Modeling Financial Distress of SMEs in Thailand for Comparative Analysis of Normal and Recession Periods

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การสร้างแบบจำลองภาวะปัญหาทางการเงินของวิสาหกิจขนาดกลางและขนาดย่อมในประเทศไทย เพื่อวิเคราะห์เปรียบเทียบช่วงเวลาปกติและเวลาเศรษฐกิจถดถอย

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ชญานิศา เสน่ห์ลักษณา : การสร้างแบบจำลองภาวะปัญหาทางการเงินของวิสาหกิจขนาดกลางและขนาดย่อมในประเทศไทยเพื่อวิเคราะห์เปรียบเทียบช่วงเวลาปกติและเวลาเศรษฐกิจถดถอย (Modeling Financial Distress of SMEs in Thailand for Comparative Analysis of Normal and Recession Periods) อ.ที่ปรึกษาวิทยานิพนธ์หลัก: ดร.นราพงศ์ ศรีวิศาล, 46 หน้า.

วิสาหกิจขนาดกลางและขนาดย่อม (SMEs) มักถูกมองว่าเป็นหัวใจสำคัญของเศรษฐกิจของประเทศเนื่องจากมีบทบาทสำคัญในการจ้างงานและการเติบโตของประเทศ การวิเคราะห์ความเสี่ยงด้านสินเชื่อสำหรับ วิสาหกิจขนาดกลางและขนาดย่อมเป็นหน้าที่สำคัญที่จะต้องดำเนินการเนื่องจากการขาดความเข้าใจและการพัฒนาเครื่องมือที่มีประสิทธิภาพในการคาดการณ์ปัญหาทางการเงินและความเสี่ยงในการผิดนัดชำระหนี้อาจทำให้เกิดผลเสียหายอย่างมหาศาลและส่งผลกระทบต่อเศรษฐกิจของประเทศ ดังนั้นงานวิจัยนี้จึงมีวัตถุประสงค์เพื่อที่จะพัฒนาแบบจำลองที่สามารถคาดการณ์ความน่าจะเป็นของภาวะปัญหาทางการเงินสำหรับวิสาหกิจขนาดกลางและขนาดย่อมในประเทศไทย โดยใช้การวิเคราะห์การถดถอยโลจิสติก (Logit Regression Analysis) และการวิเคราะห์ถดถอยค็อกซ์ (Proportional Hazard Model) นอกจากนี้ยังมีวัตถุประสงค์เพื่อที่จะศึกษาผลกระทบของภาวะเศรษฐกิจถดถอยที่มีต่อความเป็นไปได้ที่วิสาหกิจขนาดกลางและขนาดย่อมจะประสบภาวะปัญหาทางการเงิน และยังตรวจสอบผลกระทบของภาวะเศรษฐกิจถดถอยที่มีต่อแต่ละอุตสาหกรรม ผลการศึกษาชี้ให้เห็นว่าภาวะเศรษฐกิจถดถอยมีผลกระทบอย่างมากต่อความน่าจะเป็นที่วิสาหกิจขนาดกลางและขนาดย่อมในไทยจะประสบภาวะปัญหาทางการเงิน เนื่องจากในภาวะเศรษฐกิจถดถอยบริษัทมีแนวโน้มที่จะเผชิญกับความเสี่ยงที่จะประสบภาวะปัญหาทางการเงินมากขึ้น อย่างไรก็ตามยังไม่มีหลักฐานทางสถิติเพียงพอที่จะสนับสนุนถึงความแตกต่างของผลกระทบจากภาวะเศรษฐกิจถดถอยที่มีต่ออุตสาหกรรมที่พักและอาหาร อุตสาหกรรมการผลิต อุตสาหกรรมไฟฟ้าก๊าซธรรมชาติและน้ำประปา และอุตสาหกรรมอื่น ๆ

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Small and medium-sized enterprises (SMEs) are often viewed as backbone of countries' economy since they play a crucial role in countries' employment and growth. Credit risk analysis for SMEs has become an important task to perform since the lack of understanding and developing an effective tool to forecast the distress and default risk may lead to huge losses and affect the whole economy of a country. Therefore, this paper aims to develop the models that can predict for the probability of financial distress for SMEs in Thailand by employing both Logistic Regression Analysis (Logit) and Cox's Proportional Hazard model. Moreover, the objective of this study is to examine the impact of recession period on the probability of SMEs financial distress. Also, to investigate the impact of recession period on each industry. The result indicates that recession period has a significant positive impact on the probability of Thai SMEs distress as firms tend to face with higher risk of distress during recession period. However, there was no strong statistical evidence supporting the differences in the impact of recessionary period on Accommodation and Food, Manufacturing, Electricity, Gas, and Water Supply, and other industries.

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CONTENTS

Introduction

The Asian Financial crisis that was triggered in July 1997 has deeply impaired the economic development of countries in Asia, including Thailand. With the sudden currency depreciation, many firms, mostly Small and Medium-sized Enterprises (SMEs), were not being able to bear with the unpredicted changes in the economy that raise their borrowing cost. This situation put them in the position where they defaulted on their debt payment and were eventually forced to go bankrupt. From this incident, SMEs which were formerly overlooked by the government in many countries, including Thailand, have become one of the most essential component for sustainable economic growth and are often viewed as a backbone of economies in many developed and developing countries all over the world since they play a crucial role in countries' employment, growth, and innovation (Altman & Sabato, 2007). Governments throughout the world had shifted their focus to SMEs with an attempt to promote economic development (Harper, 1979). Likewise, in Thailand, SMEs account for over 99 percent of the countries' enterprises and play an important role in all economic sectors by generating 41 percent of total GDP and accounting for 80 percent of the overall employment in 2015. Furthermore, SMEs contributed 27 percent of total export value and 35 percent of total import value. (Source: The Office of SMEs Promotion, OSMEP). The definition of SMEs is different across countries and business sectors. In Thailand, according to Small and Medium Enterprise Development Bank of Thailand, SMEs are classified into three major categories which are manufacturing business (industrial production, mining, and agriculture), trading business (wholesale, retail, import, and export), and service business (hotels and tourists, transportation, etc.). For each business sector, SMEs are defined by either the value of fixed assets excluding land or the number of employees.

For business development, accessing to capital market is an essential process since investment and innovation are impossible without adequate funding. However, unlike large firms, SMEs face with the difficulties in getting finance because of their financial constraints to access the capital market (Beck, 2006). Therefore, the major source of external financing for SMEs is in the form of bank debt which forces them to have high financing costs and even go bankrupt. Whenever there is a lending activity, there will always be a credit risk or default risk at which the borrowers cannot meet their financial obligations. This risk represents the uncertainty that the borrowers may unable to repay the loan on the agreed dates due to financial distress or bankruptcy and the lenders, especially financial institutions, may lose the principal, interest, or both. Consequently, it is necessary for financial institutions to develop the models that can help preventing them from lending money to potential distress firms.

Credit risk analysis is a very important task for financial institution to perform. The lack of understanding and developing an effective tool to forecast the default risk of the clients may lead to huge losses and affect the whole economy of a country (Bartual, 2013) like in the case of Asian Financial Crisis in 1997. Not only for the financial institutions, but the firm itself also benefits from the credit risk analysis since it can act as the pre-warning system that allow the firm to take an early action to prevent itself from being in the stage of financial distress. Predicting corporate failure has become more important in many research area. According to Karels (1987), the definitions of failure differ across studies.

Previous literatures have been focusing on developing distress prediction model for the large listed firms while only few studies developed the model for SMEs. Among those studies, most of them based on the data of developed countries whereas little research had been focused on SMEs survival in developing countries. Unlike large listed firms, SMEs remain largely unexplored due to not readily available data and the data is difficult to access. The lack of appropriate and reliable data are the challenges in SMEs financial distress modelling (Filipe, 2016). In addition, since the information required in terms of accounting for SMEs is different from large listed firms and their default risk is considered to be high due to the lack of collateral and sufficient management, SMEs credit risk analysis should be different from those of the large firms.

Moreover, most previous SMEs studies were conducted without considering country's economic cycle and the impact of it tends to be neglected. According to Burns (1946), economic cycle or business cycle is a fluctuation of economic output of a country. It can be classified into the phases of expansion and recession. The National Bureau of Economic Research (NBER) defined recession as a significant decline in economic activity. On the other hand, expansion is when the economy is growing. The economic cycle can last from few months to more than years. According to Mankiw (2008), in order to define whether the country is in the phase of recession or expansion, many economists use the real gross domestic product (GDP) as a measure. The expansion period is when real GDP is rising from the trough to the peak while recession is when real GDP is falling from the peak to the trough (Nelson, 2000 and Mankiw, 2008).

As noted by Richardson (1998) and Chen (2003), the recession was found to contribute to the increase in the likelihood of bankruptcy since they are often happen with monetary and fiscal constraint. When recession occurs, the cost of borrowing increases while the loan become less available. This could reduce the profitability or even create loss for many firms. During 2014, Thailand suffered from the period of recession in which the country's real GDP decreased by over $14 billion, representing the first GDP decline rate since 2008. Moreover, a fall in real GDP caused a rise in unemployment by 0.07 percent. The reason behind the rise in unemployment rate could be from the intention to reduce costs by cutting back on hiring new workers or even business failure. Therefore, recession could be one of the significant determinants of Thai SMEs failure (Source: The World Bank).

This study aims to use the observed data of firms' bankruptcy to develop the model that can predict for the probability of financial distress for SMEs in Thailand since the financial distress could lead to bankruptcy. The main objective of this research paper is to [1] develop distress prediction models based on Logistic Regression (Logit) and Cox's Proportional Hazard model for SMEs in Thailand by incorporating the effect of qualitative information (firm's specific characteristics) and recession period. Also, to [2] investigate the impact of recession period on each industry and to [3] examine the impact of firm's specific characteristics on the probability of Thai SMEs distress.

This study contributes to the overall literatures on the SMEs and credit risk modelling in many ways. Previous studies have been focusing on examining the impact of financial information on the probability of firms becoming financial distress. Therefore, this is the first paper that use logistic regression and hazard model to develop financial distress prediction models for SMEs in Thailand by incorporating the effect of qualitative information, such as firm's specific characteristics, and recession period. The additional factors that could determine the probability of SMEs failure other than the financial variables will be identified in this paper. The result of this study will be useful for investors, financial institution in Thailand, or even the firm itself since the study developed the credit risk model that would provide an early warning signal of the financial distress and can help avoiding bankruptcy.

Literature Review

Bankruptcy Prediction Model

There have been a number of research that utilize the financial statement analysis into forecasting the bankruptcy or the default probability. The pioneers in this area was Beaver (1966). Beaver (1966) use a univariate discriminant analysis to investigate whether the 14 candidate financial ratios have the ability to predict the failure of the individual large firms. The sample consisted of 158 firms which are 79 failed and 79 non-failed firms that were matched according to their asset size and industry. As a result of this independent analysis that focused on individual ratios, he found that the cash flow to total debt ratio is the most significant determinants. He also claimed that it is possible that considering financial ratios simultaneously may yield the stronger predictive ability than considering a single ratio.

On the other hand, due to the differences in the effect of individual ratios, (E. I. Altman, 1968) developed the five-factors model based on the Multiple Discriminant Analysis (MDA) to assess the predictive ability of financial ratios in detecting corporates bankruptcy that yielded different results. He used the total of 66 manufacturing firms over the period of 1946 to 1965 divided equally into bankrupt and non-bankrupt. Altman was the first to successfully develop MDA model that achieve a accurate result of 95 percent. After the work of Altman (1968), MDA became the statistical approach that has been used widely by many researchers in credit risk analysis area (Deakin, 1972; McGurr, 1996).

The following study, Blum (1974) developed the bankruptcy prediction model based on MDA by using 115 failed firms with over one million dollars liabilities and 115 non-failed firms that were matched by industry, sales, and number of employees as the sample. He found that the model consisted of 12 variables has the predictive ability of 94 percent for predicting bankruptcy in one year before failure. Most of the studies developed bankruptcy prediction models for firms in the United States while few studies developed models for Thai firms. Buggakupta (2004) and Kiatkhajornvong (2008) attempted to establish credit risk model for Thai companies by using the approach of MDA. Buggakupta (2004) constructed the model by using the sample of 176 Thai companies divided equally into bankrupt and non-bankrupt groups. She compared the predictive power of her four-factors model with those of Altman (1993) and found that the two models provided similar results. In 2008, Kiatkhajornvoung found that the level of liabilities and frequency of losses were the significant determinants of the failure. The sample includes of 31 bankrupt and 62 non-bankrupt firms which represented the proportion of 1:2, respectively.

Despite the fact that MDA was a very popular model at that time, many researchers found that MDA suffered from serious limitations. Eisenbeis (1977) pointed out that the assumptions relating to the normal distribution of the variables and the group dispersion matrices were often violated when applying MDA. As a result of these violations, the model provides invalid results due to the impact on the test of significance. Due to the limitations of MDA, the conditional probability model including both Logit and Probit analysis were introduced with an objective to alleviate those limitations. Start with Zmijewski (1984) who used Probit analysis to construct the model. He covered 129 failed listed industrial firms in NYSE and AMEX. It was found that the predictive power of the model varied depended on the sample, such as, matched sample and non-matched sample. For matched sample, the accuracy level were 92.5 percent and 100 percent for failed and non-failed firms, respectively. Conversely, the accuracy level for non-matched sample decreased as the results showed that for failed firms, the predictive accuracy was 62.5 percent and 99.5 percent for non-failed firms.

Another strand of literature used Logit analysis in determining the bankruptcy risk of firms. In 1980, Ohlson was the first to successfully use Logistic Regression (Logit) which has different assumptions from MDA and can solve MDA’s limitations to develop the bankruptcy prediction model. He claimed that since Logit has different assumptions from MDA, it can solve the limitation that MDA suffered. Since the model was based on Logistic Regression, the model used one data for one firm due to the fact that Logit is a single-period model. Therefore, for each firm, there was only one firm-year observation. With this new model, Ohlson found that the significant determinants of failure were the financial structure, size, performance, and current liquidity. Due to the successful of developing credit risk model based on Logit, many researchers followed Ohlson’s study and used Logit instead of MDA.

The following study by Lennox (1999) compared the performance of Logit, Probit, and MDA. He covered 949 listed companies in United Kingdom. The result showed that Logit and Probit models predicted bankruptcy better than MDA. For the purpose of developing default prediction model, Low et al. (2001) applied Logit in their research. They covered 26 failed and 42 non-failed firms during 1998. The model based on Logit is 82 percent accurate. Another study by Flagg (1991) confirmed the predictive ability of the model based on Logit analysis. They developed a failure prediction model to examine the predictive accuracy by using only failed firms as their sample. The results showed that logit analysis achieved 94 percent accurate for overall failure prediction. Logit tends to be a much more popular compared to Probit since Logit does not require lots of complex computation (Dimitras, 1996).

However, LeClere (2000) pointed out that the conditional probability models are static models since they ignore the time period prior the event. Same as LeClere (2000), Shumway (2001) labeled Logit as a "Static Model" and noted that using Logistic regression to construct the credit risk model could lead to biased and inconsistent estimations of the probabilities since the model ignore the fact that firms' characteristics change through time. In line with Shumway (2001), Hillegeist (2004) demonstrated that the single-period logit model suffered from some drawbacks. First, Logit uses just one non-random sample for each failed firm which leads to the problem of sample selection bias. Second, Logit does not include the time-varying variables and fails to incorporate the risk of failure. Liu (2004) also argued that the failure rate is associated with the changes in time-series of the economic data. To address these problems, Shumway (2001) developed a multiple-period logit model which is known to be identical to a simple hazard model to evaluate the bankruptcy risk of each firm during each time by using available information. The Cox's proportional hazard model is widely used and is one of the techniques in survival analysis. Since Hazard model is a multi-period model, he treated each firm year as an observation. The results indicated that several financial ratios used in the previous bankruptcy studies were insignificant when used in hazard model. He claimed that the hazard model was superior in terms of the consistency of the estimation and the prediction of bankruptcy than Logit. Chava & Jarrow (2004) considered industry effects into their model. By using monthly data, the model can capture the changes in characteristics of firms and achieve better prediction. They concluded that adding industry effects, the intercept and slope coefficients change.

The study by Nam (2008) compared a hazard model that includes macroeconomic variables with a logit model. With the sample of 367 Korean firms from 1999 to 2000, the results suggested that hazard models yielded a better performance than a static logit model since they incorporate time-varying factors. Abdullah (2008) compared the predictive power of three models which are MDA, Logistic Regression, and Hazard models. The result indicated that hazard model achieved the highest predictive accuracy. They found that the significant determinants of the financial distressed prediction model were liability to total assets and return on assets ratios.

In 2016, Espenlaub developed bankruptcy prediction model for United Kingdom and Indian firms based on Hazard model and compared the prediction power of models in both countries. It was found that by incorporating both accounting and market information into hazard model, the model outperformed several models that used only financial ratios or market variables like Z-score model. Nevertheless, the model did not perform so well when using the data of Indian firms.

The Study of SMEs Failure

Most of previous researches were mainly focused on developing credit risk model for large listed corporations while few of them had been focused on the survival of SMEs. (Altman, & Sabato, 2007) successfully developed a bankruptcy prediction model for SMEs in United States with the single period logit model by using accounting information. Their sample includes 120 bankrupt and 1,890 non-bankrupt SMEs. Altman and Sabato claimed that banks should not apply the same approach in constructing credit risk model for SMEs as for large corporations. In addition, they demonstrated that the Logit model perform better than the MDA bankruptcy prediction model proposed by Altman (1993), even when using the same set of variables since Logit has higher ability in discriminate between failed and non-failed firms.

The following study by Ciampi (2009)used both MDA and Logit to establish the credit risk models for SMEs in Italy. The result suggested that both MDA and Logit are suitble in forecasting the bankruptcy of SMEs in Italy. In addition, they found that the credit risk model for SMES should be developed separately and differently from the model of large listed firms. Darush (2008) aimed to identify the determinants of the Swedish SMEs failure. They used the sample of 1991 failed and 1991 non-failed SMEs in Sweden to develop the bankruptcy prediction model. They found that quick ratio and return on assets were the significant determinants of Swedish SMEs failure. Cultrera (2016) developed a bankruptcy prediction model with an aim to test for predictive ability of financial ratios. They used Logistic regression with financial ratios and control variables of firm's size and age to construct the model. Their sample consisted of 7,152 SMEs in Belgium. The result showed that the profitability and liquidity ratios were the most significant determinants of bankruptcy for SMEs in Belgium.

In Thailand, Sirirattanaphonkun (2012) applied both MDA and Logit to develop failure prediction model for SMEs during 2000 to 2010 and also compared the results with the existing credit risk model for large corporates in Thailand. It was found that Logit outperformed MDA in terms of predictive power. They incorporated a set of 22 financial variables and 4 categorical variables. After stepwise procedure, they found that eight financial variables were significant; [1] Cash to total assets, [2] Working capital to total assets, [3] Current liabilities to total equity, [4] Long-term debt to total assets, [5] Total liabilities to total assets, [6] Operating income to total assets, [7] Earnings before tax to total assets, and [8] Net income to sales. From the comparison between the model developed specially for SMEs and models for large corporates, they pointed out that in order to achieve the most accurate result, the model for SMEs should be developed differently from those of large listed corporates. In 2015, Khermkhan compared the forecasting efficiency of Thai SMEs financial distress prediction models based on different methods; Logit, Probit, MDA, and Artificial Neural Network (ANN). They found that Logit and Probit were the most flexible models and easy to understand while MDA was suitable for the case where complex studies is required. On the other hand, for non-linear equation, ANN was the most appropriate method. However, it was impossible to say that which model is the best.

Determinants of Bankruptcy

In order to examine the company's health for both large listed firms and SMEs, most researchers often used financial ratios as determinants. This is because the information can be easily found in the financial statement and can provide an early warning signal for potential financial distress firms. Moreover, by using financial ratios, the performance evaluation can be done easily since the financial ratios are comparable across years. There were numerous studies confirmed the significance of the financial ratios. In 2007, Altman and Sabato classified financial ratios into five categories; liquidity, profitability, leverage, coverage, and activity. First, the liquidity ratios represent the short-term solvency of the firm's financial performance and the ability to repay their short-term obligations. Second, profitability ratios measure the growth, performance, and result of business operations. It represents the effectiveness of the firm in operating and earning profit. Third, leverage ratios related to the financing choice and financial stability of the firm which can affect business survival. Forth, coverage ratios are defined as the ability to repay long-term debt. Lastly, activity ratios represent the productiveness of the utilization of corporate's resources to generate income. It is widely known that accounting information (quantitative information) can be a significant predictor of bankruptcy. However, there often be the case where there is inadequate reliable hard financial information, especially the information related to SMEs.

Apart from theses accounting information, Grunert (2005) argued that qualitative information can be used to predict the bankruptcy of firms. Also, when using both qualitative and quantitative variables the results provided by the model will be improved than considering each of these factors separately. In 2001, Westgaard found that when incorporating liquidity, financial coverage ratio, size, and age of the firm into Logit model, the default prediction become more accurate. Nikitin (2003) applied logit regression models to examine how the determinants of bankruptcy changed during the crisis in Indonesia. It was found that the size of the establishment, the age of the firms, and the capacity utilized percentage were the major bankruptcy determinants. The following study by Altman, Sabato, and Wilson (2010) tried to construct a distress prediction model for SMEs in United Kingdom by using non-financial information as independent variables as accounting information of SMEs is unavailable. The sample consisted of over 6,000,000 failed and non-failed firms. Their study combined both qualitative and quantitative information in distress prediction model for SMEs in UK and found that the firm specific characteristics were a significant determinants of company failure that help improved the predictive accuracy of credit risk model especially for SMEs.

Some previous studies examined the impact of company size on the likelihood of distress. Most of them pointed out the significance of company size in forecasting the company failure. Many studies proved that company size and the probability of distress are negatively related (Altman, Haldeman, & Narayanan (1977); Hensher, 2007). It was found that, compared to larger size companies, small companies tend to face with higher distress risk due to insufficient experience, limited connections and constraints (Audretsch, 1995; Honjo, 2000). Moreover, they are also more vulnerable to economic instability. On the other hand, several studies found that small size has a positive impact on the probability of distress (Parker, 2002; (Lamberto, 2008). Some studies even found no interaction between the size and financial distress (Turetsky, 2001).

Opler (1994) and Berkovitch (1998) claimed that the probability of distress vary across different industries since different industries face with different degrees of competition and characteristics of financial ratios. The following study by Filipe (2016) found that the companies in accommodation and food sector face with highest probability of failure while transportation face with the lowest probability. Moreover, they also noted the importance of the number of shareholder and company location in predicting financial distress. It was found that SMEs with less than three shareholders on average tend to face with higher bankruptcy risk due to the smaller amount financial support during difficult times. In addition, these companies are more likely to have higher bankruptcy risk since they have to face with higher competition and the rental expense is higher than those in non-urban. Also, for companies in urban area, it might be difficult to get capital support during difficult time since the owner might find it more interesting to close the business and find other employment.

Impact of Recessionary Period

According to Mascarenhas & Aaker (1989), recession is considered as a significant external factor that harm a firm's performance and returns. Moreover, in 1990, as a result of recession, over 500,000 firms went bankrupt in the United States (Pearce, 2006). As noted by Richardson, Kane, & Lobingier (1998) and Chen (2003), the recession was found to contribute to the probability of corporate failure since they often come along with the monetary and fiscal constraint. When recession occurs, the cost of borrowing rises since credit become less avialable. This could result in the reduction in the profitability or even create loss for many companies. As mentioned by Richardson, Kane, & Lobingier (1998), the effect of a recessionary period on the probability of business failure varied across firm due to differences in firms' specific characteristics. Companies that are better positioned than others and can signal the recession will be able to take an action to mitigate the bankruptcy risk. Therefore, the recessionary period has a little effect on these companies' risk of failure.

Even though recession affects firms in almost every economic sector, Ogneva (2017) found that the impact of recessionary period differs across industries. Some Industries are more economically sensitive to the economic cycle while some are defensive. Firms that operate in industries which demand and employment is highly sensitive to economic cycle tend to fail during the period of recession since the demand is low. On the other hand, those that are defensive are likely to be more stable during recessionary period. Youn (2010) stated that during the economic crisis, the accommodation and food industry tends to face with higher bankruptcy risk since people tend to cut back their travel expenditures like in the case of 1990 and 1991 recession, two third of companies in Accommodation and Food industry in United States went bankrupt (Romeo, 1997). Moreover, according to Anfisa (2016), it was found that manufacturing sector is also sensitive to the economic cycle because in the periods of recession, people tend to delay their purchases of goods in order to save money and spend them on current needs. Therefore, the decline in the demand for goods lead to the reduction in production and employment in the industry. On the other hand, Thorp (2007) found that the industry of electricity, gas, and water supply is considered as a defensive industry in which sales and earnings remain stable during the economic downturn since the demand for the products tends to be fairly constant throughout the whole economic cycle.

Hypothesis Development

The primary purpose is to investigate whether there is an impact of recession period on the probability of SMEs failure and whether the impact is different for each industry. This study predicts that the recession period has a significant positive impact on the probability of SMEs failure and the impact is different for each industry. The hypotheses are developed as follow:

Hypothesis 1: There is a higher probability of a firm being distressed during the period of recession.

$$\mathrm{H}_0: E[P] = E[P^R] \qquad \text{Vs.} \qquad \mathrm{H}_1: E[P] < E[P^R]$$

Referring to Mascarenhas & Aaker (1989), recession is considered as a significant external factor that harm a firm's performance and returns. Moreover, Richardson, Kane, & Lobingier (1998) and Chen (2003) found that recessionary period contributed to the decrease in the probability of corporate failure since they are occurring with monetary and fiscal constraint. Therefore, this study hypothesizes that there is a higher probability of a firm being distressed during the period of recession which means that recessionary period has a positive impact on the probability of distress.

Hypothesis 2a: The impact of recessionary period is higher for Accommodation and Food sector

In accordance with Youn & Gu (2010), during the recession, the accommodation and food industry was found to face with higher distress risk since both people tend to cut back their travel expenditures like in the case of 1990 and 1991 that two third of hotels in United States went bankrupt (Romeo, 1997). Therefore, this study hypothesizes that the impact of recessionary period is higher for Accommodation and Food sector.

Hypothesis 2b: The impact of recessionary period is lower for Electricity, Gas, and Water Supply sector

According to Thorp (2007), it was found that the industry of electricity, gas, and water supply is considered as a defensive industry in which sales and earnings remain stable during the recession since the demand for the products tends to be fairly constant throughout the whole economic cycle. Therefore, this study hypothesizes that the impact of recessionary period is lower for Electricity, Gas, and Water Supply sector.

Hypothesis 3: Small-sized firms tend to face with higher distress probability

According to Altman, Haldeman, & Narayanan (1977) and Filipe (2016), the company size and the probability of distress for SMEs and large listed firms were found to be negatively related. It was noted that, compared to larger size companies, small companies are more likely to face with higher distress risk because of insufficient experience, limited connections, and constraints (Audretsch, 1995; Honjo, 2000). Therefore, this study hypothesizes that small-sized firms tend to face with higher distress probability.

Hypothesis 4: The number of shareholders and the probability of distress are negatively related.

The study by Filipe (2016) and Honjo (2000) found that as the number of shareholders increase, the risk of distress for SMEs decrease since firms with larger number of shareholders tend to receive larger amount of financial support during hard time. Therefore, this study hypothesizes that the number of shareholders and the probability of distress are negatively related.

Hypothesis 5: Firms locating Bangkok tend to face with higher probability of distress.

As found by Filipe (2016), SMEs locating urban area (capital city) are more likely to have higher probability of distress since they have to face with higher competition and the rental expense is higher than those in non-urban. Also, for companies in urban area, it might be difficult to get capital support during difficult time since the owner might find it more interesting to close the business and find other employment. Therefore, this study hypothesizes that firms locating Bangkok tend to face with higher probability of distress.

Data

The dependent variable will be in the form of dummy variable which will only take two values representing both healthy firms and distressed firms. If the dependent variable equal to one ($y = 1$), it means that the firm has the status of bankruptcy or absolute receivership. On the other hand, the dependent variable will equal to zero ($y = 0$), if the firm is in the healthy financial situation or reported as active. For independent variables, financial ratio is known to be one of the most significant business failure predictors in previous studies. However, by only considering financial ratio might not provide the most accurate failure prediction. Therefore, in this study, both accounting information (financial ratios) and qualitative data (firm's specific characteristics) were incorporated into the model. The status of each firm in the sample as well as financial and firm's specific data were collected from the Business Online Public Company Limited database (BOL).

Sample Selection

The sample includes 120 bankrupt and 240 non-bankrupt SMEs in Thailand, in the proportion of 1:2, respectively. This proportion represents the environment in the real world since, according to Greenstein (1996), fewer than 50 percent of countries' enterprises become distressed in a year. The firms that were reported as bankrupt and absolute receivership in BOL database during the period of 2011 to 2014 are considered as failed firms while the firms reported as active are considered as non-failed firms.

First, the firms are classified the industry into 4 categories based on their TSIC codes; [1] Accommodation and food service activities, [2] Manufacturing, [3] Electricity, gas, and water supply and [4] others. For each industry, 30 failed firms are randomly selected and matched with two non-failed firms. In line with Altman (1968), Beaver (1966), and Sirirattanaphonkun & Pattarathammas (2012), their matching criteria is adopted by matching one of a bankrupt firm with two non-bankrupt firms which are the firms that were reported as active, belong to the same industry (same TSIC code), and have similar asset size. Moreover, the sample must meet all these conditions; the firms have fiscal year-end of 31th December and have the information available at least one year before they go bankrupt.

In the case of Multi-period logit and Hazard model that treats firm-year as an observation, the criteria for classifying each firm-year are as follow: for firm-year to be classified in distressed group, both conditions must be met, [1] it should be the last firm-year before a firm leaves the sample [2] the firm should be in the status of bankruptcy or absolute receivership.

Financial Variables

The financial ratios collected in this paper are based on those that were found to be significant for SMEs in Thailand in the study of Sirirattanaphonkun & Pattarathammas (2012). The financial information from 2010 to 2014 is used in our study. The financial ratios were collected from BOL database

Table 1: List of Financial Ratios with Summary Statistics

Table 1 reports the summary statistics of financial ratios used to develop distress prediction models.

Financial Ratios	N	Minimum	Maximum	Mean	S.E.
Cash/Total Assets	1510	0	1	0.1058643	0.20577
Working Capital/Total Assets	1510	-137.808	53.01	-0.055073	3.95699
Current Liability/Total Equity	1510	0	33.054	1.383787	3.5443
Long-Term Liability/Total Assets	1510	0	20.4012	0.385	1.3173
Total Liabilities /Total Assets	1510	0.00000393	9.19	0.4995	0.714
Operating Income/Total Assets	1510	-11.95998	13.03737	1.384	1.80961
EBT/Total Assets	1510	-28.1797	14.245	-0.014	1.236
Net Income / Sales	1510	-116.5192	10.42	-0.420	3.932

Firm's Specific Variables

Apart from financial ratios, we also accounted for firm's specific characteristics. Table 2 shows the list of firm's specific characteristics used in the study.

Table 2: List of Firm's Specific Characteristics

Firm's Specific Characteristics
Size
Number of shareholders
Industry
Bangkok

The study includes two dummies for size (small and medium) as SMEs in Thailand are classified into three groups (small, medium, and large) based on number of employee and fixed assets. For number of shareholders, a dummy variable is used and assigned as one if a firm has more than three shareholders. In order to control for industry effect, three industry dummies are included into the model. The classification is based on TSIC codes; [1] Accommodation and food service activities (55-56), [2] Manufacturing (10-33), [3] Electricity, gas, and water supply (35). In addition, Bangkok dummy is also included in the study.

Table 3: Frequencies Information of the Sample

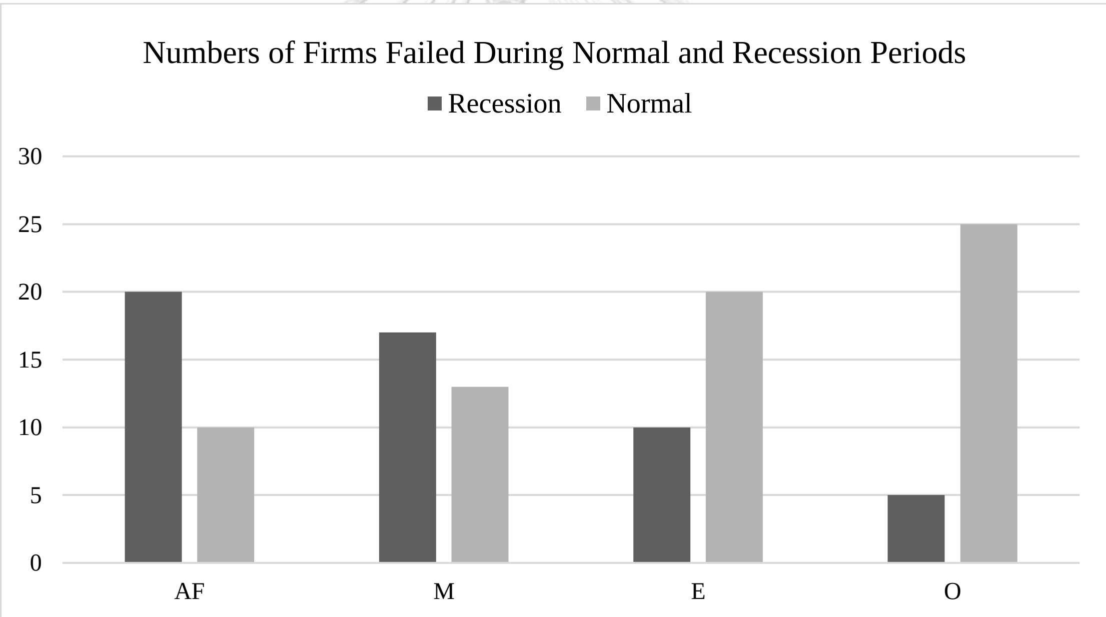
Table 3 reports the frequencies data of both firm's specific characteristics and recession period.

		Frequency (observations)	**Percent**
Status	Non-failed firm-years	1391	92
	Failed firm-years	119	8
	Total	1510	100
Size	Small	824	55
	Medium	328	22
	Large	358	24
	Total	1510	100
Shareholders	More than three shareholders	605	40
	Less than three shareholders	905	60
	Total	1510	100
Bangkok	Bangkok	705	53
	Non-Bangkok	805	47
	Total	1510	100
Recession	Recession Period	290	20
	Normal Period	1220	80
	Total	1510	100
Industry	Accommodation and Food	391	26
	Manufacturing	388	26
	Electricity, Gas, and Water Supply	348	23
	Others	383	25
	Total	1510	100

Recessionary Period Variable

In this study, the recession is defined as the event in Thailand during 2014, in which the country's GDP decreased by over $14 billion, representing the first GDP decline rate since 2008**.** To capture the impact of the recessionary period on Thai SMEs failure, the recession dummy variable (R) is added into the model. The dummy will be assigned as one if the firm-year is 2014 since it is the recession period in Thailand and zero for the period of 2010, 2011, 2012, and 2013.

Figure 1: Numbers of Failed Firms in Each Industry During Normal and Recession Periods



From Figure 1, the sample collected from BOL database shows that 20 firms in Accommodation and Food sector (AF) failed during recession period while 10 firms failed during normal period. This representing the highest number of firms that failed during recession period, compared to other sectors in this study. On the other hand, only 10 firms in Electricity, Gas, and Water Supply (E) sector went bankrupt during recession period showing that, compared to Accommodation and Food and Manufacturing sectors, Electricity, Gas, and Water Supply tend to be more defensive than others since the demand for the products tends to be fairly constant throughout the whole economic cycle.

Methodology

Stepwise Selection Method

With stepwise regression, the variables will be automatically included into the model based on their performance using statistical criteria. The process starts with adding variables that have high correlation with dependent variable into the model. Then use the Forward Selection Method to determine and add the variables outside the model that could contribute to the improvement of model performance. On the other hand, use Backward Elimination Method with the variables in the model to eliminate those that do not improve the model performance. Repeating the process until no variables is added or deleted.

Table 4: lists of candidate independent variables in Stepwise Selection Method

	Independent Variables (F_i)		**Independent Variables (C_i)**
F_1	Cash/Total Assets	C_1	Small
F_2	Working Capital/Total Assets	C_2	Medium
F_3	Current Liability/Total Equity	C_3	Number of shareholders
F_4	Long-Term Liability/Total Assets	C_4	Bangkok
F_5	Total Liabilities /Total Assets		
F_6	Operating Income/Total Assets		
F_7	Sales/Current Assets		
F_8	EBT/Total Assets		

Model 1: Static Logistic Regression (Single-Period Logit)

Logistic Regression (Logit) is considered as a binary response models that based on a cumulative probability function. Logit treats dependent variable (y) as a categorical variable that will only take on values of zero and one. In addition, the model uses just one non-random observation and does not include time-varying variables.

$$y_i = \begin{cases} 1\ if\ firm\ i\ is\ a\ financial\ distressed\ firm \\ 0\ otherwise \end{cases}$$

Since the event of interest is in the form of binary data which does not have a normal distribution, the dependent variable (y) and independent variables (x_i) have non-linear relationship. With this type of data, it is not suitable to use a typical regression because it does not give the best fit of the line. Therefore, the Logit model which does not assume the normality of variables is more appropriate in this case. The results provided by the model will be in the form of probability of the financial distress firm.

Logit Transformation

Logit is often defined as a natural logarithm of odds where the odds ratio represents the probability of failure and the probability of non-failure.

$$odds(failure) = \frac{P(failed)}{P(non-failed)} = \frac{p}{1-p} \tag{1}$$

With an adjustment, a non-linear equation is transformed into a linear equation.

$$Logit(p) = \ln(odds) = \ln\left(\frac{p}{1-p}\right)$$

$$\ln\left(\frac{p}{1-p}\right) = \beta_0 + x\beta$$

$$p = \frac{1}{[1+exp(-\beta_0 - x\beta)]} \ or \ \frac{\exp(\beta_0+x\beta)}{[1+\exp(\beta_0+x\beta)]} \tag{2}$$

where p = the probability that a firm is a failed firm

β_0 = intercept

β = a coefficient or an unknown parameter which capture the impact of independent variables (x) on dependent variable (y)

x = financial ratios and firm's specific characteristics

The probability and likelihood function can be defined as follow:

$$P_i \ = P(y_i = 1|x) \quad = \Lambda(\beta_0 + x\beta)$$

$$= \frac{\exp(\beta_0+x\beta)}{[1+\exp(\beta_0+x\beta)]} \tag{3}$$

where P_i = the probability that a firm is a failed firm

Λ = the logistic function that will yield the value between zero and one

$$1 - P_i \ = P(y_i = 0|x) \ = 1 - P(y_i = 1|x)$$

$$= 1 - \left(\frac{\exp(\beta_0+x\beta)}{[1+\exp(\beta_0+x\beta)]}\right) \tag{4}$$

where $1 - P_i$ = the probability that a firm is a non-failed firm

Λ = the logistic function that will yield the value between zero and one

In order to test for the impact of recessionary period (Hypothesis1), the static logit bankruptcy prediction model is developed. Both financial information and firm's specific characteristics are collected from the period of 2010 and used to construct the model.

$$P(fail_i = 1|x) = \Lambda(\beta_0 + \beta F_i + \gamma C_i + \phi_1 AF_i + \phi_2 M_i + \phi_3 E_i) \quad (5)$$

where Λ is logistic function

F_i is the set of financial ratios of firm i

C_i is the set of firm's specific characteristics of firm i

AF_i is an industry dummy variable for Accommodation and food

M_i is an industry dummy variable for Manufacturing

E_i is an industry dummy variable for Electricity, gas, and water supply

Maximum Likelihood Estimation (MLE)

In ordinary linear regression, parameters or the regression coefficients (β) are estimated by using the method of Ordinary Least Squares (OLS) which tries to minimize the sum of squared deviation of predicted values. However, for logistic regression, using OLS estimation is inappropriate since the estimated parameters are not minimum variance unbiased estimators. Therefore, instead of finding the best fitting line by using OLS, the Maximum Likelihood Estimation (MLE) is used to solve for the parameters in logistic model.

MLE is an approach of finding the smallest possible deviance between the observed and predicted values. Unlike a typical linear regression, the β in logistic model cannot be expressed by any closed-form formula since the optimal β are found to be estimated by an iterative search process that adjusted repeatedly until the likelihood value for the estimated parameters is maximized.

After using 2010 data to develop the model, the probability of distress for 2011 to 2014 are predicted separately to see whether the probability of distress increase in the period of recession. Moreover, in order to test whether the average probability between normal and recession periods are significantly different, t-test is performed on the probability of distress of each firms and recession dummy variable.

Goodness of Fit

In an ordinary linear regression model, R^2 (coefficient of determination) generated by OLS estimation is often used to evaluate the goodness of fit that represents the proportion that is explained by the predictors. However, in logistic regression with a categorical dependent variable, the model provides the maximum likelihood estimates that are not calculated to minimize variance. Therefore, OLS goodness-of-fit measure cannot be applied. In order to assess goodness of fit of Logit model, the Pseudo-R^2 that similar to R^2 in terms of range and interpretation were developed.

In this study, we use Count R^2, one type of Pseudo-R^2, as a goodness-of-fit measure. For any observation that has the predicted probability of 0.5 or greater, Count R^2 will treat that observation as having a predicted outcome of 1. On the other hand, if the predicted probability of an observation is less than 0.5, it will be treated as having the predicted outcome of 0. Then, the number of correct prediction is collected by counting the observations that have predicted outcome matched with their actual (predicted outcome of 1 match with actual 1 and predicted outcome of 0 match with actual 0).

$$Count\ R^2 = \frac{No.of\ correct\ prediction}{No.of\ total\ observations} \tag{6}$$

Model 2: Multi-Period Logistic Regression (Recession Dummy)

Multi-Period Logit is a logit model that use all data available in the sample. The model incorporates the time-varying covariates by does not exclude any data points. In terms of bankruptcy prediction, every firm-years available are included into the model.

$$y_{it} = \begin{cases} 1\ if\ the\ firm-year\ meet\ both\ following\ conditions: \\ \circ\ \text{it should be the last firm} - \text{year before a firm leaves the sample} \\ \circ\ \text{the firm should be in the status of bankruptcy or absolute receivership} \\ 0\ otherwise \end{cases}$$

In a multi-period logit model, the dependent variable (y) take value of one for the year prior to the failure (firm's last observation). Unlike the single-logit model, the earlier firm-year observations is also included in the sample as an active observation.

To capture the effect of recessionary period, a recession dummy variable is added into the model.

$$P(fail_{it} = 1|x) = \Lambda(\beta_0 + \beta F_{it} + \gamma C_{it} + \phi_1 AF_i + \phi_2 M_i + \phi_3 E_i + \delta R_t) \qquad (7)$$

where F_{it} is the set of financial ratios of firm i at time t

C_i is the set of firm's specific characteristics of firm i at time t

AF_i is an industry dummy variable for Accommodation and food

M_i is an industry dummy variable for Manufacturing

E_i is an industry dummy variable for Electricity, gas, and water supply

R_t is a recessionary period dummy variable at time t

The multi-period logit distress prediction model is developed as an alternative approach in order to examine the magnitude of the impact of recessionary period on the probability of distress (Hypothesis 1).

$\mathrm{H_0}: \delta = 0$ Vs. $\mathrm{H_1}: \delta > 0$

However, according to Shumway (2001), the adjustment of the test statistics produced by the logit program (static model) is needed. The test statistics from logit are incorrect for the multi-period logit model since the logit program treats each observation in the sample. In fact, we cannot treat the firm-year of a firm as independent because if the firm survived at time t, it cannot fail in $t - 1$. In order to adjust for the test statistics, the original test statistics provided by the model needed to be divided by the average number of observation per firm.

For the interpretation, the Exp(b) represents the odds value indicating how much the odds of distress changes when one-unit of dependent variable changes, holding others constant. When the odds value is greater than one, it implies that the variable and the probability of firms being distressed are positively related. On the other hand, if the odd value is less than one, the variable and the probability of firms being distressed are negatively related

Model 3: Multi-Period Logistic Regression (RxIndustry)

$$P(fail_{it} = 1|x) = \Lambda(\beta_0 + \beta F_{it} + \gamma C_{it} + \phi_1 AF_i + \phi_2 M_i + \phi_3 E_i + \delta_1 R_t + \delta_2 R_t x AF_i + \delta_3 R_t x M_i + \delta_4 R_t x E_i) \quad (8)$$

where F_{it} is the set of financial ratios of firm i at time t

C_{it} is the set of firm's specific characteristics of firm i at time t

AF_i is an industry dummy variable for Accommodation and food

M_i is an industry dummy variable for Manufacturing

E_i is an industry dummy variable for Electricity, gas, and water supply

R_t is a recessionary period dummy variable at time t

In order to examine the impact of recessionary period on each industry (Hypothesis 2a and 2b), the study develops Multi-Period Logit distress prediction model by adding the variables that represents the interaction between each industry and recessionary period (RxAF, RxM, and RxE)

Model 4: Cox's Proportional Hazard Model

For robustness check, the financial distress prediction model based on Cox's Proportional Hazard Model is developed. Hazard model is one method of survival analysis which is the technique of estimating the survival probability of an interested sample, in this case, SMEs in Thailand. Unlike static logit, hazard model analyses the time to the occurrence of financial distress. Meanwhile, hazard model is similar to logit in terms of the outcome that is dichotomous (binary) and the likelihood function. In line with multi-period logit model, hazard model uses all available firm-year data as a sample to eliminate the sample selection bias.

$$y_{it} = \begin{cases} \textit{1 if the firm-year meet both following conditions:} \\ \circ \text{it should be the last firm-year before a firm leaves the sample} \\ \circ \text{the firm should be in the status of bankruptcy or absolute receivership} \\ \textit{0 otherwise} \end{cases}$$

There are two concepts in survival analysis: survival *S(t)* and hazard function *h(t)*. *S(t)* estimates the likelihood of the firm acitve beyond time *t*.

$$S(t) = 1 - F(t) = \Pr(T > t) \tag{9}$$

where $F(t) = \Pr(T \leq t)$ is the cumulative distribution function. On the other hand, hazard (conditional failure rate at time *t*) estimates the likelihood that the distress happens within time frame, given that the firms are active since the beginning of that time.

$$h(t) = \lim_{\Delta t \to 0} \frac{\Pr(t+\Delta t > T > t | T > t)}{\Delta t} = \frac{f(t)}{S(t)} = \frac{-d \ln S(t)}{dt} \tag{10}$$

According to Cox's (1972) study, the hazard model is as follow:

$$h(t_i) = \lambda_0(t)\exp\{\beta_1 x_{i1} + \cdots + \beta_k x_{ik}\} \tag{11}$$

The equation suggests that the hazard function $h(t_i)$ is the rate of failure of observation *i* in the next instant, given that the firm was active at time *t*. It is the product of [1] $\lambda_0(t)$ which is the unspecified baseline hazard function for firm *i* and [2] exponential of the linear function of *k* fixed covariates. The hazard rate represents the risk of failure that can varies from zero to infinity.

In order to examine the impact of recessionary period on the probability of SMEs failure and for the purpose of robustness check for hypothesis 1, hazard distress prediction model is developed as follow:

$$h(t_i) = \lambda_0(t) exp\{\beta F_{it} + \gamma C_{it} + \phi_1 AF_i + \phi_2 M_i + \phi_3 E_i + \delta R_t\} \quad (12)$$

where $h(t_i)$ is the hazard function

$\lambda_0(t)$ is an unspecified baseline hazard function

F_{it} is financial ratios of firm i at time t

C_{it} is firm's specific characteristics of firm i at time t

AF_i is an industry dummy variable for Accommodation and food

M_i is an industry dummy variable for Manufacturing

E_i is an industry dummy variable for Electricity, gas, and water supply

R_t is a recessionary period dummy variable at time t

Maximum Partial Likelihood Estimation

After the stepwise procedure, the variables are selected into the model based on their significance. In order to estimate the coefficient (β) for hazard model, the maximum partial likelihood estimation is needed. The likelihood function of hazard model includes: the first part depends on both $\lambda_0(t)$ and β while the other part depends on β alone. For this estimation method, it ignores the first part and considers only the second part (partial likelihood function) by trying to find the values of β that maximize the partial likelihood since if the entire likelihood function is used to obtain the estimates, their standard errors will be too large than what it supposed to be.

For interpretation, the Exp(b) represents the hazard ratio that reflects the predicted change in the hazard function $h(t_i)$ or, in this case, the risk of firms being distressed for a unit increase in the dependent variables. The variables with hazard ratio greater than one are those that increase distress risk while decrease the survival times. On the other hand, the variables with the hazard ratio of less than one are those that decrease the risk of distress and increase the survival times.

Model 5: Cox's Proportional Hazard Model (RxIndustry)

For the purpose of robustness check for hypothesis 2a and 2b which is to examine the impact of recessionary period on each industry, the hazard distress prediction model is established by adding the variables that represents the interaction between each industry and recessionary period (RxAF, RxM, and RxE)

$$h(t_i) = \lambda_0(t)\exp\{\beta F_{it} + \gamma C_{it} + \phi_1 AF_i + \phi_2 M_i + \phi_3 E_i + \delta_1 R_t + \delta_2 RxAF_i + \delta_3 RxM_i + \delta_4 RxE_i\} \quad (13)$$

Where $h(t_i)$ is the hazard function

$\lambda_0(t)$ is an unspecified baseline hazard function

F_{it} is the set of financial ratios of firm i at time t

C_{it} is the set of firm's specific characteristics of firm i at time t

AF_i is an industry dummy variable for Accommodation and food

M_i is an industry dummy variable for Manufacturing

E_i is an industry dummy variable for Electricity, gas, and water supply

R_t is a recessionary period dummy variable at time t

Empirical Results and Discussion

Table 5: Estimates and Standard Error (In Parentheses) of Variables in Models

Variables	Model 1 (Logit)	Model 2 (Multi-logit)	Model 3 (Multi-logit)	Model 4 (Hazard)	Model 5 (Hazard)
Working Capital to Total Asset	-1.44*** (0.924)				
Total Liability to Total Asset	2.583*** (1.299)	1.696*** (0.205)	1.677*** (0.216)	0.352*** (0.041)	0.382*** (0.044)
Earnings Before Tax to Total Asset		-0.589*** (0.165)	-0.558** (0.162)	-0.111*** (0.025)	-0.116*** (0.026)
Bangkok	2.673** (3.195)	0.65** (0.247)	0.699** (0.254)	0.437** (0.202)	0.431** (0.201)
Number of Shareholders		-1.685*** (0.376)	-1.731*** (0.395)	-1.174*** (0.293)	-1.162*** (0.294)
Size: Small		1.794*** (0.475)	1.980*** (0.491)	1.389*** (0.389)	1.392*** (0.389)
Accommodation and Food	-1.358 (2.094)	-0.313 (0.348)	-1.358** (0.535)	-0.374 (0.301)	-1.333 (0.413)
Manufacturing	1.461 (1.36)	0.130 (0.330)	-0.773* (0.48)	0.414 (0.278)	-0.116** (0.382)
Electricity, Gas, and Water Supply	0.707 (1.373)	0.569 (0.351)	0.272 (0.42)	0.682** (0.277)	0.458 (0.369)
Recession		1.418*** (0.252)	0.440* (0.443)	1.926*** (0.291)	1.867*** (0.495)
RxAF			2.383** (0.699)		1.612*** (0.604)
RxM			2.346*** (0.631)		1.046*** (0.549)
RxE			1.277** (0.639)		0.459* (0.556)
R-Squared (2010)	0.984				
R-Squared (2010-2014)	0.88	0.94	0.942	0.923	0.926
Observations	318	1510	1510	1510	1510

***, **, and * indicates the significance at the 1%, 5%, and 10% levels, respectively.

For Model 1, the results show that three variables which are working capital to total asset, total liability to total asset, and Bangkok are significant in predicting Thai SMEs distress. It is shown that the significance values of each selected variables are all less than 0.05 implying that their coefficients are not equal to zero and are found to be significant. When controlling for the industry effect, working capital to total asset was found to be negatively related to the probability of distress while total liability to total asset and Bangkok have significant positive impact on the probability of distress. This finding is consistent with the studies of Filipe, Grammatikos & Michala (2016) and Sirirattanaphonkun & Pattarathammas (2012).

Table 6: Average Probability of Distress During Normal and Recession Period

Average Probability of Distress during Normal Period	14%
Average Probability of Distress during Recession Period	21%

As reported in table 6, the average probability of distress during normal period is 14 percent which is less than those during recession period. After conducting hypothesis testing, the p-value of recession dummy variable is less than 0.01 implying that during the recession period, firms are 7 percent more likely to be in the stage of financial distress. Thus, the null hypothesis (Hypothesis 1) can be rejected at 99 percent confidence. In conclusion, recessionary period is significant in predicting financial distress of Thai SMEs.

For Model 2, 3, 4, and 5, it is shown that apart from financial ratios, the qualitative information, such as Bangkok, size, and number of shareholders, included in this study are all significant in predicting Thai SMEs financial distress. When controlling for the industry effect, firms located in Bangkok tend to face with higher distress risk due to higher competition and rental costs compared to firms in Non-Bangkok areas. In terms of firm-size, in line with previous studies (Altman, Haldeman, & Narayanan, 1977; Hensher, Jones and Greene, 2007), the result indicates small-sized firms tend to become financial distress because of insufficient experience, limited connections, and financial constraints.

In terms of number of shareholders, consistent with the study of Filipe, Grammatikos & Michala (2016), as the number of shareholders increase the risk of distress decline since SMEs with larger number of shareholders tend to receive higher capital support during difficult times. As noted by Filipe, Grammatikos & Michala (2016), this advantage outweighs the higher administrative costs that the firms with more shareholders need to bear. For financial variables, the results show that as total liability to total asset ratio increase, the probability of Thai SMEs distress increase as well. On the other hand, earnings before tax to total asset is negatively related to the probability of Thai SMEs distress. Importantly, all models yield the robust results suggesting that recession period has a significant positive impact on the likelihood of firms being distress. Therefore, during recession periods, firms are more likely to be in the stage of financial distress. In conclusion, the null hypothesis (Hypothesis 1) can be rejected at 99 percent confidence in most of the model.

In addition, according to table 8, the interaction terms between recession and industry in model 3 and 5 are significant. Therefore, all industries (Accommodation and Food, Manufacturing, and Electricity, Gas, and Water Supply) are affected by recessionary period. This indicates that recessionary periods have a positive impact on every industry. However, as shown in table 8, there is no significant differences between the impact of recession on Accommodation and Food and other industries and between the impact of recession on Electricity, Gas, and Water supply and other industries. Therefore, the null hypothesis (hypothesis 2a and hypothesis 2b) cannot be rejected since there is not enough statistical evidence to conclude that the impact of recessionary period is significantly differences across industries. This is due to the fact that SMEs are more vulnerable to economic instability than large listed firms. (Audretsch & Mahmood, 1995; Honjo, 2000). Thus, even Electricity, Gas, and Water Supply industry that was considered defensive are affected by the recession period.

Table 8: Results of Two-sided T-test

This table reports the result of testing hypothesis 2a and 2b to examine whether the impact of recession period is significantly different for each industry.

Variables	P-value Model 3 (Multi-Logit)	P-value Model 5 (Hazard)
Accommodation and Food vs. Manufacturing ($H_0: \delta_2 - \delta_3 = 0 \quad vs. \quad H_1: \delta_2 - \delta_3 > 0$)	0.9687	0.3025
Accommodation and Food vs. Electricity, Gas, and Water Supply ($H_0: \delta_2 - \delta_4 = 0 \quad vs. \quad H_1: \delta_2 - \delta_4 > 0$)	0.1715	0.1453
Accommodation and Food vs. others ($H_0: \delta_2 = 0 \quad vs. \quad H_1: \delta_2 > 0$)	0.001***	0.008***
Electricity, Gas, and Water Supply vs. Manufacturing ($H_0: \delta_4 - \delta_3 = 0 \quad vs. \quad H_1: \delta_4 - \delta_3 < 0$)	0.1491	0.408
Electricity, Gas, and Water Supply vs. others ($H_0: \delta_4 = 0 \quad vs. \quad H_1: \delta_4 < 0$)	0.046**	0.4142
Manufacturing vs. Others ($H_0: \delta_3 = 0 \quad vs. \quad H_1: \delta_3 > 0$)	0.0003***	0.057*

***, **, and * indicates the significance at the 1%, 5%, and 10% levels, respectively.

Odds Value and Hazard Ratio

Table 10: Odds Value and Hazard Ratio of Variables

Variables	Model 1 (Logit)	Model 2 (Multi-Logit)	Model 3 (Multi-Logit)	Model 4 (Hazard)	Model 5 (Hazard)
Working Capital to Total Asset	0.24				
Total Liability to Total Asset	13.24	5.454	5.347	1.421	1.446
Earnings Before Tax to Total Asset		0.555	0.572	0.895	0.890
Bangkok	14.5	1.918	2.012	1.548	1.539
Number of Shareholders		0.186	0.177	0.309	0.313
Size: Small		6.014	7.242	4.011	4.024
Accommodation and Food	0.257	0.731	0.257	0.688	0.322
Manufacturing	4.31	1.139	0.462	1.514	0.890
Electricity, Gas, and Water Supply	2.028	1.767	1.313	1.978	1.581
Recession		4.129	1.553	6.859	6.469
RxAF			10.841		5.014
RxM			10.442		2.847
RxE			3.585		1.583

The table shows the values of Exp(b) of each variable in the models. Exp(b) are considered as odds value in logistic regression and hazard ratio in hazard model. In the case of logistic regression, the values represent the multiplier that indicates how the odds change for a one-unit increase in the value of the independent variables. To put it simple, odds of distress are defined as the ratio of the probability of distress and the probability of non-distress. On the other hand, hazard ratio represents the ratio of the risk of distress to the risk of non-distress.

Table 11: Interpretation of Odds Value and Hazard Ratio (Unit: Times)

Times change in odds and hazard rate = Odds Value or Hazard Ratio - 1

Variables	Model 1 (Logit)	Model 2 (Multi-Logit)	Model 3 (Multi-Logit)	Model 4 (Hazard)	Model 5 (Hazard)
Working Capital to Total Asset	-0.8				
Total Liability to Total Asset	12.24	4.454	4.347	0.421	0.446
Earnings Before Tax to Total Asset		-0.445	-0.428	-0.105	-0.11
Bangkok	13.5	0.918	1.012	0.548	0.539
Number of Shareholders		-0.814	-0.823	-0.691	-0.687
Size: Small		5.014	6.242	3.011	3.024
Accommodation and Food	-0.7	-0.269	-0.743	-0.312	-0.678
Manufacturing	3.31	0.139	-0.538	0.514	-0.11

Variables	Model 1 (Logit)	Model 2 (Multi-Logit)	Model 3 (Multi-Logit)	Model 4 (Hazard)	Model 5 (Hazard)
Electricity, Gas, and Water Supply	1.028	0.767	0.313	0.978	0.581
Recession		3.129	0.553	5.859	5.469
RxAF			9.841		4.014
RxM			9.442		1.847
RxE			2.585		0.583

According to table 11, Model 1 suggested that for a one-unit increase in working capital to total asset, the odds of becoming financial distress is expected to decrease by 0.8 times or 80 percent. On the other hand, when total liability to total asset increases by one unit, the odds of firms being distressed increases by approximately 12 times. Also, for Bangkok, this indicated that the odds of becoming financial distress for firms located in Bangkok is 13.5 times of those located in non-Bangkok.

Model 2 and Model 3 yielded similar results. When total liability to total assets increases by one unit, the odds of firms being distressed increases by approximately 4 times. On the other hand, a one-unit increase in earnings before tax to total asset decrease the odds of distress roughly by 0.45 times. For Bangkok, compared to firms in non-Bangkok area, firms locating in Bangkok have around 1 times greater odds of being distress. For number of shareholders, having larger number of shareholders reduces the odds of firms being distress by 0.7 to 0.8 times. In terms of firm-size, the odds of distress increase by approximately 3 to 6 times for small-sized firms. Lastly, Model 2 and 3 suggested that, during recessionary period, given the other variables are held constant, the odds of distress for firms increases by 0.6 to 3 times compared to normal period.

Model 4 and 5 suggested that an increase in one unit of total liability to total asset ratio will result in approximately 0.4 times increase in the risk of experiencing financial distress. On the other hand, the unit increases in earnings before tax to total asset ratio decreases the distress risk by roughly 0.1 times. For Bangkok, firms locating in Bangkok have 0.5 times greater risk of experiencing financial distress. Likewise, having larger number of shareholders reduces the hazard rates about 0.7 times. When looking at firm-size, the risk of distress is 3 times higher for small-sized firms. In terms of recession, Model 4 and 5 suggested that, during recession period, the distress risk of the firms increases by 5 to 6 times compared to normal period.

Conclusion

Credit risk analysis has been one of the most important field of business. Numerous studies have used statistical methods to measure the credit risk of firms. Logistic regression and hazard model are two of the various statistical techniques applied for credit risk analysis and are proved to be the methods with high predictive accuracy. This paper aims to use the observed data of firms' bankruptcy to develop the model that can predict for the probability of financial distress for SMEs in Thailand since the financial distress could lead to bankruptcy. The main objective of this research paper is to [1] develop distress prediction models based on Logistic Regression (Logit) and Cox's Proportional Hazard model for SMEs in Thailand by incorporating the effect of qualitative information (firm's specific characteristics) and recession period. Also, to [2] investigate the impact of recession period on each industry and to [3] examine the impact of firm's specific characteristics on the probability of Thai SMEs distress.

This research covers the data of bankrupt and non-bankrupt SMEs in Thailand during the period of 2010 to 2014, both normal and recession periods. As expected, every model yields the similar results. The results indicate that the probability of distress increase during the period of recession. Financial ratios that are found to be the important determinants of Thai SMEs' distress are working capital to asset, total liability to total asset, and earnings before tax to total asset. Moreover, as a contribution of this research paper, the qualitative information that are found to be the significant determinants of Thai SMEs distress are number of shareholders, Bangkok, and size. Number of shareholders and firms' size have a negative impact on the likelihood of firms being distress. On the other hand, firms locating in Bangkok have a significant positive impact on the probability of distress. Importantly, consistent with the hypothesis, recessionary period has a significant positive impact on the probability of Thai SMEs distress since the firms tend to face with higher risk of distress during recession period. This study also examines the interaction effects between recessionary period and each industry. However, there was no strong evidence supporting the differences in the impact of recessionary period on Accommodation and Food, Manufacturing, Electricity, Gas, and Water Supply, and other sectors due to the fact that SMEs are vulnerable to economic instability. Therefore, every sector is affected by the recession period.

The result of this study will be useful for investors, managers, financial institution in Thailand, or even the firm itself in several ways. First, the developed model can be beneficial for the purpose of credit risk analysis when there are lending activities since it is considered as a fast and efficient tool that can detect for risky firms. This could help preventing financial institutions from lending money to potential distress firms. Second, for investors, the model can be used to select out undesirable investments and avoid losses from investing in those firms. Lastly, since the model can predict firm's performance and provide an early warning signal of financial distress, the firm itself can take an early action to prevent itself from being in the stage of financial distress.

Limitations of the Study

1. This study does not employ data of all SMEs listed in BOL database during the period of 2010 to 2014 since there is a time limit on the use of the database. Moreover, the financial data can only be collected one at a time manually. Therefore, collecting the information of each firms consume huge amount of time. With this size of sample, it could lead to limited generalization of the results.
2. In terms of bankruptcy definition, this study defines bankruptcy according to the status in BOL database. On the other hand, other studies might have different bankruptcy definition that based on different criteria. Therefore, the models may yield different results compared to other studies.

Suggestions for Future Research

1. Improvement on the sample: As mentioned in the limitation of the study section, this study is limited to the time spending on collecting information from the BOL database. Therefore, not all data of SMEs available during the sampling period is included in the study. Further study could improve the results by extending the sampling time frame and collecting more data of SMEs. However, the data collection of SMEs is difficult and time consuming.
2. Improvement on independent variables: Future research could include interest rates, inflation, and unemployment rates into the financial distress prediction model to examine the relationship between these variables and the probability of SMEs distress.
3. Improvement on the methodology: Future research can adopt other statistical models, for instances, neural network or the Life-Table method to develop distress prediction model and compare the result with existing model to achieve more accurate results.

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