Early Warning Model for Bankruptcy:

The Case of Real Estate Firms in Thailand

ABSTRACT

The purpose of this study is to develop early warning models for bankruptcy of real estate firm in Thailand by using binary logistic regression and Cox proportional hazard from survival analysis. The sample data are both listed and non-listed real estate firms which consist of 32 bankruptcy firms and 64 non-bankruptcy firms collected during 2001-2009. Bankrupt firm is defined as the one that files at court under chapter 3 (liquidation) or under chapter 3/1 (reorganization). The predictor variables in this study include financial ratio, company-specific and corporate governance variables. The results from both models reveal more significant of financial ratios e.g. current liabilities to total assets and sales to inventory as leading indicators on corporate bankruptcy, than those of non-financial ratios. Only controlling ownership director shows significantly as leading indicator. All signs of leading indicators present as expected. Binary logistic model presents higher power of bankruptcy prediction than Cox proportional hazard model. Overall accuracy prediction is 96% and Type I Error is 6% for binary logistic regression model, whereas those for Cox proportional hazard model is 84% and 34%, respectively.

I. INTRODUCTION

Bankruptcy is a severe problem since it gives disaster to many parties such as creditors, investors, management, employees and customers, and finally affects the economy. The creditors and investors will lose their investments, the management will lose their reputation, the employees will lose their jobs and the customers may lose their goods (especially the customers of real estate firms who are under down payment period).

The bankruptcy of firm does not occur frequently. However, when taking place, it hits the country's economy. For instance, the series of U.S. firms' failure, e.g. Lehman Brothers, Merrill Lynch, and American International Groups during 2007 – 2008 not only led to a substantial decline in U.S.'s economy but also spilled over throughout the world's economies.

In case of Thailand, the well-known financial crisis in 1997, namely as the Asian financial crisis caused net losses about 42% of Thailand's GDP (source: World Bank). At that time, Thai Baht currency was hit heavily by over speculations and forced to float since 2 July 1997, and it became weak double. Foreign capital inflows diminished and financial institutions stopped lending to many businesses including real estate firms. Most real estate firms began to experience cash flow problems as bank lending stopped and housing demand dropped precipitously as many people stopped spending. Moreover, the real estate firms with foreign loans all suffered massive foreign exchange losses. Many real estate firms went bankrupt.

After the 1997 crisis, the number of housing developers dropped drastically, from about 2,000 companies to only 200 companies (GH Bank Housing Journal, July – December 2007). The real estate industry involves many industries: design-related professionals, construction companies, building materials producers and suppliers, and advertising companies, etc. Any real estate boom-and-bust tremendously impacts an economy. When real estate declines, construction job declines too, thus potentially increasing unemployment. It eventually leads to a decline in real estate prices, then reduces the value of everyone's homes, whether the owner want to sell it or not. This then reduces the amount of home equity loans to the homeowner, then, reduces consumer spending. A reduction in consumer spending will contribute to a downward spiral in the economy. If Bank of Thailand doesn't intervene by reducing interest rates, then the economy could fall into a recession. Real estate can weather recessions better than other segments of the economy. All real estate industry observers would like to know where the real estate market is heading so that they can develop more accuracy on their business plans.

Thai government realizes that the real estate industry is a significant driver of the country's economy. It always use policy related to real estate industry to motivate Thai economy. For example, to boost Thai economy downturn of 2009, it issued real estate policies as follows. First, buyers who buy residential property can deduct their taxable income ฿ 300,000; second, special business tax rate on selling houses is reduced from 3.3 percent to 0.11 percent; third, real estate title transfer fee is reduced from 2 percent to 0.01 percent, and the last, registration fee when real estate used as loan collateral is reduced from 1 percent to 0.01 percent. These policies' termination is just postponed from the end of March 2010 to 30 June 2010.

It is extremely beneficial to public policy makers concerned with economic development to have an efficient early warning model for bankruptcy on real estate firms on their hands. So, they can issue appropriate policies to avoid an economic downturn. Prevention an adverse event is better than solving after the problem occurs.

It is not only useful to government but also to real estate firms to be able to predict their probabilities to go bankrupt, so they can take actions to prevent the occurrence of bankruptcy. They may solve their financial problems by dealing with their creditors to have rehabilitation plans which cost less loss than bankruptcy.

The purpose of this study is to develop efficient early warning models by constructing bankruptcy models to anticipate the probability to go bankrupt of real estate firms in Thailand, and to identify leading indicators on corporate bankruptcy which are the models' significant predictor variables. We use 2 techniques, binary logistic regression and survival analysis in Cox proportional hazards form to build the models and compare the results of both models. Binary logistic regression model is the representative model of the static model, whereas the model from survival analysis is representative of dynamic model. We will discuss about these 2 approaches in section 3.

One more contribution in this paper is that it uses both real estate companies listed on the Stock Exchange of Thailand (SET) and non-listed real estate companies as sample data. All Thai journals studying on financial distress models use only listed companies as observations, even though most of bankruptcy firms were non-listed company, since it is a hard job to acquire non-listed companies' data in Thailand. We use 3 listed (9%) and 29 non-listed (91%) real estate firms, as observations of bankruptcy firms, and 24 listed and 40 non-listed real estate firms as non-bankruptcy firms. And, we use listed status to be an explanatory variable in the model to check whether it can be a leading indicator of real estate's bankruptcy. Therefore, this study will be a contribution to the literature on corporate financial distress prediction.

The high accuracy of the early warning models is very important, therefore, we use both financial ratio and non-financial ratio variables incorporated as predictor variables in the models. Non-financial ratio includes company specific data and corporate governance data. We use 32 real estate firms which experienced bankruptcy during 2001-2009, matching 64 survival real estate firms which are same sizes as sample data. Using corporate bankruptcy occurrence for different period in 9 years can capture the effect of various economic situations to the models.

The remaining of the paper is organized as follows: Section II reviews the previous literatures concerning on financial distress prediction model. Section III is the methodology mentioning about the framework and 2 techniques to establish the early warning models. Section IV is data presenting the source and definition of the observations, and bankruptcy measurement of variables. Section V discusses the results of empirical. Finally, section VI is conclusion.

II. LITERATURE REVIEW

There are a large number of papers studying on financial distress prediction which use different models, different predictor variables, and different definition of financial distress.

2.1 Model

2.1.1 Univariate Discriminant Aanlysis

Beaver (1966) was the first who created a corporate failure model by using Univariate Discriminant analysis. Beaver (1966) studied on 79 failed firms and 79 non-failed firms in the period of 1954 – 1964 by match-paired. Each pair was in the same industry and same size. Using 30 financial ratios from the 5 years prior financial statements to companies' failure, Beaver (1966) classified these financial ratios into 5 groups, (1) Cash Flow Ratios (2) Net Income Ratios (3) Debts to Total Assets Ratios (4) Liquid Assets to Total Assets Ratios (5) Turnover Ratios. Beaver (1966) found that there were 6 financial ratios include (1) Cash flow to total debt (2) Net income to total assets (3) Current liabilities plus long-term liabilities to total assets (4) Working capital to total assets (5) Current ratio (6) No-credit interval, which could predict failed firms. However, Univariate Discriminant Technique can present individually the difference of the mean of each financial ratio of the two groups. So the model may give inconsistent and confusing classifications results by using different financial ratios as a single predictor on the same firm (Altman, 1968).

2.1.2 Multiple Discriminant Analysis (MDA)

To avoid the inconsistent and confusing classification results of Univaritate Discriminant Analysis, Altman (1968) applied Multivariate Discriminant Analysis which can aggregate multiple financial ratios in a bankruptcy prediction model. Altman (1968) studied on 33 bankruptcy firms and 33 non-bankruptcy firms in the period of 1946 – 1965 by match-paired same as Beaver (1966), and used 22 financial ratios from the 5 years prior financial statements to companies' failure. Altman (1968) found that there were 5 financial ratios include (1) Working capital to total assets – same as the result of Beaver (1966) (2) Retained earnings to total assets (3) Earnings before interest and taxes to total assets (4) Market value equity to par value of debt and (5) Sales to total assets, which were the best predictor in the model of firms' bankruptcy. This paper also found that prediction in advance 1 year was accurate 94% for bankruptcy and 97% for non-bankruptcy, but the accuracy decreased when predicting in advance 2 years. The model was popularly known as Z-score model. Other studies use Multiple Discriminant Analysis such as Deakin (1972), Edmister (1972), Blum (1974), Izan (1984), etc. Even there are several papers use Multiple Discriminant Analysis, but they were criticized about potential violation on the assumption of independent multivariate's normal distribution (Eisenbeis, 1977) and assumption of homogeneity of variances. Ohlson (1980) then used logit analysis to avoid this criticism.

2.1.3 Logit Analysis (LA)

Ohlson (1980) was the first who used Logistic Analysis for bankruptcy prediction model. Ohlson (1980) studied on 105 bankruptcy firms and 2,058 non-bankruptcy firms used 4 financial ratios. Logit model is similar to MDA model as they are regression model, but logit's dependent variable is in the term of probability to be bankruptcy between 0 to 1, while MDA's dependent variable is in the term of score (Z-score) to classify the group of bankruptcy firms and non-bankruptcy firms. Ohlson (1980) found that there were 3 financial ratios include (1) Working capital to total assets – same as the result of Beaver (1966) and Altman (1968) (2) Net income to total assets – same as the result of Beaver (1966) (3) total liability to total assets, which were the best predictor in the model of firms' failure.

Aziz (1984) used both MDA and Logit Analysis to compare their efficiency of prediction. The study found that both models gave equally the power rate of prediction, and their powers were time-sensitive, showing higher rate of misclassification rate of bankruptcy and non-bankruptcy in longer period.

2.1.4 Probit Analysis

Casey, Mcgee and Stickney (1986) applied Probit Analysis to study financial distress companies. They used 57 active firms and 61 bankruptcy firms in USA during 1970 to 1981. They used sensitivity analysis and 20 independent trials for checking the accuracy of the model, which it showed that the probit analysis could perform well to discriminate firms in that period.

2.1.5 Artificial Neural Network (ANN)

Hertz, Krogh and Palmer (1991) introduced another approach, artificial neural network system (ANN). ANN is a computer algorithm that can be trained to imitate the cellular connections in the human brain. It contains a large number of interconnected elementary processing units to compute data. Many studies present the superiority of the ANN to other techniques in bankruptcy model such as Charalambous, Charitou and Kaourou (2000) and Tan and Dihardjo (2001). However, ANN method hides the network process to classify into bankruptcy and non-bankruptcy groups. This “black box” problem is ANN’s disadvantage.

2.1.6 Survival Analysis (SA)

All of the prior methods mentioned – Discriminant Analysis, Logit Anallysis and ANN, are “static models”. They assume that the time from classification as bankruptcy to actual firms’ bankruptcy occurrence within a single period. However, this assumption is violated because bankruptcy does not occur immediately after classification, but it is preceded by the deterioration in a firm’s financial health over a number of years, from “healthy” to “financial distress” and onto “bankruptcy”. To overcome the assumption of steady state for failure process, a dynamic technique – survival analysis has promptly emerged.

Survival Analysis (SA) is widely used in medical fields for the symptom identification of potentially fatal diseases. Survival analysis uses the Cox proportional hazards model (Cox, 1972) to estimate survival and failure probabilities based on historical data of previously bankruptcy firms. Survival Analysis uses independent or symptom variables (covariates) such as financial ratios, company specific factors and environmental variables as symptoms which help to identify the degree of bankruptcy.

The pioneer paper on Survival Analysis with Cox proportional model is by Lane, Looney and Wansley (1986). They created their model based on 334 successful and 130 failed banks from the period of 1979 to 1983. The model was tested on a hold-out sample with one and two year predictions. The prediction accuracy of Survival Analysis was found to be comparable with MDA, but Cox model produced lower Type I Errors. Then, Crapp and Stevenson (1987) used Cox model to some Australian credit unions with same result. Laitinen and Luoma (1991) studied on 36 failed and 36 successful Finnish firms. Its result shows slightly less power prediction when compared with MDA and LA. Shumway (2001) formed SA model by using various financial ratios and market-driven variables for over 2,000 companies from the NYSE and AMEX over 31 years. This was the first use of a multiperiod logit model to estimate the SA model coefficients. The result shows the theoretical superiority of SA over MDA and LA. Shumway (2001) only considered Type I Error. Other studies use SA such as, Raj and Rinastiti (2002), Romer (2005), and Chancharat, Davy, McCrae and Tian (2007).

2.2 Predictor Variables

2.2.1 Financial predictor variables

Financial ratios have long been widely used in probability financial distress prediction models such as Beaver (1966), Altman (1968) and Romer (2005). Beaver (1966) was the first who used 30 financial ratios as predictor variables in corporate failure prediction. He classified these financial ratios into 5 groups, (1) Cash Flow Ratios (2) Net Income Ratios (3) Debts to Total Assets Ratios (4) Liquid Assets to Total Assets Ratios (5) Turnover Ratios.

2.2.2 Non-financial predictor variables

Company-specific variables

Company's age and size are company-specific variables which are used in explaining the possibility of corporate financial distress such as Chanchat, Davy and Tian (2007).

Corporate Governance

Plenty of literatures studying Asian financial crisis in 1997 pointed out that "corporate governance" was one of the key factors associated with financial distress. For instance, Rajan and Zingales (1998) and Prowse (1998) found that ownership concentration and poor corporate governance were to major reasons that led to the onset of Asian financial crisis. Johnson, Boone, Breach and Friedman (2000) further suggested that "corporate governance variables" could be better explained the occurrence of Asian financial crisis than "macroeconomic variables".

Morck, Shleifer and Vishny (1988) found that firms with lower ownership by directors are more likely to run into financial distress. Chen and Hu (2001) pointed out that controlling shareholders might expropriate company wealth to help sustain the stock prices; they will divert the company funds to their own use, and such more significantly increases the exposure of the firm to financial distress.

Lu, Lee and Chang (2008) constructed financial distress probability models using corporate governance variables as predictors. They consisted of voting rights of controlling shareholder, cash flow rights of controlling shareholder, management participation, cross-holding, stock pledge ratio of directors, stock pledge ratio times level of stock pledge, level of director ownership and level of stock pledge. Several corporate governance variables exhibited significant effect on the occurrence of financial distress, such as voting rights of controlling shareholder, cash flow rights of controlling shareholder, management participation, cross-holding, pyramid structure, and ownership and stock pledge ratio of major shareholders, of which management participation was significant, while the factor of family control was not significantly correlated.

2.3 Definition of financial distress

There are many papers studied on “financial distress” topic, which have different definitions. The study of “financial distress” originated from the study of Beaver (1966), in which he defined “financial distress” as incurring huge overdraft, default on payment of preferred stock dividends and corporate bonds, and filing bankruptcy, whereas Altman (1968) and Ohlson (1980) defined “financial distress” as declaring or filing of bankruptcy.

According to Baldwin and Scott (1983), a firm is deemed in financial distress when it was unable to pay its debts, while the first warning signal of distress is oftentimes defaulting debt obligations or unable to pay dividends.

By definition of Hopwood, Mckeown, and Mutchler (1994), a firm is in financial distress if the following three conditions are satisfied simultaneously: (1) negative working capital for the year; (2) operating loss in any three years prior to bankruptcy; and (3) negative retained earnings in three years prior to bankruptcy; in addition, a firm is deemed mildly distressed if it incurred deficit in any of the three years prior to bankruptcy.

Opler and Titman (1994) specified distress industries as the industries which median sales growth was negative and median stock return was less than -30%. This research investigated whether high leverage firm lost their market share and had lower stock return than lower leverage firm during the decline cycle of the industry.

Whitaker (1999) defined a firm as financially distressed if the firm's first-year cash flow is less than its soon-to-be-due long-term debt; he suggested that only if the firm's cash flow exceeds the current debt is the firm ability to repay its debt.

In sum, the definition of "financial distress" in previous literatures are inability to pay debts, experiencing negative net worth, business closure, bankruptcy, reorganization, and delisting. And some quasi distress events are embezzlement, serious loss, credited tightening by the banks, check bouncing, and temporary suspension of stock trading.

2.4 Thai literature on financial distress

Comparing with other countries, in Thailand there are not many literatures studying on bankruptcy prediction model, such as Khunthong (1997), Peetawan (2005), Sookhanaphibarn, et al. (2007) and Meechai (2009). Khunthong (1997) used 17 financial ratios of listed companies in The Stock Exchange of Thailand (SET), and employed MDA and logit analysis. Khunthong (1997) found that non-financial firms could be more accurately predicted than financial firms. Peetawan (2005) used Z-score to predict "Companies under Rehabilitation" (REHABCO), the companies which had financial problems and SET put them in a special class for restructure. Peetawan (2005) showed an accuracy rate of 77 percent for the REHABCO group compared to a rate of greater than 90 percent for the normally listed group. Sookhanaphibarn, et al. (2007) used ANN and studied on financial ratio and ownership status as predictors, and studied on financial listed company during the Asian Crisis. The ownership variable was proved to play an important role on financial distress prediction. Meechai (2009) employed Cox proportional hazard model and used 11 financial ratios of 20 listed financial distress companies as predictor variables. Working capital to total asset ratio, debt to equity ratio, total debt to total asset and return on asset were found to be the significant impacts on the model.

III. METHODOLOGY

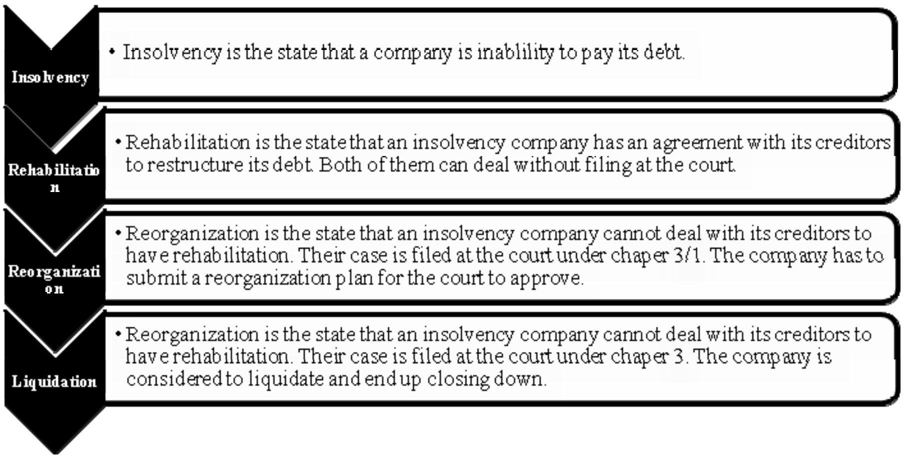
The techniques we employ are a popular traditional statistical approach, namely binary logistic regression, as well as a recently developed approach, namely survival analysis (Cox proportion hazard). Both different techniques are constructed bankruptcy prediction models. They are explained in sub-section 3.2 after theoretical framework of bankruptcy definition and predictor variables are explained in sub-section 3.1

3.1 Theoretical Framework

3.1.1 Bankruptcy

According to Thai law, bankruptcy comprises two major types: liquidation and reorganization. Liquidation proceeding has been under Thai law since 1940 (Chapter 3), while reorganization proceeding was established in 1998, after the 1997 Asian financial crisis. The devaluation of the Baht on July 2, 1997 led to numerous corporate debt defaults, for which the Thai legislative or regulatory system was inadequate. A major amendment to its antiquated bankruptcy law was made to allow for corporate restructuring similar to the United States' Chapter 11.

In April 1998 Bankruptcy Act Amendment came into force. The new Chapter 3/1 (Sections 90/1 through 90/90) was added to the original Bankruptcy Act of December 1940 (Chapter 3). The main purpose of this amendment is to give a chance to an organization which has inability to pay its creditors temporarily to reorganization instead of liquidation and closing down. It establishes a judicial process for reorganization of debtors. It includes procedures for the appointment of a reorganization plan preparer ("planner"), approval of such a plan, appointment of the plan administrator and implementation of the plan. Following diagram presents the relationship of each state of financial distress company.



In sum, bankruptcy is a legally declared inability or impairment of ability of an organization to pay its creditors. Creditors may file a bankruptcy petition against a debtor (involuntary bankruptcy) in an effort to recoup a portion of what they owned or initiate a restructuring. However, in the majority of cases, bankruptcy is initiated by debtor (voluntary bankruptcy) that is filed by the insolvent organization in an effort to set up a reorganization plan.

3.1.2 Key factors of bankruptcy occurrence

Basically, all firms want to run business on the concept of "going-concern", however, some inevitably face problems and end up with bankruptcy. The major causes of business bankruptcy are financial factors (too much debt, insufficient capital, low profitability etc.), and non-financial factors (neglect, poor experience, disaster, fraud, etc.). Most failures occur because a number of factors combine to make the business unsustainable. So in this study we will use these 2 factors to be key predictors in the early warning system of bankruptcy.

Financial factors

The use of financial ratios to predict bankruptcy has been well established since the original study of Beaver (1966). Most of the empirical literatures in this area have used financial ratios and have been successful in classification between bankruptcy and non-bankruptcy firms. Since financial ratios reflect almost all firm's performance, activity, profitability, liquidity and financial leverage.

Therefore, to develop effective bankruptcy prediction models to find out early warning signals for real estate bankruptcy, financial ratios are introduced as explanatory variables in our models. Table as follows, is presented financial ratios which were used successfully to predict bankruptcy in prior empirical studies.

Group	Factor	Ratio	Studied by						
			Beaver	Altman	Deakin	Edmister	Blum	Elam	Ohlson
1	Profitability ratios	Net Income/Sales						X	
		Funds Flow/Net Worth						X	
		Funds Flow/Total Assets						X	
		Net Income/Total Assets	X		X				X
		Net Income/Net Worth						X	
		Operating Income/Sales						X	
		EBIT/Total Assets		X					
2	Activity ratios	Quick Assets/Total Assets			X				
		Funds Flow/Sales						X	
		Current Assets/Total Assets			X				
		Net Worth/Sales				X			
		Sales/Total Assets		X				X	
		Working Capital/Total Assets	X	X	X				X
3	Financial Leverage ratios	Total Liabilities/Total Assets	X		X			X	X
		Total Liabilities/Net Worth					X	X	
		Funds Flow/Total Debts	X		X		X	X	
		Funds Flow/Current Liabilities				X			
		Retained Earnings/Total Assets		X					
		Market Value Equity/Total Liabilities		X					
4	Short-Term Liquidity ratios	Current Assets/Current Liabilities	X		X			X	
		Quick Assets/Current Liabilities			X	X		X	
		Current Liabilities/Net Worth				X			
		Current Liabilities/Total Assets						X	
5	Inventory Turnover	Sales/Inventory				X			

Group 1: Profitability ratios

Profitability ratios measure a firm's ability to generate earnings. Profit is one source of funds form operation. The more profit that a firm can generate, the more funds increase the liquidity of the firm. Many firms go bankruptcy when they have negative earning. Therefore profit often used as a predictor of bankruptcy event.

Group 2: Activity ratios

Activity ratios measure the efficiency of a firm's assets utilization to generate revenue or return. If firms can use assets efficiently, they will earn more revenue and increase liquidity and net income.

Group 3: Financial Leverage ratios

Financial Leverage ratios are concerned to the capital structure of the firm. These ratios show the sources of fund provided from external and internal and also have been used to measure the long term solvency of a firm.

Group 4: Short-Term Liquidity ratios

Short-Term Liquidity ratios measure a firm's ability to meet its obligations as they become due. Liquidity ratios also have been used to measure short term solvency. The higher level of liquidity provided a strong barrier against going bankruptcy. Most firms meet illiquidity and then become financially insolvent and eventually become bankruptcy while they still profitably operate.

Group 5: Inventory Turnover ratios

Inventory Turnover ratios measure the ability of the firm to manage its inventory. A low turnover implies poor sales and, therefore, excess inventory. A high ratio implies either strong sales or ineffective managing inventory level. High inventory levels are unhealthy because they present an investment with a rate of return of zero. It also opens the company up to trouble if the prices begin to fall.

Non-financial factors

Most of the previous literatures successful used financial ratio as predictors in their financial distress prediction models. However, financial statements provide only ex post information on corporate operations. When such financial information is disclosed, financial distress might be imminent or have already occurred. Thus there is a need to add company specific and corporate governance variables to construct early warning model for corporate financial distress models.

The prior studies suggest that company age and size affect its endurance. The younger or smaller firms are more likely to fail than bigger firms as they do not have sufficient experience in the business, low network connection and limited information. Large firms tend to get more help from external sources to avoid bankruptcy (Honjo, 2000). Lussier (2005) found that there were some non-financial ratio (industry experience, CEO's age, professional advice and planning) influenced on predicting real estate business success or failure. Lu, Lee and Chang (2008) found that several corporate governance variables exhibited significant effect on the occurrence of financial distress, such as voting rights of controlling shareholder, cash flow rights of controlling shareholders, management participation, pyramid structure, and ownership.

3.2 Model

3.2.1 Binary logistic regression Model

Binary logistic regression model is a popular tool for analyzing event that is dichotomous or binary response variable. For example, an outcome might be presence or absence of disease, died or not died, bankruptcy or non-bankruptcy etc. Binary logistic regression model was developed by Berkson (1944), and first applied to the prediction of financial distress by Ohlson (1980). Its advantages over linear probability models are that the resulting probability values will lie between 0 and 1, and the empirical data used are not required to observe the assumption of normal distribution. The purposes of logistic regression analysis are two folds: to derive significant independent variables, and to use the independent variables for predicting the probability of bankruptcy through the constructed model. The binary logistic regression model (mathematical form) used in this study is as follows:

$$Prob\ (Y_i = 1) = \frac{1}{1+e^{-Z_i}} \qquad (1)$$

Where

$$Z_i = \beta_0 + \sum \beta_j X_{ji}$$

Y_i is the dependent categorical variable assigned the value of 1 if a firm *i* is bankruptcy (as defined in Section 3.1) and zero otherwise.

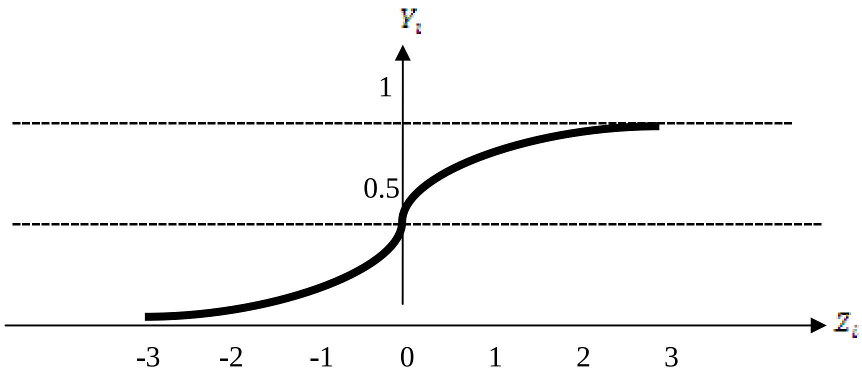
Z_i is a linear function in which β_0 is the estimated intercept, $X_{j,i}$ is the explanatory variable *j* for the firm *i*.

β_j is the coefficient of $X_{j,i}$.

Prob ($Y_i = 1$) is between 0 and 1.

The probability with firm *i* will be classified as being in bankruptcy if the computed probability exceeds 0.5 (default cut-off point = 0.5).

Function (1) can be presented as following graph:



Probability of neutral (default cut-off = 0.5) when $Z_i = 0$

Probability of a firm to go bankrupt ($Y_i > 0.5$) when its $Z_i > 0$ (positive)

Probability of a firm to survive ($Y_i < 0.5$) when its $Z_i < 0$ (negative)

From *(1)*, probability for non-bankruptcy (survival) is

$$1 - Prob\ (Y_i = 1) = 1 - \frac{1}{1+e^{-Z_i}}$$

$$Prob\ (Y_i = 0) = \frac{e^{-Z_i}}{1+e^{-Z_i}} \qquad (2)$$

$$\frac{Y_i}{1-Y_i} = e^{Z_i} \qquad (3)$$

Equation (3) is called Odds Ratio which is the probability to be bankruptcy time over probability to be non-bankruptcy. Odds ratios range from 0 to positive infinity. High odds ratio means high chance to be bankruptcy. e^{β_i} is called Factor which presents the change of odds ratio as X_i changes 1 unit while other explanatory variables are hold, Odds ratio will change e^{β_i} which called marginal effect. If β_i = 0, e^{β_i} = 1 which means no change on odds ratio. Odd ratio is logit model which can be transformed to be a linear model in order to more understanding as follows:

$$ln\left[\frac{\pi_i}{1-\pi_i}\right] = Z_i \qquad (4)$$

Where

$$Z_i = \beta_0 + \sum \beta_j X_{j,i}$$

This form is called Log-Odds. Binary logistic regression uses Maximum likelihood estimation (MLE) to calculate the logit coefficients. This contrasts to the use of ordinary least squares (OLS) estimation of coefficients in regression. OLS seeks to minimize the sum of squared distances of the data points to the regression line.

Log likelihood ratio test

The log likelihood ratio test is for testing the explanatory power of a variable to identify whether the incorporation of the variable provides explanatory significance. Thus, if the result rejects null hypothesis, it means the model has explanatory power (goodness-of-fit).

The hypothesis is as follows:

$H_0 : \beta_1 = \beta_2 = \beta_3 = \cdots \beta_n = 0$

$H_1 : \sim H_0$ $\quad$ $, at\ least\ a\ \beta \neq 0$

where β_i is the parametric estimation of explanatory variable *i* in the model.

Cox & Snell R^2 and Nagelerke R^2

These tests analyze the explanatory power of the model for data variance. Higher R^2 Value means the model is fit for analysis of sample data. The maximum of 1 cannot be obtained by using Cox & Snell R^2, while maximum value of Nagelkerke R^2 equals to 1.

Interpretation of empirical result

The explanatory variable is discrete variable.

Suppose listed status is a discrete variable. Listed company equals to 1, and non-listed company equals to 0. If odd ratio (e^{Z_i}) is bigger than 1; suppose it equals to 1.5, interpreting that listed company has higher probability to be bankruptcy than non-listed company 1.5 time, while other explanatory variables are hold. If odd ratio (e^{Z_i}) is less than 1; suppose = 0.5, interpreting that listed company has higher probability to be bankruptcy than non-listed company 0.5 time which is less than 1 time. Or, non-listed company has higher probability than listed company 2 times (1/.5), while explanatory variables are hold.

The explanatory variable is continuous variable.

Suppose net income to total asset (unit: percent) is a continuous variable. If e^{Z_i} is greater than 1 (suppose = 1.05), interpreting that net income to total asset increase 1 percent, probability to run bankrupt increase 5%, while other explanatory variables are hold. If e^{Z_i} is smaller than 1 (suppose = 0.95), interpreting that net income to total asset increase 1 percent, probability to run bankrupt decrease 5%, while other explanatory variables are hold.

3.2.2 Survival Analysis (SA)

Survival analysis is a class of statistical method for studying the occurrence and timing of events (Chancharat, Davy, McCrae and Tian, 2007). Events in our case are bankruptcies which progress over time as the financial distress worsen. Companies may state from healthy to financial distress and finally go bankruptcy over several periods. So we need a methodology which allows for dynamic path analysis as SA. SA is a dynamic model which is different from other models - Univariate Analysis, MDA, Logit Regression Analysis and ANN, called static models. Contrast to the traditional methods which only examine the level of a variable at a given point in time as they simply view the observation at a “snap-shot” in time (Leclere, 2000). It models the probability of a change in dependent variable Y_t from an origin state j to a destination state k as a result of causal factors (Blossfeld and Rohwer, 1995). It is a tool to find the time for becoming of non-bankruptcy firms to be bankruptcy firms.

SA is an appropriate method used in this case since it allows for time-varying covariates and censored observations. SA is the only well-known techniques that incorporate the time series nature of business failure process data into its model (Gepp and Kumer, 2008). Time varying covariates are the independent variables that change over time. In our case, they are financial ratios, non-financial ratio and economic variables. Most of their values change over time. Censored observations are the observations that have never experienced the event during the observation time. Censored observations occur when the duration of the study is limited in time. In our case, censored observations are the non-bankruptcy firms as they have never entered into bankruptcy during the study time. SA uses both censored observations and bankruptcy firm observations in its process.

There are 2 functions in SA, survival function and hazard function. The Survival function, *S(t),* gives the probability that the time until the firm experiences the event, *T*, is greater than a given time *t*. *T* is a random variable which is the event time for some observations, then the survival function is defined as:

$$S(t) = Pr(T > t) \tag{5}$$

As dependent variable in SA is the event time which is accumulate time period of firm from origin or some state until it face the event and has positive value, the cumulative distribution function of event time is denoted as:

$$F(t) = Pr(T \leq t) = \int_0^t f(x)dx \tag{6}$$

It can be interpreted that there is probability that event time will occur within time *t*.

So,

$$S(t) = Pr(T > t) = 1 - F(t) \tag{7}$$

It is the probability that a firm will survive when pass time *t* or greater than time *t*. The probability density function is denoted as:

$$\begin{aligned} f(t) &= \lim_{\Delta t \to 0} \frac{Pr(t \leq T \leq t+\Delta t)}{\Delta t} \\ &= \frac{dF(t)}{dt} \\ &= -\frac{S(t)}{dt} \end{aligned} \tag{8}$$

Alternatively, the survival function can be defined as:

$$S_i(t) = S_0(t)exp^{(Xi\beta)} \tag{9}$$

where $S_0(t)$ is a baseline survival function,

X is the vector of independent variables and

β is the parameter which needs to be estimated.

Another function, the hazard function, is the probability that an event will occur at time t given that the firm survives to time t. The hazard function is also known as the hazard rate since it has the form of number of events per interval of time. The hazard function can be defined as:

$$h(t) = \lim_{\Delta t \to 0} \frac{Pr(t \le T < t + \Delta t \mid T \ge t)}{\Delta t} \tag{10}$$

The survival function $S(t)$ represents the probability that a business will survive past a certain time t, while the hazard function $h(t)$ represents the instantaneous rate of bankruptcy at a certain time t. The interpretations of these two functions is very different, but either one can be derived from the other. The relationship of them as follow:

From (10)

$$\begin{aligned} h(t) &= \lim_{\Delta t \to 0} \frac{Pr(t \le T < t + \Delta t \mid T \ge t)}{\Delta t} \\ &= \lim_{\Delta t \to 0} \frac{F(t + \Delta t) - F(t)}{\Delta t \,.\, S(t)} \\ &= \lim_{\Delta t \to 0} \frac{-S(t + \Delta t) - S(t)}{\Delta t \,.\, S(t)} \\ &= -\frac{d}{dt} lnS(t) \end{aligned} \tag{11}$$

So, the hazard function is the negative of slop of natural logarithm of survival function. They have opposite direction. When a firm has a higher probability to survive, its probability to bankrupt will be lower, or vice versa.

There are 3 different techniques in SA for building models including non-parametric, semi-parametric and parametric techniques. Non-parametric techniques do not require data distribution. They use past data to calculate the functions at each specific time. They are useful to analyze past bankruptcy to help further the understanding of the bankruptcy process. But they do not have ability to make future predictions (Gepp and Kumer, 2008). Kaplan-Meier method is the most popular methods of these techniques. Parametric techniques require specification of data distribution to present survival times, such as exponential, log-normal, log-logistic and gamma distributions. Semi-parametric techniques, unlike the parametric, do not require the particular probability distribution. There are only some parts that require distribution. The remains do not require distribution assumption. That is why they are called Semi-parametric techniques. Cox proportional hazards model proposed by Cox (1972) is the most widely used for these techniques. Cox proportional hazards model is represented as:

$$h_i(t) = h_0(t)exp^{(Xi\beta)} \qquad (12)$$

$h_i(t)$,Cox proportional hazard model consists of 2 parts, $h_0(t)$ and $exp^{(Xi\beta)}$. $h_i(t)$ presents the hazard rate of company *i* at time *t*. $h_0(t)$ is a baseline hazard rate which measures the effect of time on the hazard rate for a firm whose covariates all have values of zero. Baseline hazard function or baseline hazard rate is the part that does not require distribution as mentioned before. It presents change of hazard rate effect from change of time only. While $exp^{(Xi\beta)}$ is called proportion hazard, presents change of hazard effect from change of covariates *X* as:

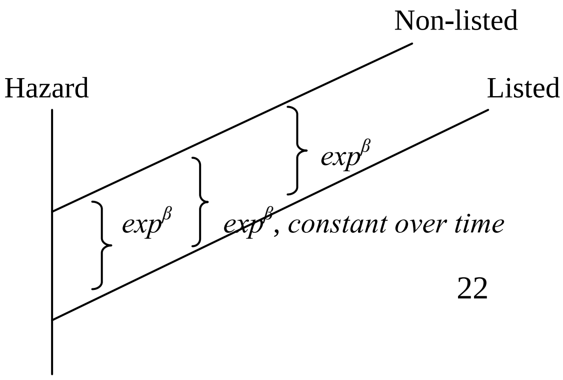
$$\frac{h_i(t)}{h_0(t)} = exp^{(Xi\beta)} \qquad (13)$$

X is the vector of covariates that influence the hazard,

β is the vector of their coefficients which need to be estimated.

The hazard at time *t* depends on the value of covariates (*X*) at time t. The covariates used in the model are time-independent variables which mean that they can change in value over the study period. Proportional hazard does not depend on time but depend on X_i and constant exp^{β}. It means that proportional hazard does not vary during the time. exp^{β} is called “hazard ratio”, which means how hazard of bankruptcy is bigger than non-bankruptcy.

It remains constant over time, but not same over time as figure simply shown below:



Time

Cox (1972) uses the method of partial likelihood to estimate the β parameter.

PH assumption test

The main assumption of Cox Proportional Hazard model is that, the effect of each independent variable in model is the same over the time. If it varies with time, the proportional hazard is violated that covariate. The consequences include biased parameter values, incorrect standard errors and biased estimates of the true hazard rate. The null hypothesis of PH assumption test is $H_0 : \rho = 0$, *while* ρ is the relationship between residual of hazard and time. This paper tests the proportional hazard assumption by testing the relationship between the Schoenfeld residuals and bankruptcy time. If no relationship (p-value > 0.05) means that the assumption is acceptable, therefore the model passes PH assumption test.

Goodness-of-fit test

Given the parameters for the different distribution functions, we can compute the likelihood of the data, and also compute the likelihood of the data under the null model, that is, a model that allows for different hazard rates in each interval. These two likelihoods can be compared by Chi-square test statistic. If this Chi-square is statistically significant at 5 percent level, then we conclude that the model fits the data significantly better than null model; that is, we accept the parameters in the model.

Interpretation of empirical result

If hazard ratio equals to one, the independent variable does not effect survival. But, if it is smaller (bigger) than one, the independent variable is associated with increased (decreased) survival.

3.2.3 Comparison of Binary Logistic Regression and Survival Analysis

Binary Logistic Regression	Survival Analysis (SA)
1. Logistic Regression is Static Approach. Predict probability of event at spot time.	1. SA is a Dynamic Approach. Analyze the time to event (event rates).

	Rate at *t* = Rate among those at risk at *t*
Binary Logistic Regression	**Survival Analysis (SA)**
2. Logistic assumes that the observation comes from two distinct populations, bankruptcy and non-bankruptcy firm.	2. SA assumes that all observations come from the same population distribution. The non-bankruptcy firms are treated as censored data, which indicates that their time of bankruptcy is not known yet.
3. LA is logistic distribution.	3. Since SA with Cox proportional hazard model is semi-parametric approach, it does not have the restrictive normal distribution assumption. Its assumption is that hazard rate is constant over time.
4. LA is designed to predict future event. The probability of the outcome is measured by the odds of occurrence of an event.	4. SA is designed to focus on determining the effects of explanatory variables on the life of business (leading indicators to be bankrupt), rather than being designed to predict outcomes such as the failure of businesses. (Gepp and Kumar, 2008).
5. Predictor Variables – Categorical or continuous	5. Predictor Variables – Categorical or continuous and Time
6. Censoring permitted - No	6. Censoring permitted - Yes
7. Mathematical model (odd ratio) : $\frac{p}{1-p} = e^{\beta}$	7. Hazard rates : $h(t) = h_0 \, e^{\beta}$
8. There is only 1 function : odd function $\frac{p}{1-p} = e^{\beta}$	8. There are 2 functions, hazard and survival functions. Hazard function: $h(t) = h_0 \, e^{\beta}$

	Survival function: $S(t) = S_0 . e^{\beta}$

IV. DATA

In this section we mention the sample data and variables used in our study.

4.1 Data

4.1.1 Definition of real estate firm

In this study, real estate firms mean developer firms which they produce residences, including detached homes, townhouses, or condominiums, to sell. It does not cover rental activity or construction service, which it differs from SET's industry classification. The Property sector of SET's industry classification covers all real estate activities - selling residences, real estate-rental service and construction service.

4.1.2 Definition of bankruptcy firm

Bankruptcy is a legal condition where a company has petitioned the bankruptcy court. So bankruptcy firm in this paper means the firm which is filed for bankruptcy under either Chapter 3 or chapter 3/1 at The Central Bankruptcy Court. Dependent variable in this study is represented as Y, which is binary variable (Y = 1 when a firm is bankruptcy, Y = 0 when a firm is non-bankruptcy).

4.1.3 Source of data

In this study, we use the data both listed and non-listed real estate firms that were bankrupt during the period 2001-2009 of which data are available. We get the list of 32 bankruptcy real estate firms from www.ratchakitcha.soc.go.th as shown in Table I. 10 real estate firms were filed for bankruptcy under Chapter 3 (liquidation) and 22 of them were filed under Chapter 3/1 (reorganization). And, the list of 64 non-bankruptcy real estate firms we got from Ministry of Commerce Thailand and www.set.or.th and www.setsmart.com, which were matched with the bankruptcy firms as the same sizes (total assets) in the proportion 1:2 (bankruptcy : non–bankruptcy), as presented in Table II. In order to have the observations which have accuracy in accounting system, we choose the observations which have total assets over than 100 million.

[Table I and Table II are here]

Table III is presented the observations classified by size (total assets) and listed status. There are 5 big firms, 16 medium firms and 11 small firms in the bankruptcy classification, and there are 10 big firms, 32 medium firms and 22 small firms in the non-bankruptcy classification. There are 3 listed firms from 32 bankruptcy firms (10 percent) and 24 listed firms from 64 non-bankruptcy firms (37 percent).

[Table III is here]

The yearly financial statement data and other relevant information of non-listed firms are acquired from Ministry of Commerce while those of listed firms are acquired from SET. As binary logistic regression technique, we will use those data which are 2 year prior occurrence of bankruptcy firms and their matching non-bankruptcy firms, while Cox proportional hazard technique uses the data at the beginning year of the study period (year 2000-2009) for all observations.

4.2 Bankruptcy predictor

Bankruptcy predictor variables which influence on going bankruptcy are classified to 2 groups – financial ratio variables and non-financial ratio variables.

4.2.1 Financial ratio variables

As Table shown in sub-section 3.1.2, we use net income to total assets ratio as representative for profitability ratio. This ratio is particularly appropriate for studies concerning with firm failure since a firm’s ultimate existence is based on the earning power of its assets.

Current assets to total assets ratio, which presents the ability of firm to manage total assets to be current assets, and sales to total assets ratio, which shows the sales generating ability from the firm’s assets, are chosen to be represented for activity ratios. They measure of management’s capacity in dealing with competitive conditions, which is quite important.

For financial Leverage ratios, we use total liability to total assets as representatives. This ratio presents the ability of firm to pay total liabilities by total assets and implies for the capital structure, how company manage source of fund from outside and outside.

Most of the prior literatures used Current assets to current liabilities ratio to be an explanatory variable in the bankruptcy prediction model, so we choose it to be representative for short-term liquidity ratio group. This ratio presents the ability of firm to pay short term liabilities from short term.

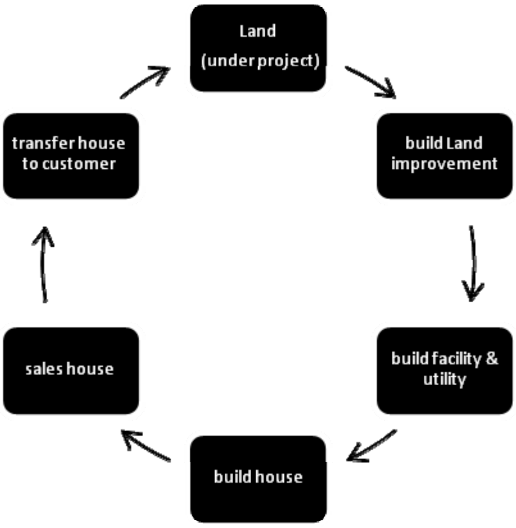
Sales to inventory ratio measures the ability of the firm to manage its inventory. This ratio is chosen to be representative for inventory turnover ratio group.

We add more 4 financial ratio variables in our study –inventory to total assets (which is in activity ratio group), current liabilities to total assets ratio, equity to total liabilities ratio and loan to total assets ratio (3 financial ratios are in financial leverage ratio group). These ratios have high different mean value of bankruptcy firms and non bankruptcy as table follows:

Financial ratio	Mean - Bankruptcy	Mean – Non Bankruptcy
Inventory to total assets	84.465%	65.961%
Current liabilities to total assets	123.493%	44.023%
Equity to total liabilities	-24.42%	150.372%
Loan to total assets	127.393%	41.716%

Mean value of bankruptcy: from financial statement 2 year before bankruptcy occurred.
Mean value of non-bankruptcy: from financial statement which is the same period of their matched bankruptcy firms.

We choose inventory to total assets as a predictor variable since inventory is very important item for real estate firm. It is a big account to total assets. The mean of inventory to total assets of the sample data bankruptcy firm and non-bankruptcy firm is 65 percent and 84 percent respectively as table above. The inventory cycle of real estate firm is longer than 1 year as diagram below, which is different from other industry – its inventory cycle is within 1 year. So, if a real estate firm has too high level of inventories and cannot sell them in proper time, it is going to have financial difficulties and may consequently face bankruptcy.



Inventory cycle of real estate firm

Current liabilities to total assets, equity to total liabilities and loan to total assets are ratio in financial leverage ratio group, which are also important in real estate firms. Most of them have high level of loan since activity to run a project needs a big amount of capital, that internal source of fund may not be inadequate. If they have high debt while their performances are low, this may cause them to go bankrupt. Current liabilities in real estate firms equal to current liabilities plus project loan. Whole amount of project loan for real estate firm is considered to be short term liability since it relate to inventory item. The money from project loan is used to construct inventory which consists of land, improvement on land, utilities and houses. Another reason is that it cannot classify project loan to be short term and long term. The firm will pay its creditor when they can sell houses.

4.2.2 Non-financial ratio variables

According to Honjo (2000), we use the size of the company to be an explanatory, which logarithm of total assets is the proxy. And we use company's age to be proxy of industry experience as Lussier (2005) found that it influenced on predicting real estate business success or failure. Lu, Lee and Chang (2008) use some corporate governance to be independent variables, that we follow him by using family status, level of director ownership, and the existence of controlling shareholder as predictor variables. The expropriation problem caused by controlling shareholders tends to be more severe when controlling shareholders serve as executive directors (Claessens et al., 2002). Firms with lower ownership by directors are more likely to go bankruptcy. Morck, Shleifer and Vishny (1988) found that firms with lower ownership by directors are more likely to run into financial distress. And we add one more variable, listed status of company, to be non-financial variable. Listed company status implies a bigger size which tends to have less probability to go bankruptcy than non-listed company.

4.2.3 Predictor variables' symbols

The proxies of 10 financial ratios as follows:

NI/TA = Net income to total assets

CA/TA = Current assets to total assets

INV/TA = Inventory to total assets

SA/TA = Sales to total assets

TL/TA = Total liabilities to total assets

EQ/TL = Equity to total liabilities

CA/CL = Current assets to current liabilities

LO/TA = Loan to total assets

CL/TA = Current liabilities to total assets

SA/INV = Sales to Inventory

And, the proxies of 6 non-financial ratios are as follows:

LnTA = logarithm of total asset

Listed = listed company status (1 = Listed company, 0 = non-listed company)

Age = company's age (year)

Family = family director status (1 = firm has at least 3 directors who have same surname, 0 = otherwise)

Control = existence of controlling shareholder director (1= firm has at least one shareholder director with more 25% of shares, 0 = otherwise)

Ownership = level of ownership director (director ownership = director who owns stock at least 5 percent)

All 16 independent variables in this study are represented as proxy above. Next is the section of empirical results.

V. EMPIRICAL RESULTS

In this section, we first check the basic quality of the sample data, correlation test (multicollinearity), in sub-section 5.1, and then construct bankruptcy prediction models based on binary logistic regression model and Cox proportion hazard model of survival analysis in sub-section 5.2 and 5.3 respectively. In both sub-sections after constructing the models, goodness-of-fit test, assumption of theoretical and robustness of the models are examined, and result of the models are interpreted. Finally, to analyze further, the results of both models will be compared in the sub-section 5.4.

5.1 Correlation test

We would have a problem with multicollinearity if we had highly correlated independent variable in the models. The degree of multicollinearity can vary and can have different effects on the model. When perfect multicollinearity occurs, it is impossible to obtain a unique estimate of regression coefficients with all the independent variables in the models.

Before checking their correlation, we first cleared out the outliers of observations which might produce the heavily effect on the statistical results. Then, check the correlation by using Pearson correlation test. If independent variables have high degree correlation (more than .5 - meaning multicollinearity) to others, only one which has a higher significant relation with dependent variable will be chosen into the models.

As table IV presents the multicollinearity of independent variables in 5 groups. The first group is multicollinearity of current asset to current liability, current liability to total asset, loan to total asset, total liability to total asset, and equity to total liability ratio. Choose current liability to total asset (CL/TA) since it has the highest significance comparing with others by running binary logistic model. The second group is the multicollinearity of sales to inventory, sales to total asset and net income to Total asset. Since sales to inventory (SA/INV) has the highest significance, we choose it to be a predictor variable in the bankruptcy prediction models. Next is the multicollinearity of 3 pairs of independent variables – inventory to total asset and current asset to total asset (correlation = .830), listed status and Ln of total asset (correlation = .506), and family director status and level of ownership director (correlation = .579). Due to their higher significances than their pairs, we select inventory to total asset (INV/TA), listed status (Listed) and level of ownership director (Ownership) are the explanatory variables in the models.

[Table IV is here]

Remaining explanatory variables - company age (Age) and Controlling Director status (Control) variables, which are not highly correlated with any variables, and those selected will be aggregated in the bankruptcy predictions models. So, we have 7 independent variables in the models – 3 financial ratio variables (INV/TA, CL/TA and SA/INV) and 4 non-financial ratio variables which are 2 company-specific variables (Listed and Age) and 2 corporate governance variables (Controlling and Ownership). All of them do not have high correlation to each others as shown in table V.

[Table V is here]

The descriptive statistics of the data employed in the study comparing between bankruptcy and non-bankruptcy firms are presented in table VI.

[Table VI is here]

The results show that bankruptcy firms have lower abilities to sales than non-bankruptcy firms. Then, their mean value of inventory to total asset ratio is higher than the one of non-bankruptcy firms. This causes the lower capability to pay their debts than non-bankruptcy firms. The results of non-financial ratio show that bankruptcy firms have mean values of listed status variable and the level of director ownership variable are lower than non-bankruptcy firms while company age variable and controlling director status variable are not quite different from ones of non-bankruptcy firms. It can be interpreted that most of bankruptcy firms are non-listed companies, and have lower level of director ownership. Before deriving models, we expect logically the sign of relationship of each predictor variable with dependent variable as shown in table VII.

[Table VII is here]

5.2 Binary Logistic Regression Model Estimation

5.2.1 Empirical results of bankruptcy prediction model

Binary logistic model is applied to construct an early warning model for 2 years prior to the event of bankruptcy of both listed and non-listed real estate firms in Thailand during 2001-2009, using financial ratio and non-financial ratio variables. Tables VIII presents the coefficient estimation *(β)*, the standard error of this estimate, Wald chi-square tests with the relative p-value for testing the null hypothesis that the coefficient of each covariate is equal to zero and odd ratio is presented in the last column. Wald statistic equals $\left(\frac{\beta}{SE}\right)^2$. P-value is small, when Wald statistic is large, or vice versa. Odd ratio equals e^{β}, as β is the coefficient in the binary logistic model. Table VIII lists the logistic regression results that CL/TA and controlling director are significant at 5% level to the event of bankruptcy of Thai real estate firms. They are positively correlated with the bankruptcy probability. If significant level is at 10%, SALES/INV will influence to the event of bankruptcy in negative relation. Four remaining variables – INV/TA, company's age, listed-status and level of director ownership are not significant to predict the probability of bankruptcy.

[Table VIII is here]

Most of variables have the sign of coefficient as expected except company's age variables. We expected company's age variable to be negative sign since we analyzed that older companies should have more industry experiences than young ones, but the result shows positive sign with high non-significant level (p-value = .865). This may be the result from choosing the sample data of bankruptcy firms that have total over than 100 million baht. Most of the young companies have total asset less than 100 million baht. Plug figure from Table VIII to equation *(1)* and *(3)* as follows:

$$Prob\ (Y_i = 1) = \frac{1}{1+e^{-Z_i}} \qquad (1)$$

where

$$Z_i = -9.349 + 0.035INV/TA + 0.100CL/TA - 0.324SALES/INV + 0.033AGE -$$

$$1.840Listed + 3.863Controlling - 1.580Ownership$$

It is more understandable to interpret in the term of odds ratio as equation *(3)*

$$\frac{Prob(Y_i = 1)}{Prob(Y_i = 0)} = e^{Z_i} \qquad (3)$$

There are 3 explanatory variables are significant at 10% level – CL/TA, SALES/INV and controlling shareholder director.

Odds ratio for CL/TA = $\frac{Prob(Y_i = 1)}{Prob(Y_i = 0)}$ = *1.106*

Increase 1% of current liability to total asset ratio is more likely to increase probability to go bankrupt 1.106 times or increase 10.6%.

Odds ratio for SALES/INV = $\frac{Prob(Y_i = 1)}{Prob(Y_i = 0)}$ = *0.723*

Increase 1% of sales to inventory ratio 1% is more likely to increase probability to go bankrupt 0.723 times or decrease 27.7%.

Odds ratio for controlling shareholder director = $\frac{Prob(Y_i = 1)}{Prob(Y_i = 0)}$ = *47.607*

Company with controlling shareholder director are 47.607 times more likely to go bankrupt than company without it.

5.2.2 Goodness-of-fit test

In the study, we test the fit of prediction model by using log likelihood ratio test, Cox & Snell R^2 and Nagelerke $R^2$to as shown in table IX. The log likelihood ratio test result is significant level to the testing of null hypothesis, that is, not all parameters are 0. The Nagelerke R^2 presents that the explanatory variables of the prediction model influence for the incidence of bankruptcy 92.5%.

[Table IX is here]

5.2.3 Robustness of model in prediction accuracy

The fit of logit models used in the study is validated by comparing the predicted value of each sample with the cutoff value. If the sample has predicted value lower than the cutoff value, the sample is classified as a bankruptcy firm, otherwise the firm is classified as a non-bankruptcy firm. We use the cutoff value at 0.5 which is the default value. The accuracy of classification of the model is presented as shown in table IX. The accuracy for the observed bankruptcy firm is 94%, 97% for the observed non-bankruptcy firm and for overall is 96%. Type I Error (bankruptcy firms are predicted to be non-bankruptcy firms) is 6% (2/32).

5.3 Cox Proportional Hazard Model Estimation

5.3.1 Empirical results of bankruptcy prediction model

In order to construct bankruptcy prediction model, 3 financial ratio and 4 non-financial ratio variables are entered into the Cox proportional hazards model. The 7 covariates used are time dependent variables covering 2000 to 2009. Time variable is the survival time which is the number of years from the beginning of the studying period (2000) to the year of bankruptcy occurrence for bankruptcy firms, or to the last year of studying period (2009) for non-bankruptcy firms. By applying the Cox proportional hazards model with financial ratios and non-financial ratios, the Cox proportional hazards model is reported in Table X.

[Table X is here]

Tables X presents the coefficient estimation (β), the standard error of this estimate, Wald chi-square tests with the relative p-value for testing the null hypothesis that the coefficient of each covariate is equal to zero and hazard ratio is presented in the last column. Wald statistic equals $\left(\frac{\beta}{SE}\right)^2$. P-value is small, when Wald statistic is large, or vice versa. Hazard ratio equals e^{β}, as β is the coefficient in the Cox proportional hazard model.

The p-values of 3 covariates present high significance at the 5 percent level. They are 2 financial ratios (CL/TA and SALES/INV) with the coefficient 0.011, and -.0136 respectively, and 1 corporate governance variable (controlling ownership director) with the coefficient 0.829. All variables have the sign of coefficient as expected.

The sign of parameter for CL/TA is positive, which means that the company with low current liability to total assets is less likely to filing bankruptcy. Hazard ratio for CL/TA is 1.011 that means for 1 percent increase in CL/TA, the risk of becoming bankruptcy increase 1.1%. The high indebtedness brings more financial obligations which must be paid. Poor firm’s ability to generate earnings the company to take more and more debt to pay these obligations and consequently, the company will get involved in the bad circle and become ultimately failure.

On the other hand, the coefficient sign of SALES/INV is negative indicating that an increase in covariate decreases the hazard of entering into bankruptcy. Hazard ratio for SALES/INV is 0.873 means that an increase of 1 percent in SALES/INV implies 12.7% decrease in risk of bankruptcy. The high sales volume reduces the risk to go bankrupt.

Only one non-financial ratio, controlling shareholder director variable is significant at 10% level and its hazard ratio is 2.291 which means that real estate firm with controlling shareholder director has risk to go bankrupt 2.291 times to one without controlling shareholder director.

5.3.2 PH Assumption Testing

Proportional hazard or PH assumption assumes that the effect of each covariate is the same at point in time. If the effect of a covariate varies with time, the PH assumption is violated for that covariate. The consequences of non-proportionality include biased parameter values, incorrect standard errors and biased estimates of the hazard rate. As following table presents that the model passes PH assumption testing since its p-value is greater than .05. It means that the effect of independent variable may not change over the follow-up period.

Test of proportional-hazards assumption
Time : Time

Covariate	chi2	Prob>chi2
INV/TA	0.01	0.9087
CL/TA	0.30	0.5840
SALES/INV	0.19	0.6656
Age	0.05	0.8193
List_Status	0.39	0.5337
Controlling_Status	0.00	0.9758
Ownership	0.91	0.3398
global test	2.70	0.9116

5.3.3 Goodness-of-fit test

As Table XI presents significantly the lower Chi-square (-2 log likelihood) of model with covariates than the Chi-square of null model, which means that the model with covariates is goodness-of-fit with the sample data.

[Table XI is here]

5.3.4 Robustness of model in prediction accuracy

To find the accuracy of Cox Proportional Hazard model, we have to calculate the predicted survival probability in each observation and comparing it with cut-off value. The survival function, shown in equation *(9)*

$$S_i(t) \quad = \quad S_0(t)\exp^{\beta X_i}$$

In this study, the cut-off value is determined as in Lane, Looney and Wansley (1986), Whalen (1991). This cut-off value is obtained by calculating as follows:

$$\textit{Cut-off value} \quad = \quad \frac{\text{number of observed survivor firms}}{\text{number of total observed firms}}$$

So, cut-off value equals to .67 (64/96). Compare cut-off value with the survival probability of each observation. If the survival probability estimator is greater than .67, it is non-bankruptcy firms. In the opposite, if the survival probability estimation is less than .67 it is bankruptcy firms.

After comparing survival prediction with cut-off value, the result presents as Table XI. The accuracy of overall is 84.4%. The accuracy of non-bankruptcy group is 93.8%, while the accuracy of bankruptcy firms is only 65.6% implies that type I error is only 34.4% (error 11 cases from 32 cases).

5.3.5 Corporate Survival Analysis Evaluation

Survival analysis contains 2 key functions called the hazard function and survival function and hazard function. Survival function denoted a company's probability of survival past time *t*, it starts with 1.00 at the beginning and declines as more companies entering bankruptcy. The survival function as equation *(9)* can be presented as Figure 1, which shows the dramatic decrease in corporate survival since 7th year up to 9th year.

[Figure 1 is here]

The hazard function as equation *(12)* presents the risk that bankruptcy will occur at time *t* given that the firm has survived up to time *t*. There is one term which is linear predictor (βX_i) which is interesting term for evaluating the risk of company bankruptcy. *X* is the vector of explanatory variables and β is the parameter which needs to be estimated. The larger value of linear predictor means the risk of bankruptcy is higher. The relationship between the average linear predictor and time is shown in Figure 2. According to the graph, it presents the high hazard to be bankruptcy since 7th year, which is consistent with the survival functions as mentioned before.

[Figure 2 is here]

There is another graph created by Nelson-Aalen which presents the hazard of bankruptcy comparing with the hazard of non-bankruptcy as Figure 3. According to the Nelson-Aalen cumulative hazard estimate graph, it presents that non-bankruptcy firms can survive during this studying period (2000-2009), while bankruptcy firms have increasing in cumulative hazard estimate along the years.

[Figure 3 is here]

The graph as Figure 4 is Cox Proportional Hazard Regression is different from the cumulative hazard graph above, which is smooth hazard function. Smooth Hazard Function provides evidence of hazard ratio for bankruptcy firms. It can be seen that the highest hazard ratio is at the 7th year, which is consistent with the graph mentioned above.

[Figure 4 is here]

5.4 Comparison of Empirical results of Logistic Regression Model and Cox Proportional Hazard Model (Survival Analysis)

According to Table XII early leading indicators derived from both models are the same – CL/TA, SALES/INV and controlling shareholder director, which also present the same signs. CL/TA and controlling shareholder director are positive relation to be bankrupt, while SALES/INV's sign is negative. The results of significant of predictor variable CL/TA and SALES/INV are consistence with Beavor (1966) and Elam (1975), and Edmister (1972) respectively. And the significant of controlling shareholder director with positive sign with occurrence of bankrupt event is consistence with La Porta et al. (1999), Claessens et al. (1999), and Chen and Hu (2001), who presented that controlling shareholders might divert the company funds to their own use, that increases the exposure of the firm to financial distress.

For the sample in this study, the results suggest that bankruptcy companies have higher leverage, lower sales to inventory and existence of controlling shareholder director. However, the study results do not support the important of inventory to total asset, company's age, listed status, and the level of ownership director.

In the point of accuracy, binary logistic model shows satisfaction of high accuracy of overall prediction (95.8%) and low Type I Error (6.3%) than Cox proportional hazard model. Type I Error is very importance for prediction task, which we do not want to predict a firm going to be bankruptcy is going to be non-bankruptcy. This result is consistence with Luoma and Laitinent (1991) which studied on prediction the failure of Finnish industrial and retailing companies by using Cox proportional hazard method comparing with traditional method, logistic and MDA. The empirical result was outperformed by logistic and MDA.

In sum, these 2 early warning models give the same results of leading indicators, but binary logistic model shows higher ability of prediction than Cox proportional hazard model. Therefore, we should use binary logistic model to predict the probability to go bankruptcy of Thai real estate firm. From both of the model, we can conclude that a Thai real estate firm which there is existence of controlling shareholder director, high current liability to total assets ratio, and low sales to inventory, is likely to be bankrupt.

Limitation in this study

In this study, the hardest job is acquiring sample data. The data of bankruptcy and non-listed company are not well organized. There is no any organization in Thailand collecting the list of bankruptcy as industry sector classification. The central bankruptcy court announces the list of bankruptcy of companies and individuals mixed up together every month and then this information is kept in Royal Thai Government Gazette (Ratchakitchanubeksa). We get the list of bankruptcy of real estate firms via www.ratchkitcha.soc.go.th by search engine the name of real estate firms since it does not also provide data in classification. Collecting non-listed company's data from Ministry of Commerce of Thailand costs time and money. We should have more complete information if the organizations concerned have well recording system.

Even all observations are real estate firms, they still record in difference accounting method of revenue. According to Accounting Standard No. 26 (Chart TAS 26), there are 3 methods to recognize real estate revenue, (1) recognize whole amount of selling price after transfer ownership to customer, (2) recognize as percentage completion of job, and (3) recognize as installment amount. We should have more effective results if all observations have the same accounting methods. However, this problem will be solved by Federation of Accounting Professions in 2011 all real estate firms have to recognize real estate revenues after transfer ownership to customer with whole amount of selling price.

VI. CONCLUSION

Even there are many literatures studying on financial distress prediction, this topic still is classic and attracts many researchers to go on studying it by improving new methodology, incorporating new predictor variables, providing new definition for the financial distress and extanding observations to various of industries. In Thailand, there are some papers study this topic, but the numbers are still quite small. This study aims to add with some contributions to the previous studies. We focus on real estate firms during 2000-2009 since this sector is quite sensitive to the economic situation than other sectors. So, early warning models which are derived from real estate firms' data are extremely useful to users, especially if they are both listed and non-listed real estate firms. All papers studying on this topic in Thailand use listed company as sample data even most of the bankruptcy firms are non-listed firm, because it is quite difficult to acquire data of companies. However, this paper utilizes the data of both listed and non-listed firm.

All prediction approaches are classified into 2 groups – static model, and dynamic model. Binary logistic regression model is represented for static model, while Cox proportion hazard is represented for dynamic. Binary logistic regression has been widely used to develop financial distress prediction model since 1980 by Ohlson since it does not need any assumption and it always give high accuracy of prediction. Whereas, Cox proportiona hazard regression is interesting to new reserchers on its concept that financial distress does not occur immediately, but it is preceded from healthy company to bankrupt company over a number of years.

We use both models in order to compare the results, whether they are consistent. For explanatory variables, we use 10 financial ratios and six non-financial ratios which are company-specific and corporate governance variables. After screening out multicollinearity variables, finally, 3 financial ratios and 4 non-financial ratios are incorporated in the models. Financial ratio variables are inventory to total assets (liquidity ratio), current liability to total assets (financial leverage ratio) and sales to inventory (activity ratio); corporate governance variables are level of ownership director and controlling shareholder director status, and company-specific variables are company's age and listed status.

The results also show that binary logistic model has higher accuracy of prediction than survival model. Overall accuracy and Type I error is 95.8% and 6.3% from binary logistic regression model, and 84.4% and 34.4% from Cox proportional hazard. Their results of leading indicators are the same which are current liability to total asset ratio, sales to inventory and controlling shareholder director. The implication from both results presents that a Thai real estate firm which has the controlling shareholder director, with high current liability to total assets and low sales to inventory has high probability to be bankrupt.

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Table I

Royal Thai Government Gazette's Announcement of bankruptcy of real estate firms during 2001-2009

ประกาศล้มละลายจากราชกิจจานุเบกษา

ลำดับที่	ประเภท/ชื่อเรื่อง	วันที่ประกาศ
1	ประกาศเจ้าพนักงานพิทักษ์ทรัพย์ เรื่อง คำสั่งให้ฟื้นฟูกิจการและตั้งผู้ทำแผน บริษัท แชลเลนจ์ พรอพเพอร์ตี้ จำกัด ลูกหนี้ (ศาลล้มละลายกลาง คดีหมายเลขแดงที่ ฟ. ๗/๒๕๕๐)	๑๔ มิถุนายน พ.ศ.๒๕๕๐
2	ประกาศเจ้าพนักงานพิทักษ์ทรัพย์ เรื่อง คำสั่งให้ฟื้นฟูกิจการและตั้งผู้บริหารชั่วคราว บริษัท เพรสิเดนท์ พาร์ค เฮ้าซิ่ง ดีเวลอปเม้นท์ จำกัด ลูกหนี้ (ศาลล้มละลายกลาง คดีหมายเลขแดงที่ ๘๙๒/๒๕๔๔ บริษัท เพรสิเดนท์ พาร์ค เฮ้าซิ่ง ดีเวลอปเม้นท์	๓๐ ตุลาคม พ.ศ.๒๕๔๔
3	ประกาศเจ้าพนักงานพิทักษ์ทรัพย์ เรื่อง คำสั่งให้ฟื้นฟูกิจการและตั้งผู้ทำแผน บริษัท พร็อพเพอร์ตี้ เพอเฟค จำกัด (มหาชน) ลูกหนี้ (ศาลล้มละลายกลาง คดีหมายเลขแดงที่ ๑๐๖/๒๕๔๔)	๒๗ มีนาคม พ.ศ.๒๕๔๔
4	ประกาศเจ้าพนักงานพิทักษ์ทรัพย์ เรื่อง คำสั่งให้ฟื้นฟูกิจการและตั้งผู้ทำแผน บริษัท พระราม ๓ แลนด์ จำกัด ลูกหนี้ (ศาลล้มละลายกลาง คดีหมายเลขแดงที่ ๑๓๐๗/๒๕๔๔ บริษัท พระราม ๓ แลนด์ จำกัด)	๒๒ มกราคม พ.ศ.๒๕๔๕
5	ประกาศเจ้าพนักงานพิทักษ์ทรัพย์ เรื่อง คำสั่งให้ฟื้นฟูกิจการและตั้งผู้ทำแผน บริษัท อาร์. เอ็ม. พร็อพเพอร์ตี้ จำกัด ลูกหนี้ (ศาลล้มละลายกลาง คดีหมายเลขแดงที่ ฟ. ๒๓/๒๕๕๐)	๒๐ กันยายน พ.ศ.๒๕๕๐
6	ประกาศเจ้าพนักงานพิทักษ์ทรัพย์ เรื่อง คำสั่งให้ฟื้นฟูกิจการและตั้งผู้ทำแผน บริษัท สุขุมวิท อินเตอร์ ดีเวลลอปเม้นท์ จำกัด ลูกหนี้ [ศาลล้มละลายกลาง คดีหมายเลขแดงที่ ๑๔๕๘/๒๕๔๖]	๓๐ กันยายน พ.ศ.๒๕๔๖
7	ประกาศเจ้าพนักงานพิทักษ์ทรัพย์ เรื่อง คำสั่งพิทักษ์ทรัพย์เด็ดขาด [ศาลล้มละลายกลาง คดีหมายเลขแดงที่ ๒๑๙๔/๒๕๔๖ บริษัท สหวิริยา ริเวอร์ไซค์ การ์เด้น จำกัด หรือบริษัท การ์เด้นท์ พาวเวอร์ จำกัด ลูกหนี้]	๑๐ กุมภาพันธ์ พ.ศ.๒๕๔๗
8	ประกาศเจ้าพนักงานพิทักษ์ทรัพย์ เรื่อง คำสั่งให้ฟื้นฟูกิจการและตั้งผู้ทำแผน บริษัท สิงห์แลนด์ จำกัด (มหาชน) ลูกหนี้ [ศาลล้มละลายกลาง คดีหมายเลขแดงที่ ๑๓๒๒/๒๕๔๕ บริษัท สิงห์แลนด์ จำกัด (มหาชน) ลูกหนี้]	๒๔ กันยายน พ.ศ.๒๕๔๕
9	ประกาศเจ้าพนักงานพิทักษ์ทรัพย์ เรื่อง คำสั่งพิทักษ์ทรัพย์เด็ดขาด (ศาลล้มละลายกลาง คดีหมายเลขแดงที่ ๑๐๐๓/๒๕๕๑ บริษัท เอ็ม แอนด์ ซี พร็อพเพอร์ตี้ เซอร์วิส จำกัด ลูกหนี้ที่ ๑)	๓ มิถุนายน พ.ศ.๒๕๕๑
10	ประกาศเจ้าพนักงานพิทักษ์ทรัพย์ เรื่อง คำสั่งให้ฟื้นฟูกิจการและตั้งผู้ทำแผน บริษัท ฟอร์จูน คันทรี จำกัด ลูกหนี้ (คดีหมายเลขแดงที่ ๗๓๒๒/๒๕๔๙)	๒๘ ธันวาคม พ.ศ.๒๕๔๙
11	ประกาศเจ้าพนักงานพิทักษ์ทรัพย์ เรื่อง คำสั่งให้ฟื้นฟูกิจการและตั้งผู้บริหารชั่วคราว บริษัท ราษฎร์ยินดี ดีเวลลอปเม้นท์ จำกัด ลูกหนี้ (ศาลล้มละลายกลาง คดีหมายเลขแดงที่ ๗๙๔/๒๕๔๔)	๑๖ ตุลาคม พ.ศ.๒๕๔๔
12	ประกาศเจ้าพนักงานพิทักษ์ทรัพย์ เรื่อง คำสั่งให้ฟื้นฟูกิจการและตั้งผู้ทำแผนบริษัท เอส จี แลนด์ จำกัด ลูกหนี้ [ศาลล้มละลายกลาง คดีหมายเลขแดงที่ ๑๔๘๕/๒๕๔๕]	๑๗ ตุลาคม พ.ศ.๒๕๔๕
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14	ประกาศเจ้าพนักงานพิทักษ์ทรัพย์ เรื่อง คำสั่งให้ฟื้นฟูกิจการและตั้งผู้ทำแผน บริษัท ธรรมธานี จำกัด ลูกหนี้ (ศาลล้มละลายกลาง คดีหมายเลขแดงที่ ๓๒/๒๕๔๔)	๒๗ กุมภาพันธ์ พ.ศ.๒๕๔๔
15	ประกาศเจ้าพนักงานพิทักษ์ทรัพย์ เรื่อง คำสั่งพิทักษ์ทรัพย์ชั่วคราว [ศาลล้มละลายกลาง คดีหมายเลขแดงที่ ๑๙๖๙/๒๕๔๗ บริษัท ศรีวราเรียลเอสเตทกรุ๊ป จำกัด (มหาชน) ลูกหนี้]	๒๔ สิงหาคม พ.ศ.๒๕๔๗
16	ประกาศเจ้าพนักงานพิทักษ์ทรัพย์ เรื่อง คำสั่งให้ฟื้นฟูกิจการและตั้งผู้ทำแผน บริษัท กอเงินเอสเตท จำกัด ลูกหนี้ [ศาลล้มละลายกลาง คดีหมายเลขแดงที่ ๑๑๔๗/๒๕๔๗]	๒๒ มิถุนายน พ.ศ.๒๕๔๗
17	ประกาศเจ้าพนักงานพิทักษ์ทรัพย์ เรื่อง คำสั่งให้ฟื้นฟูกิจการและตั้งผู้ทำแผน บริษัท สหรัตนนคร จำกัด ลูกหนี้ [ศาลล้มละลายกลาง คดีหมายเลขแดงที่ ๒๐๔๔/๒๕๔๙]	๒๐ มิถุนายน พ.ศ.๒๕๔๙
18	ประกาศเจ้าพนักงานพิทักษ์ทรัพย์ เรื่อง คำสั่งพิทักษ์ทรัพย์เด็ดขาด [ศาลล้มละลายกลาง คดีหมายเลขแดงที่ ล. ๑๒๘๓๔/๒๕๕๒ บริษัท อัลฟา แลนด์ แอนด์ เฮ้าส์ จำกัด ที่ ๑ นายปรีชา หรือชัยวิวัฒน์ วารวิจิตร ที่ ๓ ลูกหนี้]	๒๒ ธันวาคม พ.ศ.๒๕๕๒
19	ประกาศเจ้าพนักงานพิทักษ์ทรัพย์ เรื่อง คำสั่งให้ฟื้นฟูกิจการและตั้งผู้ทำแผน บริษัท เอช.ซี.ซิตี้ จำกัด ลูกหนี้ (ศาลล้มละลายกลาง คดีหมายเลขแดงที่ ๘๓๗/๒๕๔๔)	๑๘ ตุลาคม พ.ศ.๒๕๔๔
20	ประกาศเจ้าพนักงานพิทักษ์ทรัพย์ เรื่อง คำสั่งให้ฟื้นฟูกิจการและตั้งผู้ทำแผน บริษัท ห้วยแก้ว เรียล เอสเตท จำกัด ลูกหนี้ [ศาลล้มละลายกลาง คดีหมายเลขแดงที่ ๔๖๙/๒๕๔๖]	๒๒ พฤษภาคม พ.ศ.๒๕๔๖
21	ประกาศเจ้าพนักงานพิทักษ์ทรัพย์ เรื่อง คำสั่งให้ฟื้นฟูกิจการและตั้งผู้ทำแผน บริษัท สินสหกิจพัฒนา จำกัด ลูกหนี้ (ศาลล้มละลายกลาง คดีหมายเลขแดงที่ ฟ. ๘/๒๕๕๑)	๒๙ เมษายน พ.ศ.๒๕๕๑
22	ประกาศเจ้าพนักงานพิทักษ์ทรัพย์ เรื่อง คำสั่งให้ฟื้นฟูกิจการและตั้งผู้ทำแผน บริษัท ชะอำ แคมปัส ซิตี้ จำกัด ลูกหนี้ [ศาลล้มละลายกลาง คดีหมายเลขแดงที่ ๑๐๕๕/๒๕๔๕ บริษัท ชะอำ แคมปัส ซิตี้ จำกัด ลูกหนี้]	๑๓ สิงหาคม พ.ศ.๒๕๔๕
23	ประกาศเจ้าพนักงานพิทักษ์ทรัพย์ เรื่อง คำสั่งให้ฟื้นฟูกิจการและตั้งผู้ทำแผน บริษัท ธารเพชรพัฒนา จำกัด ลูกหนี้ [ศาลล้มละลายกลาง คดีหมายเลขแดงที่ ๘๐/๒๕๔๘]	๑๐ มีนาคม พ.ศ.๒๕๔๘
24	ประกาศเจ้าพนักงานพิทักษ์ทรัพย์ เรื่อง คำสั่งให้ฟื้นฟูกิจการและตั้งผู้ทำแผน บริษัท เซ็นจูรี่ ปาร์ค คอนโดมิเนียม จำกัด ลูกหนี้ (ศาลล้มละลายกลาง คดีหมายเลขแดงที่ ๑๐๒๒/๒๕๔๔)	๖ ธันวาคม พ.ศ.๒๕๔๔
25	ประกาศเจ้าพนักงานพิทักษ์ทรัพย์ เรื่อง คำสั่งให้ฟื้นฟูกิจการและตั้งผู้ทำแผน บริษัท เอสจี สตาร์ พร็อพเพอร์ตี้ส์ จำกัด ลูกหนี้ (คดีหมายเลขแดงที่ ๒๗๘/๒๕๔๔ ศาลล้มละลายกลาง)	๒๙ พฤษภาคม พ.ศ.๒๕๔๔
26	ประกาศเจ้าพนักงานพิทักษ์ทรัพย์ เรื่อง คำสั่งพิทักษ์ทรัพย์เด็ดขาด (ศาลล้มละลายกลาง คดีหมายเลขแดงที่ ๔๖๗๔/๒๕๕๐ บริษัท กรุงทองธานี จำกัด ลูกหนี้)	๑๑ กันยายน พ.ศ.๒๕๕๐
27	ประกาศเจ้าพนักงานพิทักษ์ทรัพย์ เรื่อง คำสั่งพิทักษ์ทรัพย์เด็ดขาด [ศาลล้มละลายกลาง คดีหมายเลขแดงที่ ล. ๗๘๗๔/๒๕๕๑ บริษัท วัชรดิลก ทาวเวอร์ จำกัด ลูกหนี้]	๒๗ มกราคม พ.ศ.๒๕๕๒
28	ประกาศเจ้าพนักงานพิทักษ์ทรัพย์ เรื่อง คำสั่งพิทักษ์ทรัพย์เด็ดขาด (ศาลล้มละลายกลาง คดีหมายเลขแดงที่ ๗๒๔๖/๒๕๔๙ บริษัท ศรีเจริญทอง แลนด์ แอนด์ เฮาส หรือเฮาส์ จำกัด ลูกหนี้)	๒๗ กุมภาพันธ์ พ.ศ.๒๕๕๐
29	ประกาศเจ้าพนักงานพิทักษ์ทรัพย์ เรื่อง คำสั่งพิทักษ์ทรัพย์เด็ดขาด [ศาลล้มละลายกลาง คดีหมายเลขแดงที่ ล. ๓๗๖๕/๒๕๕๒ บริษัท เค.เอส.ทาวเวอร์ จำกัด ที่ ๑ นายอภิสิทธิ์ อนันต์คูศรี ที่ ๓ ลูกหนี้]	๗ กรกฎาคม พ.ศ.๒๕๕๒
30	ประกาศเจ้าพนักงานพิทักษ์ทรัพย์ เรื่อง คำสั่งพิทักษ์ทรัพย์เด็ดขาด (ศาลล้มละลายกลาง คดีหมายเลขแดงที่ ล. ๑๕๓๙๖/๒๕๕๐ บริษัท เทพมณฑลธานี จำกัด ที่ ๑ นายธัชชัย หรือสุวัฒน์ พ่วงตามพงษ์ ที่ ๒ ลูกหนี้)	๒๙ เมษายน พ.ศ.๒๕๕๑
31	ประกาศเจ้าพนักงานพิทักษ์ทรัพย์ เรื่อง คำสั่งให้ฟื้นฟูกิจการและตั้งผู้ทำแผน บริษัท ศรีสินธร จำกัด ลูกหนี้ [ศาลล้มละลายกลาง คดีหมายเลขแดงที่ ๒๒๖๑/๒๕๔๙]	๔ กรกฎาคม พ.ศ.๒๕๔๙
32	ประกาศเจ้าพนักงานพิทักษ์ทรัพย์ เรื่อง คำสั่งให้ฟื้นฟูกิจการและตั้งผู้ทำแผน บริษัท พรีสเตจ เอสเตท จำกัด ลูกหนี้ (ศาลล้มละลายกลาง คดีหมายเลขแดงที่ ๒/๒๕๕๐)	๒๙ มีนาคม พ.ศ.๒๕๕๐

Source : www.ratchakitcha.soc.go.th

Table II

The list of real estate firms in 2001 - 2009 as observations

Bankruptcy Firm					Non - Bankruptcy Firm		
Company	Listed Staus	Bankruptcy occurrence in (year)	Bankruptcy Type	Total Asset at Year 2001 (Million Baht)	Company	Listed Staus	Total Asset at Year 2001 (Million Baht)
Challenge Property Co., Ltd.		2007	Reorganization	9,929.521	Land And Houses Pcl.	***	22,889.426
					Quality Houses Pcl.	***	10,358.492
President Park Housing Development Co., Ltd.		2001	Reorganization	8,514.788	Golden Land Property Development Pcl.	***	7,971.919
Property Perfect Plc.	***	2001	Reorganization	5,876.006	Hemaraj Land And Development Pcl.	***	6,129.161
Praram 3 Land Co., Ltd.		2001	Reorganization	4,304.912	Supalai Plc.	***	6,118.725
					M.K. Real Estate Development Pcl.	***	5,787.431
					Charoenkit Enterprise Co., Ltd.		5,620.726
					C.P. Land Co., Ltd.		4,250.429
R.M. Property Co., Ltd.		2007	Reorganization	3,264.494	Amata Corporation Pcl.	***	3,905.542
					Rojana Industrial Park Pcl.	***	3,104.041
Sukhumvit Inter Development Co., Ltd.		2003	Reorganization	2,154.039	Tararom Enterprise Co., Ltd.		2,877.331
Garden Power Co., Ltd.		2003	Liquidation	2,151.838	Asian Property Development Pcl.	***	2,197.718
					Eeastern Seaboard Industrail Estate (Rayong)		2,063.773
					Panya Properties Co., Ltd.		2,045.643
Singha Land Pcl.	***	2002	Reorganization	1,974.036	Narai Property Co., Ltd.		2,016.387
					Sammakorn Pcl.	***	1,786.316
M&C Property Service Co., Ltd.		2008	Liquidation	1,842.790	L.P.N. Development Pcl.	***	1,696.578
					Preuksa Real Estate Pcl.	***	1,621.797
Fortune Country Co., Ltd.		2006	Reorganization	1,659.978	Eastern Star Real Estate Pcl.	***	1,520.162
					N.C.Housing Pcl.	***	1,374.097
Rajyindee Development Co., Ltd.		2001	Reorganization	1,456.856	Sansiri Pcl.	***	1,322.539
					Amata City Co., Ltd.		1,304.410
SG Land Co., Ltd.		2002	Reorganization	1,455.382	Lalin Property Pcl.	***	1,295.408
					Noble Development Pcl.	***	1,262.889
Paradise Palm Co., Ltd.		2005	Reorganization	1,245.198	Pattana Dan Thong C., Ltd.		1,172.124
					Plus Property Co., Ltd.		1,149.690
Thammatani Co., Ltd.		2001	Reorganization	1,243.269	Asian Property Co., Ltd.		1,122.240
					Thai Industrial Estate Co., Ltd.		1,015.157
Srivara Real Estate Pcl.	***	2004	Liquidation	1,121.966	Home Place Group Co., Ltd.		1,008.213
Gor-Ngern Estate Co., Ltd.		2004	Reorganization	892.809	Chao Pharaya Mahanakorn Co., Ltd.		996.837
					Navanakorn Pcl.	***	993.455
					Eastern Industrial Estate Co., Ltd.		959.190
Saha Rattananakorn Co., Ltd.		2006	Reorganization	688.881	River Side Garden Marina Co., Ltd.		808.995
					Chalerm Nakorn Co., Ltd.		760.660
Alpha Land and House Co., Ltd.		2009	Liquidation	620.922	Ratthani Realty Co., Ltd.		683.085
					Thai Factory Development Pcl.	***	652.700
H.C.City Co., Ltd.		2001	Reorganization	565.525	Niran Housing Co., Ltd.		623.383
					Ekpailin Land & House Co., Ltd.		591.109
Huay Kaew Real Estate Co., Ltd.		2003	Reorganization	565.317	Krungthep Land Co., Ltd.		587.905
					Santiburi Private Communities Co., Ltd.		550.623
Sinsahakij Patana Co., Ltd.		2008	Reorganization	532.373	Kabinburi Industrial Park Co., Ltd.		545.949
					Sena Development Pcl.	***	538.852
Cha-Am Campus City Co., Ltd.		2002	Reorganization	491.411	Baan Rock Garden Pcl.	***	428.999
					City Villa Co., Ltd.		428.549
Tharnpetch Patana Co., Ltd.		2005	Reorganization	482.806	Sivadon Co., Ltd.		418.630
					Ramkhamhaeng Housing Co., Ltd.		403.969
Century Park Condomenium Co., Ltd.		2001	Reorganization	469.508	Prinsiri Pcl.	***	367.410
S.G. Star Properties Co., Ltd.		2001	Reorganization	463.776	Comfort Residence Co., Ltd.		357.513
					Siam Brother Housing Co., Ltd.		351.547
					Ocean Tower Co., Ltd.		336.969
Krungthong Thanee Co,.Ltd.		2007	Liquidation	348.556	Sribhathana Co., Ltd.		334.063
					Navathanee Co., Ltd.		332.644
Watchara Dirok Co., Ltd.		2008	Liquidation	324.639	N.C.C. Management and Development Co., Ltd.		312.940
					Thanasiri Bann Lae Suan Co., Ltd.		307.696
Sricharoenthong Land and House Co., Ltd.		2006	Liquidation	305.657	Major Development Co., Ltd.		303.474
					L.H.M. Housing Co., Ltd.		270.016
K.S. Tower Co., Ltd.		2009	Liquidation	153.841	Thanee Development Co., Ltd.		234.143
					Pinthong Industrail Park Co., Ltd.		207.580
Thepmonthon Thanee Co., Ltd.		2007	Liquidation	129.735	Metro Star Property Pcl.	***	181.990
					Supreme Team Co., Ltd.		142.652
Srisinthorn Co., Ltd.		2006	Liquidation	124.254	Rasa Property Development Pcl.	***	135.248
					Peace and Living Co., Ltd.		134.747
Pre-stage Estate Co., Ltd.		2007	Reorganization	113.536	Bangna Thani Co., Ltd.		132.010
					Pattara House & Property Co., Ltd.		127.013

The sample data of bankruptcy and non-bankruptcy real estate firms are matched as same sizes which are their total assets at the beinging year of study period 2001.

Matching proportion of bankruptcy : non - bankruptcy is 1:2.

Table III
Classification of Observations

Unit : Number of firms

Classification	Bankruptcy	Non-Bankruptcy	Total
Observations classified by size (Total Assets)			
Big size (over than 3,000 million Baht)	5	10	15
Medium size (500 < Total Assets < 3,000)	16	32	48
Small size (100 < Total Assets < 500)	11	22	33
Total	32	64	96
Observations classified by Listed-Staus			
Listed Firm	3	24	27
Non-Listed Firm	29	40	69
Total	32	64	96

The 96 observations in this study include various sizes which are 5 big sizes, 16 midium sizes and 11 small sizes in bankruptcy, and the number are double for every size in non-bankruptcy. There are 27 listed firms and 69 non-listed firms. Three listed firms went bankrupt while 24 are survivors.

Table IV
High Correlations (Multicollinearity) of Predictor variables

Group 1	**Current Asset to Current Liability**	**Current Liability to Total Asset**	**Loan to Total Asset**	**Total Liability to Total Asset**	**Equity to Total Liability**
Current Asset to Current Liability	1				
Current Liability to Total Asset	$-.735^{**}$ .000	1			
Loan to Total Asset (P-value)	$-.652^{**}$ .000	$.888^{**}$ .000	1		
Total Liability to Total Asset	$-.689^{**}$ .000	$.926^{**}$ .000	$.962^{**}$ .000	1	
Equity to Total Liability (P-value)	$.862^{**}$ .000	$-.736^{**}$ .000	$-.732^{**}$ .000	$-.778^{**}$ .000	1
Group 2	**Sales to Inventory**	**Sales to Total Asset**	**Net Income to Total Asset**		
Sales to Inventory	1				
Sales to Total Asset (P-value)	$.920^{**}$ .000	1			
Net Income to Total Asset	$.526^{**}$ .000	$.526^{**}$ .000	1		
Group 3	**Inventory to Total Asset**	**Current Asset to Total Asset**			
Inventory to Total Asset	1				
Current Asset to Total Asset (P-value)	$.830^{**}$ .000	1			
Group 4	**Ln of Asset**	**Listed Status**			
Ln of Asset	1				
Listed Status (P-value)	$.506^{**}$ .000	1			
Group 5	**Family Status**	**Ownership Director**			
Family Status	1				
Ownership Director (P-value)	$.579^{**}$ .000	1			

Multicollinearity of predictor variables (degree of correlation of each pair > .5) are found as 4 groups.
Group 1: currrent asset to current liability, current liability to total asset, loan to total asset, total liability to total asset, and equity to total liability
Group 2: sales to inventory, sales to total asset, and net income to total asset
Group 3: inventory to total asset, and current to total asset
Group 4: logarithm of total asset, and listed status
Group 5: family status, and ownership director

Table V
Low Correlations of Predictor variables

	Inventory to Total Asset	Liability to Total Asset	Sales to Inventory	Company Age	Listed Status	Control Director	Ownership Director
Inventory to Total Asset	1						
Current Liability to Total Asset	.338** .001	1					
Sales to Inventory	-.386** .000	-.498** .000	1				
Company Age	-.265** .009	-.233* .022	.161 .118	1			
Listed Status	-.234* .022	-.246* .016	.282** .005	.222* .030	1		
Control Director	.062 .549	-.092 .370	.096 .354	-.121 .242	-.144 .162	1	
Ownership Director	-.187 .069	-.310** .002	.241* .018	-.015 .883	-.179 .082	.230* .024	1

These 7 variables which have no multicollinearity (correlation of each pair < .5) are used to run in the models in this study.

Table VI

Summary Statistics

Independent Variables	The first data set 2 year prior occurrence of bankruptcy		The second data set first year of study period (year 2009)	
	Bankruptcy	Non-bankruptcy	Bankruptcy	Non-bankruptcy
Inventory to total asset				
Mean	84.465	65.961	82.392	64.664
Std. Deviation	16.307	19.403	18.683	22.538
Minimum	39.830	32.095	38.403	11.165
Maximum	100.000	99.551	100.000	99.585
Current liability to total asset				
Mean	123.493	44.023	112.437	42.447
Std. Deviation	47.888	21.879	42.547	24.351
Minimum	60.096	1.182	39.680	3.039
Maximum	215.432	97.562	184.657	98.940
Sales to inventory				
Mean	2.181	40.908	2.126	39.666
Std. Deviation	2.846	36.427	3.002	35.304
Minimum	0.000	0.000	0.000	0.259
Maximum	9.847	146.678	8.187	123.177
Company age				
Mean	12.406	14.078	10.000	12.141
Std. Deviation	2.971	6.667	2.328	7.383
Minimum	6.000	1.000	6.000	1.000
Maximum	19.000	26.000	15.000	29.000
List_Status (Dummy Variable)				
Mean	0.094	0.402	0.094	0.250
Std. Deviation	0.296	0.498	0.296	0.436
Control_Status (Dummy Variable)				
Mean	0.313	0.198	0.313	0.234
Std. Deviation	0.471	0.433	0.471	0.427
Ownership				
Mean	0.594	1.426	0.594	1.391
Std. Deviation	0.712	1.412	0.712	1.352
Minimum	0.000	0.000	0.000	0.000
Maximum	2.000	5.000	2.000	5.000

The statistic descriptives of independent variable data in this study are presented by this Table. There are 2 set of data. The first data set which are run in the binary logistic model are data of 2 years prior occurrence of bankruptcy. In this study, occurrences of bankruptcy are during 2001-2009, so the first data is during 1999-2007. While Cox proportional hazard model uses the second data set to construct the model. The study period in Cox proportional hazard model is year 2000-2009. All observations start at the beginning of the study period (2009).

Table VII
Expected sign of predictor variables

Predictor variables	Expected sign to be bankruptcy	Reason
Inventory to total asset ratio	+	Bankruptcy firms have high inventory due to low inventory turnover to sales.
Current liability to total asset ratio	+	Bankruptcy firms have high liability due to low capability to repayment their obligation.
Sales to total inventory ratio	-	Bankruptcy firms have low ability to sales.
Listed status	-	Listed firms tend to have more potential to run business than non-listed firms.
Company age	-	More aged companies tend to have more experience to run business than young company.
Ownership director	-	Firms with more shareholder directors tend to outperform other firms.
Controlling ownership director status	+	Firms with controlling ownership director status tend to run business by their families.

The 7 explanatory variable signs are expected to be in the prediction models as above.

Table VIII
The result from binary logistic regression

	B	S.E.	Wald	Sig.	Exp(B)
INV/TA	.035	.053	.446	.504	1.036
CL/TA	.100	.051	3.895	.048	1.106
SALES/INV	-.324	.191	2.885	.089	.723
Company's Age	.033	.192	.029	.865	1.033
Listed Status	-1.840	3.474	.281	.596	.159
Controlling Director	3.863	1.964	3.867	.049	47.607
Ownership Director	-1.580	1.173	1.812	.178	.206
Constant	-9.349	5.145	3.302	.069	.000

Wald statistic = $\left(\frac{\beta}{SE}\right)^2$ which is relative to p-value in opposite direction.

Big Wald statistic will affect p-value to be small. Therefore, it is significant when Wald statistic is large.

Wald statistic of SALES/INV = $\left(\frac{-.324}{0.191}\right)^2$ = 2.855, while p-value is 0.089.

Wald statistic of Age = $\left(\frac{0.033}{0.192}\right)^2$ = 0.029, while p-value is 0.865.

CL/TA and Controlling shareholder director show the significant level at 5% in the model. Add SALES/INV, when significant level is at 10%. As the result above, the bankruptcy prediction model can be developed as follows:

Probability to be bankrupt = $\frac{1}{1+e^{-Z_i}}$

where,

Z = -9.349 + .035INV/TA + .100CL/TA - .324SALES/INV - 1.840Listed + 3.863Controlling - 1.580Ownership

Table IX
Goodness-of-fit test and Prediction Accuracy of Binary Logistic Model

Goodness-of-fit test	-2 Log likelihood
1. Log likelihood ratio test	
Step 0 : Likelihood of the null model	
(without predictor variable)	122.21
Step 1 : Likelihood of the Full model	
(with predictor variable)	17.027
The decrease in likelihood	105.183
	(sig. 0.000)
2. Cox & Snell R Square	0.666
3. Nagelkerke R Square	0.925
Prediction Accuracy	**Number of Firms**
Bankruptcy	
Bankruptcy firms - observed	32
Bankruptcy firms - prediction	30
Percentage Correct	93.750%
Error Type I	6.250%
Non-Bankruptcy	
Non-Bankruptcy firms - observed	64
Non-Bankruptcy firms - prediction	62
Percentage Correct	96.875%
Error Type II	3.125%
Total	
Observed	96
Prediction Corect	92
Percentage Correct	95.833%
Error	4.167%

Goodness-of-fit tests present high fit of prediction model, especially, 92.5% of the Nagelerke R Square, meaning that the explanatory variables of the prediction model influence for the incidence of bankruptcy 92.5%.
Prediction Accuracy shows quite high percentage (95.8%) and Error type I is only 3.1%

Table X
The result from Survival Analysisis (Cox Proportional Hazard Model)

	B	S.E.	Wald	Sig.	Exp(B)
INV/TA	.015	.011	1.838	.175	1.015
CL/TA	.011	.005	4.369	.037	1.011
SALES/INV	-.136	.050	7.510	.006	.873
Company's Age	-.020	.054	.132	.716	.981
Listed Status	-.557	.689	.654	.419	.573
Controlling Director	.829	.489	2.875	.090	2.291
Ownership Director	-.631	.393	2.575	.109	.532

Wald statistic = $\left(\frac{\beta}{SE}\right)^2$ which is relative to p-value in opposite direction.

Big Wald statistic will affect p-value to be small. Therefore, it is significant when Wald statistic is large.

Wald statistic of SALES/INV = $\left(\frac{-0.136}{0.050}\right)^2$ = 7.510, while p-value is 0.006.

Wald statistic of Age = $\left(\frac{-0.02}{0.054}\right)^2$ = 0.132, while p-value is 0.716.

CL/TA and SALES/INV show the significant level at 5% in the model. Add Controlling shareholder director, when significant level is at 10%. As the result above, survival function can be developed as follows:

Probability of suvival = $S_0(t)exp^{(Xi\beta)}$

$S_i(t) = S_0(t)exp^{0.015INV/TA + 0.011CL/TA - 0.136SALES/INV - 0.020Age - 0.557Listed + .829Controlling - .631Ownership}$

Table XI
Goodness-of-fit test and Prediction Accuracy of Survival Analysis (Cox Proportional Hazard Model)

Goodness-of-fit test	-2 Log likelihood
Log likelihood ratio test	
Step 0 : Likelihood of the null model	
(without predictor variable)	281.762
Step 1 : Likelihood of the Full model	
(with predictor variable)	198.123
The decrease in likelihood	83.639
	(sig. 0.000)
Prediction Accuracy	**Number of Firms**
Bankruptcy	
Bankruptcy firms - observed	32
Bankruptcy firms - prediction	21
Percentage Correct	65.625%
Error Type I	34.375%
Non-Bankruptcy	
Non-Bankruptcy firms - observed	64
Non-Bankruptcy firms - prediction	60
Percentage Correct	93.750%
Error Type II	6.250%
Total	
Observed	96
Prediction Corect	81
Percentage Correct	84.375%
Error	15.625%

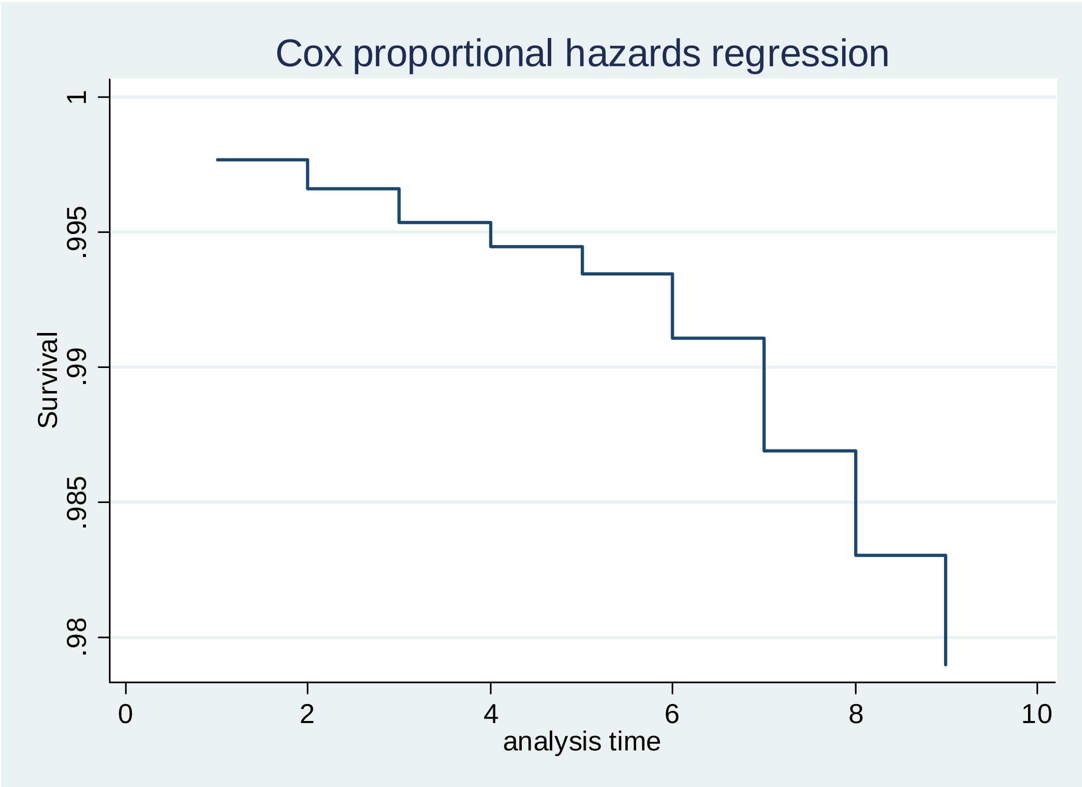
Goodness-of-fit test presents the decline in likelihood 83.639, is significant. Prediction Accuracy shows quite high percentage (84.4%) and Error type I is only 6.3%

Table XII

Comparison of the results of Binary logistic regression model and Cox proportional hazard model

Description	Binary logistic regression	Cox proportion hazard
1. Leading indicators	Financial ratio: Current liability to total asset Sales to inventory Non financial ratio: Controlling shareholder director (CL/TA and Controlling are significant at 5% level, while SALES/INV is significant at 10%)	Financial ratio: Current liability to total asset Sales to inventory Non financial ratio: Controlling shareholder director (CL/TA and SALES/INV are significant at 5% level, while Controlling is significant at 10%)
2. sign of Leading indicator signals: Current liability to total assets Sales to inventory Controlling	 + - +	 + - +
3. Sequence more power effect of leading indicator per 1 unit to probability of be bankrupt (β)	1. Controlling 0.829 2. SALES/INV 0.136 3. CL/TA 0.011	1. Controlling 3.863 2. SALES/INV 0.324 3. CL/TA 0.100
4. Over all accuracy	95.8%	84.4%
5. Type I Error	6.3%	34.4%

Figure 1
Survival Function at mean of covariates



This graph presents the Survival Function at mean of covariates.

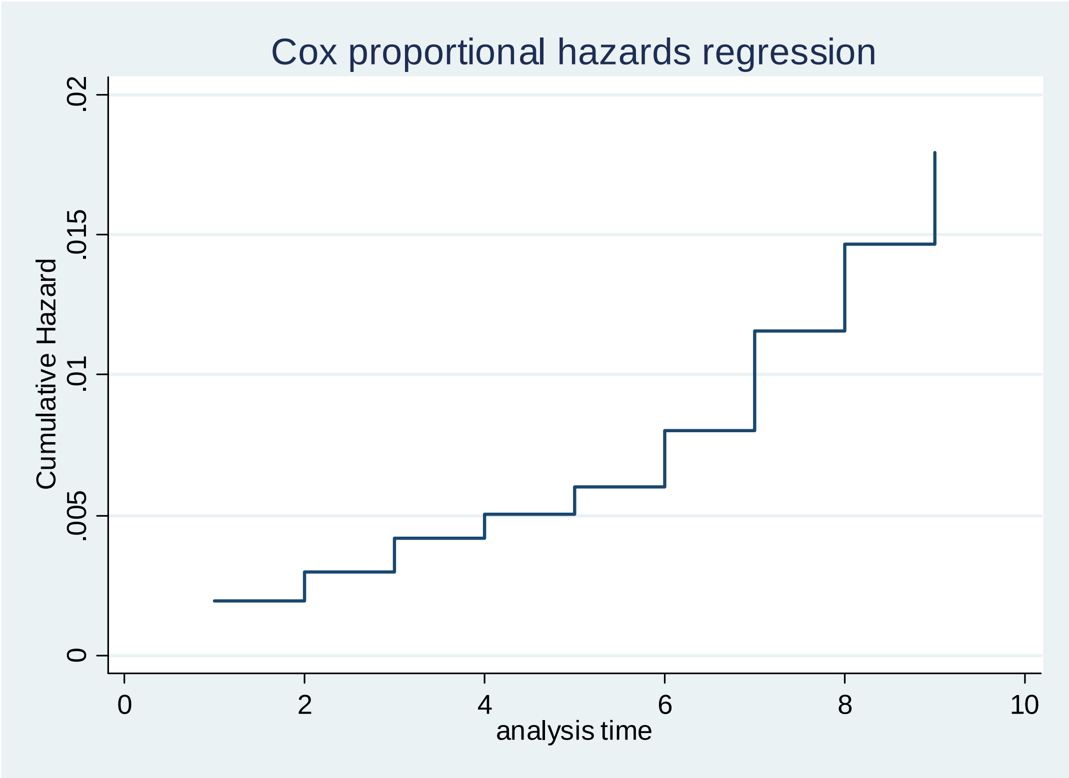
Probability of suvival $= S_0(t)exp^{(Xi\beta)}$

$$S_i(t) = S_0(t)exp^{0.015INV/TA + 0.011CL/TA - 0.136SALES/INV - 0.020Age - 0.557Listed + .829Controlling - .631Ownership}$$

where covariate means as follows:

Covariate Means	Mean
INVtoTA	70.574
CLtoTA	65.777
SALEStoINV	27.153
Age	11.427
List_Status	.198
Control_Staus	.260
Ownership	1.125

Figure 2
Hazard Function at mean of covariates



This graph presents the Hazard Function at mean of covariates.

$$h_i(t) = h_0(t)exp^{(Xi\beta)}$$

$$h_i(t) = h_0(t)exp^{0.015INV/TA + 0.011CL/TA - 0.136SALES/INV - 0.020Age - 0.557Listed + .829Controlling - .631Ownership}$$

where covariate means as follows:

Covariate Means	Mean
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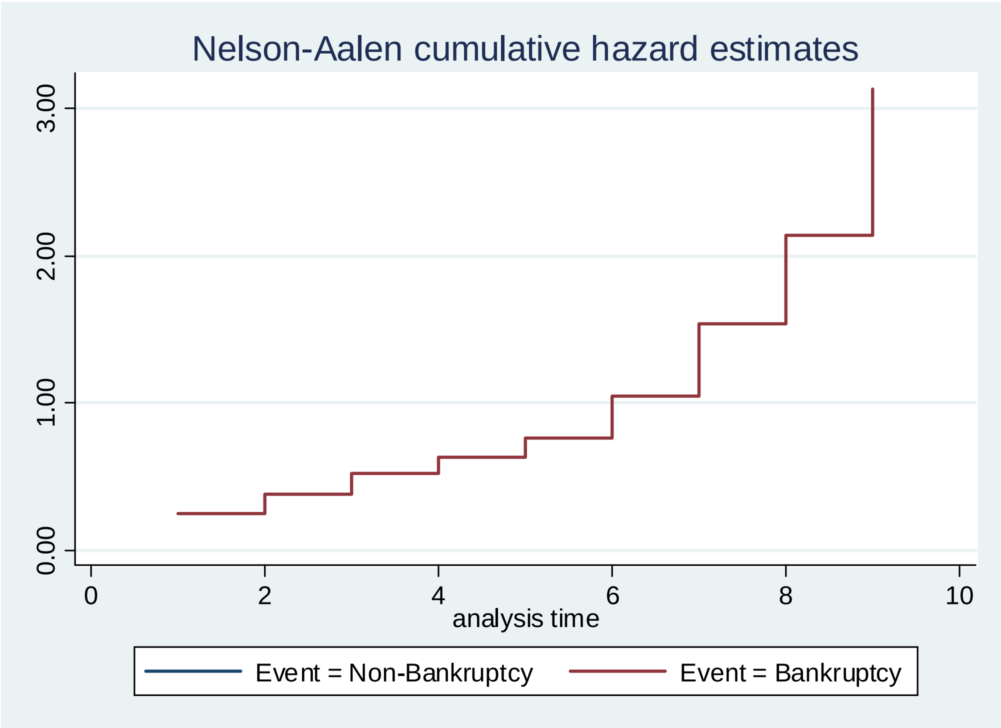
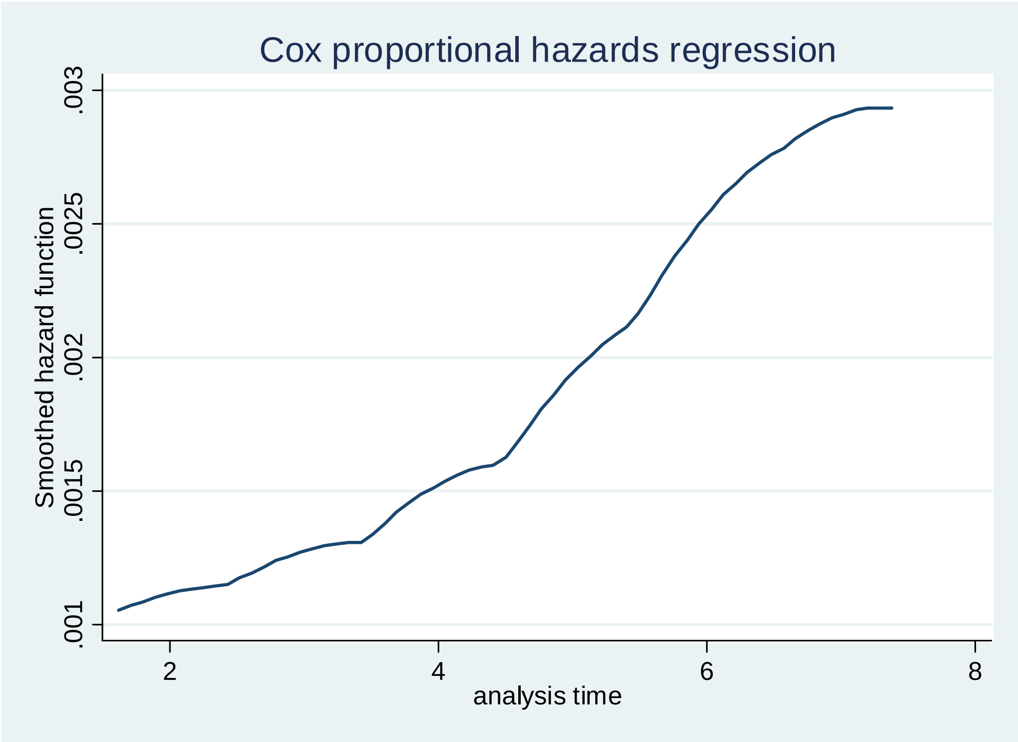
SALEStoINV	27.153
Age	11.427
List_Status	.198
Control_Staus	.260
Ownership	1.125

Figure 3
Hazard of Bankruptcy comparing with Hazard of Non-Bankruptcy



Nelson-Aalen cumulative hazard estimates: shows that non-bankruptcy real estate firms can survive during the studying period (2000-2009), while bankruptcy real estate firms have increasing in cumulative hazard estimate along the years.

Figure 4
Smoothed Hazard estimates



Smooth Hazard Estimate: presents the hazard ratio of bankruptcy firms. It gradually increases in the first sixth year and dramatically increased in the 7th year.