Differences in Financial Distress Prediction Models for Small and Medium-Sized Enterprises

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ABSTRACT

Financial problems are one of the biggest issues affecting the survival of small and medium-sized enterprises (SMEs). Consequently, providing a warning before a company fails should be an effective method to help the survival of SMEs. There are many models that are used as early warning tools, and each model performs differently. Therefore, the primary aim of this article was to compare the principles of financial distress prediction models. The methods studied consisted of: Logit, Probit, Multivariate Discriminant Analysis (MDA) and Artificial Neural Network (ANN) models. In addition, the strengths and weaknesses including the nature of prediction of each method were summarized. The forecasting efficiency of these methods was compared by reference to relevant research studies. It was found that the Logit and Probit models are flexible in application and they are also easy to understand and explain. For more complex research studies, which require more complex techniques to identify several multivariate groups, the appropriate tool is MDA. For even more complicated research requiring more sophisticated techniques or nonlinear equations, ANN modeling is the most effective tool. The variables contributing the highest opportunity to identify financial distress were also identified.

Keywords: logit, probit, artificial neural networks, multivariate discriminant analysis

บทคัดย่อ

เนื่องจากปัญหาทางการเงินของ SMEs ถือเป็นปัญหาสำคัญที่ส่งผลกระทบต่อความอยู่รอดของ SMEs ดังนั้นเพื่อเป็นสัญญาณเตือนภัยก่อนจะเกิดบริษัทล้มเหลว ควรมีเครื่องมือที่มีประสิทธิภาพมาช่วยในการทำนายเหตุการณ์ที่จะเกิดขึ้น โดยเครื่องมือที่ใช้เป็นสัญญาณเตือนภัยมีหลายเครื่องมือ ซึ่งแต่ละเครื่องมือมีประสิทธิภาพการทำงานที่แตกต่างกัน ดังนั้น บทความนี้มีวัตถุประสงค์เพื่อเปรียบเทียบการทำงานของเครื่องมือพยากรณ์ความล้มเหลวทางการเงิน ได้แก่เครื่องมือ โลจิท โพรบิท การวิเคราะห์จำแนกประเภทหลายตัวแปร และโครงข่ายประสาทเทียม นอกจากนี้ยังได้สรุปข้อดีและข้อเสีย รวมถึงลักษณะการพยากรณ์ของแต่ละวิธี และเปรียบเทียบประสิทธิภาพในการพยากรณ์ของวิธีดัง

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กล่าวจากงานวิจัยที่เกี่ยวข้อง พบว่าเครื่องมือที่มีความยืดหยุ่นในการประยุกต์ใช้และง่ายต่อการทำความเข้าใจและอธิบายเป็นแบบจำลองโลจิทและโพรบิทในส่วนของงานวิจัยที่มีความซับซ้อนมากขึ้นต้องการการจำแนกหลายกลุ่มหลายตัวแปร ดังนั้นเครื่องมือที่เหมาะสมควรใช้การวิเคราะห์จำแนกประเภทหลายตัวแปร ในส่วนงานที่มีความซับซ้อนมากขึ้นหรือข้อมูลไม่เป็นเส้นตรงต้องใช้เทคนิคที่สูงขึ้น โดยควรใช้โครงข่ายประสาทเทียม ซึ่งจะทำให้การพยากรณ์มีประสิทธิภาพมากที่สุด และทำให้ทราบตัวแปรทางการเงินที่สำคัญที่นำมาใช้มากที่สุดและมีผลต่อการล้มเหลวทางการเงิน

คำสำคัญ: โลจิท โพรบิท โครงข่ายประสาทเทียม การวิเคราะห์จำแนกประเภทหลายตัวแปร

INTRODUCTION

In Thailand, there are many corporate small and medium-sized enterprises (SMEs) that have accumulated many years of financial records on their business activities, as well as on their diversification. The problem for such corporates is to use these historical data to predict their own future. Lack of understanding of their own financial boundaries (that is, the constraints from both internal and external factors) has often led to their demise. The failure of such prediction has long been an important and broadly studied topic in accounting, auditing, and finance. Corporations, lenders, and shareholders need to predict the possibility of default of a potential counterparty before finaical failure. SMEs in Thailand are classified into three major categories: 1) production, including agricultural processing, manufacturing and mining, 2) services, and 3) trade, including wholesale and retail companies. The Thai definition of an SME is based on either the number of employees or the total value of fixed assets, depending on the business sector (Institute for Small and Medium Sized Enterprises Development, 2012).

SMEs are important contributors to all economic sectors; they form more than 99 percent of the total number of businesses in the country and play a significant role in employment and growth distribution in areas outside the Bangkok metropolitan region (Institute for Small and Medium Sized Enterprises Development, 2012). Specifically, their contribution to employment was 76.7 percent of total employment in 2011, with approximately 70 percent of businesses being located outside the Bangkok metropolitan area (Institute for Small and Medium Sized Enterprises Development, 2012). Therefore, SMEs play an important role in the nation's economy. Many countries make substantial contributions to employment and this is true for the majority of businesses (Burns & Dewhurst, 1996). In developing countries, small-scale businesses are the most important source of new employment opportunities. Governments throughout the world seek to promote economic progress through a focus on small-scale enterprises (Harper & Soon, 1979).

This study documents how the Probit, Logit, and Artificial Neural Networks (ANN) models achieve higher prediction accuracy and possess the ability of generalization. The Probit and Logit models have the best performance and are most stable. However, if the data do not satisfy the assumptions of the statistical approach, then the ANN approach can be used with advantage and achieves higher accuracy in prediction. In addition, the models used in this study to achieve higher accuracy in prediction can be generalized compared to those of Altman (1968) and Ohlson (1980). Little research had been focused on SME survival or failure. For example, in Thailand, most studies that have focused on failure or financial distress related to listed companies, (for example, Graham, King, & Bailes, 2000; Tirapat & Nittayagasetwat, 1999; Yammeesri & Lodh, 2003).

Currently, the tools used in predicting financial distress, which are considered accurate and used to predict severe financial distress are the Logit, Probit, Multivariate Discriminant Analysis (MDA) and ANN models. However, there has been no reporting on which one produces the greatest accuracy in prediction. Many studies have compared these tools in order to measure their accuracy in the different contexts; namely, Taffler and Tisshaw (1977), Darrat and Zhong (2000), Brooks and Tsolacos (2003), Rekba Pai, Annapoorani, and Pai (2004), and Chancharat and Chancharat (2011). No study clearly indicated which one is the most accurate tool. In some contexts, the Logit is the most accurate (Cheniam, 2001), while some studies claim the Probit (Chava, Stefanescu, & Turnbull, 2011) and the MDA (Rekba Pai et al., 2004) models give high accuracy. Moreover, various research studies on the ANN model reported that it has potential to provide highly accurate predictions (Brooks & Tsolacos, 2003; Darrat & Zhong, 2000).

Of these studies, the ones that compared the four tools found that the Logit, Probit, MDA, and ANN models have potential to predict failure precisely over a one to three year horizon (Lin, 2009). The previous authors indicated that in the comparative studies of the financial distress prediction tools which were conducted using various aspects and contexts. Yet, in other contexts, their outcomes were contradictory due to the different aspects, strengths, and weaknesses of these four prediction tools. Therefore, an understanding of the different aspects, strengths, and weaknesses of each tool will provide an important contribution to their more appropriate application to forecast financial distress.

The models discussed here may help investors, creditors, managers, auditors, and regulatory agencies in Thailand to predict the probability of business failure. This first section of this paper reviews bankruptcy prediction models followed by related research studies both abroad and domestic. The next section compares the attributes of the four methods and their advantages and disadvantages. The last section provides conclusions based on the study.

LITERATURE REVIEW

Review of bankruptcy prediction models

The traditional failure prediction models employing statistical techniques were pioneered by Beaver (1966) withunivariate tests and by Altman (1968) using multivariate discriminant analysis (MDA). Ohlson (1980) also includes the linear probability model (LPM) and logit regression approach (LR) as statistical prediction models. The results of Ohlson (1980) show that the Logit model is able to predict corporate failure well as does the Probit regression approach. However, the most widely-used models are MDA and LR (Altman, Haldeman, & Narayanan, 1977; Atiya, 2001). The early wave of the literature documented that, to name a few, MDA models were used in Altman (1968) and Deakin (1972) while Probit models were used in Zmijewski (1984). Comparisons of traditional statistical approaches such as that by Canbas, Cabuk, and Kilic (2005) used MDA, Logit and Probit to predict the failure of corporations. The results showed that the predictability of the MDA model was higher than those of the Logit and Probit models. However, Lin (2009) found that the Probit model has the best performance and was stable.

Not until 1990 were neural network (NN) approaches introduced to the field of failure/ bankruptcy prediction by Carvalhal and Ribeiro (2007), Coats and Fant (1993), Wilson and Sharda (1994), and Zhang, Hu, Eddy, and Indro (1999) and their experimental results showed that the NN approach significantly outperformed the other methods. However Rekba Pai et al. (2004) used the MDA and ANN approaches to predict company financial distress; their results showed that the predictability of the MDA model was higher than that of the ANN model. Therefore, it cannot be concluded that ANN is the most effective model.

Some studies have explored SME survival or failure in various countries by using different empirical methodologies (Libby, 1975). Bahnson (1987) carried out a study in San Francisco on the prediction of business failure. Some studies using the Logit model have been carried out by Aziz, Emanuel and Lawson (1988), Casey and Bartczak (1985), Darayseh, Waples, and Tsoukalas (2003). There are studies that have focused on the application of the Logit model for forecasting the financial failure of SMEs in Thailand (Chancharat & Chancharat, 2011). Different models have resulted in different findings. In this section, four failure prediction models (MDA, Logit, Probit, and ANN) that have been used in predicting SME failure in Thailand will be compared. The results of this study may be useful for providing a warning of financial problems of SMEs before the actual failure of the business occurs.

Related research in foreign countries

In foreign countries, many studies have attempted to compare the prediction tools from various aspects. For example, Aziz, Emanuel, and Lawson (1988) compared the accuracy in prediction of the MDA and Logit models using the cash flow ratio as a variable; their results showed that the predictability of both was equal. On the other hand, Morris (1997) reported that the MDA model produced greater predictabilityle than the Logit model. Study of NN (Wilson, & Sharda, 1994) and Logit (Charitou, Neophytou, & Charalambous, 2004) approaches produced outcomes suggesting that both can be reliable for forecasting failure in technical terms.

Rekba Pai et al. (2004) comparatively studied the failure prediction models based on MDA and NN and found that the MDA model was better than the ANN model. Similarly, Canbas, Cabuk, and Kilic (2005) carried out their study on predicting the failure of commercial banks in the Republic of Turkey. They found that the MDA model had the highest predictability followed by the Logit and Probit models, respectively. The greatest accuracy in prediction was found when the model had been used to forecast one year before the failure of the business. In addition, accuracy was reduced when the model was used to forecast more than one year in advance. Furthermore, some scholars who compared the four methods said that the Logit, Probit, MDA, and ANN models are able to predict precisely when they are used to predict one year and three years before the actual failure (Lin, 2009; Sirahawas & Phadoongsitthi, 2009). Yet, compared with other models that use different variables, it was found that the Probit model is more flexible and has greater efficiency in prediction than other tools (Lin, 2009).

The research studies in foreign countries that compared the methods from different aspects illustrated that the results varied with some being consistent and others inconsistent. Therefore, it was not possible to conclude which method was the most efficient in predicting financial failure.

Related research in Thailand

In Thailand, many researchers are interested in studying survival prediction. However, their studies were carried out only on the major corporates such as banks, financial institutes, or major corporations listed on the stock market. Those who studied the financial distress prediction of SMEs in Thailand were Na Rangsi (2005) using Limsombunchai (1999), Logit modeling and Temsuknirundorn (2000), and Sirahawas and Phadoongsitthi (2009) using MDA modeling with accounting information. The results of these studies were inconsistent. Furthermore, it was not identified which model had the greatest accuracy.

RESEARCH FINDINGS

Attribute comparison of the four models

The Logit and Probit models have shared attributes because they are the models that have the same probability. However, the Logit model is less complicated than the Probit model and is easier to use as well. Yet both have almost similar efficiency and little difference. They also are similar to MDA; that is, all three methods use the independent variables for weighting and calculating the Z-score ratio, while the O-score ratio of the Logit and Probit models is in the form of a failure probability. The ANN model uses an informative study by adjusting the weight for each node in order to minimize deviation. However, the ANN model performs better than other models where there is complex information as shown in Table 1.

In addition, an advantage of the Logit method is that it does not require hypothesizing in the normal discrimination of multivariates and the equality of the co-variance matrix of the independent variables of each model results in more elasticity and less complication. In contrast, MDA is a technique suitable for using multivariates to predict the dependent variables and the function of MDA can explain the variable of each group.

Although the use of Logit modeling helps to address the limitations of MDA modeling, the former method still has limitations and problems; for example, where the number of samples of bankrupted companies is less than the companies which are not bankrupt. There are many parties projecting the idea that this may result in over-classification of those not bankrupt (Type II Error). However, later studies (Lin, 2009) found that the number of samples do not necessarily have to be the same because the probability of each group can be calculated. This includes a sample which can be comparable in the terms of company size and industry sector. Some research studies (Libby, 1975) did not take into account the selection of the samples in their comparison, that is, the company size or industry sector are factors that may explain bankruptcy. Finally, there was the issue of the reliability of the predicting equations when the time period for prediction changed.

Comparison of the pros and cons of four methods

Each of these four prediction models has different limitations and in particular, the MDA model is used for multivariate discrimination, for example, for factor analysis of the financial statements, status of the company, and the status of the operations affecting the financial failure, among others. When compared with the Logit and Probit models, it has less elasticity. The latter two models have shared attributes with regard to finding the probability of financial failure. They may be differentiated in the forms of the equations they use. In addition, the Probit model has more complicated equations. The strength of these two models is that they are they can select variables for prediction by considering the relationships of variables and the ability of variable interpretation of the model. ANN models have been developed to copy the human brain (Rekba Pai et al., 2004). This model can be effectively applied to use with very complex information because it is able to produce a more accurate prediction than the three former models. The details are illustrated in Table 2.

With ANN modeling, the researcher needs to determine the suitable variable or to test the relationship of such a variable before testing in the

Table 1 Comparison of financial distress prediction models

Model	ß	Complexity	Elasticity	Accuracy	Works well with
Logit	Probability	Very low	High	Good	Linear regression
Probit	Probability	Low	High	Good	Linear regression
MDA	Coefficient	Low	Low	Good	Linear regression, Multivariate
ANN	Weight	High	Low	Good	Nonlinear and complex

Note: Analysis compiled by the authors of the current study. ß is the identifier that changes between independent variables and the dependent variable.

ANN model because this model is a study of the attributes of the information identifying which company is considered as a failed company and which group of companies will survive. The information inserted into the model has to be good and also the variables really affecting failure have to be real before using in the ANN model. Otherwise, this model will not accurately reflect the circumstances and so its outputs will not be relevant. It is difficult to explain information using simple equations because the ANN model is complicated and the model must assess the weight ratio of each node. Then there must be a study to record the attributes indicating those that represent failure or survival. The advantage of the ANN approach is that it models in a similar way to the human brain. Therefore, its performance is not only a recording of the information but also it is an informative learning process beneficial to the actual user. That is, when this model encounters different information which is relatively similar to the information inserted into the model, it will still provide correct predictions. This is different from other models because the ANN approach has the ability to learn and guess correctly from the information that has changed. For the other models, when different information is encountered from that used in setting up the model, the assessment of the results and prediction will be ineffective.

The previous comparative studies of these four models (Logit, Probit, MDA and ANN), produced inconsistent results which changed according to the information selected by the researchers. This includes the appropriateness of each research. Most studies related to the financial distress prediction models mainly aim: 1) to adjust the statistical methodology for more accurate usage (Altman, 1968; Beaver, 1966; Ohlson, 1980;

Table 2 Comparison of the advantages and disadvantages of four methods

Method	Disadvantages	Advantages
Logit	1. Limited to linear equations.	1. Convenient and easy to understand. 2. Can explain the variable as simple equations. 3. Provides good prediction when the relation of variables is linear.
Probit	1. Limited to linear equations.	1. Convenient and easy to understand. 2. Can explain the variable as simple equations. 3. Provides good prediction when the relation of variables is linear.
MDA	1. Limited to linear equations.	1. Can explain complex multivariate. 2. Provides good prediction when the relation of variables is linear.
ANN	1. Cannot explain variables as simple equations. 2. More complex than Logit, Probit and MDA. 3. No principle to clearly determine the structure of ANN such as the number of hidden layers and nodes. Each hidden layer is in a studying form. 4. No principle to clearly determine the suitable stimulated functioning.	1. High flexibility. 2. Can be used with non-linear variables. 3. Has high potential in learning information and can be used in different aspects. 4. Can be used with very complicated information.

Note: Analysis was compiled by the current authors.

Source: Adapt from Khermkhan and Chancharat (2013).

Zmijewski, 1984); 2) to extend the scope of the number of variables to cover all variables that may identify future problems that could occur, including an increase in the accuracy of prediction (Altman & Narayanan, 1997; Deakin, 1972); and 3) to test the accuracy of the models developed from actual information (Bahnson, 1987; Chancharat & Chancharat, 2011; Charitou et al., 2004).

Table 3 shows that the five variables used that contributed the greatest opportunity to financial distress were:

1. Current liabilities / Totals assets (Na Rangsi, 2005; Deakin, 1972; Lin, 2009; Ohlson, 1980)

2. Retained Earnings / Total assets (Na Rangsi, 2005; Ohlson, 1980; Altman, 1968)

3. Sales / Totals assets (Altman, 1968; Na Rangsi, 2005; Chancharat & Chancharat, 2011; Lin, 2009)

4. Net income / Total assets (Zmijewski, 1984; Abdullah & Ahmad, 2008 ; Deakin, 1972; Lin, 2009; Ohlson, 1980)

5. Current assets / Current liabilities (Deakin, 1972; Lin, 2009; Ohlson, 1980; Zmijewski, 1984)

Table 3 Variable contribution to highest opportunity to distress

Author	Variable
Altman (1968)	Working capital/Total assets Retained earnings/Total assets Earnings before interest and taxes/Total assets Market value equity/Book value of total debt Sales/Total assets
Deakin (1972)	Net income/Total assets, Current assets/Sales, Current assets/Current liabilities, Current assets/Total assets, Cash/Total
Zmijewski (1984)	Net income to total assets (return on assets) Total debt to total assets (financial leverage) Current assets to current liabilities (liquidity)
Chancharat & Chancharat (2011)	Current assets-Inventory/Current liabilities Total liabilities/Total assets Sales/Totals assets Natural logarithm of total assets
Na Rangsi (2005)	Inventory/Current assets Equity/Total assets Sale/Totals assets Current liabilities/Totals assets Retained earnings/Total assets Earning before interest, taxes depreciation and amortization/Current liabilities

Table 3 Variable contribution to highest opportunity to distress (continued)

Author	Variable
Abdullah & Ahmad (2008)	Interest cover
	Debt/asset
	Net income/Total asset
	Return on equity
	Cash/Total asset
	Cast/Current liabilities
	Net income growth
	Sales growth
	Current asset/Current liabilities
	Liabilities/Total asset
Ohlson (1980)	Total liability/Total assets
	Current liability/Current assets
	One, net income was negative last two years, zero otherwise
	Size of of total assets
	Working capital/Total assets
	Net income/Total assets
	Funds provided by operation/Total liability
	(Net income$_t$ - Net income$_{t-1}$)/(Net income$_t$ + Net income$_{t-1}$),
Lin (2009)	Total debt/Total assets
	Market value of equity/Book value of total debt
	Sales/Total assets
	Current assets/Current liabilities
	Income before tax interest and depreciation /Average total asset
	Retained earnings/Total assets
	Gross profit/Net sales
	Income before taxes/Net sales
	Bad debt expenses/Net sales
	Cash from operations/Current liabilities
	Interest cost/Average borrowings
	Growth rate of gross profit
	Growth rate of nncome before taxes
	Growth rate of equity
	Growth rate of depreciable assets
	Interest cost / Net income + interest expenses * (1/tax rate)
	Debt/Equity
	Contingent liability/Equity

CONCLUSION AND RECOMMENDATIONS

The comparison of the efficiency of the failure prediction tools found that the the Logit and Probit models are elastic in application and easy to understand and explain. For more complex research that needs to discriminate multivariate groups, the appropriate tool is the MDA model. For even more complicated study that needs the highest level of techniques and nonlinear information, ANN modeling should be used to render the highest efficiency in prediction.

There have been many comparative studies of these four financial prediction models. The results indicated that Probit, MDA, and ANN models are effective in prediction. In particular, the Probit model is able to effectively predict three years in advance of the failure, compared with the other models (Lin, 2009).

It can be seen that choosing the model is dependent on the information available and the aims of prediction. It is not possible to clearly say which model is the best or the most accurate. However, a comparison of the strengths, weaknesses, and limitations can be adopted and applied to determine the information needed. This emphasizes the context of predicting company failure. However, the review indicated that these tools can be used in other contexts such as in medicine, engineering, accounting, and other businesses. Currently, with the impending changes associated with Thailand entering the ASEAN Community, each company needs to be prepared to reduce risk factors by using suitable tools to predict any impending failure of its business. This will result in more accurate forecasting and any problems identified can be solved in time so that the likelihood of financial failure will be decreased.

The most common variables are used to predict financial distress are: Current liabilities / Totals assets, Retained earnings / Total assets, Sales / Totals assets, Net income / Total assets, and Current assets / Current liabilities.

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