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The Determinants of Financial Distress in SMEs

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Abstract

Small and medium-sized enterprises (SMEs) play a major role in economic development. Little research has examined the determinants of financial distress for SMEs in emerging economies due to limited data collection. This study aims to analyzes SMEs and integrate financial variables as suggested by previous studies, along with non-financial variables ignored in previous studies, by analyzing three distressed firms, and thereby identify the factors that explain the failure of SMEs.

Findings show that the correct prediction rate prior to financial failure is 78.3%. In addition, surprisingly, if firms are highly profitable, the owner uses a cash card, or the owner has less industry experience, they are more likely to experience financial distress, in contrast to previous results. Findings also show that as financial failure approaches, the distressed firm often becomes more profitable for a short period, and may even exhibit higher profitability than financially non-distressed firms. We argue that financially distressed firms have higher earnings management incentives to obtain bank financing than financially non-distressed firms. This paper concludes with managerial and practical implications for financial institutions and SMEs and offers future research directions.

Keywords: Financial distress, SMEs, Taiwanese leading banks, factor analysis, logistic regression

INTRODUCTION

Small and medium-sized enterprises (SMEs) play a major role in economic development in developed economies such as Japan, the U.S., and France, and in emerging economies or newly industrialized economies such as Taiwan, Hong Kong, Singapore, and the Philippines. For example, Taiwan, whose economy has thrived over the past few decades, is characterized by its flourishing SMEs. Based on statistics (White Paper on SMEs, 2020), in 2019, SMEs accounted for more than 97.65% of all firms in Taiwan and 78.73% of total employment in Taiwan. Nearly 80% of job opportunities in the country are created by SMEs, which represent the main force of economic development in Taiwan.

In addition to limitations associated with a smaller size, SMEs also experience difficulty accessing capital (Brqderl and Schqssler, 1990; Pomp and Bilderbeek, 2005). According to 2019 statistics (White Paper on SMEs, 2020), 40.39% and 56.76% of debt funding required by Taiwan large firms and SMEs are loaned by domestic banks. This highlights the importance of bank financing for SMEs amid the limited venues for SME financing. SMEs typically lack the ability to make seasoned offerings like corporate bonds or equity securities through public offerings, making bank financing the major source of SME funding. Thus, SMEs, unlike large firms, have characteristically unhealthy capital structures (high debt ratio) and face higher financial risks (Yeh, Ko, and Su, 2000). Further, because of their unhealthy capital structure, and shortage of collateral, SMEs often have difficulty raising funds from financial institutions, impairing SME operations.

The limit financing options for SMEs drives different financing behaviours and affects their survival. The survival rate of SMEs is lower than that of large firms: nearly 50% of SMEs do not survive beyond the first ten years. In 2019, statistics show that only 51.32% of SMEs had been in business for more than ten years (White Paper on SMEs, 2020). By contrast, 78.71% of large firms had been in business for more than ten years. Therefore, the unique characteristics of SMEs require exploration in order to identify the determinants of firm failure.

Most studies on prediction models or the determinants of financial distress have focused on large or listed firms in developed economies and emerging economies (*e.g.* Altman, 1968, 1973; Beaver, 1966; Deakin, 1972; Geng, Bose, and Chen, 2015; Manzaneque, Merino, and Priego, 2016; Ohlson, 1980). Because of the difficulties associated with data collection, few studies have been conducted on small- and medium-sized enterprises (SMEs), and most of these investigate SMEs in developed economies (Huyghebaert et al., 2000; Croce et al., 2015; Keasey, Pindado, and Rodrigues, 2015; Lin, Ansell, and Andreeva, 2012; Pomp and Bilderbeek, 2005). To the best of the authors' knowledge, few studies have investigated SMEs within emerging economies.

As suggested in previous studies (Brqderl and Schqssler, 1990; Caouette et al., 1998), SMEs have few resources available for them, and business and personal activities may be intertwined. This highlights the necessity of incorporating both financial and non-financial indicators in the model of financial distress. Because of data limitation, most studies of SMEs rely solely on financial ratios as research variables and fail to consider other important non-financial factors (Pomp and Bilderbeek, 2005), which are more important in the context of emerging economies. Special institutional environments in emerging economies include the lack of a well-developed product market, capital market, and labor market, as well as under-developed laws and regulations (Khanna and Palepu, 1997; Chen and Ho, 2000; Chen and Yu, 2012; Gonenc and de Haan, 2014; Huang et al., 2016). For example, it is difficult to raise funds from financial institutions without sufficient collateral. Recently, using large or listed firms as samples, scholars have indicated that non-financial variables such as corporate governance are crucial in explaining the financial distress of large firms, especially in emerging markets (Manzaneque et al., 2016; Salloum, Azoury, and Azzi, 2013). This signifies the necessity of incorporating both financial variables and non-financial variables to explore the determinants of the firm failure.

Therefore, to address the research gap, this study uses SME data from leading banks in Taiwan, and integrates financial and non-financial variables in examining the common signals of three case studies, to identify the factors that explain the failure of SMEs.

This paper is organized as follows: Section 2 reviews the literature and conducts the case study. Section 3 describes sources of data, explains the research method, and defines the variables. The results are presented in Section 4. Section 5 contains a brief conclusion, discussions, and suggestions for future research directions.

LITERATURE REVIEW

This study first defines SMEs and financial distress, and then summarizes the literature on financial distress prediction models to identify relevant financial indicators and research methods. This study then uses case studies of three financially distressed SMEs to obtain non-financial signals which can be used to build the financial distress prediction model.

Definition of SMEs

By following the definition criteria of SMEs by the Ministry of Economic Affairs in Taiwan, this study defines SMEs as those firms completing company registration or business registration and conforming to any one of the conditions: (1) firms in manufacturing, construction, mining or quarrying industries, with either paid-in capital less than USD$2.67 million or regular employees less than 200 persons; or (2) firms in other industries (i.e., wholesale, retail, food and drink, transportation, warehousing, communication, finance, insurance, etc.) with either sales revenue less than USD$3.33 million in the last year or regular employees less than 100 persons.

Definition of Financial Distress

Previous studies use different definitions for firm financial distress, and different definitions directly affect the samples chosen and empirical results obtained. Based on a narrow definition, financial distress is defined as a firm in financial distress as an enterprise, which applies for bankruptcy or liquidation (Altman, 1968; Blum, 1974; Ohlson, 1980; Zmijewski, 1984). In addition, according to the broad definition, financial distress is defined as a firm with a large bank overdraft, unpaid preferred dividends and corporate bonds, and carrying out debt restructuring or announcing insolvency (Beaver, 1966; Foster, 1977).

This study refers to the broad definitions of previous studies, SME characteristics, bank practices, and "small and medium business credit guarantee fund of Taiwan" (Taiwan SMEG)[1] regulations in constructing definitions of financial distress of SMEs. A firm in financial distress is a firm that conforms to any of the following conditions: (1) the debtor has terminated operations; (2) the debtor is unable to reimburse matured credit loans; (3) the debtor or owner of the debt firm has an account with a record of bounced checks or the clearing house declares the account dishonorable; (4) the debtor or owner of the debt firm declares bankruptcy or liquidates; or the owned real property is subject to compulsory execution, provisional attachment, or provisional injunction.; and (5) the debtor fails to comply with the payment schedule of the amortization agreement more than one month or defers the interest payment over three months.

[1] Because of the limitations of firm size, insufficient self-owned capital, lack of collateral, and defective financial reports, it is difficult for SMEs to obtain a loan from financial institutions. Thus, the Taiwan government has set up the "Small and Medium Business Credit Guarantee Fund of Taiwan" (Taiwan SMEG) to help SMEs acquire needed funds.

The Determinants of Financial Distress

Beaver (1966) pioneered the financial distress prediction model, taking 30 financial ratios as variables and using a univariate analysis of financially distressed firms and matched non-distressed firms to predict financial distress probability for firms. His empirical results show that cash flow/total liabilities, return on assets ratio, and debt ratio have the best predictive ability. However, Beaver (1966) focuses on the influence of a single financial variable over financially distressed firms, and fails to simultaneously include all variables to measure the firm's overall performance and financial condition. Altman (1968) therefore selects thirty-three bankrupt firms and thirty-three non-bankrupt firms from 1946 to 1965 as samples and extracts five significant predictive ratios from twenty-two financial indicators by using multiple discriminant analysis method, and finally uses the five ratios to build a Z score model.[2] Based on the Z score model (2.675 is taken as a "cutoff" point), firms having a Z score higher than 2.675 are classified as non-bankrupt firms and firms having a Z score lower than 2.675 are defined as bankrupt firms. Their results show that the correct prediction rate of discriminant analysis for the first, second, third, fourth and fifth year prior to financial distress are respectively 95%, 72%, 48%, 29%, and 36%. The results show that as the predictive span of financial distress becomes wider, the correct prediction rate of financial distress prediction model dramatically decreases. The correct prediction rate of the model is higher in the first two years prior to distress.

However, the samples of using discriminant analysis method must conform to normal distribution assumption, causing difficulty in subsequent researches. Therefore, a number of studies (Doumpos and Zopounidis, 2004; Martin 1977; Ohlson 1980; Zwijewski 1984) adopt logistic or probit regression to solve the non-normal distribution problem of samples. Ohlson (1980) adopts logistic regression and chooses 105 bankrupt firms and 2,058 non-bankrupt firms as samples, and finally obtains four important factors that predict firm failure: firm size, financial structure (debt ratio), performance (return on assets and cash flow ratio) and liquidity (working capital ratio and current ratio). The correct prediction rate in the first three years prior to financial distress ranges from 92.84% to 96.12%, indicating that the predictive ability of the logistic model is superior to that of discriminant analysis. Lo (1986) compares the logistic method with discriminant analysis using thirty-eight bankrupt firms and thirty-eight non-bankrupt firms as samples. His results show that the logistic method is more robust than discriminant analysis in parameter estimation, and that other liabilities/total assets ratio, return on assets ratio, and bankruptcy index are superior predictive indicators.

Previous studies provide evidence that financial variables predict firm failure. However, several recent studies find that non-financial variables such as corporate governance also play a vital role in predicting financial distress (e.g. Huang and Lu, 2000; Manzaneque et al., 2016; Salloum, Azoury, and Azzi, 2013). For example, Huang and Lu (2000) choose 21 Taiwan bankrupt listed firms and 40 non-bankrupt listed firms as samples and use the logistic method to construct the financial distress model. They find that a financial distress model incorporating financial and non-financial factors has better predictive power. The prediction rate for the first, second and third year prior to financial distress is 95.08%, 85.25%, and 83.61%. Their results show that significant predicting financial variables include cash flow ratio, equity ratio, and the equity growth rate, and significant non-financial variables include ownership ratio of block-holders, the term of directors and the ratio of stocks pledged to banks by directors. In addition, Salloum et al. (2013) select 178 Lebanese non-listed family firms as the sample and find that firms whose boards have a higher proportion of outside directors are less inclined to face financial distress than firms whose boards have a lower proportion. These findings highlight the importance of both financial and non-financial variables in predicting firm distress in emerging economies, especially in the Taiwan context.

Because of difficulties in data collection and the dearth of studies on SMEs, Pompe and Bilderbeek (2005) adopt discriminant analysis and artificial neural network analysis to construct a financial distress prediction model. They select 3,000 non-bankrupt Belgium firms and 1,288 bankrupt Belgium firms in the period of 1986-1994 as samples, and classify the samples into new firm group and old firm group based on firm age, and use financial ratios as variables. Empirical results show that the correct prediction rate of neural network is similar to that of discriminant analysis, whether firms are old or new. Findings also show that the cash flow ratio has high predictive power for both prediction models.

By following previous studies and the availability of data, this study selects twelve frequently used financial variables based on four categories: efficiency ratios (including 4 ratios: accounts receivable turnover, inventory turnover, fixed asset turnover, and total asset turnover), liquidity ratios (including 2 ratios: current ratio and quick ratio), solvency ratios (including 2 ratios: debt ratio and financial charges ratio), and profitability ratios (including 4 ratios: return on assets, return on equity, gross profit ratio, and operating income ratio) in constructing the financial distress model. Though cash flow ratio plays an important role in bankruptcy, as SMEs only provide tax filing statements including income statement and balance sheet rather than cash flow statements to banks, we cannot include the ratios of cash flow categories in the prediction model.

[2] $Z = 1.2X_1+1.4X_2+3.3X_3+0.6X_4+0.099X_5$, of which: X_1=working capital/total assets, X_2=retained earnings/total assets, X_3=earnings before interest and tax/total assets, X_4=market value of equity/total debt, X_5=sales/total assets, Z= overall score.

Most previous studies focus on listed firms, with little effort directed toward SMEs. Both financial variables and non-financial variables are found to have significant power to predict firm failure. Few studies use SMEs as samples and use non-financial variables to construct a financial distress prediction model due to data limitations. However, because of the lower financial report credibility of SMEs (Lin et al., 2004), non-financial variables play an essential role in financing decision making. Thus, this study uses case studies to identify potential non-financial variables which have predictive power for firm failure.

Case Studies for Financially Distressed Firms

This study randomly selects three cases from defaulted SMEs in 2007 and 2008 to identify potential common signs leading to financial failure, and then picks these factors as non-financial variables. For the sake of confidentiality, the three firms are respectively termed case A, case B and case C.[3] Bank loans for the three firms are used as working capital for daily operations. Case A and C are in the wholesale industry, while case B is a manufacturer. This study conducts a comprehensive survey of these cases and finds common characteristics for financially distressed firms. For example, the number of inquiries about the firms or firm owners to the Joint Credit Information Center (JCIC)[4] for the most recent 3 months indicates the frequency of financially distressed firms encountering funding shortage problems, since they often apply for loans from financial institutions when facing financial difficulties. Other distress alarms include whether the firm owner is a cash card user or constantly uses revolving credit, or whether a firm's deposits have a low average balance. Based on these case studies, this study finally selects eight variables relating to firm characteristics (any relational firms, firm age, credit irregularities of firms, turnover of owner, number of inquiries to the JCIC, bank deposits as a percentage of total assets or sales less than 5% and 2%, industry dummy) and ten variables relating to owner characteristics (age, gender, education, marriage, years of experience in the original industry, credit irregularities of owners, number of inquiries to the JCIC, use of a cash card, ratio of revolving credit to credit card greater than 20%, and financial liabilities) as eighteen non-financial variables for constructing the financial distress prediction model of SMEs and explore the determinants of SMEs' failure.

Research Methods

Beaver (1966) conducted the earliest study of the financial distress prediction model, using a univariate analysis of firm financial ratios to identify significant variables predicting firm failure. However, Beaver's model fails to simultaneously consider multiple indicators in the model and hence has difficulty measuring the overall financial condition of firms. To address these issues, Altman (1968) adopts multiple discriminant analysis (MDA) to measure the financial position of firms by applying multiple variables in the model simultaneously. Thereafter, most studies adopt this method in constructing financial distress models. However, discriminant analysis also has problems classifying its independent variables because of their non-normal distribution and does not outperform other business failure prediction models (John, 1986). Subsequent studies (Doumpos and Zopounidis, 2004; Martin 1977; Ohlson 1980; Zwijewski 1984) introduce logistic and probit methods for building financial distress prediction models, and the logistic method becomes particularly popular among researchers. Ohlson (1980) also shows that the logistic method has a prediction rate superior to that of discriminant analysis when the sample data is not in a normal distribution.

In recent years, artificial neural network models have emerged. This method massively and rapidly processes data, impelling previous studies (Odom and Sharda, 1990; Pomp and Bilderbeek, 2005) to use artificial neural networks for constructing financial distress prediction models. Odom and Sharda (1990) apply discriminant analysis and artificial neural networks to conduct an empirical comparison, and find that the predictive power of the artificial neural network is better than that of discriminant analysis. However, Pompe and Bilderbeek (2005) adopt discriminant analysis and artificial neural networks to analyze SMEs, finding that the prediction rates of discriminant analysis and artificial neural networks are similar. Artificial neural networks may sometimes have difficulty in model convergence and lack a sound theory structure to illustrate the model process, making the data analysis process appear to be a black box whose internal operations opaque.

In sum, MDA and logistic regressions have been the most commonly used methods for constructing bankruptcy models, and both statistical techniques perform similarly (Wilson and Sharda, 1994). However, when the

[3] Due to space limitation, please contact the authors for detailed information about the three financially distressed firms in case studies.

[4] The Joint Credit Information Center establishes a nationwide credit information database and provides credit records as well as financial information of economic entities to member institutions; improves the credit investigation function of the financial sector and promotes the development of credit investigation techniques; ensures the safety of credit transactions and promotes sound development of the national credit system; provides information needed by the competent authority for financial supervision. The JCIC under financial institutes' cooperation has already established a comprehensive borrower database. Any credit default of notes and debt leaves a record in the center.

research samples do not conform to a normal distribution, logistic analysis is the better method to construct the prediction model. Therefore, this study adopts logistic regression analysis in constructing its financial distress prediction model for SMEs.

DATA AND METHOD

Data

This study selects SME samples from credit clients of three large Taiwan banks in 2007 and 2008. We first pick all 65 distressed firms as initial samples, but later eliminate those with incomplete financial or non-financial data or without an available matched firm, leaving 46 financially distressed firms as the final samples. Then, following previous studies (Altman, 1968; Huang and Lu, 2000; Doumpos and Zopounidis, 2004), this study chooses another 46 matched non-distressed firms based on the criteria of same industry and similar firm size for a subsequent empirical test. Financial variables are collected from tax filing statements that firms provide, and non-financial variables collected from firms' application files for bank loans.[5] The distressed sample firms are largely manufacturing firms. Almost all employed less than 100 people, and their capital ranges from USD$93,000 to USD$1,300,000. The matched firms' capital ranges from USD$62,000 to USD$1,232,000.

Research Method

Following previous studies (Doumpos and Zopounidis, 2004; Ohlson 1980), this study adopts logistic regression to construct its financial distress prediction model. In a logistic model, the occurrence probability of event is assumed to conform to the logistic cumulative distribution model, and is primarily used to solve binary nominal and qualitative problems. The logistic model adopts maximum likelihood estimation to estimate the parameters, and adopts a likelihood ratio to test model fitness. The value equals to -2log, the likelihood is χ^2 distribution and the degree of freedom for the model is the number of independent variables. The Wald χ^2 test identifies the influence of each variable on the model. After the model is fitted to obtain parameter estimate values, forecast value Y can be acquired. The logistic model is:

$$Y_i = \beta_0 + \sum_{i=1}^{k} \beta_i X_i + \varepsilon_i \quad ... \qquad (1)$$

Where the subscript i stands for firms. Y_i is the dependent variable (Y_i=1 for financially distressed firms, and Y_i=0 for non-distressed firms). X_i are the independent variables, and ε_i is the error term.

Definition of Variables

By following previous studies (Pompe and Bilderbeek, 2005), our selected financial variables are divided into four categories: efficiency ratios, liquidity ratios, solvency ratios, and profitability ratios. The highest ratios are in efficiency, liquidity, solvency, and profitability, where to the probability of firms encountering financial distress is lower. In addition, our selected non-financial variables are divided into two categories: firm characteristics and owner characteristics. The selected variables, expected variable signs, and operating definitions are presented in Table 1:

[5] According to the operating regulations of financial institutions, clients with total granted credit under USD$930,000 should provide tax filing financial statements (Income statement and Balance sheet). According to the income tax laws, the enterprise should finish filing of income tax before the end of May each year. Therefore, in practice, most firms do not finish their tax filing until the end of May. For this reason, when firms apply for financing from finance institutions during January to May each year, the firms can only provide financial statements of the second year prior to financing because the firms do not finish income tax filing for the first year prior to the financing year. If firms applying for loans in the period mentioned above have defaulted, financial institutions cannot obtain the firms' tax filing statements of the latest year. If firms applying for loans from financial institutions during June to December default in the same year, financial institutions can then obtain the firm's prior year's tax filing statements. This study only acquires financial data for the second and third year prior to financial distress because of sample and data limitations. Because of the shortage of non-financial variables from the third year prior to distress, this study constructs a financial distress prediction model for the second year prior to financial distress.

Categories	Explanatory variables and abbreviation	Measures	Expected signs
Financial variables			
Operating Efficiency	Accounts receivable turnover(ART)	ART=Sales/account receivable	–
	Inventory turnover (IVT)	IVT=Cost of goods sold/inventory	–
	Fixed asset turnover(FAT)	FAT=Sales/fixed assets	–
	Total asset turnover(TAT)	TAT=Sales/total assets	–
Liquidity	Current ratio (CR)	CR=Current assets/current liabilities	–
	Quick ratio (QR)	QR=Quick assets/current liabilities	–
Solvency	Debt ratio (DR)	DR=Total debt/total assets	+
	Financial charges ratio (FCR)	FCR=Interest expense/sales	+
Profitability	Return on assets (ROA)	ROA=Net income/total assets	–
	Return on equity (ROE)	ROE=Net income/total equity	–
	Gross profit ratio (GPR)	GPR=Gross profit/sales	–
	Operating income ratio (OIR)	OIR=Operating income/sales	–
Non-financial variables (from case studies)			
Firm characteristics	Any relational firms (RF)	RF=1 for Yes, RF=0 for No	+
	Firm age (FA)	Ln (firm age)	–
	Credit irregularities of firms (blacklisted accounts or bounced check record) (CIC)	CIC=1 for YES, CIC=0 for No	+
	Turnover of owners for latest 3 years (TO)	TO=Turnover times of owners	+
	Inquiring times by JCIC for latest 3 months (ITC)	ITC=Inquiring times by JCIC	+
	Bank deposits as a percentage of total assets is less than 5% (BDA)	BDA=1 for Yes, BDA=0 for No	+
	Bank deposits as a percentage of annual sales is less than 2% (BDS)	BDS=1 for Yes, BDS=0 for No	+
	Industry dummy (ID)	ID=1 for Construction industry, otherwise ID= 0	+
Owner characteristics	Age (OA)	OA=Ln(age)	–
	Gender (OG)	OG=1 for Male, OG=0 for female	–
	Education (OE)	OE=1 for high school and above, Otherwise OE=0	–
	Marriage (OM)	OM=1 for Married, Otherwise OM=0	–
	Years of experience in the original industry (YEO)	YEO=Ln(years of experience)	–
	Credit irregularities of owners (CIO)(blacklisted accounts or bounced check record)	CIO=1 for Yes, CIO=0 for No	+
	Inquiring times by JCIC for latest 3 months (ITO)	ITO= Inquiring times by JCIC	+
	Use of a cash card (UCC)	UCC=1 for Yes, UCC=0 for No	+
	Ratio of revolving credit of credit card is greater than 20% (RCC)	RCC=1 for Yes, RCC=0 for No	+
	Financial liabilities (FLO) (owner & spouse)	FLO=Ln(financial liabilities)	+

Table 1 Summary of variable measures

EMPIRICAL RESULTS

Descriptive Statistics

Table 2 presents the descriptive statistics. The Kolmogorov-Smirnov test (KS) is used to test whether our samples conform to normal distribution. As Table 2 indicates, the KS values of most research variables are significant and reject the null hypothesis that the population is normally distributed. Therefore, this study adopts the nonparametric Mann-Whitney U test to compare distressed firms and non-distressed firms and determine whether any significant difference exists between the two sample groups. However, since a few variables, such as debt ratio, gross profit ratio, firm age, and age of owners cause a failure to reject the normal distribution assumption, this study adopts the mean t test to detect differences between the two firm groups.

Table 2 shows that in the third year prior to financial distress, only one financial ratio (i.e., financial charges ratio) for financially distressed firms is higher than non-distressed firms, with a marginal significance at the 10% level. More importantly, bank deposits as a percentage of annual sales is less than 2% for financially distressed firms, significantly higher than non-distressed firms. The frequency of inquiry about firms at the JCIC and use of a cash card are also significantly higher for distressed than non-distressed firms. These statistics indicate that firms already have a financial deterioration or deficiency problem in the third year prior to financial distress.

In addition, in the second year prior to financial distress, all financial variables of financially distressed firms including liquidity ratios are not significantly different from those of distressed firms. However, the number of inquiries about financially distressed firms to the JCIC is higher than for non-distressed firms, and owners of distressed firms have higher probability of using a cash card. Thus, our univariate analysis results show that as firms approach financial distress, only non-financial variables show a significant difference between financially distressed firms and non-distressed firms

Explanatory variables[a]	Second year prior to financial distress						Third year prior to financial distress					
	Distressed Group		Non-distressed Group				Distressed Group		Non-distressed Group			
	Mean	S.D.	Mean	S.D.	K-S value	Z (t) value	Mean	S.D.	Mean	S.D.	K-S value	Z (t) value
Financial ratios												
ART	9.26	16.15	39.40	209.11	3.44**	-0.42	10.27	16.81	10.16	29.02	2.67**	-0.72
IVT	16.73	32.04	10.77	31.59	2.86**	-0.76	5.65	10.78	15.72	38.31	2.82**	-1.56
FAT	85.56	216.63	63.20	99.07	2.45**	-0.82	52.36	80.29	65.27	110.50	2.11**	-0.61
TAT	1.75	1.45	1.85	1.49	1.45*	-0.24	2.35	2.59	2.02	1.75	1.93**	-0.31
CR	3.75	10.98	3.83	15.60	3.61**	-0.41	15.51	45.50	17.66	101.07	3.76**	-0.39
QR	2.74	8.75	0.92	0.85	3.07**	-0.22	10.07	28.85	1.59	3.37	3.46**	-0.49
DR	0.68	0.20	0.72	0.33	1.19	-0.46	0.56	0.28	0.67	0.32	0.88	-1.31
ROA	0.04	0.06	0.00	0.06	2.47**	-1.24	0.01	0.11	-0.01	0.09	2.49**	-0.33
ROE	0.12	0.17	0.07	0.26	2.39**	-0.52	-0.06	0.41	0.06	0.47	2.70**	-1.09
GPR	0.18	0.09	0.19	0.09	0.56	-0.43	0.20	0.08	0.19	0.09	0.52	0.41
OIR	0.02	0.05	0.02	0.05	1.55*	-0.73	-0.01	0.21	0.01	0.05	2.31**	-0.49
FCR	0.01	0.02	0.01	0.02	1.65**	-0.05	0.02	0.03	0.01	0.01	2.23**	-1.78^{+}
Non-Financial ratios												
FA	1.91	0.87	2.04	0.65	0.77	-0.63	1.71	1.03	1.88	0.73	0.81	-0.77
CIC	0.10	0.31	0.05	0.22	4.17**	-0.73	0.10	0.31	0.05	0.22	4.17**	-0.73
TO	0.20	0.70	0.05	0.22	4.05**	-0.76	0.20	0.70	0.05	0.22	4.05**	-0.76
OA	3.84	0.20	3.81	0.20	0.95	0.62	3.82	0.21	3.79	0.21	0.94	0.62
CIO	0.15	0.37	0.10	0.30	4.06**	-0.56	0.15	0.37	0.10	0.30	4.06**	-0.56
BDA	0.55	0.51	0.43	0.50	2.76**	-0.91	0.55	0.51	0.38	0.49	2.90**	-1.28
BDS	0.30	0.47	0.23	0.42	3.61**	-0.63	0.50	0.51	0.25	0.44	3.29**	-1.92^{+}
ITC	3.80	2.33	2.95	2.18	1.87**	-1.70^{+}	3.80	2.33	2.95	2.18	1.87**	-1.70^{+}
RF	0.50	0.51	0.48	0.51	2.70**	-0.18	0.50	0.51	0.48	0.51	2.70**	-0.18
ITO	3.65	1.81	3.05	1.63	1.26^{+}	-0.98	3.55	1.91	3.05	1.63	1.23^{+}	-0.75
UCC	0.35	0.49	0.13	0.34	3.80**	-2.04*	0.40	0.50	0.13	0.34	3.74**	-2.42*
RCC	0.30	0.47	0.15	0.36	3.80**	-1.36	0.30	0.47	0.15	0.36	3.80**	-1.36
YEO	2.40	0.69	2.59	0.47	1.29^{+}	-0.62	2.27	0.80	2.50	0.51	1.35^{+}	-0.62
FLO	7.10	3.18	7.18	2.78	2.19**	-0.19	7.13	3.16	7.25	2.78	2.03**	-0.06

Table 2 Summary statistics of sample firms

Note: (1)The abbreviations of the table represent the following variables: ART=account receivable turnover, IVT=inventory turnover, FAT=fixed asset turnover, TAT=total asset turnover, CR=current ratio, QR=quick ratio, DR=debt ratio, ROA=return on assets, ROE=return on equity, GPR=gross profit ratio, OIR=operating income ratio, FCR=financial charges ratio, FA=firm age, CIC= credit irregularities of firms, TO=turnover of owners, OA=age of owners, CIO=credit irregularities of owners, BDA= bank deposits as a percentage of total assets is less than 5%, BDS=bank deposits as a percentage of annual sales is less than 2%, ITC= number of inquiries about firms to the JCIC, RF=any relational firms, ITO=number of inquiries about owners to the JCIC, UCC=use of a cash card, RCC=ratio of revolving credit of credit card is greater than 20%, YEO=years of experience in original industry, FLO=financial liabilities of owners. (2) $^{+}$ $P < 0.10$; $^{*}P < 0.05$; ** $P < 0.01$

Factor Analysis

Following previous studies (Pomp and Bilderbeek, 2005; Zavgren, 1985), this study conducts a factor analysis separately on financial variables and non-financial variables of the second year prior to financial distress to obtain independent variables (principal factors) from these highly correlated variables. By using principal factor estimate and the varimax orthogonal rotation to maximize the variance of pattern loading, we obtain each factor's eigenvalue and list it in size order. Using the Kaiser principle (1960), this study retains common eigenvalue factors greater than one, determines the factor loadings for each factor, and selects variables highly correlated with the factor, representing major factor information (Zavgren, 1985). The factor analysis results in Table 3 indicate that the accumulated explanatory powers of new factors obtained from the factor analysis all exceed 70% for both financial and non-financial variables. Thus, the factor analysis results sufficiently represent the sample data. Selected financial variables in this study include return on assets, quick ratio, account receivable turnover, fixed asset turnover, and return on equity. Non-financial variables include number of inquiries about owners to the JCIC, use of a cash card, bank deposits as a percentage of total assets less than 5%, bank deposits as a percentage of annual sales is less than 2%, financial liabilities of owners, years of experience in the original industry, firm age, credit irregularities of owners, and gender of owners. These variables are used in the subsequent logistic regression analysis to construct the prediction model.

Factor	Variables	Factor loading	Explained variance	Accumulated explained variance
Financial variables				
1	Return on assets	0.880	16.945%	16.945%
	Operating income ratio	0.822		
2	Quick ratio	0.861	16.764%	33.709%
	Current ratio	0.771		
3	Account receivable turnover	0.829	14.327%	48.036%
	Total asset turnover	0.819		
4	Fixed asset turnover	-0.826	13.151%	61.187%
5	Return on equity	0.841	12.261%	73.447%
Non-financial variables				
1	Inquiring times of owners by JCIC	0.881	11.487%	11.487%
	Inquiring times of firms by JCIC	0.873		
2	Use of a cash card	0.844	11.175%	22.662%
3	Bank deposits as a percentage of total assets is less than 5%	0.848	10.813%	33.475%
	Bank deposits as a percentage of annual sales is less than 2%	0.787		
4	Financial liabilities of owners	0.744	10.548%	44.022%
5	Years of experience in the original industry	0.895	10.424%	54.446%
	Firm age	0.872		
6	Credit irregularities of owners	0.872	9.540%	63.986%
7	Gender of owners	0.857	8.101%	72.087%

Table 3 Factor analysis results for sample firms

Logistic Regression Analysis

This study applies logistic regression analysis to samples from the second year prior to financial distress to construct a financial distress prediction model. The prediction results shown in Table 4 indicate that the model is statistically significant (Chi-square=13.622, P value=0.0045) and provides evidence of fitting well for further analysis. The correct prediction rate of the model is 78.3%, quite close to the correct prediction rate (i.e., 72-76%) in the SME literature (Pompe and Bilderbeek, 2005). Predictive variables consist of financial variables (return on assets and quick ratio), and non-financial variables (use of a cash card and years of experience in the original industry). Regarding coefficient direction and significant level, return on assets is positive at the 10% significance level, showing that the higher the profitability, the higher the financial distress probability. These results clearly differ from previous findings for large firms and SMEs (Altman, 1968; Beaver, 1966; Ohlson, 1980; Lo, 1986; Pompe and Bilderbeek, 2005). In addition, the quick ratio as a measure of liquidity is positive but does not achieve a level of significance, similar to previous results. Beaver (1966) using large firms as the sample, and Pompe and Bilderbeek (2005) using SMEs as the sample, also find that liquidity ratios do not have strong predictive power for firm failure. Additionally, findings show that two non-financial variables, the use of cash card and years of experience in the original industry, are significant in the model. The coefficient on the use of cash card is significantly positive, in the expected direction. This result shows that the use of a cash card by the firm owner effectively predicts financial distress. The "years of experience in the original industry" coefficient is significantly negative. This result shows that the probability of financial distress rises if the firm owner has less experience in the firm business.

Year	Variables	Coefficient	Standard error	P value
Second year prior to financial distress	Constant	1.057	1.388	0.447
	Return on assets	11.525	5.991	0.054^{+}
	Quick ratio	0.103	0.080	0.196
	Use of a cash card	1.679	0.732	0.022^{*}
	Years of experience in the original industry	-1.015	0.571	0.076^{+}
Model fitness: Chi-square＝13.622 P value＝0.0045				
Percent correctly classified=78.3%				

Table 4 Logistic model results

Note: $^{+}$ P < 0.10; *P <0.05; ** P <0.01.

CONCLUSIONS AND IMPLICATIONS

Conclusions and discussions

This study chooses 46 Taiwan financial distressed SMEs and a matched 46 non-distressed firms from 2007 to 2008 as the sample. We incorporate financial variables as suggested in previous studies and non-financial variables through 3 case studies by using the logistic method to construct a financial distress prediction model. Our results show that the prediction rate of the second year prior to financial failures is 78.3%. In addition, significant predictive variables include return on assets ratio, quick ratio, use of a cash card by the owner, and owner's years of experience in the original industry. Further, this study finds that as the time of failure approaches, the firm in financial distress becomes more profitable and has higher profitability than financially non-distressed firms. These results show that the better the profitability, the higher the firm's probability of financial distress, contradicting previous studies (Altman, 1968; Geng et al., 2015; Huang and Lu, 2000; Ohlson, 1980; Doumpos and Zopounidis, 2004; Pompe and Bilderbeek, 2005).

To explain why our findings on profitability conflict with those of previous studies, this study considers the non-normal distribution of the sample and uses the nonparametric Mann-Whitney U test to compare whether the financial ratios in the second year and the third year prior to financial distress are strongly different for both financially distressed and non-distressed firms. As Table 5 indicates, the financially distressed group has a fixed asset turnover increase from the third year to the second year prior to financial distress, but this is not statistically significant. The financially distressed group has higher profitability (return on assets and return on equity) in the second year prior than in the third year prior to bankruptcy, while return on equity reaches the 10% significance level. This finding indicates that financially distressed firms may have poor financial performance in the third year prior to financing, but have strong intentions to adopt earnings management as window dressing for financial statements in the second year prior to financial distress to acquire a bank loan (Lin et al., 2004; Pompe and Bilderbeek, 2005). Pompe and Bilderbeek (2005) indicate that some ratios (e,g, the liquidity ratios) do not predict well just prior to bankruptcy, but did predict well many years before bankruptcy. Thus, we argue that as the time of financial failure approaches, distressed firms have great pressure to raise funds and thus display different financing behaviors (earnings management).

The operating efficiency (fixed asset turnover) and short-term liquidity (quick ratio) of the financially non-distressed group in the second year prior to bankruptcy is poorer than that in the third, and reaches the 5% significance level. Profitability (return on assets and return on equity) has a small increase but does not reach significance. These results may indicate that non-distressed firms facing financing need do not actively manage earnings to generate better-looking financial statements.

Group	Distressed group			Non-distressed group		
Variables	3rd year	2nd year	P value	3rd year	2nd year	P value
Accounts receivable turnover	10.27	9.26	0.156	10.16	39.40	0.701
Fixed asset turnover	52.36	85.56	0.872	65.27	63.20	0.027^{*}
Quick ratio	10.07	2.74	0.332	1.59	0.92	0.088^{+}
Return on assets	0.01	0.04	0.247	-0.01	0.00	0.320
Return on equity	-0.06	0.12	0.067^{+}	0.06	0.07	0.648

Table 5 Comparisons of financial ratios for sample firms

Note: $^{+}$ P < 0.10; *P <0.05; ** P <0.01.

Although the financial statement credibility of SMEs is generally lower, credit evaluators usually regard the financial statements of clients as a minor reference for a credit decision. For example, SMEs[6] in Taiwan frequently invent accounting results or manage earnings for special considerations such as tax savings, debt contracts, regulatory factors, market competition, or bank financing. These behaviors often cause deviation in reported sales, expenses, or net income in financial statements from actual figures and operating results (Lin, Wen, and Tseng, 2004), which may seriously lower financial report credibility. Table 2 reveals that solvency of financially distressed firms is lower than those of non-distressed firms before the third year prior to financial distress. Further, Table 5 reveals that the profitability of financially distressed firms may be larger in the third year prior to financial distress than in the second year prior to financial distress. Thus, this study indicates that SMEs may give off signals before financial distress and may actively dress financial statements to acquire a bank loan before the second year prior to financing. This evidence demonstrates even more that financially distressed firms have higher earnings management incentives to obtain bank financing than financially non-distressed firms.

Further, our results also show that if a firm owner uses a cash card or has less experience in the original industry, the probability of financial distress rises.

In sum, our results can contribute to scholarly research by highlighting the importance of non-financial variables in predicting firm failure, especially for SMEs subject with limited funding sources. Our findings may also be important to practitioners. Our results may be used as a reference in SME credit decisions. Financial institutions should evaluate the operating results from financial reports and available non-financial indicators in analyzing default risk. The findings of this paper show that both financial variables and non-financial variables are valuable references. SMEs may already show signs of deterioration before financing and actively upgrade their financial statements. The extent of earnings management in financially distressed firms is higher than in non-distressed firms. Therefore, financial institutions should compare financial statement figures in the first and second year prior to financing. In addition to financial reports, credit examiners should use the non-financial data of firms and firm owners' characteristics in credit decisions. Accordingly, financial institutions should determine whether the client is a cash card user and how many years of experience the client has with the company. Thus, financial institutions can ensure that the firm maintains a low financial risk and that the firm owner has sufficient capability and experience. In this manner, firms with better liquidity capability can quickly acquire funding. Financial institutions can thus maintain good quality credit, reducing default risk, and enhance overall economic development.

SMEs can use our results to detect deteriorating signs of financial conditions, prevent problems, and reduce operating risks. SME owners should accumulate experience in the original industry to maintain competitive advantage and avoid use of cash cards as a source of funding to increase their chance of long-term survival.

Research Limitation and Future Direction

This paper chooses Taiwanese SMEs as the sample for constructing a financial distress model and explore the determinants of financial failure for SMEs. Since SME characteristics are different from those of large firms, our research findings may not be applicable to large firms. Similar to previous studies (Dambolena and Khoury, 1980; Huyghebaert et al., 2000; Keasey and Watson, 1987; Laitinen, 1992), the financial distress samples of this study are not plentiful and other relevant variables may be omitted due to the difficulties of data collection.[7] Thus, the prediction rate of the model in this study is 78.3%, close to those of previous studies (Pompe and Bilderbeek, 2005). If more data is available in the future, along with a larger sample, more effective predictive variables can also be incorporated into future studies, including financial and non-financial indicators such as cash flow ratio, unpaid employee insurance and unpaid salary, and real property detained and attached, that will help enhance the model's predictive power for SMEs.

Finally, in light of sample collection difficulty, this study cannot construct a financial prediction model and explore the determinants of financial distress for different industries. Different product life cycles, marketing skills, and competitive structures in each industry cause divergence among industry financial ratios (Mensah, 1984; Platt and Platt, 1990, 1991). Subsequent researchers may build a specialized financial distress prediction model for different industries, with higher prediction model accuracy.

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[6] In Taiwan, it is common for SMEs to prepare two sets of financial statements, one for internal use by managers, and the other for external purposes such as tax reduction and bank financing.

[7] For example, Dambolena and Khoury (1980), Huyghebaert et al. (2000), Keasey and Watson (1987) and Laitinen (1992) use 23, 81, 73, and 20 bankrupt firms, respectively.

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