Predictors of Bankruptcy after Bubble Economy in Japan: What can you learn from Japan case?

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ABSTRACT

There has been a recent spate of corporate bankruptcies in Japan in the midst of a worsening economic climate. I presented the SAF model in 1999 to predict Japanese corporate bankruptcy. The model was highly evaluated for prediction of corporate bankruptcies in Japan immediately after the collapse of the bubble economy, and has been widely adopted in business circles, mainly among banking institutions. Though almost ten years have passed since the burst of the bubble economy, stock prices and interest rates are on a downward trend in Japan, making corporate bankruptcy prediction more difficult. Hence, analyzing the 9–year post-bubble period from 1992 to 2000 and using more extensive financial data on the companies that went bankrupt during this period than data for developing the SAF model, I have developed a new model for predicting corporate bankruptcy, the SAF2002 model, which better suits the current situation.

This research (1) provides in-depth analysis of the trends in the finance of bankrupt companies, (2) verifies that traditional notion of financial analysis is no longer applicable to companies approaching bankruptcy, and (3) clarifies that corporate bankruptcy cannot be predicted by simply adopting normal financial analysis and techniques.

Several countries are experiencing severe economic conditions, and neighboring countries can learn from Japanese companies who went through the end of the bubble economy about ten years ago.

Keywords: Bankruptcy Prediction Model, Financial Analysis, Bubble Economy in Japan

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I. INTRODUCTION

There has been a recent spate of corporate bankruptcies in Japan in the midst of a worsening economic climate. I presented the SAF model in 1999 to predict Japanese corporate bankruptcy. The model was highly evaluated for prediction of corporate bankruptcies in Japan immediately after the collapse of the bubble economy, and has been widely adopted in business circles, mainly among banking institutions. Though almost ten years have passed since the burst of the bubble economy, stock prices and interest rates are on a downward trend in Japan, making corporate bankruptcy prediction more difficult. Hence, analyzing the 9–year post-bubble period from 1992 to 2000 and using more extensive financial data on the companies that went bankrupt during this period than data for developing the SAF model, I have developed a new model for predicting corporate bankruptcy, the SAF2002 model, which better suits the current situation.

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II BANKRUPTCY PHENOMENON IN JAPAN

Recent Bankruptcy Tendency in Japan

Japanese corporate bankruptcies can be broken down into two patterns, legal proceedings and voluntary proceedings. Reason for bankruptcy can be broken down into the following seven patterns: (1) corporate reorganization, (2) civil rehabilitation proceedings, (3) corporate consolidation under the Commercial Code, (4) insolvency, (5) special liquidation, (6) readjustment, and (7) suspension of bank transactions due to nonpayment of a draft. As shown in Table 1, of the legal proceedings, insolvency is the most frequently taken proceeding. Prior to civil rehabilitation proceedings on April 1, 2000, legal proceedings other than insolvency occupied 2% or 3% of the total bankruptcy proceedings, to the extent that most companies going bankrupt used to be voluntarily liquidated. However, with the commencement of civil rehabilitation proceedings in April 2000 replacing the Composition Law, there has been a rapid increase in the ratio of civil rehabilitation proceedings because of its usability and due to shifts from composition, voluntary liquidation and other bankruptcy proceedings.

Table 1 Ratio of Bankruptcy Proceedings in Japan (1992～2001)

	1992	1993	1994	1995	1996	1997	1998	1999	2000	2001
Reorganization	0.18%	0.24%	0.09%	0.14%	0.07%	0.15%	0.28%	0.21%	0.13%	0.13%
Rehabilitation									2.88%	4.90%
Composition	1.38%	1.60%	1.15%	1.18%	1.20%	1.31%	1.56%	1.11%	0.24%	
Consolidation	0.13%	0.16%	0.14%	0.21%	0.17%	0.06%	0.10%	0.06%	0.02%	0.01%
Insolvency	8.16%	9.18%	10.45%	10.63%	11.57%	12.16%	13.27%	14.44%	15.68%	20.66%
Special liquidation	0.20%	0.18%	0.23%	0.44%	0.43%	0.49%	0.56%	1.57%	1.34%	1.51%

Source: Teikoku Data Bank

Note: Proceedings under Civil Rehabilitation Law began on April 1, 2000. There is no such data available up to 1999. At this time, the Composition Law was repealed.

Recently, reforms of Bankruptcy Law of Japan have been called for. The largest reform is that Composition Law was repealed at end of March and replaced with new civil rehabilitation proceedings. Of the various bankruptcy proceedings in Japan, the Corporate Reorganization Law was considered to be similar to Chapter 11 of the U.S. Federal Bankruptcy Code. In fact, however, there is considerable difference in the proceedings. Hence, to expedite corporate rehabilitation and enable earlier commencement of proceedings than under the Corporate

Reorganization Law in protecting creditors, the Civil Rehabilitation Law has been newly established as a bankruptcy proceeding similar to Chapter 11 of the U.S. Bankruptcy Code. The Corporate Reorganization Law aims to facilitate receiver-led rehabilitation, whereas the Civil Rehabilitation Law aims mainly to facilitate DIP (the debtor in possession) type of rehabilitation proceedings like Chapter 11 of the U.S. Federal Bankruptcy Code. In addition, there have been various reforms of and improvements in the legal system to facilitate corporate rejuvenation, such as establishing the Special Conciliation Act and partial amending the Corporate Reorganization Law that were difficult to implement.

III PREVIOUS STUDIES

Bankruptcy Predictors in Other Asian Country

Sung, Namsik & Lee do not focus on the discriminant power of a model. Their research presents the hypothesis that (1) there is a difference in financial pattern in the phases of economic slowdown and pickup and, (2) financial indices for discriminating bankruptcies are extracted by using C.4.5 each for the period between the second quarter of 1997 and the first quarter of 1998 during which the Korean economy faced crisis, and the period between the first quarter of 1991 and the first quarter of 1995 when the Korean economy stabilized. In the former period, 30 out of 75 bankrupt companies were listed on the Korean Stock Exchange and 54 companies survived the same period. In the latter period, 29 companies out of 56 bankrupt companies were listed on Korean Stock Exchange and 49 companies survived the period. The led to the conclusion that in a period of economic stabilization, “capital turnover ratio” and “total assets cash flow ratio” are significant, while in an economic crisis, “total capital turnover ratio,” “liabilities cash flow ratio” and “fixed assets to long-term capital ratio” are significant. Furthermore, a model has been developed for each period by adopting linear discriminant techniques and their discriminant power is compared. The model for a period of economic stabilization shows 66.6% discriminant power for holdout samples, whereas for holdout samples in a period of economic crisis, discriminate power is only 36.7%. These results suggest that, under different economic circumstances, discrimination using the same discriminant power is difficult to implement.

As well as Sung, Namsik & Lee, Shirata’s has researched an artificial intelligence approach to clarify the financial indices useful for discriminating bankruptcies that does not compete with the discriminant power of bankruptcy models. Shirata uses CART (Classification and Regression Tree), or a decision tree algorism, based on C.4.5, and, manually applies a crossing technique in a genetic algorithm to the decision tree algorithm considering accounting. Indices for discriminating bankruptcies are extracted, resulting in a bankruptcy prediction model with the strongest ever discriminant power.

SAF Model in Japan

The SAF (Simple Analysis of Failure) model predicts bankruptcy through verification analyses by CART or using artificial intelligence of the financial data of companies that failed between 1986 and 1996 in Japan considering business practice and institutional accounting.

The SAF model uses the financial data of 898 cases of bankrupt companies and the financial data of 300 cases of non-bankrupt companies that are systematically sampled from 107,034 cases. This is the largest data collection among those for similar domestic and overseas research. The financial indices that contribute to corporate bankruptcy discrimination are identified out of 65 indices. The indices identified are shown in Table 2.

Table 2　Variables for SAF Model

Var.	Name of Index	F-value	Prob>F
X2	Retained earnings to total assets	113.518	0.001
X27	Interest and discount expense to borrowings, bonds and note receivable　discounted	89.446	0.001

X40	Note payable and accounts payable to Sales	39.253	0.001
X10	Current period liabilities and shareholders equity to Previous period liability and shareholders equity	19.637	0.001

To identify the most suitable model for bankruptcy discrimination before developing the model, a linear discriminant model, a quadratic model and a non-parametric normal kernel method model were developed, and the discriminant ratio of each model was compared. The comparison, made using holdout samples five times for each model, indicated that the linear model has the strongest discriminant power.

Table 3 Discriminat Power of Each Model

Unit:%

Test	Bankrupt Group			Non-bankrupt Group			Total		
	LN	Q	NK	LN	Q	NK	LN	Q	NK
1	83.3	70.1	74.9	72.8	78.1	75.9	78.1	74.1	75.4
2	81.2	74.4	77.6	75.7	77.0	74.7	78.4	75.7	74.7
3	81.0	73.9	78.4	77.3	82.2	76.4	79.1	78.1	77.4
4	80.5	72.9	77.1	75.4	80.6	73.3	78.0	76.8	75.2
5	89.0	77.1	80.9	63.3	81.2	69.9	76.2	79.2	75.4
Ave.	83.0	73.7	77.8	72.9	79.8	74.0	78.0	76.8	75.6

Note: LN = Linear, Q = Quadratic, NK = Normal Kernel

Moreover, the models are extrapolated into listed companies that went bankrupt as sampled data that have not been included in previous data to individually compare discriminant results. The comparison revealed that the quadratic model and the normal kernel method model produce unstable results. Next, a logit model was developed and its discriminant power was compared to that of the linear model, strongest according to the previous comparisons. Significance testing was conducted on the discriminant power of both models. However, there is no significant difference in discriminant power between the linear discriminant model and the logit model (refer to Table 4). The verification results have confirmed that even a linear model functions sufficiently as a bankruptcy discriminant model.

Table 4 Discriminant Power of Linear Model and Logit Model

Unit:%

Test	Bankrupt Group		Non-bankrupt Group		Total	
	LN	LO	LN	LO	LN	LO
1	83.3	83.7	72.8	74.1	78.1	78.9
2	81.2	81.6	75.7	75.2	78.4	78.4
3	81.0	83.3	77.3	76.4	79.1	79.9
4	80.5	82.7	75.4	74.6	78.0	78.7
5	89.0	88.3	63.3	66.8	76.2	77.6
Ave.	83.0	83.9	72.9	73.4	78.0	78.7

Note: LN = Linear, LO = Logit

Hence, the following linear discriminant model formula was developed using four indices.

$$\mathbf{SAF = 0.01425\ X_{2} - 0.002876\ X_{10} - 0.05826\ X_{27} - 0.06212\ X_{40} + 0.7416}$$

In addition, since the logit model displayed the same degree of discriminant power as the linear model in the previous verification, a logit model formula was also developed as follows.

$$\mathbf{X = 0.1138\ X_{2} - 0.02911\ X_{10} - 0.5561\ X_{27} - 0.4344 X_{40} + 2.646}$$

$$\mathbf{SAFL = 1/ \exp(-X)}$$

After making a residual plot of the predicted value of each variable using a general additive model, it was confirmed that bankruptcy in Japan shows a marked linearity and that the linear discriminant model produced stable results in each analysis. From these results, it was concluded that a simple and easy-to-understand linear discriminant model should be used. The discriminant ratio of the SAF model using linear discrimination was 86.14% for the bankrupt group and 70.61% for the non-bankrupt group using the data of 63 industries and different scales.

IV SAMPLE AND METHODOLOGY

Sample data

This research identifies the problems and limitations of previous research, and overcomes then as far as possible.

There were only 130 cases of bankruptcy of listed companies in Japan between June 1964, when the collection of statistics on bankruptcy started, and December 2001. Before 1964, financial data for accounting conditions just before bankruptcy are difficult to obtain. Moreover, there is some hesitation to use this data accumulated over a long period for the same analysis considering problems of comparability of financial figures in a changing economic climate and accounting standards. Consequently, if a lot of sample data is used, then the scope must be extended to medium-sized companies. In other words, in analyzing bankrupt companies, we can not generalize bankruptcy phenomena by covering, out of the 2,536,878 corporate firms in Japan (December 2000), only bankrupt listed companies that for only a little over 0.1% of the total number of corporate firms. We need to analyze a wide range of companies.

Sampled data are carefully reviewed for both volume and content before they are used for analysis. Companies that went bankrupt in Japan between January 1993 and December 12 with total liabilities of 10 million yen or over, and whose financial statements for two consecutive terms prior to bankruptcy are available were selected. With this selected data, the financial data of 1436 companies with capital of 30 million yen or more were used from the Teikoku Data Bank Cosmos I Database. Companies with biannual accounting or those whose accounting terms changed just before bankruptcy were excluded, because it is difficult to understand the correct business performance of these companies by making numerical changes such as modifying their accounting terms to twelve months.

Systematic sampling of non-bankrupt companies, was undertaken in the order of corporate number appearing in the Teikoku Data Bank for all companies that existed as bankrupt companies and whose financial data continued to be recorded thereafter in the Teikoku Data Bank Cosmos I Database. In addition, a different number of cases was chosen for each year to avoid paired sampling as much as possible. Table 7 shows sample data used in this research using the above procedures.

Table 7 Sample Data

Year	Bankrupt Sample Data						Non-Bankrupt
	Bankrupt Year	Total No. of Bankruptcy	Bankruptcy Ratio	Bankrupt cases (Listed)	Sample Data (Total)	Sample Data (Listed)	Sample Data (Total)
1992	1993	14,041	0.60	4	129	1	259
1993	1994	13,963	0.59	0	112	0	260
1994	1995	15,086	0.63	2	123	1	558
1995	1996	14,544	0.60	1	110	1	260
1996	1997	16,365	0.66	10	118	5	851
1997	1998	19,171	0.76	7	190	3	260
1998	1999	15,460	0.61	5	182	5	253
1999	2000	19,071	0.75	12	206	12	137
2000	2001	19,441	0.76	13	266	10	596
		128,701		41	1,436	28	3,434

Source: Teikoku Data Bank.

In the bankrupt companies sampled, the average amount of capital was 298.49 million yen and the average number of employees was 89, and in the non-bankrupt companies sampled 237.366 million yen and 173. According to the bankruptcy statistics of the Teikoku Data Bank, the average number of employees of bankrupt companies was 7.35 in 1999, 9.84 in 2000 and 10.00 in 2001. The number of employees of bankrupt companies in this research is more than ten times the above-mentioned average figures, indicating that the sampled companies are an aggregate of mid-size companies among the bankrupt companies. The average number of employees of bankrupt companies in 1997 and 2000 is larger than in the other years because bankrupt companies in 1997 include Yaohan Japan Corporation and those in 2000 include Sogo Co., Ltd.

V VARIABLE SELECTION

Variables

This research selects 72 financial indices as subject indices for review, Of these 72, 62 indices are adopted for corporate assessment by banking institutions and information industry companies in Japan; the other 10 indices are based on cash flow. However, it is possible that these indices include those with a high degree of correlation or of little significance. For this reason, significance and correlation were confirmed at each stage of analysis. So, some of the indices used in previous research include those that are normally used for listed companies as subject companies (stock market prices); however, these indices were excluded simply because the sampled companies to which the indices are applied are non-listed companies and accordingly, these indices are not usable. For the cash-flow indices, a cash flow statement and an income statement was drawn up from an individual balance sheet for each sample firm using an indirect method. From the cash flow statement, each relevant index was identified. However, each index such as CF Operating Income index, CF Operating and Non-Operating Income index and Free Cash Flow index, is shown below, normalized at variance 1, mean 0, and then a single logarithm was made. The data covers accounting terms until March 2003 and does not include related contents under the revision of the Commercial Code in June 2001.

Methodology

In discriminating bankrupt companies and a non-bankrupt companies using corporate financial data, there is no assurance that the two groups can hypothesize homoscedasticity and normality. Moreover, the data used in previous research were so limited that very few examined in detail the homoscedasticity and normality of financial data, etc.

Marks-Dunn claims that the linear discriminant function is sufficient unless there is too much difference in covariance matrix. In this case, and if there is too much data, the quadratic function should be used. However, the distribution of the covariance matrix of financial data in bankrupt companies and non-bankrupt companies are easily affected by extracted samples so it is difficult to test. Furthermore, in discriminating the two groups using financial data, there are a number of non-bankrupt companies that escaped bankruptcy in spite of their extremely poor financial condition. As a result, it is highly likely that while one group shows a symmetric figure (generally, normal distribution), the other group shows an asymmetric figure. To sum up, in identifying financial indices for bankruptcy prediction, it is difficult to hypothesize sufficient conditions to enable for using the tools of previous research and whose normality and homoscedasticity are hypothesized. If each group has a different structure, and if variables are selected through linear discriminant techniques, important information may be lost in the worst case. Consequently, a non-parametric tool that does not hypothesize normality and homoscedasticity should be adopted. On the other hand, there is no proof applying linear discriminant analysis is inappropriate to identify financial data. Judging from Lachenbruch's empirical results of linear discriminant analysis shows its robustness even for discrete distribution. This research adopts a non-parametric approach for the selection of variables, and a traditional linear discriminant technique is used to test discriminant power.

Hence, to identify indices, the variables would be identified using a CART model, considered to be the most powerful non-parametric tool for a hypothesis-searching approach, which can be used as a substitute for a traditional linear logistic model or additive logistic model.

The CART model is a decision tree model, with independent variables having high branching weight at its root and which classifies data into bankrupt companies and non-bankrupt companies. Even if a number of independent variables with strong correlation with other variables are used at the same time, the independent variables with a strong relation to the induced variables are first selected at the root of a tree, and thereafter, the model's tree-type structure does not change even if independent variables with weak relation to the induced variables are added or removed. The CART model is therefore a suitable tool for selecting, from variables with a strong correlation among indices such as financial data, a set of variables effective indiscriminating two groups. Because the CART model does not hypothesize the normality or homoscedasticity of variables and is protected against outliers, it was decided that all the sample data including abnormal values would be used in analysis. Also, a model available with S-Plus Ver.5.1 and based on Chou's research is used.

Data Screening

This research conducted data screening from an accounting viewpoint and from a statistical viewpoint.

There are a number of indices that, just before corporate bankruptcy, suddenly begin to show right and wrong tendency not consistent with accounting theory. These indices must be excluded from the subject bankruptcy prediction indices because it is difficult to distinguish companies with a good standing and companies on the verge of bankruptcy. Furthermore, all the samples used in this research are based on data accumulated over a nine-year period. Therefore, even if data distribution throughout the total period is consistent with the theory, it does not indicate that the distribution is consistent with the theory in all years when each index is observed from time-series viewpoint. The time-series distribution status of each index for all data, and the data after abnormal values are removed, is confirmed. As a result, the indices shown in Appendix I produced a reversal in distribution during the nine-year period. The value indicated in Appendix I is obtained by subtracting the mean value of bankrupt companies from the mean value of non-bankrupt companies, both for the data after abnormal values are removed and all data including abnormal values. The values of financial indices are, as corporate financial standing worsen, naturally deviate in an opposite direction to the distribution of going concerns. For this reason, the difference in mean value between the non-bankrupt group and the bankrupt group must always be unified to be either plus or minus. However, because the indices in Appendix I show a distributional reversal between the non-bankrupt group and the bankrupt group in certain years, there is a mixture of plus values and minus values in the difference in mean value.

There are the following reversal trends: indices such as “Cash Flow Margin” and Ratio of “Long-term Assets to Long-term liabilities and Equity” that cause a reversal of the distribution at the turn of a certain year, and indices such as trade account payable turnover period and CF Version acid test ratio, in which the mean value of the bankrupt group becomes higher or smaller than the mean value of the non-bankrupt group. In both cases, these indices threaten to distort the analysis results for producing statistics and so will be excluded from further analysis. In addition, cash flow ratios, 682 cases of deficit value (112 cases of bankrupt companies and 570 cases of non-bankrupt companies) will also be excluded.

Variable Selection

After the data screening, there were 42 financial indices for identification, as shown in Appendix II.

The financial indices significant for bankruptcy discrimination were identified first by using all the sample data. The following procedures were then followed: (1) the data were sorted in chronological order, and (2) significant indices for bankruptcy discrimination were identified for each year and (3) they were compared with the indices throughout the period.

The CART model has the form of a tree with independent variables having high branching weight at its root and branches the data into bankrupt companies and non-bankrupt companies. However, high branching weight does not indicate strong significance to discriminate bankruptcy. If excluding the data non-bankrupt group is better than dividing the two groups, variables with high branching weight for non-bankrupt data would appear at the root of a tree. A bankruptcy prediction model seeks bankrupt companies among many non-bankrupt companies. So significant indices cannot be identified by extracting only variables close to the root of the CART model. Considering all these factors, in identifying indices, interpreting each index from an accounting standpoint is important, while fluctuation in indices and corporate behavior were considered to finally identify indices for discriminating bankrupt companies.

The results are shown in Table 8.

Table 8 Final Selected Variables through the Period

Rank	Var.	Name of Index	Classification Value
1	X7	Retained Earnings to Total Assets	<8.86175
2	X10	Net Income before tax to Total Assets	<0.5857
3	X26	Interest and discount expense to Sales	>1.05925
4	X37	Inventory Turnover Period	>2.00055
5	X36	Account Receivable Turnover Period	>2.5604
6	X46	Account Receivable to Accounting Payable	<75.1193

An analytical difference between the SAF model and the SAF2002 model is that the amount of data from the non-bankrupt group is larger than that of the bankrupt group. The CART structure for the data throughout the entire period indicates that instead of selecting bankrupt companies, non-bankrupt companies with good standing, are selected. Of the companies remaining, another selection is made of companies satisfying bankruptcy requirements. As a result, the structure of the decision tree model is more complicated than that of the SAF model.

The analysis results show that the data can be divided into two groups, first through the X7 the ratio of Retained Earnings to Total Assets. When the ratio of Retained Earnings to Total Assets is below 8.16175%, these companies are on the left side of a tree as companies facing potential bankruptcy. If the ratio is below 8.16175%, these companies are on the right side of a tree as companies with a low possibility of going bankrupt. The companies thus divided into the left branch of the tree are further divided into bankrupt companies (left side) and a non-bankrupt companies (right side), depending on whether the X10 ratio of Net Income before tax to Total Assets, is below or above 0.5875%. Even if the X10 ratio of Net Income before tax to Total Assets is above 0.5875%, when the X37 Inventory Turnover Period exceeds 2.00055 months, these companies are judged to be almost bankrupt. Moreover, of companies categorized as bankrupt companies (left side) through X10, the ratio of Net Income before tax to Total Assets, the companies whose X26 ratio of Interest and discount expense to Sales is over 1.05925% and whose X36 Account Receivable Turnover Period exceeds 2.5604 months are deemed to be bankrupt. However, even companies whose X36 Account Receivable Turnover Period is less than 2.5604 months, but whose X46 ratio of Account Receivable to Accounting Payable is below 75.1193% are judged to be bankrupt.

These analysis results clarify the structure in post-bubble Japan, where even though Retained Earnings to Total Assets remain, there are growing interest payments amid declining operating revenue, arrears in receivable accounts and slowdown in inventory turnover, all leading to bankrupt.

While four indices are used in the SFA model, SAF2002 provisionally extracts six variables. Hence, under this model a judgment was made on whether reducing these variables would be possible for the purpose of making comparisons with SAF model easier and for the reason that the number of indices would hopefully be reduced to make simple the model. For this purpose, a stepwise variable selection method (based on Klecka's research) using the STEPDISC procedure of SAS Version 8.1 was used. The results are shown in Table 9.

Table 9 Discriminant Power Ranking by STEPDISC or CART Model

Rank	STEPDISC Procedure		Partial R-Square	F Value	Pr > F	CART Model	
1	X7	Retained Earnings to Total Assets	0.1737	818.63	<.0001	X7	Retained Earnings to Total Assets

2	X37	Inventory Turnover Period	0.0592	244.98	<.0001	X10	Net Income before tax to Total Assets
3	X26	Interest Expenses to Sales	0.0175	69.27	<.0001	X26	Interest Expenses to Sales
4	X10	Net Income before tax to Total Assets	0.0136	53.79	<.0001	X37	Inventory Turnover Period
5	X36	Account Receivable Turnover Period	0.0047	18.49	<.0001	X36	Account Receivable Turnover Period
6	X46	Account Receivable to Accounting Payable	0.0040	15.74	<.0001	X46	Account Receivable to Accounting Payable

Considering value F, the X7 ratio of Retained Earnings to Total Assets was in first place at 818.63, displaying a high level of discriminant power. When comparing the second and lower places, there were changes in the order of significance between the analysis results of CART and STEPDISC. However, the indices in the top four places are the same. The index appearing at the division close to the root of CART stands at high value F. The top four variables extracted were (1) the X7 ratio of Retained Earnings to Total Assets, (2) the X37 Inventory Turnover Period, (3) the X26 ratio of Interest Expenses to Sales, and (4) the X10 ratio of Net Income before tax to Total Assets l.

Although the top four indices could be selected as final indices, indices in the order of value F (from high to low) may not provide a model with strong discriminant power. In chronological models, these four indices were all identified coincidentally. However, it does not indicate that the four indices have the strongest discriminant power. Accordingly, to select the most appropriate combination of indices, different combinations of eight indices were examined; six indices were adopted in period models, plus two models of (1) the X18 ratio of Average Interest burden to Interest bearing Liabilities, adopted in most years using the chronological selection of indices and adopted in SAF models, and (2) the X53 Interest Coverage Ratio whose significance was confirmed in each chronological analysis.

Five tests were for each model on holdout samples.

The results are shown in Table 10.

Table 10　Misclassification Ratio by Each Model

Unit:%

Test	No. of Data	Bankrupt Group				Non-Bankrupt Group				Total			
		M1	M2	M３	M4	M1	M2	M３	M4	M1	M2	M３	M4
1	3,028	19.6	17.1	20.1	18.0	22.1	24.3	22.0	28.3	20.8	20.7	21.1	23.1
2	3,005	19.4	18.0	19.5	17.7	21.2	23.3	21.9	27.3	20.3	20.7	20.7	22.5
3	3,008	19.1	18.2	20.8	18.9	20.8	23.2	21.4	28.9	19.9	20.7	21.1	23.9
4	2,999	21.4	19.8	21.6	20.9	21.3	22.0	21.5	27.2	21.3	20.9	21.6	24.1
5	3,044	19.3	18.2	17.7	17.9	21.1	23.0	23.5	27.1	20.2	20.6	20.6	22.5
Ave.	3,017	19.7	18.3	19.9	18.7	21.3	23.2	22.1	27.8	20.5	20.7	21.0	23.2
Test	Test Data	Bankrupt Group				Non-Bankrupt Group				Total			
		M5	M6	M7	M8	M5	M6	M7	M8	M5	M6	M7	M8
1	3,028	17.8	18.3	17.9	16.5	23.7	23.5	23.7	27.6	20.7	20.9	20.8	22.1
2	3,005	17.9	18.2	17.9	18.7	22.9	22.7	22.8	26.4	20.4	20.5	20.3	22.5
3	3,008	19.8	18.7	18.9	17.3	22.9	23.1	22.7	25.2	21.4	20.9	20.8	21.3
4	2,999	20.3	21.8	20.7	17.0	21.9	21.6	22.0	25.3	21.1	21.7	21.4	21.2
5	3,044	18.0	17.9	18.0	17.1	22.2	22.2	22.0	25.0	20.1	20.0	20.0	21.1
Ave.	3,017	18.7	19.0	18.7	17.3	22.7	22.6	22.6	25.9	20.7	20.8	20.7	21.6

Variables for Each Model：
Model 1: x7 x10 x26 x36 x37 x46
Model 2: x7 x10 x26 x36 x37
Model 3: x7 x10 x26 x37 x46
Model 4: x7 x10 x26 x37 x53
Model 5: x7 x10 x18 x26 x37
Model 6: x7 x10 x18 x37
Model 7: x7 x10 x26 x37
Model 8: x7 x10 x26 x36

As shown in Table 10, there is no marked difference among the models other than Model 3, Model 4 and Model 8. If they display the same level of discriminant power, then the models that have a smaller number of constituent indices have higher discriminant power. Accordingly, because Model 6 and Model 7 are four-variable models and addition to Model 8, the following combinations were chosen: a combination of the X7 ratio of Retained Earnings to Total Assets, the X10 ratio of Net Income before tax to Total Assets, the X18 ratio of Average Interest burden to Interest Bearing Liabilities and the X37 Inventory Turnover Period (Model 6), and a combination of the X7 ratio of Retained Earnings to Total Assets, the X10 ratio of Net Income before tax to Total Assets, the X26 ratio of interest expenses to sales and the X37 Inventory Turnover Period (Model 7).

It is noteworthy that the two models selected have almost the same combination of indices. There is only one different index in the two models, or the ratio of Average Interest burden to Interest Bearing Liabilities and the ratio of Interest Expenses to Sales, both of which indicate a company's financial burden ratio. So, either combination can be selected to analyze the mechanisms of corporate bankruptcy. Then, to compare and examine the significance of each variable, value F was obtained from the five indices in these two models using the STEPDISC procedure of SAS Version 8.1. The results are shown in Table 11.

Table 11 F-value of Selected Variables

Rank	STEPDISC Procedure		Partial R-Square	F Value	Pr > F
1	X7	Retained Earnings to Total Assets	0.1671	830.00	<.0001
2	X37	Inventory Turnover Period	0.0593	260.73	<.0001
3	X26	Interest Expenses to Sales	0.0186	78.31	<.0001
4	X10	Net Income before tax to Total Assets	0.0114	47.56	<.0001
5	X18	average interest burden to interest bearing liabilities	0.0051	21.11	<.0001

As shown by the results, there was a twofold difference in value F between the X26 ratio of Interest Expenses to Sales and the X18 ratio of Average Interest burden to Interest Bearing Liabilities. For this reason, a combination of the X7 ratio of Retained Earnings to Total Assets, the X10 ratio of Net Income before tax to Total Assets, the X26 ratio of Interest Expenses to Sales and the X37 Inventory Turnover Period (Model 7) were adopted.

Empirical Results

Discriminant power for chronological sample data were analyzed considering the indices used in the 1999 SAF model and those used in this research as the final indices.

The results are shown in Table 12.

Table 12 Discriminant Power between SAF Variables and Final Variables

	Sample Data		SAF Variables			Final Variables		
Year	Hold-out	Test	Bankrupt	Non-bankrupt	Average	Bankrupt	Non-bankrupt	Average
1992	1,873	236	4.17%	45.71%	24.94%	6.25%	26.43%	16.34%
1993	1,640	217	12.12%	50.33%	31.23%	10.61%	35.10%	22.85%
1994	1,922	414	11.58%	41.07%	26.32%	16.84%	36.05%	26.45%
1995	1,869	226	10.53%	34.67%	22.60%	9.21%	26.00%	17.61%
1996	1,820	569	31.65%	30.61%	31.13%	30.38%	27.14%	28.76%
1997	1,862	272	25.44%	27.22%	26.33%	17.54%	18.99%	18.27%
1998	1,915	251	18.64%	33.08%	25.86%	16.95%	24.06%	20.50%
1999	1,822	209	18.98%	26.39%	22.68%	18.25%	20.83%	19.54%
2000	1,678	541	23.08%	28.05%	25.56%	14.74%	21.82%	18.28%
Ave.	1,822	326	17.35%	35.24%	26.29%	15.64%	26.27%	20.96%

Note: Higher discriminant Power are highlighted.

The results show that the model indices in this research display higher level of discriminant power except for 1994. This explains that the huge investment (increase in total assets) and the demands for deferral of payment (trade payable turnover period) made by companies just before bankruptcy and which are clarified in the SAF model are not seen in the bankruptcies of recent years.

As an index indicating company's interest burden ratio, the ratio of Average Interest burden to Interest Bearing Liabilities has the second highest discriminant power after the ratio of Retained Earnings to Total Assets. This research adopts the ratio of Interest Expenses to Sales. However, when significant indices are extracted chronologically, the ratio of average interest burden to interest bearing liabilities is found in the division close to the root of the decision tree model in four years out of nine, showing that this index is still effective for bankruptcy discrimination. This index was not finally adopted in this model because with recent interest close-to-zero rates, the difference of the said index has been squeezed between a group of bankrupt companies and a group of non-bankrupt companies. In other words, in this business climate, the ratio of Interest Expenses to Sales is adopted as an index that indicates the company's interest burden ratio as a substitute for the ratio of Average Interest burden to Interest Bearing Liabilities. The interest burden ratio is undoubtedly influences corporate bankruptcy in Japan. Also, because the ratio of Interest Expenses to Sales is an index, in an era of low interest rates with an expanding difference, between bankrupt companies and non-bankrupt companies, whether it is still significant needs to be confirmed. Furthermore, the ratio of average interest burden to interest bearing liabilities does not display discriminant power with low interest rates but is expected to display an equivalent discriminant power when interest rates exceed a certain level. So, when interest rates recover, incorporating the ratio of Average Interest burden to Interest Bearing Liabilities into a model instead of the ratio of Interest Expenses to Sales should be reviewed.

Corporate Behavior Patterns

There are assumptions about corporate behavior patterns leading to bankruptcy in the SAF model that was developed immediately after the collapse of the bubble economy, and about the indices used in this research ten years later, following the collapse of the bubble economy. Changes in financial indices in the process leading to bankruptcy reflect corporate behavior patterns before bankruptcy. The final indices indicate that the following behavior patterns lead to corporate bankruptcy.

It is noteworthy that there is an upward trend of an “Inventory Turnover Period” in companies since the collapse of the bubble economy. Since inventory adjustment is used as an economic indicator, we assume that when the economy is sluggish, Inventory Turnover Period rises. However, from the marked difference in the index in companies in the same industries, change in the economic climate does not always worsen the index. However, the index worsening may indicate the slowdown of the economy. Management must undertake inventory adjustment of goods and products depending on changes in the economy. If inventory increases, business funds are less available. Now that “minimizing difference between forecast and result” has shifted from “if we manufacture, we can sell,” which prevailed before and after the bubble economy, this index displays marked significance. The *t* value in testing the difference between bankrupt group and non-bankrupt group was 14.58, which is relatively small. In addition, this index has a broad distribution base close to the higher value area for both bankrupt group and non-bankrupt group. However, compared to the non-bankrupt group there are a larger number of bankrupt companies that congregate in the distribution area of extremely large values beyond the mean. This indicates that inventory has not been adjusted due to error in sales forecast, leading to bankruptcy.

New Model **(ten years after the collapse of the bubble economy)**	**Previous SAF Model** **(right after the collapse of the bubble economy)**
Management error in sales forecast and production schedule; increase of inventory of products and goods and delay of purchases due to incomplete inventory management (rising of inventory turnover period)	The status of the capital having suffered a deficit already or being likely to suffer one in immediate future =almost no self - financing capability (lowering of the ratio of retained earnings to total assets)
Spread of credit insecurity	Requesting extension of payment to customers to make up for shortage of fund (trade payable turnover period is prolonged)
Fund procurement at low interest rate becomes difficult (rising of the ratio of interest expenses to sales= expanding of non-operating expenses)	Spread of credit insecurity
Lowering of profit ratio due to decline of sales and expansion of costs (lowering of the ratio of net income before tax to assets)	Fund procurement at low interest rate becomes difficult (rising of the ratio of average interest burden to interest bearing liabilities)
As a result, capital is reduced and company falls into status of almost no self - financing capability. (Lowering of the ratio of retained earnings to total assets)	Procuring large amount of fund in a short period (rising of total capital increase ratio)

In addition, in the ratio of Interest Expenses to Sales, there is a large difference between the bankrupt group and the non-bankrupt group around 1996, when Japan entered an almost zero interest era. In the bankrupt group, the ratio of Interest Expenses to Sales remains flat (or rises a little) with zero interest rates; the index in the non-bankrupt group shows a downward trend in line with interest rates. This expands the difference between the two groups although the difference is significant. Low interest rates favorably affect companies. In fact, however, these external factors cannot be successfully assimilated. This is a feature of the bankrupt firm after the collapse of the bubble economy.

Because of the big difference in the development of the SAF model and the SAF2002 model, significant indices for bankruptcy discrimination are different between the two, except the ratio of Retained Earnings to Total Assets. However, the strong discriminant power of the ratio of Retained Earnings to Total Assets is worthy of attention. In addition, the discriminant power of the ratio of Retained Earnings to Total Assets has grown for recent data compared to when the first SAF model was developed (financial data from 1986 to 1996). The ratio of Retained Earnings to Total Assets is an essential index for bankruptcy discrimination, which clarifies the distinction between bankrupt companies and non-bankrupt companies. In addition, considering that bond credit rating agencies always rank “retained earnings ratio” high as an explanatory variable, the index is useful not only for corporate bankruptcy discrimination but also for assessment of bond security.

Recently, companies with great amounts of retained earnings are often asked by shareholders to pay a good dividend. There is a conflict of interests between shareholders and corporate executives who want stable management. It is evident that through the results of analysis that equalizing the ratio of retained earnings and total capital is necessary for stable management, is necessary. Most stable companies in Japan who huge retained earnings are maintained by tolerant shareholders through cross sharing, etc. In this case, when there is dissolution of cross sharing, corporate governance is controlled by new shareholders in the future, retained earnings will flow out of the company, and as a result, the company will encounter difficulty. In predicting future corporate bankruptcy, it is necessary to pay attention to relations between shareholder's movement and the ratio of Retained Earnings to Total Assets.

VI MODELING

Model Type

As with the development of the SAF model, in developing this new model, (1) three models, that is, a linear discriminant model, a quadratic model and a normal method with normal density estimation were developed using SAS Discrim procedures, (2) the discriminant power of each model was compared and, (3) the most suitable discriminant power selected as the bankruptcy prediction model for Japanese companies. Further, the linear discriminant model and a logit model were compared for discriminant power before discrimination results were compared between the SAF model and the model of this study. Five comparisons were made for holdout samples for each model.

Table 13 shows the comparison results of the discriminant power of each model.

Table 13 Discriminant Power of Each Model

Unit:%

Test	No. of Sample	Bankrupt Group			Non-bankrupt Group			Total		
		LN	Q	NK	LN	Q	NK	LN	Q	NK
Test	3,028	17.89	36.45	30.48	23.66	21.37	25.29	20.77	28.91	27.89
1	3,005	17.90	36.24	33.45	22.79	21.51	23.92	20.34	28.87	28.68
2	3,008	18.91	36.79	31.32	22.72	20.85	22.54	20.81	28.82	26.93
3	2,999	20.71	39.76	33.41	21.99	18.66	21.18	21.35	29.21	27.29
4	3,044	17.97	33.33	31.59	22.01	20.08	20.88	19.99	26.71	26.24
5	3,017	18.68	36.51	32.05	22.63	20.49	22.76	20.65	28.50	27.41

Note: LN = Linear, Q = Quadratic, NK = Normal Kernel

According to these results, the linear model had a 20.65% misclassification ratio at the mean value, displaying the strongest discriminant power. In discrimination in the bankrupt group, the linear discriminant model constantly showed much stronger discriminant power than the other two models. In discrimination in the non-bankrupt group, the quadratic model constantly showed strong discriminant power. On the other hand, the normal method with normal density estimation displayed stronger power than the quadratic model in discrimination in the bankrupt group, whereas it displayed the same level of discriminant power as the linear discriminant model in discrimination in the non-bankrupt group.

Analysis using SAF model indices indicates that the discrimination results of the normal method with normal density estimation turned were the poorest in the entire non-bankrupt group and bankrupt group. In contrast, the results of this analysis conducted of the data after the collapse of the bubble economy revealed the matching discriminant power of the normal method with normal density estimation, which did not hypothesize normality or the correctness of a covariance matrix. This is because there are recently many companies with different financial values in Japan, broadening databases and transforming the previous structure of a number of companies that congregate around certain value. Accordingly, with this data structure with a broader database and an incorrect covariance matrix, analysis through obtaining and comparing mean values is irrational. In financial analysis using financial indices, there is a tendency to obtain the mean value for each of these categories as the same trade and the same scale, compare it with the value of the company to be analyzed and measure the safety level of the company. However, when the data constituting the entire sphere has too broad a base, the mean value obtained does not always represent the relevant parent population. The analysis conducted in this research unveiled the increasingly complex structure of recent financial trends in Japanese companies, which makes analysis by outside stakeholders much more difficult.

Moreover, in the analysis of the SAF model, the linear discriminant model displayed strong discriminant power in the bankrupt group, whereas in the total of the bankrupt group and the non-bankrupt group, the misclassification ratio of each model had a narrow margin. In contrast, in this analysis using a new model, the linear discriminant model showed by far the strongest discriminant power in comparison with the other two models in spite of complicated corporate financial structure. This indicates the strength of the linear discriminant model and verifies it although statistical constraint conditions are not satisfied in Lachenbruch's research. The linear discriminant model, which is stable relative to other models, is the most useful for bankruptcy prediction of today's companies with complicated financial structures amid an ever-changing economic climate.

Linear v.s. Logit Model

Discrimination results were compared between the logit model, which has been popular as a bankruptcy discriminant model since 1980, and the linear discriminant model. In the logit model, the following assumption was made; dummy variable is prepared with a

$$X_i = \beta_0 + \sum_{j=i} \beta_j x_{ij} + \varepsilon_i$$

bankrupt firm and a non-bankrupt firm set at 0 and 1, respectively; Xij is assumed to be the ith company's jth financial ratio; then, latent variable is set up and applied to logistic distribution. To be exact, bankruptcy probability is obtained. Therein, a logit model is developed by using S-Plus glm procedures as per Formula 1.

$$\boldsymbol{X_i = 0.085X7 + 0.203X10 - 0.351X37 - 0.112X26 + 0.831}$$

$$\boldsymbol{SAFL = 1/1 + \exp(-X_i)} \quad \text{......} \textbf{Formula 1}$$

Likewise, the linear model is developed as in the same way as Formula 2.

$$\boldsymbol{SAF2002 = 0.0104X7 + 0.0268X10 - 0.0661X37 - 0.0237X26 + 0.7077} \quad \text{......} \textbf{Formula 2}$$

The residual standard deviation of the linear discriminant model was 0.39824 and its contribution ratio was 21.52%. To distinguish it from the SAF model, this model is called the SAF2002 model.

The following indices are assigned to each of the above formulas.

X7	**Retained Earnings to Total Assets**
X10	**Net Income before tax to Total Assets**
X37	**Inventory Turnover Period**
X26	**Interest Expenses to Sales**

The discriminant point in the logit model analysis would be the one at which the same level of discrimination results as those indicted in the linear discriminant model obtained. As a result, the discriminant power of the bankrupt group at a discriminant point of 0.74 increased from 86% to 88%, while that of the non-bankrupt group increased from 71% to 74%, indicating the highest discriminant power of 80.1% on average. For this reason, the discriminant point in the logit model was set at 0.74. This was then compared with the misclassification ratio of the linear discriminant model, which showed the highest discriminant power in model comparisons so far. The results are shown in Table 14.

Table 14 Misclassification ratios of Lear and Logit Model

Unit:%

Test	No. of Hold-out Sample	Bankrupt Group		Non-bankrupt Group		Total	
		LN	LO	LN	LN	LO	LN
1	3,028	17.89	11.02	23.66	29.13	20.77	20.08
2	3,005	17.90	12.64	22.79	27.14	20.34	19.89
3	3,008	18.91	11.85	22.72	28.17	20.81	20.01
4	2,999	20.71	13.47	21.99	26.89	21.35	20.18
5	3,044	17.97	12.96	22.01	25.73	19.99	19.35
Ave.	3,017	18.68	12.39	22.63	27.41	20.65	19.90

Note: LN = Linear, LO = Logit

Comparison of the discrimination results of the two models shows that there is not much difference in the discriminant power between the two models for the total of the bankrupt group and non-bankrupt group on average. The same results were clearly indicated in a similar analysis in the SAF model.

However, the analysis results indicate that the logit model has a high level of discriminant power for the bankrupt group, whereas its discriminant power is not high for the non-bankrupt group. If matching discrimination results are to be obtained using the logit model, it is necessary to shift the discriminant point down to where discriminant power for the bankrupt group and the non-bankrupt group is at a reasonable value. In fact, the overall discriminant power slightly lowered.

The linear discriminant model has proved to be strong in each case. However, the logit model is still useful, displaying the same level of discriminant power as the linear discriminant model. When two models have the same level of discriminant power, the simpler model should be adopted. If the logit model is adopted, it should be superior to the linear discriminant model in corporate bankruptcy discrimination, gathering information that the linear discriminant model may not identify. However, conclusive proof has not been obtained through the empirical analysis so far. On the contrary, the discrimination results of the linear discriminant model and the logit model are almost the same, making it difficult to determine which is more useful as a bankruptcy discrimination model.

Compared to the data when developing the SAF model, this data has a broader distribution, which makes it almost impossible to hypothesize its normality. Under these circumstances, this research shows that there is still no difference in the discriminant power of the linear discriminant model and the logit model as confirmed by the SAF model. To sum up, corporate bankruptcy is linear phenomenon. So, it does not make sense to discuss whether the linear discriminant model or the logit model provides more accurate discrimination results. On the contrary, clearly either model gave satisfactory discrimination results as long as really useful indices for bankruptcy discrimination are combined and incorporated into the model. Recent research on bankruptcy models tends to place little importance on selecting indices and focus developing a new model.

Cut-Off Point

In making bankruptcy discrimination, it is necessary to consider bankruptcy costs before determining a discriminant point. In Japan, with bankruptcy costs, social costs of misclassification of the bankrupt group (type I error) surpass costs of misclassification of the non-bankrupt group (misclassifying non-bankrupt companies as companies on the verge of going under) (type II error). A type I error is the aggregate amount of credit to the firm, while type II error costs are the result of opportunity loss. Outside Japan, mergers and amalgamations intended to rescue those on the brink of going under are not subject to the antitrust law. When there is a corporate merger due to easy type II error, economic losses incurred by the whole market are greater than for type I error suffered by a number of companies. However, in Japan, there are very few cases of buying unviable companies from the above motives and moreover, procurement of funds in Japan is mainly through indirect financing unlike in the United States where direct financing is dominant. For the above reasons, emphasis should be placed on type I error.

Misclassification ratios in the bankrupt and non-bankrupt groups were obtained at each discriminant point. The results are shown in Table 15.

Table 15 Misclassification Raito at each Cut-Off Point

Unit:%

Cut-Off Point	Bankrupt Group	Non-Bankrupt Group	Average
0.60	32.68	15.15	23.92
0.61	30.83	15.62	23.23
0.62	29.30	16.60	22.95
0.63	26.25	17.54	21.90
0.64	24.40	18.16	21.28
0.65	22.55	19.19	20.87
0.66	20.26	20.56	20.41
0.67	18.30	21.78	20.04
0.68	16.67	22.77	19.72
0.69	15.58	24.41	20.00
0.70	13.51	26.01	19.76
0.71	12.20	27.52	19.86
0.72	10.78	29.54	20.16
0.73	9.48	31.00	20.24
0.74	8.06	32.69	20.38
0.75	6.64	34.76	20.70
0.76	5.99	36.74	21.37
0.77	4.90	38.38	21.64
0.78	4.25	40.59	22.42
0.79	3.70	42.24	22.97
0.80	3.38	43.98	23.68
Ave.	15.22	27.39	21.31

The misclassification ratio of the bankrupt and non-bankrupt groups was the lowest at the discriminant point of 0.68, which was 19.72%. When a 95% or over discrimination ratio of the bankrupt group is sought in the SAF model, the discrimination ratio of the non-bankrupt group lowered to 50%. On the other hand, in this model, even when 95% or the same level of discriminant power is sought in the bankrupt group, the discriminant power of the non-bankrupt group remains at 60% or more, bringing more stable results. The compromising point (discriminant point) cannot be determined based on a reasonable theory and is also subjectively determined by the researcher. Therefore, when an analyst seeks a more exact model for the discrimination of bankrupt companies, he or she may set the discriminant point high, or when he or she seeks a more exact model for the discrimination of non-bankrupt companies, the discriminant point may be set lower.

Figure 1 shows histogram of SAF values of SAF2002 values excluding outliers.

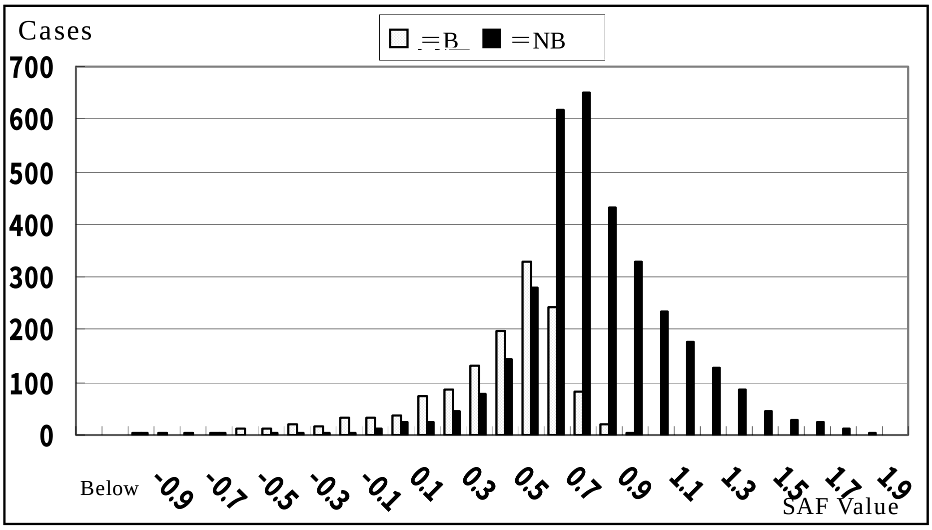

Figure 1 Histogram of SAF values of SAF2002

In the discrimination analysis of the data of 1407 cases bankrupt companies' using Formula 2, 99% of companies showed a 0.9 or less SAF value. There were 14 bankrupt companies that had a 0.9 or higher SAF value, the highest SAF value being 1.4; however, they are obviously considered as outliers of bankrupt companies. In contract, 31% or more of non-bankrupt companies showed a 0.9 or higher SAF value. Accordingly, there are very few bankrupt companies with a 0.9 or higher SAF value.

VII CONCUSION

This research provides a new bankruptcy prediction model, the SAF2002 model, which is currently appropriate developed using extensive financial data from 1992 to 2000 following the collapse of the bubble economy. The SAF2002 model displays an 86% or more discriminant power.

This research compares the SAF model with a subject period of eleven years spanning the bubble economy and the SAF2002 model whose subject period after a lapse of ten years follows the collapse of the bubble economy. It is clear that there are different financial modes of behavior in companies prior to bankruptcy. This research has verified that the real factor leading to corporate bankruptcy is lack of self-financing capability and that this is a universal and common factor in all eras, under all business circumstances. This research confirms that in detecting Japanese corporate bankruptcy probability, simply observing P/L information, cash flow information and other flow information is not sufficient. It is more useful to observe self-financing capability, or stock information representing the extent of retained earnings.

If company evaluation projects the profitability of shares, then these research results may not be as useful. However, when company evaluation forecasts whether a company will continue or not, the SAF2002 model developed in this research provides useful information.

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APPENDIX 1 DISTRIBUTIONAL REVERSAL BETWEEN NON-BANKRUPT GROUP AND BANKRUPT GROUP DURING 9 YEARS -MEAN VALUE DIFFERENCE BETWEEN TWO GROUPS-

	X2 (Current period liabilities and shareholders equity/Previous period liability and shareholders equity)-1		X4 (Current period operating income/ Previous period operating income)-1		X9 EBIT/total assets		X17 Accounts payable x 12/Sales	
	Non-Bank - Bankrupt		Non-Bank - Bankrupt		Non-Bank - Bankrupt		Non-Bank - Bankrupt	
Year	Without Outlier	With Outlier	Without Outlier	With Outlier	Without Outlier	With Outlier	Without Outlier	With Outlier
1992	▲ 0.9709	▲ 3.7122	18.9067	40.5619	0.4212	0.7447	▲ 0.0348	▲ 0.0448
1993	1.6182	0.5106	19.8646	28.2782	▲ 0.1267	0.1578	0.1166	0.1229
1994	0.1423	▲ 0.6044	5.0599	11.7880	0.2075	0.3973	0.1172	0.0714
1995	1.1807	1.0467	▲ 4.1239	▲ 2.3346	0.1788	0.2631	0.0415	0.0434
1996	1.7402	1.4627	▲ 1.1978	0.1243	0.4026	0.4891	▲ 0.0040	0.0114
1997	2.4353	2.3325	0.6115	0.3471	0.6836	0.7411	▲ 0.0687	▲ 0.0621
1998	▲ 0.2206	▲ 0.5798	9.7124	12.7356	0.5699	0.6268	0.1328	0.1421
1999	1.4704	0.9881	2.8921	14.3161	0.0400	0.1639	0.0582	0.0338
2000	4.0209	3.4664	12.2124	40.4984	0.4984	0.6693	0.1075	0.1135

	X19 Non-operating revenue/Sales		X20 Non-operating expense/Sales		X27 Working capital/total assets		X28 Interest income/(Short term loans + long term loans + securities + long-term assets investment + investment + cash)	
	Non-Bank - Bankrupt		Non-Bank - Bankrupt		Non-Bank - Bankrupt		Non-Bank - Bankrupt	
Year	Without Outlier	With Outlier	Without Outlier	With Outlier	Without Outlier	With Outlier	Without Outlier	With Outlier
1992	▲ 0.1279	▲ 0.2108	▲ 0.0918	▲ 0.2197	1.1198	1.1497	0.7968	0.7271
1993	0.5814	0.2888	0.1508	0.1469	▲ 1.0557	▲ 0.7034	0.2549	0.0560
1994	0.1784	▲ 0.1210	▲ 0.0260	▲ 0.2994	0.0208	0.7868	▲ 0.1342	▲ 0.1357
1995	0.1788	▲ 0.0028	▲ 0.1072	▲ 0.1514	1.0049	1.0201	0.0923	▲ 0.1014
1996	▲ 0.1440	▲ 0.2478	0.0055	0.0146	▲ 0.6564	0.0846	0.1158	0.1279
1997	▲ 0.3435	▲ 0.3928	0.2379	0.2134	1.3906	1.7578	0.0570	0.0247
1998	▲ 0.1583	▲ 0.4716	0.0612	0.0442	3.1868	3.2918	0.1171	0.1138
1999	0.0272	▲ 0.0559	0.1365	0.0467	3.7577	5.9125	0.2153	0.2026
2000	▲ 0.1836	▲ 0.5249	▲ 0.0103	▲ 0.0335	3.5066	3.8770	0.1266	0.1263

	X29 Long-term assets x 12/Sales		X31 Tangible long-term assets x 12/sales		X32 (Note receivable + accounts receivable) x 12/Sales		X33 (Note receivable + accounts receivable) x 12/Sales	
	Non-Bank - Bankrupt		Non-Bank - Bankrupt		Non-Bank - Bankrupt		Non-Bank - Bankrupt	
Year	Without Outlier	With Outlier	Without Outlier	With Outlier	Without Outlier	With Outlier	Without Outlier	With Outlier
1992	▲ 0.6525	▲ 0.6822	▲ 0.2981	▲ 0.3732	0.5559	0.3131	0.4510	0.3386
1993	0.2313	0.1896	0.0428	0.0997	0.0425	0.0658	▲ 0.4564	▲ 0.5225
1994	▲ 0.2090	▲ 0.4289	▲ 0.1750	▲ 0.3064	▲ 0.1110	▲ 0.1557	▲ 0.6643	▲ 0.8663
1995	▲ 0.3737	▲ 0.4224	▲ 0.1921	▲ 0.3292	0.1806	0.0837	▲ 0.4456	▲ 0.5213
1996	0.0356	▲ 0.0291	0.1547	0.1478	0.2080	0.1243	▲ 0.9722	▲ 0.9960
1997	▲ 0.0126	▲ 0.0888	0.2112	0.1098	0.1684	0.1884	▲ 0.4462	▲ 0.4349
1998	▲ 0.1703	▲ 0.2516	▲ 0.1281	▲ 0.2165	0.1716	0.1571	▲ 0.5615	▲ 0.5612
1999	▲ 0.2609	▲ 1.0691	▲ 0.3504	▲ 0.6550	0.3724	0.3655	0.3306	0.1609
2000	▲ 0.8864	▲ 1.3816	▲ 0.8127	▲ 1.1562	0.2101	0.1574	▲ 0.4730	▲ 0.5299

Year	X34 (Note receivable + note receivable discounted) x12/Sales		X39 Tangible assets/Number of employees		X40 Sales/Number of Employees		X41 Gross Margin/Number of employees	
	Non-Bank - Bankrupt		Non-Bank - Bankrupt		Non-Bank - Bankrupt		Non-Bank - Bankrupt	
	Without Outlier	With Outlier	Without Outlier	With Outlier	Without Outlier	With Outlier	Without Outlier	With Outlier
1992	0.6182	0.4625	1990.30	▲ 294.23	7194.98	9412.06	539	291
1993	▲ 0.1681	▲ 0.1823	1871.81	1857.23	8174	6094	1254	1272
1994	▲ 0.3317	▲ 0.3855	283.01	311.99	2182	2587	375	563
1995	0.1540	▲ 0.0223	495.03	485.60	7501	8419	1847	1896
1996	▲ 0.7129	▲ 0.7200	▲ 649.66	▲ 457.24	▲ 7710	▲ 6016	971	807
1997	▲ 0.2470	▲ 0.2400	1565.70	988.46	▲ 4968	▲ 4701	▲ 766	▲ 830
1998	▲ 0.0092	▲ 0.0197	1362.02	80.07	7006	9676	713	683
1999	0.8416	0.8986	▲ 976.23	▲ 2063.64	4416	6851	1014	941
2000	▲ 0.2667	▲ 0.2975	▲ 2305.35	▲ 3567.13	5167	5354	1061	928

Year	X42 Selling and administrative expense/ Number of employees		X44 Current assets/Current liabilities		X51 Long-term assets/Long-term liabilities and equity		X52 (Tangible assets at end of period - tangible assets at beginning of period)/Tangible assets at beginning of period	
	Non-Bank - Bankrupt		Non-Bank - Bankrupt		Non-Bank - Bankrupt		Non-Bank - Bankrupt	
	Without Outlier	With Outlier	Without Outlier	With Outlier	Without Outlier	With Outlier	Without Outlier	With Outlier
1992	▲ 185	▲ 251	6.8403	3.2931	2.9842	0.5385	0.5673	0.6730
1993	231	64	▲ 0.2199	▲ 0.7204	2.1801	1.8849	0.9323	0.9438
1994	425	459	2.5923	4.1748	5.9250	5.5992	▲ 0.5471	▲ 0.6081
1995	215	274	5.6950	4.4355	2.7485	3.3162	▲ 0.2277	0.0154
1996	▲ 111	22	1.6254	3.8948	14.8470	15.5702	▲ 1.2506	▲ 0.8140
1997	▲ 916	▲ 1079	2.9812	3.1199	3.7897	▲ 0.0912	▲ 0.3746	▲ 0.2879
1998	▲ 105	▲ 258	5.8392	5.6678	▲ 2.4481	▲ 2.6164	▲ 0.4684	▲ 0.9235
1999	322	199	12.4532	12.0166	▲ 3.3678	▲ 5.3182	▲ 0.0163	▲ 0.0493
2000	7	25	4.8579	7.8998	▲ 12.3352	▲ 11.3270	▲ 1.3249	▲ 1.3211

Year	X62 Cash/(Selling and administrative expense/365)		X63 Operating CF income / Operating CF expense		X65 (Operating + Non-Operating income) / (Operating + Non-Operating expense)		X69 (Long-term liabilities + Current Liabilities) / Free Cash Flow	
	Non-Bank - Bankrupt		Non-Bank - Bankrupt		Non-Bank - Bankrupt		Non-Bank - Bankrupt	
	Without Outlier	With Outlier	Without Outlier	With Outlier	Without Outlier	With Outlier	Without Outlier	With Outlier
1992	79.7341	74.6014	▲ 0.0672	▲ 0.5321	1.1539	0.8148	0.1622	0.0482
1993	78.6087	76.9685	▲ 0.9750	▲ 1.0967	0.4460	0.3993	▲ 0.1234	0.4520
1994	13.1998	13.5267	▲ 0.0098	▲ 0.0053	1.3598	1.2859	▲ 0.4462	▲ 0.6761
1995	69.2589	69.8720	▲ 2.2798	▲ 3.2022	0.0517	▲ 0.2601	0.6765	1.0798
1996	▲ 4.1939	▲ 10.7815	▲ 2.2051	▲ 2.6373	▲ 0.4405	▲ 1.1617	▲ 1.6354	▲ 2.0906
1997	46.4091	47.5320	▲ 1.0845	▲ 1.2014	0.4096	0.2018	0.0861	▲ 0.4784
1998	42.2691	44.1213	0.7773	0.6201	1.7845	1.5728	0.7791	0.4883
1999	95.4547	93.2783	1.5002	1.1478	2.1827	1.9801	0.0120	▲ 0.1835
2000	85.3418	89.4205	1.4267	1.6072	2.2018	2.4380	▲ 3.1444	▲ 4.4060

Year	X70 Operating CF/sales		X71 Operating C/Current Liabilities	
	Non-Bank - Bankrupt		Non-Bank - Bankrupt	
	Without Outlier	With Outlier	Without Outlier	With Outlier
1992	▲ 0.4258	▲ 0.4531	1.9441	0.3818
1993	▲ 1.1201	▲ 1.1201	0.2465	0.0805

1994	▲ 0.5467	▲ 0.5619	1.1350	1.2401
1995	▲ 4.0803	▲ 4.0803	▲ 5.1225	▲ 4.8015
1996	▲ 2.4894	▲ 2.4894	▲ 1.7001	▲ 3.4580
1997	▲ 1.1716	▲ 1.1716	▲ 0.5792	▲ 0.5185
1998	0.4917	0.5400	2.4874	2.7341
1999	1.1040	1.1040	1.7649	1.1096
2000	1.4288	1.4411	2.8175	3.3400

APPENDIX II 42 FINANCIAL INDICES FOR ANALYSIS

Var.	Name of Index	Var.	Name of Index
X1	(Sales at beginning of a period/Sales at end of a period)-1	X37	Inventory x 12/Sales
X3	(Current period equity/Previous period equity)-1	X38	Finished goods x 12/Sales
X5	Sales/total assets	X43	Operating income/Number of employees
X6	Operating income/Liabilities and shareholders equity	X45	Quick assets/current liability
X7	Retained earnings/total assets	X46	(Note receivable + accounts receivable) /(Note payable + accounts payable)
X8	(Operating income + interest and discount expense) /Liabilities and shareholders equity	X47	(Current liabilities + Long-term Liabilities) / Equity
X10	Net income before tax/total assets	X48	Equity/Liabilities and shareholders equity
X11	Operating income/Equity	X49	(Short term borrowings + long term borrowings + corporate bond + note receivable discounted) /Liabilities and equity + note receivable discounted
X12	Net income after tax/Equity	X50	Fixed assets/Equity
X13	Liabilities and shareholders equity x12/Sales	X53	Operating income + interest income/interest and discount expense
X14	Fix assets x 12/Sales	X54	(Current liabilities and Long-term liabilities) x 12/Sales
X15	Note payable + accounts payable) x 12/Sales	X55	Current liabilities x 12/Sales
X16	Note payable x 12/Sales	X56	Short term borrowings x12/Sales
X18	Interest and discount expense/ (Short term borrowings + long term borrowings + corporate bond + convertible bond + note receivable discounted)	X58	Long-term liabilities x 12/Sales
X21	Non-operating expense/Sales	X59	(Corporate bond + long term borrowings) x 12/Sales
X22	Operating income/Sales	X60	Cash x 365/Sales
X23	Net income before tax/Sales	X61	Defensive Interval
X24	Net income after tax/Sales	X64	Operating CF income - Operating CF expense
X25	(Interest income - interest and discount expense)/Sales	X66	(Operating + Non-Operating income) – (Operating + Non-Operating expense)
X26	Interest and discount expense/Sales	X67	(Operating + Non-Operating Income) - (Operating + Non-Operating expense) – (tax + dividend + directors' bonus)
X36	Accounts receivable x 12/Sales	X68	Operating CF + interesting receivable/interesting payable