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運用市場基礎模型預測營造公司財務危機之研究

-以美國營造公司及台灣營建業為例

Predicting Construction Contractor Default

with Market-based Credit Models - in Cases of North American Construction Contractors and Taiwan Construction Industry

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本論文係**蔡榮根**（D96521016）在國立臺灣大學土木工程學系博士班完成之博士學位論文，於民國 100 年 1 月 14 日承下列考試委員審查通過及口試及格，特此證明

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（指導教授）

系　主　任

致謝

恍然間磋跎三年半歲月，今日論文初成，雖淺薄如斯，仍不勝欣慰。

本論文的完成仰仗了諸多師友的幫助。首先，要向我的指導教授曾惠斌博士和廖咸興博士表示最誠摯的謝意，兩位恩師都是治學嚴謹，待人寬厚的彬彬君子，也是我最心儀的那種學者典型。曾惠斌教授給予我修讀博士的機會，並在我面臨人生關卡和學習瓶頸時，給予全力的支持和指導，如果不是他，我不可能完成博士學位。廖咸興教授自我就讀台大 EMBA 以來悉心指導，他總是立刻回應我的疑惑並逐字修改我的發表期刊論文。因此，有幸受教於兩位恩師門下修讀學位，雖然過程艱辛，但是卻如沐春風。

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摘要

營造公司的違約預警問題一向為營建項目業主及其他利害關係人所關注。為提升對營造公司財務危機的預測能力，過去的營建管理學者將與管理能力及經濟因素相關的變數，加入一般會計基礎預測模型之建構中。然而，管理變數必須依賴專家主觀的判斷，會計數據容易受到管理階層的操縱，而且和經濟數據同屬過時的資訊，用它們來做為模型的輸入變數，引起一些學者的質疑。

近年來，以公司股價為主要輸入變數的市場基礎信用風險預測模型，引起學者們廣泛的研究，由於營建業特殊的產業特性和會計處理原則，前述研究大部分將營建業排除在其驗證樣本之外。本文針對營建業，採用美國營造公司為驗證樣本，研究市場基礎模型對營造公司發生財務危機的預測能力。不同於以往營建管理相關文獻以配對方式選取少數樣本，本研究採取大橫斷面樣本，以避免選樣偏差。同時，本研究採用接受者操作特徵曲線（ROC Curve）衡量不同模型依據營造公司可能發生財務危機之風險高低排列的能力，用以挑選出真正對營建項目業主及其他利害關係人有用的模型。

本文研究結果顯示：市場基礎模型區分財務危機與正常營造公司的能力優於Severson et al.(1994),及 Russell and Zhai (1996)所建構加入管理能力或經濟相關變數的會計基礎加強模型；此外，市場基礎模型在依據營造公司可能發生財務風險機率高低排列的能力上，明顯優於傳統會計基礎模型，其預測效力也高於Reisz and Perlich (2007)對整體產業但排除營建業樣本的驗証。本研究另以台灣營建公司為樣本驗證模型的效力，發現市場基礎模型的預測能力仍不低於會計基礎模型。本文因此建議可採用市場基礎模型為評估營建業發生財務危機可能性的替代方法，本研究最主要的貢獻是為營建業之違約風險預測問題開拓一新的研究方法。

關鍵字：營建業、財務危機預測、市場基礎模型、會計基礎模型、ROC 曲線

ABSTRACT

The prediction of construction contractor default has always been an important issue for construction owners and other stakeholders. Previous construction contractor default prediction models incorporated managerial or economic variables into traditional accounting-based models to enhance predicting power. However managerial variables are qualitative and depend on human judgment, while accounting numbers are subject to manipulation by management. Furthermore, both economic variables and accounting ratios are only available periodically and may not provide necessary information in time. Using these variables as model inputs has caused doubt among scholars.

The market-based default prediction models which use stock market information in predicting company default risk have appealed to scholars in recent years. Perhaps due to the unique industrial characteristics and accounting rules in the construction industry, the construction industry is usually excluded in their empirical validation. This is the first study applying market-based models to predict the default of American construction contractors and assert that the option-pricing framework is very suitable to describe the behavior of contractor default. Different from existing literature of contractor default prediction models, this research builds and validates models using a large cross-section of contractors, and uses all available firm-years data during sample selection period in empirical analyses to alleviate sample selection biases. The Receiver Operating Characteristics (ROC) curve is employed to assess the model performance in ranking contractors from riskiest to safest, as to choose the optimal model for construction owners and other stakeholders.

The empirical results of this study exhibit that the market-based models have a smaller misclassification rate in classifying defaulted and non-defaulted contractors than the enhanced accounting-based models, which, as proposed by Severson et al. (1994), and Russell and Zhai (1996), additionally incorporate managerial or economic variables into accounting-based models. Besides, the market-based models obviously outperforms traditional accounting-based model in ranking contractors from riskiest to safest. They also have markedly better discriminatory power than that of Reisz and Perlich (2007) based on the data set of all industries except the construction industry. The overall results conclude that the market-based models, which use stock market information in predicting company default risk, has significant advantage for the construction industry, and it provides an alternative to measure construction contractor default. The contribution of current research is that it proposes the possibility to explore the default risk of the construction industry using a more powerful new tool.

Keywords: construction industry, credit risk, default prediction, market-based model, accounting-based model, ROC curve

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CHAPTER 1. INTRODUCTION

1.1 Research Background and Motivation

Construction contractors are vulnerable to financial distress or bankruptcy due to the unique characteristics of the industry. The construction industry is easily influenced by changes of the business cycle and there are considerable fluctuations in construction volume, over optimism in recognizing revenue, high operational risks, and unique deliverables. The economic and social damages resulted from the failure of construction contractors go beyond the obvious and quantifiable costs to the company owners, creditors, and employees (Mason and Harris, 1979), and may even cause significant rippling effects in an economy. Therefore, evaluating the financial failure probability of the construction industry has always been an important issue for government organization, construction owners, lending institutions, surety underwriters, and contractors. It is important for public and private owners to identify contractors with high probability of failure and avoid awarding contracts to them. Information on the default probability of a contractor is important to surety underwriters as it can speed up the process of bonding and reach a more reliable and objective bond/not bond decision (Al-Sobiei et al. 2005). Lending institutions usually charge different interest rate spread of contractor loans to compensate for bearing different contractor default risk. Under Basel II framework (2006), banks are allowed to develop their own approaches to set capital charges with respect to the credit risks of their portfolios (Agarwal and Taffer 2008) and decrease their capital requirement (Mejstrik et al., 2008). Hence, research in this area assumes great significance for lending institutions to manage their credit risk exposure of contractor loans. General contractors and subcontractors often undertake a project together, thus they have to identify and avoid companies that have high bankruptcy risks. Such kind of evaluation can also provide an early warning mechanism which is able to serve as an effective tool for monitoring contractors to avoid continuing poor corporate performance or eventual insolvency. (Edum-Fotwe et al. 1996).

Prior researches on financial early warning models aimed at the whole industry, and few focused on specific industries. The main reason is that often there are not enough samples to focus on one single industry since samples of defaulted companies are very scarce compared to samples of non-defaulted companies. Another reason is that early warning models were built in the hope of being applicable to all industries. However, Russell and Jaselskis (1992) suggested that generic credit risk models for all sectors tend to be too general and may lack the ability to provide adequate predictive power by sector type (e.g., construction, manufacturing, aerospace, and chemical refining). Chava and Jarrow (2004) also pointed out that different industries face different levels of competition and have different accounting conventions; therefore, the likelihood of bankruptcy can differ for firms in different industries with otherwise identical balance sheets. Kangari et al. (1992) suggested that the construction industry in the United States has several unique characteristics which distinguish it from other sectors of the economy. These characteristics contribute in many ways to the high business failure rate in the industry. Edum-Fotwe et al. (1996) also stated that the construction industry has always experienced a relatively high proportion of insolvencies compared with the rest of the British economy. Koksal and Arditi (2004) suggested that according to Dun and Bradstreet's 1997 data, the total value of failure liability in the construction industry constituted 5% of the total value of failure liabilities in the U.S. in that year. Furthermore, the failure rate per 10,000 firms was 88 for all industries whereas it was 116 for the construction industry in 1997. The same pattern of higher numbers of business failures in the construction industry is observed consistently in the previous years as well (Dun and Bradstreet 1989–1993). Tserng (2010) compared the capital structures of different industries in Taiwan, and results showed that the construction industry had the second highest debt ratio and a relatively high bankruptcy ratio. Due to the above reasons, past researches on bankruptcy prediction models, such as Beaver (1996), Altman (1968), Brockman and Turtle (2003), and Reisz and Perlich (2007), mostly excluded the construction industry from their sample. As a result, credit risk models built for the entire industry are not applicable to the construction industry. Therefore, construction contractor default forecast is a significant issue for academics and practitioners.

1.2 Problem Statement

The most traditional corporate failure prediction methods employed by researchers are the accounting-based or financial ratio statistical models, including univariate analysis (Beaver 1966), multivariate discriminant analysis (MDA) (Altman 1968, Deakin 1976, Blum 1974, Taffler 1984), linear probability modeling (LPM) (Meyer and Pifer 1970), logit modeling (Ohlson 1980), probit modeling, and the Cumulative Sums (CUSUM) procedure (Theodossiou 1993). All prior studies used only accounting or financial ratios as predicting variables in their models, and most of them were applied to all sectors in the economy rather than to a single one of the economy.

Russell and Jaselskis (1992) argued that the previous business failure models focus primarily on corporate financial conditions and ignore management factors that are significantly related to the operating performance of construction companies, and these factors affect their probability of failure. Severson et al. (1994) used logistic regression to derive a model to predict claim and non-claim contracts. The misclassification rate was greater than 30% when only using corporate financial variables, and improved to 12.5% when additionally including a management-related variable, the cost monitoring variable. Abidali and Harris (1995) built an A-score which includes the managerial performance variables. By linking A-score value and Z-score value, it is possible to predict the probability of construction contractor failure more precisely. However, these managerial variables are subjective and qualitative. In addition, these models do not incorporate the effects of economic condition on the risk of contractor failure (Russell and Zhai 1996).

The Dun and Bradstreet (D&B) Corporation estimated that over 60% of construction contractor failures are due to economic factors (Russell 1991). Prior failure predictive models using only financial ratio information did not consider the effects of the dynamics of the state of the economy on the financial health of contractors. Russell and Zhai (1996) developed a failure prediction model by incorporating the stochastic dynamics of both macroeconomic variables and a given contractor's financial variables. Their model's misclassification rate was 15.5% for testing sample and 22% for validation sample.

Several previous studies raised questions on the effectiveness of the previously mentioned models. First, because financial ratios or macroeconomic variables are only available periodically, it is difficult to obtain information in time for using these models (Hillegeist et al. 2004). Second, the financial ratio models are constructed by comparing the characteristics of defaulted and non-defaulted firms using a statistical technique to derive the variables that best discriminate between the two groups. This methodology is ad hoc and heavily dependent on the prior specification of firms as defaulters or non-defaulters (Gharghori et al. 2006). Third, the parameters in the models may need periodical adjustment due to changes in economic conditions and market trends (Russell and Zhai 1996). Fourth, accounting numbers are subject to manipulation by management (Agarwal and Taffer 2008).

In addition to financial soundness, management capability, and economic condition, technical expertise is also one of the factors essential to construction contractors' success. Russell and Skibniewski (1988) presented all the relevant factors involved in the construction contractor prequalification decision-making process, which are closely related to contractor default risk. Since many of these factors are qualitative and depend on human judgment, it is difficult to incorporate them into the default prediction model without bias.

Recent integration and innovation in the financial literature have given rise to another kind of credit risk models, the market-based models. They are based on the option pricing theory which was established by Black and Scholes (1973) and further developed by Merton (1974). The market-based models have an advantage for business default prediction by only using stock market information. For listed contractors, because stock price incorporate both their quantitative and qualitative information, the market-based models are supposed to be more suitable for the default prediction of construction constructors. Although several recent papers used this approach for assessing the likelihood of corporate failure, and the predictive accuracies of the models were regarded as satisfactory. However there are no researchers, to our knowledge, employing market-based models to do contractor failure prediction. In addition, it also encounters problems such as market inefficiency and inappropriate assumptions of value distributions.

To summarize, previous literature has incorporated traditional accounting-based models developed for general industries with related managerial factors or economic factors as explanatory variables in construction contractor default prediction models. Nevertheless, besides managerial factors, there are still considerable un-quantitative factors that affect the success of construction industry such as expertise skills, the changes of governmental regulations, public policy issues (environmental protection). These factors are qualitative, thus it is hard to incorporate them in the process of constructing model. However, the market-based models' main input is stock price, and based on its assumption that stock market can reflect a company all managerial or other related information. This research attempts to adopt the market-based models in construction contractor default prediction and to evaluate its performance.

1.3 Characteristics of Construction Industry

1.3.1. Contractor Profiles

This section discusses the unique characteristics that differentiate the construction industry from other industries, resulting in need of a different approach for business failure forecasting. In general, the construction industry covers the enterprise (the construction contractor) that physically constructs the building/facility or infrastructure. Typically, contractors are categorized as a general contractor, a builder/heavy constructor, or a trade or specialty contractor. A general contractor normally assumes responsibility under a single contract with the owner to construct the entire project. The general contractor will typically subcontract portions of the work to various trade/specialty contractors as well as suppliers. Overall construction responsibility, however, remains with the general contractor. Thus, the general contractor must schedule the objectives of scope, cost, time, quality and co-ordinates the work of the specialty subcontractors, supervises the construction, and undertakes quality control and safety requirements. Sometimes the general contractor will use own forces to perform certain parts of the work. This varies from one project to another. A builder comprises establishments involved in constructing residential, industrial, commercial, and institutional buildings. A heavy constructor is traditionally used to describe contractors who perform engineering construction works such as roads, bridge, airports, ports, dams, utilities, and pipelines. Heavy construction contractors typically require heavy equipment, professional management teams, skilled labour force and material resources necessary to meet market demand within this industry. Their clients tend to be governments, public sector agencies, utilities etc. A trade or specialty contractor is an independent specialty contractor who works as part of a team with the general contractor to complete a project for an owner. The trade/specialty contractor is contracted to perform a particular service and/or certain types of work such as concrete work, masonry, structural steel, mechanical, including plumbing, sheet metal, heating and controls etc. When engaged directly by the owner, the trade/specialty contractor is referred to as a prime contractor. When engaged by a general contractor, the trade/specialty contractor is called a subcontractor.

1.3.2. Special Characteristics of Construction Industry

Construction contractors have several potential default barriers resulting from special characteristics of the construction industry, which result in a higher probability of default or bankruptcy.

First, construction projects produce unique products. It is the owners who first conceptualize the project and initiate the construction process; that is, owners identify their requirements, project funding level, and contract conditions. After that, the construction contractors fulfill the owner's requirements. All major aspects of the project must meet with the owner's approval. If contractors fail to provide or adequately perform any of the work, deliverables, or services called for by the contract within the time specified, the project will not be accepted by the owner and the contractor will suffer from construction disputes and possible litigation. When construction disputes are not resolved in a timely manner, contractors will suffer from great financial loss.

Second, the production period of a construction project is relatively long. The process of producing the construction product includes contracting, design, material manufacturing, on site construction, commissioning, and final acceptance--the duration of this process usually exceeds one year. Thus, the operation of contractors is easily influenced by change of governmental regulations, public policy issues, raw material inflation, and the business cycle.

Third, the construction process is quite complicated. Each product of the construction industry is unique due to its own specific characteristics such as a different construction site, contract terms and design drawings. Many influencing factors including workers, location, time, and on-site situations, result in the quality of construction deliverables being difficult to control. Thus, risk in the construction industry is higher than in other sectors.

Fourth, the construction industry is highly dependent on the capability of several professionals who need to work together in an integrated fashion. As a result of growth in project scale, progression of construction techniques, and complication of materials and equipment, a single construction contractor is not able to complete a project alone. Thus, a successful construction project is highly dependent on the cooperation of individuals. On the other hand, if one of them defaults or goes bankrupt, the others will also be affected.

Fifth, construction contractors face high operational risks. Any on-site casualties, hurricanes, floods, or earthquakes may lead to additional losses and damages to the contractor. Any of these unwanted situations will increase expenses to the contractor or even lead to default or bankruptcy.

1.3.3. Financial Risk of Construction Industry

As the characteristics of the construction industry are vastly different from other industries, the financial risk profile is also different for the following reasons:

1. Poor financial stability: Construction is a highly competitive business that tends to makes it difficult for contractors to obtain work and make a reasonable profit considering the risk. During economic downturns, some contractors adopt a strategy of providing low bid prices to win awards. This kind of behavior puts their firms in great jeopardy of ultimately going bankrupt.

2. Over optimism about recognized revenue: The percentage of completion method is typically used by contractors to forecast revenues on construction projects. This method has an advantage in that income can be recognized earlier for the firm. However, contractors may suffer from insufficient liquidity due to the combination of the risky nature of the construction industry and the over optimism in accounting for revenues. One only knows at the end of the project, how much money was truly realized.

3. High inventory ratio: Contractors typically carry higher inventory of materials and supplies compared to other industries due in part to the greater economies of scale when purchasing in larger quantities and the need to meet on-going project schedule

demands. Since high inventory reduces cash, the contractor can potentially suffer from insufficient liquidity for servicing payment obligations such as matured debts, debt service, accounts payable and others, which can often lead to default events. This kind of default is defined as flow-based credit risk (Ross et. al. 2005).

4. High debt to equity ratio: When a project is underway, the project manager applies for advanced payment or progress payments on a monthly basis from the owner based upon the value of construction work performed. Prior to receiving reimbursement from the owner, most contractors rely on short-term loans to make payments on material, equipment, and labor with a relatively low level of equity funding (Abidali and Harris 1995). Moreover, long-term capital funding can be a challenge for construction contractors causing financial instability and the potential for high interest payments. In addition, the construction industry has a low level of fixed assets compared to manufacturing which possesses land, factories, equipment and other assets. From the above characteristics, the construction industry also has a higher debt ratio compared to most of other industries (Metz and Cantor 2006).

1.4 Research Objectives

The primary objective of this research is to propose a quantitative model for construction contractor default prediction, and thus avoiding the need to use subjective managerial parameters. This research uses a cross-section of construction contractors to build and empirically validate an accounting-based model, and compare its contractor default risk measuring ability with market-based models. This research also attempts at combing accounting-based and market-based models into a hybrid model. After empirically exploring the contractor-default-predicting power of each model, the optimal model is concluded. All the research objectives are listed as follows:

(1) Develop a quantitative model for construction contractor default prediction, and release human judgement bias using enhanced ratio models suggested by prior literatures.

(2) Allow construction project owners to prequalify contractors correctly and avoid awarding contracts to contractors with high probability of failure.

(3) Allow surety underwriters to speed up the process of bonding to contractor, and to reach a more reliable and objective bond/not bond decision.

(4) Provide financial lending institutions a more efficient internal ratings-based approach to set capital charges with respect to the credit risks of their contractor loans.

(5) Provide an early warning mechanism which is able to serve as an effective tool for contractors to assess themselves correctly, and avoid continuing poor corporate performance or eventual insolvency.

1.5 Research Scope and Constraint

Contractor default early warning model have been broadly researched by many previous construction management scholars. But they merely used accounting-based methods to construct or investigate their models. This research extends the research methodology to an innovative approach- the market-based method, which uses option-pricing framework to predict business failure, and has not yet explored by construction management scholars. Besides, the dataset of this research mainly screens from USA construction industry consists of 1,484 firm-year observations representing 92 healthy contractors and 29 failed contractors for years 1970 to 2006. All of the selected samples were listed construction company. The USA contractor dataset was selected as empirical sample for three reasons: first, most of accounting-based contractor default prediction models mentioned in prior literatures investigate U.S. construction industry. Using U.S. dataset can compare the predictive power of the models discussed in this research with the models mentioned in the previous literatures. Second, the accounting information of U.S. listed firms are regard as relative transparent. Third, the market-based models rely heavily on economic theories about market efficiency. The model contains embedded assumptions about the comprehensiveness of the information contained in stock price when used within the structure of the model. The U.S. stock market is deemed as the most efficient market in the world. For comparison, chapter 7 uses dataset selected from Taiwan construction industry to empirical validate the predictive power of the models discussed in this research.

The market-based models using the contingent claims framework introduced by Merton are examples of a structural model. The usefulness of such an approach depends on how closely its assumptions and structure capture the true nature of the firm dynamics as well as the accuracy with which the model's variables are estimated (Sobehart and Stein, 2000). The assumptions and limitations of using market-based models discussed in this research state as follow:

(1) The stock market where contractors are publicly traded must be efficient. If the contractors are not traded in an efficient market, the stock price that is the main input of market-based models may not embed all the information related to the contractors' survivability or failure, and can not reach a successful prediction.

(2) The market-based model assumes that asset returns are normally distributed, while Moody's-KMV, using their own propriety dataset, observe that the asset returns of

defaulted firms have a leptokurtic distribution, which may cause an underestimation in default probabilities.

(3) It does not distinguish between different types of debt and assumes that the firm only has a single zero coupon loan. Actual firms have convertible securities, pay dividends, coupons and interest payments. These liabilities need to be explicitly modeled to generate a reasonable measure of default risk—particularly in the cases where these payments are unusually large (Dwyer and Qu, 2007).

(4) The Merton model assumes that once the company puts a debt structure forward, it leaves it unchanged. In reality, Borrowers will often adjust their liabilities as they near default. Sometimes highly leveraged companies have the ability to renegotiate the terms of their loans and/or securing fresh longer-term funding with their lenders. By rescheduling their debt, companies avoid foreclosure by creditors.

(5) For simplification, the instantaneous risk-free rate r is assumed to be constant over time. It is more realistic to assume that the default risk free interest rate is stochastic (Vasicek, 1977).

1.6 Procedure of the Research

The procedure of this research is described in Figure 1. 1. As can be seen in Figure 1.1, this research contains of eight parts. Each part describes the main process which contributes to the final result of this research.

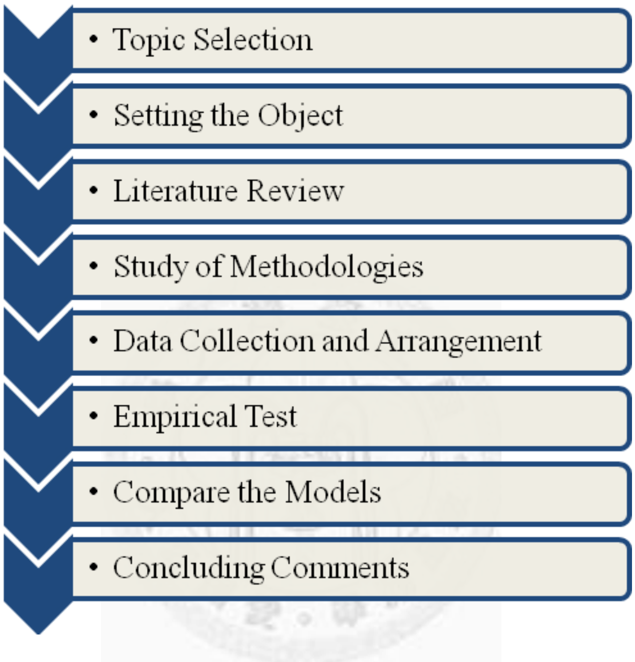

Figure 1.1 Procedure of research

1.7 Structure of the Dissertation

This dissertation is organized as follows:

(1) Chapter 1 provides an overview, giving an account for the motivations and objectives of this research, setting the research orientation, scope and discussing the research constraint, describing the research process and the structure of this dissertation.

(2) Chapter 2 reviews past studies and current theory on business failure prediction or financial early warning models. The scope of literature review includes the whole industry and the construction industry.

(3) Chapter 3 proposes the framework of methodology using in this research, and discusses the dataset and sample selection criteria.

(4) Chapter 4 constructs a traditional accounting-based default prediction model with a logistic regression technique for construction industry. This accounting-based model is provided as a benchmark for evaluating the performance of other models proposed in this research.

(5) Chapter 5 empirical validates the predictive power of market-based models for construction contractor default. The market-based models include three Merton-type models and barrier option model (DOC model). This chapter indentifies the best performance of three Merton-type models and compares it with the performance of barrier option model and enhanced accounting-based models proposed by prior construction management scholars. This chapter also compares the performance of market-based models using in construction industry with using in whole industry documented in previous literatures.

(6) Chapter 6 proposes a hybrid default-predicting models that integrate accounting-based model and market-based model, and measure its performance of forecast construction contractor default. Compare the results of four models (hybrid model, Merton model, barrier option model, and accounting-based models). Finally, this research will suggest the best default-predicting model for the construction industry.

(7) Chapter 7 uses three models mentioned in the previous chapters to calculate the

default probabilities of Taiwanese construction contractors. The default prediction abilities of each model are compared, and the applicability of using each model on Taiwanese construction company data is explored.

(8) Chapter 8 summarizes the research conclusions, research contributions, and suggestions for future studies.

CHAPTER 2. LITERATURE REVIEW

This chapter describes the characteristics, the strengths and limits, empirical results, and development of different business failure forecast models. The scope of literature review includes the whole industry and the construction industry. It also includes the definitions of business failure (default) in past studies.

2.1. Expert Systems

Traditionally, financial institutions have relied on banker expert system to assess the credit quality of borrowers. These are based on various borrower characteristics, called as the "5Cs" of credit: (1) Character (reputation), (2) Capital (leverage), (3) Capacity (earnings volatility), (4) Collateral, and (5) Cycle (macroeconomic condition). Until recently, many banks including large international banks still use such credit rating tool in the loan processing, credit monitoring, loan pricing, management and decision-making (Treacy et al., 2000). The same holds for the credit rating agencies where judgment of the "lead analyst" and the "rating committee" is the final word in determining the rating of an issue or issuer (Standard & Poor's, 2008). However, banker expert system may be inconsistent and subjective since its risk weights are based on human judgment. Thus, statistical approaches and other credit rating methods had been explored by academics and practitioners in order to construct a more objective and consistent credit risk early warning system.

2.2. Accounting-Based Models

Accounting-based (or ratio-based) models are typically constructed by searching through a large number of financial ratios (primarily based on accounting statements) with the ratio weightings estimated on a sample of defaulted and non-defaulted firms. Since the financial ratios and their weightings are derived from sample analysis, such models are likely to be sample-specific. Previous literatures on different accounting-based models and their development are shown below:

2.2.1. Univariate Discriminant Analysis

Beaver (1966) conducted the first modern statistical evaluation of models to predict business financial failure. He compared a list of 30 financial ratios individually for 79 failed firms and a matched sample of 79 healthy firms for the period from 1954 through 1964. The majority of these firms operated in the manufacturing industry. No construction firm was included. Consequently, Beaver found that six financial ratios could discriminate well between healthy and defaulted firms five years before the failure occurs–with differences increasing as the year of failure approached. Three ratios are tremendously useful in the prediction of failure: total debt/total assets, cash flow/total debt, and net income/total assets. In the year prior to bankruptcy, these ratios misclassified 19 percent, 13 percent, and 13 percent of the sample, respectively. However, since univariate analysis uses individual financial ratios as a single predictor of failure, the model may give inconsistent and confusing classifications results for different ratios on the same firm (Altman, 1968).

2.2.2. Multivariate Discriminant Analysis, MDA

Beaver's (1966) univariate ratio analysis was improved and extended by Altman's (1968) multivariate ratio analysis. Altman (1968) matched 33 failed companies with 33 healthy firms between 1946 and 1965, and provided a multivariate discriminant analysis (MDA) on 22 financial ratios. Finally he constructed the well-known Z-score model that consisted of 5 ratios. The model is:

$$Z=1.2X_1+1.4X_2+3.3X_3+0.6X_4+1.0X_5 \qquad (2\text{-}1)$$

Where X_1 = working capital / total assets, X_2 = retained earnings / total assets, X_3 = EBIT / total assets, X_4 = market value equity / book value of debt, X_5 = sales/total assets.

Accordingly, firms were classified as follows: firms with Z-scores less than 1.81 implied high probabilities of bankruptcy, while firms with Z-scores greater than 2.70 had low probabilities of bankruptcy. Firms with Z-scores between 1.81 and 2.70 were regarded as at risk. In Altman's initial sample, the model was extremely accurate (94%) in predicting bankruptcy one year prior to the bankruptcy and 72% accurate two years prior to bankruptcy filing. Because Altman's (1968) model suffered several limitations such as it was developed from small listed firms and the US manufacturing industry, Altman futhermore expanded his model to larger firms (Altman,1977), non-listed companies (Altman,1983) and non-manufacturing companies (Altman,1993). Following Altman's (1968) research, many studies also used MDA to predict a firm's default. For instance, Deakin (1972) modified Altman and Beaver's studies, using a quadratic function to build a more precise classification model of financial distress prediction. Taffler (1984) utilized data from British companies, and developed a UK-based Z-score model which is derived in a similar way to Altman (1968).

Although the Z-score models derived from MDA approach are well-known and still widely used today, the MDA assumes that the covariance matrices of two groups (defaulted and non-defaulted firms) are identical and both groups need to be described by a multivariate normal distribution. Clearly, these assumptions do not always exist in the real world (Deakin 1976; Hamer 1983). Other critiques of the MDA include Joy and Tollefson (1975), Eisenbeis (1977), McLeay and Omar (2000).

2.2.3. Logit and Probit Models

Martin (1977) was the first author who used logit methodology for bankruptcy prediction for US banking sector. Ohlson (1980) applied it more generally. Logit analysis provides the relationship between binary or ordinal response probability and explanatory variables. It incorporates nonlinear effects, and uses the logistical cumulative function in predicting bankruptcy (Min and Lee 2005). Unlike MDA, the logistic model does not require multivariate normality or the equality of covariance matrices of two groups. Like MDA, this technique weights the independent variables and assigns a Z score in a form of failure probability to each sample company.

Ohlson (1980) sampled 105 bankrupt firms and 2058 non-bankrupt firms between 1970–1976, and constructed the well-known O-score model using 9 explanatory variables, which are log (total assets / price index), debt ratio, working capital to total assets, current ratio, return on total assets, cash flow from operating activities to total assets, dummy variable 1(1 if debt is greater than assets, otherwise 0), dummy variable 2 (1 if net income is less than 0, otherwise 0), and net sales variation. The model accuracy rate is 84%. This line of research was pursued by many scholars, such as Mensah (1983), Casey and Bartczak (1985), as well as Gentry et al. (1985). However, the logit methology suffers some problems such as the assumption that the cumulative distribution of the error term is logistic what does not always hold in reality.

Zmijewski (1984) applied probit regression when predicting financial distress. The probit model is similar to the logit model, which can also deal with the non-normal distribution of independent variables. But empirical results show that logit model is superior to probit model in the majority of cases.

Besides logit model and probit model, other accounting-based models for default prediction have also been developed, such as the classification trees (Breiman et al., 1984), neural networks (Zhang, et al., 1999), genetic algorithms (Back et al., 1996), hazard models (Shumway (1998), Hillegeist et al. (2004)), etc. All prior studies used only financial ratios as predicting variables in their models, and most of them were applied to the whole industry rather than to a single sector of the industry.

2.2.4. Neural Network Models

From the late 1980s, artificial intelligence (AI), such as Artificial Neural Networks (ANN), was successfully applied to corporate financial distress forecasting. A large number of studies compared ANN's prediction performance with other classification methods and proved that ANN had better prediction performance than other methods (Odom and Sharda, 1990; Coats and Fant, 1993; Zhang et al., 1999).

In the late 1990s, the Support Vector Machine (SVM), was introduced to deal with the classification problem. Fan and Palaniswami (2000) applied SVM to select the financial distress predictors. They pointed out that SVM created an optimal separating hyperplane in the hidden feature space in terms of the principle of structure risk minimization and used the quadratic programming to obtain an optimal solution.

Many studies which use ANN for default prediction (Lin, 2009; Kim and Sohn, 2010; Muller et al., 2009; Neves and Vieira, 2006; Ahn et al., 2006; Wang, 2005; Atiya et al., 2001; Yeh et al., 2010; Shin et al., 2005) rely on matched samples or partially adjusted unequal matched samples to test alternative methodologies or estimation methods. Zmijewski (1984) argued persuasively that this sample-matching method produces choice-based biases and sample selection biases. Tserng et al.(2010) put in all usable firm-years data, and used an enforced SVM approach in the field of default prediction, to avoid choice-based biases and sample selection biases.

Other ANN models include recursively partitioned decision trees, case-based reasoning (CBR) model, neural networks (NN), and genetic algorithms (GA). Researchers heavily rely upon computer programs to do failure prediction. Although many ANN models have been developed, they are still in the testing and improving stage.

2.3. Construction Industry-Specific Accounting-based Models

Mason and Harris (1979) developed the earliest financial ratio model specific on U.K. construction industry in order to identify potentially insolvent contractors and to avoid awarding them contracts. They built an operational model made up of six variables, which measure five distinct aspects of the company: profitability, working capital position, financial leverage, quick assets position and trend. The predicting ability using data two years or more before bankruptcy is not as good as using data just one year before bankruptcy.

Analysis performed by Langford et al. (1993) with financial data from three failed construction companies showed that one company exhibiting the characteristics of solvency (as defined by the model of Mason and Harris (1979)) had actually failed. Preliminary financial analyses of U.S. construction firms for identifying symptoms of business failure were conducted by Abbinante (1987) and Kangari (1988). Kangari et. al. (1992) indicated that the unique characteristics of construction firms contribute in the high rate of business failure and models developed for the manufacturing industry are not appropriate for the construction industry. They presented a quantitative model based on six financial ratios, which are current ratio, total liabilities to net worth, total assets to revenues, revenues to net working capital, return on total assets, return on net worth, to assess financial performance.

Severson et al. (1994) investigated trends in contractor financial data to help predict their likelihood of experiencing a claim. Trend analysis was performed to determine how different variables changed over three years for claim and non-claim contractors. The financial variables which better differentiated claim companies from non-claim companies were: accounts receivable, underbillings, accounts payable, notes payable, total long-term debt, retained earnings, cost of sales, and gross profit.

Russell and Jaselskis (1992) argued that the previous business failure models are not appropriate for construction industry because they ignore management factors that are significantly related to the operating performance of construction companies. Severson et al. (1994) collected financial statements of 87 contractors (36 claims and 51 non-claims). Predicting the failure probability of construction firms solely on financial data led to a 30% misclassification rate. After a management-related variable was introduced (performance of cost monitoring) the misclassification rate was reduced to 12.5%, but the management information of a certain company is not easy to get. This fact influences the accuracy of the model. Edum-Fotwe et al. (1996) proposed two ways to improve the shortcomings of financial ratio analytical methods them. First, to reduce the variation in different expert evaluations and lead to a more uniform assessment, the assessment criteria of subjective index methods for the construction industry should be standardized. Second, as a means of improving the efficiency of ratio models, the transformation approach was recommended.

Abidali and Harris (1995) built a Z-score model including seven financial ratios, which are profit after tax and interest / Net capital employed, current assets / net assets, turnover / net assets, short term loans / profit before tax and interest, tax trend over three years, profit after tax trend over three years, short term loan trend over three years. Another A-score was developed to reinforce the financial approach, whereby managerial performance aspects are weighted. By linking A-score value and Z-score value, it is possible to predict the probability of construction contractor failure more precisely.

Russell (1991) pointed out that, according to Dun and Bradstreet (D&B), 60% of operational failure in construction companies are due to economic factors. Russell and Zhai (1996) combined dynamic economic index with financial variables to build the financial warning model for construction companies. A random coefficient method is proposed to describe the stochastic dynamics, i.e., the future position, the trend, and the volatility. A discriminant function for detecting failed contractors has been developed using stepwise regression. The discrimination function includes the following variables: (1) trend–prime interest rate; (2) future position–new construction value in-place; (3) trend–new construction value in place; (4) future position–net worth / total asset; (5) trend–gross profit / total asset; and (6) volatility–net working capital / total asset. Misclassification rate is 15.5% for the original data, and 22% for the secondary data. The result reveals that the economic and market conditions have significant impact on the risk of contractor failure. But the dynamical variables in this function increase the complexity of prediction.

Several previous studies raised questions on the effectiveness of the previously mentioned accounting-based models. First, because accounting ratios or macro-economic variables are only available periodically, it is difficult to obtain information in time for using these models (Hillegeist et al. 2004).

Second, the accounting-based models are constructed by comparing the characteristics of defaulted and non-defaulted firms using a statistical technique to derive the variables that best discriminate between the two groups. This methodology is ad hoc and heavily dependent on the prior specification of firms as defaulters or non-defaulters (Gharghori et al. 2006).

Third, the parameters in the models may need periodical adjustment due to changes in economic conditions and market trends (Russell and Zhai 1996).

Fourth, accounting numbers are subject to manipulation by management (Agarwal and Taffer 2008). Liao et al. (2004) proposed an integrated model that incorporated both accounting and market credit information, by putting the default probability generated from the Merton model as a predicting variable into the traditional logistic model. The empirical results showed that the addition of market information improves the predictive power of the original accounting information based logistic models. However, this study used companies from a wide range of industries, thus it is not applicable to the construction industry.

2.4. The Market-Based Models

Due to the advent of innovative corporate debt products and credit derivatives, academics and practitioners have recently shown renewed interest in models that forecast corporate defaults (Bharath and Shumway 2008). One line of innovative forecasting models is based on the option pricing theory derived by Black and Scholes (1973) and later developed by Merton (1974). The main advantages of using option pricing framework in default prediction are that they provide guidance about the theoretical determinants of default risk and they supply the necessary structure to extract bankruptcy-related information from market prices. Thus, they are also referred as market-based models. The Merton model (the standard option-based model) and the barrier option model (DOC model) are two kinds of market-based models discussed in the previous literature.

2.4.1. The Merton Model

Based on the seminal work of Black and Scholes (1973), Merton (1974) stated that a firm's equity value is the value of a call option on a firm's asset value and the firm's total debt is the strike price of the option. Under certain assumptions, the Black-Scholes-Merton option-pricing framework (the Merton model) can be used to estimate the default probabilities (DPs) for individual firms, where a firm's DP is the probability that the value of the firm's assets is less than its book value of liabilities at the maturity of the option. In an efficient market, the stock (equity) prices of publicly traded firms already reflect all known information (quantitative and qualitative) affecting the survivability of the firms. Accordingly, the stock market provides an alternative and potentially superior source of information regarding the probability of bankruptcy because it aggregates information from other sources in addition to the financial statements (Hillegeist et al. 2004). Therefore, Merton model using the Black and Scholes (1973) and Merton (1974) contingent claims approach provides an appealing alternative for business default prediction.

Agarwal and Taffer (2008) pointed out that the Merton model counters most of the criticisms of accounting-based models: (i) it provides a sound theoretical model for firm bankruptcy, (ii) in efficient markets, stock prices will reflect all the information contained and not contained in accounting statements (iii) market variables are unlikely to be influenced by firm accounting policies, (iv) market prices reflect future expected cash flows, and hence should be more appropriate for prediction purposes, and (v) the output of such models is not time or sample dependent.

For listed contractors, because Merton model incorporate both quantitative and qualitative aspects of their internal (including financial status, management capability, and technical expertise) and external (including macroeconomic conditions, governmental regulations change, and public issues) information, it is supposed to be more suitable for the default prediction of construction constructors. Although several recent papers used this approach to assess the likelihood of corporate failure (e.g., Crosbie and Bohn 2003; Hillegeist et al. 2004; Reisz and Perlich 2007; Vassalou and Xing 2004; Campbell et al. 2008; Agarwal and Taffer 2008; Bharath and Shumway 2008), there are no researchers, to our knowledge, employing Merton model to do contractor failure prediction.

However, the Merton model is a structural model and applying it requires a number of assumptions. First, the stock market where companies are publicly traded must be efficient. Second, as Saunders and Allen (2002) point out, BSM framework assumes that asset returns are normally distributed, while Moody's-KMV, using their own propriety dataset, observe that the asset returns of defaulted firms have a leptokurtic distribution, which may cause an underestimation in default probabilities. Third, it does not distinguish between different types of debt and assumes that the firm only has a single zero coupon loan. Fourth, The Merton model assumes that once the company puts a debt structure forward, it leaves it unchanged. Of course, this is not true in reality. Borrowers will often adjust their liabilities as they near default. Lenders will also adjust their lending to high leveraged companies if they believe that company's debt is reaching a critical level or if they decide to follow a "credit rationing" policy.

Fifth, the BSM model makes no allowance for the possibility of debt renegotiation between equity and debt holders in the event of bankruptcy. In reality, sometimes highly leveraged companies have the ability to renegotiate the terms of their loans and/or securing fresh longer-term funding with their lenders. By rescheduling their debt, companies avoid foreclosure by creditors. Sixth, the instantaneous risk-free rate r is assumed to be constant over time. It is more realistic to assume that the default risk free interest rate is stochastic and follows for example a mean reverting process (Vasicek, 1977). Nonetheless, the Merton model is widely understood and provides a useful theoretical framework for complex issue of company default. It can be applied to any company listed on the stock market. Furthermore, it is “forward looking” because it is based on the mark-to-market valuation of company rather than historic book value accounting data. A direct advantage of the structural models, from the standpoint of pricing and managing default risk, is that they provide a conceptual basis for linking default probabilities to the firm’s economic fundamentals. They rely on the economic argument that a firm defaults when its asset value drops to the value of its contractual obligation.

The empirical investigation on the performance of market-based models is mixed. Kealhofer (2003) and Oderda et al. (2003) found that such models outperform credit ratings. Hillegeist et al. (2004) pointed out, two popular accounting-based measures, Altman’s (1968) Z-Score and Ohlson’s (1980) O-Score, were compared to Black–Scholes–Merton option-pricing model. Tests show that the Merton Model provides significantly more information than either of the two accounting-based measures. This finding is robust to various modifications of Z-Score and O-Score, including updating the coefficients, making industry adjustments, and decomposing them into their lagged levels and changes. Gharghori et al. (2006) investigated the performance of market-based and accounting-based approaches in Australia. The results found that the market-based models clearly outperform the accounting-based model, and the performance of the BSM model and the DOC model is quite similar. Agarwal and Taffer (2008) found that traditional accounting-based bankruptcy risk models are, in fact, not inferior to market-based models for credit risk assessment purposes, and dominate in terms of potential bank profitability when differential error misclassification costs and loan prices are taken into account.

2.4.2. Barrier Option Model (DOC model)

In place of the conventional view of equity as a standard call option, Brockman and Turtle (2003) argued that corporate equity is a down-and-out call (DOC) option on corporate assets. The standard call option model (the Merton model) is path-independent because default can only occur at maturity when the underlying asset value falls below liabilities. This means that a firm remains alive regardless of the degree of decline in asset value prior to maturity, which is of course inconsistent with reality. In contrast, a DOC option takes the asset value prior to maturity into consideration. With a DOC option, the firm bankrupts and the equity becomes zero if the asset value either falls below liabilities at maturity, or if it falls below a pre-specified level, referred as the barrier, before maturity. Proponents of applying barrier options to value equities argue that the additional risk of default before maturity is the additional component of default risk that is not captured by the standard option model (Gharghori et. al. 2006).

Brockman and Turtle (2003) provided empirical validation of the DOC option model by showing that implied barriers are statistically and economically significant for a large cross-section of industrial firms. They also applied the barrier option framework to bankruptcy prediction and found that its prediction ability significantly outperforms Altman's Z-scores. However, construction contractors were not included in their empirical samples. Contractors have several special industrial characteristics such as high asset variability, high financial leverage, and low capitalization. Brockman and Turtle (2003) pointed out that firms with these characteristics are likely to exhibit a higher probability of hitting the barrier before the expiration date than firms without such characteristics. Brockman and Turtle (2003) also suggested that there are many types of corporate barriers. To obtain debt financing, managers may agree to maintain certain financial ratios above specified levels (e.g., debt-to-equity ratios, current ratio, times-interest-earned, etc). Breaking any of these barriers may trigger a debt recall, default, or bankruptcy. In addition, an unleveraged firm is still exposed to potential barriers, such as legal issues which may occur at any time and can potentially cause a corporate failure. Firms may become bankrupt due to regulatory violations or criminal code infractions. In sum, the general framework of Brockman and Turtle (2003) is valid for any situation in which equity value can be knocked out prior to a scheduled debt payment. Reisz and Perlich (2007) argued for the inclusion of a firm-specific early bankruptcy barrier so as to reflect the nature of many bankruptcy codes, jurisdictions and covenant, which allow bondholders to extract value or to force liquidation/reorganization when some trigger event occurs.

Reisz and Perlich (2007) compared the performance of different models in predicting default with 5,784 industrial firms in the period 1988-2002 with barrier model. It was found that the barrier model outperformed both the Merton model and Crosbie and Bohn's (2003) KMV approach when predicting bankruptcies one, three, five, and ten years ahead in terms of ranking and calibration. However, Altman Z-scores outperformed all the above mentioned models in the one-year-ahead default prediction, although they fare poorly as the forecast horizon is extended. Thus it was concluded that (backward-looking) accounting-based measures are most relevant for short-term bankruptcy prediction, while (forward-looking) market-based structural models are best suited for medium-and long-term. It was also found that the implicit barrier is on average equal to 30% of the firm's market value of assets and increases (decreases) with leverage (asset volatility).

2.5. Definitions of Business Default

In building a business default-predicting model, it is critical to use a definition of business failure (default) that is consistent with an actual economic loss suffered on the part of creditors or, for the construction industry, suffered on project owners as well as creditors. Business failure is never caused overnight. Newton (1975) perceived that firms in financial distress passed through four stages of deterioration before declaring bankruptcy: incubation, cash shortage, financial insolvency and total insolvency. Past literatures have had many different definitions of "default." Beaver used a broad definition by defining failure as any of the following occurrences: bankruptcy, bond default, overdrawn bank account and non-payment of a preferred stock dividend. Altman (1968) defined failure as a company that had filed a bankruptcy petition under Chapter 10 of the Bankruptcy Act. In Ohlson's (1980) study, the definition is purely legalostic. The failed companys must have filed for bankruptcy in the sense of Chapter 10, Chapter 11, or some other notification indicating bankruptcy proceedings. Gilbert et al. (1990) defined default firms as firms that declared bankruptcy and firms that had negative cumulative earnings over three consecutive years. Westerfield and Jaffe (2006) stated that “Financial distress is a situation where a firm’s operating cash flows are not sufficient to satisfy current obligations and the firm is forced to take corrective action”.

Altman (1971) distinguishes between failure, insolvency and bankruptcy. Accordingly, failure is merely when the company does not earn an adequate return on risk capital and can go on doing this for years without closing down. Insolvency means the failure to make a contractually required payment by its due date, which includes a bond payment and payment on a bank loan. Such an event is considered a default regardless of how long the payment is delayed. This kind of insolvency is defined as flow-based credit risk (Ross et. al. 2005), and it is thus a technical insolvency. But insolvency in a bankruptcy sense is much more serious as it implies that the fair valuation of a firm’s assets falls below its liabilities and the company has a negative net worth. A bankruptcy should be thought of as a filing for legal protection from creditors due to financial distress. In the U.S., this would include either Chapter 11 or Chapter 7 filings. In Canada, it includes the filing under the Creditors Arrangement Act. In the U.K., it would include an Administrative order. In Japan, it includes both bankruptcy and rehabilitation. In Japan, the specific application differs by the type and the size of the company (Dwyer and Qu, 2007).

This research, following Dichev (1998) and Brockman and Turtle (2003), uses a broad definition of default that firms are de-listed because of bankruptcy or poor performance. The types of poor performance include insufficient capital or market-makers, price too low, delinquency in filing, etc.

CHAPTER 3. DATA AND METHODOLOGY

3.1. Data Collection and Analysis

The empirical investigation of this research considers a large cross-section of construction contractors. This research selects samples from Compustat Industrial file-Quarterly data (Wharton Research Data Services 2009) as well as the Center for Research in Securities Prices (CRSP) for firms on the New York Stock Exchange (NYSE), American Exchange (AMEX), and Nasdaq. This research restricts its attention to construction contractors with December fiscal year-ends by choosing firms with SIC codes between 1,500 and 1,799. Similar to the researches of Severson et al. (1994) and Russell and Zhai (1996), the sample contractors include three construction categories:

Major Group 15: Building construction, general contractors, and operative builders. The construction of buildings subsector comprises establishments involved in constructing residential, industrial, commercial, and institutional buildings.

Major Group 16: Heavy construction other than building construction contractors. The heavy and civil engineering subsector includes establishments involved in infrastructure projects. For example, water, sewer, oil, and gas pipelines; roads and bridges, power plants.

Major Group 17: Construction special trade contractors. The specialty trade contractors engage in activities such as plumbing, electrical work, masonry, carpentry, and roofing that are generally needed in the construction of all building types.

Due to the restriction of collecting firms only in the construction industry, we were able to obtain a limited sample size. Thus, the samples cover an extended time period from 1970 to 2006. The sample selection has three criteria. First, contractors that do not have financial statements for at least five years are removed from the sample. Next, data must be available in CRSP for at least six years prior to default time for the data completeness. Third, default is defined by CRSP delisting code of 550 to 585. Following Dichev (1998), Brockman and Turtle (2003), this research uses a definition of default that firms are de-listed because of bankruptcy or poor performance. The types of poor performance include insufficient capital or market-makers, price too low, delinquency in filing, etc. To clarify, the definition of default in this research indicates a default event which leads to financial problem of a construction contractor.

The researches of Severson et al. (1994) and Russell and Zhai (1996) are used as benchmarks to compare with the empirical validation results of the Merton-type models in this research. The sample design employed by Severson et al. (1994) and Russell and Zhai (1996) has been used to match a set of default firms with some multiple of healthy firms. This research also uses matched samples to compare the performance of Merton-type models and previous studies specific on the default-predicting of construction industry. Each defaulted contractor was matched with two non-defaulted contractors at the year of default. Before screening, the considered sample consists of 121 contractors. After screening, the final sample consists of 87 contractors, including 29 defaulted contractors and 58 solvent contractors. Table 3.1 shows the financial characteristics of contractors in screened samples and un-screened samples. Table 3.2 shows the number of contractors in each construction type. Table 3.3 shows the number of contractors defaulted each year, categorized by default reason. Table 3.4 shows the information of the defaulted contractors.

Table 3.1 Financial characteristics of contractors in screened samples and un-screened samples

	Screened samples		Un-screened samples (121 firms)
	Default (29 firms)	Non-default (58 firms)	
Assets (USD $M)			
Maximum	2842.200	3559.269	21364.999
Average	304.803	401.815	602.817
Minimum	3.981	8.660	1.601
Net worth (USD $M)			
Maximum	774.900	789.266	6452.900
Average	94.561	119.269	197.683
Minimum	1.177	1.067	0.062
Debt ratio			
Maximum	99.20%	99.61%	99.77%
Average	69.55%	56.06%	60.42%
Minimum	14.66%	9.10%	4.64%

Table 3.2 Number of contractors in each construction type

Type	Default	Total
Building construction	18	67
Heavy construction	4	28
Special trade construction	7	26
Total	29	121

Table 3.3 Number of contractors defaulted each year, categorized by default reason

(From 1970 to 2006)

*Default year	Bankruptcy	Poor performance
1978	1	
1983	1	
1990	2	
1991		2
1992	2	1
1995		2
1996		2
1998		1
1999	1	4
2000		1
2001		3
2003	1	1
2004		2
2005		1
2006		1
Total	8	21

Note: The years which are not presented in the default year column are those which have neither bankrupt nor poor performance samples.

Table 3.4 Information of the defaulted contractors

Ord	Code	Company's name	Defaulted year	Observed firm-years
1	80220	ABLE TELCOM HOLDING CORP	1999	1994 - 1999
2	86110	ALSTOM -ADR	2003	1998 - 2003
3	60409	AMERICAN MEDICAL BLDGS INC	1989	1978 - 1989
4	85607	ATKINSON (G F) CO/CA	1997	1985 - 1997
5	63095	BANK BUILDING &EQUIP CORP AM	1989	1973 - 1989
6	64880	CALPROP CORP	1995	1988 - 1995
7	79327	CALTON INC	2003	1988 - 2003
8	58641	CANISCO RESOURCES INC	1998	1982 - 1998
9	11694	CAPITAL PACIFIC HOLDINGS INC	2002	1988 - 2002
10	11109	CEC INDUSTRIES CORP	1994	1987 - 1994
11	82731	CHINA CONVERGENT CORP -ADR A	2000	1996 - 2000
12	81246	DUALSTA TECHNOLOGIES CORP	2000	1995 - 2000
13	31705	EDWARDS INDUSTRIES INC	1982	1974 - 1982
14	11901	ENTRX CORP	2004	1988 - 2004
15	48952	ERNST (E.C.) INC	1977	1973 - 1977
16	62586	FAIRFIELD COMMUNITIES INC	1991	1988 - 1991
17	80106	INCO HOMES CORP	1998	1993 - 1998
18	80106	INSITUFORM GROUP LTD -ORD	1991	1986 - 1991
19	89106	INTL AMERICAN HOMES INC	1990	1985 - 1990
20	11338	KIMMINS CORP	1998	1987 - 1998
21	55079	MORRISON KNUDSEN CORP OLD	1995	1972 - 1995
22	10036	NEUROTECH DEVELOPMENT CORP	1990	1986 - 1990
23	83165	OAK RIDGE CAPITAL GROUP INC	2002	1996 - 2002
24	76432	RYAN MURPHY INC	1994	1990 - 1994
25	79423	SUNDANCE HOMES INC	1998	1993 - 1998
26	85882	TOUSA INC	2006	1998 - 2006
27	53997	VERIT INDUSTRIES	1991	1972 - 1991
28	77074	WILLIAM LYON HOMES	2005	1991 - 2005
29	77831	XXSYS TECHNOLOGIES INC	1998	1992 - 1998

Because default are relatively rare events, Zmijewski (1984) argued that this sample-matching method produces choice-based biases and sample selection biases. Unless one builds a model based on the entire population, the estimated coefficients will be biased, and the resulting predictions will be unreliable. To avoid these biases, many recent studies use all available firm-quarters or firm-years during the sample period to construct the default prediction models, thereby improving the accuracy of the coefficient estimates and increasing the prediction power of the models relative to prior studies (e.g., Brockman and Turtle, 2003; Bharath and Shumway, 2004; Hillegeist et al., 2004; Reisz and Perlich, 2004; Gharghori et al. 2006, Agarwal and Taffer, 2008). There are no researchers, to our knowledge, who use available firm-quarters or firm-years sample on construction contractor default prediction.

To avoid sampling error, this research uses every firm-year for which data are available during 1970 to 2006 to empirically explore the performance of different models mentioned in this research. The final combined sample of solvent and defaulted contractors consists of 1,484 firm-year observations representing 121 individual contractors (includes 29 defaulted contractors and 92 non-defaulted contractors). Table 3.5 presents the basic descriptive summary statistics for the model input variables, including means, medians, standard deviations, minimums, and maximums for the 1,484 available observations across firm-years.

Table 3.5 Summary statistics for the contractor sample

	Mean	Median	Std Dev.	Min.	Max.
V_A (\$M)	774.89	169.30	2,020.22	0.89	25,503.59
V_E (\$M)	361.45	58.94	1,059.95	0.32	11372.55
D (\$M)	413.43	88.30	1,218,18	0.10	22,979.89
D/V_A	0.56	0.59	0.24	0.00	1
σ	0.32	0.26	0.23	0.06	1.65

3.2. Research Methodology

This section illustrates the basic theory of market-based models, and the validation method of the predictive performance of market-based models and accounting-based models mentioned in this research. Several adopted models and validation method in this study are described as below.

3.2.1. Accounting-based Model

Along with Jaselskis and Ashley (1991), Russell and Jaselskis (1992), Severson et al. (1994) have successfully built their logistic regression models to predict contractor performance. This paper also employs the logistic regression model as the representative of our accounting-based model and a comparison benchmark to other models.

The logistic regression model is defined as a statistical modeling technique seeking the relationship between a binary dependent variable and other selected independent variables (Koo and Ariaratnam, 2006). Let $\boldsymbol{y}_i \in \{0,1\}$ $y_i \in \{0,1\}$ for all i = 1 to n, logistic regression model estimates the probability that the label is 1 for a given example $\boldsymbol{X}$ using the model (Bellotti and Crook, 2009):

$$DP = (Y = 1 \mid Explanatory\ variables) = \frac{1}{1+e^{-z}} \tag{3-1}$$

where DP is the default probability.

$$Z=\beta_0 + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + \beta_4 X_4 + \ldots + \beta_k X_k$$

X_k is the k^th explanatory variable. β_0 is the intercept of the regression; β_k is the coefficient of the k^th explanatory variable. Coefficient $\boldsymbol{\beta}$ can be estimated using the maximum likelihood procedure to maximize the log-likelihood function,

$$L(\beta)=\sum_{i=1}^{n} y_i \log DP_i + (1- y_i)\log(1- DP_i) \tag{3-2}$$

where DP_i is default probability of i^{th} observation

$y_i=1$, if the i^{th} observation goes into default and $y_i=0$, if not.

3.2.2. The Merton-type Models

This research uses three Merton-type models to predict construction default: the original Black and Scholes (1973) and Merton (1973, 1974) contingent claims model (the BSM model), the refined BSM model by Crosbie and Bohn (2003), and the naïve BSM model by Bharath and Shumway (2008). According to Merton (1974), the equity of a levered firm can be viewed as a European call option on the market value of the firm's assets with the book value of total liabilities as the strike price, because equity holders are the residual claimants to the firm's assets and are only subject to limited liability when the firm is bankrupt. The payoffs to equity holders are the same as for a call option. If the market value of assets is greater than the level of liabilities at maturity, then equity holders exercise their option on the firm's assets and the firm continues to exist. If, on the contrary, the market value of assets is less than the level of liabilities, equity holders do not exercise their option on the firm's assets and the firm defaults. Figure 3.1 shows the concept of the Merton-type credit model.

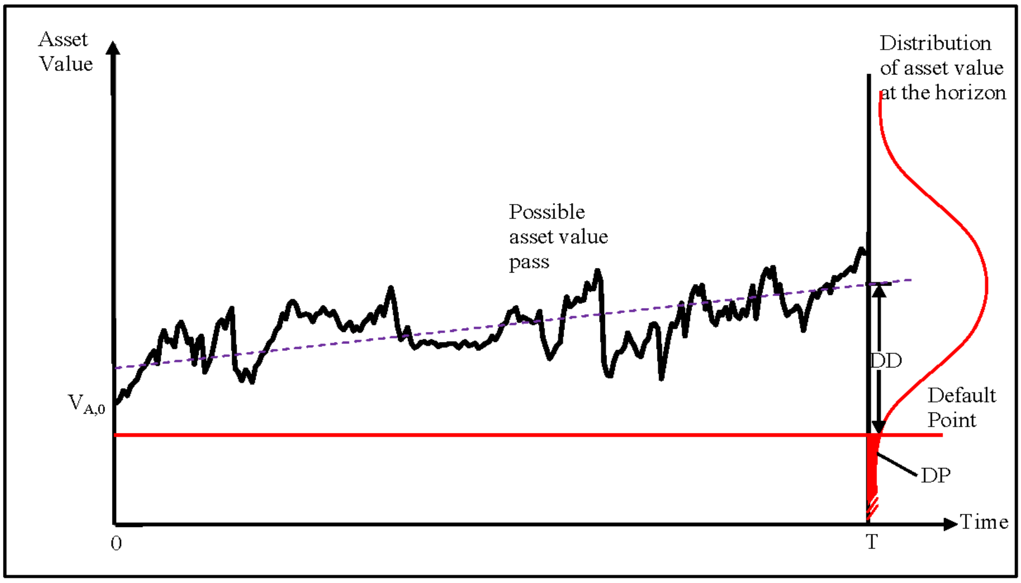

Figure 3.1 Concept of the Merton-type credit model

In the Black-Scholes-Merton (BSM) framework (Black and Scholes 1973; Merton 1973,1974), the market value of a firm's assets follows a geometric Brownian motion (GBM) of the equation, Eq.(3-3):

$$dV_A = \mu V_A dt + \sigma_A V_A dW \tag{3-3}$$

where V_A is the firm's assets value, with an instantaneous drift μ, and an instantaneous volatility σ_A. W is a standard Wiener process.

The equation for valuing the market value of equity, V_E, as a European call option on the value of the firm's assets is given by the Black-Scholes (1973) equation for call options shown in Eq.(3-4).

$$V_E = V_A N(d_1) - Xe^{-rT} N(d_2) \tag{3-4}$$

where

$$d_1 = \frac{\ln(V_A / X) + (r + \frac{1}{2}\sigma_A{}^2)T}{\sigma_A \sqrt{T}}, d_2 = d_1 - \sigma_A \sqrt{T}$$

X is the book value of liabilities maturing at time T, r is the risk-free rate, and N is the cumulative density function of the standard normal distribution.

It is straightforward to show that equity and asset volatility are related by the Eq.(3-5):

$$\sigma_E = \frac{V_A}{V_E} \Delta \sigma_A \tag{3-5}$$

where Δ is the hedge ratio, $N(d_1)$.

Observable inputs for the Black-Scholes equation (3-4) are V_E, X, and r. This research sets r as Treasury bill rate, V_E as the daily market capitalization (equal to share price times the number of outstanding shares), and X as the book value of total liabilities. The asset value and volatility implied by the equity value, equity volatility, and liabilities, are calculated by solving the call price and hedge equations, Eq.(3-4) and Eq.(3-5), simultaneously.

Crosbie and Bohn (2003) found that general firms do not default when their asset value reaches the book value of their total liabilities. The long-term nature of some of their liabilities eases the payment pressure of these firms. They found that the default threshold, the asset value at which the firm will default, generally lies somewhere between total liabilities and current, or short-term, liabilities. Following Crosbie and Bohn (2003) and Vassalou and Xing (2004), the second BSM model used in this paper defines the strike price X as the sum of short-term liabilities and one-half of long-term liabilities. Furthermore, Crosbie and Bohn (2003) suggested that the market leverage moves around far too much for Eq.(3-5) to provide reasonable results. Worse yet, the model bias the probabilities in precisely the wrong direction. For example, if the market leverage is decreasing quickly then Eq.(3-5) will tend to overestimate the asset volatility and thus the default probability will be overstated as the firm's credit risk improves. Conversely, if the market leverage is increasing rapidly then Eq.(3-5) will underestimate the asset volatility and thus the default probability will be understated as the firm's credit risk deteriorates. The net result is that default probabilities calculated in this manner provide little discriminatory power. To resolve this problem, they adopted an iterative procedure to calculate σ_A. The procedure uses daily V_E from the past 12 months to obtain an estimate of the volatility of equity σ_E which becomes an initial estimate of σ_A. Using this initial estimate of σ_A, one can solve the Black-Scholes equation to obtain daily estimates of V_A and then compute the standard deviation of those V_A's, which becomes the new estimate of σ_A, for the next iteration. This procedure is repeated until the value of σ_A converges to 10E-4. Once the converged value of σ_A is obtained, the daily V_A can be solved through Eq.(3-4).

Under the BSM model, the default probability (DP) is the probability that the market value of a firm's assets will be less than the face value of the firm's liabilities (i.e., $V_A < X$) at time T, which can be expressed as Eq.(3-6):

$$DP_t = \Pr(V_{A,t+T} \leq X_t \,|\, V_{A,t}) = \Pr(\ln(V_{A,t+T}) \leq \ln(X_t) \,|\, V_{A,t}) \tag{3-6}$$

Since the change in the value of the firm's assets follows the GBM of Eq.(3-2), the value of the assets at any time t is as Eq.(3-7):

$$\ln(V_{A,t+T}) = \ln(V_{A,t}) + (\mu - \frac{\sigma_A^{\ 2}}{2})T + \sigma_A\sqrt{T}\varepsilon_{t+T} \tag{3-7}$$

$$\varepsilon_{t+T} = \frac{W(t+T) - W(t)}{\sqrt{T}}, \text{ and } \varepsilon_{t+T} \sim N(0,1) \tag{3-8}$$

Therefore, the default probability equation can be rewritten as Eq.(3-9):

$$DP_t = \Pr\left(\ln(V_{A,t}) - \ln(X_t) + (\mu - \frac{\sigma_A^{\ 2}}{2})T + \sigma_A\sqrt{T}\varepsilon_{t+T} \leq 0 \right)$$

$$DP_t = \Pr\left(-\frac{\ln(\frac{V_{A,t}}{X_t}) + (\mu - \frac{\sigma_A^{\ 2}}{2})T}{\sigma_A\sqrt{T}} \geq \varepsilon_{t+T} \right) \tag{3-9}$$

The distance to default (*DD*) is defined as Eq. (3-10):

$$DD_t = \frac{\ln(V_{A,t}/X) + (\mu - \frac{1}{2}\sigma_A^{\ 2})T}{\sigma_A\sqrt{T}} \tag{3-10}$$

The *DD* indirectly indicates a firm’s default risk, the higher *DD*, the lower default risk. The default probability can be computed directly from the *DD* if the probability distribution of the assets is known, or, equivalently, if the default rate for a given level of distance-to-default is known. The BSM model assumes that the firm’s asset returns is Normally distributed, and as a result the default probability can be defined in terms of the cumulative Normal distribution as Eq.(3-11):

$$DP = N(-DD) = N\left(-\frac{\ln(V_{A,t}/X) + (\mu - \frac{1}{2}\sigma_A^{\ 2})T}{\sigma_A\sqrt{T}} \right) \tag{3-11}$$

Note that the value of the call option in Eq.(3-4) is derived under the assumption of risk-neutrality where all assets are expected to grow at the risk-free rate. However, the probability of bankruptcy depends upon the actual distribution of future asset values, which is a function of the actual return on assets, μ. Once daily values of V_A are estimated, we can compute the drift μ, by calculating the mean of the change in ln V_A. Our daily estimate of μ is the daily change in V_A given by ln ($V_{A,t}/V_{A,t-1}$). The annualized μ is therefore the sum of the daily μ's for the past year. In many cases, the actual return on assets, μ, is negative. Since expected returns cannot be negative, Hillegeist et al. (2004) set expected growth rate equal to the risk-free rate in these cases. μ_t is calculated as Eq.(3-12):

$$\mu_t = \max\left[\frac{V_{A,t} - V_{A,t-1}}{V_{A,t-1}}, r\right] \tag{3-12}$$

The model of Bharath and Shumway (2008) differed from BSM model and Crosbie and Bohn (2003) in that V_A and σ_A are estimated for computations of probability of failure using equation (3-11). Bharath and Shumway (2008) constructed a simple alternative model that does not require simultaneously solving equations (3-4) and (3-5) numerically or implementing the iterative procedure for values of V_A and σ_A. They approximated future debt payment, X, as face value of all liabilities. Thus,

$$V_A = V_E + X \tag{3-13}$$

Since firms that are close to default have very risky debt, and the risk of their debt is correlated with their equity risk, they approximate the volatility of each firm's debt as Eq.(3-14):

$$\sigma_D = 0.05 + 0.25 * \sigma_E \tag{3-14}$$

Bharath and Shumway (2008) included five percentage points in this term to represent term structure volatility and also included twenty-five percent times equity volatility to allow for volatility associated with default risk. This gives an approximation to the total volatility of the firm's assets as Eq.(3-15):

$$\sigma_A = \frac{V_E}{V_A}\sigma_E + \frac{X}{V_A}\sigma_D \tag{3-15}$$

Bharath and Shumway (2008) also simplified the way to estimate expected return of assets, μ. They used the previous year stock return bounded between the risk free rate and 100% as a proxy of expected return of the firm's assets. Agarwal and Taffer (2008) argued that using past returns as a proxy for expected returns is problematic as it is not true in reality.

The estimation of the three Merton-type credit models used in this research is summarized as the follows:

BSM: V_A and σ_A are estimated simultaneously by solving the call option Eq.(3-4) and hedge Eq.(3-5), and expected return is estimated from Eq.(3-12) bounded between the risk free rate and 100%. The strike price, X, is set equal to the book value of total liabilities.

CB: V_A and σ_A are estimated by an iterative procedure and expected return is estimated from Eq.(3-12) bounded between the risk free rate and 100%. The strike price, X, is defined as the sum of short-term liabilities and one-half of long-term liabilities (Crosbie and Bohn 2003).

BS: V_A and σ_A are estimated using Eq.(3-13) to (3-15). The previous year's stock return bounded between the risk free rate and 100% is used as a proxy of expected return of the firm's assets. The strike price, X, is set equal to the book value of total liabilities. (Bharath and Shumway 2008).

Figure 3.2 is a summarization of three Merton-type models.

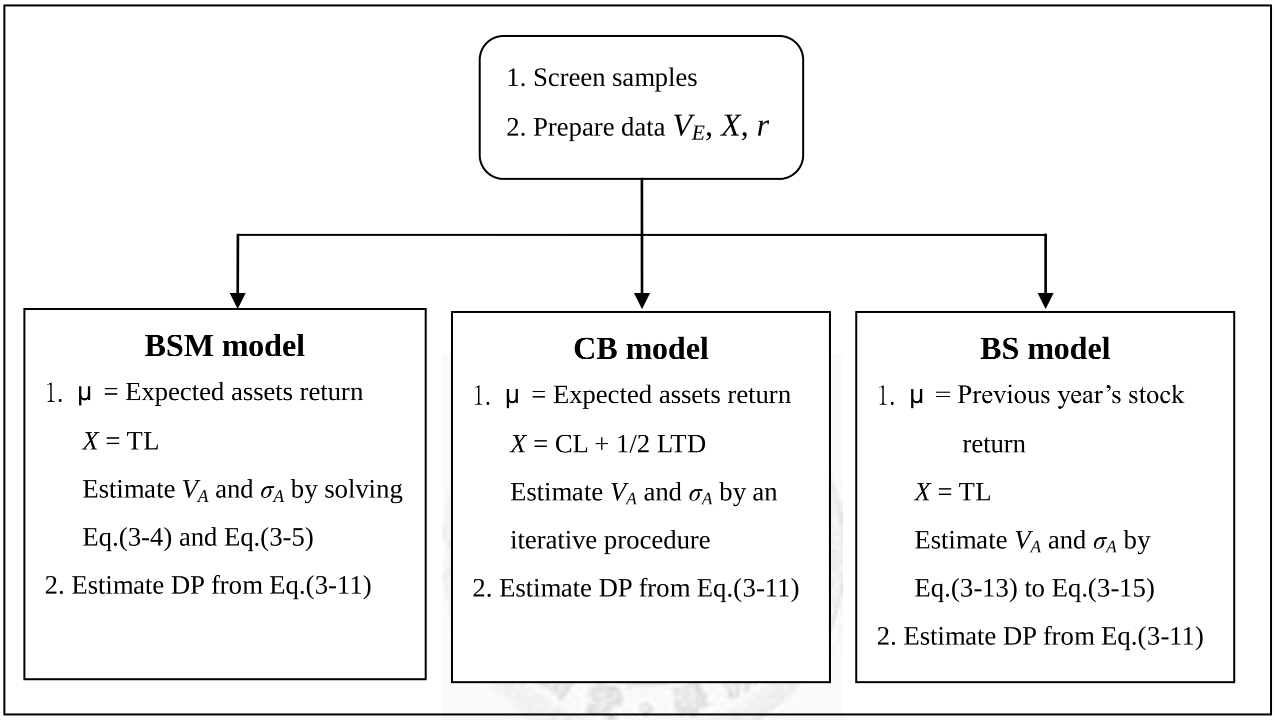

Figure 3.2 Analysis flowchart of Merton-type models

3.2.3. The barrier option (DOC) model

One of the implications of modeling equity as a standard call option is that default can only occur at the maturity of the option. This implies that a firm can only default when debt repayments are due. In reality, the existence of debt covenants implies that default can occur at any time. This is the main argument for modeling corporate equity as a barrier option (Gharghori et. al. 2006). The primary feature distinguishing a barrier call option from a standard call option is the existence of a barrier, which causes the termination of the option whenever the barrier is hit at any time before maturity. Figure

3.3 shows the concept of the barrier option credit model.

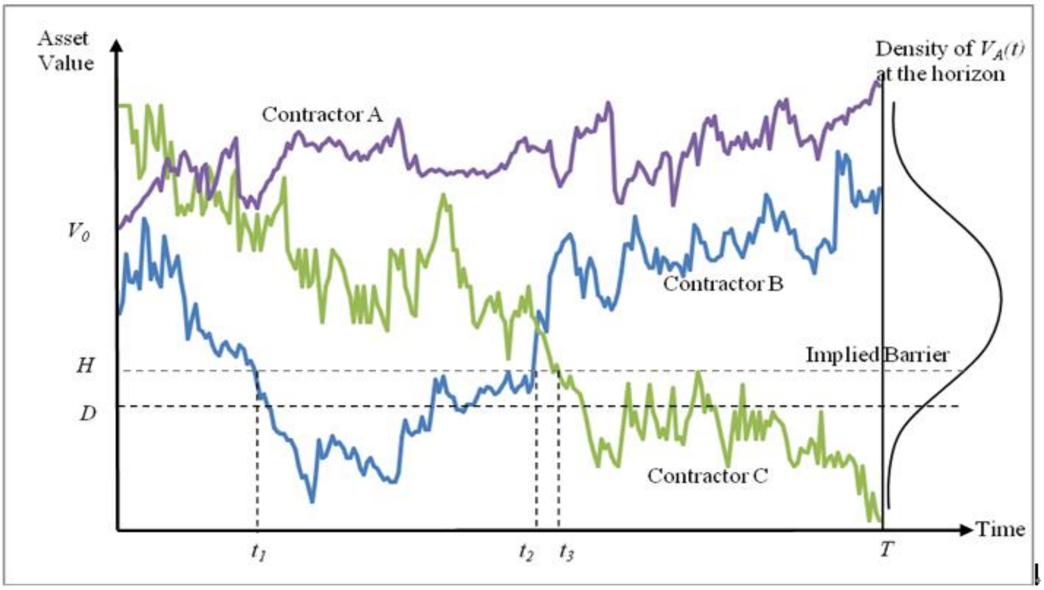

Figure 3.3 Concept of the barrier option credit model

When using barrier option model to measure a contractor’s default risk, the contractor is modeled as an entity fully financed with a share of equity and a single zero-coupon bond, and assume both of which are traded on a perfect financial market (no arbitrage opportunities, no taxes or transaction costs, and continuous trading) (Reisz and Perlich, 2007). The DOC (down-and-out call) barrier option framework explicitly recognizes the consequences of bankruptcy whenever asset values fall below a pre-specified barrier value. Asset ownership is transferred from shareholders to creditors, and any subsequent rise in asset values will accrue to creditors since equity holders’ residual claims have been permanently extinguished. In this way, equity value behaves as a DOC option on the underlying assets of the contractor. Bondholders behaves as owing a portfolio of risk-free debt, a short put option on contractor’s assets, and a long down and-in call (DIC) option on contractor’s assets. The value of a DOC option is then the difference between a European SC (standard call option) and a DIC option (Brockman and Turtle, 2003). In this context, the market value of a contractor's equity, V_E can be written as Eq.(3-16)

$$V_E = DOC = SC - DIC \tag{3-16}$$

The formula of SC is the famous Black-Scholes equation as Eq.(3-17). When $D \geq H$, the close form formula of DIC had been derived by Reiner and Rubinstein (1991) as Eq.(3-18).

$$SC = V_A N(a_1) - De^{-rT} N(a_1 - \sigma\sqrt{T}) \tag{3-17}$$

$$DIC = V_A \left(\frac{H}{V_A}\right)^{2\eta} N(b_1) - De^{-rT} \left(\frac{H}{V_A}\right)^{2\eta-2} N(b_1 - \sigma\sqrt{T}) \tag{3-18}$$

where

$$a_1 = \frac{\ln(\frac{V_A}{D}) + (r + \frac{\sigma^2}{2})T}{\sigma\sqrt{T}}, \quad b_1 = \frac{\ln(\frac{H^2}{V_A D}) + (r + \frac{\sigma^2}{2})T}{\sigma\sqrt{T}}, \quad \eta = (\frac{r}{\sigma^2} + \frac{1}{2})$$

V_A is the market value of contractor's assets; D is the debt payment due at maturity; r is the continuously compounded risk-free rate of return; T is the time until the option expires. σ is the annual volatility of a contractor's assets; $N(x)$ is the standard normal cumulative distribution function evaluated at x; H is the value of the contractor's assets that triggers default (this is the barrier or knock-out value of the contractor).

By substituting Eq.(3-17) and Eq.(3-18) into Eq.(3-16), then the DOC formula is given as Eq.(3-19):

$$V_E = V_A N(a_1) - De^{-rT} N(a_1 - \sigma\sqrt{T}) - \left[V_A \left(\frac{H}{V_A} \right)^{2\eta} N(b_1) - De^{-rT} \left(\frac{H}{V_A} \right)^{2\eta-2} N(b_1 - \sigma\sqrt{T}) \right] \quad (3\text{-}19)$$

Similar to above, the DOC formula when $D < H$ is derived as Eq.(3-20):

$$V_E = V_A N(a_2) - De^{-rT} N(a_2 - \sigma\sqrt{T}) - \left[V_A \left(\frac{H}{V_A} \right)^{2\eta} N(b_2) - De^{-rT} \left(\frac{H}{V_A} \right)^{2\eta-2} N(b_2 - \sigma\sqrt{T}) \right] \quad (3\text{-}20)$$

where

$$a_2 = \frac{\ln(\frac{V_A}{H}) + (r + \frac{\sigma^2}{2})T}{\sigma\sqrt{T}}, \quad b_2 = \frac{\ln(\frac{H}{V_A}) + (r + \frac{\sigma^2}{2})T}{\sigma\sqrt{T}}, \quad \eta = (\frac{r}{\sigma^2} + \frac{1}{2})$$

Inputs for Eq.(3-19) and Eq.(3-20) are V_E, V_A, D, r, σ, and T. Robustness tests for Brockman and Turtle (2003) show that barrier estimates are not particularly sensitive to lifespan (T) assumptions. When applying the model to contractor evaluation, the T can be set as the average production duration of a construction project, which is usually between one to two years. This study sets T as one year, in order to compare with the results of Reisz and Perlich (2007), based on the data set of all industries except the construction industry. Since Treasury bill rate is commonly used as a proxy of risk-free rate in literature, r is set as a one-year Treasury bill rate; This paper uses the average equity and average asset value of Dec as V_E, and V_A, and employs annual volatility of asset return in the previous year as σ to measure the default probabilities of contractors in the following year. To calculate V_E, V_A, and σ as inputs of Eq.(3-19) and Eq.(3-20), the researchers firstly calculate the daily V_E, V_A, and daily asset return of each trading day in previous year. Following Brockman and Turtle (2003), daily V_A is estimated as the daily market value of equity plus the quarter book value of total debt (BVD), daily

V_E is equal to share price times the number of outstanding shares of each trading day. Once daily V_A are estimated, the estimate of daily asset return is the change of sequent trading days in V_A given by ln ($V_{A,t}/V_{A,t-1}$). The annual volatility of a contractor's assets, σ, is the annualized percent standard deviation of daily asset returns and is estimated from the previous year's asset return data for each day. Then all inputs of Eq.(3-19) and Eq.(3-20) are known except for H, and we can solve for H. For example, consider a contractor in the empirical sample, which defaulted in Sep. 1992 and had an implied barrier of 46.67 ($M) at the end of 1991. The process of calculating the implied barrier, H, is elaborated as follow:

Step 1: calculate the daily value and daily return of V_A of each traded day during 1991. Table 3.6 illustrates the relevant values and calculations for them. Briefly, only the results of a week during Dec. is shown in Table 3.6.

Table 3.6 Calculation of daily V_E, V_A and daily return of V_A in barrier option model

Date	Stock Price ($)	Shares Outstanding	V_E = Stock Price × Shares Outstanding ($M)	Debt ($M)	$V_A = V_E$ + Debt ($M)	Daily return of V_A $ln(V_{A,t}/V_{A,t-1})$
2/12	0.2500	12535000	3.13	45.43	48.56	-1.6%
3/12	0.3125	12535000	3.92	45.43	49.35	1.6%
4/12	0.3000	12535000	3.76	45.43	49.19	-0.3%
5/12	0.2500	12535000	3.13	45.43	48.56	0%
6/12	0.3750	12535000	4.70	45.43	50.13	3.18 %

Step2: calculate equity value, V_E, asset value, V_A, and asset volatility, σ, for solving Eq.(3-19) and Eq.(3-20). This paper uses average daily V_E and V_A of Dec. as inputs of V_E and V_A, that is V_E = 4.33 ($M), V_A = 49.76 ($M). The asset volatility, σ = 24.91%, is the annualized percent standard deviation of asset returns and is estimated from the

daily asset return data of each traded day of 1991. Table 3.7 summarizes all the input variables for solving Eq.(19) and Eq.(20).

Table 3.7 Summary of Input Variables in barrier option model

Variable	Value	Notes
V_E	4.33 ($M)	Stock Price × Shares Outstanding
D	45.43($M)	Book value of total debt in the end of Dec.,
V_A	49.76 ($M)	$V_E + D$
σ	24.91 %	the annualized percent standard deviation of asset returns
r	4.37%	One-year Treasury bill rate
T	1 year	

Step 3: the implied barrier solved from Eq.(3-19) and Eq.(3-20) by numerical analysis is, H = 46.67 ($M).

Equity is knocked out by bankruptcy when the asset market value V_A falls below the barrier H. To apply the down-and-out barrier call option to the problem of construction contractor default prediction, the implied failure probability (IFP) of contractors is calculated from barrier option model. Eq.(3-21) implies a failure probability over the interval from 0 to T. Continuing with our example, the corresponding IFP from Eq.(3-21) is 84.43%, means that this contractor has 84.43% probability of default in following one year.

$$IFP = 1 - N(a_1) + \exp\left(2\left(r - \frac{\sigma^2}{2}\right)\ln\left(\frac{H}{V_A}\right)\Big/\sigma^2\right)N(b_1), \quad for \quad D \geq H$$

$$or \qquad (3\text{-}21)$$

$$1 - N(a_2) + \exp\left(2\left(r - \frac{\sigma^2}{2}\right)\ln\left(\frac{H}{V_A}\right)\Big/\sigma^2\right)N(b_2), \quad for \quad D < H$$

Eq.(3-21) estimates only a risk-neutral probability of default, but this still provides a meaningful ranking of contractors according to their possibility to failure. Similar to Cox and Miller (1965), Ingersoll (1987), Rich (1994) and Brockman and Turtle (2003), for simplicity, this paper employs risk-neutral (i.e. setting r as one-year Treasury bill rate) probabilities of default to evaluate the discriminatory power of the barrier option model. Discriminatory power and calibration are two criteria to measure the performance of default prediction models. Discriminatory power measures how well a model rank firms according to their risk. The calibration of a model assesses whether the predicted probabilities indeed correspond to actual default frequencies. It is generally easy to recalibrate a powerful model to reflect expected default frequencies, whereas improvements in model power are very hard to achieve. Thus, calibration is not relevant for tests of predictive ability of models (Stein 2005,2007).

3.3. Model Evaluation Approach

This paper employs discriminatory power to assess which model has the best predictive performance for contractor default risk. The discriminatory power measures to what extent the model can differentiate firms that are more likely to default from firms that are less likely to default. In a perfect discriminating model, all firms that actually default are assigned a larger probability of default than any surviving firm. The Receiver Operating Characteristics curve (ROC curve, Figure 3.4) is widely used in the field of medicine for testing the efficacy of various treatments and diagnostic techniques. It is also a popular technique for assessing discriminatory power of various credit scoring and rating models (Stein 2007; Agarwal and Taffler 2008).

Many prior studies in the business default prediction literature relied on prediction-oriented tests to distinguish between alternative statistical models. The shortcoming of the prediction-oriented test is that it produces only two ratings (good or bad), which are only valid for a specific model cut-off point, and leads to a dichotomous decision. However, a decision-maker of contract awarding and his stakeholders will typically make decisions by ranking contractors according to their default probabilities. For example, project owners choose the most competent construction contractor according to the ranking of the default probability of the contractors. Lending institutions determine which interest rate to charge on a specific construction loan according to the estimated default probability of the contractor. Surety underwriters charge different premiums to different contract surety bonds according to the default probability of the contractors they underwrite. Furthermore, the prediction-oriented test typically assumes that the costs of each type of classification error are equal. This does not hold true in the real world, where Type I errors are substantially more costly than Type II errors. For example, the costs of awarding contracts to an impending contractor who might fail will typically be much larger than the costs of rejecting a healthy contractor. Since prediction-oriented testing does not allow for these continuous choices, this study uses the discriminatory power to evaluate the performance of a default model. The discriminatory power measures to what extent the model can differentiate firms that are more likely to default compared to firms that are less likely to default. With a perfect model, all firms that actually default are assigned a larger probability of default than any surviving firm. The ROC curve is a useful tool for assessing discriminatory power of the credit scoring model.

ROC curve is constructed by scoring all credits, arranging the non-defaults from riskiest to safest on the x axis, and then plotting the percentage of defaults excluded at each level on the *y* axis. So the *y* axis is formed by associating every score on the *x* axis with the cumulative percentage of defaults with a score equal to or worse than that score in the test data. In other words, ROC curve plots the Type II error against one minus the Type I error. In the case of default prediction, it describes the percentage of non-defaulting firms that must be inadvertently denied credit (Type II) in order to avoid lending to a specific percentage of defaulting firms (1-Type I) when using a specific default model (Stein 2007). ROC curve generalizes different relative performances across all possible cut-off points associated with the costs of each type of classification error, and it provides a form of cost-benefit analysis for decision-makers.

The ROC curve of an entirely random prediction corresponds to the main diagonal whereas a perfect model will have a ROC curve that goes straight up from (0,0) to (0,100) and then across to (100,100). Given two models, the one with better ranking will display a ROC curve that is further to the top left than the other. The area under the curve (AUC) is commonly used as a summary statistic for the quality of a ranking. A model with perfect ranking has an AUC of one whereas a model with constant or random predictions has an AUC of 0.5 (Reisz and Perlich 2007). The general rule is: If AUC=0.5, this suggests no discrimination; if 0.7≦AUC<0.8, this is considered as an acceptable discrimination; if 0.8≦AUC<0.9, this is considered as an excellent discrimination; if AUC≧0.9, this is considered as an outstanding discrimination (Hosmer and Lemeshow 2000). Accuracy ratio (AR) is a statistic derived from a ROC curve (shown in Eq.(3-22)). The AR measures a model's ability to rank defaulted and non-defaulted firms correctly. Engelmann et al. (2003) showed that the accuracy ratio is just a linear transformation of the area under the ROC curve, i.e.:

$$Accuracy\ ratio = 2 * \left(AUC - 0.50\right) \qquad (3\text{-}22)$$

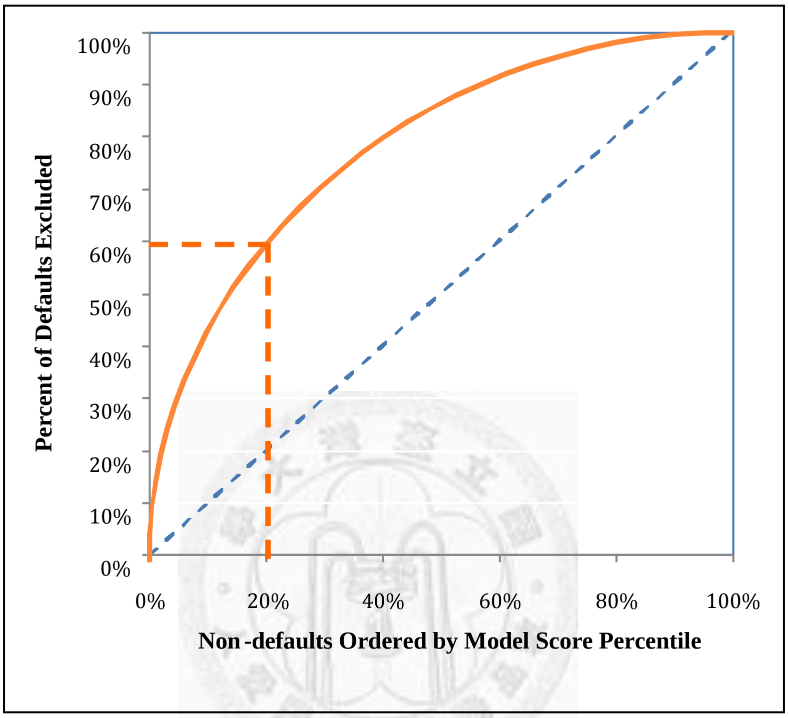

Figure 3.4 Concept of a Receiver Operating Characteristic (ROC) curves

CHAPTER 4. ACCOUNTING-BASED MODEL DEVELOPMENT

4.1. Accounting-based Model Development

The traditional accounting-based ratio model is provided as a benchmark to evaluate the forecasting ability of the other models mentioned in this research when applied to the construction industry. Beaver (1966) and Altman (1968) are pioneers of using financial ratio models to discriminate between observed defaulters and non-defaulters. Beaver's (1966) univariate ratio analysis was improved and extended by Altman's (1968) multiple discriminant analysis (MDA). Ohlson (1980) is the first scholar to apply the Logistic Regression model to business bankruptcy prediction research. This modeling approach provides the relationship between binary response probability and explanatory variables. It uses the logistical cumulative function to predict default. Jaselskis and Ashley (1991), Russell and Jaselskis (1992), Severson et al. (1994) have successfully built logit models to predict contractor performance. This research also employs logistic regression to create a accounting-based contractor default prediction model.

4.1.1. Financial Variable Selection

The first stage in deriving an accounting-based model is selecting the accounting ratios or financial variables related to the contractor default risk. Following Chin (2009), the ratios or variables are selected based on a review of the prior literatures that specified on the construction industry, as follows:

(1) Mason and Harris (1979) Proceedings, Institution of Civil Engineering

(2) Kangari, Farid and Elgharib (1992), Journal of CEM

(3) Severson, Jaselskis and Russell (1993), Journal of CEM

(4) Langford, Iyagba and Komba (1993), Journal of CME

(5) Severson, Russell and Jaselskis (1994), Journal of CEM

(6) Abidali and Harris (1995), Journal of CME

(7) Russell and Zhai (1996), Journal of CEM

(8) Kangari and Bakheet (2001), Journal of CEM

(9) Halpin (1985), John Wiley & Sons Inc.

Table 4.1 summarizes the financial variables used by these references, which can be classified into four categories, that is, liquidity, leverage, activity, and profitability. Liquidity measure a company's ability to meet its short-term obligations; Leverage measure what extent a company has been financed by debt; Activity ratios measure how effectively a company has been using its resources; Profitability ratios measure management's overall ability in generating "profits." Numbers in the parenthesis are corresponding to the reference above, which represents the variables was used by these researches.

Table 4.1 Summary of variables used in prior literatures (Chin 2009)

Category	**Variable**	**Used in research**
Liquidity	Current Liabilities / Current Assets	[1]
	Current Ratio	[2], [4], [8], [9]
	Quick Ratio	[4], [9]
	Total Long-term Debt / Sales	[3]
	Current Liabilities / Sales	[5]
	Short-term Loans / EBIT	[6]
	Short-term Loan Trend	[6]
	Net Working Capital / Total Assets	[4], [7]
	Current Assets / Net Assets	[6]
	Net Working Capital / Backlog	[8]
	Fixed Assets to Net Worth	[8], [9]
Leverage	Total Liabilities / Net Worth	[2], [8], [9]
	Retained Earnings / Sales	[3], [5]
	Net Worth / Fixed Assets	[4]
	Net Worth / Total Liabilities	[4]
	Net Worth / Total Assets	[7]
	Net Worth / Backlog	[8]
	Debt Ratio	[9]
	Time Interest Earned	[9]
Activity	Debtors / Creditors	[1]
	Days Debtors	[1]
	Creditors Trend	[1]
	Total Assets / Revenues	[2]
	Revenues / Net Working Capital	[2], [9]
	Account Receivable Turnover	[3], [8], [9]
	Account Payable Turnover	[3], [8]
	Underbillings	[3]
	Cost of Sales	[3]
	Underbillings / Sales	[5]
	Sales / Net Assets	[6]
	Sales / Net Worth	[8], [9]
	Turnover of Total Assets	[9]
	Quality of Inventory	[9]
	Revenues to Fixed Assets	[9]

Table 4.1 Summary of variables used in prior literatures (cont'd)

Category	Variable	Used in research
Profitablitity	EBIT / Net Assets	[1]
	EBIT / Net Capital Employed	[1]
	ROA	[2], [9]
	ROE	[2], [4], [8], [9]
	Gross Profit	[3]
	ROS	[5], [8], [9]
	EAIT / Net Capital Employed	[6]
	Tax Trend	[6]
	EAIT Trend	[6]
	Gross Profit / Total Assets	[7]
	Gross Profit / Sales	[8]
	Profit to Net Working Capital	[9]

The variables were screened for further developing default-predicting model based on three criteria. First, the variable has been used by more than two references. Second, the variable must be intuitively consistent with the financial characteristics of construction industry. Third, all of these variables have a predicted relationship with contractor default risk. As a result, 20 variables are chosen and shown in Table 4.2. These variables are defined as R1, R2, R3...... to R20, and their definition were given in Table 4.3. The statistical characteristics of these variables are shown in Table 4.4.

Table 4.2 Variables chosen for further research

Liquidity	Leverage	Activity	Profitability
1. Current Ratio	6.Total Liabilities to Net Worth	10. Revenues to Net Working Capital	17. ROA
2. Quick Ratio	7.Retained Earnings to Sales	11. Accounts Receivable Turnover	18. ROE
3. Net Working Capital to Total Assets	8. Debt Ratio	12. Accounts Payable Turnover	19. ROS
4.Current Assets to Net Assets	9.Times Interest Earned	13. Sales to Net Worth	20. Profits to Net Working Capital
5. Fixed Assets to Net Worth		14. Quality of Inventory	
		15. Turnover of Total Assets	
		16. Revenues to Fixed Assets	

Table 4.3 Definition of financial variables

	Financial Variables	Definition
R1	Current Ratio	Current Assets / Current Liabilities
R2	Quick Ratio	(Current Assets – Inventories) / Current Liabilities
R3	Net Working Capital to Total Assets	(Current Assets – Current Liabilities) / Total Assets
R4	Current Assets to Net Assets	Current Assets / (Total Assets – Current Liabilities)
R5	Fixed Assets to Net Worth	Fixed Assets / Net Worth
R6	Total Liabilities to Net Worth	Total Liabilities / Net Worth
R7	Retained Earnings to Sales	Retained Earnings / Net Sales
R8	Debt Ratio	Total Liabilities / Total Assets
R9	Times Interest Earned	Earnings Before Interest and Taxes / Interest Expense
R10	Revenues to Net Working Capital	Net Sales / (Average Current Assets – Average Current Liabilities)
R11	Accounts Receivable Turnover	Net Sales / Average Receivables
R12	Accounts Payable Turnover	Net Sales / Average Payables
R13	Sales to Net Worth	Net Sales / Average Net Worth
R14	Quality of Inventory	Cost of Sales / Average Inventories
R15	Turnover of Total Assets	Net Sales / Average Total Assets
R16	Revenues to Fixed Assets	Net Sales / Average Fixed Assets
R17	ROA	(Net Profit After Interest and Taxes + Interest Expense) / Total Assets
R18	ROE	Net Profit After Interest and Taxes / Net Worth
R19	ROS	Net Profit After Interest and Taxes / Net Sales
R20	Profits to Net Working Capital	Net Profit After Interest and Taxes / (Current Assets – Current Liabilities)

Table 4.4 The statistical characteristics of the selected financial variables (Chin 2009)

	Financial variables	**Mean**	**Standard deviation**	**Min**	**Max**
R1	Current ratio	3.414	5.047	0.071	98.294
R2	Quick ratio	1.396	1.648	0.026	26.413
R3	Net working capital to total asset	0.357	0.260	-0.724	0.979
R4	Current asset to net assets	1.183	1.099	-5.456	23.136
R5	Fixed assets to net worth	1.249	10.384	-110.943	306.447
R6	Total liabilities to net worth	2.958	26.215	-436.810	644.652
R7	Retained earnings to sales	0.863	36.550	-202.517	999.9
R8	Debt ratio	0.609	0.193	0.046	1.576
R9	Times interest earned ratio	50.808	315.941	-1980	9480
R10	Revenue to net working capital	5.215	75.651	-1616.581	1858
R11	Accounts receivable turnover	68.785	249.275	-0.036	4844.444
R12	Accounts payable turnover	25.774	83.978	-0.020	999.9
R13	Sales to net worth	8.446	130.550	-161.544	5150.797
R14	Quality of inventory	19.629	54.336	0.000	971.384
R15	Turnover of total assets	1.571	0.995	-0.018	7.604
R16	Revenue to fixed assets	10.712	22.687	-0.060	305.474
R17	Return on assets (ROA)	0.040	0.120	-1.485	0.327
R18	Return on equity (ROE)	-0.053	3.758	-71.048	85.423
R19	Return on sales (ROS)	1.178	35.831	-40.429	999.9
R20	Profits to networking capital	0.122	7.919	-229.172	133.612

4.1.2. Over-fitting Problem

Although each of these variables may provide important perspectives on a contractor's condition, including all the number and type of variables in a quantitative model may yield a model that is "overfitted". An overfitted model is one that closely reproduces the training data on the model by collecting peculiarities of the training data. The model generates complex peculiarities by including extra unnecessary variables, interactions, and variable construction(s) in the model, and all of them are not part of the sought-after predominant pattern in the data. Therefore, a major characteristic of an overfitted model is involving too many variables. The overfitted model can be regarded as too perfect in the predominant pattern by mainly memorizing the training data instead of capturing the desired pattern (Ratner 2010**.** In other words, the model performs excellent on in-sample data used to develop the model, but have a poor performance in out-of-sample on new data (Dwyer et al. (2004)).

Contrasted to the overfitted model, a well-fitted model is one that faithfully represents the sought-after predominant pattern within the data, ignoring the peculiarities in the training data. A well-fitted model is defined by a handful of variables as it does not include peculiarly variables. Even though training data is unacquainted, the holdout data can expect to fit into the model and faithfully render the predominant pattern to produce good predictions. The accuracy of the well-fitted model on the holdout data will be nearby the accuracy of the model based on the training data. (Ratner 2010). To avoid building an "overfitted" model, this research uses stepwise regression to select a limited number of variables to achieve a powerful model.

4.1.3. The Logistic Regression Model

The logistic regression model is defined as a statistical modeling technique seeking the relationship between a binary dependent variable and other selected independent variables that are assumed to be related to the binary dependent variable (Koo and Ariaratnam, 2006). Like MDA, this technique weights the independent variables and assigns a Z score in a form of failure probability to each company in a sample. The advantage of this method is that it does not assume multivariate normality and equal covariance matrices as MDA does. The logistic regression incorporates nonlinear effects, and uses the logistical cumulative function in predicting a bankruptcy (Min and Lee, 2005). In addition, selecting variable using stepwise regression can avoid "overfitted" problem by selecting a limited number of variables to yield a powerful model. This research applies forward stepwise logistic method to eliminate the variables that do not add any explanatory ability to the model.

In the stepwise regression process, this research first calculates the single regressions for each 20 variables shown in Table 4.2, and choices the variable which has the highest significance level as the first variable of "chosen variables". Other variables which were not chosen denote as "un-chosen variables". Then, this process inputs the "chosen variables" and each un-chosen variable into individual logistic regressions, and choices the variable which has the highest significance level of un-chosen variables. The variable which added to the "chosen variables" must be at a given significance level (0.05 in this study). The chosen variables will be removed if the significance level decrease to a given significance level (0.1 in this study) as subsequent variable just entered into the model. This process repeats until no further variable can be added or removed. Table 4.5 shows the result of logistic regression using stepwise selection process.

Table 4.5 Result of stepwise regression process

			Coefficient	S.E.	Significance P – value
Step 1	**R17**	Return on Assets	-3.214	0.675	0.000
		Intercept	-3.910	0.195	0.000
Step 2	**R5**	Fixed Assets to Net Worth	.015	0.006	0.010
	R17	Return on Assets	-3.199	0.678	0.000
		Intercept	-3.966	0.199	0.000
Step 3	**R5**	Fixed Assets to Net Worth	3.557	0.988	0.000
	R8	Debt Ratio	.011	0.006	0.068
	R17	Return on Assets	-2.936	0.790	0.000
		Intercept	-6.325	0.736	0.000
Step 4	**R5**	Fixed Assets to Net Worth	3.643	0.992	0.000
	R8	Debt Ratio	.001	0.000	0.031
	R11	Accounts Receivable Turnover	.011	0.006	0.063
	R17	Return on Assets	-3.018	0.795	0.000
		Intercept	-6.478	0.746	0.000

Note:

Variable chosen in step 1: Return on Assets

Variable chosen in step 2: Fixed Assets to Net Worth

Variable chosen in step 3: Debt Ratio

Variable chosen in step 4: Accounts Receivable Turnover

After the stepwise regression process, 4 variables are chosen from 20 variables. These 4 variables do not show highly correlation as the result shown in Table 4.6.

Table 4.6 Correlation matrix of 4 variables

	R5	**R8**	**R11**	**R17**
R5	1.000			
R8	-0.195	1.000		
R11	0.026	0.074	1.000	
R17	0.016	0.051	-0.080	1.000

Finally, the logistic function is used as shown in Eq. (4-1). The model, including four explanatory variables, is shown in Eq. (4-2). The coefficient estimates for the logistic regression model are shown in Table 4.7.

$$DP = (Y = 1 \mid Explanatory\ variables) = \frac{1}{1+e^{-z}} \qquad (4\text{-}1)$$

$Y=1$, if the observation goes into default and $Y=0$, if not.

$$Z=\beta_0 + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + \beta_4 X_4 \qquad (4\text{-}2)$$

X_1= Debt Ratio

X_2= Accounts Receivable Turnover

X_3= Fixed Assets to Net Worth

X_4= ROA

After the forward stepwise regression, the selected variables includes four aspects of measure, including one leverage measure (Debt Ratio), one activity measure (Accounts Receivable Turnover), one liquidity measure (Fixed Assets to Net Worth), and one profitability measure (ROA). The perspectives of these measures go as follows: Debt Ratio indicates the proportion of a company's assets which are financed through debt. It can be viewed as the proportion of leverage used by a contractor. Accounts Receivable Turnover indicates how many times, on average, receivables are collected during the period. Fixed Assets to Net Worth indicates the degree of which the contractor's cash is frozen in the form of brick, mortar and machinery, and the degree of funds which are available for the contractor’s operations. ROA indicates how contractor’s profit is relative to its total assets. ROA gives an insight that how efficient management is by using its assets to generate earnings. With the exception of ROA, our selected variables are expected to have a positive relationship with default risk. For example, as debt ratio increases, default risk should increase as well. The only expected negative relationship is between ROA and default risk. The Coefficient estimates for the logistic regression model are shown in Table 4.7. The results confirm our expectations, as β_1, β_2, and β_3 are all positive figures, while β_4 is negative.

Table 4.7 Coefficient estimates for the logistic regression model

Coefficient	β_0	B_1	β_2	β_3	β_4
	-6.478***	3.643***	0.001**	0.011*	-3.018***
(S.E.)	(0.746)	(0.992)	(0.000)	(0.006)	(0.795)
VIF		1.021	1.008	1.014	1.012

*** indicates statistical significance at the level of 0.01
** indicates statistical significance at the level of 0.05
* indicates statistical significance at the level of 0.1

From Table 4.7, the values of VIF show that these 4 variables do not have highly multicollinearity, and give more confirmation of the correction of the accounting-based model used in this study.

4.2. Empirical Validation Result

4.2.1. Cross-validation Method

The key assessment criterion for the accounting-based model is the out-of-sample performance, thus the pooled sample is generally separated into two groups: training and testing groups in previous studies. The training group data is used to construct the models, while the testing group data is used to examine the performance of the models. Different selections of training data and testing data yield different results and sometimes lead to different conclusions. To avoid this problem, this research conducts cross-validation method. Cross-validation is a technique for assessing how accurately a predictive model will perform in practice. One round of cross-validation involves partitioning a group of data into complementary subsets, performing the analysis on one subset (called the training group), and validating the analysis on the other subset (called the testing group). In order to reduce variability, multiple rounds of cross-validation are performed using different partitions, and the validation results are averaged over the rounds.

The most common types of cross-validation using in default prediction model is *K*-fold cross-validation and leave-one-out cross-validation (LOOCV). In *K*-fold cross-validation, the original sample is divided into *K* subsamples randomly. Next, a single subsample is retained as the validation data for testing the model, and the remaining $K-1$ subsamples are used as training data. The cross-validation process is then repeated *K* times (the folds) by using each of the *K* subsamples once as the validation data. Finally, the *K* results from the folds can be averaged to produce a single estimation. The advantage of this method by over repeating random sub-sampling is that all observations are used for both training and validation, and each observation is used for validation exactly once. 10-fold cross-validation is commonly used.

Leave-one-out cross-validation (LOOCV) involves using a single observation from the original sample as the validation data, and the remaining observations as the training data. This is repeated such that each observation in the sample is used once as the validation data. Similarly to *K*-fold cross-validation, Leave-one-out cross-validation applies *K* equal to the number of observations in the original sample. Also, Leave-one-out cross-validation is usually very time-consuming because of the large number of times the training process is repeated.

In this research, the leave-one-out method will be utilized by the support from Excel software. In each time, one firm-year observation is kept as out-of-sample data, and the remaining firm-years are used as the training data to build the model. Then, the observation kept out-of-sample data is put back into the pool, and the next observation is kept as out-of-sample data. This process is repeated until every firm-year observation in the pooled sample is tested. After finished the whole process, the validation result set generated by cross-validation is a predictive collection of each out-of-sample data in the model (based on in-sample data), and that can be used to analyze the performance of the model. It is worth notice that the market-based model is based on a physical framework, thus it does not require any priors on whether a firm subsequently defaults. The cross-validation could be presented as follows:

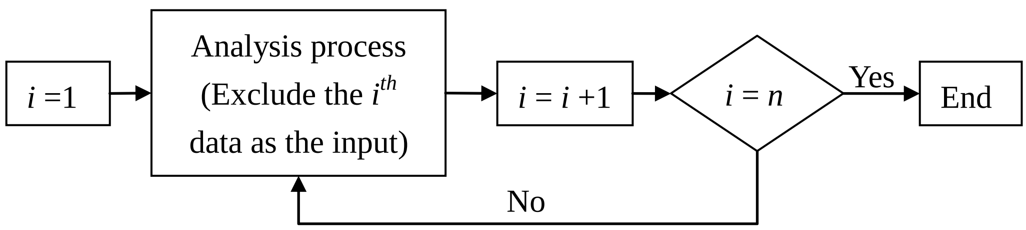

Figure 4.1 The cross - Validation algorithm

4.2.2. Validation Result

Figure 4.2 shows the empirical validation result of the accounting-based model, with sample consisting of 1,484 firm-year observations representing 121 individual construction contractors during 1970 to 2006.

In this research, the first model includes all 20 variables, and applies a multivariate setting for analysis. The second model, only include the four variables that were selected by forward stepwise logistic method. The argument of analyzing all 20 variables in multivariate setting is that they are chosen due to having a predictive ability in contractor default risk in the previous literature. Although a single variable may not be univariately significant, it may be significant when regressed in conjunction with other variables.

The result shows that the discriminatory powers of accounting-based models are acceptable. In addition , after using stepwise method to select limited explanation variables, the model's predicting power is improved compared to the logistic regression model using all 20 variables as explanation variables (from AUC=0.6066 to AUC=0.7519). More input variables add more training time in the models, yet don't have a positive effect in the predicting performance. What is more, sometimes too many variables are considered to be disturbance thus reduce the model's predicting ability.

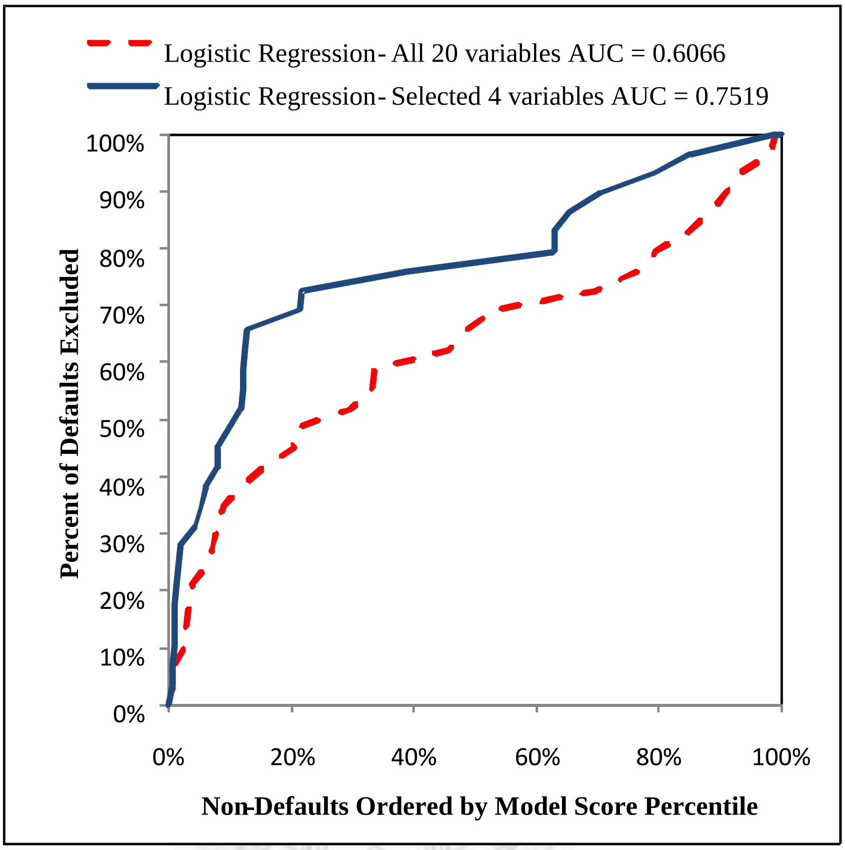

Figure 4.2 Performance for different accounting-based models

4.3. Summary

This research applied the logistic regression method to build the accounting-based business default prediction model in construction industry. Unlike the prior studies matched failed samples with non-failed samples, this research utilized all available firm-years data to construct the model to avoid sample-selection biases generated by the sample-matching method. Besides, to deal with the problem of "overfitted model", this research uses the forward stepwise logistic method to select the most important input variables for analyses. The final accounting-based model includes one leverage variable

(Debt Ratio), one activity variable (Accounts Receivable Turnover), one liquidity variable (Fixed Assets to Net Worth), and one profitability variable (ROA). After using Leave-one-out cross-validation method, the predictive performance is acceptable. The accounting-based model constructed in this section will provide as a benchmark model in the following research.

CHAPTER 5. VALIDATION OF MARKET-BASED MODELS

5.1. Validation of Merton-type Models

5.1.1. Summary Statistics

Table 5.1 presents the summary statistics for both defaulted and non-defaulted construction contractors. The summary statistics comprise all the inputs and outputs for the three Merton-type models. The most important phenomenon observed from this table is that the average default probability (DP) for contractors that subsequently default is significantly higher than the contractors that do not default for all the models considered. It preliminarily indicates that the market-based methodologies have a quite well ability of differentiating the risk of defaults and non-defaults. Although the sample selection matched the defaulted and non-defaulted contractors with comparable asset size of the defaulted contractors at the year of default, the defaulted contractors have much smaller V_E values than non-defaulted contractors. The equity and assets value of defaulted contractors fluctuated more obviously than non-defaulted contractors, as measured by σ_E and σ_A. The difference between μ and r for non-defaults shows that the equity premium is about 4.5%-8.9%. Not surprisingly, the asset of defaulted contractors has fallen to negative returns in the year prior to default.

Table 5.1 Basic descriptive statistics of Merton-type models

Variable		Mean All	Defaults	Non-Defaults	P-value For Difference
X_1		531.42	765.16	414.55	0.155
X_2		720.12	1005.44	577.46	0.103
V_E		415.43	68.82	588.73	0.000
σ_E (%)		84.45	139.35	57.00	0.000
r (%)		5.13	5.04	5.18	0.783
V_A	BSM	1027.90	1006.05	1038.82	0.001
	CB	861.05	788.95	897.10	0.001
	BS	1135.55	1074.26	1166.20	0.003
σ_A (%)	BSM	41.31	63.37	30.28	0.268
	CB	49.35	77.03	35.51	0.047
	BS	46.13	61.81	38.29	0.000
μ (%)	BSM	14.00	-8.34	25.18	0.002
	CB	13.81	-16.16	28.80	0.000
	BS	9.61	-52.87	40.85	0.000
DP (%)	BSM	15.45	40.71	2.82	0.000
	CB	17.43	46.30	3.00	0.000
	BS	17.80	37.98	7.72	0.000

Note: All figures in millions of US dollars. This table presents summary statistics for both defaulted and non-defaulted construction contractors.
X_1 : the sum of short-term liabilities and one-half of long-term liabilities (CL+1/2 LTD)
X_2 : total liabilities(TL)
V_E : market value of equity
V_A : contractor's assets value
σ_E : equity volatility
σ_A : asset volatility
r :one-year Treasury bill rate
μ: actual return on assets
DP : default probability

5.1.2. Model Calibration

The calibration of a model assesses whether the predicted probabilities correspond to actual default frequencies. Figure 5.1 plots the default history for the North American publicly traded firms and construction contractors from 1970 through 2006. The percentage of defaulted publicly-traded contractors estimated using Compustat data is plotted as the solid line (related to the left hand axis). The number of defaulted publicly traded firms that matched with Moody's default database (Dwyer and Qu 2007), is plotted as the dashed line (related to the right hand axis). The chart shows that the overall default rate varies considerably over time. As expected, the annual default rates of contractors are relatively higher during recession years. The average annual default rate of construction contractors was 3.33% during our sample period.

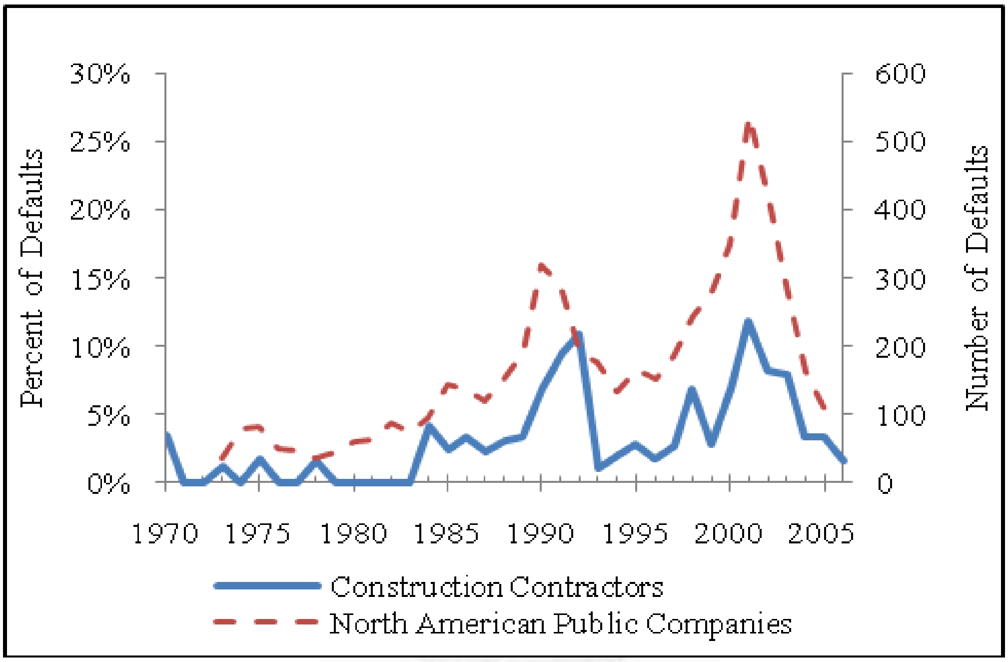

Figure 5.1 Default history for the North American publicly traded firms and construction contractors from 1970 through 2006

Table 5.1 shows that the average DPs for non-defaulted contractors predicted by BSM, CB and BS models are around 2.82%, 3.00%, and 7.72%, respectively. This implies that the BSM and CB model which use simultaneous equations or iterative procedures to estimate V_A and σ_A, are better-calibrated than the naïve model (BS model), and the CB model is slightly better-calibrated than the BSM model.

The degree of calibration is an additional performance criterion that is independent of prediction power (Reisz and Perlich 2007). Following Stein (2007), it is generally easy to recalibrate a powerful model to reflect expected default frequencies, whereas improvements in model power are very hard to achieve. Thus, the academics and practitioner prefer the models with a high discriminatory power.

5.1.3. Model Discriminatory Power

In Figure 5.2., the researchers compare the discriminatory power of the three Merton-type models to differentiate contractors that are more likely to default from those that are less likely to default within one year. It clearly shows that: (1) the ROC curves for these models are quite similar, thus there is little difference among these models, and (2) the CB model has a slightly larger area under the ROC curve (AUC) than the other two models, demonstrating a marginal out-performance of the CB model.

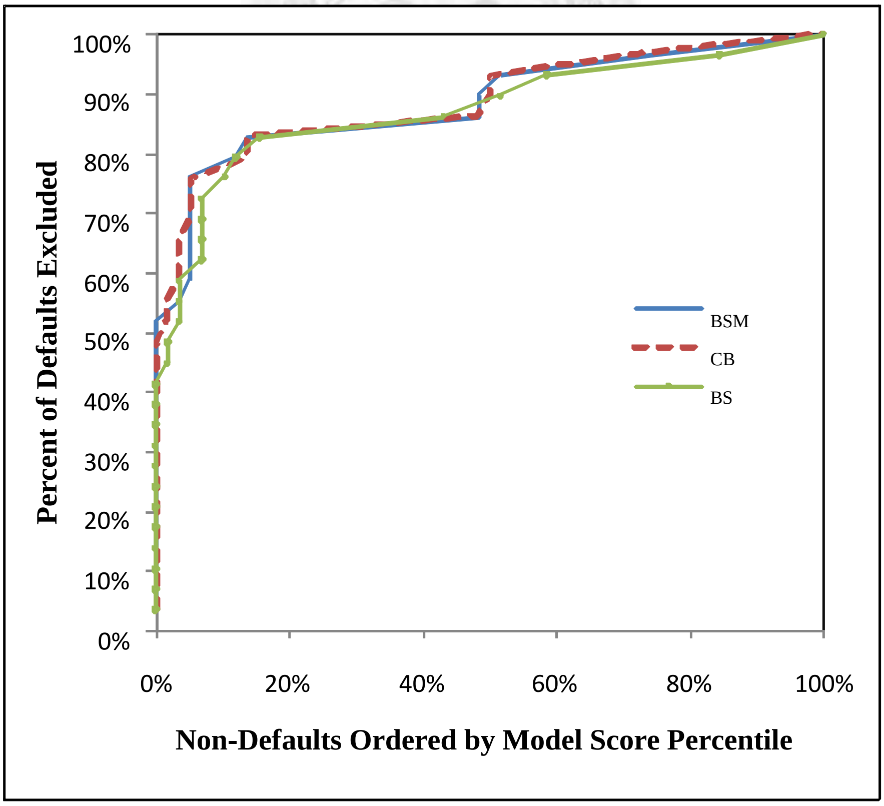

Figure 5.2 ROC curves for default probability rankings of Merton-type models

Summary statistics for all the models along with those for market leverage and volatility are presented in Table 5.2. Consistent with the visual inspection, the AR of the CB model (80.86%) is higher than those of the BSM model (80.50%) and the BS model (78.12%). This implies that the CB model and the BSM model have an outstanding discriminatory power, and the CB model is superior to the BSM and BS models in ranking construction contractors based on their default risk. This study also ranks defaulted and non-defaulted construction contractors based on market leverage (V_E/TL) and volatility (σ_E), which are two key inputs of the market-based models. Notably, σ_E produces an excellent discrimination power with a high AR of 72.89%. V_E/TL has an acceptable discrimination power with an AR of 56.24%. The result is not surprisingly because σ_E is the most crucial predictor of default risk capturing the likelihood that the value of the firm's assets will decline to such an extent that the firm will be unable to repay its debts.

Table 5.2 Area under ROC curves and accuracy ratios of Merton-type models

Model	AUC	AR
BSM	0.9025	80.50%
CB	0.9043	80.86%
BS	0.8906	78.12%
V_E / TL	0.7812	56.24%
σ_E	0.8644	72.89%

Note:
AUC: Area under ROC curves.
AR: Accuracy Rate.
V_E / TL: Market leverage (market value of equity/ total liabilities).
σ_E : Equity volatility.

Table 5.3 shows that the bivariate logistic regression with σ_E and V_E/TL as explaining variables has a considerably high AR of 77.05%. The result shows that market leverage adds explanatory ability for the models. For comparison, Table 5.3

presents both univariate and bivariate logistic regressions of the binary default variable against the DP measure of CB model, σ_E, and V_E/TL. The constant terms of all regressions are not reported. The coefficients on the DP of CB model, σ_E, and V_E/TL are significant, implying that all of these variables are significant predictors of default. For bivariate logistic regressions that include DP of CB model and σ_E, or DP of CB model and V_E/TL, both the coefficients of σ_E and V_E/TL are insignificant. Additionally, they have lower AR measures than that of the CB model. Thus, we conclude that the DP measure of the market-based model captures important elements of contractor default risk missed by non-market-based models. Table 5.3 also shows the McFad R^2 of the regressions which is a goodness-of-fit measure for logistic regressions.

Table 5.3 Default risk univariate and bivariate logistic regressions of CB model

Variable	CB	σ_E	V_E/TL	CB σ_E	CB V_E/TL	V_E/TL σ_E
CB	10.20***			12.21***	9.62***	
σ_E		3.43***		0.92		3.24***
V_E / TL			- 0.89**		- 0.21	- 0.67*
McFad R^2	0.479	0.356	0.119	0.483	0.490	0.408
AR	80.86%	72.89%	56.24%	77.88%	79.07%	77.05%

* significant at 10% ; ** significant at 5% ; *** significant at 1%

Note: This table reports univariate and bivariate logistic regressions with single or binary variable of default risk as the dependent variable, respectively. All regressions include an unreported constant.

5.1.4. Comparison Between Merton-type Models and Enhanced Ratio Models

Table 5.4 shows the comparison of misclassification rates between the three Merton-type models and two prior construction contractor default prediction models proposed by Severson et al. (1994) and Russell and Zhai (1996), respectively. The misclassification rates measure the model's predictive power to classify defaulted and non-defaulted contractors within the next one year. Severson et al. (1994) built their model with four accounting ratios including underbillings/sales, total current liabilities/sales, retained earnings/sales, and net income before taxes/sales. A misclassification rate greater than 30% was found. After a management-related variable, cost monitoring, was introduced into the model- building process, the misclassification rate significantly reduced to 12.5%. The market-based models, BSM and CB approaches correctly classify approximately 90% of the observed samples, thus the misclassification rate is 10%. Even the BS model, a naïve approach of market-based model, has a misclassification rate of 12.7%. Hence, Merton-type models have a comparable performance with the model proposed by Severson et al. (1994) based on the data set from 1988 to 1991. Additionally, Merton-type models outperform the model suggested by Russell and Zhai (1996) based on the data set from 1975 to 1993. A misclassification rate of 22% was found in their validation sample. Russell and Zhai (1996) developed the contractor default prediction model based on the stochastic dynamics of economic variables and accounting ratios, including prime interest rate, new construction value in-place, net worth/total assets, gross profit/total assets, and net working capital/total assets. Hence, this study concludes that the Merton-type models which uses only stock market information in predicting company default risk has significant advantage for the construction industry.

Table 5.4 Misclassification of Merton-type models and enhanced ratio models

	Original Samples	Validation Samples
Severson et al. (1994)	-	12.5%
Russell and Zhai (1996)	15.5%	22%
BSM Model	-	10%
CB Model	-	10%
BS Model	-	12.7%

5.2. Validation of Barrier Option Model

5.2.1. Verification of implied barrier of construction industry

According to the valuation equation of the DOC option presented in Eq.(3-19) and Eq.(3-20), the DOC option collapses to a standard call when the barrier is equal to zero. This section uses a large cross-section of construction firm-year observations to empirically investigate if there is a barrier in the corporate valuation of contractors. Table 5.5 presents the basic descriptive summary statistics for the barrier option model input variables, including means, medians, standard deviations, minimums, and maximums for the 1,484 available observations across firm-years. Comparing our summary statistics with those of Brockman and Turtle (2003), who empirically validated the barrier option model based on the data set of all industries except the construction industry from 1989 to 1998, this study finds that the mean (774.89) and median (169.30) of firm market value of our sample are much smaller than those of all industries (6662.53 and 1044.71, respectively). The mean and median of debt proportion of our results (0.56 and 0.59, respectively) are larger than those of all industries (0.45 and 0.46). The contractor samples also have larger asset volatility (mean of 0.32 and median of 0.26) compared to the sample of all industries (mean of 0.29 and medium of 0.23). These comparison results support our primary contention that construction contractors have low capitalization, high financial leverage, and high asset variability.

Table 5.5 Statistics for the pooled contractor sample of barrier option model

	Mean	Median	Std Dev.	Min.	Max.
V_A ($M)	774.89	169.30	2,020.22	0.89	25,503.59
V_E ($M)	361.45	58.94	1,059.95	0.32	11372.55
D ($M)	413.43	88.30	1,218,18	0.10	22,979.89
D/V_A	0.56	0.59	0.24	0.00	1
σ	0.32	0.26	0.23	0.06	1.65

Table 5.6 presents the average implied barrier of the pooled contractor sample, which we verify with Eq.(3-19) and Eq.(3-20). The barrier is defined as proportions of the firm's total market value of assets. The average implied barrier is 0.589 with a corresponding standard deviation of 0.278. With a null hypothesis of barrier equal to zero, the associated Students-t test statistic is 81.628 and has a p-value extremely close to 0.001. The result shows that in the pooled contractor sample, there is strong evidence that implied barriers are statistically different from zero.

Table 5.6 Implied barrier average of pooled sample

Observations	Barrier average	Std Dev.	t-statistic	p-value
1,484	0.589	0.278	81.628	0.000

Table 5.7 shows the implied barrier estimates grouped according to debt ratios. The contractors are divided into ten groups corresponding to deciles of debt ratios and then the average barrier is computed for each group. As expected, average implied barriers monotonically increase over the contractor's debt proportion. The average implied barrier in the first decile is 0.087, and 0.984 in the last decile. Implied barriers are statistically significant even for contractors with relatively low levels of financial leverage. Thus, it is confirmed that implied default barriers are statistically significant in the corporate security valuation of the construction industry across all capital structures. Based on the barrier option framework, the researchers can test its default prediction ability for the construction contractors.

Table 5.7 Implied barrier estimates by debt load

Debt ratio	Observations	Barrier average	Std Dev. of barrier	t-statistic	p-value
≦0.1	72	0.087	0.041	18.14	0.000
0.1~0.2	81	0.198	0.066	27.08	0.000
0.2~0.3	98	0.282	0.070	39.74	0.000
0.3~0.4	141	0.363	0.101	42.80	0.000
0.4~0.5	150	0.456	0.102	54.86	0.000
0.5~0.6	222	0.562	0.142	59.18	0.000
0.6~0.7	230	0.647	0.170	57.77	0.000
0.7~0.8	224	0.801	0.140	85.73	0.000
0.8~0.9	181	0.925	0.072	173.59	0.000
＞0.9	85	0.984	0.017	533.36	0.000

5.2.2. Measuring contractor default risk with barrier option model

This section calculates the implied failure probability of the pooled contractor sample from the DOC barrier option model with Eq. (3-21). Table 5.8 is a summary of the statistical results and comprises all inputs and outputs for the barrier option model. The most important phenomenon observed from this table is that the average implied failure probability (IFP) for firm-year observations that subsequently default is significantly higher than the firm-year observations that do not default. It preliminarily indicates that the barrier option methodologies perform quite well in differentiating the risk of defaulted and non-defaulted construction contractors. Besides, the defaulted firm-year observations have much smaller average market value of equity, V_E, than non-defaulted observations. The asset value of defaulted firm-year observations fluctuated more obviously than non-defaulted firm-year observations, as measured by σ.

Table 5.8 Basic descriptive statistics of barrier option model

Variable	Mean			P-value For Difference
	All	Defaults	Non-Defaults	
D ($M)	413.43	1005.44	401.63	0.091
V_A ($M)	774.89	1074.26	768.91	0.003
V_E ($M)	361.45	68.82	367.29	0.000
σ (%)	25.95	37.54	25.73	0.000
r (%)	6.31	5.04	6.34	0.020
IFP (%)	13.45	52.26	12.68	0.000

5.3. Comparison between Barrier option model and Merton model

5.3.1. Preliminaries

Table 5.9 shows the summary statistics of the comparison between the barrier option model and the Merton model. The empirical sample consists of 1,484 firm-year observations representing 121 individual construction contractors during 1970 to 2006. The Merton model is the refined type (CB model): V_A and σ_A are estimated by an iterative procedure and expected return is bounded between the risk free rate and 100%. The strike price, X, is defined as the sum of short-term liabilities and one-half of long-term liabilities (Crosbie and Bohn 2003), V_E for defaults is much smaller than that of the non-defaulters.

Table 5.9 Summary Statistics of Merton-CB model and barrier option model

Variable			Mean		
			All	Defaults	Non-Defaults
X			353.72	765.16	345.93
D			479.09	1005.44	469.12
V_E			344.43	68.82	349.65
σ_E	(%)		62.83	139.28	61.38
r	(%)		6.29	5.04	6.32
H			629.17	1033.86	621.50
V_A		Merton-CB	682.93	805.35	680.70
		Barrier	823.51	1074.26	818.76
σ_A	(%)	Merton-CB	33.29	76.17	32.48
		Barrier	25.95	37.54	25.73
DP	(%)	Merton-CB	8.15	46.33	7.43
		Barrier	24.96	57.12	24.35

Another noticeable result is the average DP of non-defaults from Barrier model (24%) is three times as large as the average DP of non-defaults from Merton-CB model (8%). This indicates 24% of non-defaults will default in the coming year by estimation of the Barrier model, which seems grossly exaggerated. As the default event is very rare in reality, this high DP (DP=24%) in Barrier model may be due to the fact that H is higher than the debt in both defaulters and non-defaulters.

In modeling the Barrier model, the debt is considered riskless thus the book-value of debt (BVD) is used for estimation and no discount is needed. However, in real situation, it is necessary to discount the future value of debt repayments back to a present value, its market value. Notably, the average V_A estimated by the Barrier models is higher than the average V_A estimated by the Merton-CB models. This difference is due to the Barrier model using BVD approximation to value debt, which implies an inflated V_A will be generated. When using BVD and an inflated V_A in solving the H in

DOC valuation, H is forced to be greater than D. Apparently, with a higher barrier, the V_A is most likely to reach the barrier before maturity, that is, a high DP will be generated. Our estimated H is higher than the debt, H>D. This is consistent with the findings of Brockman and Turtle (2003) and Gharghori et al. (2006). Indeed, it is worth to notice that in reality, firms are unlikely to default when they still have a positive residual equity value after they do the debt payments. Although this discrepancy happened, the barrier model still performs differentiable DPs in defaulter and non-defaulter.

5.3.2. Model Discriminatory Power

The ROC curve is applied to evaluate the discriminatory power of our models. In Figure 5.3, this paper compares the discriminatory power of two market-based models to differentiate contractors that are more likely to default from those that are less likely to default within one year. It clearly shows that the Merton-CB model has a larger area under the ROC curve (AUC) than the Barrier model.

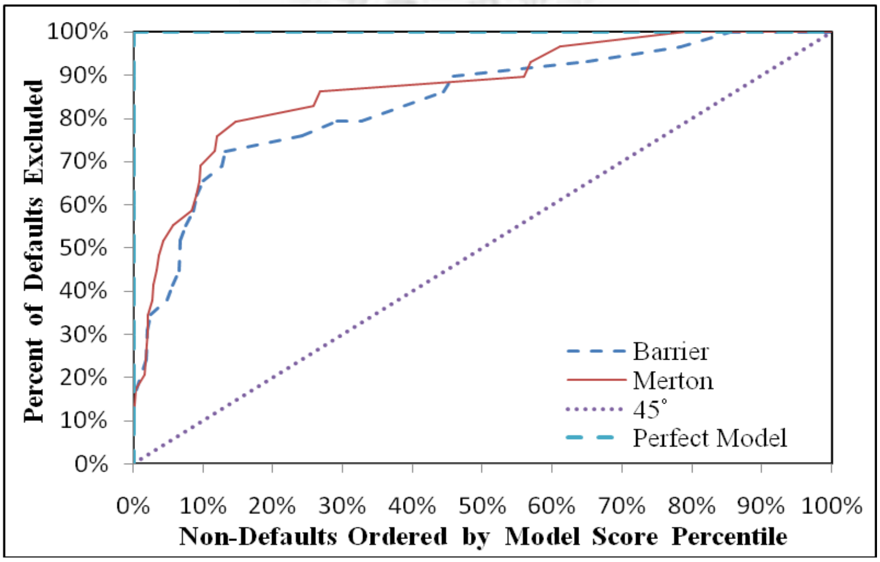

Figure 5.3 ROC curves for default probability rankings of Merton-CB model and Barrier option model

By comparing the AUC in Table 5.10, the AUC of the Merton-CB model (0.8581) is larger than that of the Barrier model (0.8253). The Merton-CB model also has high AR (AR=71.61%) compared to the Barrier model (AR=65.07%). Despite this drawdown, the discrimination power of the Barrier model is still considered as excellent level as the Merton-CB model. Additionally, using the Merton-CB model and the Barrier option model to predict contractor defaults also has markedly better discriminatory power than that of Reisz and Perlich (2007) based on the data set of all industries except the construction industry from 1988-2002. The overall results conclude that the Barrier option model, which uses stock market information in predicting company default risk, also has significant advantage for the construction industry, and it provides as an alternative to measure construction contractor default. The limitations of using the Barrier option model to predict construction contractor default are that the framework is only applicable to listed contractors and that the stock market is efficient.

Table 5.10 Area under ROC curves and accuracy ratios of Merton-CB model and Barrier option model

Model	AUC	AR
Merton-CB	0.8581	71.61%
Barrier	0.8253	65.07%

Note:
AUC: Area under ROC curves.
AR: Accuracy Rate.

5.4. Summary

This research predicts contractor default by employing three Merton-type credit models (BSM, CB, and BS) based on stock market information, and the empirical results show that all of the models have strong discriminatory power in ranking contractors from riskiest to safest. The misclassification rates of the three models are BSM: 10%, CB: 10%, and BS: 12.7%, all of which are smaller than that of the enhanced ratio model developed by Russell and Zhai (1996) (22%), and two of which are smaller than that of the model developed by Severson et al. (1994) (12.5%). The results show that Merton-type credit models are good alternatives for construction contractor default prediction.

In place of the conventional view of equity as a standard call option, Brockman and Turtle (2003) argued that corporate equity is a barrier call option on corporate assets. With the barrier option framework, the value of equity can be knocked out prior to a scheduled debt payment, which is more consistent with the real world practices. This research also empirically validates the contractor default forecast performance of the Barrier option model. The results present strong evidence that an implied barrier exists in the corporate valuation of the construction industry. Based on the barrier option framework, the default prediction ability for the construction industry was tested; it was discovered that the Barrier option model also has excellent performance for differentiating the risk of defaulted and non-defaulted construction contractors. Additionally, using the Barrier option model to predict contractor defaults also has markedly better discriminatory power than that of Reisz and Perlich (2007) based on the data set of all industries except the construction industry from 1988-2002. Comparing the performance of Merton-CB model and Barrier option model, the Merton-CB model outperforms the Barrier option model. In the following research, market-base model or Merton model is indentified as Merton-CB model.

CHAPTER 6. HYBRID MODEL AND COMPARISONS OF MODELS

6.1. The Concept of Hybrid Model

This section develops a hybrid-form model incorporating financial statement data and market information for measuring construction contractor default risk. The hybrid model combines two credit risk modeling approaches: (a) a statistical model constructed through empirical analysis of historical financial data (such as the accounting-based model), and (b) a structural model based on option-pricing theory (such as the Merton model). In fact, most statistical models are based on some theoretical framework to aid in problem formulation, and most theoretical models rely on statistics to determine the appropriate values for key parameters, such as volatility, or to map structural models to the default probabilities (Khandani, 2001).

The analyses and empirical results in the prior chapter show that financial statements only provide information about a firm's past performance and financial soundness, thus accounting-based model is limited in that it cannot provide information about a firm's future and qualitative factors relative to contractor's success. The Market-based model (Merton model) solves the above problem and has significant advantages for the construction contractor default prediction. However, Merton model has its limitations in application. In particular, the Merton model relies heavily on the condition that the market is efficient. When used within the structure of the model, the model contains embedded assumptions about the comprehensiveness of the information contained in market price. The effectiveness of such an approach depends on how closely its assumptions and structure capture the true nature of the firm dynamics as well as the accuracy with which the model's variables are estimated. Sobehart et al.

(2001) argued that since most firms' assets and liabilities do not possess the idealized characteristics and liquidity required by Merton models, there are lots of value uncertainty and potential arbitrage situations. For example, large denominations and thin trading in the bond and loan markets, against a background of fluctuating stock prices, are inconsistent with the idealized conception of debt-holders as writers of perfectly liquid options on the unobservable assets of the firm proposed in pure Merton model.

Another key problem with the Merton model stems from the fact that even fully informed equity prices are marginal prices and, therefore, primarily reflect marginal reallocative supply and demand conditions rather than the value of the aggregate capital stock of the firm. Besides, Merton’s original contingent claims model, and most subsequent refinements of it, does not contemplate cases in which firms default on their debt obligations due to severe liquidity problems. Stein (1999) pointed out that Merton-type models are not complete: even when conditioned on Merton-type variables, additional information provides better discrimination between defaulters and non-defaulters. Keenan and Sobehart (1999) claim that, “The fundamental limitations of all the variants of the Merton model suggest the need for more general types of default risk models.” Sobehart and Stein (2000) have found it to be most useful when market information is coupled with fundamental information on the firm and its business environment. A detailed examination of a firm’s balance sheet, income statement and cash flows remains a critical component of any analytical risk assessment framework. By combining the Merton approach with accounting variables, they produce a new model that outperforms the default predictive power of the Merton approach. Liao et al. (2004) proposed an integrated model that incorporated both accounting and market credit information, by putting the default probability generated from the Merton model as a predicting variable into the traditional logistic model. The empirical results showed that the addition of market information improves the predictive power of the original accounting information based logistic models. However, this research used companies from a wide range of industries, thus it is not applicable to the construction industry (Wang, 2010).

This research, therefore, builds and empirically validates the performance of a hybrid model that combines information from accounting-based and market-based models. The performance of the hybrid model is compared to that of the Merton model and the accounting based model.

6.2. Hybrid Model Development

The hybrid model is structured by introducing an extra variable from Merton model, the Default Probability (DP), into the accounting-based logit model. The hybrid model is expected to have a better predictive power since it incorporates both accounting information that reflects a contractor’s long-term credit quality and market information that echo the most recent evaluation results by stock market.

This research constructs three hybrid models. In Hybrid model 1, the DP calculated from the Merton model joins the 20 accounting variables in section 4.1.1 as the 21th variable. Using stepwise method, four variables are selected, including the DP, Net working capital/total assets, Accounts receivable turnover, and ROA. Hybrid model 1 is thus a logit model with these four most significant variables as inputs.

Hybrid model 2 is identical to Hybrid model 1 except that instead of performing the stepwise method again, DP directly joins the four most significant variables used in the accounting-based model. Those four accounting variables are Debt ratio, Accounts receivable turnover, Fixed assets/net worth, and ROA.

The coefficients of Accounts receivable turnover and Fixed assets/net worth are not significant in the logistic regression equation of Hybrid model 2. Thus, in Hybrid model 3, the above two variables are excluded, and only DP, Debt ratio, and ROA are inputted into the logit model.

Table 6.1 shows the empirical results of the three hybrid models. The three hybrid models show very similar discriminatory power, with Hybrid model 2 having the best predictive performance. Hybrid model 3, which excluded two insignificant variables from Hybrid model 2, has only slightly lower predictive ability than Hybrid model 2.

Table 6.1 Empirical results of the three hybrid models.

Model	**Intercept**	**DP**	**Net Working Capital to Total Assets**	**Debt Ratio**	**Accounts Receivable Turnover**	**Fixed Assets to Net Worth**	**ROA**	**AUC of Validation**
Hybrid Model 1	-4.5171 *** (0.3511)	4.2982 *** (0.5932)	-1.8802 ** (0.7403)		0.0002 ** (0.0001)		-2.0944 ** (0.923)	0.8597
Hybrid Model 2	-5.9529 *** (0.6708)	3.9520 *** (0.6123)		1.4876 * (0.9016)	0.0001 (0.0001)	0.007 (0.0066)	-2.3942 *** (0.82)	0.8732
Hybrid Model 3	-5.9085 *** (0.6635)	4.0959 *** (0.5985)		1.4831 * (0.895)			-2.3776 *** (0.8147)	0.8615

* significant at 10% ; ** significant at 5% ; *** significant at 1%

6.3. Comparison Between Models

This section empirically compares the performance of the Hybrid model to accounting-based model and Merton model (market-based model). Since Hybrid model 2 has the best predictive performance, the “Hybrid model” refers to Hybrid model 2 from now on.

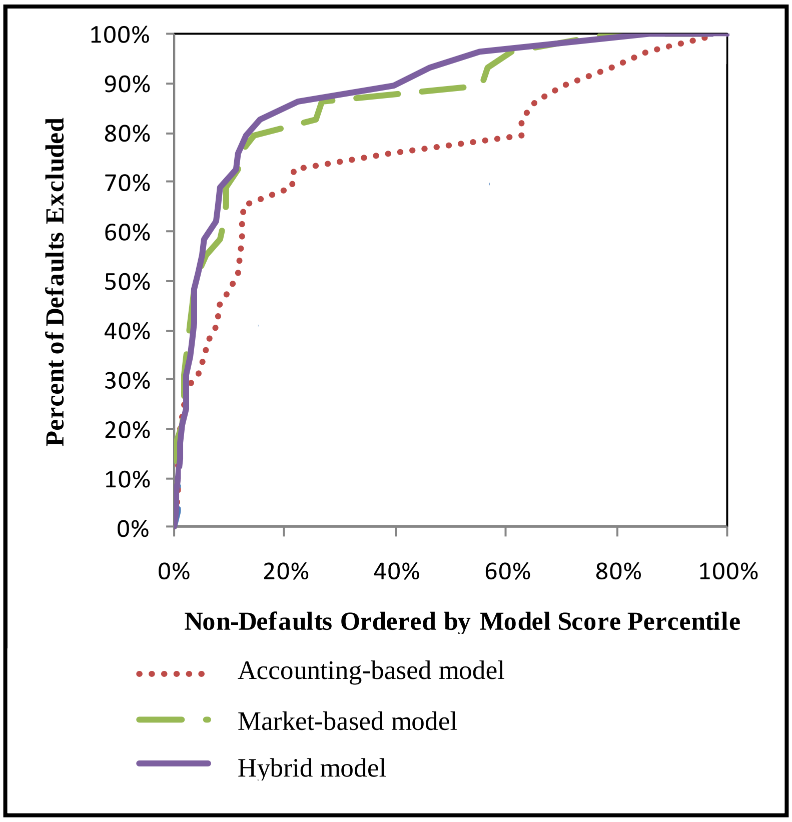

Figure 6.1 Performance for different models

Figure 6.1 compares the AUC results of Hybrid model, Merton model, and accounting-based model.

As out-of-sample performance is the key assessment criterion for accounting-based credit risk model, the pooled sample is generally separated into two groups of data:

training and testing groups. The training group data is used to construct the models, while the testing group data is used to examine the performance of the models. Different selections of training data and testing data yield different results and sometimes lead to different conclusions. To avoid this problem, this research conducts cross validations herein. The validation result set can then be used to analyze the performance of the accounting-based model. Note that the market-based model is based on a theoretical framework —it does not require any priors on whether a firm subsequently defaults.

AUC measures in Figure 6.1 show that the market-based model (Merton model) has excellent discriminatory powers (AUC=0.8581). In predicting contractor default, the market-based model obviously outperforms the accounting-based model, which has acceptable discriminatory power (AUC=0.7867).

Although this research intends to construct a hybrid model that combines the advantages of the market-based model and accounting-based model, the empirical validation shows that the performance of the hybrid model (AUC=0.8732) is only marginally higher than that of Merton model (AUC=0.8581). The hybrid model does not significantly improve the market-based approach of default risk measurement. This implies that not only are the market-based models superior to the accounting-based model, accounting information contributes only a very small amount of predictive power when it joins market information.

The empirical validation result of this research does not strongly support the finding of Sobehart et al. (2001). In fact, Kealhofer and Kurbat (2001)'s replication of the empirical results of Sobehart et al. (2001) on the Merton approach yields decisively contrary results. They found that the Merton approach significantly outperforms available alternatives in predicting default. In particular, it had fewer type 2 errors (incorrect identification of default) than the alternatives for any level of correct predictions. More significantly, they find that there is no additional information in the well-known accounting variables that they use. In fact, mixing accounting variables with the output of the Merton approach does not improve its performance but rather degrades it.

6.4. Practical Implication and Discussion

The construction industry has a relatively high failure rate compared with other industries. It is important for project owners, surety underwriters, and lending institutions to identify potential failure contractors and to avoid awarding them contracts. Besides, general contractors and subcontractors have to mutually assess the failure probability of one another to avoid undertaking a project with companies that have high default risks. It is also important for construction contractors to find an early warning mechanism which is able to serve as an effective tool for regular evaluation of their performance in order to adopt timely and appropriate strategies to survive in business.

As many qualitative factors including managerial ability, technical expertise, governmental regulations change, and public policy issues affect the risk of contractor failure, contractor default measurement is still commonly performed by construction professionals using their accumulated experience and judgment. The results vary since the training, background, and experience of construction professionals vary considerably.

The most traditional business default prediction method employed by researchers is the accounting-information-based statistical model, which had satisfactory predictive accuracies. These credit risk models were developed for all sectors and tend to be too general to deal with the construction industry, which has unique characteristics and different accounting treatment. Prior literatures intended to incorporate managerial or economic variables into the traditional accounting ratio model-building process to build the contractor default prediction model. However human judgment is still used to determine the managerial variables, and the parameters in the models may need periodical adjustment due to changes in economic conditions and market trends (Russell and Zhai 1996).

Based on option pricing theory that is established by Black and Scholes (1973) and later developed by Merton (1974), Merton model (market-based model) introduced a market valuation approach into the issue of failure prediction problems. This research measures the default risk of the construction industry with a large cross-section of construction contractors, and finds that market-based model obviously outperforms accounting-based model in ranking contractors from riskiest to safest based on their default risk. This implicates that the users can predict contractor default only with in time market information, and release human judgement bias and periodical adjustment of using enhanced ratio models. The empirical results of this study support the researcher's contention that the stock price is forward-looking and reflect all quantitative and qualitative information related to the survivability of the contractors. This research also develops a hybrid-form model by incorporating DP from Merton model as an extra variable into the accounting- based logit model. The empirical validation shows that the forecast ability of hybrid model marginally higher than that of Merton model. The result shows that accounting variables add little forecasting ability for contractor default risk at the present of market-based model.

The different accounting treatments in the construction industry may be the reason accounting-based model cannot effectively predict contractor default. Since the production period of a construction project is relatively long, percentage-of-completion method is the most common approach used for revenue recognition in the construction industry. Under the percentage of completion method, revenue and expenses are recognized in income as the contract activities progress by reference to the stage of completion of a contract. The costs incurred in reaching the stage of completion are matched with this revenue, resulting in the reporting of revenue, expenses and profit which can be attributed to the proportion of work completed. The advantage of the percentage-of-completion method is that the amount of profit to be recognized in each period during construction is matched with the progress toward completion.

However, the following conditions may cause over-optimistic revenue recognition: first, if contractors fail to provide or adequately perform any of the deliverables called for by the contract, the contractor will suffer from construction disputes and possible litigation. When construction disputes are not resolved in a timely manner, revenue which has been recognized may not be realized. Second, any on-site casualties or natural disasters may lead to increase expenses to the contractor. In addition, the percentage-of-completion method has the shortcoming that profits for each period and the measure of progress toward completion are subjective estimates.

6.5. Summary

The overall conclusion on construction contractor default risk measures between different models in this section is that market-based measures are superior to accounting-based model. In addition, as the performance of hybrid models is almost identical to that of market-based models, the use of hybrid models to measure default risk is unwarranted. One should opt for the more parsimonious model and use market-based model to measure construction contractor default risk.

CHAPTER 7. EMPIRICAL VALIDATIONS OF THE MODELS USING TAIWANESE CONTRACTOR SAMPLES

In this chapter, the researcher will use three models mentioned in the previous chapters to calculate the default probabilities of Taiwanese construction contractors. The first model is a market-based model derived from Merton's (1974) insight that equity can be viewed as a call option on a firm's assets, such as Merton-CB model do. The second model is an accounting-based model developed the same way as chapter 4 do, but the training sample is collected from Taiwan's construction contractors. The third model is the hybrid model which incorporates both market and accounting information in a simple way: inputting the default probability from the market-based model into the accounting ratio model as an input variable. After calculating the default probabilities from each model, the models are assessed to see how good each model is at differentiating defaulted or non-defaulted Taiwanese construction contractors. Finally, this research compares the results from each model and attains the conclusion.

7.1. Data Collection

The empirical investigation of this research considers a cross-section of Taiwanese construction contractors. The data is collected from Taiwan Economic Journal (TEJ). This research restricts its attention to listed and delisted construction contractors with December fiscal year-ends by choosing firms with TEJ codes 25 (construction companies and building companies). However, there are not enough Taiwanese construction contractors' samples in TEJ to establish a well accounting-based model. Thus, this study also includes the Taiwanese building companies' samples as the sample set. The sample period is from 1995 to 2008.

The final sample includes 48 non-defaulted (currently listed) and 24 defaulted (once listed, and as defined by TEJ) construction companies, which are shown in Table 7.1 and Table 7.2, respectively. Combining firms with the sample period, the total number of firm-years is 623, with 24 defaulted samples and 599 non-defaulted samples. All firm-years between 1995 and 2008 with TEJ code 25 were included, with a few exceptions due to the absence of information provided on TEJ. The 4-digit numbers shown in the non-defaulted list is the stock code of these companies.

This study uses a definition of default according to TEJ. According to TEJ definition, firms are de-listed because of any of the following reasons: bounced check, bankruptcy, operation difficulties, reorganization, financial crisis, management takeover, suspension of work, negative or low net worth, etc. The default date, as defined by TEJ, is the date when any of the above situation occurred for the first time.

Table 7.1 List of non-default contractors (Wang, 2010)

1436 福益	2526 大陸	2546 根基	5516 雙喜
1442 名軒	2527 宏璟	2547 日勝生	5519 隆大
1808 國賓大	2530 華建	2548 華固	5520 力泰
2501 國建	2534 宏盛	2841 台開	5521 工信
2504 國產	2535 達欣工	4416 三圓	5522 遠雄
2505 國揚	2536 宏普	5213 亞昕	5523 宏都
2509 全坤建	2537 聯上發	5505 和旺	5525 順天
2511 太子	2538 基泰	5508 永信建	5529 志嘉
2515 中工	2539 櫻建	5511 德昌	5530 大漢
2516 新建	2542 興富發	5512 力麒	5531 鄉林
2520 冠德	2543 皇昌	5514 三豐	5533 皇鼎
2524 京城	2545 皇翔	5515 建國	5534 長虹

Table 7.2 List of Defaulted Contractors (Wang, 2010)

Firm	**Default Date**	**Firm**	**Default Date**	**Firm**	**Default Date**
太設	2001/10/16	金尚昌	2000/11/10	易欣	1999/8/26
寶建	2002/4/16	啟阜	1999/4/18	尖美	1999/1/7
長谷	2000/11/30	德利	2001/9/6	宏福	1998/11/20
長億	2000/9/6	金腦科	1998/3/1	三采	1999/9/28
宏總	2000/7/29	龍田	2001/8/28		
德寶	2006/4/28	榮美開發	2001/7/18		
寶祥	2002/6/30	信南	2000/9/17		
皇普	2000/4/28	長鴻	2008/10/27		
仁翔	1998/12/29	大日	2001/8/23		
昱成	2004/2/9	竞誠建築	2006/10/14		

7.2. The Accounting-based Model of Taiwan’s Construction Industry

In building the accounting-based model following the methodology in Chapter 4, the first step is to calculate the 20 financial variables in Table 4.2 according to the financial statement of each construction company. Next the variable selection is used to avoid the “over-fitting” problem. Finally, the logistic function for Taiwanese construction contractor companies is used as shown in Eq. (7-1). The model, including four explanatory variables, is shown in Eq. (7-2).

$$DP = (Y = 1 \,|\, Explanatory\ variables) = \frac{1}{1+e^{-z}} \qquad (7\text{-}1)$$

$Y=1$, if the observation goes into default and $Y=0$, if not.

$$Z=\beta_0 + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + \beta_4 X_4 \qquad (7\text{-}2)$$

X_1= Net Working Capital to Total Assets

X_2= Debt Ratio

X_3= ROA

X_4= ROE

After the variable selection, the selected variables are: Net Working Capital to Total Assets, Debt Ratio, ROA, and ROE. Comparing them to the selected variables in the model developed from American data, Net Working Capital to Total Assets and ROE are new, and Accounts Receivable Turnover and Fixed Assets to Net Worth are no longer in the picture. The Coefficient estimates for the logistic regression model are shown in Table 7.3.

Table 7.3 Coefficient estimates for the logistic regression model

Coefficient	β_0	β_1	β_2	β_3	β_4
	-5.200***	-0.015	3.305*	-5.177***	0.142
(S.E.)	(1.341)	(1.334)	(1.868)	(1.659)	(0.145)

*** indicates statistical significance at the level of 0.01

** indicates statistical significance at the level of 0.05

* indicates statistical significance at the level of 0.1

This established Taiwanese construction contractor's accounting model shows that these four ratios, Net Working Capital to Total Assets, Debt Ratio, ROA, and ROE, have the better abilities in predicting whether a Taiwanese construction contractor will default in future.

In present, the Taiwanese construction contractors are based on their past construction experience be divided into three grades. Construction contractor with each grade has its limitation in taking different scale of construction projects. A construction contractor with the highest grade can take the construction project only under the following simple rules: 1. The Net worth of the construction constructor not lower than the one-twelfth of the budget of a bidding project. 2. The current asset of the construction constructor not below its current liability. 3. Total liability of the construction constructor cannot excesses four times of its net value. These three rules are only the minimum criteria to evaluate the financial soundness of a construction contractor, and these rules are lack of the ability to rank the construction contractors with its financial ability to awarding contract. The empirical result of this study indicates that besides the present contractor's pre-qualification rules, the profitability (ROA, ROE) of a construction contractor is also related to whether the construction contractor will go default in future. Therefore, based on this empirical result, this research highly suggests that the contractor's pre-qualification process of Taiwanese construction contractor could be included the profitability index into consideration to establish a synthesized index, and according to the degree of this index to rank construction contractors for awarding contract.

7.3. The Market-based Model of Taiwan's Construction Industry

Table 7.4 presents the summary statistics of prediction results with market-based model for both defaulted and non-defaulted Taiwanese construction contractors' sample. The final sample consists of 623 firm-year observations, representing 72 individual construction contractors during 1995 to 2008. The result shows that the average default probability (DP) of subsequently defaulted contractors is significantly higher than those of contractors that do not default, as the p-value between defaults and non-defaults extremely closes to 0.001. This shows the implication of the market-based model has a quite well ability in differentiating the potential risk of Taiwanese defaulted and non-defaulted contractors.

In order to illustrate the market-based model can capture the characteristic with Taiwanese construction contractors in both defaulted and non-defaulted samples, the comparison of two Taiwanese construction contractors' default probabilities with market-based model during 1997 to 2001 are shown in Figure 7.1. In Figure 7.1, the solid line shows one of the defaulted construction contractor samples, coding as 2512; whereas, the dotted line shows one of the non-defaulted construction contractor samples, coding as 2535. For the defaulted construction contractor sample-2512, its default probabilities with market-based model rises dramatically from 1998 to 2001, and it actually defaulted year was at 2002. For the non-defaulted construction contractor sample- 2535, its default probabilities with market-based model maintain at a relatively low level, and its default probabilities fluctuate in the observed period. Consequently, market-based model processes a great ability in differentiating potential subsequent default construction contractors and health construction contractors by generating relatively higher default probabilities for those which are likely to default.

Table 7.4 Summary statistics of prediction results of market-based model with Taiwanese construction contractors' sample

Variable		Mean			P-value For Difference
		All	Defaults	Non-Defaults	
DP (%)	Merton-CB	8.2	20.03	7.60	0.001

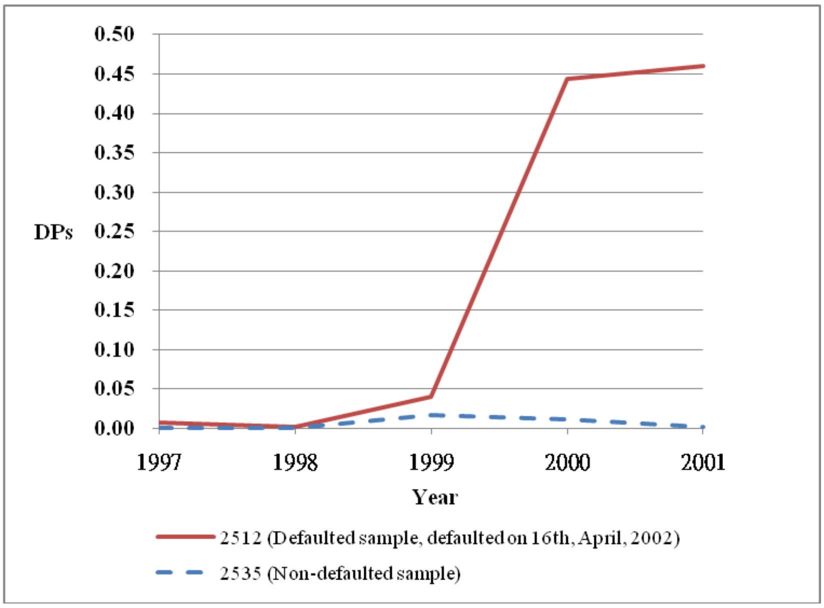

Figure 7.1 Comparison of two Taiwanese construction contractors' default probabilities with Market-based model from 1997 to 2001

During the period of working on this research (from 2007 to 2010), Professor Huang, a professor of National Chiao Tung University, concurrently attempts to apply market-based model to assess the default probabilities of Taiwanese construction contractors (Huang 2008, 2009). The results of his studies indicate that the market-based model can effectively distinguish the normal construction firms and defaulting construction firms.

7.4. The Hybrid Model of Taiwan's Construction Industry

Following the methodology in Chapter 6, the hybrid model of Taiwan's construction industry is structured by introducing an extra variable from Merton model, the Default Probability (DP), into the accounting-based logit model. Following the same way in Chapter 6, this research adds the 4 selected variables in Section 7.2 into the building of the hybrid model of Taiwan's construction industry. The resulting model has

5 input explanatory variables：(1) DP, (2) Net Working Capital to Total Assets, (3) Debt Ratio, (4) ROA, and (5) ROE.

7.5. Comparison between Models and Discussion

This section empirically compares the performance of the Hybrid model to accounting-based model and Merton market-based model in Taiwan's construction industry.

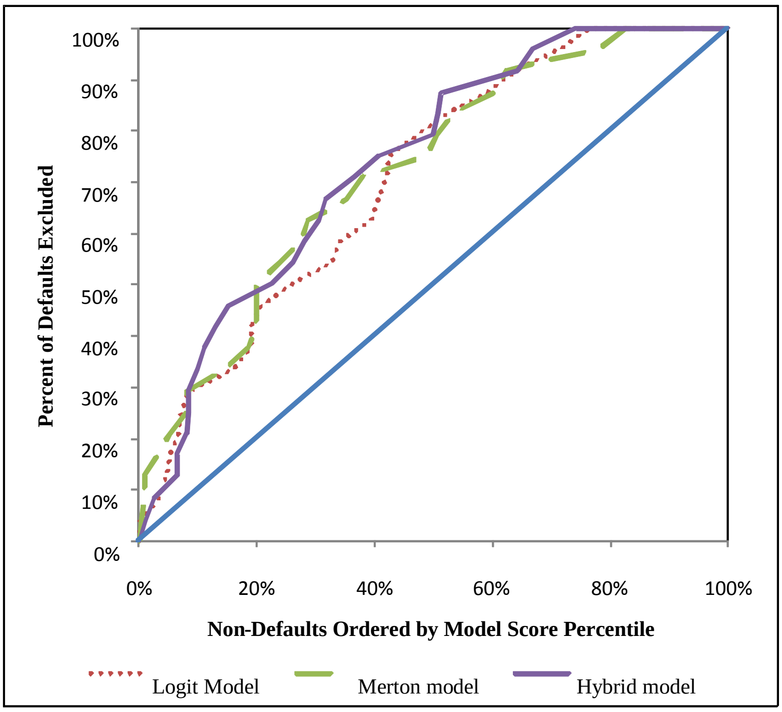

Figure 7.2 Comparison of AUC results in Taiwan's construction industry: Hybrid, Merton, and Logistic

Figure 7.2 compares the AUC results of Hybrid model, Merton model, and accounting-based logit model. The empirical result shows that:

(1) When conducting empirical analysis on Taiwan's construction contractor samples, the predicting performance of Merton model is just slightly better than that of

the accounting-based model, and this is different from the results using American construction contractor samples. One way to explain this is that the Merton model is based on the option pricing theory, which assumes that the stock market is efficient and reflects all information. The Taiwanese stock market is not always efficient and it is a lot smaller than the American stock market, thus the market price can easily be manipulated and will fluctuate due to the irrational behavior of investors. Another way to explain is that the scale of Taiwanese construction contractors is relatively smaller than that of the North American. They are vulnerable to the negative effect of on-site casualties or natural disaster to bankrupt. Because of so, when using the Merton model to predict financial distress in Taiwan's construction industry, the predicting performance of Merton model (AUC=0.7038) is only marginally better than that of the accounting-based model (AUC=0.6912).

(2) In accord with the model results using American data in the previous chapters, when applied to Taiwanese construction company samples, the hybrid model (AUC = 0.7232) also only improves marginally from the Merton model (AUC = 0.7038).

7.6. Summary

This section applied the default predicting models in Chapter 6, including the market-based model (Merton model), the accounting-based model, and the hybrid model, on Taiwanese construction contractors. Unlike the results using American samples, when using Taiwanese samples, the market-based model does not perform significantly better than the accounting-based model. This might be due to the inefficiency in Taiwan's stock market, causing a violation on the basic assumptions in the Merton model, which in turn results in the unsatisfactory predicting performance of the market-based model in Taiwan. For the same reasons, the hybrid model, which uses the DP estimated from the Merton model as an additional variable, does not have obvious improvements from the accounting-based model either. How to accurately predict the financial distress in Taiwanese construction contractors is a topic that requires further study.

CHAPTER 8. CONCLUSIONS AND SUGGESTIONS

8.1. Conclusions

The prediction of contractor default is highly different from the predicting of default in other sectors, mainly due to the distinctive nature of the construction industry. To enhance predictive power, previous studies on construction contractor default prediction models additionally incorporated managerial or economic variables into traditional accounting-based models. However, managerial variables are subjective and qualitative, and both economic variables and financial ratios are only available periodically and are backward-looking information. Additionally, technical expertise, regulatory changes, and public policy changes also affect the risk of contractor failure. All of these variables are qualitative and depend on human judgments. Therefore, it is difficult to incorporate them into an unbiased default prediction model.

The market-based default prediction models which use only stock market information in predicting company default risk have been appealing to scholars in recent years. Merton (1974) viewed the firm's equity value as the value of a standard call option on the firm's asset value. In place of the conventional view of equity as a standard call option, Brockman and Turtle (2003) argued that corporate equity is a barrier call option on corporate assets. With the barrier option framework, the value of equity can be knocked out prior to a scheduled debt payment, which is more consistent with the real world practices. Although several recent papers have used market-based models to assess the likelihood of corporate failure, the construction industry is usually excluded in their empirical validation due to the unique industrial and accounting rules in the construction industry.

In order to find the optimal approach for predicting default in the construction industry, this research compared the performance of an accounting-based model, two market-based models, and a hybrid model, four models in total. The four models used in this study are: (1) the Logistic model (accounting-based model), which uses stepwise regression to select a limited number of accounting ratios that yield a powerful model, (2) the Merton model (market-based model), which is based on Crosbie and Bohn (2003) and selected after comparing three Merton-type models, (3) the Barrier option model (market-based model), which is based on Brockman and Turtle (2003), and (4) the hybrid model. The hybrid default prediction model combines information from both accounting-based and market-based models. The hybrid model inputs the default probability from the Merton Model into the logistic model. This study also uses the above models to empirically validate their applicability on the default prediction of construction contractors in Taiwan.

According to the empirical results, there were four major conclusions in this research. First, the Merton model has excellent discriminatory power in ranking contractors from riskiest to safest. The misclassification rates of the Merton model is 10%, which is smaller than that of the enhanced ratio model developed by Russell and Zhai (1996) (22%), and Severson et al. (1994) (12.5%). This implicates that the users can predict contractor default using only in time stock information, and avoid human judgement bias and periodical adjustment of using enhanced ratio models.

Second, the Merton model and Barrier option model obviously outperform the accounting-based model. Both of them have excellent performance in differentiating the risk of defaulted and non-defaulted construction contractors. Additionally, using them to predict contractor defaults also has markedly better discriminatory power than that of

Reisz and Perlich (2007) based on the data set of all industries except the construction industry from 1988-2002. This result is consistent with my primary contention that market-based models have an advantage for construction contractor default prediction.

Third, the Merton model outperforms the Barrier option model, and the performance of the hybrid model (AUC=0.8732) is only marginally higher than that of Merton model (AUC=0.8581). The hybrid model does not significantly improve the market-based approach of default risk measurement. This implies that not only are the market-based models superior to the accounting-based model, accounting information contributes only a very small amount of predictive power when it joins market information. The use of hybrid models to measure contractor default risk is unwarranted. Based on these findings, this research suggests that one should opt for the more parsimonious model and use Merton model to measure construction contractor default risk.

Fourth, due to the inefficiency in Taiwan's stock market, when using Taiwanese construction contractors as samples, the Merton model and hybrid model only have acceptable performances and do not significantly outperform the accounting-based model.

8.2. Research Contributions

The academic and practical contributions of this research are stated below:

8.2.1. Academic Contributions

(1) Although several recent papers, such as Brockman and Turtle (2003), Reisz and Perlich (2007), have used the Black and Scholes (1973) and Merton (1974) option-pricing framework to assess the likelihood of corporate failure, the construction industry is usually excluded in their empirical validation. This paper

uses, for the first time, the market-based models to measure the construction contractor default risk. The empirical results of this study support the researchers' contention that market-based models have an advantage for construction contractor default prediction and they provide an alternative to measure construction contractor default by using only stock market information. The current research proposes the possibility to explore the default risk of the construction industry using a more powerful tool.

(2) Previous studies developed construction contractor default prediction models rely on matched samples or partially adjusted unequal matched samples to test alternative methodologies or estimation methods. Zmijewski (1984) argued persuasively that this sample-matching method produces choice-based biases and sample selection biases. This research builds and validates models using a large cross-section of contractors, and put in all usable firm-years data in sample to avoid choice-based biases and sample selection biases. It is a novel approach in the research of construction default prediction models.

(3) All prior studies in the construction contractor default prediction literature relied on prediction-oriented tests to distinguish between alternative statistical models. It produces only two ratings (good or bad), which are only valid for a specific model cut-off point, and leads to a dichotomous decision. This is not consistent with the real world where a contract-awarding decision-maker and their stakeholders will typically make a continuous decision choice by ranking contractors from riskiest to safest. Contrary to prior studies in the construction contractor default prediction, this research proposes a new model evaluation approach- ROC curve, which employs discriminatory power to assess which model has the best predictive performance for

contractor default risk. The discriminatory power measures to what extent the model can differentiate firms that are more likely to default from firms that are less likely to default.

8.2.2. Practical Contributions

(1) This research presents a quantitative model based on market information to assess the financial performance of a construction contractor, and its chances of business survival. The model can be applied as part of a contractor evaluation process performed by project owners to develop a short list of contractors prior to contract award, and to select the competent contractor to finish the project on time and reduce disputes.

(2) Provide a powerful tool for surety underwriters to speed up the process of bonding and reaching a more reliable and objective bond/not bond decision.

(3) Contractors are highly reliant on financing from lending institutions. Under Basel II framework (2006), lending institutions are allowed to develop their own approaches to set capital charges with respect to the credit risks of their portfolios. This research provides an internal ratings-based approach for financial lending institutions to manage their credit risk exposure of contractor loans.

(4) Provide an approach for contractors to identify and avoid working with potential contractors or subcontractors that have high default risks. It can also provide an early warning mechanism which serves as an effective tool for contractors to monitor themselves and avoid continuing poor corporate performance or eventual insolvency.

8.3. Suggestions

(1) The scope of this research was limited to publicly listed contractors which trade in an efficient market. Besides, this research follows the general practice of assessing the probability of default over a one-year time horizon. The non-listed contractors in a partially efficient market and different time horizon can be included in future studies to ensure the practical applicability of the construction contractor default prediction model. Furthermore, this research have not bring into the data of construction contractors in North America after 2007 global financial tsunami as samples, further study could involve the North American data after 2007 and compare with Taiwanese samples.

(2) The costs of awarding contracts to an impending contractor who might fail will typically be much larger than the costs of rejecting a healthy contractor. To assessing the performance of different default prediction model, this research uses the ROC curve and its associated discriminatory power statistic to generalize different relative performances across all possible cut-off points, which can be associated with the costs of each type of classification error. While differential misclassification costs issue does not include in this research. It is essential to take into account the costs of awarding contracts to an impending failure contractor and the costs of rejecting a healthy contractor in the future research, which can relate the discriminatory power of the model to the optimal contract awarding decision of the project owner.

(3) The contractor potentially suffer from flow-based credit risk due to higher inventory ratio and high debt to equity ratio, which often lead to default events. Merton's original contingent claims model, and other subsequent refined models discussed in this research, does not contemplate cases in which firms default on their debt

obligations due to severe liquidity problems. The future studies can explore how to modify the current market-based models to meet the potential insufficient liquidity problem of contractors, and improve the predictive ability of market-based models in the construction industry.

(4) The current contractor’s pre-qualification system in Taiwan mainly focuses on the construction contractors’ past experience. For the financial ability, it only sets a minimum standard for contractors’ liabilities and assets to awarding contract. However, the result of this research indicates that the profitability is one of the most crucial factors in evaluating the default probabilities of construction contractors. Therefore, this research suggests the contractor’s pre-qualification system should also incorporate the profitability index of a construction contractor to generate a synthesized index. According to the degree of the synthesized index, project owners could rank construction contractors for awarding contract to a right contractor.

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