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Applying Z-score model to distinguish insolvent construction companies in China

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A B S T R A C T

Fierce competition in the construction industry in China in recent years has brought many challenges to construction contractors. It is important that any potential company insolvency be recognized at the earliest opportunity. Using financial ratios and the Altman *Z*-score modelling methodology, an insolvency warning model is developed in order to evaluate the performance of construction contractors in China. The model derived from this study has consistent predictability based on a three-year window of data. It combines seven financial ratios, covering a company's finance of operation, profitability, solvency and cash flow. A single performance index is derived to differentiate whether a company has good financial standing or exhibits characteristics of insolvent companies. A mechanism to detect insolvent contractors is proposed for sustaining corporate development in construction. It is recommended for a contractor to develop a complete precaution system of financial crisis and have a regular checking of the key financial ratios as well as operation status so as to avoid insolvency.

Introduction

The reform in China since 1978 has given rise to a remarkable success in the country's economic development. To accommodate the rapid expansion in economic activities and the ever growing demand for better living standard, China's construction industry has been experiencing an extraordinary growth over the last three decades (Low & Jiang, 2003). According to the China Statistical Yearbook, the gross output value of construction in 2008 which was about US$240 billion has surged by more than 20 times when compared with that in 1978, while the percentage of value added of construction versus the gross domestic product over the same period has increased from 3.8 to 5.6%. Despite being overshadowed by the financial tsunami in 2008, the demand for construction facilities in China especially in the second and third-tier cities remains strong thanks to a healthy internal economy (Gallagher, 2008; Wearden & Stanway, 2008).

Nonetheless, local construction companies are facing increasing competitions and challenges from international companies after China's accession to the World Trade Organization in 2001. The problem is aggravated by the fragmented nature of the industry, low entry barrier and high uncertainties involved (Kale & Arditi, 1999; Kangari, 1988). Construction companies are particularly vulnerable to impacts brought by the reform of economic system, adjustment in macroeconomic policy, changes in the structure of market demand, increasing price of raw material, etc. These would threaten the operation of a contracting firm and eventually bring those incapable and inexperienced companies to the fate of insolvency (Schaufelberger, 2003).

While it is not unusual to unfold the financial healthiness of a contractor before they are invited to tender or commissioned to carry out a project (Russell & Zhai, 1996), to distinguish which contractor is more susceptible to bankruptcy may not be easy as a company with reasonable performance may suddenly collapse due to financial insolvency (Davidson & Maguire, 2003). The effect of employing an insolvent contractor is deep rooted as another contractor has to be brought in to complete the construction project which could inevitably result in time and cost overrun (Mason & Harris, 1979). Recognizing the possible distress caused to a construction project, it is desirable to predict the chance of contractor failure especially at times of economic austerity and when there is a lack of knowledge about the contractors in a specific country like China.

Despite that, most of the financial failure studies in the construction discipline tended to focus at the project level for prequalification purposes (e.g. Hall, 1982; Morris & Hough, 1987). Some studies, on the other hand, addressed the issue from the legal and organizational theory perspectives (Kale & Arditi, 1999; Russell & Casey, 1992). Some earlier works dedicated to the company level (e.g. Abidali & Harris, 1995; Mason & Harris, 1979) followed the

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Altman's studies, which aimed at developing models or indicators to distinguish between financially distressed and financially healthy construction companies (Hanzaee, 2010). However, the applicability of the *Z*-score model for insolvency prediction within the construction industry particularly in China is still unclear.

This study, therefore, aims to develop an insolvency warning model to evaluate the financial performance of construction contractors in China. The paper begins by presenting the tools being used for predicting construction company insolvency. The accuracy of previous *Z*-score models for predicting the insolvency of Chinese contractors is then examined. The research methodology which includes the data set and the modelling techniques adopted for this study are highlighted. It is then followed by a description of the resultant model for early warning of financial crisis and the presentation of the results of model validation. Finally, discussions on the implications of the findings conclude the paper.

Methods for predicting company insolvency

While novel approaches such as support machine vector (Xu, Chen, & Ren, 2006), ontology-based portal (Kotsiantis, Kanellopoulos, Kariotì, & Tampakas, 2009), semi-parametric modelling approach (Kim & Yoo, 2006), independent component analysis (Chen & Vieira, 2009), Bayesian networks (Sun & Shenoy, 2007), etc. have been proposed by researchers to predict the financial healthiness of

Table 1
Previous studies on predicting insolvency in construction.

Author(s)	Country	Work done	Modelling technique	Determining factors	Source of data
Mason and Harris (1979)	UK	Developed a Z-score model in construction comprising 6 financial ratios	LDA	5 distinct aspects: profitability; working capital position; financial leverage; quick asset position; and trend	Extel services cards; 20 failing plus 20 sound civil contractors
Kangari (1988)	US	Modelling construction business failure using macroeconomic factors	Multiple regression	Amount of construction activity, interest rates, inflation, new business activity/new competitors	Official macroeconomic data (1977–1986)
Kangari, Farid, and Elgharib (1992)	US	Developed a performance index to grade a company by regressing 6 financial ratios	Multiple regression	Current ratio, total liabilities to net worth, total assets to revenues, revenues to net working capital, return on total assets, return on net worth	Dun and Bradstreet; 126 construction companies (6 groups)
Russell and Jaselskis (1992)	US	Developed a model to predict the probability of contractor failure at the project level	Logit regression	Amount of owner-contractor evaluation; owner's cost monitoring; level of support received by PM; early involvement of contractor's PM	20 public plus 28 private projects survey; 23 out of 48 companies involved failure
Hall (1994)	UK	Identified factors distinguishing survivors from failures	Logit regression	93 potential explanatory variables were test. Key factors: taking expert advice on tax matters, owner's education, human capital, financial management, marketing and strategic management	Survey on 58 small construction companies
Abidali and Harris (1995)	UK	Developed a model to predict construction company failure using 7 financial ratios & 13 managerial factors	Z-Score on financial ratios using LDA; and A-score on managerial performance by survey	Key financial variables e.g. ratio of earnings after tax and interest charge to net capital employed; ratio of current assets to net assets; tax trend, etc.	Extel services cards; 11 failed companies; 20 non-failed companies
Russell and Zhai (1996)	US	Examined the pattern of stochastic dynamics: percentage changes, trends and volatility for economic and financial variables to predict contractor failure	Multiple regression	Trend-prime interest rate; future position-new construction value in-place, trend-new construction value in-place, future position-net worth/total asset, trend-gross profit/total asset; volatility-net working capital/total asset	Dun and Bradstreet; 49 failed and 71 non-failed contractors
Kale and Arditi (1999)	US	Explored age-dependent business failure pattern in US construction industry	Age-dependent failure analysis	Risk of failure increases initially with increasing age, reaches a peak point and then decreases as companies grow older	Dun and Bradstreet; 1973–1994; 7608 failed companies
Koksal and Arditi (2004)	US	Developed a model to determine a company's healthiness comprising 11 organizational factors	Factor analysis and logit regression	Specialization, standardization, advanced managerial practices, advanced construction technologies, managers' work experience/business knowledge/managerial experience, defining competitive advantage, etc.	1) Westlaw; 2) LexisNexis; 3) Survey; 11 failing and 41 sound companies
Chan, Tam, & Cheung (2005)	HK	Assessed the financial performance of the construction firms in Hong Kong.	Ratio analysis	Operating profit margin; return on equity; return on asset; total asset turnover; quick ratio; earning per share; and debt ratio	Annual reports of 8 large contractors; 1997–2002
Huang (2009)	Taiwan	Investigated the viability of using structural models of credit risk for predicting contractor default probabilities.	Ratio analysis and logit regression	Asset volatility, risk-free rate, book leverage ratio, coupon rate, default cost proxies (firm size, industry distress, ratio of replacement cost *t* total assets), growth rate of construction-in-place, the P/E ratio	10 defaulting and 30 non-defaulting companies; 1999–2006

a company, traditional prediction techniques including (i) financial analysis; (ii) *Z*-score model; (iii) conditional probability model; and (iv) subjective assessment methods remain the most commonly used approaches for predicting the insolvency of construction companies (Altman, 1968; Altman, Haldeman, & Narayanan, 1977; Beaver, 1966; Deakin, 1972; Edmister, 1972; Ohlson, 1980). Table 1 summarizes previous studies on predicting company insolvency in the construction industry.

Ratio analysis

In essence, the ratio analysis assesses various financial statements of a business to unveil the performance and competence of a company. It performs two complementary roles in ensuring the survival of a company, i.e. monitoring and evaluating the implementation of its business strategy as a basis for future planning of organizational objectives, which assumes a predictive status on insolvency (Edum-Fotwe, Price, & Thorpe, 1996). According to Edum-Fotwe et al. (1996); Harris & McCaffer (1995); Jordan & Sons (1993); and Padget (1991), traditional financial ratios can be classified into the following four broad categories:

(a) *Liquidity ratios* (e.g. current ratio, solvency ratio) which measure a company's ability to meet its short-term commitments;
(b) *Profitability ratios* (e.g. return on assets, return on equity) which measure the overall performance, or returns, which management has been able to achieve;
(c) *Leverage ratios* (e.g. gearing ratio, interest cover) which measure the extent to which a company has been financed by debt and shareholders' funds; and
(d) *Activity ratios* (asset turnover, stock turnover) which measure how well a company has been using its resources.

By comparing with the industry averages (i.e. the competitor's ratios), judgements relating to the company's position within the industry can be easily made (Edum-Fotwe et al., 1996; Landford, Iyagba, & Komba, 1993). In addition, a trend about the performance of a business can be depicted when ratios over several consecutive years are examined. Chan, et al. (2005) adopted this approach to review the financial performance of construction contractors in Hong Kong before the formulation of appropriate corporate strategies. The performance of simple financial ratios in providing signals required for predicting insolvency have been proven inadequate (Athanassakos, 2007), and this has led to the emergence of ratio models to obviate the deficiency of financial ratio analyses (Inman, 1991).

Z-Score model

The *Z*-score model is based on the statistical technique of multivariate discriminant analysis (MDA) which has been extensively used by researchers, government agencies and the commercial sector to identify potential insolvent companies (Mason & Harris, 1979). The approach includes constructing the solvency profile of a company on the basis of its published financial accounts, and it is then compared against the profiles of those which are known to be financially healthy or otherwise insolvent. The closer the company in question resembles those insolvent companies, the more likely it is to bankrupt and vice versa. The solvency profile of a company is summarized as a single index, known as a *Z*-score, derived from the MDA.

The *Z*-score model approach is a classification method which projects high-dimensional data onto a line and performs classification in this one-dimensional space (Fisher, 1936). The projection maximizes the distance between the means of the two classes while minimizing the variance within each class (Klecka, 1980). An MDA consists of a linear combination of variables, which provides the best distinction between the solvent and insolvent firms (Balcaen & Ooghe, 2006). The discriminant function is as follows (Lachenbruch, 1975):

Table 2
Financial ratios and the Z-score of Chinese construction companies.

Company	X_1	X_2	X_3	X_4	X_5	X_6	Z
A^{ST}	−0.01	−0.02	0.82	5.13	1.58	−0.38	−68.03
B^{ST}	0.15	0.04	0.80	2.14	2.60	0.01	−21.40
C^{ST}	0.01	0.01	0.53	1.00	2.01	−0.08	−7.97
D^{ST}	−0.05	−0.04	0.42	6.84	1.06	0.19	−91.95
E	0.03	0.03	0.78	0.62	2.06	−0.04	−2.24
F	0.01	0.01	1.29	1.10	2.16	7.69	−49.81
G	0.02	0.02	1.35	1.56	2.24	−0.35	−20.12
H	0.12	0.08	1.83	1.21	2.08	−0.25	−5.88
I	0.05	0.04	1.06	0.58	1.73	1.51	−4.80
J	0.05	0.05	0.70	0.92	1.52	0.40	0.40
K	0.01	0.01	0.48	1.00	1.31	0.45	−4.54
L	0.11	0.07	0.59	0.96	1.55	0.69	3.49

Note: ST indicates companies in the "special treatment" category due to insolvency under the Chinese securities laws and regulations.

Table 3
Selected financial indices for modelling.

Category	Financial index	
Solvency index	X_1	Current ratio = current asset ÷ current liabilities
	X_2	Quick ratio = (current asset − inventory) ÷ current liabilities
	X_3	Debt-to-asset ratio = total liabilities ÷ total asset
	X_4	Interest cover ratio = Earnings before tax and interest ÷ interest expense
Profit index	X_5	Operating margin = total profit ÷ turnover
	X_6	Return on equity = net profit ÷ share holder's equity
	X_7	Return on asset = total profit ÷ total asset
	X_8	Cost expense profit margin = net profit ÷ operation cost
	X_9	Earnings per share = net profit ÷ total number of equity shares
Operation index	X_{10}	Receivable turnover = net value of sales ÷ average receivable debt
	X_{11}	Fixed asset turnover = net value of sales ÷ average fixed asset
	X_{12}	Current asset turnover = net value of sales ÷ average current asset
	X_{13}	Operation asset over total asset = (current asset − current liabilities) ÷ total asset
Cash flow index	X_{14}	Profit quality index = net operation cash flow ÷ operational profit
	X_{15}	Net operating cash flow over current liabilities = net operating cash flow ÷ current liabilities
	X_{16}	Net operating cash flow over total liabilities = net operating cash flow ÷ total liabilities
	X_{17}	Total cash flow ratio = net operating cash flow ÷ (fund-raising cash flow in + investment cash flow out)
	X_{18}	Sales cash flow ratio = net operating cash flow ÷ turnover
	X_{19}	Total asset cash recovery ratio = net operating cash flow ÷ total asset
	X_{20}	Structure ratio = operating cash inflow ÷ operating cash outflow
Scale of firms	X_{21}	Log total asset = Log (total asset)
	X_{22}	Fixed asset ratio = fixed asset ÷ total asset

$$Z_i = d_0 + d_1X_{i1} + d_2X_{i2} + \ldots + d_nX_{in} \quad (1)$$

where Z_i is the discriminant score for company i; X_{ij} is the value of attribute X_j (with $j = 1, \ldots, n$) for company i; d_0 is the intercept; and d_j is the linear discriminant coefficient for attribute j. Several company characteristics or attributes are combined into a single multivariate discriminant score, Z_i, *with* a value ranging from $-\infty$ to $+\infty$ which provides an indication of a company's financial healthiness.

Evidence from Beaver's (1966) study indicated that financial analysis could be useful in the prediction of business failure for at least five years before the company collapses. However, while the MDA is called a 'continuous scoring' system, the discriminant score is simply an ordinal measure that allows the ranking of firms. In addition, it should be noted that it is possible that variables that seem insignificant on a univariate basis actually supply significant information in the multivariate context of the MDA model (Altman, 1968) or that some coefficients have unexpected, counter-intuitive signs (Ooghe & Verbaere, 1985). Furthermore, it should be stressed that the coefficients of the MDA model do not indicate the relative importance of the composing variables (Taffler, 1983) i.e. the output if the MDA model has little intuitive interpretation.

Conditional probability model

A conditional probability model allows the use of the non-linear maximum likelihood method to estimate the probability of insolvent conditional on a range of firm characteristics (Balcaen & Ooghe, 2006). It is built based on a certain assumption concerning the probability distribution. Typically, the logit models assume a logistic distribution (Maddala, 1977) while the probit models assume a cumulative normal distribution (Theil, 1971). In logit regression, a non-linear maximum likelihood estimation procedure is used to obtain the parameter estimates of the following logit model (Gujarati, 2003):

$$\begin{aligned} P_1(X_i) &= 1/[1 + \exp - (b_0 + b_1X_{i1} + b_2X_{i2} + \ldots + b_nX_{in})] \\ &= 1/[1 + \exp - (D_i)] \quad (2) \end{aligned}$$

where $P_1(X_i)$ is the probability of failure given the vector of attributes X_i; X_{ij} is the value of attribute j (with $j = 1, \ldots, n$) for company i; b_j is the coefficient for attribute j; b_0 is the intercept; and D_i is the 'logit' of company i. The logit regression model combines several company characteristics or attributes into a multivariate probability score, which indicates the company's insolvent probability or vulnerability to failure.

Table 4
The discriminating financial ratios.

Variable	Classification	Step						
		1	2	3	4	5	6	7
X_{13}	Operation index	0.276	0.815	0.565	0.386	0.207	0.205	0.203
X_{12}	Operation index		0.276	0.201	0.201	0.195	0.195	0.194
X_7	Profit ratio			0.151	0.138	0.119	0.118	0.084
X_1	Solvency ratio				0.064	0.039	0.038	0.036
X_5	Profit ratio					0.025	0.024	0.023
X_{17}	Cash flow index						0.007	0.006
X_4	Solvency ratio							0.006

The logistic function implies that the logit score P_1 has a value in the [0, 1] interval and is increasing in D_i. When the failed status is coded as zero, a low logit score indicates a high insolvent probability. The underlying logistic function of the logit regression model implies that an extremely weak company, as compared to a firm that has an average financial health, must experience a proportionally larger amelioration in its variables in order to ameliorate its financial health score (Laitinen & Kankaanpää, 1999). More desirable than the MDA model, the estimated coefficients b_j of the MDA model can be interpreted separately as representing the importance or significance of each of the independent variables in the explanation of the estimated failure probability (Mensah, 1984; Ohlson, 1980), provided that there is no multicollinearity among the variables.

In a classification context, the essence of the logit regression model is that it assigns firms to the failing or the non-failing group based on their logit score and a certain cut-off score for the model. In the case where a high logit score indicates a high failure probability, a firm is classified into the failing group if its logit score exceeds the cut-off point and into the non-failing group if its score is lower than or equal to the cut-off point. Similar to MDA, the logit regression model is based on the resemblance principle whereby firms are assigned to the group they most closely resemble.

Logit regression does not require multivariate normal distributed variables or equal dispersion matrices (Ohlson, 1980; Zavgren, 1983). Therefore, the logit regression method is commonly considered as less demanding than MDA. It also allows for categorical qualitative variables (Keasey & Watson, 1987). Yet, logit regression has two basic assumptions. First, it assumes the dependent variable to be dichotomous, with the groups being discrete, non-overlapping, and identifiable. Second, the cost of type I and type II error rates should be considered when defining the optimal cut-off score of the logit model. A type I error is made when a failing firm is misclassified as

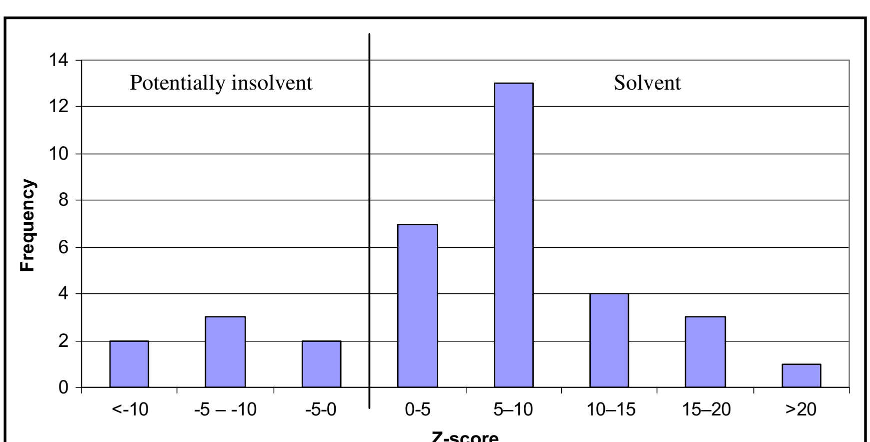

Fig. 1. Classification of solvent and potentially insolvent companies.

a non-failing firm, where type II error is made when a non-failing firm is wrongly assigned to the failing group (Balcaen & Ooghe, 2006). Furthermore, the logit regression models are sensitive to multicollinearity (Ooghe, Joos, De Vos, & De Bourdeaudhuij, 1994), as well as to outliers and missing values (Joos, Vanhoof, Ooghe, & Sierens, 1998).

Subjective assessment

Financial ratio models, by their nature, may not be able to consider every aspect of an insolvent company's characteristics. There could be a company that does not respond to a prediction model and fail, despite the fact that the model shows it as being solvent. It is, therefore, important that any prediction models should not used as the sole decision tool, subjective assessment has a role to play in predicting company insolvency. For instance, Abidali and Harris (1995) developed an "*A*-score" to systematize failure prediction by quantification measures based on perceptions on management features and then linked the *Z*-scores. The justification for amalgamating the *A*-scores with the ratio models is because corporate failures can be attributed to other internal factors identified such as poor management (Agenti, 1980). The counter argument is that for a company which is in financial difficulty it is usually associated with inadequate management ability and/or errors perpetrated earlier. Clients who need to assess and select a contractor would be benefited from a tool which can distinguish a failing company from both the financial and managerial perspectives. However, the allocation of weightings to and the way of assessing the managerial indicators can be subjective (Balcaen & Ooghe, 2006). Besides, for the purpose of strategic management, any warnings during the final phase of failure are often too late for a construction company to rectify their financial problems (Edum-Fotwe et al., 1996).

Subject index is one of the subjective assessment methods which employs experts' perception of an acceptable level for the financial figures of a company, derive a composite measure of its performance (Edum-Fotwe et al., 1996). Notable within this category is the index of risk approach developed by Tamari (1978). This utilizes a subjective assessment on a combination of relevant financial ratios to assess how vulnerable a company is to possible insolvency and hence determine whether disqualification for credit is needed. The points for the individual variables are aggregated to obtain the index between 0 and 100 for the company. A high index indicates a favourable financial standing, or in other words, less susceptibility to insolvency.

Moses & Liao (1987) presented another interesting risk index model by determining the optimal cut-off points for each of the composing ratios based on a univariate analysis and then creating a dichotomous variable for each of the ratios and assigning a score of one in the case where a firm's ratio value exceeds the optimal cut-off point. Then, the risk index simply adds the values of the dichotomous variables, so that a high score is associated with a financially healthy situation (Balcaen & Ooghe, 2006). The index of risk expresses theoretical considerations of a rational approach for enhancing the effectiveness of financial ratios as a tool for evaluating companies. Although the index method provides a greater scope for judgement, the inclusion of subjective assessment implies that no single measure of universal acceptability can be employed in evaluating different companies (Edum-Fotwe et al., 1996).

Predictability of *Z*-score model for Chinese contractors

Among the above-mentioned prediction methods, the *Z*-score model has been more extensively used by researchers to identify insolvent construction firms (Edum-Fotwe et al., 1996). Based on Altman's study (1968); Mason & Harris (1979) put forward a six-variable *Z*-score model based on a sample of 20 failed and 20 non-failed companies in the UK civil engineering sector. Using MDA, a discriminant function as shown in Equation (3) was developed:

Table 5
Classification of potential insolvent and solvent companies in 2006.

Groups	Classified as	
	Potential insolvent	Solvent
Potential insolvent group	7 (100)	0
Solvent group	0	28 (100)

Note: Figures in parentheses are percentages of total groups.

$$Z = 25.4 - 51.2X_1 + 87.8X_2 - 4.8X_3 - 14.5X_4 - 9.1X_5 - 4.5X_6 \quad (3)$$

where X_1 is the profit before interest and tax to net assets; X_2 is the profit before interest and tax to capital employed; X_3 is the debtors to creditors; X_4 is the current liabilities to current assets; X_5 is the $\log_{10}$ days debtors; and X_6 is the creditors trend measurement. A positive *Z*-score represents a long-term solvency, while a company with a negative score would be classified as being potentially insolvent. While the classical *Z*-score model was developed in the 1970s, it is still the most popular cross-sectional technique and the predominant statistical method for corporate failure prediction research (Balcaen & Ooghe, 2006), due to its effective performance and a high degree of accuracy in measuring the overall healthiness of a business (Edum-Fotwe et al., 1996).

Abidali (1990) also developed a *Z*-score model for vetting construction companies on the tender lists. However, inconsistent coefficients were identified in the model which undermines its reliability (Edum-Fotwe et al., 1996). While Mason and Harris's *Z*-score model appears to be the more relevant and robust model for predicting contractors' solvency, its reliability is scrutinized by fitting the financial data of 12 randomly selected publicly listed Chinese construction companies into the model. Using the financial profile of those companies as in year 2006, their solvency is assessed by Mason and Harris's *Z*-score model.

As shown in Table 2, the predictive power of Mason and Harris's *Z*-score model on the insolvency of Chinese contractors is questionable. Although unhealthy companies (i.e. Companies A, B, C & D) have been correctly classified, six out of the eight financially sound construction companies in the test have been detected as insolvent as revealed by the negative *Z*-scores. Abbinante (1987) and Kangari (1988) postulated that any statistical models developed from financial ratios would only be useful to an individual industry. Therefore, there is a need to devise an insolvency prediction model specifically for the construction industry in China (*cf*: Li, Li, & Wu, 2009).

The analysis

Financial data constitute the most significant element in monitoring the performance of a company and predicting the trend

Table 6
Classification of potential insolvent and solvent companies in 2005 and 2004.

Groups	Classified as			
	2005		2004	
	Potential insolvent	Solvent	Potential insolvent	Solvent
Potential insolvent group	4 (80)	1 (20)	4 (80)	1 (20)
Solvent group	0	27 (100)	0	26 (100)

Note: Figures in parentheses are percentages of total groups.

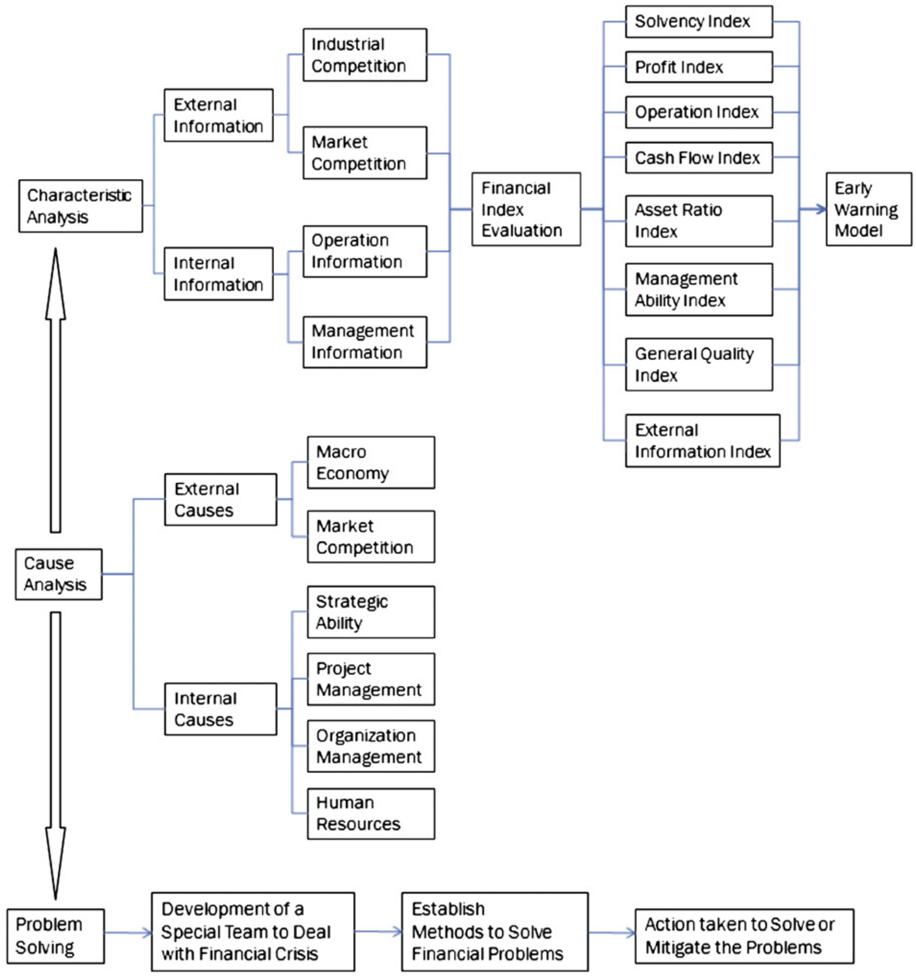

Fig. 2. Operation mechanisms for early warning of insolvency.

of failure (Edum-Fotwe et al., 1996). Financial ratio analysis was, therefore, applied to provide an early warning mechanism for corporate performance and solvency. All 35 construction companies listed in the Shanghai and Shenzhen Stock Exchanges formed the sample for this study. The data of those identified listed companies are considered reliable and comprehensive as it is extremely difficult to collect information from bankrupt companies when they become “inactive” (Koksal & Arditi, 2004). Of the 35 construction companies, 5 were categorized as Special Treatment (ST) companies by the Stock Exchanges indicating their insolvency status (Javvin, 2008). A total of 22 key financial ratios (Table 3) of those 35 companies covering five aspects of insolvency measurement as suggested by Singh and Tiong (2006) and other relevant studies were collected through the GTIOne database, which provides comprehensive financial information and services in China. These insolvency measurement aspects cover the managerial efficiency, long-term solvency, short-term liquidity, profit generating ability and cash position of a company.

Two major steps were involved in developing an insolvency warning model for construction contractors in China which include the (i) cluster analysis; and (ii) MDA. The cluster analysis was used to classify the 35 sampled contractors. A variety of computational methods including the agglomerative hierarchical clustering method and homogeneity criteria are involved in the analysis to minimize the statistical distance within a group while at the same time maximizes the statistical distance between groups by considering the distribution and closeness of the input data (Jensen, 1971; Tan, Steinbach, & Kumar, 2006). A number of researchers (e.g. Dimitras, Zanakis, & Zopounidis, 1995; Gupta & Huefner, 1972) adopted the cluster analysis in predicting the financial performance of companies. Having identified various cluster groups, the observations are assigned to the predefined groups according to their financial characteristics through discriminant analysis (Alam, Booth, Lee, & Thordarson, 2000). The analyses were conducted using a statistic package SPSS 15.0 (Norusis, 2006).

Through the cluster analysis, the 35 Chinese construction contractors were classified into two groups with all the 30 financially sound contractors being classified into Cluster 1: ‘solvent companies’ while the 4 contractors originally in the ST category were grouped into Cluster 2: ‘potentially insolvent companies’. The remaining contractor in the ST category was, however, classified into Cluster 1 as it shares similar financial characteristics with the solvent companies. This predefined grouping was then applied into the MDA.

The process of developing the linear discriminant model begins by identifying the variables that discriminate most between the groups of known ‘solvent’ and ‘insolvent’ companies. The best discriminating variable is selected according to the Wilks lambda criteria, whereby the *F*-ratio is established and differences among the centroids are ascertained. The variable which maximizes the *F*-ratio and minimizes the Wilks lambda is a measure of group discrimination. LDA also takes into consideration of the difference between the group centroids and the cohesion within the groups. The procedure continues until there is very little discrimination after including a further variable, i.e. the specified criterion is satisfied. The criterion is the probability of entry and removal set at 0.05 and 0.10 respectively. In a classification context, companies are classified as solvent or potentially insolvent based on their discriminant score and the optimal cut-off point of the LDA model. In this way, companies are assigned to the group they most closely resemble.

The resultant model

Based on the result of the cluster analysis as mentioned in the previous section, the 22 financial indices of those 35 construction contractors in China were entered into the MDA using the financial data in 2006. Applying the Wilks' Lambda rule, seven key financial ratios (Table 4) were selected to discriminate the potentially insolvent construction companies. The following seven-variable linear function is resulted:

$$Z = -1.13X_1 + 0.004X_4 - 0.64X_5 + 3.97X_7 - 0.32X_{12} + 2.09X_{13} - 0.006X_{17} + 1.86 \quad (4)$$

where Z is the Z-score; and X_k denotes the discriminant variables as indicated in Table 3.

The constituent variables include the indices measuring the finance of operation, profitability, solvency and cash flow. The two selected operation indices which have the highest discriminating power are the current asset to turnover (X_{12}) and working capital to total asset (X_{13}). The current asset to turnover (net value of sales ÷ average current asset) assesses the ability of companies to generate turnover using the current assets while the working capital to total asset ratio is a measure of the net liquid assets of the contractor relative to total capitalization, which were also included in Altman's Z-score model. The two profit indices, i.e. total profit to turnover (X_5) and the return on assets (X_7) are also essential to the solvency of companies in long term (Singh & Tiong, 2006).

In addition, two solvency indices including the current ratio (X_1) and the interest cover ratio (X_4) are identified as the key financial ratios in the discriminant function. The current ratio (i.e. current asset ÷ current liabilities) is a measure of the short-term liquidity of a company to solve current obligations without liquidating the non-liquid asset (Edum-Fotwe et al., 1996). While the interest cover ratio (i.e. earnings before interest and tax ÷ interest cost) appraises whether the earnings of a contractor can cover its interest cost (Huang, 2009). Kim, Ramaswamy, and Sundaresan (1993) stated that default could trigger if the firm fails to generate sufficient cash flow to cover its current interest obligations. On the other hand, the total cash flow ratio (X_{17}) was also selected by the discriminant functions to measure the healthiness of cash flow for a company. Generally speaking, a sound contractor should have a higher proportion of cash flow in operation and lesser cash flow in fund-raising and investment (Arditi, Koksal, & Kale, 2000; Enshassi, Al-Hallaq, & Mohamed, 2006).

The model produced a histogram of Z-scores for the potentially insolvent and solvent groups as shown in Fig. 1. Companies with positive Z-scores are classified as 'solvent' and those with negative scores as potentially 'insolvent'. Table 5 is the classification table for the two groups used to form the model. The success rate of the model is 100%, with no misclassification, but the reliability of the model should be tested with independent data. Alternative results were obtained using 2004 and 2005 data. As shown in Table 6, 100 percent and 80% of the companies were correctly classified as solvent and potentially insolvent respectively. The 20% error in the insolvent group is probably due to the limitation that there are only 5 'ST' companies in the analysis so that the difference between quantities of samples in the two groups is large leading to a matching problem between groups. However, the Z-score for that misclassified company in 2004 and 2005 were 0.98 and 1.77 respectively, which indicates its solvency was in a 'vulnerable region'.

However, it should be stressed that by the nature of the model's simplicity it cannot take into consideration every aspect of a bankrupt company's characteristics. As stressed by Mason and Harris (1979), a company may not respond to the model and fail, despite the fact that the model shows it as being solvent. It is, therefore, important that the model should not be used as the sole decision tool but only as part of the decision process.

The developed Z-model can measure the extent to which a company's policies and problems have resulted in poor performance (Freear, 1985). It can also help establish an early warning management mechanism of insolvency for contractors to pinpoint potential problems and to ensure a healthy operation and development. The proposed mechanism, based on an extensive review of literature on business failure in construction, is through the combination of characteristic analysis, cause analysis and problem solving as shown in Fig. 2.

It is imperative to develop a complete precaution system of financial crisis and have regular checking of the key financial ratios as well as operation status so as to prevent financial crisis from happening. As shown in Fig. 2, through a continuous assessment of various financial ratios, including both the external and internal information, an early warning mechanism can be formulated. The financial characteristic analysis would focus on the latent period of financial distress. When the financial status of a company is deteriorating, the company must analyze the external and internal causes of the potential insolvency immediately so that strategies and measures to solve the problem can be formulated as early as possible. Business failure mostly appears as a consequence of a complex process and is rarely dependent on a single factor. If insolvency of a contractor is eventually arising, timely and effective actions should be undertaken by the company executives. It is sensible to appoint a specialized team to formulate effective strategies and measures to cope with the financial crisis so as to minimize the losses instigated by the financial problems.

Conclusions

Company failure is an extremely disruptive force in the construction industry. It is important that any potential bankruptcy be recognized at the earliest opportunity. Since construction is an important industry in China whilst companies in the industry are facing fierce competition, establishing a reliable model to assess the solvency for construction companies is timely and important. Previous researches on financial performance of construction companies based on financial ratios were very limited. No comprehensive quantitative model for determining insolvency of the Chinese construction companies existed.

This paper presents a quantitative model based on financial ratios for the continuous monitoring financial performance of a construction company. The model derived from this study has consistent predictability based on a three-year window of data. It combines seven financial ratios, covering a company's finance of operation, profitability, solvency and cash flow, into a single performance index to indicate whether a company is in good financial standing or exhibits characteristics of potentially insolvent companies. This is also valuable for commercial lending institutions, investors, and clients to evaluate candidate companies' vulnerability to failure at an early stage. An early warning management system of insolvency for contractors is also presented to sustain corporate development in construction.

Further research on the market mechanism is valuable to reveal how the market affects the insolvency of a contractor in China. In addition, discriminant analysis is, but only a tool among various prediction methods. Alternative modelling techniques of predicting business failure such as artificial neural network, case based-reasoning and data mining techniques could be applied for future study.

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