicate that one non- financial factor (Auditing-Disclosure Factor) has its *Sig.* value less than 0.05. In other words, Auditing-Disclosure Factor, which was extracted from non-financial variables, is a significant predictor of growth enterprises' financial distress at the five per cent level. Therefore, for Model 3, the Null Hypothesis 4 has to be rejected.

Hypothesis 6:

Null Hypothesis 6: For the proposed model incorporating firm-specific financial, firm-specific non-financial and macroeconomic factors, the macroeconomic factors are not significant predictors of growth enterprises' financial distress.

Alternative Hypothesis 6: For the proposed model incorporating firm-specific financial, firm-specific non-financial and macroeconomic factors, the macroeconomic factors are significant predictors of growth enterprises' financial distress.

According to the findings presented in Table 5.22, Macroeconomic Factor, which consists of four macroeconomic variables, has its *Sig.* value more than 0.05. Macroeconomic Factor is not a significant predictor of growth enterprises' financial distress. Thus, for Model 3, the Null Hypothesis 6 cannot be rejected.

Hypothesis 8:

Null Hypothesis 8: The proposed model incorporating firm-specific financial, firm-specific non-financial and macroeconomic factors is not better than the model which only includes firm-specific financial factors in financial distress prediction.

Alternative Hypothesis 8: The proposed model incorporating firm-specific financial, firm-specific non-financial and macroeconomic factors is better than the model which only includes firm-specific financial factors in financial distress prediction.

The findings presented in Table 5.15 and Table 5.21 reveal that the classification accuracy of Model 3 (98 per cent) is higher than the classification accuracy of Model 1 (89 per cent). The firm-specific non-financial and macroeconomic factors helped enhance the classification accuracy of the model. These results confirmed that Model 3 is better than Model 1 in classification accuracy. Based on all the findings, the Null Hypothesis 8 has to be rejected.

To sum up, for Year T-1, the Null Hypothesis 2 has to be rejected; the Null Hypothesis 4 has to be rejected; the Null Hypothesis 6 cannot be rejected; the Null Hypothesis 7 cannot be rejected; the Null Hypothesis 8 has to be rejected.

5.3 Data analysis for data of Year T-2

5.3.1 Using the Mann-Whitney-Wilcoxon test to test Hypothesis 1, 3 and 5 (Year T-2)

According to statistical theory, the MWW test is used to determine whether there is a difference between two populations. The present study used the MWW test to test Hypothesis 1, Hypothesis 3 and Hypothesis 5.

In order to test these three hypotheses, the present study firstly inputted the values of all ten corporate financial ratios, four non-financial variables and four macroeconomic variables into the SPSS. It then used the MWW test to identify the difference in financial ratios, non-financial variables and macroeconomic variables between distressed and non-distressed growth enterprises. Hypothesis 1, Hypothesis 3 and Hypothesis 5 were tested by using the MWW test as follows.

Hypothesis 1:

Null Hypothesis 1: There are no significant differences in financial ratios between distressed and non-distressed growth enterprises.

Alternative Hypothesis 1: There are significant differences in financial ratios between distressed and non-distressed growth enterprises.

Table 5.23 presents the MWW test statistics for financial ratios. In this table, the Z means the Z-score and the Asymp. Sig. (2-tailed) refers to the two-tailed *p* value which has been corrected for ties. The output of the test indicates that all the financial ratios except for expense ratio, gross profit margin and quick ratio have two-tailed *p* values less than 0.05. Seven financial ratios' results of MWW test, with correction for Z-score conversion and ties, are significant at five per cent level of significance. Therefore, for seven financial ratios, the Null Hypothesis 1 can be rejected. However, for expense ratio, gross profit margin and quick ratio, the Null Hypothesis 1 cannot be rejected.

Table 5.23 Test statistics for financial ratios [a, b] (Year T-2)

	ROA	ROE	Cash return on sales	Expense ratio	Asset turnover
MWW	230.500	292.000	601.500	833.000	615.500
Wilcoxon W	695.500	757.000	1066.500	3318.000	1080.500
Z	-6.164	-5.702	-3.374	-1.632	-3.268
Asymp. Sig. (2-tailed)	.000	.000	.001	.103	.001
	Gross profit margin	Debt to total assets	Cash debt coverage	Current ratio	Quick ratio
MWW	880.500	773.500	481.500	785.500	828.500
Wilcoxon W	1345.500	3258.500	946.500	1250.500	1293.500
Z	-1.275	-2.080	-4.276	-1.990	-1.666
Asymp. Sig. (2-tailed)	.202	.038	.000	.047	.096

a. Grouping variables: financial status of the growth enterprises
b. Number of observations: 100

Hypothsis 3:

Null Hypothesis 3: There are no significant differences in non-financial variables between distressed and non-distressed growth enterprises.

Alternative Hypothesis 3: There are significant differences in non-financial variables between distressed and non-distressed growth enterprises.

Table 5.24 displays MWW test statistics for non-financial variables. The output of the test indicates that three out of four non-financial variables have two-tailed p values less than 0.05. Accordingly, these three non-financial variables' results of MWW test, with correction for Z-score conversion and ties, are significant at five per cent level of significance. Only one non-financial variable (profit warning) has two-tailed p value more than 0.05. Thus, the results of

MWW test reveals that there are significant differences in the Year T-2's three non-financial variables between the distressed growth enterprises and non-distressed growth enterprises. On the other hand, there are no significant differences between distressed and non-distressed growth enterprises when applying profit warning. Therefore, for three non-financial variables ('changing auditors', 'delay in releasing financial statements' and 'auditors' report with qualified opinion and/ or explanatory paragraph'), the Null Hypothesis 3 can be rejected. However, for profit warning, the Null Hypothesis 3 cannot be rejected.

Table 5.24 Test statistics for non-financial variables of Year T-2[a, b]

	Delay in releasing financial statements	Changing auditors	Auditors' report with qualified opinion and/ or explanatory paragraph	Profit warning
MWW	735.000	562.000	835.000	1015.000
Wilcoxon W	3220.000	3047.000	3320.000	3500.000
Z	-4.774	-5.084	-3.262	-1.528
Asymp. Sig. (2-tailed)	.000	.000	.001	.127

a. Grouping variables: non-financial status of the growth enterprises
b. Number of observations: 100

Hypothesis 5:

Null Hypothesis 5: There are no significant differences in macroeconomic variables between distressed and non-distressed growth enterprises.

Alternative Hypothesis 5: There are significant differences in macroeconomic variables between distressed and non-distressed growth enterprises.

Table 5.25 displays the MWW test statistics for macroeconomic variables of Year T-2. The two-tailed *p* values of two macroeconomic variables (real GDP growth rate and average interest rate on loans), which have been corrected for ties, are less than 0.05. There are two macroeconomic variables (Business Climate Index and Entrepreneur Confidence Index) which have their two-tailed *p* values larger than 0.05. Hence, the MWW test demonstrates that there are significant differences in the Year T-2's two macroeconomic variables for the distressed growth enterprises and non-distressed growth enterprises.

Therefore, for two macroeconomic variables (real GDP growth rate and average interest rate on loans), the Null Hypothesis 5 has to be rejected. For two macroeconomic variable (Business Climate Index and Entrepreneur Confidence Index), however, the Null Hypothesis 5 cannot be rejected.

Table 5.25 Test statistics for macroeconomic variables of Year T-2[a, b]

	Real GDP growth rate	Average interest rate on loans	Business Climate Index	Entrepreneur Confidence Index
MWW	760.000	661.000	801.000	883.000
Wilcoxon W	1225.000	1126.000	1266.000	1348.000
Z	-2.247	-3.014	-1.929	-1.294
Asymp. Sig. (2-tailed)	.025	.003	.054	.196

a. Grouping variables: macroeconomic variables
b. Number of observations: 100

To sum up, the results of hypotheses testing are as follows. First, for seven financial variables, the Null Hypothesis 1 can be rejected; for expense ratio, gross profit margin and quick ratio, the Null Hypothesis 1 cannot be rejected. Second, for three non-financial variables, the Null Hypothesis 3 can be rejected; for profit warning, the Null Hypothesis 3 cannot be rejected. Finally, for two macroeconomic variables (real GDP growth rate and average interest rate on loans), the Null Hypothesis 5 has to be rejected; for two macroeconomic variables (Business Climate Index and Entrepreneur Confidence Index), the Null Hypothesis 5 cannot be rejected.

5.3.2 Using factor analysis and logistic regression to analyse data and test hypotheses (Year T-2)

As was discussed previously, the present study used factor analysis to reduce a group number of financial ratios to several financial factors. The essential non-financial and macroeconomic factors were then extracted from a set of non-financial and macroeconomic variables. This led to a manageable number of factors which could be used in logistic regression.

The dependent variable is whether the growth enterprise experienced distress or not (distressed = 1, non-distressed = 0). The present study then used logistic regression analyses to establish three types of financial distress prediction models and test Hypothesis 2, Hypothesis 4, Hypothesis 6 , Hypothesis 7 and Hypothesis 8.

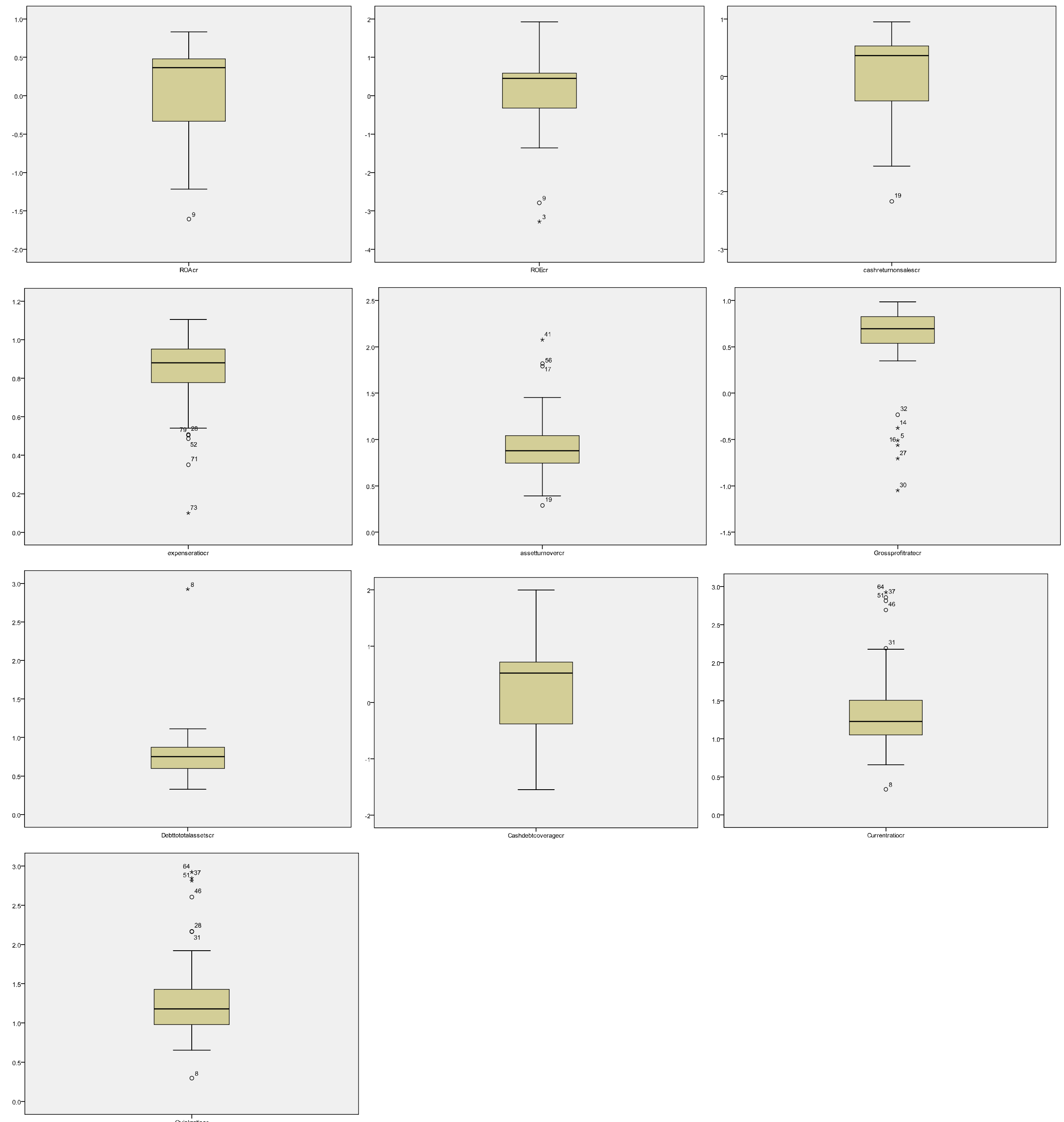
5.3.2.1 Assumption testing for factor analysis

According to Pallant (2007), there are four assumptions underlying the application of factor analysis. The first assumption is the sample size. As was discussed previously, the overall sample size of 100 or more than 100 is acceptable and a minimum of five cases for each of the variables is required for factor analysis (Coak, 2005, p.154; Pallant, 2007, p.185). For the Year T-2, 100 growth enterprises' data are selected. These data incorporate the values of ten financial variables, four non-financial variables and four macroeconomic variables. Therefore, the sample size for the Year T-2 is suitable for factor analysis.

Second, since factor analysis is sensitive to outlying cases or outliers, these cases should be either removed from the data set or recoded to a less extreme value (Pallant, 2007, p.186). Given that the values of all non-financial variables are discrete data, they are not suitable for detecting outliers. The present study only detected the outliers of financial ratios and macroeconomic variables. The first option for reducing the impact of outliers is to transform the variables (Tabachnick and Fidell, 2007, p.77). The cube root is a commonly used transformation for both positive and negative data (Peck, Olsen and Devore, 2008, p. 249). The present study used cube root transformation and takes cube root of the values of the financial ratios and macroeconomic variables.

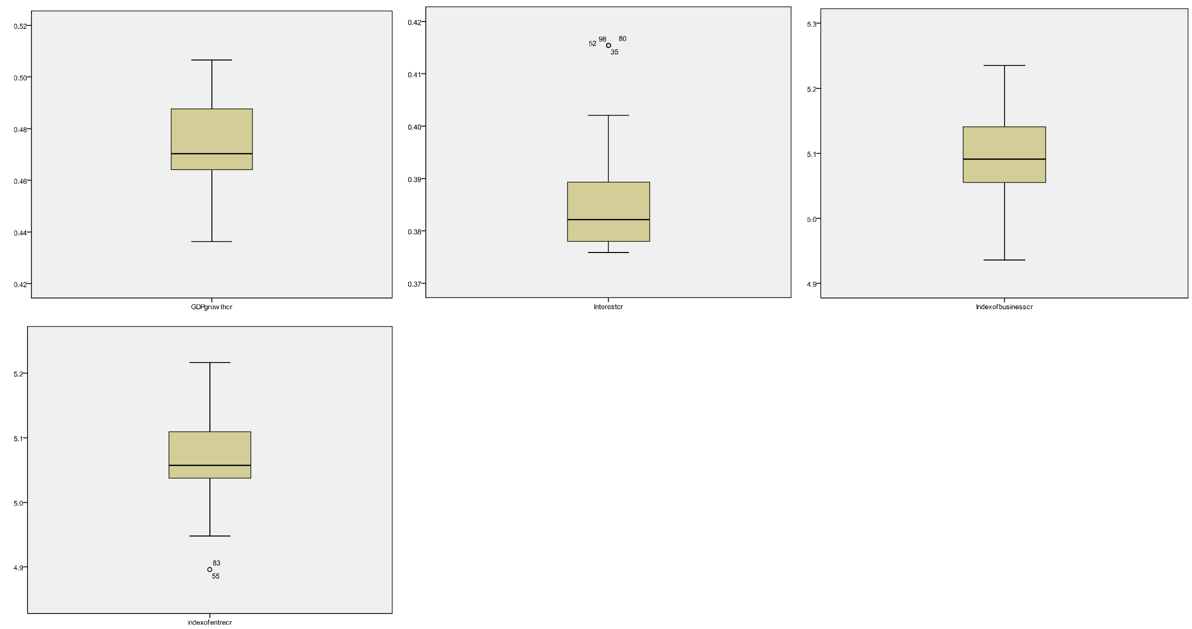
After data transformation, this study used SPSS to detect the outliers of the data. For the data of Year T-2, nine out of ten financial ratios' values have outliers (see Figure 5.6).

Figure 5.6 Box plots of all financial ratios (Year T-2)



In addition, two out of four macroeconomic variables' values have outliers (see Figure 5.7).

Figure 5.7 Box plots of all macroeconomic ratios (Year T-2)



Given the limited cases deployed in the present study, deletion of the cases with outliers is not a reasonable strategy to reduce the influence of outliers. Besides deleting the cases with outliers, changing the score(s) on the outlying case(s) is an alternative method to reduce the influence of outliers. According to Tabachnick and Fidell (2007, p. 77), the present study changed the value of outliers to the value of the next highest or lowest (non-outlier) case. As a result, the influence of all the outliers for Year T-2 was eliminated.

The third assumption is that the correlation matrix should have at least some correlations with *r* being no less than 0.3. Moreover, the Kaiser-Meyer-Olkin value ranges from 0 to 1 and should be no less than 0.5 (Child, 2006, p.55). The Bartlett's test of Sphericity should have a *p* value less than 0.05 (Pallant, 2007, p.185).

For the financial ratios of the Year T-2, the correlation matrix of all financial ratios is presented as Table 5.26. Table 5.26 shows that the correlation matrix of all financial variables for the Year

T-2 has ten correlations with *r* being greater than 0.3. With respect to non-financial variables and macroeconomic variables of the Year T-2, the correlation matrix of all non-financial variables and macroeconomic variables is presented as Table 5.27. This table provides that the correlation matrix of all non-financial variables and macroeconomic variables for the Year T-2 has seven correlations with *r* being greater than 0.3. Therefore, the matrix is suitable for factoring analysis.

Table 5.26 Correlation matrix of financial ratios for the Year T-2

	ROA	ROE	Cash return on sales	Expense ratio	Asset turnover	Gross profit rate	Debt to total assets	Cash debt coverage	Current ratio	Quick ratio
ROA	1.000	.801	.656	-.296	.222	.269	-.363	.725	.291	.314
ROE	.801	1.000	.553	-.321	.173	.285	-.141	.620	.122	.135
Cash return on sales	.656	.553	1.000	-.202	.203	.168	-.298	.833	.242	.263
Expense ratiocr	-.296	-.321	-.202	1.000	.292	-.846	.270	-.263	-.306	-.353
Asset turnover	.222	.173	.203	.292	1.000	-.369	.263	.090	-.150	-.166
Gross profit rate	.269	.285	.168	-.846	-.369	1.000	-.285	.248	.318	.344
Debt to total assets	-.363	-.141	-.298	.270	.263	-.285	1.000	-.304	-.829	-.803
Cash debt coverage	.725	.620	.833	-.263	.090	.248	-.304	1.000	.212	.236
Current ratio	.291	.122	.242	-.306	-.150	.318	-.829	.212	1.000	.966
Quick ratio	.314	.135	.263	-.353	-.166	.344	-.803	.236	.966	1.000

Table 5.27 Correlation matrix of non-financial and macroeconomic variables for the Year T-2

	Real GDP growth rate	Average interest rate on loans	Business Climate Index	Entrepreneur Confidence Index	Delay in releasing financial statements	Change auditors	Auditors' report with qualified opinion and/ or explanatory paragraph	Profit warning
Real GDP growth rate	1.000	.604	.959	.941	-.037	-.171	.027	-.110
Average interest rate on loans	.604	1.000	.540	.487	-.054	-.247	-.079	.208
Business Climate Index	.959	.540	1.000	.970	.003	-.127	.034	-.125
Entrepreneur Confidence Index	.941	.487	.970	1.000	-.012	-.118	.048	-.149
Delay in releasing financial statements	-.037	-.054	.003	-.012	1.000	.372	.124	-.029
Change auditors	-.171	-.247	-.127	-.118	.372	1.000	.179	-.042
Auditors' report with qualified opinion and/ or explanatory paragraph	.027	-.079	.034	.048	.124	.179	1.000	-.032
Profit warning	-.110	.208	-.125	-.149	-.029	-.042	-.032	1.000

The Kaiser-Meyer-Olkin measure of sampling adequacy and the results of the Bartlett's test of Sphericity are illustrated in Table 5.28 and Table 5.29. Table 5.28 indicates the Kaiser-Meyer-Olkin Measure and Bartlett's test for financial ratios in the Year T-2. The Kaiser-Meyer-Olkin value is 0.712 which is far greater than 0.5. It means that the financial ratios are adequate for factor analysis. Moreover, the Bartlett's test of Sphericity is significant with the *p* value less than 0.05. It suggests that there are significant correlations between the financial ratios.

Table 5.28 Kaiser-Meyer-Olkin Measure and Bartlett's Test for financial variables (Year T-2)

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		.712
Bartlett's Test of Sphericity	Approx. Chi-Square	869.009
	df	45
	Sig.	.000

Table 5.29 indicates the Kaiser-Meyer-Olkin Measure and Bartlett's test for non-financial and macroeconomic variables in the Year T-2. The Kaiser-Meyer-Olkin value is 0.756 which is far greater than 0.5. This suggests that the non-financial and macroeconomic variables are adequate for factor analysis. Furthermore, the Bartlett's test of Sphericity is significant with the *p* value less than 0.05. It indicates that there are significant correlations between the variables.

Table 5.29 Kaiser-Meyer-Olkin Measure and Bartlett's Test for non-financial and macroeconomic variables (Year T-2)

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		.756
Bartlett's Test of Sphericity	Approx. Chi-Square	608.866
	df	28
	Sig.	.000

On the whole, according to the correlation matrix, Kaiser-Meyer-Olkin measure of sampling adequacy and Bartlett's Test of Sphericity, it can be concluded that the data of the present study is suitable for factor analysis.

To test the fourth assumption, the present study used scatter plots to check the linearity of the data. The scatter plots of financial ratios are presented in Appendix Figure A5.3 shows that there is no clear evidence of curvilinear relationship between any two financial ratios. The scatter plots of non-financial and macroeconomic variables are presented in Appendix Figure A5.4 shows that there is no clear evidence of curvilinear relationship between any two non-financial and macroeconomic variables. Therefore, the values of financial ratios, non-financial and macroeconomic variables are safe to do factor analysis (Pallant, 2007, p.185).

To sum up, all these four basic assumptions for factor analysis were used to assess the suitability of the data for factor analysis. They underlie the application of factor analysis. Based on the results of assumption testing, all these four basic assumptions for factor analysis are satisfied. Hence, the Year T-2's financial ratios, non-financial and macroeconomic variables for the present study are suitable for factor analysis.

5.3.2.2 Conducting factor analysis for financial ratios

5.3.2.2.1 Factor extraction

The present study used factor extraction to determine the smallest number of financial factors that could best represent the interrelations among a group of financial ratios. All the financial ratios for the Year T-2 were inputted into the SPSS. The most commonly used extraction technique (principal components) was then used to extract the underlying financial factors.

Firstly, Kaiser's criterion was used to assist in the decision concerning retaining the factors. As was discussed in Chapter 4, factors with eigenvalue greater than 1 could be retained for further investigation. In Table 5.30, there are three factors (Factor 1, 2 and 3) with their eigenvalues greater than 1. Overall, these three factors explain about 81 per cent of the original variance.

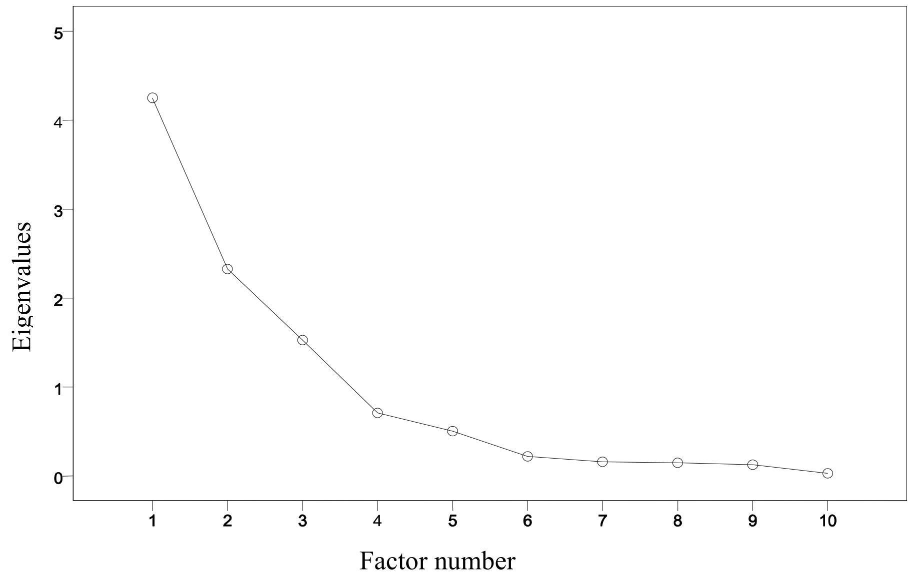
Table 5.30 Total variance explained for financial factors (Year T-2)

Factor	Initial Eigenvalues			Extraction Sums of Squared Loadings			Rotation Sums of Squared Loadings[a]
	Total	Percentage of Variance	Cumulative Percentage	Total	Percentage of Variance	Cumulative Percentage	Total
1	4.251	42.506	42.506	4.251	42.506	42.506	3.260
2	2.327	23.273	65.779	2.327	23.273	65.779	2.775
3	1.527	15.272	81.051	1.527	15.272	81.051	2.071
4	.708	7.081	88.132				
5	.504	5.041	93.173				
6	.220	2.198	95.371				
7	.159	1.595	96.965				
8	.147	1.467	98.432				
9	.127	1.270	99.702				
10	.030	.298	100.000				

Extraction Method: Principal Component Analysis.
a. When components are correlated, sums of squared loadings cannot be added to obtain a total variance.

Secondly, in Figure 5.8, the scree plot line begins to flatten out at around the fourth factor. As a result, according to theory of Catell's scree test discussed in Chapter 4, the scree plot also suggests that it is appropriate to retain three factors.

Figure 5.8 Scree plot for financial factors (Year T-2)



5.3.2.2.2 Factor rotation and interpreting factors

In order to interpret the factors, SPSS provides several methods for rotating the factors. As discussed previously, there are two main approaches to rotation (the orthogonal approach and the oblique approach). The orthogonal approach produces factors which are uncorrelated. In contrast, the oblique approach allows the extracted factors to be highly correlated. In the present study, the extracted factors would be saved as the independent variables for logistic regression and these independent variables should be uncorrelated. Consequently, the orthogonal approach would be a more appropriate approach for the present study and the most commonly used orthogonal approach - Varimax method - was used in the study.

After the rotation, the number of complex variables among factors decrease and the factors become easier to be interpreted. The rotated factors are shown in the rotated factor matrix. Table

5.31 presents the items which constitute the three most important factors and these items' factor loadings. The cut off point for the absolute value of factor loading was set at 0.5.

Table 5.31 Rotated financial factor matrix[a] (Year T-2)

	Factor		
	1	2	3
ROA	.886		
Cash debt coverage	.868		
ROE	.845		
Cash return on sales	.842		
Current ratio		.956	
Quick ratio		.938	
Debt to total assets		-.896	
Gross profit rate			-.902
Expense ratio			.873
Asset turnover			.616

Extraction Method: Principal Component Analysis.
Rotation Method: Varimax with Kaiser Normalization.
a. Rotation converged in 5 iterations.

Table 5.31 indicates that Factor 1 comprises four items with factor loadings ranging from 0.886 to 0.842 and the most important item is ROA. The present study labels Factor 1 as Profitability-Solvency Factor because Factor 1 consists of three profitability ratios (ROA, ROE and cash return on sales) and one solvency ratio (cash debt coverage).

Factor 2 comprises three items with factor loadings ranging from 0.956 to -0.896 and the most important item is current ratio. The present study labels Factor 2 as Liquidity-Solvency Factor because Factor 2 consists of two liquidity ratios (current ratio and quick ratio) and one solvency ratio (debt to total assets).

Factor 3 also includes three items: gross profit rate, expense ratio and asset turnover. The factor loadings of these three items are -.902, 0.873 and 0.616 respectively. The item which makes the most significant contribution to factor 3 is gross profit rate with factor loading of -0.902. The present study labels Factor 3 as Profitability Factor because Factor 3 consists of three profitability ratios (gross profit rate, expense ratio and asset turnover).

5.3.2.3 Conducting factor analysis for non-financial and macroeconomic variables

5.3.2.3.1 Factor extraction

The present study used factor extraction to determine the smallest number of non-financial and macroeconomic factors that can best represent the interrelations among non-financial and macroeconomic variables. All the non-financial and macroeconomic variables for the Year T-2 were inputted into the SPSS. The present study then applied the most commonly used extraction technique (principal components) to extract the underlying non-financial and macroeconomic factors.

Kaiser's criterion is used to decide the number of factors to retain and the factors with eigenvalue greater than 1 can be retained for further investigation. In Table 5.32, there are also three factors (Factor 1, 2 and 3) with their eigenvalues greater than 1. These three factors explain about 74 per cent of the totally original variance.

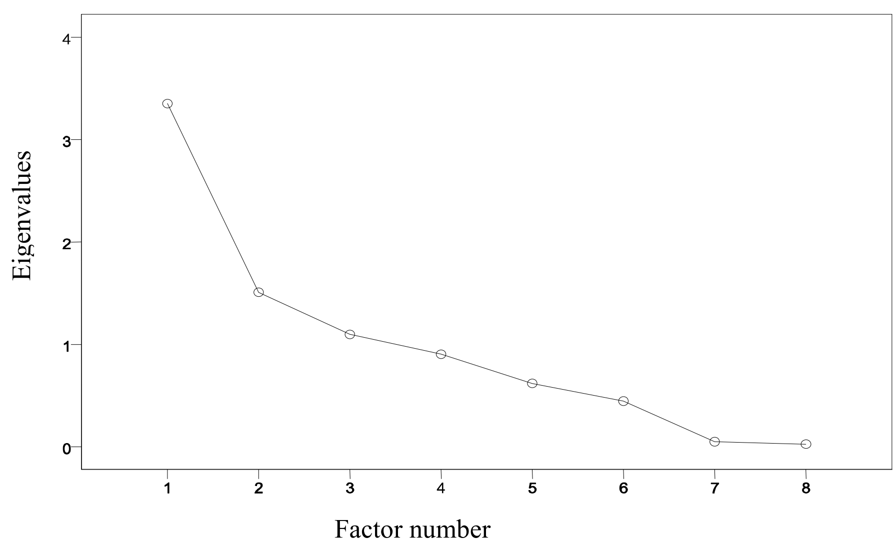
Table 5.32 Total variance explained for non-financial and macroeconomic factors (Year T-2)

Factor	Initial Eigenvalues			Extraction Sums of Squared Loadings			Rotation Sums of Squared Loadings
	Total	Percentage of Variance	Cumulative Percentage	Total	Percentage of Variance	Cumulative Percentage	Total
1	3.352	41.902	41.902	3.352	41.902	41.902	3.329
2	1.509	18.857	60.759	1.509	18.857	60.759	1.489
3	1.097	13.713	74.472	1.097	13.713	74.472	1.139
4	.903	11.293	85.765				
5	.618	7.730	93.495				
6	.446	5.579	99.074				
7	.049	.612	99.686				
8	.025	.314	100.000				

Extraction Method: Principal Component Analysis.

In Figure 5.9, the scree plot line begins to change in shape and flatten out between the third and the fourth factor. According to theory of Catell's scree test, it is appropriate to retain three factors.

Figure 5.9 Scree plot for non-financial and macroeconomic factors (Year T-2)



5.3.2.3.2 Factor rotation and interpreting factors

In the present study, the rotation of financial factors is similar to the rotation of non-financial and macroeconomic factors. In addition, all of the extracted factors will be saved as independent variables for logistic regression and those independent variables should be uncorrelated. Hence, the orthogonal approach and the most commonly used orthogonal approach (Varimax method) were also used for extracting non-financial and macroeconomic factors in the present study.

After the rotation, the number of complex variables among factors decreased and the factors became easier to be interpreted. The rotated factors are shown in the rotated factor matrix. Table 5.33 presents the items which constitute the three extracted factors and these items' factor loadings. The cut off point for the absolute value of factor loading is 0.5.

Table 5.33 Rotated non-financial and macroeconomic factor matrix[a] (Year T-2)

	Factor		
	1	2	3
Real GDP growth rate	.979		
Business Climate Index	.977		
Entrepreneur Confidence Index	.961		
Average interest rate on loans	.670		
Changing auditors		.777	
Delay in releasing financial statements		.771	
Auditors' report with qualified opinion and/ or explanatory paragraph		.511	
Profit warning			.934

Extraction Method: Principal Component Analysis.
Rotation Method: Varimax with Kaiser Normalization.
a. Rotation converged in 4 iterations.

Table 5.33 indicates that Factor 1 comprises four items with factor loadings ranging from 0.979 to 0.67 and the most important item is the real GDP growth rate. Furthermore, Business Climate Index and Entrepreneur Confidence Index are other two important items, with their factor loadings close to the factor loading of real GDP growth rate. The present study interpreted Factor 1 as Macroeconomic Factor because Factor 1 refers to four macroeconomic variables which include Business Climate Index, Entrepreneur Confidence Index, real GDP growth rate and average interest rate on loans.

Factor 2 consists of three items with factor loadings ranging from 0.777 to 0.511 and the most important item is ‘changing auditors’. Below this item, the items ‘delay in releasing financial statements’ and ‘auditors’ report with qualified opinion and/ or explanatory paragraph’ have factor loadings of 0.771 and 0.511 respectively. The present study labelled Factor 2 as Auditing-Disclosure Factor because Factor 2 consists of two non-financial variables concerning auditing (‘changing auditors’ and ‘auditors’ report with qualified opinion and/ or explanatory paragraph’) and one non-financial variable referring to corporate disclosure (‘delay in releasing financial statements’).

Factor 3 has only one item and the item is ‘profit warning’. This item with a factor loading of 0.934 contributes the most to Factor 3. As a result, the present study simply labelled Factor 3 as the Profit Warning Factor.

In summary, there are three financial factors extracted from financial ratios. Based on the items that constitute the factors, the present study labelled the three factors as Liquidity- Solvency Factor, Profitability- Solvency Factor and Profitability Factor. Additionally, three non-financial and macroeconomic factors were generated from non-financial and macroeconomic variables. According to the items that constitute these factors, the present study labelled the three factors as Macroeconomic Factor, Auditing-disclosure Factor and Profit Warning Factor. All of these six factors were used as independent variables for logistic regression analyses.

5.3.3 Logistic regression analysis (Year T-2)

After the MWW test and factor analysis, the extracted financial, non-financial and macroeconomic factors were used as independent variables for logistic regression analyses. The dependent variable is whether the growth enterprise experienced distress or not (distressed = 1, non-distressed = 0). The present study then used logistic regression analysis to establish three types of financial distress prediction models and test related hypotheses.

The first type of model considered firm-specific financial factors only, whereas the second type of model considered firm-specific non-financial factors and macroeconomic factors. The third type of model considered not only firm-specific financial factors but also firm-specific non-financial factors and macroeconomic factors. These three models were referred to as Model 1, Model 2 and Model 3 respectively. The study compared classification accuracy of Model 1 with that of Model 2. Subsequently, the study compared classification accuracy of Model 1 with that of Model 3. Finally, all the hypotheses in the present study were tested and the results were discussed.

5.3.3.1 Assumptions testing for logistic regression

As was discussed in Chapter 4, the first assumption refers to the number of cases in the sample and the number of independent variables included in the logistic regression model. The present study produced three logistic regression models. Model 1 considered three financial factors as independent variables; Model 2 considered three non-financial and macroeconomic factors as independent variables; Model 3 considered all the six factors as independent variables which included financial, non-financial and macroeconomic factors. Moreover, there were 100 growth enterprises considered in this study. In other words, there were a relatively small number of independent variables with a relatively large sample. Hence, the sample size of this study and its independent variables are suitable for logistic regression.

The second assumption is about checking for intercorrelations or multicollinearity among independent variables. Ideally, the independent variables should not be strongly related to each other and the highly intercorrelating variables have to be removed (Pallant, 2007, p.167). In the present study, given the orthogonal approach always results in uncorrelated factors, the three financial factors extracted by using the orthogonal approach (Varimax method) should be uncorrelated. In the same way, the three non-financial and macroeconomic factors also should be uncorrelated.

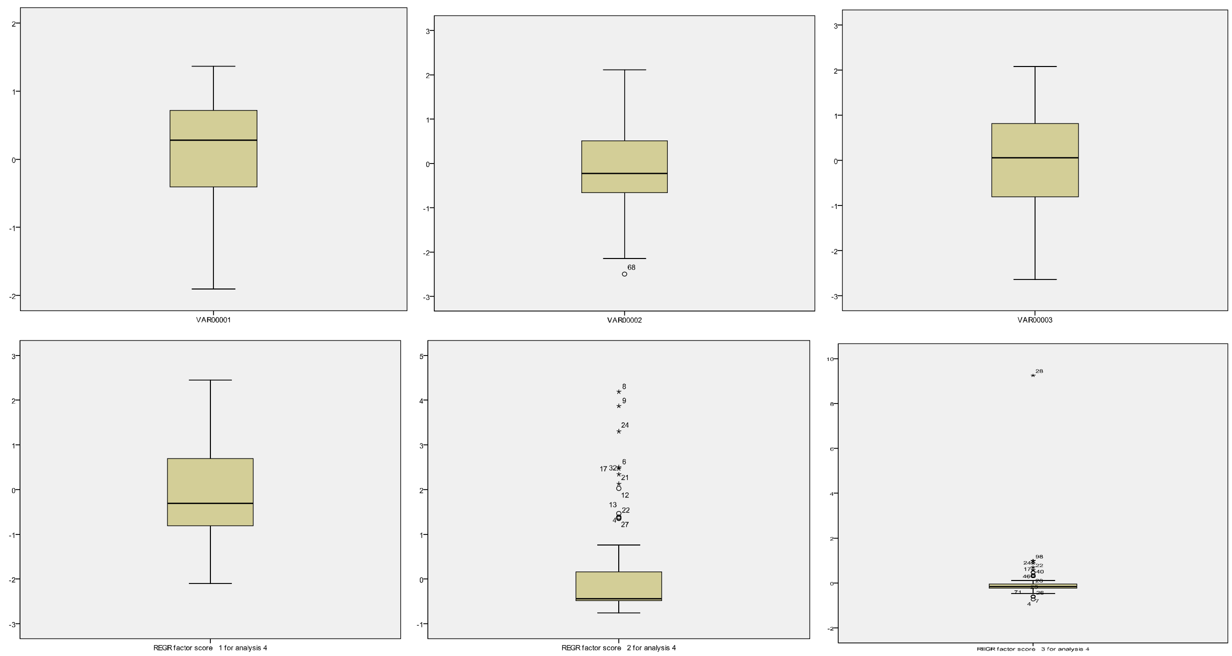
In order to check the multicollinearity of all these six factors, the present study checked the intercorrelation among these factors. Multicollinearity occurs when these factors are highly correlated with the value of r being no less than 0.9 (Tabachnick and Fidell, 2007, p. 88). The values of Pearson correlation in Table 5.34 show that the values of r are all less than 0.9. Therefore, there are no multicollinearities among these six factors and all these factors can be retained.

Table 5.34 Pearson Correlation of all factors (Year T-2)

	Profitability-Solvency Factor	Liquidity-Solvency Factor	Profitability Factor	Macroeconomic Factor	Auditing-Disclosure Factor	Profit Warning Factor
Profitability-Solvency Factor	1.000	.118	.049	.043	.008	-.296
Liquidity-Solvency Factor	.118	1.000	.051	.073	.028	-.222
Profitability Factor	.049	.051	1.000	-.178	-.130	.080
Macroeconomic Factor	.043	.073	-.178	1.000	-.157	-.602
Auditing-Disclosure Factor	.008	.028	-.130	-.157	1.000	.006
Profit Warning Factor	-.296	-.222	.080	-.602	.006	1.000

Finally, because of outliers influencing the results of logistic regression, the third assumption is about checking for the presence of outliers. If there are some cases that are not well explained by the model, these outlying cases would be removed or recoded to a lesser value (Tabachnick and Fidell, 2007, p. 77). In SPSS, histograms, box plots and descriptive statistics of each variable or ratio are used to identify outliers (Pallant, 2007). After checking the outliers, this study found three out of these six factors had outlying cases (see Figure 5.10).

Figure 5.10 Box plots of all factors (Year T-2)



As has been discussed previously, the present study changed the value of outliers to the value of the next highest or lowest (non-outlier) case. As a result, the influence of all the outliers for all the factors was eliminated.

5.3.3.2 Conducting logistic regression analysis for financial factors

As discussed previously, the three financial factors were used as independent variables and whether the growth enterprise having experienced distress was regarded as a dependent variable. The dependent variable was coded as follows: 0 was used to indicate the growth enterprise having not experienced financial distress and 1 was used to indicate the growth enterprise having experienced financial distress. The present study inputted these three independent variables and one dependent variable into SPSS and ran the logistic regression to analyse them. This logistic regression analysis was referred to as Model 1 for Year T-2 in this study.

The output of the logistic regression analysis (Model 1) and the interpretation of the output are as follows.

At the beginning, the Omnibus Tests of Model Coefficients provides an overall prediction of how well the model with three financial independent variables performs compared with the model without considering independent variables (Pallant, 2007, p.174). Panel A of Table 5.35 presents the significant value for Omnibus Tests of Model Coefficients as less than 0.05. Hence, the model with three financial factors used as independent variables is better than the model without using any financial factors as independent variables. The χ^2 (3, N = 100) = 39.982 with p < 0.001 also indicates that the model including three financial independent variables is able to distinguish between growth enterprises which have experienced financial distress and which have not experienced financial distress (Pallant, 2007, p.178).

The results shown in Panel B of Table 5.35 also provide some information about the usefulness of the model. The value of Cox and Snell R Square and the value of Nagelkerke R Square, which are from a minimum value of 0 to a maximum value of 1, indicate the amount of variation in the dependent variable explained by the model (Pallant, 2007, p.174). It can been seen from Table 5.35 (Panel B), that the value of Cox and Snell R Square and the value of Nagelkerke R Square are 0.33 and 0.467 respectively. In other words, between 33 per cent and 46.7 per cent of the variability in the dependent variable is explained by the independent variables.

Table 5.35 The performance and usefulness of Model 1

Panel A Omnibus Tests of Model Coefficients for Model 1

		Chi-square	df	Sig.
Step 1	Step	39.982	3	.000
	Block	39.982	3	.000
	Model	39.982	3	.000

Panel B Model Summary for Model 1

-2 Log likelihood	Cox and Snell R Square	Nagelkerke R Square
82.191[a]	.330	.467

a. Estimation terminated at iteration number 5 because parameter estimates changed by less than .001.

As discussed previously, when the independent variables are not entered into the model, the overall percentage of correctly classified cases is 70 per cent (see Table 5.14). On the other hand, Table 5.36 shows the overall percentage of correctly classified cases when the model includes all independent variables. The present study compared this with the overall percentage of correctly classified case in Table 5.36 to see the improvement of including the independent variable in the model. Therefore, the model with the independent variable correctly classified 82 per cent of cases overall and has a great improvement over the 70 per cent of accuracy in classification for the model without using independent variables.

Table 5.36 Classification for Model 1[a] (with the independent variables)

Observed		Predicted		
		Status		Percentage Correct
		0	1	
Status	0	66	4	94.3
	1	14	16	53.3
Overall Percentage				82.0

a. The cut value is .500

As shown in Table 5.37, only one independent variable (Profitability-Solvency Factor) has a *Sig.* value less than 0.05. Therefore, Profitability-Solvency Factor made a statistically significant contribution to the model at the five per cent level. The other two financial independent variables (Liquidity- Solvency Factor and Profitability Factor) do not contribute significantly to the model.

The *B* values provided in Table 5.37 can be used in an equation to compute the probability of a case falling into a specific category (Pallant, 2007, p.175). For the significant independent variable in Model 1, Profitability-Solvency Factor has a negative *B* value (-1.763). This suggests that: if a growth enterprise has higher Profitability-Solvency Factor, it is less likely to experience financial distress.

Table 5.37 Financial independent variables in the equation for Model 1

	B	S.E.	Wald	df	Sig.	Exp(B)
Profitability-Solvency Factor	-1.763	.360	23.937	1	.000	.172
Liquidity-Solvency Factor	-.117	.268	.192	1	.662	.889
Profitability Factor	-.093	.280	.111	1	.739	.911
Constant	-1.089	.286	14.460	1	.000	.337

5.3.3.3 Conducting logistic regression analysis for non-financial and macroeconomic factors

As discussed previously, the three non-financial and macroeconomic factors were used as independent variables and whether the growth enterprise having experienced distress was regarded as a dependent variable. The dependent variable was coded as follows: 0 was used to indicate the growth enterprise having not experienced financial distress and 1 was used to indicate the growth enterprise having experienced financial distress. The present study inputted these three independent variables and one dependent variable into SPSS and ran the logistic regression to analyse them. This logistic regression analysis was referred to as Model 2 for Year T-2 in this study.

The output of the logistic regression analysis (Model 2) and the interpretation of the output are as follows.

At the beginning, the Omnibus Tests of Model Coefficients provides an overall prediction of how well the model with three independent variables performs compared with the model without considering independent variables (Pallant, 2007, p.174). Panel A of Table 5.38 presents the significant value for Omnibus Tests of Model Coefficients as less than 0.05. Hence, the model with three factors used as independent variables is better than the model without using any factors as independent variables. The χ^2 (3, N = 100) = 40.992 with p < 0.001 also indicates that the model including three independent variables is able to distinguish between growth enterprises which have experienced financial distress and which have not experienced financial distress (Pallant, 2007, p.178).

Table 5.38 (Panel B) presents that the value of Cox and Snell R Square and the value of Nagelkerke R Square are 0.336 and 0.477 respectively. In other words, between 33.6 per cent and 47.7 per cent of the variability in the dependent variable is explained by the independent variables.

Table 5.38 The performance and usefulness of Model 2

Panel A Omnibus Tests of Model Coefficients for Model 2

		Chi-square	df	Sig.
Step 1	Step	40.992	3	.000
	Block	40.992	3	.000
	Model	40.992	3	.000

Panel B Model summary for Model 2

-2 Log likelihood	Cox and Snell R Square	Nagelkerke R Square
81.181[a]	.336	.477

a. Estimation terminated at iteration number 5 because parameter estimates changed by less than .001.

As discussed previously, when the independent variables are not entered into the model, the overall percentage of correctly classified cases is 70 per cent (see Table 5.14). On the other hand, Table 5.39 shows the overall percentage of correctly classified cases when the model includes all independent variables. The present study compared this with the overall percentage of correctly classified case in Table 5.39 to see the improvement of including the independent variable in the model. Therefore, the model with the independent variable correctly classified 83 per cent of cases overall and has a great improvement over the 70 per cent of accuracy in classification for the model without using independent variables.

Table 5.39 Classification for Model 2[a] (with the independent variables)

Observed		Predicted		
		Status		Percentage Correct
		0	1	
Status	0	64	6	91.4
	1	11	19	63.3
Overall Percentage				83.0

a. The cut value is .500

As shown in Table 5.40, one independent variable (Auditing-Disclosure Factor) has its *Sig.* value less than 0.05. Therefore, Auditing-Disclosure Factor makes a statistically significant contribution to the model at the five per cent level.

The *B* values provided in Table 5.40 can be used in an equation to compute the probability of a case falling into a specific category (Pallant, 2007, p.175). For the significant independent variable in Model 2, Auditing-Disclosure Factor has positive *B* value which is 2.999. This suggests that: if a growth enterprise has higher Auditing-Disclosure Factor, it is more likely to experience financial distress.

Table 5.40 Non-financial and macroeconomic independent variables in the equation for Model 2

	B	S.E.	Wald	df	Sig.	Exp(B)
Macroeconomic Factor	-.404	.354	1.303	1	.254	.667
Auditing-Disclosure Factor	2.999	.588	26.004	1	.000	20.061
Profit Warning Factor	-1.225	1.659	.545	1	.460	.294
Constant	-.698	.425	2.695	1	.101	.497

5.3.3.4 Testing Hypothesis 7

Hypothesis 7 is tested based on the outputs of Model 1 and Model 2 as follows.

Hypothesis 7:

Null Hypothesis 7: The model incorporating firm-specific financial factors is not better than the model which includes firm-specific non-financial and macroeconomic factors in financial distress prediction.

Alternative Hypothesis 7: The model incorporating firm-specific financial factors is better than the model which includes firm-specific non-financial and macroeconomic factors in financial distress prediction.

The findings presented in Table 5.36 indicate that the model 1 correctly classified 82 per cent of cases. The findings presented in Table 5.39 indicate that the model 2 correctly classified 83 per cent of cases. The classification accuracy of Model 2 (83 per cent) is slightly higher than the classification accuracy of Model 1 (82 per cent). Therefore, Null Hypothesis 7 cannot be rejected.

5.3.3.5 Conducting logistic regression analysis for all factors

As discussed previously, the six factors, including financial, non-financial and macroeconomic factors, were used as independent variables and whether the growth enterprise had experienced distress was regarded as a dependent variable. The dependent variable was coded as 0, 1. 0 was used to indicate the growth enterprise having not experienced financial distress, and 1 was used to indicate the growth enterprise had experienced financial distress. The present study inputted these six independent variables and one dependent variable into SPSS and ran the logistic regression to analyse them. This logistic regression analysis was referred to as Model 3 for Year T-2 in this study.

The output of the logistic regression analysis (Model 3) and the interpretation of the output are as follows.

At the beginning, the Omnibus Tests of Model Coefficients provides an overall prediction of how well the model with six independent variables performs compared with the model, without considering independent variables (Pallant, 2007, p.174). Panel A of Table 5.41 presents that the significant value for Omnibus Tests of Model Coefficients is less than 0.05. Hence, the model with six factors used as independent variables is better than the model without using any factors as independent variables. The χ^2 (6, N = 100) = 58.313 with p < 0.001 also indicates that the model covering six independent variables is able to distinguish between growth enterprises which have experienced financial distress and which have not experienced financial distress (Pallant, 2007, p.178).

The results shown in Table 5.41(Panel B) also provide some information about the usefulness of the model. It can be seen from Panel B of Table 5.41 that the values of Cox and Snell R Square and the value of Nagelkerke R Square are 0.442 and 0.626 respectively. In other words, between

44.2 per cent and 62.6 per cent of the variability in the dependent variable is explained by the independent variables.

Table 5.41 The performance and usefulness of Model 3
Panel A Omnibus Tests of Model Coefficients for Model 3

		Chi-square	df	Sig.
Step 1	Step	58.313	6	.000
	Block	58.313	6	.000
	Model	58.313	6	.000

Panel B Model Summary for Model 3

-2 Log likelihood	Cox and Snell R Square	Nagelkerke R Square
63.860[a]	.442	.626

a. Estimation terminated at iteration number 5 because parameter estimates changed by less than .001.

As discussed previously, when the independent variables are not entered into the model, the overall percentage of correctly classified cases is 70 per cent (see Table 5.14). On the other hand, Table 5.42 shows the overall percentage of correctly classified cases when the model includes all independent variables. The present study compared this with the overall percentage of correctly classified cases in Table 5.42 to see the improvement of including the independent variable in the model. Therefore, the model with six independent variables correctly classified 89 per cent of cases overall and has a great improvement over the 70 per cent of accuracy in classification for the model without using independent variables.

Table 5.42 Classification for Model 3 [a] (with the independent variables)

Observed		Predicted		
		Status		Percentage Correct
		0	1	
Status	0	66	4	94.3
	1	7	23	76.7
Overall Percentage				89.0

a. The cut value is .500

As shown in Table 5.43, there are two independent variables (Profitability-Solvency Factor and Auditing-Disclosure Factor) with their *Sig.* values less than 0.05. Therefore, Profitability-Solvency Factor and Auditing-Disclosure Factor contribute significantly to the predictive ability of the model at the five per cent level. The other four independent variables (Liquidity-Solvency Factor, Profitability Factor, Macroeconomic Factor and Profit Warning Factor) do not contribute significantly to the model.

As discussed previously, the *B* values provided in Table 5.43 can be used to compute the probability of a case falling into a specific category. For the two significant independent variables in this model, Profitability-Solvency Factor has a negative *B* value (-1.461), whereas Auditing-Disclosure Factor has a positive *B* values (2.549). The *B* value of Profitability-Solvency Factor indicates that if a growth enterprise has a higher value in Profitability-Solvency Factor, this growth enterprise was less likely to experience financial distress in two years. In contrast, the *B* value of Auditing-Disclosure Factor shows that if a growth enterprise more frequently had the problems in auditing and disclosure, this growth enterprise was more likely to experience financial distress in two years.

Table 5.43 Independent variables in the equation for Model 3

	B	S.E.	Wald	df	Sig.	Exp(B)
Profitability-Solvency Factor	-1.461	.415	12.390	1	.000	.232
Liquidity- Solvency Factor	-.006	.326	.000	1	.986	.994
Profitability Factor	-.229	.328	.490	1	.484	.795
Macroeconomic Factor	-.314	.418	.567	1	.451	.730
Auditing-Disclosure Factor	2.549	.669	14.531	1	.000	12.790
Profit Warning Factor	.547	2.098	.068	1	.794	1.729
Constant	-.640	.499	1.645	1	.200	.527

5.3.3.6 Testing Hypothesis 2, 4, 6 and 8

Hypothesis 2, Hypothesis 4, Hypothesis 6 and Hypothesis 8 were tested based on the outputs of Model 3 as follows.

Hypothesis 2:

Null Hypothesis 2: For the proposed model incorporating firm-specific financial, firm-specific non-financial and macroeconomic factors, the firm-specific financial factors are not significant predictors of growth enterprises' financial distress.

Alternative Hypothesis 2: For the proposed model incorporating firm-specific financial, firm-specific non-financial and macroeconomic factors, the firm-specific financial factors are significant predictors of growth enterprises' financial distress.

As discussed previously, the findings presented in Table 5.43 indicate that only one of the financial factors (Profitability-Solvency Factor) has a *Sig.* value less than 0.05. In other words, the Profitability-Solvency Factor, which was extracted from financial ratios, is a significant predictor of growth enterprises' financial distress at the five per cent level. Therefore, for Model 3, the Null Hypothesis 2 has to be rejected.

Hypothesis 4:

Null Hypothesis 4: For the proposed model incorporating firm-specific financial, firm-specific non-financial and macroeconomic factors, the firm-specific non-financial factors are not significant predictors of growth enterprises' financial distress.

Alternative Hypothesis 4: For the proposed model incorporating firm-specific financial, firm-specific non-financial and macroeconomic factors, the firm-specific non-financial factors are significant predictors of growth enterprises' financial distress.

The findings presented in Table 5.43 also indicate that one non- financial factor (Auditing-Disclosure Factor) has its *Sig.* value less than 0.05. In other words, Auditing-Disclosure Factor, which was extracted from non-financial variables, is a significant predictor of growth enterprises' financial distress at the five per cent level. Therefore, for Model 3, the Null Hypothesis 4 has to be rejected.

Hypothesis 6:

Null Hypothesis 6: For the proposed model incorporating firm-specific financial, firm-specific non-financial and macroeconomic factors, the macroeconomic factors are not significant predictors of growth enterprises' financial distress.

Alternative Hypothesis 6: For the proposed model incorporating firm-specific financial, firm-specific non-financial and macroeconomic factors, the macroeconomic factors are significant predictors of growth enterprises' financial distress.

According to the findings presented in Table 5.43, Macroeconomic Factor, which consists of four macroeconomic variables, has its *Sig.* value more than 0.05. Macroeconomic Factor is not a significant predictor of growth enterprises' financial distress. Thus, for Model 3, the Null Hypothesis 6 cannot be rejected.

Hypothesis 8:

Null Hypothesis 8: The proposed model incorporating firm-specific financial, firm-specific non-financial and macroeconomic factors is not better than the model which only includes firm-specific financial factors in financial distress prediction.

Alternative Hypothesis 8: The proposed model incorporating firm-specific financial, firm-specific non-financial and macroeconomic factors is better than the model which only includes firm-specific financial factors in financial distress prediction.

The findings presented in Table 5.36 and Table 5.42 reveal that the classification accuracy of Model 3 (89 per cent) is higher than the classification accuracy of Model 1 (82 per cent). The firm-specific non-financial and macroeconomic factors helped enhance the classification accuracy of the model. These results confirmed that Model 3 is better than Model 1 in classification accuracy. Based on all the findings, the Null Hypothesis 8 has to be rejected.

To sum up, for Year T-2, the Null Hypothesis 2 has to be rejected; the Null Hypothesis 4 has to be rejected; the Null Hypothesis 6 cannot be rejected; the Null Hypothesis 7 cannot be rejected; the Null Hypothesis 8 has to be rejected.

5.4 Data analysis for data of Year T-3

5.4.1 Using the Mann-Whitney-Wilcoxon test to test Hypothesis 1, 3 and 5 (Year T-3)

According to statistical theory, the MWW test is used to determine whether there is a difference between two populations. The present study used the MWW test to test Hypothesis 1, Hypothesis 3 and Hypothesis 5.

In order to test these three hypotheses, the present study firstly inputted the values of all ten corporate financial ratios, four non-financial variables and four macroeconomic variables into the SPSS. It then used the MWW test to identify the difference in financial ratios, non-financial variables and macroeconomic variables between distressed and non-distressed growth enterprises. Hypothesis 1, Hypothesis 3 and Hypothesis 5 were tested by using the MWW test as follows.

Hypothesis 1:

Null Hypothesis 1: There are no significant differences in financial ratios between distressed and non-distressed growth enterprises.

Alternative Hypothesis 1: There are significant differences in financial ratios between distressed and non-distressed growth enterprises.

Table 5.44 presents the MWW test statistics for financial ratios. In this table, the Z means the Z-score and the Asymp. Sig. (2-tailed) refers to the two-tailed *p* value which has been corrected for ties. The output of the test indicates that five financial ratios have two-tailed *p* values less than 0.05. Five financial ratios' results of MWW test, with correction for Z-score conversion and ties, are significant at five per cent level of significance. Therefore, for five financial ratios, the Null Hypothesis 1 can be rejected. However, for expense ratio, current ratio, quick ratio, debt to total assets and gross profit margin, the Null Hypothesis 1 cannot be rejected.

Table 5.44 Test statistics for financial ratios [a] (Year T-3)

	ROA	ROE	Cash return on sales	Expense ratio	Asset turnover
MWW	437.500	418.500	746.000	797.500	659.000
Wilcoxon W	902.500	883.500	1211.000	3282.500	1124.000
Z	-4.607	-4.750	-2.287	-1.899	-2.941
Asymp. Sig. (2-tailed)	.000	.000	.022	.058	.003
	Gross profit margin	Debt to total assets	Cash debt coverage	Current ratio	Quick ratio
MWW	882.500	1046.000	716.500	1014.000	1030.000
Wilcoxon W	1347.500	3531.000	1181.500	1479.000	1495.000
Z	-1.260	-.030	-2.509	-.271	-.150
Asymp. Sig. (2-tailed)	.208	.976	.012	.787	.880

a. Grouping variables: financial status of the growth enterprises
b. Number of observations: 100

Hypothsis 3:

Null Hypothesis 3: There are no significant differences in non-financial variables between distressed and non-distressed growth enterprises.

Alternative Hypothesis 3: There are significant differences in non-financial variables between distressed and non-distressed growth enterprises.

Table 5.45 displays MWW test statistics for non-financial variables. The output of the test indicates that two out of four non-financial variables (‘changing auditors’ and ‘delay in releasing financial statements') have two-tailed *p* values less than 0.05. Accordingly, these two non-financial variables’ results of MWW test, with correction for Z-score conversion and ties, are significant at five per cent level of significance. Two non-financial variables (‘profit warning’ and 'auditors' report with qualified opinion and/ or explanatory paragraph') have two-tailed p values greater than 0.05. Thus, the results of MWW test reveals that there are significant differences in the Year T-3's two non-financial variables between the distressed growth enterprises and non-distressed growth enterprises. On the other hand, there are no significant differences between distressed and non-distressed growth enterprises when applying 'profit warning' and 'auditors' report with qualified opinion and/ or explanatory paragraph'. Therefore, for two non-financial variables ('changing auditors' and 'delay in releasing financial statements'), the Null Hypothesis 3 can be rejected. However, for 'profit warning' and 'auditors' report with qualified opinion and/ or explanatory paragraph', the Null Hypothesis 3 cannot be rejected.

Table 5.45 Test statistics for non-financial variables of Year T-3[a, b]

	Delay in releasing financial statements	Changing auditors	Auditors' report with qualified opinion and/ or explanatory paragraph	Profit warning
MWW	875.000	626.500	995.000	1015.000
Wilcoxon W	3360.000	3111.500	3480.000	3500.000
Z	-3.485	-4.663	-1.400	-1.528
Asymp. Sig. (2-tailed)	.000	.000	.161	.127

a. Grouping variables: non-financial status of the growth enterprises
b. Number of observations: 100

Hypothesis 5:

Null Hypothesis 5: There are no significant differences in macroeconomic variables between distressed and non-distressed growth enterprises.

Alternative Hypothesis 5: There are significant differences in macroeconomic variables between distressed and non-distressed growth enterprises.

Table 5.46 displays the MWW test statistics for macroeconomic variables of Year T-3. The two-tailed p values of three macroeconomic variables, which have been corrected for ties, are less than 0.05. There is only one macroeconomic variable (average interest rate on loans) which has a two-tailed p value larger than 0.05. Hence, the MWW test demonstrates that there are significant differences in the Year T-3's three macroeconomic conditions for the distressed growth enterprises and non-distressed growth enterprises.

Therefore, for three macroeconomic variables (real GDP growth rate, Entrepreneur Confidence Index and Business Climate Index), the Null Hypothesis 5 has to be rejected. For one macroeconomic variable (average interest rate on loans), however, the Null Hypothesis 5 cannot be rejected.

Table 5.46 Test statistics for macroeconomic variables of Year T-3[a, b]

	Real GDP growth rate	Average interest rate on loans	Business Climate Index	Entrepreneur Confidence Index
MWW	711.500	906.500	782.500	757.500
Wilcoxon W	1176.500	1371.500	1247.500	1222.500
Z	-2.618	-1.110	-2.069	-2.262
Asymp. Sig. (2-tailed)	.009	.267	.039	.024

a. Grouping variables: macroeconomic variables
b. Number of observations: 100

To sum up, the results of hypotheses testing are as follows. First, for five financial variables, the Null Hypothesis 1 can be rejected; for expense ratio, current ratio, quick ratio, debt to total assets and gross profit margin, the Null Hypothesis 1 cannot be rejected. Second, for two non-financial variables ('changing auditors' and 'delay in releasing financial statements'), the Null Hypothesis 3 can be rejected; for the other two non-financial variables ('profit warning' and 'auditors' report with qualified opinion and/ or explanatory paragraph'), the Null Hypothesis 3 cannot be rejected.

Finally, for three macroeconomic variables, the Null Hypothesis 5 has to be rejected; for one macroeconomic variable (average interest rate on loans), the Null Hypothesis 5 cannot be rejected.

5.4.2 Using factor analysis and logistic regression to analyse data and test hypotheses (Year T-3)

As was discussed previously, the present study used factor analysis to extract several financial factors from ten financial ratios. The essential non-financial and macroeconomic factors were then extracted from a set of non-financial and macroeconomic variables. This led to a manageable number of factors which could be used in logistic regression.

The dependent variable is whether the growth enterprise experienced distress or not (distressed = 1, non-distressed = 0). The present study then used logistic regression analyses to establish three types of financial distress prediction models and test Hypothesis 2, Hypothesis 4, Hypothesis 6， Hypothesis 7 and Hypothesis 8.

5.4.2.1 Assumption testing for factor analysis

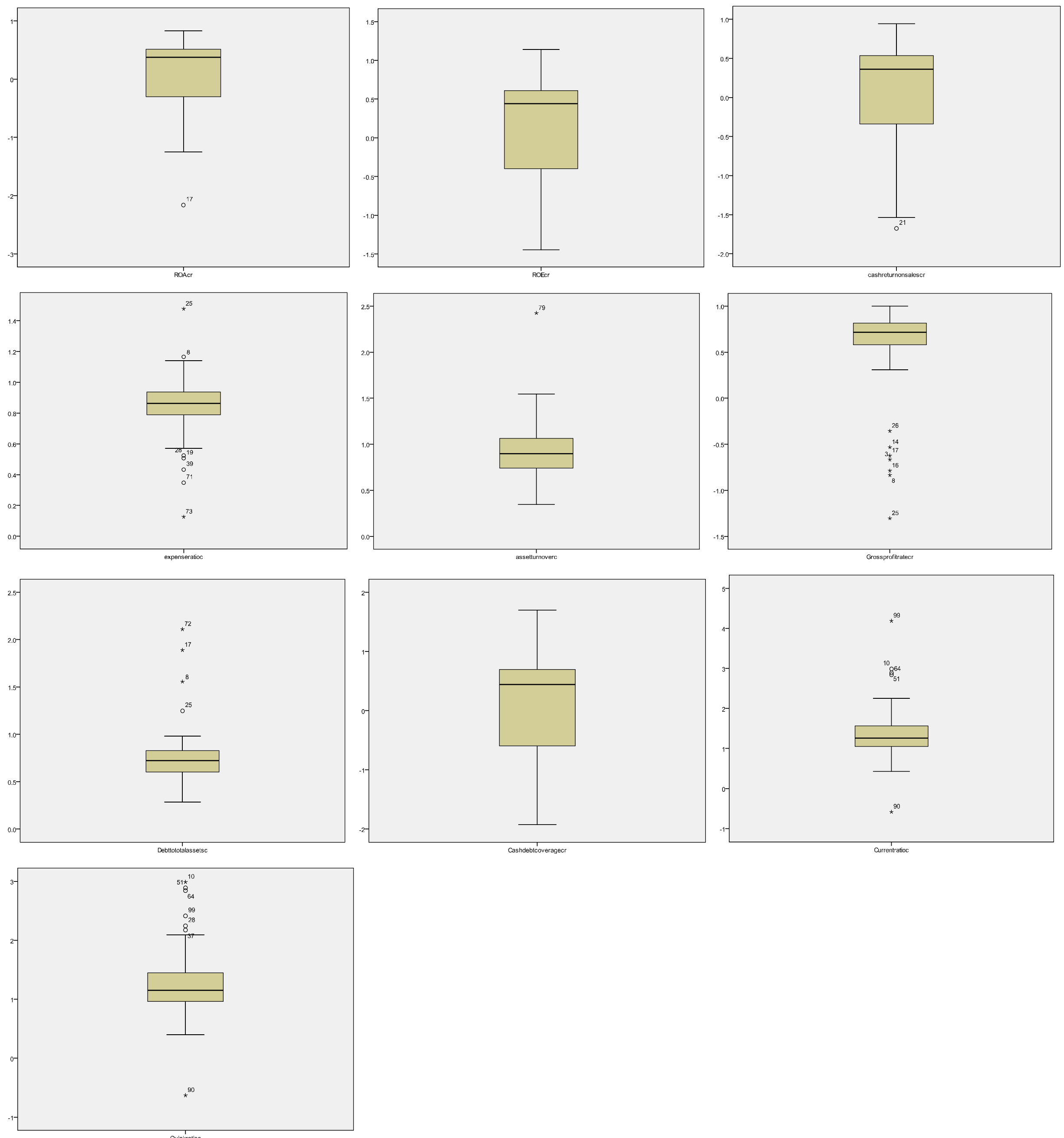
According to Pallant (2007), there are four assumptions underlying the application of factor analysis. The first assumption is the sample size. As was discussed previously, the overall sample size of 100 or more than 100 is acceptable and a minimum of five cases for each of the variables is required for factor analysis (Coak, 2005, p.154; Pallant, 2007, p.185). For the Year

T-3, 100 growth enterprises' data are selected. These data incorporate the values of ten financial variables, four non-financial variables and four macroeconomic variables. Therefore, the sample size for the Year T-3 is suitable for factor analysis.

Second, since factor analysis is sensitive to outlying cases or outliers, these cases should be either removed from the data set or recoded to a less extreme value (Pallant, 2007, p.186). Given that the values of all non-financial variables are discrete data, they are not suitable for detecting outliers. The present study only detected the outliers of financial ratios and macroeconomic variables. The first option for reducing the impact of outliers is to transform the variables (Tabachnick and Fidell, 2007, p. 77). The cube root is a commonly used transformation for both positive and negative data (Peck, Olsen and Devore, 2008, p. 249). The present study used cube root transformation and takes cube root of the values of the financial ratios and macroeconomic variables.

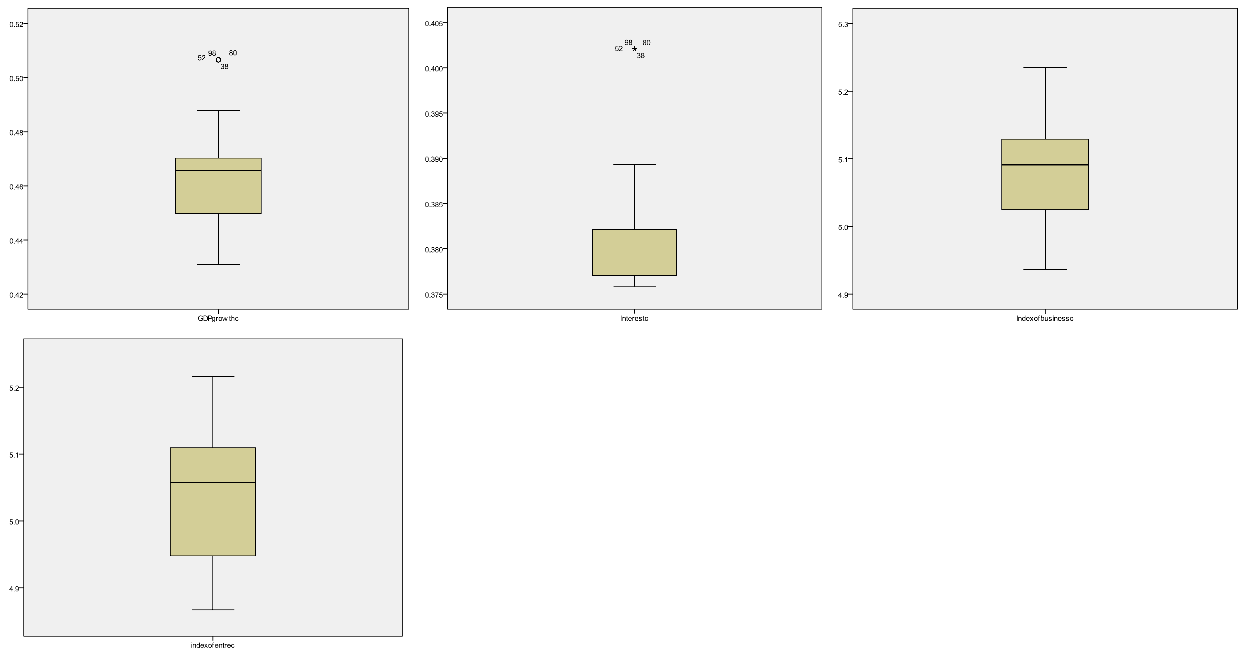
After data transformation, this study used SPSS to detect the outliers of the data. For the data of Year T-3, eight out of ten financial ratios' values have outliers (see Figure 5.11).

Figure 5.11 Box plots of all financial ratios (Year T-3)



In addition, two out of four macroeconomic variables' values have outliers (see Figure 5.12).

Figure 5.12 Box plots of all macroeconomic ratios (Year T-3)



Given the limited cases deployed in the present study, deletion of the cases with outliers is not a reasonable strategy to reduce the influence of outliers. Besides deleting the cases with outliers, changing the score(s) on the outlying case(s) is an alternative method to reduce the influence of outliers. According to Tabachnick and Fidell (2007, p. 77), the present study changed the value of outliers to the value of the next highest or lowest (non-outlier) case. As a result, the influence of all the outliers for Year T-3 was eliminated.

The third assumption is that the correlation matrix should have at least some correlations with *r* being no less than 0.3. Moreover, the Kaiser-Meyer-Olkin value ranges from 0 to 1 and should be no less than 0.5 (Child, 2006, p.55). The Bartlett's test of Sphericity should have a *p* value less than 0.05 (Pallant, 2007, p.185).

For the financial ratios of the Year T-3, the correlation matrix of all financial ratios is presented as Table 5.47. Table 5.47 shows that the correlation matrix of all financial variables for the Year T-3 has 17 correlations with *r* being greater than 0.3. With respect to non-financial variables and macroeconomic variables of the Year T-3, the correlation matrix of all non-financial variables and macroeconomic variables is presented as Table 5.48. This table provides that the correlation matrix of all non-financial variables and macroeconomic variables for the Year T-3 has four correlations with *r* being greater than 0.3. Therefore, the matrix is suitable for factoring analysis.

Table 5.47 Correlation matrix of financial ratios for the Year T-3

	ROA	ROE	Cash return on sales	Expense ratio	Asset turnover	Gross profit rate	Debt to total assets	Cash debt coverage	Current ratio	Quick ratio
ROA	1.000	.963	.632	-.400	.397	.294	-.274	.638	.351	.322
ROE	.963	1.000	.594	-.390	.371	.301	-.273	.590	.324	.300
Cash return on sales	.632	.594	1.000	-.294	.224	.191	-.279	.745	.211	.215
Expense ratiocr	-.400	-.390	-.294	1.000	.084	-.854	.409	-.408	-.455	-.469
Asset turnover	.397	.371	.224	.084	1.000	-.154	.202	.186	-.067	-.135
Gross profit rate	.294	.301	.191	-.854	-.154	1.000	-.448	.311	.392	.410
Debt to total assets	-.274	-.273	-.279	.409	.202	-.448	1.000	-.245	-.749	-.798
Cash debt coverage	.638	.590	.745	-.408	.186	.311	-.245	1.000	.200	.217
Current ratio	.351	.324	.211	-.455	-.067	.392	-.749	.200	1.000	.972
Quick ratio	.322	.300	.215	-.469	-.135	.410	-.798	.217	.972	1.000

Table 5.48 Correlation matrix of non-financial and macroeconomic variables for the Year T-3

	Delayinreleasingc	Changeauditorsc	Qualifiedexplanatoryc	Profitwarningc	GDPgrowthc	Interestc	Indexofbusinessc	indexofentrec
Delayinreleasingc	1.000	.332	.227	-.023	.049	-.057	-.034	-.014
Changeauditorsc	.332	1.000	.179	-.048	.077	-.024	.051	.007
Qualifiedexplanatoryc	.227	.179	1.000	-.018	.050	-.035	.049	.060
Profitwarningc	-.023	-.048	-.018	1.000	-.104	-.075	-.091	-.121
GDPgrowthc	.049	.077	.050	-.104	1.000	.299	.905	.898
Interestc	-.057	-.024	-.035	-.075	.299	1.000	.102	.104
Indexofbusinessc	-.034	.051	.049	-.091	.905	.102	1.000	.980
Indexofentrec	-.014	.007	.060	-.121	.898	.104	.980	1.000

The Kaiser-Meyer-Olkin measure of sampling adequacy and the results of the Bartlett's test of Sphericity are illustrated in Table 5.49 and Table 5.50. Table 5.49 indicates the Kaiser-Meyer-Olkin measure and Bartlett's test for financial ratios in the Year T-3. The Kaiser-Meyer-Olkin value is 0.731 which is far greater than 0.5. It means that the financial ratios are adequate for factor analysis. Moreover, the Bartlett's test of Sphericity is significant with the value less than 0.05. It suggests that there are significant correlations between the financial ratios.

Table 5.49 Kaiser-Meyer-Olkin Measure and Bartlett's Test for financial variables (Year T-3)

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		.731
Bartlett's Test of Sphericity	Approx. Chi-Square	991.806
	df	45
	Sig.	.000

Table 5.50 indicates the Kaiser-Meyer-Olkin Measure and Bartlett's test for non-financial and macroeconomic variables in the Year T-3. The Kaiser-Meyer-Olkin value is 0.636 which is far greater than 0.5. This suggests that the non-financial and macroeconomic variables are adequate for factor analysis. Furthermore, the Bartlett's test of Sphericity is significant with the *p* value less than 0.05. It indicates that there are significant correlations between the variables.

Table 5.50 Kaiser-Meyer-Olkin Measure and Bartlett's Test for non-financial and macroeconomic variables (Year T-3)

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		.636
Bartlett's Test of Sphericity	Approx. Chi-Square	540.412
	df	28
	Sig.	.000

On the whole, according to the correlation matrix, Kaiser-Meyer-Olkin measure of sampling adequacy and Bartlett's Test of Sphericity, it can be concluded that the data of the present study is suitable for factor analysis.

To test the fourth assumption, the present study used scatter plots to check the linearity of the data. The scatter plots of financial ratios are presented in Appendix Figure A5.5 shows that there is no clear evidence of curvilinear relationship between any two financial ratios. The scatter plots of non-financial and macroeconomic variables are presented in Appendix Figure A5.6 shows that there is no clear evidence of curvilinear relationship between any two non-financial and macroeconomic variables. Therefore, the values of financial ratios, non-financial and macroeconomic variables are safe to do factor analysis (Pallant, 2007, p.185).

To sum up, all these four basic assumptions for factor analysis were used to assess the suitability of the data for factor analysis. They underlie the application of factor analysis. Based on the results of assumption testing, all these four basic assumptions for factor analysis are satisfied. Hence, the Year T-3's financial ratios, non-financial and macroeconomic variables for the present study are suitable for factor analysis.

5.4.2.2 Conducting factor analysis for financial ratios

5.4.2.2.1 Factor extraction

The present study used factor extraction to determine the smallest number of financial factors that could best represent the interrelations among financial ratios. All the financial ratios for the Year T-3 were inputted into the SPSS. The most commonly used extraction technique (principal components) was then used to extract the underlying financial factors.

Firstly, Kaiser's criterion was used to assist in the decision concerning retaining the factors. As was discussed in Chapter 4, factors with eigenvalue greater than 1 could be retained for further investigation. In Table 5.51, there are three factors (Factor 1, 2 and 3) with their eigenvalues greater than 1. Overall, these three factors explain about 80 per cent of the original variance.

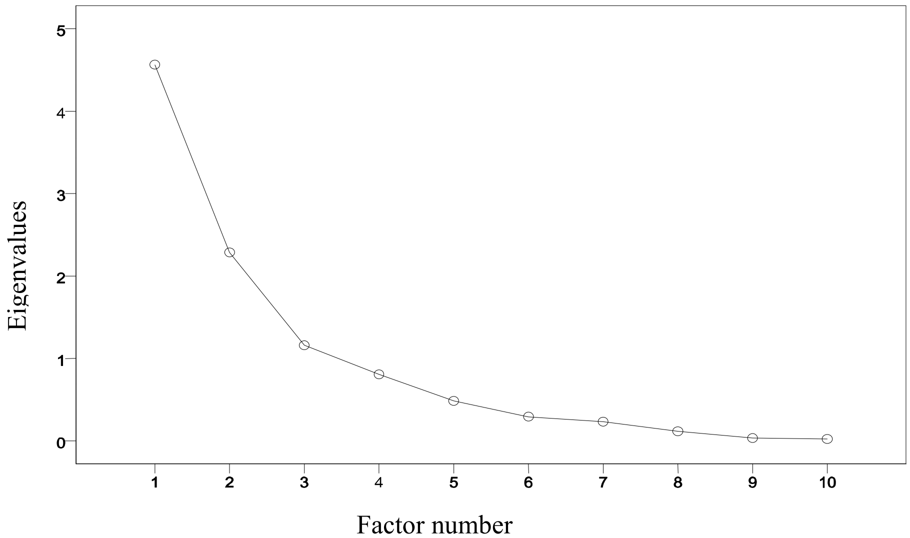
Table 5.51 Total variance explained for financial factors (Year T-3)

Factor	Initial Eigenvalues			Extraction Sums of Squared Loadings			Rotation Sums of Squared Loadings[a]
	Total	Percentage of Variance	Cumulative Percentage	Total	Percentage of Variance	Cumulative Percentage	Total
1	4.562	45.619	45.619	4.562	45.619	45.619	3.258
2	2.287	22.874	68.493	2.287	22.874	68.493	2.780
3	1.159	11.593	80.086	1.159	11.593	80.086	1.971
4	.808	8.075	88.162				
5	.484	4.841	93.003				
6	.293	2.934	95.936				
7	.233	2.331	98.268				
8	.117	1.171	99.439				
9	.033	.334	99.773				
10	.023	.227	100.000				

Extraction Method: Principal Component Analysis.
a. When components are correlated, sums of squared loadings cannot be added to obtain a total variance.

Secondly, in Figure 5.13, the scree plot line begins to flatten out at around the fourth factor. As a result, according to theory of Catell's scree test discussed in Chapter 4, the scree plot also suggests that it is appropriate to retain three factors.

Figure 5.13 Scree plot for financial factors (Year T-3)



5.4.2.2.2 Factor rotation and interpreting factors

In order to interpret the factors, SPSS provides several methods for rotating the factors. As discussed in Chapter 4, there are two main approaches to rotation (the orthogonal approach and the oblique approach). The orthogonal approach produces factors which are uncorrelated. In contrast, the oblique approach allows the extracted factors to be highly correlated. In the present study, the extracted factors would be saved as the independent variables for logistic regression and these independent variables should be uncorrelated. Consequently, the orthogonal approach would be a more appropriate approach for the present study and the most commonly used orthogonal approach - Varimax method - was used in the study.

After the rotation, the number of complex variables among factors decrease and the factors become easier to be interpreted. The rotated factors are shown in the rotated factor matrix. Table

5.52 presents the items which constitute the three most important factors and these items' factor loadings. The cut off point for the absolute value of factor loading was set at 0.5.

Table 5.52 Rotated financial factor matrix[a] (Year T-3)

	Factor		
	1	2	3
ROA	.902		
ROE	.877		
Cash return on sales	.782		
Cash debt coverage	.762		
Asset turnover	.596		
Quick ratio		.955	
Current ratio		.943	
Debt to total assets		-.847	
Gross profit rate			.895
Expense ratio			-.856

Extraction Method: Principal Component Analysis.
Rotation Method: Varimax with Kaiser Normalization.
a. Rotation converged in 4 iterations.

The Table 5.52 indicates that Factor 1 comprises five items with factor loadings ranging from 0.902 to 0.596 and the most important item is ROA. The present study labels Factor 1 as Profitability-Solvency Factor because Factor 1 consists of four profitability ratios (ROA, ROE, asset turnover and cash return on sales) and one solvency ratio (cash debt coverage).

Factor 2 comprises three items with factor loadings ranging from 0.955 to -0.847 and the most important item is quick ratio. The present study labels Factor 2 as Liquidity-Solvency Factor because Factor 2 consists of two liquidity ratios (current ratio and quick ratio) and one solvency ratio (debt to total assets).

Factor 3 includes two items: gross profit rate and expense ratio. The factor loadings of these two items are 0.895and -0.856 respectively. The item which makes the most significant contribution to factor 3 is gross profit rate. The present study labels Factor 3 as Profitability Factor because Factor 3 consists of two profitability ratios (gross profit rate and expense ratio).

5.4.2.3 Conducting factor analysis for non-financial and macroeconomic variables

5.4.2.3.1 Factor extraction

The present study used factor extraction to determine the smallest number of non-financial and macroeconomic factors that can best represent the interrelations among non-financial and macroeconomic variables. All the non-financial and macroeconomic variables for the Year T-3 were inputted into the SPSS. The present study then applied the most commonly used extraction technique (principal components) to extract the underlying non-financial and macroeconomic factors.

Kaiser's criterion is used to decide the number of factors to retain and the factors with eigenvalue greater than 1 can be retained for further investigation. In Table 5.53, there are also three factors (Factor 1, 2 and 3) with their eigenvalues greater than 1. These three factors explain over 68 per cent of the totally original variance.

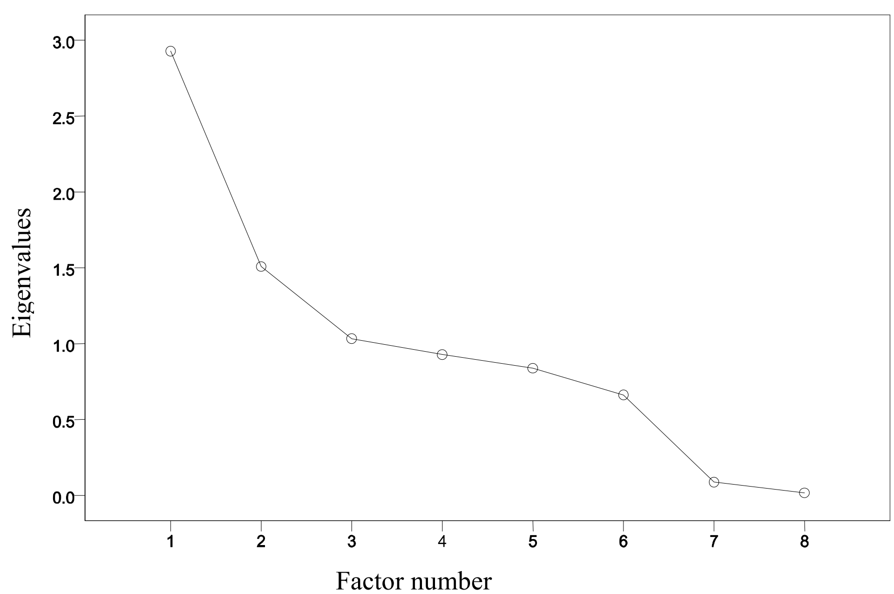
Table 5.53 Total variance explained for non-financial and macroeconomic factors (Year T-3)

Factor	Initial Eigenvalues			Extraction Sums of Squared Loadings			Rotation Sums of Squared Loadings
	Total	Percentage of Variance	Cumulative Percentage	Total	Percentage of Variance	Cumulative Percentage	Total
1	2.928	36.596	36.596	2.928	36.596	36.596	2.852
2	1.508	18.852	55.448	1.508	18.852	55.448	1.514
3	1.033	12.907	68.355	1.033	12.907	68.355	1.102
4	.927	11.593	79.948				
5	.838	10.472	90.420				
6	.662	8.275	98.696				
7	.087	1.092	99.787				
8	.017	.213	100.000				

Extraction Method: Principal Component Analysis.

In Figure 5.14, the scree plot line begins to change in shape and flatten out between the third and the fourth factor. According to theory of Catell's scree test, it is safe to retain three factors.

Figure 5.14 Scree plot for non-financial and macroeconomic factors (Year T-3)



5.4.2.3.2 Factor rotation and interpreting factors

In the present study, the rotation of financial factors is similar to the rotation of non-financial and macroeconomic factors. In addition, all of the extracted factors will be saved as independent variables for logistic regression and those independent variables should be uncorrelated. Hence, the orthogonal approach and the most commonly used orthogonal approach (Varimax method) were also used for extracting non-financial and macroeconomic factors in the present study.

After the rotation, the number of complex variables among factors decreased and the factors became easier to be interpreted. The rotated factors are shown in the rotated factor matrix. Table 5.54 presents the items which constitute the three extracted factors and these items' factor loadings. The cut off point for absolute value of the factor loading is 0.5.

Table 5.54 Rotated non-financial and macroeconomic factor matrix[a] (Year T-3)

	Factor		
	1	2	3
Business Climate Index	.987		
Entrepreneur Confidence Index	.983		
Real GDP growth rate	.943		
Delay in releasing financial statements		.766	
Changing auditors		.729	
Auditors' report with qualified opinion and/ or explanatory paragraph		.602	
Profit warning			-.726
Average interest rate on loans			.721

Extraction Method: Principal Component Analysis.
Rotation Method: Varimax with Kaiser Normalization.
a. Rotation converged in 4 iterations.

Table 5.54 indicates that Factor 1 comprises three items with factor loadings ranging from 0.987 to 0.943 and the most important item is the Business Climate Index. Furthermore, Entrepreneur Confidence Index and real GDP growth rate are other two important items, with their factor loadings quite close to the factor loading of Business Climate Index. The present study interpreted Factor 1 as Macroeconomic Factor because Factor 1 refers to three macroeconomic variables which include Business Climate Index, Entrepreneur Confidence Index and real GDP growth rate.

Factor 2 consists of three items with factor loadings ranging from 0.766 to 0.602 and the most important item is ‘delay in releasing financial statements’. Below this item, the items ‘changing auditors’ and ‘auditors’ report with qualified opinion and/ or explanatory paragraph’ have factor loadings of 0.729 and 0.602 respectively. The present study labelled Factor 2 as Auditing-Disclosure Factor because Factor 2 consists of two non-financial variables concerning auditing (‘changing auditors’ and ‘auditors’ report with qualified opinion and/ or explanatory paragraph’) and one non-financial variable referring to corporate disclosure (‘delay in releasing financial statements’).

Factor 3 has two items and the items are ‘average interest rate on loans’ and ‘profit warning’. The factor loadings of these two items are 0.721and -0.726 respectively. As a result, the present study simply labelled Factor 3 as the Profit Related Factor.

In summary, there are three financial factors extracted from financial ratios. Based on the items that constitute the factors, the present study labelled the three factors as Profitability- Solvency Factor, Liquidity- Solvency Factor and Profitability Factor. Additionally, three non-financial and macroeconomic factors were generated from non-financial and macroeconomic variables. According to the items that constitute these factors, the present study labelled the three factors as Macroeconomic Factor, Auditing-disclosure Factor and Profit Related Factor. All of these six factors were used as independent variables for logistic regression analyses.

5.4.3 Logistic regression analysis (Year T-3)

After the MWW test and factor analysis, the extracted financial, non-financial and macroeconomic factors were used as independent variables for logistic regression analyses. The dependent variable is whether the growth enterprise experienced distress or not (distressed = 1, non-distressed =0). The present study then used logistic regression analysis to establish three types of financial distress prediction models and test related hypotheses.

The first type of model considered firm-specific financial factors only, whereas the second type of model considered firm-specific non-financial factors and macroeconomic factors. The third type of model considered not only firm-specific financial factors but also firm-specific non-financial factors and macroeconomic factors. These three models were referred to as Model 1, Model 2 and Model 3 respectively. The study compared classification accuracy of Model 1 with that of Model 2. Subsequently, the study compared classification accuracy of Model 1 with that of Model 3. Finally, all the hypotheses in the present study were tested and the results were discussed.

5.4.3.1 Assumptions testing for logistic regression

As was discussed in Chapter 4, the first assumption refers to the number of cases in the sample and the number of independent variables included in the logistic regression model. The present study produced three logistic regression models. Model 1 considered three financial factors as independent variables; Model 2 considered three non-financial and macroeconomic factors as independent variables; Model 3 considered all the six factors as independent variables which included financial, non-financial and macroeconomic factors. Moreover, there were 100 growth enterprises considered in this study. In other words, there were a relatively small number of independent variables with a relatively large sample. Hence, the sample size of this study and its independent variables are suitable for logistic regression.

The second assumption is about checking for intercorrelations or multicollinearity among independent variables. Ideally, the independent variables should not be strongly related to each other and the highly intercorrelating variables have to be removed (Pallant, 2007, p.167). In the present study, given the orthogonal approach always results in uncorrelated factors, the three financial factors extracted by using the orthogonal approach (Varimax method) should be uncorrelated. In the same way, the three non-financial and macroeconomic factors also should be uncorrelated.

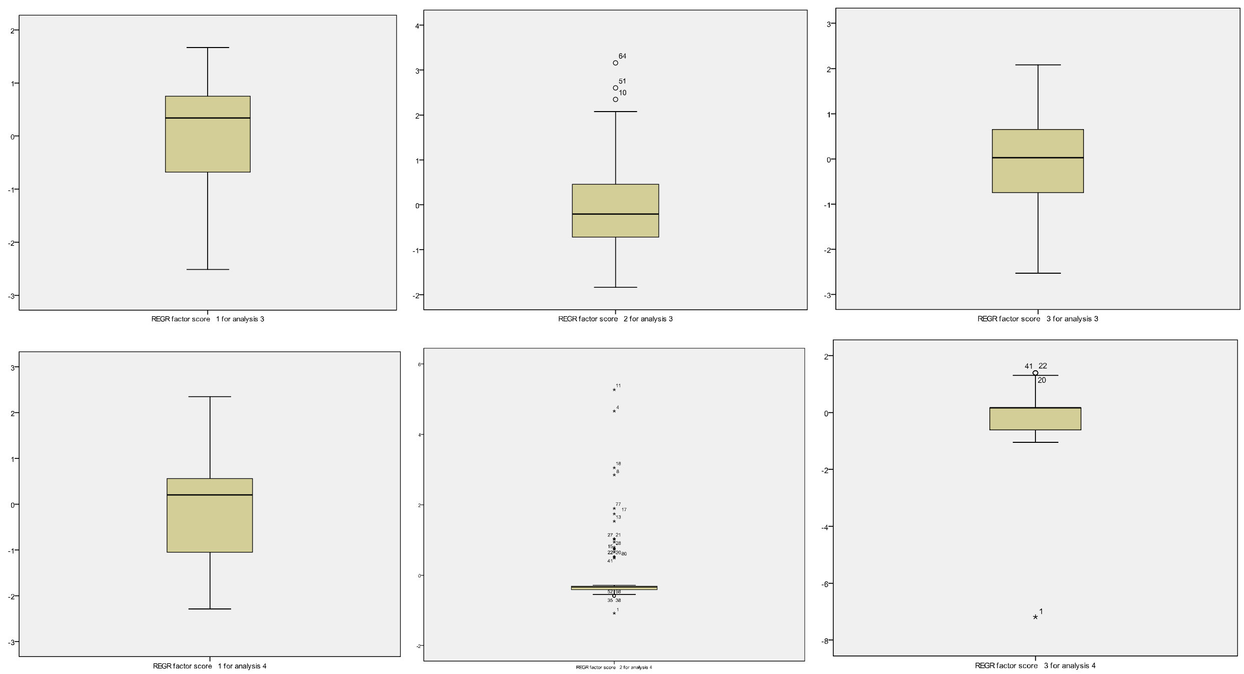
In order to check the multicollinearity of all these six factors, the present study checked the intercorrelation among these factors. Multicollinearity occurs when these factors are highly correlated with the value of *r* being no less than 0.9 (Tabachnick and Fidell, 2007, p. 88). The values of Pearson correlation in Table 5.55 show that the values of *r* are all less than 0.9. Therefore, there are no multicollinearities among these six factors and all these factors can be retained.

Table 5.55 Pearson Correlation of all factors (Year T-3)

	Profitability-Solvency Factor	Liquidity-Solvency Factor	Profitability Factor	Macroeconomic Factor	Auditing-Disclosure Factor	Profit Warning Factor
Profitability-Solvency Factor	1.000	-.070	-.103	-.104	.111	.021
Liquidity-Solvency Factor	-.070	1.000	.092	-.149	.171	.101
Profitability Factor	-.103	.092	1.000	-.115	.047	.092
Macroeconomic Factor	-.104	-.149	-.115	1.000	-.329	.120
Auditing-Disclosure Factor	.111	.171	.047	-.329	1.000	-.218
Profit Warning Factor	.021	.101	.092	.120	-.218	1.000

Finally, because of outliers influencing the results of logistic regression, the third assumption is about checking for the presence of outliers. If there are some cases that are not well explained by the model, these outlying cases would be removed or recoded to a lesser value (Tabachnick and Fidell, 2007, p. 77). In SPSS, histograms, box plots and descriptive statistics of each variable or ratio are used to identify outliers (Pallant, 2007). After checking the outliers, this study found three out of these six factors had outlying cases (see Figure 5.15).

Figure 5.15 Box plots of all factors (Year T-3)



As has been discussed previously, the present study changed the value of outliers to the value of the next highest or lowest (non-outlier) case. As a result, the influence of all the outliers for all the factors was eliminated.

5.4.3.2 Conducting logistic regression analysis for financial factors

As discussed previously, the three financial factors were used as independent variables and whether the growth enterprise having experienced distress was regarded as a dependent variable. The dependent variable was coded as follows: 0 was used to indicate the growth enterprise having not experienced financial distress and 1 was used to indicate the growth enterprise having experienced financial distress. The present study inputted these three independent variables and one dependent variable into SPSS and ran the logistic regression to analyse them. This logistic regression analysis was referred to as Model 1 for Year T-3 in this study.

The output of the logistic regression analysis (Model 1) and the interpretation of the output are as follows.

At the beginning, the Omnibus Tests of Model Coefficients provides an overall prediction of how well the model with three financial independent variables performs compared with the model without considering independent variables (Pallant, 2007, p.174). Panel A of Table 5.56 presents the significant value for Omnibus Tests of Model Coefficients as less than 0.05. Hence, the model with three financial factors used as independent variables is better than the model without using any financial factors as independent variables. The χ^2 (3, N = 100) = 28.981 with $p < 0.001$ also indicates that the model including three financial independent variables is able to distinguish between growth enterprises which have experienced financial distress and which have not experienced financial distress (Pallant, 2007, p.178).

The results shown in Table 5.56 (Panel B) also provide some information about the usefulness of the model. The value of Cox and Snell R Square and the value of Nagelkerke R Square, which are from a minimum value of 0 to a maximum value of 1, indicate the amount of variation in the dependent variable explained by the model (Pallant, 2007, p.174). It can be seen from Panel B of Table 5.56 that the value of Cox and Snell R Square and the value of Nagelkerke R Square are 0.252 and 0.357 respectively. In other words, between 25.2 per cent and 35.7 per cent of the variability in the dependent variable is explained by the independent variables.

Table 5.56 The performance and usefulness of Model 1

Panel A Omnibus Tests of Model Coefficients for Model 1

		Chi-square	df	Sig.
Step 1	Step	28.981	3	.000
	Block	28.981	3	.000
	Model	28.981	3	.000

Panel B Table 5.63 Model Summary for Model 1

-2 Log likelihood	Cox and Snell R Square	Nagelkerke R Square
93.192[a]	.252	.357

a. Estimation terminated at iteration number 5 because parameter estimates changed by less than .001.

As discussed previously, when the independent variables are not entered into the model, the overall percentage of correctly classified cases is 70 per cent (see Table 5.14). On the other hand, Table 5.57 shows the overall percentage of correctly classified cases when the model includes all independent variables. The present study compared this with the overall percentage of correctly classified case in Table 5.57 to see the improvement of including the independent variable in the model. Therefore, the model with the independent variable correctly classified 77 per cent of cases overall and has a great improvement over the 70 per cent of accuracy in classification for the model without using independent variables.

Table 5.57 Classification for Model 1[a] (with the independent variables)

Observed		Predicted		
		Status		Percentage Correct
		0	1	
Status	0	64	6	91.4
	1	17	13	43.3
Overall Percentage				77.0

a. The cut value is .500

As shown in Table 5.58, only one independent variable (Profitability-Solvency Factor) has a *Sig.* value less than 0.05. Therefore, Profitability-Solvency Factor made a statistically significant contribution to the model at the five per cent level. The other two financial independent variables (Liquidity- Solvency Factor and Profitability Factor) do not contribute significantly to the model.

The *B* values provided in Table 5.58 can be used in an equation to compute the probability of a case falling into a specific category (Pallant, 2007, p.175). For the significant independent variable in Model 1, Profitability-Solvency Factor has a negative *B* value (-1.271). This suggests that: if a growth enterprise has higher Profitability-Solvency Factor, it is less likely to experience financial distress.

Table 5.58 Financial independent variables in the equation for Model 1

	B	S.E.	Wald	df	Sig.	Exp(B)
Profitability-Solvency Factor	-1.271	.281	20.373	1	.000	.281
Liquidity-Solvency Factor	.306	.265	1.339	1	.247	1.358
Profitability Factor	-.181	.263	.474	1	.491	.834
Constant	-1.063	.268	15.693	1	.000	.345

5.4.3.3 Conducting logistic regression analysis for non-financial and macroeconomic factors

As discussed previously, the three non-financial and macroeconomic factors were used as independent variables and whether the growth enterprise having experienced distress was regarded as a dependent variable. The dependent variable was coded as follows: 0 was used to indicate the growth enterprise having not experienced financial distress and 1 was used to indicate the growth enterprise having experienced financial distress. The present study inputted these three independent variables and one dependent variable into SPSS and ran the logistic regression to analyse them. This logistic regression analysis was referred to as Model 2 for Year T-3 in this study.

The output of the logistic regression analysis (Model 2) and the interpretation of the output are as follows.

At the beginning, the Omnibus Tests of Model Coefficients provides an overall prediction of how well the model with three independent variables performs compared with the model without considering independent variables (Pallant, 2007, p.174). Panel A of Table 5.59 presents the significant value for Omnibus Tests of Model Coefficients as less than 0.05. Hence, the model with three factors used as independent variables is better than the model without using any factors as independent variables. The χ^2 (3, N = 100) = 24.897 with p < 0.001 also indicates that the model including three independent variables is able to distinguish between growth enterprises which have experienced financial distress and which have not experienced financial distress (Pallant, 2007, p.178).

Table 5.59 (Panel B) presents that the value of Cox and Snell R Square and the value of Nagelkerke R Square are 0.22 and 0.312 respectively. In other words, between 22 per cent and 31.2 per cent of the variability in the dependent variable is explained by the independent variables.

Table 5.59 The performance and usefulness of Model 2

Panel A Omnibus Tests of Model Coefficients for Model 2

		Chi-square	df	Sig.
Step 1	Step	24.897	3	.000
	Block	24.897	3	.000
	Model	24.897	3	.000

Panel B Model Summary for Model 2

-2 Log likelihood	Cox and Snell R Square	Nagelkerke R Square
97.276[a]	.220	.312

a. Estimation terminated at iteration number 5 because parameter estimates changed by less than .001.

As discussed previously, when the independent variables are not entered into the model, the overall percentage of correctly classified cases is 70 per cent (see Table 5.14). On the other hand, Table 5.60 shows the overall percentage of correctly classified cases when the model includes all independent variables. The present study compared this with the overall percentage of correctly classified case in Table 5.60 to see the improvement of including the independent variable in the model. Therefore, the model with the independent variable correctly classified 78 per cent of cases overall and has a great improvement over the 70 per cent of accuracy in classification for the model without using independent variables.

Table 5.60 Classification for Model 2[a] (with the independent variables)

Observed		Predicted		
		Status		Percentage Correct
		0	1	
Status	0	61	9	97.1
	1	13	17	56.7
Overall Percentage				78.0

a. The cut value is .500

As shown in Table 5.61, three independent variables (Macroeconomic Factor, Auditing-Disclosure Factor and Profit Related Factor) have their *Sig.* values less than 0.05. Therefore, Macroeconomic Factor, Auditing-Disclosure Factor and Profit Related Factor make statistically significant contributions to the model at the five per cent level.

The *B* values provided in Table 5.61 can be used in an equation to compute the probability of a case falling into a specific category (Pallant, 2007, p.175). For the significant independent variables in Model 2, Auditing-Disclosure Factor and Profit Related Factor have positive *B* values which are 17.722 and 0.864 respectively. Macroeconomic Factor has a negative *B* value which is -0.81. These outputs suggest that: if a growth enterprise has higher Auditing-Disclosure Factor and Profit Related Factor, it is more likely to experience financial distress; In contrast, if a growth enterprise has higher Macroeconomic Factor, it is less likely to experience financial distress

Table 5.61 Non-financial and macroeconomic independent variables in the equation for Model 2

	B	S.E.	Wald	df	Sig.	Exp(B)
Macroeconomic Factor	-.810	.281	8.322	1	.004	.445
Auditing-Disclosure Factor	17.722	4.403	16.202	1	.000	4.973E7
Profit Related Factor	.864	.425	4.133	1	.042	2.373
Constant	5.488	1.559	12.390	1	.000	241.699

5.4.3.4 Testing Hypothesis 7

Hypothesis 7 is tested based on the outputs of Model 1 and Model 2 as follows.

Hypothesis 7:

Null Hypothesis 7: The model incorporating firm-specific financial factors is not better than the model which includes firm-specific non-financial and macroeconomic factors in financial distress prediction.

Alternative Hypothesis 7: The model incorporating firm-specific financial factors is better than the model which includes firm-specific non-financial and macroeconomic factors in financial distress prediction.

The findings presented in Table 5.57 indicate that the model 1 correctly classified 77 per cent of cases. The findings presented in Table 5.60 indicate that the model 2 correctly classified 78 per cent of cases. The classification accuracy of Model 2 (77 per cent) is slightly higher than the classification accuracy of Model 1 (78 per cent). Therefore, the Null Hypothesis 7 cannot be rejected.

5.4.3.5 Conducting logistic regression analysis for all factors

As discussed previously, the six factors, including financial, non-financial and macroeconomic factors, were used as independent variables and whether the growth enterprise had experienced distress was regarded as a dependent variable. The dependent variable was coded as 0, 1. 0 was used to indicate the growth enterprise having not experienced financial distress, and 1 was used to indicate the growth enterprise had experienced financial distress. The present study inputted these six independent variables and one dependent variable into SPSS and ran the logistic regression to analyse them. This logistic regression analysis was referred to as Model 3 for Year T-3 in this study.

The output of the logistic regression analysis (Model 3) and the interpretation of the output are as follows.

At the beginning, the Omnibus Tests of Model Coefficients provides an overall prediction of how well the model with six independent variables performs compared with the model, without considering independent variables (Pallant, 2007, p.174). Panel A of Table 5.62 presents that the significant value for Omnibus Tests of Model Coefficients is less than 0.05. Hence, the model with six factors used as independent variables is better than the model without using any factors as independent variables. The χ^2 (6, N = 100) = 39.132 with p < 0.001 also indicates that the model covering six independent variables is able to distinguish between growth enterprises which have experienced financial distress and which have not experienced financial distress (Pallant, 2007, p.178).

The results shown in Table 5.62 (Panel B) also provide some information about the usefulness of the model. As can be seen in Panel B of Table 5.6, the values of Cox and Snell R Square and the value of Nagelkerke R Square are 0.324 and 0.459 respectively. In other words, between 32.4 per cent and 45.9 per cent of the variability in the dependent variable is explained by the independent variables.

Table 5.62 The performance and usefulness of Model 3
Panel A Omnibus Tests of Model Coefficients for Model 3

		Chi-square	df	Sig.
Step 1	Step	39.132	6	.000
	Block	39.132	6	.000
	Model	39.132	6	.000

Panel B Model Summary for Model 3

-2 Log likelihood	Cox and Snell R Square	Nagelkerke R Square
83.041[a]	.324	.459

a. Estimation terminated at iteration number 6 because parameter estimates changed by less than .001.

As discussed previously, when the independent variables are not entered into the model, the overall percentage of correctly classified cases is 70 per cent (see Table 5.14). On the other hand, Table 5.63 shows the overall percentage of correctly classified cases when the model includes all independent variables. The present study compared this with the overall percentage of correctly classified cases in Table 5.63 to see the improvement of including the independent variable in the model. Therefore, the model with six independent variables correctly classified 83 per cent of cases overall and has a great improvement over the 70 per cent of accuracy in classification for the model without using independent variables.

Table 5.63 Classification for Model 3 [a] (with the independent variables)

Observed		Predicted		
		Status		Percentage Correct
		0	1	
Status	0	63	7	90.0
	1	10	20	66.7
Overall Percentage				83.0

a. The cut value is .500

As shown in Table 5.64, there are two independent variables (Profitability-Solvency Factor and Auditing-Disclosure Factor) with their *Sig.* values less than 0.05. Therefore, Profitability-

Solvency Factor and Auditing-Disclosure Factor contribute significantly to the predictive ability of the model. The other four independent variables (Liquidity-Solvency Factor, Profitability Factor, Macroeconomic Factor and Profit Warning Factor) do not contribute significantly to the model.

As discussed previously, the *B* values provided in Table 5.64 can be used to compute the probability of a case falling into a specific category. For the two significant independent variables in this model, Profitability-Solvency Factor has a negative *B* value (-1.001) and Auditing-Disclosure Factor has a positive *B* value (13.674). The negative *B* value of Profitability-Solvency Factor indicates that if a growth enterprise has a higher value in Profitability-Solvency Factor, this growth enterprise was less likely to experience financial distress in three years. In contrast, the *B* value of Auditing-Disclosure Factor shows that if a growth enterprise more frequently had the problems in auditing and disclosure, this growth enterprise was more likely to experience financial distress in three years.

Table 5.64 Independent variables in the equation for Model 3

	B	S.E.	Wald	df	Sig.	Exp(B)
Profitability-Solvency Factor	-1.001	.303	10.895	1	.001	.367
Liquidity- Solvency Factor	.374	.275	1.848	1	.174	1.454
Profitability Factor	-.005	.279	.000	1	.986	.995
Macroeconomic Factor	-.587	.313	3.521	1	.061	.556
Auditing-Disclosure Factor	13.674	4.844	7.967	1	.005	868143.681
Profit Related Factor	.713	.462	2.374	1	.123	2.039
Constant	3.894	1.730	5.065	1	.024	49.102

5.4.3.6 Testing Hypothesis 2, 4, 6 and 8

Hypothesis 2, Hypothesis 4, Hypothesis 6 and Hypothesis 8 were tested based on the outputs of Model 3 as follows.

Hypothesis 2:

Null Hypothesis 2: For the proposed model incorporating firm-specific financial, firm-specific non-financial and macroeconomic factors, the firm-specific financial factors are not significant predictors of growth enterprises' financial distress.

Alternative Hypothesis 2: For the proposed model incorporating firm-specific financial, firm-specific non-financial and macroeconomic factors, the firm-specific financial factors are significant predictors of growth enterprises' financial distress.

As discussed previously, the findings presented in Table 5.64 indicate that only one of the financial factors (Profitability-Solvency Factor) has a *Sig.* value less than 0.05. In other words, the Profitability-Solvency Factor, which was extracted from financial ratios, is a significant predictor of growth enterprises' financial distress at the five per cent level. Therefore, for Model 3, the Null Hypothesis 2 has to be rejected.

Hypothesis 4:

Null Hypothesis 4: For the proposed model incorporating firm-specific financial, firm-specific non-financial and macroeconomic factors, the firm-specific non-financial factors are not significant predictors of growth enterprises' financial distress.

Alternative Hypothesis 4: For the proposed model incorporating firm-specific financial, firm-specific non-financial and macroeconomic factors, the firm-specific non-financial factors are significant predictors of growth enterprises' financial distress.

The findings presented in Table 5.64 also indicate that one non- financial factor (Auditing-Disclosure Factor) has its *Sig.* value less than 0.05. In other words, Auditing-Disclosure Factor, which was extracted from non-financial variables, is a significant predictor of growth enterprises' financial distress at the five per cent level. Therefore, for Model 3, the Null Hypothesis 4 has to be rejected.

Hypothesis 6:

Null Hypothesis 6: For the proposed model incorporating firm-specific financial, firm-specific non-financial and macroeconomic factors, the macroeconomic factors are not significant predictors of growth enterprises' financial distress.

Alternative Hypothesis 6: For the proposed model incorporating firm-specific financial, firm-specific non-financial and macroeconomic factors, the macroeconomic factors are significant predictors of growth enterprises' financial distress.

According to the findings presented in Table 5.64, Macroeconomic Factor, which consists of three macroeconomic variables, has its *Sig.* value greater than 0.05. Macroeconomic Factor is not a significant predictor of growth enterprises' financial distress at five per cent level. Thus, for Model 3, the Null Hypothesis 6 cannot be rejected.

Hypothesis 8:

Null Hypothesis 8: The proposed model incorporating firm-specific financial, firm-specific non-financial and macroeconomic factors is not better than the model which only includes firm-specific financial factors in financial distress prediction.

Alternative Hypothesis 8: The proposed model incorporating firm-specific financial, firm-specific non-financial and macroeconomic factors is better than the model which only includes firm-specific financial factors in financial distress prediction.

The findings presented in Table 5.57 and Table 5.63 reveal that the classification accuracy of Model 3 (83 per cent) is higher than the classification accuracy of Model 1 (77 per cent). The firm-specific non-financial and macroeconomic factors helped enhance the classification accuracy of the model. These results confirmed that Model 3 is better than Model 1 in classification accuracy. Based on all the findings, the Null Hypothesis 8 has to be rejected.

To sum up, for Year T-3, the Null Hypothesis 2 has to be rejected; the Null Hypothesis 4 has to be rejected; the Null Hypothesis 6 cannot be rejected; the Null Hypothesis 7 cannot be rejected; the Null Hypothesis 8 has to be rejected.

5.5 Summary and interpretation of the results

Table 5.65, Table 5.66 and Table 5.67 present the summary results of hypothesis testing for Year T-1, T-2 and T-3 respectively.

Table 5.65 Summary results of hypothesis testing (Year T-1)

Null hypothesis	Test result
1. There are no significant differences in financial ratios between distressed and non-distressed growth enterprises.	Null Hypothesis 1 is rejected.
2. For the proposed model incorporating firm-specific financial, firm-specific non-financial and macroeconomic factors, the extracted financial factors are not significant predictors of growth enterprises' financial distress.	Null Hypothesis 2 is rejected.
3. There are no significant differences in non-financial variables between distressed and non-distressed growth enterprises.	Null Hypothesis 3 is rejected.
4. For the proposed model incorporating firm-specific financial, firm-specific non-financial and macroeconomic factors, the extracted firm-specific non-financial factors are not significant predictors of growth enterprises' financial distress.	Null Hypothesis 4 is rejected.
5. There are no significant differences in macroeconomic variables between distressed and non-distressed growth enterprises.	For three macroeconomic variables (real GDP growth rate, average interest rate on loans and Business Climate Index), the Null Hypothesis 5 is rejected; for one macroeconomic variable (Entrepreneur Confidence Index), Null Hypothesis 5 cannot be rejected.
6. For the proposed model incorporating firm-specific financial, firm-specific non-financial and macroeconomic factors, the extracted macroeconomic factors are not significant predictors of growth enterprises' financial distress.	Null Hypothesis 6 cannot be rejected.
7. The model incorporating firm-specific financial factors is not better than the model which includes firm-specific non-financial and macroeconomic factors in financial distress prediction.	Null Hypothesis 7 cannot be rejected.
8. The proposed model incorporating firm-specific financial, firm-specific non-financial and macroeconomic factors is not better than the model which only includes firm-specific financial factors in financial distress prediction.	Null Hypothesis 8 is rejected.

Table 5.66 Summary results of hypothesis testing (Year T-2)

Null hypothesis	Test result
1. There are no significant differences in financial ratios between distressed and non-distressed growth enterprises.	For eight out of ten financial ratios, the Null Hypothesis 1 is rejected; for expense ratio, gross profit margin and quick ratio, the Null Hypothesis 1 cannot be rejected.
2. For the proposed model incorporating firm-specific financial, firm-specific non-financial and macroeconomic factors, the extracted financial factors are not significant predictors of growth enterprises' financial distress.	Null Hypothesis 2 is rejected.
3. There are no significant differences in non-financial variables between distressed and non-distressed growth enterprises.	For three non-financial variables ('delay in releasing financial statements', 'changing auditors' and 'auditors' report with qualified opinion and/ or explanatory paragraph'), Null Hypothesis 3 is rejected; for 'profit warning', Null Hypothesis 3 cannot be rejected.
4. For the proposed model incorporating firm-specific financial, firm-specific non-financial and macroeconomic factors, the extracted firm-specific non-financial factors are not significant predictors of growth enterprises' financial distress.	Null Hypothesis 4 is rejected.
5. There are no significant differences in macroeconomic variables between distressed and non-distressed growth enterprises.	For two macroeconomic variables (real GDP growth rate and average interest rate on loans), Null Hypothesis 5 is rejected; for two macroeconomic variable (Business Climate Index and Entrepreneur Confidence Index), Null Hypothesis 5 cannot be rejected.
6. For the proposed model incorporating firm-specific financial, firm-specific non-financial and macroeconomic factors, the extracted macroeconomic factors are not significant predictors of growth enterprises' financial distress.	Null Hypothesis 6 cannot be rejected.
7. The model incorporating firm-specific financial factors is not better than the model which includes firm-specific non-financial and macroeconomic factors in financial distress prediction.	Null Hypothesis 7 cannot be rejected.
8. The proposed model incorporating firm-specific financial, firm-specific non-financial and macroeconomic factors is not better than the model which only includes firm-specific financial factors in financial distress prediction.	Null Hypothesis 8 is rejected.

Table 5.67 Summary results of hypothesis testing (Year T-3)

Null hypothesis	Test result
1. There are no significant differences in financial ratios between distressed and non-distressed growth enterprises.	For five out of ten financial ratios, the Null Hypothesis 1 is rejected; for expense ratio, current ratio, quick ratio, debt to total assets and gross profit margin, the Null Hypothesis 1 cannot be rejected.
2. For the proposed model incorporating firm-specific financial, firm-specific non-financial and macroeconomic factors, the extracted financial factors are not significant predictors of growth enterprises' financial distress.	Null Hypothesis 2 is rejected.
3. There are no significant differences in non-financial variables between distressed and non-distressed growth enterprises.	For two non-financial variables ('changing auditors' and 'delay in releasing financial statements'), the Null Hypothesis 3 is rejected; for 'profit warning' and 'auditors' report with qualified opinion and/ or explanatory paragraph', the Null Hypothesis 3 cannot be rejected.
4. For the proposed model incorporating firm-specific financial, firm-specific non-financial and macroeconomic factors, the extracted firm-specific non-financial factors are not significant predictors of growth enterprises' financial distress.	Null Hypothesis 4 is rejected.
5. There are no significant differences in macroeconomic variables between distressed and non-distressed growth enterprises.	For three macroeconomic variables (real GDP growth rate, Entrepreneur Confidence Index and Business Climate Index), the Null Hypothesis 5 is rejected; for one macroeconomic variable (average interest rate on loans), the Null Hypothesis 5 cannot be rejected.
6. For the proposed model incorporating firm-specific financial, firm-specific non-financial and macroeconomic factors, the extracted macroeconomic factors are not significant predictors of growth enterprises' financial distress.	Null Hypothesis 6 cannot be rejected.
7. The model incorporating firm-specific financial factors is not better than the model which includes firm-specific non-financial and macroeconomic factors in financial distress prediction.	Null Hypothesis 7 cannot be rejected.
8. The proposed model incorporating firm-specific financial, firm-specific non-financial and macroeconomic factors is not better than the model which only includes firm-specific financial factors in financial distress prediction.	Null Hypothesis 8 is rejected.

In existing literature, financial ratios or factors are the most commonly used predictors in the models that forecast corporate financial distress. Most studies also found they were significant predictors to forecast the financial distress (Altman 1968; Altman, Haldeman and Narayanan 1977; Barnes 1987; Wu, 2004; Jones and Hensher, 2004; Smith, 2005; Chen, 2008). However, the present study found that the logistic regression model incorporating firm-specific non-financial and macroeconomic factors was better than the model which only includes firm-specific financial factors in predicting growth enterprises' financial distress. Additionally, the logistic regression model incorporating firm-specific financial, firm-specific non-financial and macroeconomic factors was better than the model which includes firm-specific financial factors in predicting growth enterprises' financial distress. Based on these findings, it can be concluded that the financial distress of growth enterprises on Hong Kong GEM is more sensitive to firm-specific non-financial and macroeconomic factors than to firm-specific financial factors.

Kuo et al. (2003) pointed out that some SMEs had the problem of revealing unreliable financial data. Similarly, Jaikengkit (2004) suggested that an enterprise's financial data can be window-dressed through earnings management. In terms of the growth enterprises on the Hong Kong GEM, several researchers found that some growth enterprises were prone to window-dressing or even falsifying their accounting data prior to releasing their financial statements because growth enterprises had higher risks than other listed enterprises (He and Liu, 2008; Xin, 2008). In the study done by He and Liu (2008), they took one growth enterprise, 'Wah Sang Gas', as an example. This growth enterprise was suspended from trading on the GEM and a huge administrative penalty was imposed because it provided faked financial statements with false profit numbers in 2004. Undoubtedly, the window-dressed financial data with false information cannot reflect the real performance of growth enterprises. Thus, one reason for Model 2 being better than Model 1 and Model 3 being better than Model 1 in financial distress prediction is that growth enterprise might publish window-dressed financial data.

In terms of the relationship between firm-specific non-financial variables and financial distress of growth enterprises, He and Liu (2008) found that distressed growth enterprises usually experienced some non-financial problems before the financial distress happened. These non-financial problems include changing auditor(s), delaying releasing financial statement(s), having an auditors' report with qualified opinion and/ or explanatory paragraph, etc. For instance, 13 distressed growth enterprises, according to the published information revealed by Hong Kong GEM, had delayed releasing financial statement(s) before they experienced financial distress by March, 2008 (He and Liu, 2008). Moreover, in a recent Asian study, Tsai, Lee and Sun (2009) found that the model including auditors' opinions, macroeconomic factors, industry factors and market factors performed better than the model only using financial ratios in predicting financial distress of public listed companies in Taiwan.

To sum up, these two studies provided the evidence that non-financial factors with macroeconomic factors contain incremental information beyond financial ratios in predicting financial distress in some developing countries. Therefore, another reason why Model 2 is better than Model 1 in financial distress prediction could be that some firm-specific non-financial and macroeconomic factors are more relevant to financial distress than firm-specific financial factors for growth enterprises on Hong Kong GEM.

Chapter 6 Conclusions

6.1 Introduction

This chapter is the final chapter of the thesis. It contains a summary of the thesis, discussion of the results, contributions and limitations of the present study and the suggestions for future research. The following sections of this chapter are listed as follows:

Section 6.2 summarizes the whole thesis. It then discusses the findings of the present study.

Section 6.3 discusses the contributions of the present study. These contributions include the contributions to original academic research, the benefits to the investors, managements and independent auditors of growth enterprises and suggestions for the authorities of GEMs.

Section 6.4 presents the two major limitations of the present study. These two limitations are missing values of financial ratios and the small sample size of growth enterprises.

Section 6.5 makes two suggestions for future research. The first suggestion is that the future studies can incorporate more growth enterprises to address a limitation of the present study. The second suggestion is that future studies can consider some other non-financial variables.

6.2 Discussion and summary

6.2.1 Thesis summary

In the past three decades, China has made enormous progress in its economic development. With the development of Chinese economy, growth enterprises, particularly those enterprises that have high technology, good business ideas or growth potential, have become important in the economic development and industrialization process in China (Keizo, 1998). Furthermore, the continued health of growth enterprises is essential to China's global economic competitiveness (CSRC, 2008). However, a great number of growth enterprises did not fulfil the profitability or track record requirements of the major stock exchanges in mainland China and Hong Kong and these enterprises were therefore unable to obtain a listing. This limited their financing options and reduced the range of risk-return profiles available to the investors.

6.2.1.1 The importance of the present study

In order to provide a fund raising venue and an exit ground for high-growth and high-risk enterprises in all industries, the HKEx established the Hong Kong GEM in 1999. The GEM has lowered the entry barriers to attract an increasing number of small or medium growth enterprises to capitalize on this market. The Hong Kong GEM has therefore become an alternative securities market for Chinese growth enterprises.

Given Hong Kong's independent judicial, monetary and financial systems, most growth enterprises from mainland China prefer to be listed on the mainland's securities market. Hence, to expand the securities market of mainland China, the proposal of establishing a secondary securities market like Hong Kong GEM was first put forth by the CSRC in the late 1990s and the SZSE also began to explore the possibility of building a GEM in 2001. In October, 2009, the CSRC announced the launch of a long-awaited GEM in Shenzhen, which is similar to the GEM in Hong Kong, as another direct financing platform for growth companies.

There is no doubt that the lower entry thresholds of GEMs enable growth enterprises with growth potential but without a proven track record of performance to capitalize on the growth opportunities of China by raising expansion capital on a well-established market (Vong and Zhao, 2008). Nevertheless, the future performance of growth companies, particularly those without a profit track record, is susceptible to great uncertainty. Because of the high financial risk and imperfections in the financial constitution of growth enterprises, the investors are cautious about investing in Hong Kong GEM and in the newly established GEM in mainland China (Chen, Sun and Zhang, 2005). Therefore, it has become very important to develop a reliable financial distress prediction model which covers appropriate methods and predictors to predict the financial distress of growth enterprises on the GEMs.

In the present study, the GEM in mainland China and the growth enterprises on the GEM cannot be examined because the GEM is a newly established secondary stock exchange without enough data available for doing financial prediction research. Compared to the GEM in mainland China, the Hong Kong GEM has more than ten years' trading history and has sufficient data available for doing research. Since Hong Kong was handed over to China in 1997, Hong Kong has become more integrated with the economy of mainland China. In particular, as an international financial centre, Hong Kong has also become an important capital raising centre for Chinese enterprises. Consequently, this study has focused on Hong Kong GEM and the growth enterprises on it.

6.2.1.2 The gaps in the literature

The present study then reviewed all the major studies on financial distress prediction and two gaps in the literature on predicting corporate financial distress were identified.

Firstly, although the financial ratios, non-financial variables and macroeconomic variables have been demonstrated to have correlation with corporate financial distress, the prior research has not considered the combined effect of financial ratios, non-financial variables and macroeconomic variables on growth enterprises' distress prediction. In most of the existing research studies on financial distress, researchers focused their attention on the predictive ability of firm-specific financial ratios. Furthermore, many other financial distress predictive research studies have examined the firm-specific financial ratios, non-financial variables and macroeconomic variables separately or formulated their research by combining two out of the three kinds of variables, but no studies covered all three kinds until recently.

Secondly, there is currently an extensive and well-developed body of literature that examines the financial distress predicting in stock-issued companies and there are even some research studies on financial distress predicting of SMEs. However, there is a lack of studies on growth enterprises on the secondary stock exchange, namely the GEM, in emerging economies because of the limitation of growth enterprises' financial data and company population.

Based on the literature, eight hypotheses were developed. In order to test these hypotheses, the data of 100 growth enterprises derived from the official portal of Hong Kong GEM and the methods including MWW test, factor analysis and logistic regression were used in the present study. The summary of the data analysis progress and results of hypotheses testing are as follows.

6.2.1.3 Summary of data analysis and results (Year T-1)

According to statistical theory, the MWW test is used to determine whether there was a difference between two populations. In the present study, the MWW test was firstly run to test Hypothesis 1, Hypothesis 3 and Hypothesis 5 for the data of Year T-1.

Hypothesis 1 is related to Research Question 1(*Are there significant differences in firm-specific financial ratios between distressed and non-distressed growth enterprises?*). Hypothesis 1 states that there are significant differences in financial ratios between distressed and non-distressed growth enterprises. The output of the MWW test shows that there are significant differences in the Year T-1's financial performance, which includes nine financial ratios, between the distressed growth enterprises and non-distressed growth enterprises. Therefore, for all the tested financial variables except for quick ratio, the Null Hypothesis 1 has to be rejected. For only one financial variable (quick ratio), however, the Null Hypothesis 1 cannot be rejected.

Hypothesis 3 is related to Research Question 2 (*Are there significant differences in firm-specific non-financial variables between distressed and non-distressed growth enterprises?*). Hypothesis 3 states that there are significant differences in non-financial variables between distressed and non-distressed growth enterprises. The output of the MWW test shows there are significant differences in the Year T-1's four non-financial variables between the distressed growth enterprises and non-distressed growth enterprises. In other words, the Null Hypothesis 3 can be rejected.

Hypothesis 5 is related to Research Question 3 (*Are there significant differences in macroeconomic variables between distressed and non-distressed growth enterprises?*). Hypothesis 5 states that there are significant differences in macroeconomic variables between distressed and non-distressed growth enterprises. The output of the MWW test for macroeconomic variables shows that there is only one macroeconomic variable (Entrepreneur Confidence Index) which has a two-tailed p value larger than 0.05. Hence, the Null Hypothesis 5 has to be rejected for three macroeconomic variables (real GDP growth rate, average interest rate on loans and Business Climate Index). However, the Null Hypothesis 5 cannot be rejected for one macroeconomic variable (Entrepreneur Confidence Index).

Based on the results of testing Hypothesis 1, Hypothesis 3 and Hypothesis 5, the research objective 1 (*To identify whether there are significant differences in financial, non-financial and macroeconomic variables between distressed and non-distressed growth enterprises.*) has been achieved.

After the MWW test, the present study used factor analysis to reduce the large number of financial ratios to several financial factors. The essential non-financial and macroeconomic factors were then extracted from a set of non-financial and macroeconomic variables. The extracted key financial, non-financial and macroeconomic factors were then served as inputted independent variables for logistic regression. Finally, the present study used logistic regression analyses to establish three types of financial distress prediction models (Model 1, Model 2 and Model 3) for Year T-1 and test Hypothesis 2, Hypothesis 4, Hypothesis 6, Hypothesis 7 and Hypothesis 8.

Hypothesis 2 is related to Research Question 4 (*Do firm-specific financial factors significantly predict whether growth enterprises have experienced financial distress?*). Hypothesis 2 states that financial factors extracted from financial ratios are significant predictors of growth enterprises' financial distress for the proposed model incorporating firm-specific financial, firm-specific non-financial and macroeconomic factors. Hypothesis 2 is tested based on the results of logistic regression analysis. The results of logistic regression analysis for financial factors (Model 3) indicate that only one of the financial independent variables (Profitability-Solvency Factor), which was extracted from financial ratios, is a significant predictor of growth enterprises' financial distress. Therefore, for Model 3, the Null Hypothesis 2 has to be rejected.

Based on the results of testing Hypothesis 2, the research objective 2 (*To examine the relationship between financial factors and the occurrence of financial distress in the growth enterprise.*) has been achieved.

The Hypothesis 4 is related to Research Question 5 (*Do firm-specific non-financial factors significantly predict whether growth enterprises have experienced financial distress?*). Hypothesis 4 states that firm-specific non-financial factors are significant predictors of growth enterprises' financial distress for the proposed model incorporating firm-specific financial, firm-specific non-financial and macroeconomic factors. The output of Model 3 indicates that one non-financial independent variable (Auditing-Disclosure Factor), which was extracted from financial ratios, is a significant predictor of growth enterprises' financial distress at the five per cent level. Therefore, for Model 3, the Null Hypothesis 4 has to be rejected.

Based on the results of testing Hypothesis 4, the research objective 3 (*To examine the relationship between non-financial factors and the occurrence of financial distress in the growth enterprise.*) has been achieved.

The Hypothesis 6 is related to Research Question 6 (*Does macroeconomic factor significantly predict whether growth enterprises have experienced financial distress?*). Hypothesis 6 states that macroeconomic factors are significant predictors of growth enterprises' financial distress for the proposed model incorporating firm-specific financial, firm-specific non-financial and macroeconomic factors. According to the output of Model 3, there is no macroeconomic factor with its *Sig.* value less than 0.05. Thus, for Model 3, the Null Hypothesis 6 cannot be rejected.

Based on the results of testing Hypothesis 6, the research objective 4 (*To examine the relationship between macroeconomic factors and the occurrence of financial distress in the growth enterprise.*) has been achieved.

Hypothesis 7 is related to Research Question 7 (*Does the model that considers firm-specific financial factors perform better than the model that considers firm-specific non-financial and macroeconomic factors in financial distress prediction?*). Hypothesis 7 states that the model incorporating firm-specific financial factors is better than the model which includes firm-specific non-financial and macroeconomic factors in financial distress prediction. The output of the model 1 correctly classified 89 per cent of cases. The output of the model 2 correctly classified 94 per cent of cases. The classification accuracy of Model 2 (94 per cent) is higher than the classification accuracy of Model 1 (89 per cent). Therefore, the Null Hypothesis 7 cannot be rejected.

Based on the results of testing Hypothesis 7, the research objective 5 (*To examine whether the model that uses financial factors to predict financial distress of growth enterprise performs better in predicting financial distress than the model that uses non-financial and macroeconomic factors to predict financial distress.*) has been achieved.

Hypothesis 8 is related to Research Question 8 (*Does the model based on firm-specific financial, firm-specific non-financial and macroeconomic factors perform better than the model that includes firm-specific financial factors in financial distress prediction?*). Hypothesis 8 states that the proposed models incorporating firm-specific financial, firm-specific non-financial and macroeconomic factors are better than the models which only include firm-specific financial

factors in financial distress prediction. The output of Model 1 and Model 3 reveal that the classification accuracy of Model 3 (98 per cent) is higher than the classification accuracy of Model 1 (89 per cent). The firm-specific non-financial and macroeconomic factors helped enhance the classification accuracy of the model. These results confirmed that Model 3 is better than Model 1 in classification accuracy. Based on all the findings, the Null Hypothesis 8 has to be rejected.

Based on the results of testing Hypothesis 8, the research objective 6 (*To examine whether the model that uses financial, non-financial and macroeconomic factors to predict financial distress of growth enterprise performs better in predicting financial distress than the model that only uses financial factors to predict financial distress.*) has been achieved.

6.2.1.4 Summary of data analysis and results (Year T-2)

As discussed previously, the MWW test was firstly run to test Hypothesis 1, Hypothesis 3 and Hypothesis 5 for the data of Year T-2.

Hypothesis 1 is related to Research Question 1(*Are there significant differences in firm-specific financial ratios between distressed and non-distressed growth enterprises?*). Hypothesis 1 states that there are significant differences in financial ratios between distressed and non-distressed growth enterprises. The output of the MWW test shows that there are significant differences in the Year T-2's seven financial ratios between the distressed growth enterprises and non-distressed growth enterprises. Therefore, for the seven financial ratios, the Null Hypothesis 1 can be rejected. However, for expense ratio, gross profit margin and quick ratio, the Null Hypothesis 1 cannot be rejected.

Hypothesis 3 is related to Research Question 2 (*Are there significant differences in firm-specific non-financial variables between distressed and non-distressed growth enterprises?*). Hypothesis 3 states that there are significant differences in non-financial variables between distressed and non-distressed growth enterprises. The output of the MWW test shows there are significant differences in the Year T-2's three non-financial variables between the distressed growth enterprises and non-distressed growth enterprises. Therefore, for three non-financial variables ('changing auditors', 'delay in releasing financial statements' and 'auditors' report with qualified opinion and/ or explanatory paragraph'), the Null Hypothesis 3 can be rejected. However, for 'profit warning', the Null Hypothesis 3 cannot be rejected.

Hypothesis 5 is related to Research Question 3 (*Are there significant differences in macroeconomic variables between distressed and non-distressed growth enterprises?*). Hypothesis 5 states that there are significant differences in macroeconomic variables between distressed and non-distressed growth enterprises. The output of the MWW test for macroeconomic variables shows that there are two macroeconomic variable (Business Climate Index and Entrepreneur Confidence Index) which has a two-tailed p value larger than 0.05. Hence, the Null Hypothesis 5 has to be rejected for two macroeconomic variables (real GDP growth rate and average interest rate on loans). However, the Null Hypothesis 5 cannot be rejected for one macroeconomic variable (Business Climate Index and Entrepreneur Confidence Index).

Based on the results of testing Hypothesis 1, Hypothesis 3 and Hypothesis 5, the research objective 1 (To identify whether there are significant differences in financial, non-financial and macroeconomic variables between distressed and non-distressed growth enterprises.) has been achieved.

After the MWW test, the present study used factor analysis to reduce the large number of financial ratios to several financial factors. The essential non-financial and macroeconomic factors were then extracted from a set of non-financial and macroeconomic variables. The extracted key financial, non-financial and macroeconomic factors were then served as inputted independent variables for logistic regression. Finally, the present study used logistic regression analyses to establish three types of financial distress prediction models (Model 1, Model 2 and Model 3) for Year T-2 and test Hypothesis 2, Hypothesis 4, Hypothesis 6, Hypothesis 7 and Hypothesis 8.

Hypothesis 2 is related to Research Question 4 (*Do firm-specific financial factors significantly predict whether growth enterprises have experienced financial distress?*). Hypothesis 2 states that financial factors extracted from financial ratios are significant predictors of growth enterprises' financial distress for the proposed model incorporating firm-specific financial, firm-specific non-financial and macroeconomic factors. Hypothesis 2 is tested based on the results of logistic regression analysis. The results of logistic regression analysis for financial factors (Model 3) indicate that only one of the financial independent variables (Profitability-Solvency Factor), which was extracted from financial ratios, is a significant predictor of growth enterprises' financial distress. Therefore, for Model 3, the Null Hypothesis 2 has to be rejected.

Based on the results of testing Hypothesis 2, the research objective 2 (*To examine the relationship between financial factors and the occurrence of financial distress in the growth enterprise.*) has been achieved.

The Hypothesis 4 is related to Research Question 5 (*Do firm-specific non-financial factors significantly predict whether growth enterprises have experienced financial distress?*). Hypothesis 4 states that firm-specific non-financial factors are significant predictors of growth enterprises' financial distress for the proposed model incorporating firm-specific financial, firm-specific non-financial and macroeconomic factors. The output of Model 3 indicates that one non-financial independent variable (Auditing-Disclosure Factor), which was extracted from financial ratios, is a significant predictor of growth enterprises' financial distress at the five per cent level. Therefore, for Model 3, the Null Hypothesis 4 has to be rejected.

Based on the results of testing Hypothesis 4, the research objective 3 (*To examine the relationship between non-financial factors and the occurrence of financial distress in the growth enterprise.*) has been achieved.

The Hypothesis 6 is related to Research Question 6 (*Does macroeconomic factor significantly predict whether growth enterprises have experienced financial distress?*). Hypothesis 6 states that macroeconomic factors are significant predictors of growth enterprises' financial distress for the proposed model incorporating firm-specific financial, firm-specific non-financial and macroeconomic factors. According to the output of Model 3, there is no macroeconomic factor with its *Sig.* value less than 0.05. Thus, for Model 3, the Null Hypothesis 6 cannot be rejected.

Based on the results of testing Hypothesis 6, the research objective 4 (*To examine the relationship between macroeconomic factors and the occurrence of financial distress in the growth enterprise.*) has been achieved.

Hypothesis 7 is related to Research Question 7 (*Does the model that considers firm-specific financial factors perform better than the model that considers firm-specific non-financial and macroeconomic factors in financial distress prediction?*). Hypothesis 7 states that the model incorporating firm-specific financial factors is better than the model which includes firm-specific non-financial and macroeconomic factors in financial distress prediction. The output of the model 1 correctly classified 82 per cent of cases. The output of the model 2 correctly classified 83 per cent of cases. The classification accuracy of Model 2 (83 per cent) is higher than the classification accuracy of Model 1 (82 per cent). Therefore, the Null Hypothesis 7 cannot be rejected.

Based on the results of testing Hypothesis 7, the research objective 5 (*To examine whether the model that uses financial factors to predict financial distress of growth enterprise performs better in predicting financial distress than the model that uses non-financial and macroeconomic factors to predict financial distress.*) has been achieved.

Hypothesis 8 is related to Research Question 8 (*Does the model based on firm-specific financial, firm-specific non-financial and macroeconomic factors perform better than the model that includes firm-specific financial factors in financial distress prediction?*). Hypothesis 8 states that the proposed models incorporating firm-specific financial, firm-specific non-financial and macroeconomic factors are better than the models which only include firm-specific financial

factors in financial distress prediction. The output of Model 1 and Model 3 reveal that the classification accuracy of Model 3 (89 per cent) is higher than the classification accuracy of Model 1 (82 per cent). The firm-specific non-financial and macroeconomic factors helped enhance the classification accuracy of the model. These results confirmed that Model 3 is better than Model 1 in classification accuracy. Based on all the findings, the Null Hypothesis 8 has to be rejected.

Based on the results of testing Hypothesis 8, the research objective 6 (*To examine whether the model that uses financial, non-financial and macroeconomic factors to predict financial distress of growth enterprise performs better in predicting financial distress than the model that only uses financial factors to predict financial distress.*) has been achieved.

6.2.1.5 Summary of data analysis and results (Year T-3)

As discussed previously, the MWW test was firstly run to test Hypothesis 1, Hypothesis 3 and Hypothesis 5 for the data of Year T-3.

Hypothesis 1 is related to Research Question 1(*Are there significant differences in firm-specific financial ratios between distressed and non-distressed growth enterprises?*). Hypothesis 1 states that there are significant differences in financial ratios between distressed and non-distressed growth enterprises. The output of the MWW test shows that there are significant differences in the Year T-3's five financial ratios between the distressed growth enterprises and non-distressed growth enterprises. Therefore, for the five financial ratios, the Null Hypothesis 1 can be rejected.

However, for expense ratio, current ratio, quick ratio, debt to total assets and gross profit margin, the Null Hypothesis 1 cannot be rejected.

Hypothesis 3 is related to Research Question 2 (*Are there significant differences in firm-specific non-financial variables between distressed and non-distressed growth enterprises?*). Hypothesis 3 states that there are significant differences in non-financial variables between distressed and non-distressed growth enterprises. The output of the MWW test shows there are significant differences in the Year T-3's two non-financial variables between the distressed growth enterprises and non-distressed growth enterprises. Therefore, for two non-financial variables ('changing auditors' and 'delay in releasing financial statements'), the Null Hypothesis 3 can be rejected. However, for 'profit warning' and 'auditors' report with qualified opinion and/ or explanatory paragraph', the Null Hypothesis 3 cannot be rejected.

Hypothesis 5 is related to Research Question 3 (*Are there significant differences in macroeconomic variables between distressed and non-distressed growth enterprises?*). Hypothesis 5 states that there are significant differences in macroeconomic variables between distressed and non-distressed growth enterprises. The output of the MWW test for macroeconomic variables shows that there is only one macroeconomic variable (average interest rate on loans) which has a two-tailed p value larger than 0.05. Hence, the Null Hypothesis 5 has to be rejected for three macroeconomic variables (real GDP growth rate, Entrepreneur Confidence Index and Business Climate Index). However, the Null Hypothesis 5 cannot be rejected and for one macroeconomic variable (average interest rate on loans).

Based on the results of testing Hypothesis 1, Hypothesis 3 and Hypothesis 5, the research objective 1 (To identify whether there are significant differences in financial, non-financial and macroeconomic variables between distressed and non-distressed growth enterprises.) has been achieved.

After the MWW test, the present study used factor analysis to reduce the large number of financial ratios to several financial factors. The essential non-financial and macroeconomic factors were then extracted from a set of non-financial and macroeconomic variables. The extracted key financial, non-financial and macroeconomic factors were then served as inputted independent variables for logistic regression. Finally, the present study used logistic regression analyses to establish three types of financial distress prediction models (Model 1, Model 2 and Model 3) for Year T-3 and test Hypothesis 2, Hypothesis 4, Hypothesis 6, Hypothesis 7 and Hypothesis 8.

Hypothesis 2 is related to Research Question 4 (*Do firm-specific financial factors significantly predict whether growth enterprises have experienced financial distress?*). Hypothesis 2 states that financial factors extracted from financial ratios are significant predictors of growth enterprises' financial distress for the proposed model incorporating firm-specific financial, firm-specific non-financial and macroeconomic factors. Hypothesis 2 is tested based on the results of logistic regression analysis. The results of logistic regression analysis for financial factors (Model 3) indicate that only one of the financial independent variables (Profitability-Solvency Factor), which was extracted from financial ratios, is a significant predictor of growth enterprises' financial distress. Therefore, for Model 3, the Null Hypothesis 2 has to be rejected.

Based on the results of testing Hypothesis 2, the research objective 2 (*To examine the relationship between financial factors and the occurrence of financial distress in the growth enterprise.*) has been achieved.

The Hypothesis 4 is related to Research Question 5 (*Do firm-specific non-financial factors significantly predict whether growth enterprises have experienced financial distress?*). Hypothesis 4 states that firm-specific non-financial factors are significant predictors of growth enterprises' financial distress for the proposed model incorporating firm-specific financial, firm-specific non-financial and macroeconomic factors. The output of Model 3 indicates that one non-financial independent variable (Auditing-Disclosure Factor), which was extracted from financial ratios, is a significant predictor of growth enterprises' financial distress at the five per cent level. Therefore, for Model 3, the Null Hypothesis 4 has to be rejected.

Based on the results of testing Hypothesis 4, the research objective 3 (*To examine the relationship between non-financial factors and the occurrence of financial distress in the growth enterprise.*) has been achieved.

The Hypothesis 6 is related to Research Question 6 (*Does macroeconomic factor significantly predict whether growth enterprises have experienced financial distress?*). Hypothesis 6 states that macroeconomic factors are significant predictors of growth enterprises' financial distress for the proposed model incorporating firm-specific financial, firm-specific non-financial and macroeconomic factors. According to the output of Model 3, there is one macroeconomic factor (Macroeconomic Factor) with its *Sig.* value greater than 0.05. Thus, for Model 3, the Null Hypothesis 6 cannot be rejected.

Based on the results of testing Hypothesis 6, the research objective 4 (*To examine the relationship between macroeconomic factors and the occurrence of financial distress in the growth enterprise.*) has been achieved.

Hypothesis 7 is related to Research Question 7 (*Does the model that considers firm-specific financial factors perform better than the model that considers firm-specific non-financial and macroeconomic factors in financial distress prediction?*). Hypothesis 7 states that the model incorporating firm-specific financial factors is better than the model which includes firm-specific non-financial and macroeconomic factors in financial distress prediction. The output of the model 1 correctly classified 77 per cent of cases. The output of the model 2 correctly classified 78 per cent of cases. The classification accuracy of Model 2 (78 per cent) is higher than the classification accuracy of Model 1 (77 per cent). Therefore, Null Hypothesis 7 cannot be rejected.

Based on the results of testing Hypothesis 7, the research objective 5 (*To examine whether the model that uses financial factors to predict financial distress of growth enterprise performs better in predicting financial distress than the model that uses non-financial and macroeconomic factors to predict financial distress.*) has been achieved.

Hypothesis 8 is related to Research Question 8 (*Does the model based on firm-specific financial, firm-specific non-financial and macroeconomic factors perform better than the model that includes firm-specific financial factors in financial distress prediction?*). Hypothesis 8 states that the proposed models incorporating firm-specific financial, firm-specific non-financial and macroeconomic factors are better than the models which only include firm-specific financial

factors in financial distress prediction. The output of Model 1 and Model 3 reveal that the classification accuracy of Model 3 (83 per cent) is higher than the classification accuracy of Model 1 (77 per cent). The firm-specific non-financial and macroeconomic factors helped enhance the classification accuracy of the model. These results confirmed that Model 3 is better than Model 1 in classification accuracy. Based on all the findings, the Null Hypothesis 8 has to be rejected.

Based on the results of testing Hypothesis 8, the research objective 6 (*To examine whether the model that uses financial, non-financial and macroeconomic factors to predict financial distress of growth enterprise performs better in predicting financial distress than the model that only uses financial factors to predict financial distress.*) has been achieved.

6.2.2 Discussion of results

In the existing literature, financial ratios or factors are the most frequently used predictors in the models that forecast corporate financial distress. Some important research studies suggested they were the most important predictors for forecasting the financial distress (Altman, 1968; Altman, Haldeman and Narayanan, 1977; Ohlson, 1980). In contrast, the present study's findings were different: the logistic regression model incorporating firm-specific non-financial and macroeconomic factors was better in predicting growth enterprises' financial distress than the model which only included firm-specific financial factors. Furthermore, the model incorporating firm-specific financial, firm-specific non-financial and macroeconomic factors was better than the model which includes firm-specific financial factors in financial distress prediction.

Several researchers found that some growth enterprises were prone to window-dressing or even falsifying their accounting data prior to releasing their financial statements because growth enterprises had higher risks than other listed enterprises (He and Liu, 2008; Xin, 2008). Therefore, one reason for Model 2 being better than Model 1 in financial distress prediction is that growth enterprises might publish window-dressed financial data.

In addition to that, He and Liu (2008) found that distressed growth enterprises usually experienced some non-financial problems before the financial distress happened. These non-financial problems include changing auditor(s), delaying releasing financial statement(s), having an auditors' report with a qualified opinion and/ or explanatory paragraph, etc. For instance, 13 distressed growth enterprises, according to the published information revealed by Hong Kong GEM, had delayed releasing financial statement(s) before they met financial distress by March, 2008 (He and Liu, 2008).

In terms of the relationship between the macroeconomy and performance of growth enterprises, Tsai, Lee and Sun (2009) provided evidence that some macroeconomic factors contain incremental information beyond financial ratios in predicting financial distress in some developing countries.

Therefore, the second reason why Model 2 is better than Model 1 in financial distress prediction could be that some firm-specific non-financial and macroeconomic factors are more relevant to financial distress than firm-specific financial factors for growth enterprises on the Hong Kong GEM.

6.3 Contributions of the present study

According to the results revealed previously, the contributions of the present study can be divided into three respects. These three respects include the contributions to original academic research, the benefits to the investors, managements and independent auditors of growth enterprises and suggestions for the authorities of GEMs. All these three aspects are summarized as follows.

6.3.1 The contributions to theory and original academic research

The present study constructs a financial distress prediction model, which took not only firm-specific financial ratios into account, but also non-financial and macroeconomic variables. In this study, extraordinary findings, which are different from the findings of most existing studies, were revealed. The remarkable findings include: the logistic regression model incorporating growth enterprises' firm-specific non-financial and macroeconomic factors was better than the model which only includes growth enterprises' firm-specific financial factors; furthermore, the firm-specific financial, non-financial and macroeconomic factors were more significant than firm-specific financial factors in predicting financial distress using the model that incorporated firm-specific financial, firm-specific non-financial and macroeconomic factors. In other words, the growth enterprises' firm-specific non-financial and macroeconomic factors are better predictors of financial distress than growth enterprises' financial factors.

In addition, as discussed previously, although growth enterprises are responsible for much of an emerging economy's dynamism, there is a lack of research on growth enterprises in emerging countries. The present study made the first attempt to construct a financial distress prediction model for Chinese growth enterprises. In the study, a financial distress prediction model, which uses financial ratios, non-financial variables and macroeconomic variables, was established. The predictive ability of this model is greater than the model which only considers financial ratios and this model is particularly useful for predicting the financial distress of Chinese growth enterprises on Hong Kong GEM. In the future, this model can be used to predict the financial distress of other Chinese growth enterprises on the newly established GEM in mainland China.

6.3.2 Benefits to the investors, the managements and the independent auditors of Chinese growth enterprises

The present study has established an improved financial distress model for Chinese growth enterprises on the GEM. Based on the results of the study, the firm-specific non-financial and macroeconomic factors are more effective than firm-specific financial factors in predicting growth enterprises' financial distress. Since investors and managements of Chinese growth enterprises are concerned about the corporate financial performance, they can benefit from the findings of the present study.

In terms of the investors or potential investors of Chinese growth enterprises, they have to make decisions concerning investing in the enterprises. Hence, the investors or potential investors can benefit from this study on financial distress prediction because the study would enable them to better assess the probability of the growth enterprises' financial distress and make investment decisions concerning these enterprises. In addition, the investors or potential investors, who are aware that firm-specific non-financial and macroeconomic factors are more effective than firm-specific financial factors in predicting growth enterprises' financial distress, should be able to forecast the financial distress of growth enterprises with higher accuracy and make better investment decisions.

For the managements of Chinese growth enterprises, they have the responsibilities to prevent the financial distress of the enterprises and protect the interests of their investors. Based on the results of the present study, these managements can focus on the enterprises' non-financial status and macroeconomic climate that enterprises experience in addition to financial ratios in predicting potential financial distress. As a result, the managements can more accurately predict financial distress of their growth enterprises and take appropriate actions to prevent financial distress.

The independent auditors may also have a role to play. While provide an audit report, the auditors may like commenting on the growth enterprises' non-financial situation and macroeconomic conditions rather than just confining their attention to financial data.

6.3.3 Suggestions for the authorities of Growth Enterprise Markets

As discussed previously, the firm-specific non-financial and macroeconomic factors are more significant than firm-specific financial factors in predicting growth enterprises' financial distress. One of the reasons for that is the growth enterprise might publish window-dressed financial data, as the window-dressed financial data with false information cannot reflect the real status of growth enterprises. Bildersee and Kahn (1987) suggested that enterprises window-dressing their financial data can be motivated by the desire of managements of the enterprises to present a positive image.

The authorities of the GEMs include regulators and rules makers of the GEMs. With respect to the regulators of the GEMs, they have to take actions against enterprises' illegal window dressing and disclose the illegal activities of enterprises to the public. Although window dressing of corporate financial reports is not an observable phenomenon, the regulators need to pay more attention to the growth enterprises which have good-looking financial data but are in bad non-financial situation and bad macroeconomic conditions. They are the enterprises which might fall into financial distress in the near future and might have their financial data window-dressed.

With respect to the rule makers of the GEMs, they also have the responsibility to prevent enterprises' illegal window dressing. The rule makers, who are in charge of making and issuing the listing rules for growth enterprises on the GEMs, should issue strict rules and regulations against illegal window dressing, like falsifying their accounting data.

6.4 Limitations of the present study

Like many other studies, the major limitations should be acknowledged in interpreting the results of the present study. For the present study, two major limitations can be summarized as follows.

6.4.1 Missing values of financial ratios

The present study has a problem about missing values of financial ratios. In prior studies on corporate financial distress, the inventory turnover, which measures the liquidity of firm's inventory (Weygandt, et al., 2007), was also considered being related to the financial distress of corporations (Kuo et al., 2003; Wu, 2004). According to the definition of inventory turnover, this financial ratio equals cost of sales divided by the average inventory of the corporation (Weygandt, et al., 2007). However, the present study did not account for inventory turnover because many growth enterprises did not release the values of average inventory or had values of average inventory being equal to 0.

In addition, there have been several studies that have used the times interest earned as a predictor for prediction of corporate financial distress (Wu, 2004; Cheng, Yeh and Chiu, 2007). Times interest earned measures the ability of a firm to meet its interest payments as they fall due (Weygandt, et al., 2007).This ratio equals profit before income taxes and interest expense divided by interest expense. Since many growth enterprises did not release this values of times interest earned or had values of times interest earned equal to 0, this ratio, times interest earned, is not valid for data analysis in the present study.

6.4.2 Small sample size of growth enterprises

In the present study, the small number of growth enterprises is another limitation. Since there were only 245 listed and delisted growth enterprises for Hong Kong GEM by the end of 2009, 100 growth enterprises were selected in the present study. In addition, the growth enterprises on the GEM of mainland China are excluded from the present study because the growth enterprises on the newly found GEM cannot provide three successive years' data for analysis.

The small number of growth enterprises brings two major limitations for the present study. The first limitation concerns the application of factor analysis and the other limitation concerns industrial analysis.

In terms of factor analysis, Coakes and Steed (2005, p.154) pointed out ‘a sample of 100 subjects is acceptable, but sample sizes of more than 200 are preferable’. Hence, in the present study, 100 growth enterprises is a sufficient sample size for factor analysis. On the other hand, if a larger group of growth enterprises could be used as a sample for factor analysis, a better result might be generated.

In terms of industrial sectors for predicting corporate financial distress, several studies found that the incidence of corporate financial distress might vary between different industrial sectors and the models for predicting financial distress can be exclusively designed for particular industrial sectors (Smith and Liou, 2007). In Smith and Liou’s (2007) study, they examined 1112 distressed firms in 17 industrial sectors and concluded that there was a significant relationship between the incidence of financial distress and the industrial sector. However, given the relatively small sample size, in the present study which has only 70 non-distressed and 30 distressed growth enterprises, it is hard to investigate the financial distress across industrial sector.

6.5 Suggestions for future research

For future research, there are two aspects which can be developed upon the present study. These two aspects are as follows

6.5.1 Enlarge the sample size of growth enterprises

Future studies can be improved to address the limitations of the present study. As mentioned previously, the newly established GEM in mainland China has less than 2 years' history and had only 130 listed growth enterprises by the end of October, 2010. Less than two years' information of growth enterprises is not sufficient for the data analysis in the present study which considered three successive years' financial and non-financial information. Therefore, one limitation of the present study is that the growth enterprises on the GEM of mainland China cannot be included in the analysis.

In the future, it can be expected that an increasing number of growth enterprises would be listed on the GEM and longer period of GEM growth enterprises' financial and non-financial information would be released. Accordingly, the future studies will be able to incorporate both the growth enterprises on Hong Kong GEM and the growth enterprises on the GEM of mainland China to eliminate this limitation. In other words, although it is impossible to do any research on the growth enterprises of mainland China's GEM recently, the extended study in the future can cover all the growth enterprises on both GEMs.

6.5.2 Include more variables

The results of the present study reveal that some non-financial factors extracted from non-financial variables significantly correlated with the growth enterprises' financial distress. Furthermore, these non-financial factors have even better ability to forecast financial distress of growth enterprises than the financial factors extracted from major financial ratios. As firm-specific non-financial variables covering various variables, some other non-financial variables, which are not considered in the present study, can be further explored to predict financial distress in future studies. For instance, some variables about corporate governance which are not released by the growth enterprises and the variables of quantifying financial risk (like volatility factors) could be considered in future studies.

In future research, some other non-financial variables may incorporate the remuneration of the board, the proportion of outside directors on board, the frequency of the enterprise delaying the payment of bank loans, the magnitude of the enterprise's short-term debt and the number of the enterprise's correspondent banks (Kuo et al., 2003; Chancharat, 2008). The values of all these variables cannot be obtained from publicly available information. Unlike the present study which only used data from growth enterprises' annual reports or materials released by the GEM, further studies need to carry out surveys of growth enterprises' senior-level management to attain the values of these variables.

On the whole, future studies using more non-financial variables and larger sample would provide a more complete understanding of the financial distress of Chinese growth enterprises. It would become a useful contribution to the present study.

Appendix

Figure
A5.1

Figure A5.1 Scatter plots of financial ratios (Year T-1)

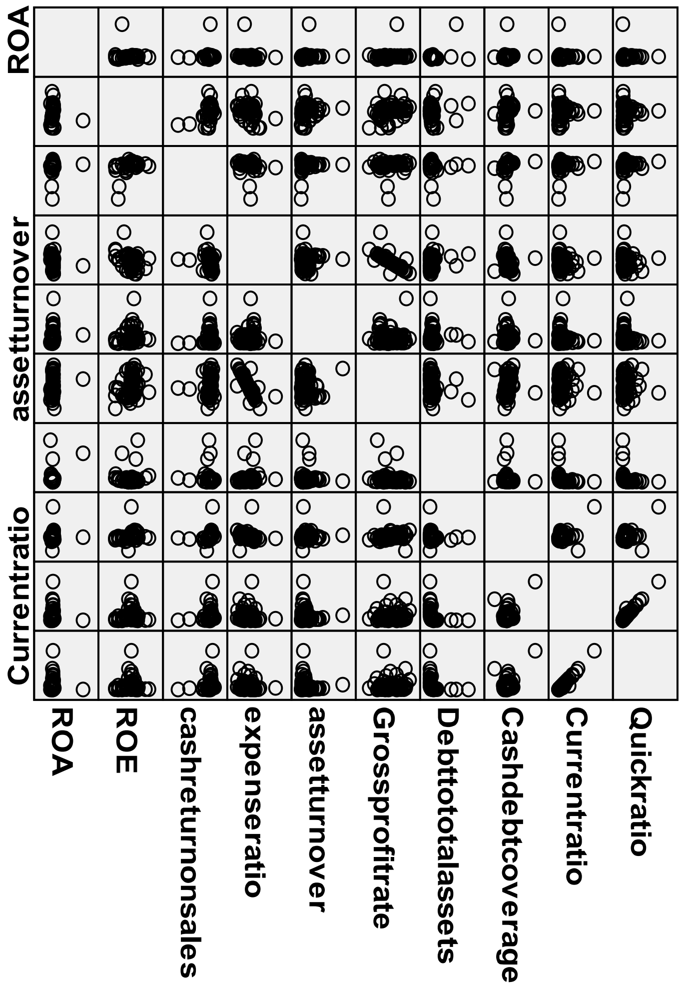


Figure A5.2

Figure A5.2 Scatter plots of non-financial and macroeconomic variables (Year T-1)

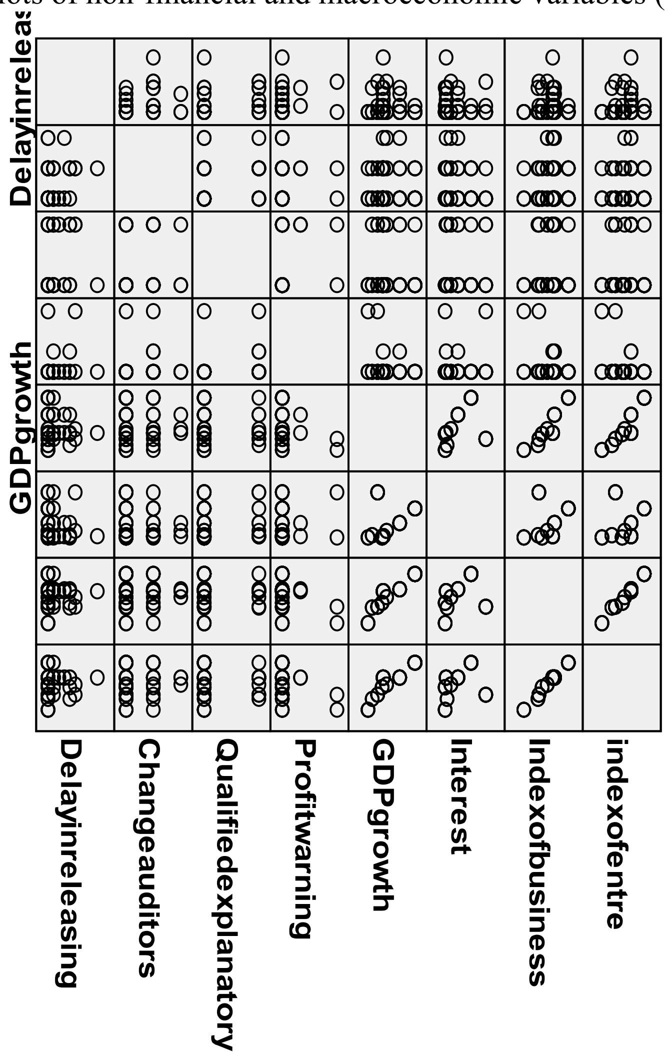


Figure
A5.3

Figure A5.3 Scatter plots of financial ratios (Year T-2)

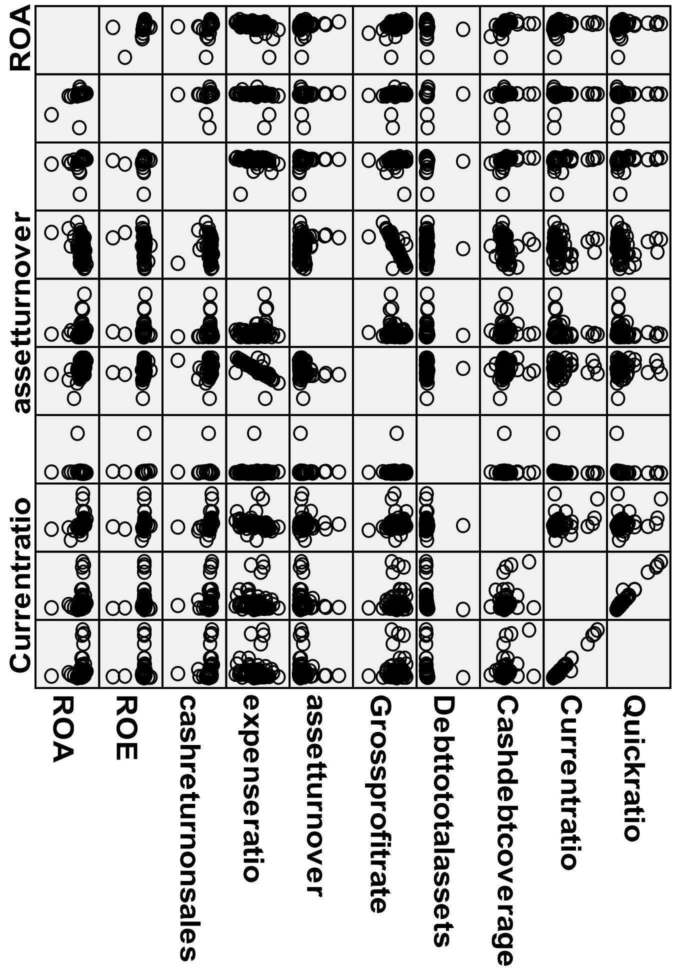


Figure A5.4 Scatter plots of non-financial and macroeconomic variables (Year T-2)

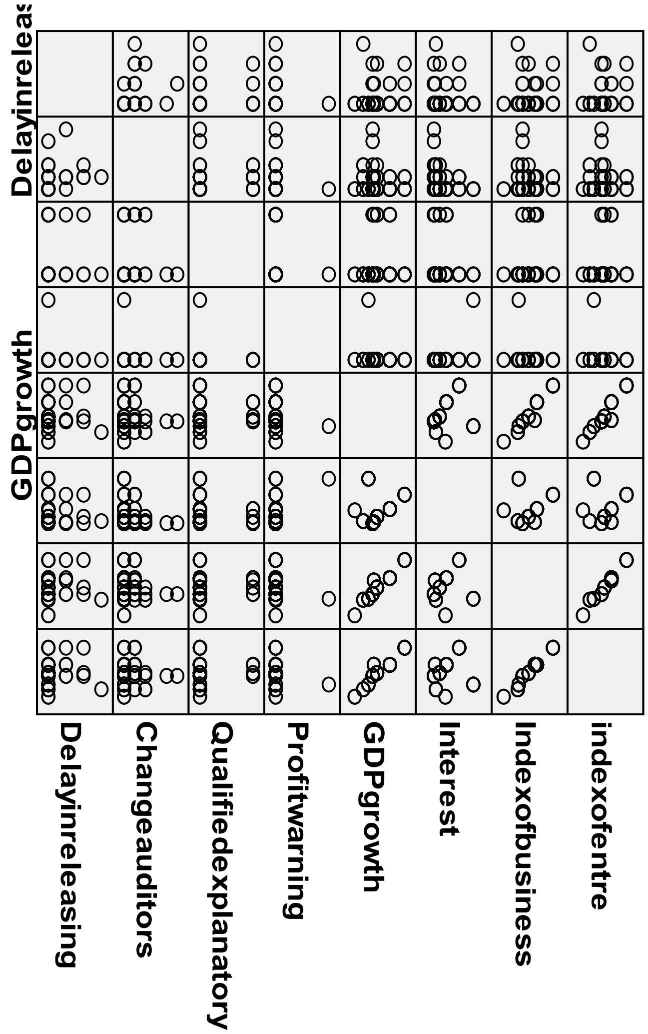


Figure
A5.5

Figure A5.5 Scatter plots of financial ratios (Year T-3)

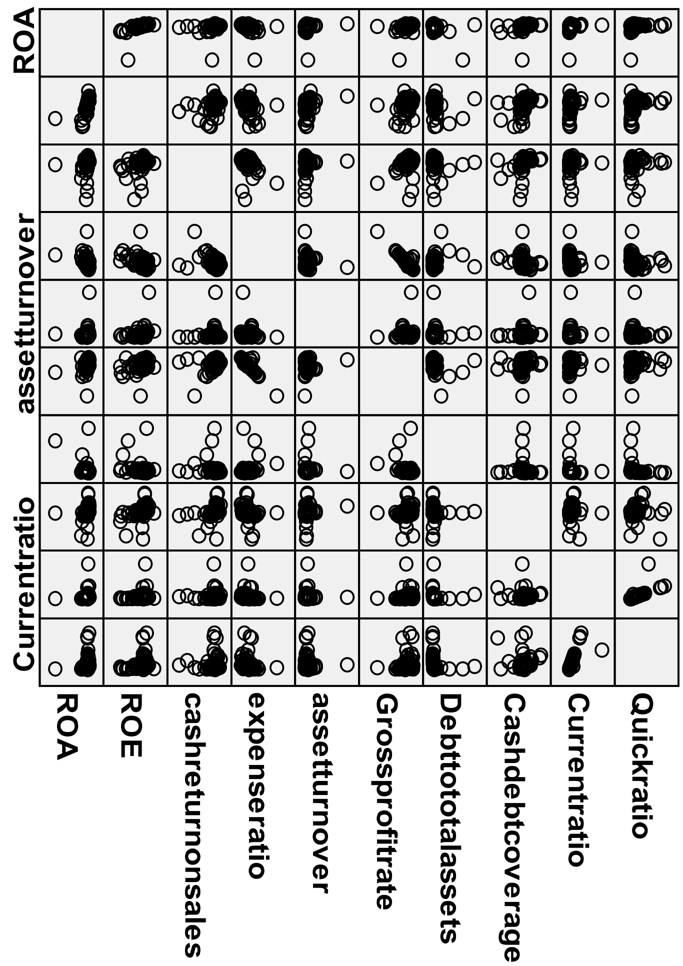
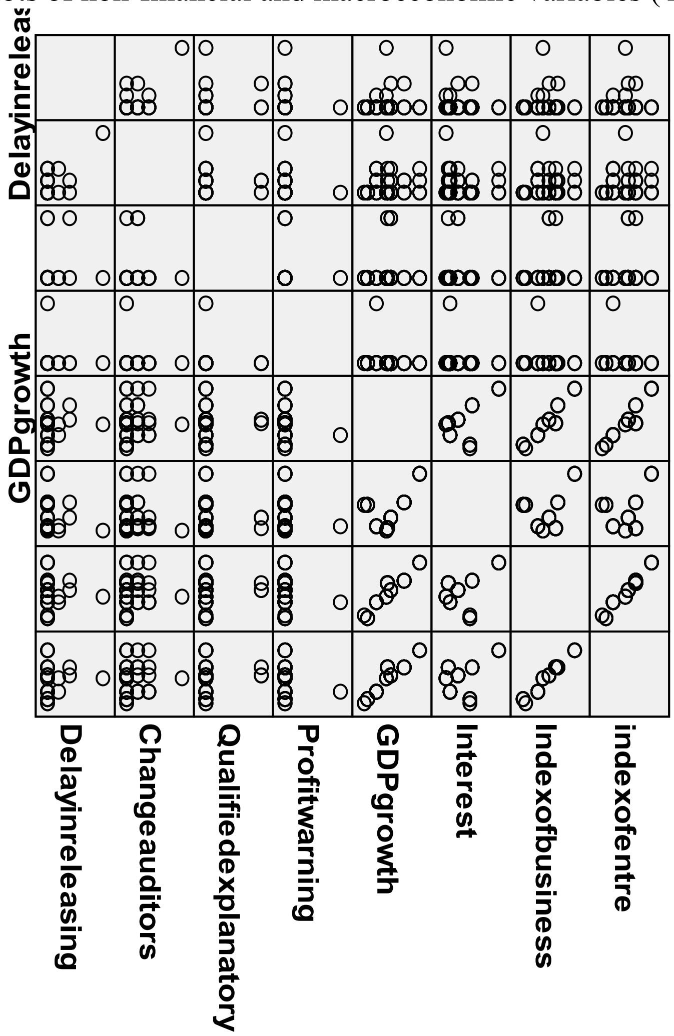


Figure A5.6 Scatter plots of non-financial and macroeconomic variables (Year T-3)



List of Publications

Articles in Peer-refereed Journals:

Hu, H. and Wee, F.L.K., Foreign Currency Derivative and Firm Value– an Australian study, *Global Business and Finance Review*, 15(1), spring, 2010, pp.68-78.

Islam, J., Talukder, M. and **Hu, H.** The Impact of Technology, Job Complexity and Religiosity on Managerial Performance, *Australasian Accounting Business and Finance Journal* (forthcoming).

Islam, J., Ali, M.M. and **Hu, H.**, The Prospects Concept of Breakthrough Thinking for Operations Management in Bangladesh: an analysis, *Journal of Planology* (forthcoming).

Conference Papers/Presentations:

Hu, H. and Sathye, M., A Study of Financial Distress Prediction for Chinese Growth Enterprise Market, the 10th Hawaii International Conference on Business Proceedings, Honolulu, May 26-30, 2010.

Hu, H. A Theoretical Analysis on the Sequence of China's Economic Liberalization, The International Workshop on Economics, The International Conference on E-Business and E-Government, Shanghai, May 6-8, 2011.

Hu, H. and Wang, D. The Corporate Social Responsibility and Accountability in the Modern Corporation, The International Workshop on Economics, The International Conference on E-Business and E-Government, Shanghai, May 6-8, 2011.

Islam, J., Ali, M.M. and **Hu, H.**, Problems and Prospects of Breakthrough Thinking for Operations Management in Bangladesh: an analysis, Global Business and Management Forum, Southeast University, Dhaka, December 23, 2010.

Islam, J., Sathye, M. and **Hu, H.**, The Evolution of Corporate Governance Practices in Bangladeshi Banks with the Implementation of the Code of Corporate Governance, the Second International Conference of Global Business and Management Forum, University of Dhaka, December 22-23, 2009.

Islam, J., Sathye, M. and **Hu, H.**, Has the Introduction of the Code of Corporate Governance (CGC) improved corporate Governance practices of banks in Bangladesh? – An Empirical Investigation, the Third New Zealand Management Accounting Conference, University of Canterbury, November 19-20, 2009.

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