Asian Economic and Financial Review, 2016, 6(1): 54-65

Asian Economic and Financial Review

ISSN(e): 2222-6737/ISSN(p): 2305-2147

URL: www.aessweb.com

CORPORATE FAILURE PREDICTION MODELS FOR ADVANCED RESEARCH IN CHINA: IDENTIFYING THE OPTIMAL CUT OFF POINT

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ABSTRACT

The rapid growth of the Chinese economy has resulted in Chinese listed companies entering numerous global supply chains, and thereby contributing to the globalization of economies. Accurately predicting corporate distress is a crucial concern for enterprises, managers, investors, creditors, and supervisors. In this study, data from the 2003-2013 (excluding 2008) was analyzed, and a logistic model was applied to analyze critical factors. We developed Special Treatment (ST) model to measure distress of companies listed in China. The results indicate that the optimal cut-off point (one, two, three and fourth quarters before a failure), and the debt ratios (one quarter before a failure) or unadjusted economic value added (two, three and fourth quarters before a failure) is superior in predicting corporate failure in China.

Keywords: Corporate failure prediction, China, Cut off point, Economic value added, Special treatment, Distress.

JEL Classification: M40, M41.

Received: 4 August 2015/ **Revised:** 27 January 2016/ **Accepted:** 30 January 2016/ **Published:** 3 February 2016

Contribution/ Originality

The results indicate that the optimal cut-off point for corporate failure prediction explained that most of the accuracy in the debt ratios (one quarter before a failure) and unadjusted economic value added (the models range from the two quarters to the fourth quarters before a failure).

1. INTRODUCTION

For decades, financial distress prediction (FDP) has been a central topic in both practical and academic corporate finance. From a practical perspective, stockholders, creditors, senior management, and auditors are all interested in FDP because it greatly influences their decision making. In addition, financial distress also results in serious social problems, such as unemployment, economic depression, and financial crisis, particularly if several companies run into financial distress at the same time. An accurate, stable, and practical FDP tool is therefore urgently required, and several academic researchers have been focusing on developing such a tool (Sun and Li, 2012).

China is the most prominent emerging market and is in the process of financial liberalization from a closed to a market-oriented and integrated economy. China experienced its first increase in bankruptcy cases starting from 2002 and peaking in 2007 (3207 cases) (Wang and Campbell, 2010c). In June 2007, a distressed firm removal system

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DOI: 10.18488/journal.aefr/2016.6.1/102.1.54.65

ISSN(e): 2222-6737/ISSN(p): 2305-2147

based on China's securities market's bankruptcy law was implemented, and is expected to exert a substantial influence on the market.

Previous studies have analyzed early warning systems in China. It is widely argued that the majority of studies on corporate failures thus far have relied too heavily on financial ratios (Li and Sun, 2010; Li *et al.*, 2010b; Wang and Campbell, 2010c; Li *et al.*, 2011a; Li and Sun, 2011a; Sun *et al.*, 2011a; Li *et al.*, 2011b; Sun *et al.*, 2011b; Li and Sun, 2011d; Biscontri *et al.*, 2012; Li and Sun, 2012; Sun and Li, 2012; Xiao *et al.*, 2012; Zhou *et al.*, 2012; Zhang *et al.*, 2013; Dong *et al.*, 2014; Geng *et al.*, 2015). Therefore, using financial ratios to detect distress could be beneficial.

A substantial amount of effort in the academic literature has been devoted to forecasting corporate failure. The methodologies employed have been based mainly on various statistical models. Bapat and Nagale (2014) indicated that logistic regression can be used as part of an early warning system to establish a cutoff point or level of probability (typically, 0.5) that categorizes a corporate as failed[1]. However, this value is subjective and optimal cut off points should be determined. If a firm, whose observed status is bankrupt, is classified to be non-bankrupt, such error is referred as a type I error and the reverse is a type II error. To show the relationship between the cut-off point and type I and type II errors, we address the following two questions: (1).Do performance outcomes of bankruptcy prediction models depend on the arbitrary choice of the cut-off point? (2) Procedure to determine the optimal cut-off point. The two research questions focus on the critical role of the cut-off point as it affects bankruptcy prediction models. Therefore, in this study, we adopted cut off points to predict corporate failures and identify which point is superior in comparison to various financial ratios (accuracy).The main contribution of this study to the literature is that, based on our research, it is the first study to examine the association between cut off points and performance outcomes of bankruptcy prediction models in China.

By investigating whether cut off points influence a firm's failure prediction, this study provides provide insight to the fundamental question concerning the choice of failure prediction models which are critical in the optimal allocation of resources. The remainder of the paper is organized as follows. Section 2 presents a brief review of the related literature. Section 3 provides details of the research design and sample selection procedure and develops our model. Section 4 presents our empirical findings. Section 5 contains a summary and conclusions.

2. LITERATURE REVIEW

Since the late 1960s, numerous studies have focused extensively on methods to predict bankruptcy, and several models have been developed to predict bankruptcy. Classical statistical techniques influenced the formation of these models such as logistic (Wang and Campbell, 2010c; Dong *et al.*, 2014)；Rough Set (Xiao *et al.*, 2012)；Support Vector Machine (Sun and Li, 2012; Dong *et al.*, 2014)；nearest-neighbour support vectors (Li and Sun, 2012)；

Linear regression (Zhou *et al.*, 2012)；probit regression (Zhou *et al.*, 2012)；linear discriminant analysis (Zhou *et al.*, 2012)；k-nearest neighbor methods (Zhou *et al.*, 2012)；Decision tree (Zhou *et al.*, 2012)；Naïve Bayes classifiers (Zhou *et al.*, 2012)；neural network (Zhou *et al.*, 2012)；neural network (Zhou *et al.*, 2012; Dong *et al.*, 2014)；AdaBoost (Zhou *et al.*, 2012)；multiple discriminant analysis (Biscontri *et al.*, 2012)；case-based reasoning

Support vector machine (Li and Sun, 2011a)；technique for order performance by the similarity to ideal solution (Li *et al.*, 2011b)；genetic algorithm (Sun *et al.*, 2011b)； random subspace binary logit (Li *et al.*, 2011a)；principal

[1]The cut-off value is 0.5. It means that if the estimated probability calculated as above is greater than 0.5 the company would be predicted as bankrupt.

component analysis (Li and Sun, 2011d) ; AdaBoost (Sun *et al.*, 2011a); single attribute test (Sun *et al.*, 2011a) ; decision tree (Sun *et al.*, 2011a) ; hybrid case-based reasoning (Li and Sun, 2010) ; classification and regression tree (Li *et al.*, 2010b) ; proportional hazards model (Bhattacharjee and Han, 2014) : Datamining (Zhang *et al.*, 2013; Geng *et al.*, 2015).

In reference to these statistical techniques associated with business failures in public companies in China, Zhu (2012) suggested that financial ratios (liquidity, profitability, operational efficiency, growth, structural factors, and cash flow) were effective variables to predict and explain corporate failures. The application of these traditional accounting tools for measuring corporate performance has been questioned, for various reasons. The tools are suitable for analyzing historical data, but not for future decision-making (Rappaport, 1995). Several studies have considered EVA(economic value added) to be a crucial tool for measuring performance (Sharma and Kumar, 2010; Ismail, 2011; Haddad, 2012; Parvaei and Farhadi, 2013) and managers worldwide have adopted it as a corporate strategy (Sharma and Kumar, 2010). Thus, companies would face bankruptcy, which explains a direct correlation exists between bankruptcy and companies that apply the EVA (Timo and Virtanen, 2001; Pasaribu, 2008; Anvarkhatibi *et al.*, 2013)

3. METHODOLOGY

Financial ratios were used to predict financial distress in China by using data from the RESSET database (2003-2007 ; 2009-2013). The study comprised 3485 samples, and financial companies were excluded. A logistic model was adopted to analyze the data. The variables and research model of the current study are presented in the following sections.

Dependent variables: Corporate Failures (ST model)

A financially distressed company is defined as a company with negative net profit for 2 consecutive years (Sun and Li, 2011). The abnormal financial status of these companies is also the main criterion for ST for Chinese companies listed on the Chinese Stock Exchange. The value of the dummy variable was 1 for distress, and 0 was the contrary the variable……………………… ……………………………… (1)

Independent variables: financial ratios[2]

Zhu (2012) suggested that financial ratios (liquidity, profitability, operational efficiency, growth, structural factors, and cash flow) were effective variables to predict and explain corporate failures in China. Therefore, in this study, we adopted debt-to-asset、current ratios、quick ratios、accounts receivable turnover、inventory turnover ratios、growth of net assets、cash to current liabilities.EVA can be used to detect corporate failure (Timo and Virtanen, 2001; Pasaribu, 2008; Anvarkhatibi *et al.*, 2013).

Control variables: macroeconomic factors[3]

Xie *et al.* (2011) indicated that macroeconomic indicators were useful to explain the interaction between the environment and corporate problems. The macroeconomic variables in this study were incorporated into the model, and the macroeconomic shock channels that contributed to corporate failures were identified. In this study, we used correlation coefficients[4] between net profit and the macroeconomic indicators (GDP, M2, Consumer Price Index (CPI), real interest rate, and the RMB: USD exchange rate) to measure the sensitivity of companies to macroeconomic changes, and all macroeconomic variables and profit data were semi-annual.

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[2]Zhu (2012). stated healthy firms had higher current ratios , quick ratios, accounts receivable turnover, inventory turnover ratios, growth of net assets, cash to current liabilities, cash to total liabilities, and non-healthy firms had higher debt-to-asset ratio

[3]AREMOS database

[4]Xie, Luo and Yu (2011).

Empirical model[5]

The study used the logistic method. The proxy variables are as follows: DAR_{it} was debt compared with assets in year t ; CR_{it} was current assets compared with current liabilities in year t ; QR_{it} was quick assets compared with current liabilities in year t ; ART_{it} was sales compared with average accounts receivable in year t ; $INVT_{it}$ was cost of sales compared with average accounts payable in year t ; GE_{it} was change in equity in year t ; CCL_{it} was cash compared with to current liabilities in year t ; $UAEVA_{it}$ is the unadjusted economic value added[6]compared with the outstanding shares in year t; $AEVA_{it}$ is the adjusted economic value (added join adjusted items) [7]compared with the outstanding shares in year t; $EDAEVA_{it}$ represents the adjusted economic value added (join adjusted items and economic deprecation adjusted items[8]compared with the outstanding shares in year t. $NIGDP_{it}$ was the correlation coefficients between net profit and the GDP in year t; NIM_{it} was the correlation coefficients between net profit and the money supply (M2)in year t ; $NICPI_{it}$ was the correlation coefficients between net profit and the CPI in year t ; $NIRI_{it}$ was the correlation coefficients between net profit and the real interest rate in year t; $NIEX_{it}$ was the correlation coefficients between net profit and the RMB:USD exchange rate in year t

Performance Measures[9]

Lu and Chang (2009) proposed an early warning model for the quarters (1Q, 2Q, 3Q, and 4Q) prior to the event of corporate distress that used financial ratios. If a bankrupt firm is classified as bankrupt, then it is considered TP. By contrast, if a non-bankrupt firm is classified as non-bankrupt, then it is considered TN. Any non-bankrupt firm that is classified as bankrupt produces a FP and any bankrupt firm that is classified as a non-bankrupt firm produces an FN (Divsalar *et al.*, 2011).

Robustness-Test

We test the predictive ability of our model both in and out of sample. We also repeat the same analyses out-of-sample to tackle a possible sample specific issue and get more robust and general results.

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[5]To shorten the tables, we omitted the solution because this paper has 720 empirical models. One financial ratio is the independent variable (ranging from failure prior to Q-1 to Q-4), and one prediction models is the dependent variable; five control variables are used in each logistical model.

[6]Huang and Liu (2010).

[7]Ibid.

[8]Ibid.

[9]"FN" is a type I error (If a firm, whose observed status is bankrupt, is classified to be non-bankrupt) ;"FP" is a type II error (If a firm, whose observed status is non-bankrupt, is classified to be bankrupt)。

4. RESULTS

4.1. Descriptive Statistics

Table 2 shows that the proportion of long-term debt at 30.17% shows it to be financial conservative. Current ratios, quick ratios and Equity growth[10]show that public firms in China are doing well. Conversely, the mean of the EVA is positive, showing that the public firms in China have a considerable ability to be profitable or to manage funds efficiently. In particular, the adjusted EVA (join accounting adjusted items and economic deprecation adjusted items) is the highest, and the adjusted EVA (join adjusted items) is the lowest. The aforementioned economic factors, the sensitivity of companies to macroeconomic changes, money supply (M2) is higher than other economic factors.

4.2. Empirical Test[11]

Banks with cut-off points[12]above 0.5 were classified as bankrupt banks and banks under 0.5 were classified as successful banks. The comparisons of predicted and actual bankruptcy classifications are shown in Tables 3-10.Because the financial crisis of 2008 might have restructured the global financial market; we separated data from before 2008 and after 2008 to obtain the accuracy of the logistic model.

Table 3-10 presents the classification ability of the logit models applied at cut-off point range from 0.1 to 0.9 in terms of classification rate, Type I and Type II error, and also the wrong classified cases for each group firms[13].As indicated in Table 3 (one quarter before a failure, and before 2008), debt to asset shad the optimal cut-off point (the accuracy of the logistic model was 33.18%) when the cut-off point was 0.8 employed to predict corporate failure. As indicated in Table 4 (one quarter before a failure, and after 2008), debt to assets had the optimal cut-off point (the accuracy of the logistic model was 25.79%) when the cut-off point was 0.9 employed to predict corporate failure. The empirical results show that the debt to assets exhibited greater accuracy (%) than that of the other financial ratios (one quarter before a failure).The debt to assets likely reflects an enterprise's financial conservative and can be employed to prevent distress. Thus, the accuracy of corporate failure prediction has been increased. Compared to Table 3 and Table 4, as indicated in Table 5 (two quarters before a failure, and before 2008), unadjusted economic value added had the optimal cut-off point (the accuracy of the logistic model was 35.17%) when the cut-off point was 0.6 employed to predict corporate failure. As indicated in Table 6(two quarters before a failure, and after 2008), unadjusted economic value added had the optimal cut-off point (the accuracy of the logistic model was 40.12%) when the cut-off point as 0.6 employed to predict corporate failure.

As indicated in Table 7 (three quarters before a failure, and before 2008), unadjusted economic value added had the optimal cut-off point (the accuracy of the logistic model was 44.38%) when the cut-off point was 0.6 employed to predict corporate failure. As indicated in Table 8 (three quarters before a failure, and after 2008), unadjusted economic value added had the optimal cut-off point (the accuracy of the logistic model was 45.99%) when the cut-off point was 0.6 employed to predict corporate failure. As indicated in Table 9 (fourth quarters before a failure, and before 2008), unadjusted economic value added had the optimal cut-off point (the accuracy of the logistic model was 50.12%) when the cut-off point was 0.6 employed to predict corporate failure. As indicated in Table 10 (fourth quarters before a failure, and after 2008), unadjusted economic value added had the optimal cut-off point (the accuracy of the logistic model was 54.42%) when the cut-off point was 0.6 employed to predict corporate failure. The

[10]Equity growth at 2.76%

[11]The rate of errors (Type I or II) is calculated as the number of firms that are misclassified over number of firms in the group. As a cut-off point moves toward 1, the type I error increases. In contrast, type II error decreases as the cut-off point increases. Because the fitted probability as generated using the logistic model can be zero or greater than one, the rate of type I errors can be far less than one. The rate of type II error can also be tilted above zero, even if the cut-off point is chosen to be one.

[12]Erdogan (2008).

[13]An appropriate cut off point should minimize the cost of misclassification (e.g., minimize the sum of type-I errors and type II errors)

empirical results show that the unadjusted economic value added exhibited greater accuracy (%) than that of the other financial ratios (ranging from failure prior to Q-2 to Q-4). The economic value added likely reflects an enterprise's real economic value and can be employed to prevent the inefficient management of funds (i.e., income excess capital cost) to ensure that corporations do not waste resources. Thus, the accuracy of corporate failure prediction has been increased.

Results from variance inflation factors to explain variables for correlation; the result lies between 1.687 and 1.893 (Variance Inflation Factors <10)[14].There is no correlation problem. We repeat the same analyses out-of-sample to tackle a possible sample specific issue and get general robust results[15]. Overall, the analysis of the prediction model show that all measures of predictive ability, there are differences between these models. The significance in difference provides strong evidences in the best prediction trends regarding corporate failure in China. Thus, the debts to assets or the unadjusted economic value added could be the optimal index for predicting corporate failure in China

5. CONCLUSION

This study used data from 2003-2013(excluding 2008), and a logistic model to analyze the factors that influence financial early warning systems in China. We developed Special Treatment model to measure distress of companies and presented the classification ability of the logit models applied at cut-off point range from 0.1 to 0.9 in terms of classification rate. The results indicate that the optimal cut-off point (e.g., an appropriate cut-off point should minimize the sum of type I errors and type II errors) and the proposed logistic model for corporate failure prediction explained that most of the accuracy in the debt ratios (one quarter before a failure) and unadjusted economic value added (the models range from the two quarters to the fourth quarters before a failure). Thus, debt ratios or unadjusted economic value added may be the optimal index to detect corporate failure in China.

China will adopt the International Financial Reporting Standards. Thus, using the logit models, to study how the adoption of these standards will affect accounting numbers to predict bankruptcy and to judge the capacity of the IFRS to produce more relevant accounting numbers. This model should be tested in various industries in China to determine whether these financial factors indicate corporate failures equally effectively, if not, alternative models should be developed.

Funding: This study received no specific financial support.

Competing Interests: The authors declare that they have no competing interests.

Contributors/Acknowledgement: All authors contributed equally to the conception and design of the study.

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[14]In order to shorten the tables, we omit the solution

[15]We adopted 1(in sample) to1 (out of sample)

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Table-1. Confusion matrix

		Predicted class	
		Bankrupt	**Non-bankrupt**
Actual Class	Bankrupt	TP	FN
	Non-bankrupt	FP	TN

Source: Authors investigation

$$\text{Accuracy (\%)} = \frac{TP+TN}{TP+FP+FN+TN} \times 100 \qquad (2)$$

Table-2. Descriptive statistics (%；US dollars)

	Max	**Min**	**Avg**
DAR_{it}	56.75	28.36	30.17
CR_{it}	235.72	76.35	125.62
QR_{it}	218.32	69.77	108.23
ART_{it}	48.27	12.55	27.55
$INVT_{it}$	45.72	20.65	27.78
GE_{it}	10.65	0.86	2.76
CCL_{it}	158.32	86.77	108.65
$UAEVA_{it}$	2.36	-0.35	0.89
$AEVA_{it}$	2.17	-1.36	0.32
$EDAEVA_{it}$	1.89	0.36	1.07
$NIGDP_{it}$	0.345	0.126	0.256
NIM_{it}	0.667	0.456	0.552
$NICPI_{it}$	0.442	0.231	0.328
$NIRI_{it}$	0.387	0.168	0.226
$NIEX_{it}$	0.552	0.342	0.421

Source: Authors investigation

Table-3. Performance Measures: One Quarter Before a Failure (before 2008)

		Cut-off.								
		0.1	**0.2**	**0.3**	**0.4**	**0.5**	**0.6**	**0.7**	**0.8**	**0.9**
DAR_{it}	Type I+ Type II	27.55	17.76	23.28	14.36	19.55	10.37	11.36	9.96	12.33
	Accuracy %	21.99	24.15	22.18	24.97	23.76	30.55	28.77	33.18	26.75
CR_{it}	Type I+ Type II	33.15	27.35	33.77	28.15	34.17	27.66	36.61	27.46	20.55
	Accuracy %	20.12	22.55	19.95	20.96	19.26	21.19	17.35	22.41	28.32
QR_{it}	Type I+ Type II	19.99	20.35	22.17	19.56	17.67	18.36	15.32	17.78	22.35
	Accuracy %	23.77	23.02	22.55	23.92	25.02	24.15	25.38	24.93	21.36
ART_{it}	Type I+ Type II	20.35	19.97	22.34	28.17	15.32	10.36	10.05	12.36	11.47
	Accuracy %	23.22	24.71	19.75	16.72	29.72	32.42	32.79	30.72	31.85
$INVT_{it}$	Type I+ Type II	30.55	32.27	28.32	27.51	30.26	22.13	24.15	20.36	25.17
	Accuracy %	20.35	19.52	23.27	24.31	21.18	28.37	27.42	29.77	26.39
GE_{it}	Type I+ Type II	32.17	30.56	25.37	26.18	24.32	20.55	25.88	24.99	28.56
	Accuracy %	18.31	21.09	25.72	24.38	26.37	28.32	25.41	26.14	22.05
CCL_{it}	Type I+ Type II	27.79	32.17	27.58	30.06	28.37	24.15	22.08	25.77	26.72
	Accuracy %	21.12	15.64	21.36	18.32	19.35	24.33	26.27	23.42	22.17
$UAEVA_{it}$	Type I+ Type II	28.18	29.35	24.36	25.51	29.98	20.17	26.62	25.33	24.78
	Accuracy %	23.77	22.18	27.72	25.99	21.96	29.09	25.18	26.32	27.14
$AEVA_{it}$	Type I+ Type II	30.55	33.18	27.79	30.54	26.18	23.15	22.94	25.98	27.23
	Accuracy %	21.95	17.82	22.75	22.04	23.99	25.76	26.92	24.37	22.94
$EDAEVA_{it}$	Type I+ Type II	34.16	35.17	29.95	28.55	25.36	20.87	19.92	24.77	27.15
	Accuracy %	21.18	20.02	24.74	25.36	26.12	29.14	29.97	26.77	25.98

Source: Authors investigation

Table-4. Performance Measures (%): One Quarter Before a Failure (after 2008)

		Cut-off.								
		0.1	**0.2**	**0.3**	**0.4**	**0.5**	**0.6**	**0.7**	**0.8**	**0.9**
DAR_{it}	Type I+ Type II	29.32	27.89	33.16	27.72	29.46	24.17	21.18	19.98	15.11
	Accuracy %	19.87	22.04	16.55	22.15	18.72	23.63	23.84	24.59	25.79
CR_{it}	Type I+ Type II	27.76	28.35	29.55	28.15	27.81	26.32	27.78	28.12	25.55
	Accuracy %	19.07	17.49	17.06	18.66	18.31	19.38	18.92	18.79	20.16
QR_{it}	Type I+ Type II	33.17	33.42	32.55	29.98	27.36	25.17	25.55	22.19	24.38
	Accuracy %	17.98	17.86	18.36	20.79	21.08	23.99	23.72	24.18	24.05
ART_{it}	Type I+ Type II	27.74	29.38	32.17	25.67	24.35	26.19	18.35	22.65	21.06
	Accuracy %	16.98	14.32	10.65	17.94	18.33	17.02	23.78	19.93	20.97
$INVT_{it}$	Type I+ Type II	28.72	29.55	26.18	32.19	29.94	24.17	22.99	25.36	20.77
	Accuracy %	18.35	17.91	19.37	14.21	17.63	20.96	22.74	19.96	24.32
GE_{it}	Type I+ Type II	28.55	29.92	30.16	29.99	31.52	27.66	24.55	26.32	25.18
	Accuracy %	16.87	16.05	14.77	15.92	13.86	17.99	19.95	18.91	19.07
CCL_{it}	Type I+ Type II	30.12	32.52	29.81	30.72	27.58	28.11	26.33	23.18	25.37
	Accuracy %	14.65	12.08	14.82	14.06	15.42	15.02	17.93	20.51	18.16
$UAEVA_{it}$	Type I+ Type II	27.57	29.78	25.18	26.37	25.68	26.32	20.17	26.18	23.11
	Accuracy %	18.32	16.18	20.66	19.54	20.12	19.65	25.05	19.97	22.07
$AEVA_{it}$	Type I+ Type II	29.67	32.07	29.16	29.97	28.32	30.15	25.18	23.97	30.27
	Accuracy %	16.28	12.87	16.55	16.04	17.88	15.86	20.38	22.09	15.76
$EDAEVA_{it}$	Type I+ Type II	32.16	34.18	30.18	29.36	32.56	24.82	26.31	20.98	24.36
	Accuracy %	14.74	12.18	15.79	16.37	14.36	21.16	19.98	25.52	21.37

Source: Authors investigation

Table-5. Performance Measures: Two Quarters Before a Failure (before 2008)

		Cut-off.								
		0.1	**0.2**	**0.3**	**0.4**	**0.5**	**0.6**	**0.7**	**0.8**	**0.9**
DAR_{it}	Type I+ Type II	36.77	34.12	28.36	30.25	27.32	32.74	20.55	21.16	24.36
	Accuracy %	16.72	18.35	25.16	23.77	26.32	20.99	33.15	32.79	29.98
CR_{it}	Type I+ Type II	29.98	28.96	26.32	30.54	32.16	34.15	25.12	23.08	20.92
	Accuracy %	24.62	25.94	27.32	23.91	21.64	19.38	28.92	30.57	33.09
QR_{it}	Type I+ Type II	35.17	29.98	30.51	32.15	29.67	27.36	30.12	27.35	28.86
	Accuracy %	18.62	23.77	22.81	20.94	23.85	24.59	23.01	24.62	24.16
ART_{it}	Type I+ Type II	37.75	34.15	33.87	35.78	34.56	28.92	28.89	29.37	31.52
	Accuracy %	13.22	17.13	18.86	15.79	16.98	22.28	22.35	21.74	20.85
$INVT_{it}$	Type I+ Type II	30.09	31.42	28.52	30.17	27.52	26.77	28.19	24.19	25.62
	Accuracy %	23.94	22.05	25.12	23.74	26.74	27.04	25.27	28.87	27.92
GE_{it}	Type I+ Type II	27.28	28.35	28.26	30.52	30.79	29.36	28.17	26.18	30.17
	Accuracy %	26.19	25.36	25.82	23.72	23.08	24.32	25.94	27.36	23.97
CCL_{it}	Type I+ Type II	32.18	30.77	28.17	27.65	25.36	28.99	24.16	22.85	22.79
	Accuracy %	20.36	22.17	24.99	25.39	26.62	24.62	27.73	29.93	30.06
$UAEVA_{it}$	Type I+ Type II	33.76	32.65	28.36	29.98	20.65	18.32	20.67	23.56	27.32
	Accuracy %	20.78	21.62	25.72	24.86	33.56	35.17	33.42	30.72	26.89
$AEVA_{it}$	Type I+ Type II	34.52	30.17	28.35	31.14	27.58	34.12	22.17	26.78	29.35
	Accuracy %	19.97	24.05	25.55	23.97	26.89	20.08	30.08	27.38	24.99
$EDAEVA_{it}$	Type I+ Type II	27.52	32.74	28.35	32.17	26.32	22.82	25.31	25.61	30.15
	Accuracy %	25.99	20.05	24.88	20.76	26.89	29.98	27.72	27.55	22.71

Source: Authors investigation

Table-6. Performance Measures: Two Quarters Before a Failure (after 2008)

		Cut-off.								
		0.1	**0.2**	**0.3**	**0.4**	**0.5**	**0.6**	**0.7**	**0.8**	**0.9**
DAR_{it}	Type I+ Type II	31.27	25.31	21.05	22.45	20.28	24.29	15.18	15.72	18.09
	Accuracy %	21.66	28.76	32.95	31.78	33.77	29.36	37.76	37.27	34.12
CR_{it}	Type I+ Type II	25.53	21.54	19.54	22.66	23.86	25.34	18.65	17.14	15.55
	Accuracy %	27.42	30.82	33.72	30.05	29.97	27.78	34.92	35.18	37.65
QR_{it}	Type I+ Type II	29.91	22.25	22.64	23.86	22.36	20.31	22.35	20.39	21.42
	Accuracy %	20.67	29.97	29.42	28.71	29.77	31.89	29.82	31.72	30.74
ART_{it}	Type I+ Type II	32.75	25.34	25.13	26.54	25.64	21.47	21.44	21.83	23.39
	Accuracy %	20.09	26.45	26.89	25.72	26.27	29.87	30.12	29.72	27.84
$INVT_{it}$	Type I+ Type II	25.59	23.32	21.17	22.39	20.43	19.87	20.93	17.97	19.02
	Accuracy %	26.71	28.77	30.85	29.83	31.97	32.44	31.74	35.16	32.61
GE_{it}	Type I+ Type II	22.27	21.49	20.98	22.65	22.85	21.79	20.91	20.25	22.39
	Accuracy %	29.97	30.87	31.89	22.62	22.41	30.65	32.08	32.27	29.86
CCL_{it}	Type I+ Type II	27.37	22.83	20.91	20.53	18.83	21.52	17.94	16.97	16.93
	Accuracy %	27.32	31.87	33.48	33.77	35.12	32.95	35.87	36.55	36.68
$UAEVA_{it}$	Type I+ Type II	28.71	24.23	21.64	22.25	15.35	13.62	15.36	17.44	20.28
	Accuracy %	26.33	29.94	32.95	31.94	37.72	40.12	37.55	35.62	33.18
$AEVA_{it}$	Type I+ Type II	29.36	22.39	21.49	23.11	20.47	25.31	16.47	19.88	21.78
	Accuracy %	21.18	27.76	31.12	25.62	31.75	24.77	35.52	32.28	30.84
$EDAEVA_{it}$	Type I+ Type II	23.41	24.29	21.49	23.87	19.54	16.95	18.79	19.02	22.38
	Accuracy %	28.91	26.85	30.82	27.76	32.72	35.04	33.46	32.97	29.92

Source: Authors investigation

Table-7. Performance Measures: Three Quarters Before a Failure (before 2008)

		Cut-off.								
		0.1	**0.2**	**0.3**	**0.4**	**0.5**	**0.6**	**0.7**	**0.8**	**0.9**
DAR_{it}	Type I+ Type II	26.59	18.79	15.65	15.57	14.74	17.37	10.88	11.62	12.48
	Accuracy %	27.82	33.19	37.62	37.92	38.52	34.22	42.61	41.76	40.35
CR_{it}	Type I+ Type II	21.72	16.96	14.42	15.71	17.33	18.12	13.85	12.65	10.81
	Accuracy %	34.16	38.11	39.12	38.35	37.85	37.02	39.98	40.15	42.99
QR_{it}	Type I+ Type II	25.44	16.53	16.56	16.54	16.17	14.54	15.77	14.91	14.68
	Accuracy %	28.36	36.62	36.28	36.44	36.85	38.62	37.22	38.15	38.44
ART_{it}	Type I+ Type II	27.85	18.82	18.38	18.39	18.62	15.36	15.43	15.92	15.98
	Accuracy %	26.32	33.72	34.17	34.07	33.91	37.72	37.49	37.08	36.94
$INVT_{it}$	Type I+ Type II	21.77	17.32	15.49	15.52	14.85	14.22	14.79	13.21	13.32
	Accuracy %	30.64	35.18	37.82	37.67	38.65	38.89	38.77	40.12	39.95
GE_{it}	Type I+ Type II	18.94	15.97	15.35	15.85	16.84	15.59	14.77	14.81	15.32
	Accuracy %	34.17	37.44	38.47	37.86	36.25	38.18	38.87	38.74	38.51
CCL_{it}	Type I+ Type II	23.45	16.96	15.43	14.24	13.69	15.40	12.72	12.68	11.72
	Accuracy %	28.33	37.72	38.18	39.15	39.92	38.36	40.74	40.89	41.35
$UAEVA_{it}$	Type I+ Type II	24.35	18.02	15.83	15.43	11.17	9.77	10.94	12.83	13.93
	Accuracy %	29.34	34.18	37.41	37.76	41.35	44.38	42.31	40.32	39.77
$AEVA_{it}$	Type I+ Type II	24.97	16.63	15.72	16.02	14.88	18.72	11.71	14.55	14.92
	Accuracy %	27.82	35.42	36.62	35.87	38.11	32.91	41.55	38.22	37.89
$EDAEVA_{it}$	Type I+ Type II	19.91	18.04	15.72	16.55	14.21	12.14	13.31	13.95	15.32
	Accuracy %	32.91	33.46	36.62	35.78	37.63	39.57	38.72	38.24	36.89

Source: Authors investigation

Table-8. Performance Measures: Three Quarters Before a Failure (after 2008)

		Cut-off.								
		0.1	**0.2**	**0.3**	**0.4**	**0.5**	**0.6**	**0.7**	**0.8**	**0.9**
DAR_{it}	Type I+ Type II	22.62	13.97	11.46	10.82	10.73	12.44	7.85	8.74	8.78
	Accuracy %	32.41	40.97	42.06	42.62	42.91	41.18	45.17	44.92	44.72
CR_{it}	Type I+ Type II	18.48	12.62	10.56	10.91	12.61	12.98	9.96	9.46	7.68
	Accuracy %	32.55	39.76	41.35	41.08	39.97	39.42	42.18	42.57	45.87
QR_{it}	Type I+ Type II	21.64	12.22	12.12	11.49	11.77	10.43	11.23	11.05	10.23
	Accuracy %	30.71	38.61	38.76	40.18	39.97	41.76	40.56	40.79	41.95
ART_{it}	Type I+ Type II	23.69	13.99	13.45	12.76	13.54	11.63	10.99	11.76	11.09
	Accuracy %	28.35	37.42	38.16	38.82	37.92	40.14	40.96	39.87	40.65
$INVT_{it}$	Type I+ Type II	18.52	12.88	11.34	10.78	10.81	10.46	10.55	9.85	9.34
	Accuracy %	31.74	38.67	39.75	40.18	40.14	40.67	40.42	41.79	42.22
GE_{it}	Type I+ Type II	16.11	11.88	11.24	11.65	12.25	11.18	10.54	10.98	10.66
	Accuracy %	34.61	39.72	40.32	39.97	38.92	40.56	41.12	40.84	41.02
CCL_{it}	Type I+ Type II	19.95	12.62	11.39	9.95	9.97	11.04	9.12	9.48	8.28
	Accuracy %	32.18	38.14	38.65	41.06	40.95	38.78	41.35	41.12	41.76
$UAEVA_{it}$	Type I+ Type II	20.71	13.48	11.59	10.72	8.15	7.03	7.89	9.59	9.74
	Accuracy %	30.76	38.17	40.38	41.42	43.26	45.99	45.25	42.77	42.61
$AEVA_{it}$	Type I+ Type II	21.24	12.37	11.51	11.13	10.83	13.40	8.42	10.32	10.39
	Accuracy %	30.62	37.66	38.54	38.72	39.55	37.05	41.35	39.97	39.76
$EDAEVA_{it}$	Type I+ Type II	16.94	13.41	11.51	11.49	10.35	8.72	9.53	10.38	10.66
	Accuracy %	31.56	35.48	37.52	37.66	38.65	40.98	39.76	38.52	38.17

Source: Authors investigation

Table-9. Performance Measures: Fourth Quarters Before a Failure (before 2008)

		Cut-off.								
		0.1	**0.2**	**0.3**	**0.4**	**0.5**	**0.6**	**0.7**	**0.8**	**0.9**
DAR_{it}	Type I+ Type II	19.24	10.78	8.45	7.54	7.83	8.93	5.76	6.71	6.34
	Accuracy %	34.62	42.18	44.86	45.72	45.24	44.62	48.72	46.11	46.62
CR_{it}	Type I+ Type II	15.72	9.48	7.74	7.67	9.19	9.32	7.22	5.61	7.21
	Accuracy %	39.76	46.28	48.26	48.07	46.62	46.42	48.76	49.05	48.92
QR_{it}	Type I+ Type II	18.41	9.11	8.87	8.08	8.58	7.56	7.31	8.33	8.98
	Accuracy %	38.12	46.72	47.24	47.99	47.56	48.44	48.66	47.72	47.06
ART_{it}	Type I+ Type II	20.65	10.42	9.85	8.88	9.86	8.36	7.93	7.86	8.83
	Accuracy %	34.18	43.75	44.36	45.92	44.18	46.92	47.55	47.78	46.19
$INVT_{it}$	Type I+ Type II	15.76	9.61	8.31	7.51	7.89	7.52	7.62	7.49	6.71
	Accuracy %	39.27	44.18	45.77	47.62	46.82	47.42	47.18	47.76	48.82
GE_{it}	Type I+ Type II	13.71	8.86	8.24	8.11	8.93	8.41	7.62	7.58	8.28
	Accuracy %	40.76	46.65	47.35	47.62	46.18	46.96	47.93	48.17	47.18
CCL_{it}	Type I+ Type II	16.97	9.48	8.35	6.94	7.28	7.94	6.01	7.23	6.64
	Accuracy %	38.17	44.82	45.78	47.87	46.55	46.06	48.35	46.72	48.07
$UAEVA_{it}$	Type I+ Type II	17.62	10.04	8.57	7.47	5.96	5.08	5.79	7.31	6.97
	Accuracy %	39.76	45.12	46.82	47.45	49.67	50.12	49.76	47.72	48.32
$AEVA_{it}$	Type I+ Type II	18.07	9.22	8.44	7.75	7.95	9.62	6.15	7.82	7.47
	Accuracy %	37.04	45.12	45.68	47.28	46.77	44.87	48.55	46.92	47.52
$EDAEVA_{it}$	Type I+ Type II	14.41	9.93	8.44	8.08	7.55	6.28	6.92	7.86	7.58
	Accuracy %	39.72	43.78	44.55	44.72	45.82	47.74	46.99	45.16	45.72

Source: Authors investigation

Table-10. Performance Measures: Fourth Quarters Before a Failure (after 2008)

		Cut-off.								
		0.1	**0.2**	**0.3**	**0.4**	**0.5**	**0.6**	**0.7**	**0.8**	**0.9**
DAR_{it}	Type I+ Type II	16.75	8.47	6.23	5.58	5.73	6.44	4.49	5.32	4.95
	Accuracy %	40.35	47.16	48.75	50.76	49.97	48.28	52.07	51.08	51.36
CR_{it}	Type I+ Type II	13.69	7.85	5.72	5.62	6.72	6.71	5.51	5.67	4.47
	Accuracy %	43.19	48.55	50.89	51.36	49.62	49.76	51.78	51.17	52.28
QR_{it}	Type I+ Type II	16.67	6.81	6.54	5.89	6.28	5.46	6.71	6.47	5.59
	Accuracy %	40.05	49.52	49.78	51.48	50.38	52.02	49.62	50.19	51.77
ART_{it}	Type I+ Type II	17.98	7.78	7.26	6.47	7.27	6.34	5.99	6.82	5.95
	Accuracy %	39.24	48.16	48.66	49.87	48.47	50.07	51.18	49.76	51.42
$INVT_{it}$	Type I+ Type II	13.73	7.18	6.13	5.48	5.78	5.43	5.19	5.87	5.77
	Accuracy %	42.55	49.72	50.64	51.89	51.18	52.08	52.28	51.06	51.32
GE_{it}	Type I+ Type II	11.94	6.64	6.08	5.91	6.53	6.69	5.78	6.43	5.77
	Accuracy %	43.72	49.86	51.08	51.44	49.97	49.72	51.67	50.08	51.86
CCL_{it}	Type I+ Type II	14.78	7.08	6.16	5.76	5.39	5.73	5.11	4.73	5.69
	Accuracy %	42.36	48.54	49.82	50.72	51.35	50.87	51.82	52.15	51.04
$UAEVA_{it}$	Type I+ Type II	15.34	7.49	6.32	5.45	4.38	3.69	4.51	5.75	5.37
	Accuracy %	44.35	50.36	51.52	52.71	53.92	54.42	53.72	52.44	52.82
$AEVA_{it}$	Type I+ Type II	15.74	6.89	6.23	5.66	5.82	6.93	4.76	6.11	5.72
	Accuracy %	39.91	47.96	48.45	51.12	49.92	47.52	51.78	48.77	50.93
$EDAEVA_{it}$	Type I+ Type II	12.55	7.41	6.23	5.89	5.53	4.55	5.29	6.14	5.77
	Accuracy %	42.37	46.35	48.62	49.72	50.17	51.62	50.37	48.96	49.92

Source: Authors investigation