

## **Company Failure in the Construction Industry: A Critical Review and a Future Research Agenda**

**James M.W. WONG and S. Thomas NG, Hong Kong**

**Key words:** company failure, construction, failure prediction model, strategic management

### **SUMMARY**

Company failure is not only extremely disruptive to an industry but may also cause significant rippling effects in an economy. Construction companies are vulnerable to bankruptcy due to the fragmented nature of the industry, high competition, the high uncertainty and risk involved, and considerable fluctuations in construction volume. It is important to recognise any potential company failures at the earliest opportunity. While bankruptcy prediction has long been regarded as a critical topic in the accounting and finance sectors, this research topic is still under-explored in the context of the construction industry. This paper aims to provide a synthesis of the previous business failure prediction models for construction companies and put forward a future agenda in this research area. Common causes of construction company failures are also reviewed. Using the results from the proposed research, it is anticipated that construction companies will be better able to prevent business failure and this should be relevant to the current needs of the construction industry and significant to the society.

# Company Failure in the Construction Industry: a Critical Review and a Future Research Agenda

James M.W. WONG and S. Thomas NG, Hong Kong

## 1. INTRODUCTION

The risk of business failure exists in every industry. However, construction companies are particularly vulnerable to bankruptcy due to the fragmented nature of the industry, excessive competition, relatively low entry barrier, high uncertainty and risk involved, and unpredictable fluctuations in construction volume (Edum-Fotwe *et al.*, 1996; Kangari, 1988; Kale and Arditi, 1999). A slump in construction volume after 1998 has resulted in the bankruptcy of many construction companies in Hong Kong and caused significant rippling effects to the economy. This phenomenon could be replicated under the dramatic change in economic climate in recent times. Construction companies must, therefore, evaluate of their financial performance regularly so that timely and appropriate strategies can be put in place to maintain their survival.

The economic and social damages resulted from the failure of construction businesses go beyond the obvious and quantifiable costs to the company owners, creditors and employees (Mason and Harris, 1979). It is, therefore, important to recognise any potential company failures at the earliest opportunity. Russell and Zhai (1996) postulated that construction company evaluation is a critical step in successfully completing a project. At present, the method used for selecting contracting firms is not heavily geared towards discriminating between solvent and potentially bankrupt firms. With an increasing concern about public accountability and the need to employ financial resources competently, it seems necessary to devise an assessment tool to identify impending company failures.

Despite bankruptcy prediction has long been regarded as a critical topic and has been studied extensively in the accounting and financial sectors, this research area is still under-explored within the construction domain. This paper aims to provide a synthesis of the previous business failure prediction models for construction companies and to put forward a future agenda in research for this industry. Following this introductory section, the next section identifies the factors causing company failure in construction. Prevailing prediction models are then reviewed. The strengths and limitations of those prediction methods are assessed. Lastly, a research framework for the establishment of an advanced prediction model for the construction industry is proposed.

## 2. WHAT CAUSES CONSTRUCTION COMPANY TO FAIL?

Business failure mostly appears in a critical situation as a consequence of a complex process and is rarely dependent on a single factor. Arditi *et al.* (2000) found budgetary and macroeconomic issues as the main reasons for construction company failure in the US. Over 80% of the failures were caused by five factors, namely insufficient profits (27%), industry

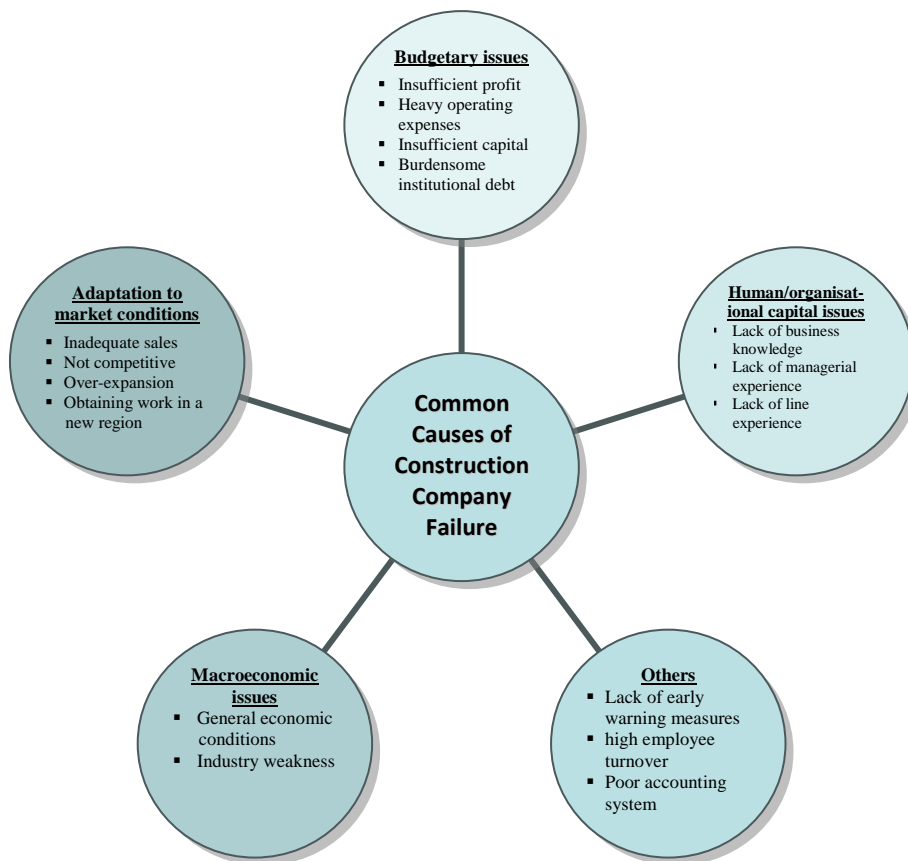
weakness (23%), heavy operating expenses (18%), insufficient capital (8%) and burdensome institutional debt (6%). All these factors, except for industry weakness, are budgetary issues and should therefore be handled by companies that are cognisant of the effects of these factors on their survivability.

Kivrak and Arslan (2008) examined the critical factors causing the failure of construction companies through a survey conducted among 40 small to medium-sized Turkish construction companies. A lack of business experience and country's economic conditions were found to be the most influential factors to company failure. A scrutiny of the sub-factors related to the lack of business experience confirms that difficulties with cash flow and poor relationship with the client drove the contractors' failure. In addition, preparing an accurate and realistic bid proposal with the profit margin being carefully determined is highly critical (Arslan *et al.*, 2006). However, due to high competition, companies are usually forced to reduce their profit in order to win the bid and this would increase the default risk substantially. Kangari (1988) found that more than half of business failures in construction were due to unrealistic profit margin.

Schaufelberger (2003) studied business failure at the subcontractor level and found that the primary causes of subcontractor business failure were insufficient capital/excessive debt, lack of managerial maturity, lack of early warning measures, increase in project scope, poor billing procedures, failure to evaluate project profitability, unfamiliarity with new geographical areas, and poor use of accounting systems. Davidson and Maguire (2003), based on their accountancy experience, identified ten most common causes for contractor failures: (i) growing too fast; (ii) obtaining work in a new geographic region; (iii) dramatic increase in single job size; (iv) obtaining new types of work; (v) high employee turnover; (vi) inadequate capitalisation; (vii) poor estimating and job costing; (viii) poor accounting system; (ix) poor cash flow; and (x) buying useless stuff. Osama (1997), on the other hand, presented a study of the factors that contribute to the failure of construction contractors in Saudi Arabia and found that the most important factors were: difficulty in acquiring work, bad judgment, lack of experience in the firm's line of work, difficulty with cash flow, lack of managerial experience, and low profit margins. The above review on causes of business failure in construction are summarised and portrayed in Figure 1.

### **3. TECHNIQUES FOR PREDICTING COMPANY FAILURE**

Numerous models related to the prediction of business failure have been proposed (e.g. Beaver, 1966; Altman, 1968; Edmister, 1972; Deakin, 1972; Ohlson, 1980). However, little research has been done to predict the failure of construction firms when comparing with the banking and finance sectors. Pertinent prediction techniques for construction company failures include the (i) ratio analysis; (ii) multiple discriminant analysis; (iii) conditional probability models; and (iv) subjective assessment. Table 1 summarises previous studies on predicting company failure in the construction industry.



**Figure 1** Common Causes of Construction Company

### 3.1 Ratio analysis

In essence, the ratio analysis assesses various financial ratios of a business to unveil the financial weaknesses of a company in advance of failure. A cut-off point is estimated for each measure or ratio in the analysis. The classification procedure is carried out separately for each measure, based on a firm's value for the measure and the corresponding optimal cut-off point. Landford *et al.* (1993) asserted that the ratio analysis should enable the analysts to examine the operating performance in terms of:

- whether the firm is utilising its assets;
- whether its profit margins are in line with assets;
- whether there is excessive investment in fixed assets;
- whether the business is adequately financed;
- whether there are signs of liquidity strains;
- whether collection of receivables is efficient.

**Table 1** Previous studies on predicting failure in construction

Author(s)	Country	Deliverables	Modelling technique	Determining factors of business failure	Source of data
Mason and Harris (1979)	UK	Developed a Z-model in construction comprising 6 financial ratios	MDA	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	Macroeconomic data (1977-1986)
Kangari <i>et al</i> (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	The amount of owner-contractor evaluation; whether cost monitoring was performed by the owner; the level of support received by the project manager; the early involvement of the contractor's project manager	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 tested. Key factors: taking expert advice on tax matters, owners 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	MDA	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		Risk of failure increases initially with increasing age, reaches a peak point and decreases thereafter 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 organisational factors	Factor analysis and Logit regression	Specialisation, standardisation, 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 <i>et al</i> (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 full scale inter-firm comparison of the ratio analysis would enable the above questions to be resolved into more essential factors such as, whether production costs are higher than competitors, whether the labour costs and utilisation rates are in line with the industry's average and how would one's overheads compare with others. The extremes could readily be identified and a cut-off point be established from predictive experience in order to measure the healthiness of a company. Based on the studies by Padget (1991), Jordan and Sons (1993) and Harris and McCaffer (1995), Edum-Fortwe *et al.* (1996) classified the traditional financial ratios into four broad categories:

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

Tamari (1966) stressed that an analyst cannot merely rely on one ratio, particularly when it comes to analysing construction companies. A trend of the performance of a business can be depicted by comparing with the industry's norm over a long period of time. The assessment would indicate areas worthy of attention by the managers of the company. The univariate analysis is a relatively simple method and the application requires minimal statistical knowledge (Balcaen and Ooghe, 2006). On the other hand, this technique is based on the stringent assumption of a linear relationship between all measures and the failure status. 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. However, in the strict sense, ratio assessment cannot be considered a prediction but rather an early warning mechanism of failure.

### 3.2 Multiple discriminant analysis

The multiple discriminant analysis (MDA) is a classification method which projects high-dimensional data onto a line and performs classification in this one-dimensional space (Fisher, 1936). The projection maximises the distance between the means of the two classes while minimising the variance within each class (Klecka, 1980). An MDA consists of a linear combination of variables, which provides the best distinction between the failing and non-failing firms (Balcaen and Ooghe, 2006). The discriminant function is as follows (Lachenbruch, 1975):

$$Z_i = d_0 + d_1X_{i1} + d_2X_{i2} + \dots + d_nX_{in} \quad [1]$$

where  $Z_i$  is the discriminant score for company  $i$ ;  $X_{ij}$  is the value of attribute  $X_j$  (with  $j = 1, \dots, n$ ) 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 one single multivariate

discriminant score,  $Z_i$ .  $Z_i$  has a value between  $-\infty$  and  $+\infty$  and gives an indication of a company's financial health.

The Z-score model developed by Altman (1968) which is based on the MDA has been extensively used by government agencies and the commercial sector to identify potential insolvent companies. The approach first constructs the profile of a company on the basis of its published financial accounts and then compares it with the profiles of known financially healthy or previously insolvent companies. The closer the company in question resembles previous insolvency, the more likely it is to fail and vice versa. The solvency profile is summarised in a single index, known as a Z-score, derived from the MDA. Altman selected 66 large US companies including 33 non-bankrupt companies and 33 bankrupt companies to develop the Z-score model with five financial ratios. However, no construction companies were involved in the analysis.

Mason and Harris (1979) therefore developed a six-variable Z-score model based on a sample of 20 failed and 20 non-failed companies in the civil engineering sector of the UK. Applying the MDA, the discriminant function was developed as Equation [2]. A positive Z-score indicates a long-term solvency, while a company with a negative value was classified as a potentially failure.

$$Z = 25.4 - 51.2X_1 + 87.8X_2 - 4.8X_3 - 14.5X_4 - 9.1X_5 - 4.5X_6 \quad [2]$$

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 debtors / creditors,  $X_4$  is current liabilities / current assets,  $X_5$  is  $\log_{10}$  days debtors, and  $X_6$  is the creditors trend measurement. Abidali (1990) also developed a Z-score model for used in vetting construction companies on the tender lists. However, inconsistent coefficients were found in the model (Edum-Fotwe *et al.*, 1996).

Although the MDA is called a 'continuous scoring' system, a 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 and Verbaere, 1985). Furthermore, it should be stressed that the coefficients of the MDA model do not indicate the relative importance of the composing variables as they cannot be interpreted like the coefficients of a regression (Taffler, 1983) i.e. the output if the MDA model has little intuitive interpretation. In addition, there are certain statistical requirements imposed on the distribution properties of the predictors (Yang *et al.*, 1997).

### 3.3 Conditional probability models

Conditional probability models allow the use of the non-linear maximum likelihood method to estimate the probability of failure conditional on a range of firm characteristics (Balcaen and Ooghe, 2006). These models are 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):

$$P_1(X_i) = 1 / [1 + \exp - (b_0 + b_1X_{i1} + b_2X_{i2} + \dots + b_nX_{in})] = 1 / [1 + \exp - (D_i)] \quad [3]$$

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  $j = 1, \dots, n$ ) 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 failure probability or vulnerability to failure.

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 failure probability and, hence, poor financial health. 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 and 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 (Ohlson, 1980; Mensah, 1984), 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. Similarly to MDA, the logit regression model is based on the resemblance principle whereby firms are assigned to the group they most closely resemble.

When applying logit regression, no assumptions are made regarding any prior probabilities of failure or the distribution of the independent variables. 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 and Watson, 1987). Nevertheless, logit regression has two basic assumptions. First, it assumes the dependent variable to be dichotomous, with the groups being discrete, nonoverlapping, 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 a non-failing firm, where type II error is made when a non-failing firm is wrongly assigned to the failing group (Balcaen and Ooghe, 2006). Furthermore, the logit regression models are sensitive to multicollinearity, as well as to outliers and missing values (Joos *et al.*, 1998).



A number of business failure models for construction companies were developed using conditional probability modelling approach. Kangari *et al.* (1992) developed a quantitative model based on the financial ratios to assess the financial performance and the grade for a construction company, and hence its chances of survival. The current ratio, total liabilities to net worth, total assets to revenues, revenues to net working capital, return on total assets, and return on net worth were used for developing the model. Based on questionnaire surveys, Russel and Jaselskis (1992) and Hall (1994) identified factors which can distinguish the survivors from failures in US and UK respectively for predicting purpose. Using logit regression analysis, apart from financial ratios, a wider range of independent variables including company profile, management attributes, etc. were tested.

In addition, Koksai and Arditi (2004) developed a model to determine a company's healthiness comprising 11 organisational factors associated with the company. This study demonstrates that non-financial aspects, such as organisation structure, human capital issues, and strategic posture, are important in assessing the condition of a company *vis-à-vis* decline/failure. However, the research study showed that it is extremely difficult to collect the information from bankrupt companies as these companies are mostly "inactive". On the other hand, research completed by Kangari (1988) resulted in a model for forecasting the rate of contractor failure based on the effect of macroeconomic factors on business failures in the construction industry. Russell and Zhai (1996) further examined the stochastic dynamic patterns of economic indicators and financial variables of 120 failed and non-failed contractors. A discriminant function for detecting failed contractors was developed using stepwise regression.

### 3.4 Subjective assessment

Financial ratio models, by their nature, may not be able to consider every aspect of a bankrupt 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 be used as the sole decision tool, subjective assessment has a role to play in predicting company failure. For instance, Abidali and Harris (1995) developed an "A score" to systematise failure prediction by quantification measures based on perceptions on management features and then linked the Z-scores.

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 utilises 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 bankruptcy.

Moses and 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 and 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 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).

#### **4. FUTURE RESEARCH AGENDA: DEVELOPING AN ADVANCED PREDICTION MODEL**

##### **4.1 Key issues and problems**

While company failure is extremely disruptive in the construction industry (Kangari, 1988), failure prediction for the Hong Kong construction industry has not been rigorously examined. The slump in construction volume after 1998 has resulted in a symbolic failure case of one of the local giant contractors – the Dickson Group which seriously disrupted the public housing construction programme. This phenomenon could be replicated under the volatile global economic environment. Therefore, it is timely to explore methods of early detection of business failure.

Understanding the mechanism of failure is the key in attempting to avoid business failure. But most of the failure studies in the construction field focused at the project level for prequalification purposes (e.g. Hall, 1982; Russell and Jaselskis, 1992). They were also addressed from the legal and organisational theory perspectives (Russell and Casey, 1992; Kale and Arditi, 1999). Some early works at the company level (e.g. Abidali and Harris, 1995) followed the Altman's studies, which aimed at developing indicators to distinguish the financially distressed and the financially healthy construction companies. Little attention has been given to predict the probability of construction company failure. In addition, comparison between statistical models and artificial intelligent techniques including the neural networks, decision trees, fuzzy set theory, case-based reasoning, etc. is still under-explored.

##### **4.2 Research objectives**

The purpose of this study is, therefore, to develop a robust prediction model, constructed from financial and macroeconomic variables, to assess the solvency of construction companies and estimate the chance of business failure. To achieve the desired purpose, the following objectives are envisaged:

- i) To assess the recent trend of business failure in the local construction industry and the common causes of failure;
- ii) To identify the key variables determining the solvency of a company;

- iii) To develop a prediction model, based on the variables identified in (ii), to detect the impending insolvent company and estimate the chance of business failure in the construction industry; and
- iv) To verify the predictability and robustness of the developed prediction model.

### 4.3 Research methodology

*Objective 1: To assess the recent trend of business failure in the local construction industry and the common causes of failure*

Recognising the trend and primary causes of failure in construction would undoubtedly enable construction industry stakeholders preparing themselves for the changes in the industry. To achieve that, data will be collected from economic reports and companies' financial statements as well as pertinent authorities including the Companies Registry Hong Kong and Dun & Bradstreet. The causes of business failure specific to the construction industry will further be cross-referenced with the published literature (e.g. Hall, 1994; Arditi *et al.*, 2000; Kivrak and Arslan, 2008) as well as a series of semi-structured interviews with local industry experts. The relationship between the economic/financial factors and business failure will also be unveiled via the interviews. This information will form the basis of empirical analysis targeting on establishing the failure prediction model in construction.

*Objective 2: To identify the key variables determining the solvency of a company*

Once the causes of business failure in construction have been explored, it is required to identify the appropriate variables for predicting the chance of business failure in construction. Extensive literature will be reviewed to achieve this objective. Modelling macroeconomic impact on the construction business failure involves endogenising some of the economic variables based on economic theory. Economic factors which may be candidates for inclusion in the predictive failure model include interest rate, inflation, gross national product, construction output, new business activity, etc. (Kangari, 1988). Various financial variables of construction companies will also be scrutinised to be incorporated into the business failure modelling, including net worth that represents the company's equity, gross profit indicating the financial productivity, and net working capital representing the short-term financial capacity of a construction company (Russell and Zhai, 1996). The nature and availability of the pertinent variables will be examined through accessing the financial reports of the local construction companies as well as relevant statistical reports. Various modelling approaches to predict company failure will also be reviewed and explored. The aim of the review is to gain potential learning points and improvements from the most up to date knowledge to develop the business failure forecasting model for the construction industry.

*Objective 3: To develop a statistical model to detect the impending insolvent company and predict the chance of business failure in the construction industry*

Empirical analysis will be conducted to develop a model to detect insolvent company and predict business failures in the construction industry. Logit regression model will be developed to identify the likelihood of an outcome being in one of the two discrete classes: failure versus non-failure. This modelling technique has also been used quite extensively in the fields outside construction, particularly in the areas of transportation, biomedical

applications, sociology, marketing, and econometrics (Hensher and Johnson, 1981; Aldrich and Nelson, 1984; Ben-Akiva and Lerman, 1985; Ohlson, 1980). It could estimate the probability of failure conditional on a range of firm characteristics (Russell and Jaselskis, 1992; Balcaen and Ooghe, 2006).

On the other hand, artificial intelligent techniques including the neural networks, decision trees, fuzzy set theory, case-based reasoning, etc. will be applied to bankruptcy prediction in construction. Comparisons between the regression models and intelligent techniques are to be carried out. The goal is to establish a robust prediction model for defining the impact that both external economic factors and internal financial strength that have on failures in construction, so that companies can monitor these factors and avoid failures by realising the impact that these changes have on failure risk. A sensitivity analysis will be performed to more thoroughly understand the variables and their influences on predicting failure.

*Objective 4: To verify the predictability and robustness of the developed prediction model*

The developed prediction model will be validated through various diagnostic tests and goodness of fit tests to ascertain the accuracy and robustness. Verification for any misclassification will also be carried out. This is based on applying a new set of data inputs to the model and verifying its ability to correctly categorise the failure company and predict a company failure. Lastly, the prediction ability of the developed model will be compared with the Z-score model which serves as a benchmark.

#### **4.4 Deliverables and significance of the research**

It is anticipated that the research could bring the following deliverables:

- i) A review of the trends in business failure in the Hong Kong construction industry and their causes of failure;
- ii) A database archiving all macro-economic and financial information pertinent to modelling the financial healthiness of construction companies;
- iii) A report highlighting the relationships between economic and financial variables and the solvency of a construction company; and
- iv) A set of models supporting the decision-makers for construction to assess and identify the risk of corporate business failure.

Despite the importance of the Hong Kong construction industry to the economy, there is always delayed response from the industry to the economic change. Since the unstable economic environment would bring a significant impact to the local construction companies, establishing a robust and accurate model to assess the solvency and predict the chance of business failure in construction is timely and important. It can provide a quality control system to be used for the continuous monitoring of a company's financial performance. This is also valuable for commercial lending institutions, investors, and clients to evaluate candidate companies' failure probability or vulnerability to failure. It should be noted that a valid application of the statistical methodology for depends on the quality of the explanatory data when estimating the parameters of the business prediction model.

The model to be developed not only could identify a short list of companies that are ‘at risk’ of failure, and that it is also able to give an indication of the proportion of these firms that are likely to fail in the near future, based on specific inputs of financial condition and overall industry indicators. A “what-if” study can thus be conducted by modifying the inputs such that the incremental differences in the probability of failure under specific variables conditions can be computed. For example, if a prediction model is developed as shown in Equation [4], a contractor might reduce its volatility in net working capital by improving the financial management and thereby minimise the amount of debt when work becomes less available. Financial productivity (i.e. profitability) should be continuously improved to avoid reaching the baseline of failure. The contractor can also study impact of the fluctuations of interest rate and construction value to the company’s risk of failure.

$$Y = 2.59 - 0.07X_1 + 0.01X_2 - 1.09X_3 - 2.24X_4 \quad [4]$$

where Y is failure detection score,  $X_1$  is prime interest rate,  $X_2$  is construction output (new works),  $X_3$  is gross profit / total assets, and  $X_4$  is net working capital / total assets.

Hence, the prediction model enables companies to make trade-offs between the variables and also provides direction for reducing the risk of failure (Russell and Zhai, 1996). What the model cannot do is to predict what management team, debenture holders, bankers and creditors will react, and it is for this reason that the model cannot forecast whether a company will actually fail. It is therefore important that the model should not be used as the sole decision tool but as part of the decision process.

Apart from its practical use, the research can also contribute significantly to the knowledge of academic field as currently the area of business failure in the construction discipline is still under-explored. This study helps to fill the gap by providing new information on the interrelationships between the economic factors along with corporate financial variables and company failure. More importantly, this research provides a valuable theoretical frontier and offers a new attempt that intelligent techniques being applied to the failure prediction of Hong Kong construction companies as well as a comprehensive financial assessment of the industry. Such analyses will encourage information exchange in the Asia-Pacific regions so as to develop a benchmarking system and facilitate comparative studies.

## 5. CONCLUSION

Business failure information provides critical guidance to entrepreneurs who are contemplating to start a business. It gives a clear indication of the risk factors in the industry. It also provides experience for the professionals who are involved in managing risks. However, theoretical development in this area has been less sophisticated than those on the start-up and growth of business. Since construction is an important industry in any economy whilst companies in the Hong Kong construction industry are facing fierce competition, establishing a reliable model to assess the solvency for the construction companies is timely and important.

This paper provides an interim report on an ongoing research of predicting business failures in construction. The common causes of failures and techniques to predict company failure are reviewed and discussed. A research framework is proposed to establish an advanced prediction model. Using the results from the research, it is anticipated that construction companies will be better able to prevent business failure and therefore relevant to the current needs of the construction industry and significant to the society.

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## REFERENCES

- Abidali, A.F. (1990) A methodology for predicting company failure in the construction industry, PhD thesis, Loughborough University of Technology, Loughborough.
- Abidali, A.F. and Harris, F. (1995) A methodology predicting failure in the construction Industry, *Construction Management and Economics*, 13(3), 189-196.
- Aldrich, J.H. and Nelson, F.D. (1984) *Linear Probability, Logit and Probit Models*. Sage, Beverly Hills, Calif.
- Altman, E.I. (1968) Financial ratios, discriminant analysis, and prediction of corporate bankruptcy, *Journal of Finance*, 23(4), 589-610.
- Arditi, D., Koksal, A. and Kale, S. (2000) Business failures in the construction industry, *Engineering, Construction and Architectural Management*, 7(2), 120-132.
- Arslan, G., Tuncan, M., Birgonul, M. T., and Dikmen, I. (2006) E-bidding proposal preparation system for construction projects, *Building and Environment*, 41(10), 1406-1413.
- Balcaen, S. and Ooghe, H. (2006) 35 years of studies on business failure: an overview of the classic statistical methodologies and their related problems, *The British Accounting Review*, 38(1), 63-93.
- Beaver, W.H. (1966) Financial ratios as predictors of failure, *Empirical Research in Accounting: Selected Studies*, University of Chicago, Chicago, Ill., 71-111.
- Ben-Akiva, M. and Lerman, S.R. (1985) Financial ratios as predictors of failure, *Empirical Research in Accounting: Selected Studies*, University of Chicago, Chicago, Ill., 71-111.
- Chan, J.K.W., Tam, C.M. and Cheung, R.K.C. (2005) Construction firms at the crossroads in Hong Kong, *Engineering, Construction and Architectural Management*, 12(2), 111-124.
- Davidson, R.A. and Maguire, M.G. (2003) Top common causes of construction contractor failures, *Journal of Construction Accounting and Taxation*, Jan/Feb 2003.
- Deakin, E.B. (1972) A discriminant analysis of predictors of business failure, *Journal of Accounting Research*, Spring, Institute of Professional Accounting, Chicago, Ill., 167-179.
- Edmister, R.O. (1972) An empirical test of financial ratio analysis for small business failure prediction, *Journal of Financial Quantitative Analysis*, Mar., University of Washington, Seattle, 1477-1493.

- Edum-Fotwe, F., Price, A. and Thorpe, A. (1996) A review of financial ratio tools for predicting contractor insolvency, 14(3), 189-198.
- Fisher, R. A. (1936) The use of multiple measurements in taxonomic problems, *Annals of Eugenics*, 7, 179-188.
- Gujarati, D.N. (2003) *Basic Econometrics*. Fourth Ed. McGraw-Hill, London.
- Hall, G. (1982) *Great Planning Disasters*. University of California Press, Berkeley, CA.
- Hall, G. (1994) Factors distinguishing survivors from failures amongst small firms in the UK construction sector, *Journal of Management Studies*, 31(5), 737-760.
- Harris, F. and McCaffer, R. (1995) *Modern Construction Management*. Blackwell Science, Oxford.
- Hensher, D.A. and Johnson, L.W. (1981) *Applied Discrete-choice Modelling*. Croom Helm, London.
- Huang, Y. (2009) Prediction of contractor default probability using structural models of credit risk: an empirical investigation, *Construction Management and Economics*, 27(6), 581-596.
- Joos, P., Vanhoof, K., Ooghe, H. and Sierens, N. (1998) Credit classification: a comparison of logit models and decision trees, Proceedings Notes of the Workshop on Application of Machine Learning and Data Mining in Finance, 10th European Conference on Machine Learning, April, 24, Chemnitz (Germany), 59-72.
- Jordan and Sons (1993) *FAME: Financial Analysis Made Easy*, CD-ROM. Bureau Van Dijk and Jordan and Sons, London.
- Kale, S. and Ardit, D. (1999) Age-dependent business failures in the US construction industry, *Construction Management and Economics*, 17(4), 493-503.
- Kangari, R. (1988) Business failure in construction industry, *Journal of Construction Engineering and Management*, 114(2), 172-190.
- Kangari, R., Farid, F. and Elgharib, H.M. (1992) Financial performance analysis for construction industry, *Journal of Construction Engineering and Management ASCE*, 118(2), 349-361.
- Keasey, K. and Watson, R. (1987) Non-financial symptoms and the prediction of small company failure: a test of Argenti's hypotheses, *Journal of Business Finance & Accounting*, 14(3), 335-354.
- Kivrak, S. and Arslan, G. (2008) Factors causing construction company failure, *Building Abroad*, October 2008, 297-305.
- Klecka, W. R. (1980) *Discriminant Analysis*. Sage Publications, Beverly Hills, CA.
- Koksal, A. and Ardit, D. (2004) Predicting construction company decline, *Journal of Construction Engineering and Management ASCE*, 130(6), 799-807.
- Lachenbruch, P.A. (1975), *Discriminant Analysis*. New York: Hafner.
- Laitinen, T. and Kankaanpää, M. (1999) Comparative analysis of failure prediction methods: the Finnish case, *European Accounting Review*, 8(1), 67-92.
- Landford, D., Iyagba, R. and Komba, D.M. (1993) Prediction of solvency in construction companies, *Construction Management and Economics*, 11(5), 317-325.
- Maddala, G.S. (1977) *Econometrics*. McGraw-Hill, New York.
- Mason, R.J. and Harris, F.C. (1979) Predicting company failure in the construction industry, *Proceedings Institution of Civil engineers*, 66, 301-307.

- Mensah, Y.M. (1984) An examination of the stationarity of multivariate bankruptcy prediction models: a methodological study, *Journal of Accounting Research*, 22 (1), 380-395.
- Moses, D. and Liao, S.S. (1987) On developing models for failure prediction, *Journal of Commercial Bank Lending*, 69, 27-38.
- Ohlson, J. A. (1980) Financial ratios and the probability of bankruptcy, *Accounting Research*, 18(1), 109-131.
- Ooghe, H. and Verbaere, E. (1985) Predicting business failure on the basis of accounting data: The Belgian experience, *The International Journal of Accounting*, 9(2), 19-44.
- Osama, J. M. (1997) Reasons for construction business failures in Saudi Arabia, *Project Management Journal*, 28(2), 32-36.
- Padgett, P. (1991) *Accounting in the Construction Industry*. CIMA, London.
- Russell, J.S. and Casey Jr., J.J. (1992) Design engineer/contractor failure from prior to contract award, *Journal of Management in Engineering ASCE*, 8(3), 278-297.
- Russell, J.S. and Jaselskis, E.J. (1992) Predicting construction contractor failure prior to contract award, *Journal of Construction Engineering and Management ASCE*, 118(4), 791-811.
- Russell, J.S. and Zhai, H. (1996) Predicting contractor failure using stochastic dynamics of economic and financial variables, *Journal of Construction and Engineering Management*, 122(2), 183-191.
- Schaufelberger, J. E. (2003) Causes of subcontractor business failure and strategies to prevent failure, *Construction Research Congress 2003*, Hawaii, USA.
- Taffler, R.J. (1983) The assessment of company solvency and performance using a statistical model, *Accounting and Business Research*, 13(52), 295-307.
- Tamari, M. (1966) Financial ratios as a means of forecasting bankruptcy, *Management International Review*, 4, 15-21.
- Tamari, M. (1978) *Financial Ratios, Analysis and Prediction*. Paul Elek Ltd., London.
- Theil, H. (1971) *Principles of Econometrics*. J. Wiley and Sons, New York.
- Yang, Z.R., James, H. and Packer, A. (1997) The failure prediction of UK private construction companies. In *COBRA Construction and Building Research Conference of The Royal Institution of Chartered Surveyors*, September 10-12, University of Portsmouth, UK.
- Zavgren, C. (1983) The prediction of corporate failure: the state of the art, *Journal of Accounting Literature*, 2(1), 1-38.

## BIOGRAPHICAL NOTES

Dr. Wong is a Post-doctoral Fellow at the Department of Civil Engineering Department, The University of Hong Kong. He has about 7 years hands-on research experience in diversified areas including construction economics and forecasting, industry development, construction procurement systems, project management, professional development, and education in the built environment.

## CONTACTS



Dr. James M.W. Wong  
Department of Civil Engineering  
The University of Hong Kong  
Pokfulam  
HONG KONG  
Tel. +852 2241-5348  
Fax + 2559-5337  
Email: [jmwwong@hkucc.hku.hk](mailto:jmwwong@hkucc.hku.hk)