Print ISSN: 1738-3110 / Online ISSN 2093-7717
JDS website: http://www.jds.or.kr/
http://dx.doi.org/10.15722/jds.20.10.202210.61

Predicting Financial Distress Distribution of Companies

Giang Huong VU[1], Chi Thi Kim NGUYEN[2*], Dang Van PHAM[3], Diu Thi Phuong TRAN[4], Toan Duc VU[5]

Received: July 03, 2022. Revised: August 04, 2022. Accepted: September 05, 2022.

Abstract

Purpose: Predicting the financial distress distribution of an enterprise is important to warn enterprises about their future. Predicting the possibility of financial distress helps companies have action plans to avoid the possibility of bankruptcy. In this study, the author conducted a forecast of the financial distress distribution of enterprises. **Research design, data and methodology:** The forecasting method is based on Logit and Discriminant analysis models. The data was collected from companies listed on Vietnam Stock Exchange from 2012 to 2020. In which there are both companies suffer from financial distress and non-financial distress. **Results:** The forecast analysis results show that the Logistic model has better predictability than the Discriminant analysis model. At the same time, the results also indicate three main factors affecting the financial distress of enterprises at all three research stages: (1) Liquidity, (2) Interest payment, and (3) firm size. In addition, at each stage, the impact of factors on financial distress differs. **Conclusions:** From the results of this study, the author also made several recommendations to help companies better control company operations to avoid falling into financial distress. Adjustments to current assets, debt, and company expansion considerations are the most important factors for companies.

Keywords: Financial Distress Distribution, Financial distress, Forecasting, Logit, Discriminant Analysis.

JEL Classification Code: D30, G17, G33

1. Introduction

Listing on the stock exchange is done by companies with many goals. Firstly, the listing will help businesses promote the company brand better. Secondly, capital raising becomes more diversified based on the issuance of shares. However, the listing will also be canceled, leading to bad information for businesses. The delisting is also a sign that the business operation is difficult.

Financial distress has resulted in an inability to pay the accounts payable, leading to bankruptcy (Altman, 2021). Financial distress distribution is divided into two possibilities: Delisting on the stock exchange-Financial distress; not canceled on the stock exchange-Non-Financial distress. Currently, the enterprises clearly show financial

1 First Author. Lecturer, Hanoi Open University, Vietnam.
Email: giangvh@hou.edu.vn
2 Corresponding Author or Second Author, Lecturer, Hanoi University of Business and Technology, Vietnam,
Email: nguyenchihubt@gmail.com
3 Third Author, Lecturer, Hanoi University of Business and Technology, Vietnam.
Email: phamvandang@hvtc.edu.vn
4 Fourth Author, Lecturer, Academy of Finance, Vietnam.
Email: tranphuongdiu@hvtc.edu.vn
5 Fifth Author, Central Capital, Vietnam.
Email: vuductoan@gmail.com

distress when listed on the stock market. Financial distress leads to stock prices falling for listed companies as investors are no longer interested in stock codes. At the same time, there are also problems with employees' salaries, payments to partners, and creditors (Opler & Titman, 1994). Therefore, when facing financial distress, listed companies make the operation situation even more complicated when they cannot attract new investors. Also, for this reason, enterprises are likely to be bankrupt (For listed companies, financial distress leads to delisting when three consecutive years report losses in financial statements).

The financial downturn forced management to take action to improve efficiency, resulting in improved corporate performance (Jensen, 1989). However, well-managed companies are less likely to benefit from managerial responses than those facing financial distress due to poor management (Whitaker, 1999). For investors to make the right decision on the stock market, the companies predict their enterprises' difficult situation. Forecasting financial distress or delisting companies will help stakeholders solve the above issues. Typical numerical analysis models are Altman's Z-score grading model and the Logit model of Ohlson's (1980), which are widely applied in predicting the ability default of the companies. In Vietnam, relevant studies are often associated with the forecast of bankruptcy risk or credit scoring in commercial banks, most of which apply and adjust the Z-score model of Altman. However, in the studies conducted in Vietnam, the financial difficulty variable has not been clearly defined, and the forecasting methods are still limited. Therefore, the author analyzes factors affecting listed companies' bankruptcy/delisting ability on Vietnam's stock market.

2. Literature Review

The first definition of financial distress argues that bank loans must be paid when a business lacks the money to pay off concessional debt or dividends (Beaver, 1966; Zmijewski, 1984). In addition, the financial distress of the company is widened with signs of lack of equity, shortage of highly liquid assets, not only cash but also bank deposits or other short-term financial assets, negative net asset status, when the debt exceeds the value of corporate assets (Zopounidis & Doumpos, 1999a). In addition, financial distress is a term that describes the financial status of an enterprise when it meets the symptoms summarized by Ross et al. (2022), including business failure, bankruptcy, and when the company's net assets are negative. Altman later perfected the concept of financial distress, pointing out that corporate bankruptcy is considered an official definition of financial distress.

Forecasting financial distress is associated with recognizing the financial predicament of a future entity from the past and present indicators (Angassa, 2014; Ding et al., 2008). The forecast of financial distress is derived from the theory of periods leading to financial distress (Fitzpatrick, 2022). It is quite possible to detect signs of financial distress before an enterprise becomes officially involved (Fitzpatrick, 2022). Therefore, models with different forecasting techniques and bases have been developed to improve the accuracy of the forecast results. Two important factors affect the accuracy of an enterprise's financial distress forecast model: (1) the selection of forecast indicators because when different indicators are used, then the forecast results will be different even if the analysis method is not constant; (2) related to analytical and forecasting techniques, which can increase the accuracy of the forecasting model even though the forecasting indicators are unchanged (Lin et al., 2015).

Following the prediction models of Altman (1968, 1984) followed by Ohlson (1980) introduced the technique of Discriminant analysis to forecast financial distress with the Z-score model. After that, the use of the Discriminant analysis model was reduced due to the appearance of the Logit analysis technique developed by Ohlson (1980). In later studies, forecasting financial distress is increasingly accomplished with the application of modern machine learning algorithms such as the Decision Tree model such as random forest or Neural Network. Widely used models include the Altman's Z-score models; Ohlson's Logit model. All models forecast financial distress for companies listed on the stock market.

3. Research Methods

3.1. Data

The data was collected on the stock exchange from 2012-to 2020 (890 companies operating on the stock exchange). In particular, 170 companies canceled listings from 2012-to 2020 were collected. In addition, the data includes 22 financial ratios for listed and delisted companies. After collecting data, the author conducted data separation and analysis in 3 stages: 1 year before delisting, two years ago delisting, and three years ago delisting. A detailed description of research variables in table 1 and description of collected data of each variable in table 2.

3.2. Data Analysis

To select predictive variables for this study, the author used the research results of Lin et al. (2015). Lin et al. (205) combined two approaches: expert (empirical) and statistical methods, to extract characteristics more effectively for prediction in the model. Since then, a system of 22 forecasting indicators has been developed, including: (1) group of indicators describing solvency, (2) group of indicators related to net cash flow, (3) group of indicators describing the performance, the group of indicators describing the profitability of the enterprise, and (5) group of indicators describing the capital structure of the enterprise. Those indicators were selected in this study because of the similarities in the context of the study in the method of creating those indicators.

To perform a model estimation with the dependent variable delisting of enterprise: get value one if the company delisted; 0 if the company is still listed. After analyzing data, the author conducted a logit model to evaluate the factors affecting the delisting of companies. Discrimination analysis model to assess the discrimination in the model assessing the impact of factors on delisting.

The variables are described in table 1.

Table 1: The descriptive variables

Code	Description
CA	Current assets / short-term liabilities
AEC	Assets easily convertible to cash / short-term debt
WC1	Working capital / Total assets
WC2	Working capital/sales revenue
CCC	(Current assets - Inventories - Prepayments) * 365 / (Total business expenses in the period - Depreciation expenses)
IP	Interest payment / equity
BV	(Current stock price * outstanding shares) / total liabilities
IP2	Interest payment / total revenue
DA	(Total assets in year i - total ts in year i-1) / total assets in year i-1
CF1	Cash flow / total assets
CF2	Cash flow / total liabilities
CF3	Cash flows / equity
NS	Net sales / Average total assets
NPFT1	Net profit from business activities after-tax/total stock
REP	Retained profits / total assets
NPFT2	Net profit from company activities before tax / total assets
GP	Gross profit / net sales
EBIT	EBIT / Total assets
NP	Net profit/equity
LEV	Total liabilities / total assets
PR	Stock price
SIZE	Total asset

Source: Author compiled from previous studies

Logit model:

The logit model was introduced by Ohlson (1980) with the Binary Logistic analysis technique.

The probability for an event to occur P (Y = 1) is as follows:

$$P(Y=1)=\frac{e^{-(\alpha+\beta_1X_1+\beta_2X_2+\cdots+\beta_nX_n)}}{1+e^{-(\alpha+\beta_1X_1+\beta_2X_2+\cdots+\beta_nX_n)}}$$

The probability that P(Y = 0) does not occur is as follows:

$$P(Y=0)=1-\frac{e^{-(\alpha+\beta_1X_1+\beta_2X_2+\cdots+\beta_nX_n)}}{1+e^{-(\alpha+\beta_1X_1+\beta_2X_2+\cdots+\beta_nX_n)}}$$

Y will get a value of 1 if the company delisted and 0 if the company does not delist.

Discrimination analysis model

The Discrimination analysis model has a linear form as follows:

$$D = b_0 + b_1X_1 + b_2X_2 + b_3X_3 + \cdots + b_kX_k$$

In which
D: Discrimination
b: coefficient or weight
Xi: Independent variables

Coefficients or weights (bi) are calculated so that the groups with different discriminating function values (D-numbers) differ as much as possible. This will occur when the sum of squared deviations of the difference between groups to the sum of the squared deviations of the difference within the groups is maximized. This discriminatory function is, in turn, estimated, defines the significance level, and calculates the cutting point.

4. Results

4.1. Description

The variables are collected and encoded into STATA software for analysis. The descriptive statistical values for the initial variables are shown in table 2. The mean of CA is 1.38; The mean of AEC is 0.68; The mean of WC1 is 0.08; WC2's mean is 3.88; The mean of CCC is -6.43; Mean of IP is -0.09; The mean BV was 2.73; IP2 mean of is -0.94; Mean DA was 0.07; The mean of CF1 is -0.002; The mean CF2 is 0.003; The mean of CF3 is 0.002; Mean of NS is 1.73; The mean NPFT1 was 841; Mean REP is 0.02; The mean NPFT2 is 0.02; Mean of GP is 0.15; Mean of EBIT is 0.15; Mean of NP is 0.02; The mean of LEV is 0.61; Mean of PR is 4256. The detail in table 2.

Table 2: Descriptive statistics

Variable	Mean	Std. Dev.	Min	Max
CA	1.38	8.33	-0.94	446.41
AEC	0.68	5.76	0.00	330.87
WC1	0.08	0.72	-27.00	1.00
WC2	3.88	696.88	-33797.90	43030.74
CCC	-6.44	255.28	-20148.70	2067.50
IP	-0.10	1.33	-58.31	41.71
BV	2.73	12.99	-0.96	447.52
IP2	-0.95	55.10	-4265.86	41.00
DA	0.07	1.33	-1.00	69.20
CF1	0.00	0.14	-6.17	0.79
CF2	0.00	2.89	-77.07	120.41
CF3	0.02	2.08	-31.72	161.76
NS	1.17	1.50	-0.01	29.40
NPFT1	841.43	3694.62	-64526.60	51427.73
REP	0.02	0.10	-1.96	0.95
NPFT2	0.02	0.77	-55.32	0.85
GP	0.15	0.48	-18.33	18.20
EBIT	0.14	6.54	-54.90	572.32
NP	0.03	0.78	-55.32	1.10
LEV	0.62	0.75	0.00	27.07
PR	4256.16	9039.61	0.00	127461.60

Source: Summary results from SPSS software

To forecast the financial distress of enterprises, the author analyzes two Logit models and Discrimination analysis.

4.2. Logit Model

With the logit model, the author analyzes the forecast analysis into three parts: (1) Forecasting on data 3 years before delisting; (2) Forecasting on data 2 years before delisting; (3) Forecast for one year before delisting. Results are obtained in table 3.

Table 3: The result of the Logit model

The variable name has statistical significance		B	p-value
Forecasting on data 3 years	WC	+	0.008
	IP	-	0.000
	NS	-	0.009
	NPFT1	+	0.046
	NPFT2	-	0.018
	PR	+	0.045
	SIZE	+	0.044
	Constant	-	0.003
	The ability to accurately forecast		84.60%
Forecasting on data 2 years before delisting	WC1	+	0.002
	IP	-	0.005
	DA	+	0.012
	CF3	-	0.006
	REP	+	0.032
	NPFT2	-	0.002
	EBIT	-	0.002
	NP	+	0.003
	SIZE	+	0.041
	Constant	-1.133	0.002
	The ability to accurately forecast		86.50%
Forecast for one year	WC1	0.964	0.052
	IP	-0.135	0.067
	NS	-0.509	0.001
	SIZE	0	0.062
	Constant	-0.923	0.01
	The ability to accurately forecast		88.20%

Source: Summary results from SPSS software

A model forecasting result three years ago revealed that WC1, NPFT1, PR, and SIZE all have the same directional effect on delisting. Delisting is influenced by the variables IP, NS, and NPFT2. The ability to anticipate the model's accuracy is 84.60 percent.

Two years ago, the model predicted: The factors WC1, DA, REP, and SIZE all had the same effect on delisting, according to the results of the analysis. Delisting is influenced by the variables NS, NPFT2, and EBIT. The model has an 86.5 percent predictability

The variables WC1 and SIZE had the same directional effect on delisting, according to the model from a year ago. Delisting is negatively influenced by the variables IP and NS. The correctness of the model may be predicted with an accuracy of 88.20 percent.

The variables WC1, IP, NPFT2, and SIZE all have an impact on the delisting of enterprises during the three projection periods. These findings indicate that these three study variables are all significant in the listing and delisting of businesses.

This is a factor that shows the company's liquidity for WC1 (current assets / short-term liabilities). The lower the WC1 coefficient, the greater the chance that the company may default on its short-term obligations. In contrast to significant current assets, it is possible to pay as much as possible on short-term obligations. The larger the WC1, the more stable the short-term financial situation.

The IP (interest payment/equity) has a negative impact on delisting, indicating that the cost of interest is a factor influencing company delisting. The interest payment is even higher when businesses use more external loans. Large debt is an issue that puts strain on businesses as they operate. The amount of debt used is well in excess of the ability to maintain debt. When interest rates are higher than the enterprise's ROA performance, the danger of interest payment is very substantial.

Finally, the SIZE (total asset) has a beneficial impact on the delisting of corporations. This finding suggests that the larger a company is, the more likely it is to be delisted. The operating capital needed for large-scale firms is also very high. As a result, while business operations provide enormous gains, they also bring big hazards, especially when the investment capital is large. According to the trade-off principle, the bigger the investment with the goal of increasing profits, the greater the risk for businesses.

The 1-year advance model is most likely to be the most accurate, based on the results of the 3-year, 2-year, and 1-year advance models (88.20 percent). However, it is clear that the longer the forecast, the less accurate the predicting skill becomes. As a result, the logit model should be adopted in businesses on an annual basis. Every year, a synthesis and forecast analysis is performed in order to offer the best possible results to the logit model.

4.3. The Results of the Model of Discriminant Analysis

The results of the discriminant analysis are described in table 4. The Lambks 'P-value' Lambda is equal to 0.000 and less than 0.05, so there is a difference in the effect of the independent variable.

The results of standardized analysis for one year before delisting show that variables BV and REP have the greatest impact on delisting. The ability to accurately forecast the model reaches 85.3%.

Forecast results for two years before delisting show that variables NPFT2 and EBIT have the greatest effect on delisting. The ability to predict the model's accuracy is 82.8%.

The differential analysis results before three years of forecast: the standardized coefficient analysis shows that the variables BV and NPFT2 have the greatest effect on delisting. The forecast is 70.3%.

Table 4: The result of the Discriminant analysis

	Standardized Canonical Discriminant Function Coefficients			
Forecast for one year before delisting	CA	-0.609	NS	0.213
	AEC	-0.147	NPFT1	0.224
	WC1	-0.17	REP	0.739
	WC2	0.213	NPFT2	-0.025
	CCC	0.095	GP	0.182
	IP	0.668	EBIT	-0.14
	BV	0.086	NP	-0.127
	IP2	-0.001	LEV	0.012
	DA	-0.033	PR	-0.083
	CF1	0.208	SIZE	0.143
	Wilks' Lambda			0.000
	The ability to accurately forecast			85.3%
Forecast for two years before delisting	CA	-0.292	NS	0.185
	AEC	-0.275	NPFT1	0.084
	WC1	-0.283	REP	-0.445
	WC2	0.189	NPFT2	1.189
	CCC	0.205	GP	0.233
	IP	0.540	EBIT	0.654
	DA	-0.207	NP	-0.039
	CF1	0.055	LEV	-0.081
	CF2	-0.084	PR	0.044
	CF3	-0.208	SIZE	0.143
	Wilks' Lambda			0.000
	The ability to accurately forecast			82.8%
Forecast for three years before delisting	CA	-0684	NS	0.366
	AEC	-0.234	NPFT1	-0.071
	WC1	-0.239	REP	-1.822
	WC2	0.125	NPFT2	2.052
	CA	0.336	GP	0.457
	AEC	0.707	EBIT	-0.294
	CA	-0.078	NP	-0.107
	AEC	0.042	LEV	-0.065
	WC1	-0.173	PR	0.286
	WC2	-0.114	SIZE	0.2
	Wilks' Lambda			0.000
	The ability to accurately forecast			70.3%

Source: Summary results from SPSS software

The aggregate results show that the Logit model has better predictability than the Discriminant analysis model. The detail in table 5.

Table 5: The general result

Classifications	Logit	Discriminant analysis
Forecast for one year before delisting	88.2%	85.3%
Forecast for two years before delisting	86.5%	82.8%
Forecast for three years before delisting	84.6%	70.3%

Source: Summary results from SPSS software

5. Conclusions

The study has built a predictive model of financial distress distribution based on two models: logit and discriminant analysis. The logit model has superior predictability than the Discriminant analysis model, according to predictive analysis results for two logit models and the Discriminant analysis model. Simultaneously, the findings of both models reveal that the 1-year forecast is the most likely to be correct. The author also proposed that, based on the findings of this study, an annual financial distress distribution assessment be conducted in order to have the best forecasting capacity. In addition, rather of using a discriminant analysis model, a logit model is advised.

Furthermore, generating annual estimates regarding the likelihood for financial hardship results in delisting. The study also offers advice on how to improve the current assets to current debt ratio. The first step is to increase liquidity by raising current assets in the business to assist it better deal with emergency situations; the second step is to lower interest expenses in the company: Reducing the rate of external debt is a frequent approach for businesses to save interest costs. In addition, corporations can expand source capital and reduce loan interest by making loans to units with lower interest rates or non-bank units on exchanges (such as the bond market or issuing more shares). Finally, implementation of scale investment control to provide better performance on each investment decision instead of overinvestment leads to risks for companies

Although the study has found the factors that predict the delisting of enterprises, the study still has some limitations: Firstly, the study has not paid attention to the endogenous phenomenon while analyzing the model. Secondly, the study makes a forecast on delisting without paying attention to the default of listed companies. Thirdly, delisting can come for many different reasons. Of which the cause of bankruptcy is only one.

The authors also recommend further studies on these limitations: Firstly, further studies on the same topic can use correction for possible endogenous factors. Secondly, the next study can collect more data on defaulting enterprises to predict further the factors affecting corporate default. Also, consider how the predictors for delisting and default are similar and different.

References

Altman, E. (1999). *Constrained Markov Decision Processes: Stochastic Modeling (1st ed.).* Routledge. https://doi.org/10.1201/9781315140223

Altman, E. I. (1968). Financial Ratios, Discriminant Analysis and the Prediction of Corporate Bankruptcy. *The Journal of Finance*, *23*(4), 589. https://doi.org/10.2307/2978933

Altman, E. I. (1984). A Further Empirical Investigation of the Bankruptcy Cost Question. *Journal of Finance*, *39*(4), 1067-1089. https://doi.org/10.2307/2327613

Angassa, A. (2014). Effects of grazing intensity and bush encroachment on herbaceous species and rangeland condition in Southern Ethiopia. *Land Degradation and Development*, *25*(5), 438-451. https://doi.org/10.1002/LDR.2160

Beaver, W. H. (1966). Financial Ratios as Predictors of Failure. *Journal of Accounting Research*, *4*(1), 71. https://doi.org/10.2307/2490171

Ding, G., Jiang, Q., Li, L., Zhang, L., Zhang, Z. G., Ledbetter, K. A., Panda, S., Davarani, S. P., Athiraman, H., Li, Q., Ewing, J. R., & Chopp, M. (2008). Magnetic Resonance Imaging Investigation of Axonal Remodeling and Angiogenesis after Embolic Stroke in Sildenafil-Treated Rats: *Http://Dx.Doi.Org/10.1038/Jcbfm.2008.33*, *28*(8), 1440-1448. https://doi.org/10.1038/JCBFM.2008.33

Fitzpatrick. (2022). Transitional Stages of a Business Failure on JSTOR. *Accounting Review*, *9*(4), 337-340. https://www.jstor.org/stable/238525

Jensen, M. C. (1989). Active investors, Lbos, and the privatization of bankruptcy. *Journal of applied corporate finance*, *2*(1), 35-44.

Lin, L., Li, Y. K., Xu, X. L., Zhang, F. W., Du, Y. G., Liu, S. L., Guo, X. W., & Cao, G. M. (2015). Predicting parameters of degradation succession processes of Tibetan Kobresia grasslands. *Solid Earth*, *6*(4), 1237-1246. https://doi.org/10.5194/SE-6-1237-2015

Ohlson, J. A. (1980). Financial Ratios and the Probabilistic Prediction of Bankruptcy. *Journal of Accounting Research*, *18*(1), 109. https://doi.org/10.2307/2490395

Opler, T. C., & Titman, S. (1994). Financial Distress and Corporate Performance. *The Journal of Finance*, *49*(3), 1015-1040. https://doi.org/10.1111/J.1540-6261.1994.TB00086.X

Ross, S., Best, J. L., Zon, L. I., & Gill, G. (2002). SUMO-1 Modification Represses Sp3 Transcriptional Activation and Modulates Its Subnuclear Localization. *Molecular Cell*, *10*(4), 831–842. https://doi.org/10.1016/S1097-2765(02)00682-2

Whitaker, R. B. (1999). The early stages of financial distress. *Journal of Economics and Finance 1999 23:2*, *23*(2), 123-132. https://doi.org/10.1007/BF02745946

Zmijewski, M. E. (1984). Methodological Issues Related to the Estimation of Financial Distress Prediction Models. *Journal of Accounting Research*, *22*(1), 59. https://doi.org/10.2307/2490859

Zopounidis, C., & Doumpos, M. (1999a). A Multicriteria Decision Aid Methodology for Sorting Decision Problems: The Case of Financial Distress. *Computational Economics 1999 14:3*, *14*(3), 197-218. https://doi.org/10.1023/A:1008713823812