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# FINANCIAL STATEMENT ANALYSIS OF CORPORATE BANKRUPTCY

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**SUMMARY**

The purpose of this study is to construct bankruptcy prediction models of listed firms in Japan by multiple discriminant analysis.

First, we checked which data we should use to construct more accurate and reliable models, (i) nonadjusted financial statement data or those adjusted to reflect the exceptions appearing in the audit report; (ii) accrual base financial indices or cash base ones; (iii) index values for three years before failure or only for the first year before failure; and (iv) only ratios or a combination of ratios and absolute amounts.

Secondly, we considered differences in cost of error between the Type I and Type II errors. We established six cutoff points with their own reasons, and decided to leave the choice of a cutoff point to the individual users. All discriminant models we constructed were tested using these six cutoff points to select the best model.

## 1. Introduction

Corporate bankruptcy becomes an object of management analysis. This is firstly due to the fact that, since bankruptcy is an ultimate state of a firm to be observed as an objective fact, the effectiveness of any given index or method for management analysis can be verified depending on whether or not the index or the method is sufficient enough to explain or to predict an event of corporate bankruptcy. Secondly, since the impact of bankruptcy to the society may not be ignored, autopsy or prediction of bankruptcy, if, possible, will contribute greatly to effective distribution of economic resources.

Different analysis may make different approaches to study corporate bankruptcy depending on the positions they are in. The position which the authors took in this study was that of public investors or stockholders. Therefore, the object to be analyzed is limited to bankruptcy of listed firms, which can be their investment objects. Also, we used published financial statement as our only sources of financial statement data because they are assured, by the disclosure system in this country, to be sources of accurate, fair and timely information, and because they may be perhaps the source of financial information available to public investors.

Corporate bankruptcy prediction models have been developed in the U.S. since the 1960's. There is a lot to be learned from Altman [1968], Altman, Haldeman, and Narayanan [1977], Altman [1979], Beaver [1966], Cooley [1975], Deakin [1972], Ohlson [1980], and Wilcox [1973]. However, in the case of failed firms in Japan, more exceptions are seen in their audit reports than in those of non-failed firms, and to ignore this might impair the accuracy of prediction. Taking this point into consideration, this study aims at preparing an accurate and practical model or models which can be used to predict bankruptcy of Japanese firms.

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Note: This study was originally published in Japanese in Research Monograph No. 1, KEIO KEIEI KANRI GAKUKAI, YOKOHAMA, JAPAN, 1979.

Reference was made to the recent development of this study since 1979 in the U.S. and Japan in this paper.

## 2. Features of This Study

### 2.1 Data and Indices Used

(1) Altman et al. [1977] constructed a prediction model using financial statement data not only for the first year, but also for the several years before failure.

We constructed various models using financial statement data for three years as well as the first year before failure. The reason why we used financial statement data for three years before failure was that, having found certain financial ratios and indices showing somewhat typical values in the third or the second year before failure, we considered that improved predictability might be obtained by developing a model or models using financial statement data not only for the first year before failure but also those for the second and/or third years before failure. Secondly, bankruptcy is thought to be a phenomenon which does not occur abruptly but emerges gradually, hence we thought that the accuracy of prediction might be improved by taking into account the behaviors and the trends of financial ratios and indices during a certain span of time. Thirdly, we thought that it might be possible that some financial indices might recover in the first year before failure so closely to the level of nonfailed firms so that no significant difference could be found between the failed and nonfailed groups unless their respective ratios and indices for the first year before failure are compared with those for the second and/or third years before failure. The only reason why we limited the number of years before failure to three was because the number of listed firms which had gone bankrupt four or more years after the date of listing was so limited as to render statistical analysis extremely difficult.

(2) We adopted both absolute amounts and ratios as Altman et al. did. This was because absolute amounts might possibly have some bearings to bankruptcy. Hence, we prepared prediction models using ratios only and models using both ratios and absolute amounts, and compared their respective predictabilities with each other.

(3) While Altman et al. constructed a model using a combination of accrual base financial indices and cash base indices, we constructed prediction models using cash base financial indices alone, in addition to those using accrual base indices. The primary reason was that for the accrual base income statement purpose, no transaction could be free from the management's subjectivity in its recognition or measurement. In other words, there is always room for manipulation. On the contrary, however, there is little room for such manipulation problems in case of cash base financial statement data(1). Secondly, the direct cause of bankruptcy is insolvency caused by shortage of cash funds. Hence we thought that some cash base ratios might be excellent predictors of bankruptcy. For the above mentioned reasons, we compared the respective prediction abilities of models using cash base ratios and those using accrual base ratios with each other.

(4) We made appropriate adjustments to financial statements data to property reflect exceptions in the audit reports. Since audit reports are prepared by impartial certified public accountant to assure the fairness and correctness of the financial

(1) See the Reference [16] listed at the bottom hereof.

statements, when exceptions are made in their audit reports, users of the financial statements should pay attention to those exceptions when reading the statements. To our knowledge, there is no prior study in Japan which has attended to the audit report.(2) Under these circumstances, we have prepared several prediction models using adjusted financial statement data as well as several models using unadjusted financial statement data and compared their respective prediction abilities with each other.

The purpose of these tests is find an optimum model from among the various alternative models we constructed using various combinations of financial statement data.

### 2.2 Cutoff Points

There is a big difference between the Type I error and Type II error(3) in costs of errors. In other words, Type I error cause investors and creditors to suffer actual economic losses resulting from inability to collect loans or charge off their equity investments, while no damage is recognized from Type II errors other than opportunity costs resulting from loss of investment opportunities due to a little too conservative investment decision.

Generally the probability of failure is far smaller than the probability of nonfailure. Cooley [1975] has demonstrated by using a simulation model he constructed that the cutoff point varies depending on whether or not misclassification costs and/or the probability of misclassification are taken into consideration. To select the best cutoff point, Altman et al. and Altman [1979] determined misclassification costs based on extensive inquiries conducted by them with respect to commercial bank lendings alone. As mentioned earlier, however, the position we took in this study was that of public investors and stockholders. Indeed it is more difficult to determine misclassification costs to public investors and stockholders than those to creditors such as commercial banks.

When one actually tries to predict bankruptcy of a firm, he will not, we believe, make such prediction by a single cutoff point. Rather, he will make his own judgment in consideration of several cutoff points such as the most conservative point, the most optimistic point, or the point where bankruptcy may occur with such and such statistical probability percentage. Thus, in our actual prediction model, we employed an approach which can provide users with plural prediction results based on six cutoff points which have their own reasons, leaving the final judgment up to the individual users. In our definition, the best model is the one which demonstrates invariably high predictability regardless of the cutoff point used.

## 3. Selection of Sample Firms

All sample firms in this study are manufacturing firms listed in the Tokyo

(2) See the Reference [8], [9], [11], [13], [15], [19], [20] listed at the bottom hereof.

(3) "Type I error" means misclassification of a failed firm as nonfailed, and "Type II error" means misclassification of a nonfailed firm as failed.

Stock Exchange. According to the statistics, the number of listed firms included in the total number of bankrupt firms is very small. Most of them are unlisted firms. We agree that it might be of practical signicance to study bankruptcy of middle or smaller sized corporations. As mentioned earlier, however, the position we took in this study was that of public investors, whose investment targets are listed firms.

### 3.1 Definition of Failure

There is no established definition of bankruptcy today. Therefore, for the purpose of this study, " failure " or " bankruptcy " is deemed to have occurred with respect to any firms, when it falls under any one of the following events :[4]

a. that is fails to honor any bill or check drawn or accepted by it on its due date, and its banking transactions are suspended by way of penalty ;
b. that a petition under the Corporate Reorganization Act is filed by or against it with any district court ;
c. that arrangement proceedings are initiated by or against it under Article 381 of the Commercial Code ;
d. that arrangement proceedings are initiated by or against it under the Composition Act; or
e. that its creditors meet together to initiate its preliminary liquidation.

Among the listed firms which went bankrupt after 1961, we have selected as sample firms 40 corporations whose financial statements for at least three years before failure were available. Of the above mentioned five events, filing of a petition under the Corporate Reorganization Act comes first as causes of the failure, and quite a few firms included in our sample failed firms now have been successfully reorganized.

The first year before failure with respect to any failed firm means its fiscal year next preceding to the day of its bankruptcy. For this purpose the date of submission of its last securities report under the Securities & Exchange Act is used. Therefore, if its financial statements were made public just a day before its bankruptcy, the fiscal year covered by the financial statements is regarded as the first year before failure.[5] Since the securities reports should be submitted within three months from the last day of each fiscal year, they are usually made public on or about the day three months after the end of each fiscal year. The period between the day of bankruptcy and the last day of the first year before failure is hereafter called " lead time." The minimum lead time is three months. The average lead time of the failed firms was 6.98 months.

### 3.2 Selection of Initial Sample

The initial sample we selected for analysis consists of 72 firms ; 36 firms which went bankrupt during the period from 1962 to 1976 and 36 nonfailed firms selected by pair sampling. As noted before, the failed firms are manufacturing firms listed

(4) See the Reference [ 7 ] listed at the bottom hereof.

(5) Ohlson [1980] also notices some importance in the relation between the date of failure and the date of disclosure of the financial statements.

in the Toko Stock Exchange of whom financial data for the three years before failure are fully available. Here, " pair sampling " means to select a nonfailed firm for each failed firm on the basis that (1) it belongs to the same industry, (2) it had a substantially same fiscal year system and (3) it has a similar asset size. Altman, Altman et al., Deakin, Wilcox and Beaver also employed pair sampling. Its purpose is to eliminate industry, time period and asset size effects and to find out differences, if any, among the sample firms caused by any other factors. Therefore, if any of the sampling bases itself is an excellent predictor of failure—where, for example, different industries show distinguishedly different rates of bankruptcy occurrences—such factor could in no way be reflected in the findings of the study.(6)

Asset size was measured based on the total assets shown in the balance sheet. As a result of the sampling, the average asset size during the first year before failure was ¥11.3 billion (about $47.1 million)(7) for the failed group, ranging from ¥0.4 to 162.1 billion ($1.6 to 675.4 million), while it was ¥12.5 billion ($52.1 million) for the nonfailed group, ranging from ¥1.1 to 78.3 billion ($4.6 to 326.3 million). As a result of the " T " Test, no significant difference in the mean values was found between these two groups, while some significant differences were noticed as a result of the Mann-Whitney's " W " Ranking Test. The maximum time lag we permitted between the balance sheet date of a failed firm and that of its non-failed mate was three months.

The list of the sample firms to be studied is given in Appendix 5.

### 3.3 Sampling for Firms for Verification Test (Secondary Sample)

Whether a prediction model is effective or not can be determined by a prediction accuracy test applying the model to firms, other than those constituting the initial sample, whose out-come (whether failed or not) is known.

There can be two ways in which to test the prediction accuracy of the model. One is to test it against the secondary sample using its financial statement data for fiscal years subsequent to those covered by the model (from 1962 to 1976 in this study)—noncontemporaneous test, and the other is to test it against the secondary sample using its financial statement data for the same fiscal years as those covered by the model—contemporaneous test. The former is effective to verify the universality of the model in light of time changes, while the latter is effective to find biases, if any, in the process of constructing the model, such as biases in selecting the initial sample. In this study the secondary sample has been so designed as to make both tests possible.

The secondary sample is composed of four failed firms which went bankrupt in 1977 and 44 nonfailed firms surviving as of 1977. (None of the firms constituting the secondary sample is included in the initial group.) Nine out of the 44 nonfailed firms were selected based on the three pair sampling criteria explained previously using the failed firms included in the secondary sample as their pair

(6) Pair sampling is discussed to some extent in the Reference [17] p. 60 "Appendix I, Pair Sampling ".

(7) Translated into dollars at an exchange rate of US$1.00=¥240.00.

mates. In case of those 9 firms, the year 1977 is their first year before failure for the purpose of this study. The remaining 35 firms were selected based on the three pair sampling criteria using the failed firms included in the initial sample as their pair mates. The period studied of those 35 firms is same as that of their respective failed pairs.

The fact that the number of the failed firms in the secondary sample is far less than that of the nonfailed is because in economic reality, the number of failed firms is very small as compared to the number of nonfailed firms and because the number of firms which actually went bankrups was unusually small in 1977. The firms constituting the secondary sample are listed in Appendix 6.

## 4. Development of Prediction Models

In this section 4 we will discuss the procedures we have taken to construct bankruptcy prediction models.

Figure 1 below illustrates how the corporate bankruptcy prediction models were developed.

### 4.1 Collection and Adjustment of Financial Statement Data

The data collected from the financial statements of the original sample firms selected for discriminant analysis and the secondary sample firms selected for verification test were adjusted to reflect the exceptions appearing in their respective audit reports.

Generally exceptions appearing in audit reports can be classified into the following three categories:

( i ) exception or finding that a certain item or items in the financial statements are not properly accounted for in a accordance with the generally accepted accounting principles (hereinafter referred to as "Paragraph 1 Exception");

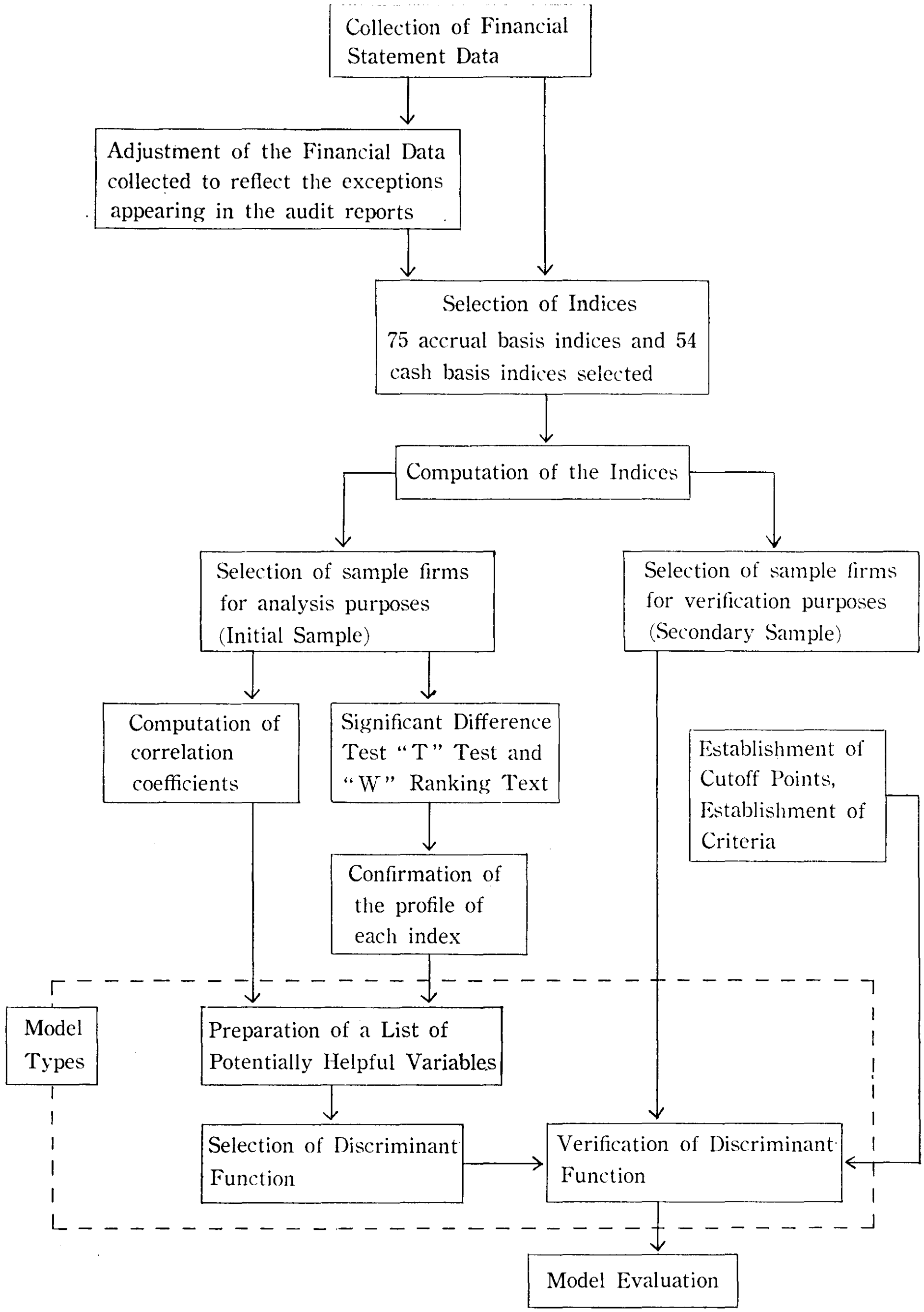
( ii ) exception or finding that a certain item or items in the financial statements are not properly accounted for in accordance with the accounting principles consistently applied in the previous years (hereinafter referred to as the "Paragraph 2 Exception"); and

(iii) exception of finding that the form of the financial statements does not conform to the requirements set forth in the Financial Statements Regulation (hereinafter referred to as "Paragraph 3 Exception").

We made adjustments to reflect Paragraphs 1 and 3 Exceptions only, but not Paragraph 2 Exceptions, because there were no appropriate methods to make proper adjustments to reflect Paragraph 2 Exceptions(8). The adjustments we made gave a greater impact on the earnings data of failed firms than nonfailed firms.
As a result of the "T" Test and "W" Ranking Test, a significant difference was noticed between failed and nonfailed firms with respect to both "Amount of

(8) For the detailed reasons for not making any adjustments to reflect the Paragraph 2 Exceptions, see pages 60-62 of "Examples of Adjustments to Reflect Exceptions in Audit Report" attached as Adpendix II to the refence [17] listed in the bottom hereof.

Fig. 1. Process Flow Chart for Development of Models.



Profit/Loss Adjusted to Reflect Exceptions" and "Accumulated Amound of Profit/Loss Adjusted to Reflect Exceptions" with a significance level of 5%.

## 4.2 Selection of Indices for Discriminant Analysis

As accrual base indices, 75 indices consisting of 61 ratios and 14 absolute amounts were selected.

The 61 ratios selected can be classified into five categories, i.e., (i) Earnings Indices; (ii) Financial Structure Indices; (iii) Production Indices; (iv) Profit Distribution Indices; and (v) Others. The absolute selected include sales, total assets and earnings. Three criteria were used to select the 75 accrual base indices. The first criterion was popularity-frequent appearance in literature. The second was that the indices performed well in one of the previous studies. The third was that the indices were expected to show some meaning-ful changes during three years prior to failure.

In addition to the prediction model based on the accrued base indices, we developed another model based on cash base indices to compare their respective prediction abilities with each other.

Case base indices are indices computed from cash base financial statement items. They are usually prepared by means of adjusting and converting accrual base financial data.

We selected 54 cash base indices consisting of 45 ratios and 9 absolute amounts. With few exceptions, they correspond to the accrual base indices mentioned above.

## 4.3 Development of Discriminant Functions

4.3.1 Prediction Model Types

The maximum number of variables which the computer program we have selected permits us to use for discriminant analysis is 25.(9) If each index requires three variables—a case where for example Current Ratio for each of the three years before failure is available, the maximum number of indices we can use for any discriminant model is eight, which altogether produce 24 variables. It is true that the more variables we can use for discriminant function, the greater discriminant efficiency the discriminant function could have. Therefore we have decided to develop discriminant models each using 24 variables.(10)

One can develop several different types of prediction models using different types of financial statement data and indices. In other words, (i) which financial statement data he will use, nonadjusted data or those adjusted to reflect the exceptions appearing in the audit report; (ii) which financial indices he will use, accrual base indices or cash base indices; (iii) whether he will use index values for three

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(9) BMD 04 M: BMD 04 M is a computer program designed to make dichotomous classification using multiple discriminant function consisting of $p$ variables ($2 \leq p \leq 25$).

(10) We did not reduce the number of independent variables, because we thought that reducing the number of independendint variables to be used would not result in substantially reducing the cost of research including computer data processing fees and that the demerit accruing from reducing their number would be greater than the demerit of possible multicolinearity accruing from using too many variables.

Fig. 2. 17 Prediction Models Used for the Study.

| Materials Studied | Data Used | Period Before Failure Covered | Indices | Model Code Name |
|---|---|---|---|---|
| Accrual Base Financial Statements | Nonadjusted Data | 3 years | Ratios | (1) |
| | | | Ratios/Absolute Amounts | (2) |
| | | 1st year | Ratios | (3) |
| | | | Ratios/Absolute Amounts | (4) |
| | Adjusted Data | 3 years | Ratios | (5) |
| | | | Ratios/Absolute Amounts | (6) |
| | | 1st year | Ratios | (7) |
| | | | Ratios/Absolute Amounts | (8) |
| Cash Base Financial Statements | Nonadjusted Data | 3 years | Ratios | (9) |
| | | | Ratios/Absolute Amounts | (10) |
| | | 1st year | Ratios | (11) |
| | | | Ratios/Absolute Amounts | (12) |
| | Adjusted Data | 3 years | Ratios | (13) |
| | | | Ratios/Absolute Amounts | (14) |
| | | 1st year | Ratios | (15) |
| | | | Ratios/Absolute Amounts | (16) |
| Accrual and Cash Bases Financial Statements | Adjusted Data | 3 years before failure | Ratios/Absolute Amounts | (17) |

years before failure or only for the first year before failure; or (iv) whether he will use as indices only ratios or a combination of ratios and absolute amounts. Combination of (i), (ii), (iii) and (iv) above can produce 16 different model types. We developed a discriminant function for each of the 16 model types. In addition we also developed a discriminant function to be used for the seventeenth model type which uses both ratios and absolute amounts derived from adjusted accrual base and cash base financial statement data for three years before failure, to compare its discriminating power with the other 16 models.(11) Thus, we established 17 model types altogether. Those 17 model types are shown in Figure 2.

4.3.2. Selection of Discriminant Functions

In the course of developing a discriminant function for each of the 17 model types, we established and utilized the following criteria to select the most appropriate variables to be used in such function:

(i) that they have the ability to discriminate one group from another;
(ii) that they are easy to measure;
(iii) that the smaller their inter-correlations the better.

The first criterion is quite natural and essential for the purpose of developing discriminant functions having predictive ability. In this study we used the "T" Test for testing the difference, if any, between the failed group and the nonfailed group with respect to the mean values of each ratio or index, and the "W" Ranking Test for testing the difference, if any, between the two groups in their distribution, so that we could select those indices and ratios which shows the most significant difference between the two groups.

We see no problem in applying the second criterion to financial statement data indices, because under the current disclosure system users of financial statements are assumed to have the ability to make financial analysis.

The third criterion was employed to ensure diversity in the information used for the discriminant analysis. We believe that using variables having relatively less inter-correlations will make a greater contribution to the improvement of the discriminating power of a discriminant function than using those having relatively high inter-correlations.(12)

Thus, we tried to select as variables to be used with discriminant functions those indices and ratios which show the most significant differences between the failed and nonfailed groups in their mean values and distributions, and which have the smallest inter-correlations.

(11) If one wishes to ascertain strictly the predictive ability of models using both accrual base and cash base financial statements, he can establish eight models through combination of the methods (i), (iii) and (iv) above.

(12) The discriminant efficiency of a discriminant function which comprises two variables is as follows:

where $D_2^2$=Discriminant efficiency
$\bar{x}_i^{(1)}$=Mean of $i$ variable in the first group
$\bar{x}_i^{(2)}$=Mean of $i$ variable in the second group
$\alpha$=Sample in the first group
$\beta$=Sample in the second group
$i, j$=Variable
$r(r_{ij})$=Correlation matrix
$n_1$=Number of samples in the first group

However we encountered cases where we could not reduce the number of variables to the maximum limit permitted by the computer program, 25, simply applying these two requirements to the 75 accrual base indices or ratios and 54 cash base indices or ratios initially selected and computed. So, we first selected variables which satisfy the two requirements. (The variables so selected are hereinafter referred to as "Potentially Useful Variables".) Then we prepared several combinations of Potentially Useful Variables within the said limit. A discriminant function was then set up for each of the combinations. The discriminant functions were then tested for discriminant efficiency as determined by Mahalanobis' square distance between the respective barycenters of the two groups to choose a discriminant function having the highest discriminant efficiency for each of the 17 prediction model types. The 17 discriminant functions thus selected are shown in Table 1 below.

4.3.3 Comparative Analysis of Prediction Model Types

The results of a comparative analysis we have conducted of the prediction model types will be discussed in this subsection 4.3.3.

(1) The model types using adjusted financial statement data outperformed those using nonadjusted financial statement data in discriminant efficiency in six model type pairs out of eight (Model Code 1<5, 2<6, 3>7, 4<8, 9>13, 10<14, 11<15, 12<16). Thus, it may be safe to say that prediction models using adjusted financial statement data have greater prediction ability than those using nonadjusted financial statement data.

(2) The model types using accrual base indices or ratios outperformed those using cash base ones in seven model type pairs out of eight (Model Code 1>9, 2>10, 3>11, 4>12, 5>13, 6>14, 7<15, 8>16). Thus, it may be safe to say that prediction models using accrual base indices or ratios have greater prediction ability than those using cash base ones.

(3) The model types using financial statement data for three years before failure outperformed those using financial statement data for only the first year before failure in all eight model type pairs (Model Code 1>3, 2>4, 5>7, 6>8, 9>11,

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$n_2$=Number of samples in the second group

$$d_i=\bar{x}_i^{(1)}-\bar{x}_i^{(2)}$$

$$S_{ij}^{(1)}=\sum_{\alpha}^{n1}(x_{\alpha i}^{(1)}-\bar{x}_i^{(1)})(x_{\alpha j}^{(1)}-\bar{x}_j^{(1)})$$

$$S_{ij}^{(2)}=\sum_{\beta}^{n2}(x_{\beta i}^{(2)}-\bar{x}_i^{(2)})(x_{\beta j}^{(2)}-\bar{x}_j^{(2)})$$

$$V_{ij}=(S_{ij}^{(1)}+S_{ij}^{(2)})/(n_1+n_2-2)$$

and if the inverse matrix of $V(V_{ij})$ is $V^{-1}(V^{ij})$,

$$D_2^2=V^{11}d_1^2+V^{22}d_2^2+2V^{22}d_1d_2=(V_{22}d_1^2+V_{11}d_2^2-2V_{12}d_1d_2)/(V_{11}V_{12}-V_{12}^2)$$

if standardization is made so that $x_1x_2$ will become variance 1,

$$V_{11}=V_{22}=1 \quad V_{12}=r_{12}$$

$$\therefore D_2^2=(d_1^2+d_2^2-2r_{12}d_1d_2)/(1-r_{12}^2)$$

No matter how great the difference—significant difference—between the means of the two groups, $|d_1|$, $|d_2|$ is, $D_2^2$ does not necessarily improve as long as $|r_{12}|$ is big *and* $r_{12}d_1d_2$ is positive. Therefore if $r_{12}d_1d_2$ is positive (or if the samples are distributed along the axis of the discriminant function) the smaller $|r_{12}|$ is, the better. On the other hand, if $r_{12}d_1d_2$ is negative (or if the samples are distributed along its orthogonal axis), the larger $|r_{12}|$ is, the better.

Table 1. Discriminant Efficiency Test of Bankruptcy Prediction Models

| Model Code Name | Model Type | Variable (*) (24 variables) | Discriminant Efficiency (Mahalanobis' Square Distance) | "F" Test Value (Significance Level) | Mean Above: Nonfailed Below: Failed | Standard Diviation Above: Nonfailed Below: Failed |
|---|---|---|---|---|---|---|
| 1 | Accrual Base Indices<br>Nonadjusted Data<br>3 years Before Failure<br>Ratios | 2 18 19 21 25<br>28 48 50 | 5.02424 | 2.53006<br>(0.005) | −0.01310<br>−0.08487 | 0.03284<br>0.03118 |
| 2 | Accrual Base Indices<br>Nonadjusted Data<br>3 years Before Failure<br>Ratios/Absolute Amounts | 2 18 21 25 26<br>28 48 68 | 5.90251 | 2.97232<br>(0.005) | −0.03922<br>−0.12354 | 0.03554<br>0.03386 |
| 3 | Accrual Base Indices<br>Nonadjusted Data<br>1st year Before Failure<br>Ratios | 1 2 9 14 15<br>16 17 19 21 22<br>24 25 26 28 29<br>34 39 48 50 52<br>53 57 58 64 | 4.20827 | 2.11916<br>(0.025) | −0.71625<br>−0.77679 | 0.02430<br>0.03377 |
| 4 | Accrual Base Indices<br>Nonadjusted Data<br>1st year Before Failure<br>Ratios/Absolute Amounts | 1 2 9 14 16<br>17 18 19 21 22<br>25 26 28 34 39<br>48 50 53 57 58<br>62 66 68 78 | 5.31191 | 2.67492<br>(0.005) | −0.33131<br>−0.40720 | 0.02856<br>0.03675 |
| 5 | Accrual Base Indices<br>Adjusted Data<br>3 years Before Failure<br>Ratios | 2 18 19 21 25<br>28 29 48 | 5.47912 | 2.75913<br>(0.005) | −0.05438<br>−0.13266 | 0.03327<br>0.03361 |
| 6 | Accrual Base Indices<br>Adjusted Data<br>3 years Before Failure<br>Ratios/Absolute Amounts | 2 18 21 25 26<br>28 48 68 | 6.11596 | 3.07982<br>(0.005) | −0.06249<br>−0.14986 | 0.03636<br>0.03427 |
| 7 | Accrual Base Indices<br>Adjusted Date<br>1st year Before Failure<br>Ratios | 1 2 9 14 15<br>16 17 19 21 22<br>24 25 26 28 29<br>34 39 48 50 52<br>53 57 58 62 | 3.50429 | 1.76466<br>(0.050) | 0.24946<br>0.19504 | 0.02484<br>0.03055 |
| 8 | Accrual Base Indices<br>Adjusted Data<br>1st year Before Failure<br>Ratios/Absolute Amounts | 1 2 9 14 16<br>17 19 21 22 25<br>26 28 34 39 48<br>50 53 57 58 62<br>66 68 73 75 | 6.03178 | 3.03743<br>(0.055) | 0.23713<br>0.15096 | 0.03198<br>0.03793 |
| 9 | Cash Base Indices<br>Nonadjusted Data<br>3 years Before Failure<br>Ratios | ( 1) ( 2) ( 4) ( 5) (17)<br>(26) (33) (34) | 4.12645 | 2.07796<br>(0.025) | 0.55309<br>0.49414 | 0.02383<br>0.03342 |
| 10 | Cash Base Indices<br>Nonadjusted Data<br>3 years Before Failure<br>Ratios/Absolute Amounts | ( 1) ( 2) ( 4) ( 5) (20)<br>(34) (49) (50) | 3.39374 | 1.70899<br>(0.100) | −0.05447<br>−0.10296 | 0.02157<br>0.03033 |

Table 1. (Continues)

| Model Code Name | Model Type | Variable (*) (24 variables) | Discriminant Efficiency (Mahalanobis' Square Distance) | "F" Test Value (Significance Level) | Mean Above: Non-failed Below: Failed | Standard Diviation Above: Non-failed Below: Failed |
|---|---|---|---|---|---|---|
| 11 | Cash Base Indices Nonadjusted Data 1st year Before Failure Ratios | ( 1) ( 2) ( 3) ( 4) ( 5) ( 7) ( 8) (11) (13) (17) (18) (19) (20) (22) (25) (26) (34) (35) (37) (38) (39) (40) (41) (43) | 3.12771 | 1.57502 (0.100) | −0.25561 −0.30028 | 0.02448 0.02601 |
| 12 | Cash Base Indices Nonadjusted Data 1st year Before Failure Ratios/Absolute Amounts | ( 1) ( 2) ( 3) ( 4) ( 5) ( 8) (11) (13) (17) (18) (19) (20) (22) (25) (34) (35) (37) (38) (39) (40) (41) (43) (50) (54) | 2.98258 | 1.50194 (None) | −0.14775 −0.19036 | 0.02293 0.02630 |
| 13 | Cash Base Indices Adjusted Data 3 years Before Failure Ratios | ( 1) ( 2) ( 4) ( 5) (17) (26) (33) (34) | 3.96319 | 1.99575 (0.050) | 0.40526 0.34864 | 0.02258 0.03326 |
| 14 | Cash Base Indices Adjusted Data 3 years Before Failure Ratios/Absolute Amounts | ( 1) ( 2) ( 4) ( 5) (20) (34) (49) (50) | 3.69434 | 1.86036 (0.050) | −0.10490 −0.15768 | 0.02490 0.02980 |
| 15 | Cash Base Indices Adjusted Data 1st year Before Failure Ratios | ( 1) ( 2) ( 3) ( 4) ( 5) ( 7) ( 8) (11) (13) (17) (18) (19) (20) (22) (25) (26) (34) (35) (37) (38) (39) (40) (41) (43) | 3.60605 | 1.81590 (0.050) | 0.02978 −0.02174 | 0.02488 0.02920 |
| 16 | Cash Base Indices Adjusted Data 1st year Before Failure Ratios/Absolute Amounts | ( 1) ( 2) ( 3) ( 4) ( 5) ( 8) (11) (13) (17) (18) (19) (20) (22) (25) (34) (35) (37) (38) (39) (40) (41) (43) (50) (54) | 3.44804 | 1.73633 (0.100) | −0.08511 −0.13437 | 0.02379 0.02901 |
| 17 | Accrual Base Indices Cash Base Indices Adjusted Data 3 years Befere Failure Ratios/Absolute Amounts | 21 25 28 48 68 ( 1) (34) (49) | 6.22992 | 3.13721 (0.005) | 0.06469 −0.02431 | 0.03353 0.03767 |

(*) Code numbers in parentheses denote that the variables represented thereby are those based on cash base financial statement date, and those without parentheses denote that the variables represented thereby are those based on accrual base financial statement data. For identificantion of the valuables, see Appendices 1 and 2.

10>12, 13>15, 14>16). Thus, it may be safe to say that prediction models using financial statement data for three years before failure have greater prediction ability than those using financial statement data for only the first year before failure.

(4) When comparing prediction models using only ratios with those using a combination of ratios and absolute amounts, entirely different results were obtained

between the model pairs using absolute amounts and/or ratios derived from accrual base financial statement data and the model pairs using those derived from cash base financial statement data.

The models using a combination of ratios and absolute amounts outperformed those using ratios alone in all four model pairs using accrual base financial statement data (Model Code $1<2$, $3<4$, $5<6$, $7<8$). On the other hand, however, the models using ratios alone outperformed those using a combination of ratios and absloute amounts in all four model pairs using cash base financial statement data (Model Code $9>10$, $11>12$, $13>14$, $15>16$).

Thus, it can be said that when accrual base financial statement data are used, models using a combination of ratios and absolute amounts have greater prediction ability than do those using ratios alone and that when cash base financial statement data are used, models using ratios alone have greater prediction ability than those using a combination of ratios and absolute amounts.

(5) We then tested each of the 17 discriminant functions for the dichotomous classification ability—the ability to discriminate failed firms from nonfailed firms. For this purpose, we used the " F " Test with a null hypothesis that " this variable has no dichotomous classification ability."

As a result of the test, the null hypothesis was rejected with respect to all prediction models except Model 12—a model which uses a combination of ratios and absolute amounts derived from nonadjusted cash base financial statement data for the first year before failure—with a significance level of 10% or more. Therefore it may be safe to say that all discriminant functions except that for Model 12 have dichotomous classification ability. Particularly, Models 1, 2, 4, 5, 6, 8 and 17 have distinguished dichotomous classification ability, since the null hypothesis was rejected with respect to them at a significance level of 0.5%.

(6) Model 6—a model which uses a combination of ratios and absolute amounts derived from adjusted accrual base financial statement data for three years before failure—showed the highest discriminant efficiency among Models 1 through 16. But Model 17—a model which as mentioned earlier we have tentatively developed and which uses a combination of ratios and absolute amounts derived from adjusted financial statement data, both accrual and cash bases, for three years before failure—showed slightly higher discriminant efficiency than Model 6, indicating the possibility of enhancing the discriminant efficiency by use of both accrcal and cash bases financial statement data. It is still premature, however, to make any definite conclusion that models using both accrual and cash bases financial statement data have better discriminant efficiency that those using either accrual or cash base financial statement data. It is still necessary, as mentioned earlier, to develop additional 8 models using both accrual and cash bases financial statement data.

## 5. Verification Test of Prediction Models

### 5.1 Establishment of Cutoff Points

To make bankruptcy predictions using a discriminant function, it is necessary to establish at least one cutoff point in the scale Z scores where a firm will be classified as either failed or nonfailed based on its general discriminant score. In this study we established several well-grounded cutoff points for each prediction model under assumption that users of discriminant functions would make their own decisions in overall consideration of conservative and optimistic points, so that the model could provide them with different predictions depending on which cutoff point they would use.

We established six cutoff points, $C_A$ through $C_F$.

(A) Cutoff Point $C_A$; the point which will minimize the overall probability of misclassification, assuming that both populations have normal distribution. Cutoff Point $C_A$ can be determined by the formula 1 below:

$$\frac{(C_A-\mu_B)^2}{\sigma_B^2}=\frac{(C_A-\mu_A)^2}{\sigma_A^2} \qquad \cdots (1)$$

where $\mu_B$=Mean of the failed firms
$\mu_A$=Mean of the nonfailed firms
$\sigma_B^2$=Variance of the failed firms
$\sigma_A^2$=Variance of the nonfailed firms

(B) Cutoff Point $C_B$; the point at which the probability of the Type I error—misclassification of failed firms as nonfailed firms—will become 1%, assuming that both populations have normal distribution. Cutoff Point $C_B$ can be determined by the formula 2 below:

$$\frac{C_B-\mu_B}{\sigma_B}=Z_{0.01}=2.326 \qquad \cdots (2)$$

if

$$F(z')=\int_{-\infty}^{z'}\frac{1}{\sqrt{2\pi}}\exp^{(-1/2)z^2}dz$$

(C) Cutoff Point $C_C$; the point at which the probability of the Type I error will become 5%, assuming that both populations have normal distribution. Cutoff Point $C_C$ can be determined by the formula 3 below:

$$\frac{C_C-\mu_B}{\sigma_B}=Z_{0.05}=1.645 \qquad \cdots (3)$$

(D) Cutoff Point $C_D$; the point which will minimize the number of firms misclassified. This point can be determined by the formula 4 below:

$$C_D=(Z_A+Z_B)/2 \qquad \cdots (4)$$

where, $Z_A=Z$ score of the nonfailed firm which has been correctly classified as nonfailed and whose $Z$ score is the smallest among the nonfailed firms correctly classified.
$Z_B=Z$ score of the failed firm which has been correctly classified as failed and whose $Z$ score is the largest among the failed firms correctly classified.

(E) Cutoff Point $C_E$; the point at which the number of the failed firms misclassified as nonfailed will become zero. This point can be determined by the formula 5 below:

$$C_E = Z_{B'} \qquad \cdots (5)$$

where, $Z_{B'} = Z$ score of the failed firm whose $Z$ score is the largest among all failed firms

(F) Cutoff Point $C_F$; the point at which the number of the nonfailed firms misclassified as failed (Type II error) will become zero. This point can be determined by the formula 6 below:

$$C_F = Z_{A'} \qquad \cdots (6)$$

where, $Z_{A'} = Z$ score of the nonfailed firm whose $Z$ score is the smallest among all nonfailed firms

Our study of the classification ability of each of the six cutoff points indicates that if one employs Cutoff Point $C_B$, $C_C$ or $C_E$, the Type I error will decrease, while the Type II errors will increase. Therefore he would miss more investment opportunities than had he used any one of the other three cut-off points. In that sense Cutoff Points $C_B$, $C_C$ and $C_E$ can be described as conservative cutoff points. On the contrary, if he uses Cutoff Point $C_F$, the Type I errors will increase, while the Type II error will decrease. In that sense this cutoff point can be described as optimistic or risky cutoff point. Cutoff Points $C_A$ and $C_D$ come in between conservative and optimistic. Anyway, it should be remembered that meaningful cutoff points could not be established unless the probabilities of failure and nonfailure and the differences in the nature and magnitude of the cost of misclassiffcation between the Type I and Type II errors are taken into consideration. The prediction models we have developed will be useful particularly to those investors who have limited time within which to investigate the credit standing of a large number of firms to make investment decisions. It is practically impossible for those investors to check the credit or investment worthiness of all firms in detail. However, if they use the prediction models we have developed, they can find out without substantial difficulty those firms which need detail financial analysis. For such limited purpose, it will be useful to delineate a grey area, such as the area between the Cutoff Points $C_E$ and $C_F$, where prediction of failure or nonfailure cannot be mechanically made, rather than to establish a single cutoff point to make clear-cut classification of firms into either failure or nonfailure.

### 5.2 Criteria for Evaluating Prediction Ability

We applied each of the 17 discriminant functions to the verification (secondary) sample, using the six different cutoff points, to see if it can make correct predictions. To determine the prediction ability ranking of the 17 discriminant functions by cutoff points, the following two criteria were employed:

(i) that the probability of the Type I error is small; and

(ii) that the probability of the Type II error is small.

The first priority was given to the criterion (i), and the second priority to the criterion (ii). Their prediction abilities were compared with each other by applying the criterion (i) first. If as a result of such comparison any two or more discrim-

Table 2. Ranking in Terms of Prediction Ability

| Cutoff Proints / Model Code Name | Initial Sample | | | | | | Secoudary Sample | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | A | B | C | D | E | F | A | B | C | D | E | F |
| 1 | 3 | 4 | | 3 | 4 | | | 2 | | | | 4 |
| 2 | | 2 | 1 | | 1 | | 3 | 1 | 4 | 3 | 1 | 4 |
| 3 | | | | | | | | | 1 | | 3 | |
| 4 | | | | | | | | | 4 | | 4 | |
| 5 | 1 | | 3 | 1 | | 2 | 4 | 2 | | | | |
| 6 | 3 | 1 | 2 | 4 | 1 | 4 | 1 | 2 | | 2 | 2 | 2 |
| 7 | | | | | 4 | 1 | | | 1 | 4 | | |
| 8 | | | | | | | 4 | 2 | | | | |
| 9 | | | | | | | | | | | | 3 |
| 10 | | | | | | | | | | | | |
| 11 | | | | | | | | | | | | |
| 12 | | | | | | | | | | | | |
| 13 | | | | | | | | | | | | |
| 14 | | | | | | | | | | | | |
| 15 | | | | | | | | | | | | |
| 16 | | | | | | | | | | | | |
| 17 | 2 | 3 | 3 | 2 | 3 | 2 | 1 | 2 | 3 | 1 | | 1 |

(*) Only the first through fourth places in the ranking are shown in this table.

inant functions ranked pari passu, we then applied the criterion (ii) to determine the ranking among them. The reason why we placed the first priority on the criterion (i) was because we thought that the cost of misclassifying failed firms as nonfailed would be far greater than that of misclassifying nonfailed firms as failed.

### 5.3 Results of Prediction Ability Test

To determine the ranking of the 17 prediction models in terms of the ability to make correct classifications, each model was tested using the six different cutoff points. The ranking was determined in accordance with the two criteria mentioned in paragraph 5.2 relating to the number of the Type I errors and that of the Type II errors made by such test. The ranking of the 17 models as so determined using the initial and secondary samples are shown in Table 2.

Models 6 and 17 showed relatively higher prediction ability regardless of the cutoff point used. These two models invariably use adjusted financial statement data for three years before failure. More precisely, Model 6 used both ratios and absolute amounts obtained from the adjusted accrual base financial statement data, and Model 17 both ratios and absolute amounts obtained from both adjusted accrual and cash bases financial statement data.

Though it seems at the first glance that Models 6 and 17 have almost equa. prediction abilities, we have decided to use the Model 17 as the model for its relatively small variance in ranking caused by the use of the different cutoff points. This observation coincides with the findings based on discriminant efficiency discussed in subparagraph 4.3.3 above.

## 5.4 Factors Involved in Misclassification

The accuracy of the best model, Model 17, was simulated on the initial sample of 36 pairs and secondary samples of 4 failed and 44 nonfailed firms based on various cutoff points. The results of the simulation is shown in Table 3. In the simulation of the model on the secondary samples, nine nonfailed firms—Nippon Crucible, Toshin Steel, The Weston, Nitchitsu Industries, Mitsui Mining, Sumitomo Coal Mining, Hokkaido Colliery & Steamship, Jujo Paper Mfg. and Koike Sanso Kogyo—are always misclassified as failed (Type II errors), regardless of the cutoff points used.

When Cutoff Point $C_A$ was used, three failed firms (Yamato Woolen Textile

Table 3. Results of Prediction Ability Test of Best Prediction Model

| Cutoff Points | | Secondary Sample | | Initial Sample | | |
|---|---|---|---|---|---|---|
| | | Numbers | Ratios | Numbers | Ratios | |
| $C_A$ | Type I Error | 0 | 0 | 3 | 8.3 | 6.9 |
| | Type II Error | 9 | 20.5 | 2 | 5.6 | |
| $C_B$ | Type I Error | 0 | 0 | 0 | 0 | 26.4 |
| | Type II Error | 19 | 43.2 | 19 | 52.8 | |
| $C_C$ | Type I Error | 0 | 0 | 1 | 2.8 | 13.9 |
| | Type II Error | 13 | 29.5 | 9 | 25.0 | |
| $C_D$ | Type I Error | 0 | 0 | 1 | 2.8 | 5.6 |
| | Type II Error | 9 | 20.5 | 3 | 8.3 | |
| $C_E$ | Type I Error | 0 | 0 | — | — | 22.2 |
| | Type II Error | 14 | 31.8 | 16 | 44.4 | |
| $C_F$ | Type I Error | 0 | 0 | 6 | 16.7 | 8.4 |
| | Type II Error | 9 | 20.5 | — | — | |

(*) Numbers represent the number of misclassified firms, and ratios represent percentage of misclassificantion ratios.

Mfg., Taio Seishi and Japan Special Steel) and two nonfailed firms (Nippon Stainless Steel and Nitto Metal Industry) were misclassified on the initial sample. Accordingly, we attempted to identify the major factors causing our prediction model to make such misclassifications, and found:

(1) that the industries to which those misclassified firms belong had different characteristics as compared to other manufacturing industries in general and that the ratios and indices of those misclassified firms were substantially different from those of the other firms in the samples;

(2) that certain qualitative factors not appearing in the financial statements contributed greatly to bankruptcy; and

(3) that some of the nonfailed firms misclassified as failed were in fact failed firms but for some social and/or political reasons were kept in business as solvent firms.

A further investigation of the failed firms which were misclassified as nonfailed revealed that Taio Seishi had gone bankrupt due to internal troubles among its top executives, their loss of interest in managing the firm as evidenced by the sale of a substantial part of their shares and the lack of unity among its major banks in rescue financing programs and that in case of Japan Special Steel, internal troubles among its top executives, a chaotic state in its management, the burden of its huge guarantee obligations relating to its affiliated companies' debts which had previously been hidden from the eyes of its major banks and the extremely poor financial position of its affiliated companies were the major causes of its bankruptcy. With respect to Yamato Woolen Textile Mfg., however, no such concrete qualitative factors or causes were found.

## 6. Concluding Remarks

Our study indicates that when one attempts to construct a model or models for predicting corporate bankruptcy in Japan using a discriminant analysis technique, he could develop discriminant functions having extremely high prediction ability, if he uses (i) financial statement data adjusted to reflect all exceptions, if any, appearing in the audit report; (ii) both accrual and cash bases financial statement data; (iii) both ratios and absolute amounts; and (iv) not variables for the first year bear before failure alone, but those for three years before fiilure. Among several models we constructed, we selected a model using six cutoff points, believing that it would be more practical to establish several cutoff scores and leave the choice of an appropriate cutoff score up to the decision of the individual users made in light of their own purposes for which the model would be used or the nature of the investment decisions they would be required to make, and to introduce and delineate a grey or unpredictable area or areas depending on the combination of cutoff scores. As a result of the verification test of the model, no Type I errors were found, regardless of the cutoff score used.

We believe that the accuracy of the model could be further improved by (i) identifying the qualitative factors, if any, contributing to failure or nonfailure and somehow incorporating those factors into the variables; (ii) if more sample failed and nonfailed firms become available, stratifying those sample firms into several groups according to industry and asset size and developing best suitable discriminant function for each of the groups; (iii) developing a discriminant function which uses as variables the deviations of the firm's ratios from industry means;(13) or (iv) using not only linear discriminant function, but also quadratic discriminant function.(14)

One must be very careful in making any prediction using a discriminant function developed to make dichotomous classification, when given sample objects can in fact be classified into more than two groups. Our study is based on an assumption that each of the sample firms belongs to either one of the two groups, the failed group and the nonfailed group. However, there may be cases where failed firms or nonfailed firms or both can be further classified into two or more subgroups sufficiently independent from each other.(15) If that is the case, the number of misclassifications will necessarily increase. This problem, however, could be resolved and the accuracy of prediction improved, by developing some composite ratios or indices, such as discriminant functions having trichotomous or polychotomous classification ability and constructing a new prediction model which can classify sample firms into three or more groups according to their scores of such composite ratios or indices.

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(13) See the reference [10] listed at the bottom hereof.

(14) See the reference [3] listed at the bottom hereof.

(15) In the study to which the reference [17] listed at the bottom hereof relates, the authors made a principal component analysis using a model which was substantially same as Model 6 in this study. In their study the authors presented hypotheses (i) that failed firms can be classified into two groups, a group having a poor financial structure and that having poor cash flow; and (ii) that included in failed firms are, though rare, those firms whose financial structure and case flow are not bad.

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## Appendix 1 Accrual Base Indices

1 Net Profit Before Taxes to Total Assets at the Beginning of the Year
2 Net Profit After Taxes to Sales
3 Cost of Sales to Sales
4 Cost of Materials to Sales
5 Labor Cost to Sales
6 Production Expenses to Sales
7 Selling and General Administration Expenses to Sales
8 Nonoperating Revenues to Sales
9 Nonoperating Expenses to Sales
10 Extraordinary Profit to Sales
11 Extraordinary Loss to Sales
12 Operating Profit to Sales

13 Operating Earnings to Sales
14 Ordinary Profit to Total Assets
15 Ordinary Profit to Sales
16 Ordinary Profit Before Financial Expenses to Sales

17 Current Ratio
18 Quick Ratio
19 Working Capital Ratio
20 Current Assets Ratio
21 Current Liabilities Ratio
22 Fixed Liabilities plus Net Worth to Fixed Assets
23 Fixed Assets Ratio
24 Fixed Liabilities plus Net Worth to Total Assets
25 Net Worth to Fixed Assets
26 Equity Ratio
27 Earned Surplus plus Special Reserves to Total Assets
28 Voluntary Reserves plus Unappropriated Surplus to Assets
29 Borrowed Capital Ratio

30 Total Assets Turnover Ratio
31 Cash on Hand and Cash at Bank Turnover Ratio
32 Trade Receivables Turnover Ratio
33 Inventory turnover Ratio
34 Raw Materials Turnover Ratio
35 Work-in-Process Turnover Ratio
36 Products Turnover Ratio
37 Fixed Assets Turnover Ratio
38 Trade Payables Turnover Ratio

39 Value Added to Sales
40 Capital Investment Efficiency Ratio
41 Facilities Utilization Ratio
42 Sales per Employee
43 Labor Productivity
44 Capital Intension Ratio
45 Investment Efficiency Ratio
46 Labor Equipment Ratio
47 Personnel Expenses to Sales
48 Borrowed Expenses to Sales
49 Labor Cost and Personnel Expenses to Value Added
50 Borrowed Expenses to Value Added
51 Earnings to Value Added

52 Cash Flow/Total Debt
53 No Credit Interval
54 Sales Growth Ratio
55 Long-Term Accounts Receivable Ratio
56 Financial Expenses to Borrowed Capital

57 Tangible Fixed Assets Increase Ratio
58 Net Increase of Tangible Fixed Assets/Net Increase of Long-Term Capital Ratio
59 Net Increase in Net Working Capital
60 Net Increase in Notes and Bills Discounted and Current Borrowings
61 Current/Long-Term Borrowings Ratio
62 Ordinary Profit/Loss Ratio
63 Lowest Closing Stock Price/Par Value Ratio

64 Sales
65 Total Assets
66 Net Profit After Taxes
67 Value Added
68 Earned Surplus
69 Cash on Hand and Cash at Bank
70 Fixed Assets
71 Other Investments
72 Working Capital
73 Ordinary Profit

74 Amount of Profit/Loss Adjusted to Reflect Exceptions
75 Accumulated Amount of Profit/Loss Adjusted to Reflect Exceptions

## Appendix 2 Cash Base Indices

(1) Increase in Residual Value to Cash Sales
(2) Expenses Outlaid to Cash Sales
(3) Interest and Dividends Received to Cash Sales
(4) Cash Proceeds Realized from Sale of Fixed Assets to Cash Sales
(5) Cost of Capital to Cash Sales
(6) Cash Purchases to Cash Sales
(7) Personnel Expenses Outlaid to Cash Sales
(8) Expenses Outlaid to Cash Sales
(9) Net Operating Income to Cash Sales
(10) Net Operating and Other Income to Cash Sales
(11) Gross Earnings to Cash Sales
(12) Net Operating Income to Operating Capital
(13) Net Operating and Other Income to Total Assets

(14) Long-Term Capital to Long-Term Investment
(15) Long-Term Investment to Total Assets
(16) Long-Term Capital to Total Assets
(17) Net Worth to Long-Term Investment
(18) Net Worth to Total Assets
(19) Residual Value to Total Assets
(20) Borrowed Capital to Total Assets

(21) Cash Sales to Total Assets

(22) Cash Sales to Cash on Hand and Cash at Bank
(23) Cash Sales to Net Increase in Trade Receivables
(24) Cash Sales to Net Increase in Inventory
(25) Cash Sales to Long-Term Investment

(26) Value Added Ratio
(27) Capital Investment Efficiency Ratio
(28) Facilities Utilization Ratio
(29) Investment Efficiency Ratio
(30) Labor Distribution Ratio
(31) Financial Expenses Distribution Ratio
(32) Net Worth Distribution Ratio

(33) Ordinary Profit/Loss Ratio
(34) Ordinary Profit to Total Assets
(35) Increase in Residual Value to Total Liabilities
(36) Cash Sales Growth Ratio
(37) Tangible Fixed Assets Increase Ratio
(38) Net Increase in Tangible Fixed Assets to Net Increase in Long-Term Capital
(39) Cash Sales to Operating and Other Income
(40) Cash Purchases to Operating and Other Expenses Outlaid
(41) Personnel Expenses Outlaid to Operating and Other Expenses Outlaid
(42) Expenses Outlaid to Operating and Other Expenses Outlaid
(43) Cost of Capital to Net Operating and Other Income
(44) Net Increase in Tangible Fixed Assets to Net Increase in Short-term Borrowed Capital
(45) Trade Payables to Cash Purchases

(46) Cash Sales
(47) Total Assets
(48) Increase in Residual Value
(49) Value Added
(50) Residual Value
(51) Net Increase in Cash on Hand and Cash at Bank
(52) Long-Term Investment
(53) Investment and Other Assets
(54) Operating Profit/Loss

## Appendix 3 Cash Base Indices Calculation Formulae

(a.1) : Cash Sales = Sales − net increase in trade receivables + net increase in advance received

(a.2) : Interest and Dividends Received = Interest received + dividends received + interest on installment sales − net increase in accrued income + net increase in deferred income

(a.3) : Cash Proceeds Realized from Sale of Fixed Assets = Cash proceeds realized from sale of fixed assets + cash proceeds realized from sale of marketable securities (a.4) : Funds Generated by Net Decrease in Short-Term Loans=Net decrease in short-term loans+net decrease in marketable securities

(a.5) : Operating and Other Income=(a.1)+(a.2)+(a.3)+(a.4)

(b.1) : Cash Purchase=Total purchases of raw materials and merchandise−net increase in trade payables+net increase in advance payments

(b.2) : Personnel Expenses Outlaid=Salaries, wages, bonuses and allowances paid to employees and included in selling and general administration expenses+labor cost included in manufacturing cost+amount credited to employees severance pay reserve account+severance pay actually paid−net increase in accrued bonuses−net increase in employees severance pay reserve−net increase in employees' deposits

(b.3) : Expenses Outlaid Excluding Taxes=Selling and general administration expenses (excluding taxes and personnel expenses)+expenses included in manufacturing cost+net increase in prepaid expenses−net increase in miscellaneous accounts payable−net increase in accrued expenses +expenses outlaid for deferred assets

(b.4) : Taxes Paid=Excise taxes+franchise taxes+corporation tax paid during the year+other taxes, rates and dues

(b.5) : Funds Outlaid Due to Net Increase in Short-Term Loans=Net increase in short-term loans+net increase in marketable securities

(b.6) : Expenses Outlaid=(b.3)+(b.4)

(b.7) : Cost and Expenses Outlaid=(b.1)+(b.2)+(b.6)

(b.8) : Operating and Other Expenses=(b.1)+(b.2)+(b.5)+(b.6)

(c.1) : Cost of Capital=Dividends paid+interest paid+bond premiums paid+bond issue cost paid+stock issue cost paid

(d.1) : Net Operating Income=(a.1)−(b.1)−(b.2)−(b.3)

(d.2) : Gross Earnings for the Year=(a.5)−(b.8)

(d.3) : Net Operating and Other Income=(d.2)−(c.1)

(d.4) : Increase in Residual Value=(d.3)−(original cost of tangible and intangible fixed assets disposed of during the year+original cost of investment and other assets converted into cash and collected during the year)

(e.1) : Long-Term Investment=Tangible fixed assets+intangible fixed assets+ investment and other assets (including long-term loans and marketable securities)—construction in process

(e.2) : Total Assets=Cash on hand and cash at bank+(e.1)

(f.1) : Short-Term Borrowed Capital=Short-term borrowings+portions of long-term borrowings and bonds becoming due within one year+notes payable issued for the payment for and accounts payable for capital assets and included in current liabilities+notes and bills discounted

(f.2) : Long-Term Borrowed Capital=Bonds+long-term borrowings+long-term notes payable and accounts payable

(f.3) : Borrowed Capital=(f.1)+(f.2)

(f.4) : Invested Capital=Capital stock+proceeds from insurance of additional shares +capital reserve

(f.5) : Funds Raised=(f.3)+(f.4)

(f.6) : Residual Value Carried Forward=Accumulated (d.4) at the end of the previous year=(e.2) at the beginning of the year−(f.5) at the beginning

of the year
(f.7) : Residual Value=(f.6)+(d.4)
(f.8) : Total Capital=(f.5)+(f.7)=(e.2)

(1) "Net Increase" of any item represents the amount of such item at the end of the year less the amount of such item at the beginning of the year.
(2) Unless any specific reference is made to "at the beginning of the year" or "previous year", all figures, amounts and values to be used in the above calculation formulae are the figures, amounts and values at the end of or for the current year.
(3) For the purpose of those calculation formulae, "tangible fixed assets" or "intangible fixed assets" means the original cost of "tangible fixed assets" or "intangible fixed assets", as the case may be, before deduction of accumulated depreciation expenses.

**Appendix 4 Discriminant Function of Best Prediction Model**

| Variables | Year(s) before failure | | |
|---|---|---|---|
| | 3 ($x_{i1}$) | 2 ($x_{i2}$) | 3 ($x_{i3}$) |
| $x_{1j}$=Net worth to Fixed Assets | 0.01039 | 0.07658 | −0.01444 |
| $x_{2j}$=Current Liabilities Ratio | −0.05687 | 0.05147 | −0.03447 |
| $x_{3j}$=Voluntary Reserves plus Unappropriated Surplus to Total Assets | −0.040231 | 0.22167 | 0.13213 |
| $x_{4j}$=Borrowed Expenses to Sales | 1.00945 | −0.72363 | −0.34111 |
| $x_{5j}$=Earned Surplus | 0.00814 | −0.01366 | 0.00685 |
| $x_{6j}$=Increase in Residual Value to Cash Sales | 0.14522 | −0.03596 | 0.00545 |
| $x_{7j}$=Ordinary Profit to Total Assets | −0.13034 | 0.07848 | 0.02901 |
| $x_{8j}$=Value Added | 0.00031 | 0.00010 | −0.00007 |

$$x_{6j}=\frac{(d.4)}{(a.1)}$$

$$x_{7j}=\frac{(a.1)+(a.2)-(b.1)-(b.2)-(b.6)-(c.1)}{(e.2)\text{ at the Beginning of the Year}}$$

$$x_{8j}=(a.1)-(b.1)$$

## Appendix 5 Sample Firms for Analysis Purpose (Initial Sample)

| Industry | Failed Firm's Name | Date of Failure | Nonfailed Firm's Name |
|---|---|---|---|
| Mining | Shinkohatsu Mining | 1970 | Chugai Mining |
| | Kaijima Coal Mining | 1976 | Nittetsu Mining |
| | Nichiman Kogyo | 1964 | Matsushima Kosan |
| | Matsuo Mining | 1968 | Nitto Metal Industry |
| | Bandai Electric Express Railway | 1968 | Showa Mining |
| Construction | Giken Kogyo | 1970 | Hasegawa Komuten |
| Foods | Nagoya Seito | 1971 | Taito |
| | Shinsei Milk Industry | 1964 | Morinaga Milk Industry |
| | Fukuizumi Sake Distillation | 1964 | Toyo Jozo |
| | Monde Distilleries | 1972 | Yomeishu Seizo |
| Textiles | Yamato Woolen Textile Mfg. | 1974 | The Nankai Worsted Spinning |
| | Japan Textile Mfg. | 1965 | Toyo Seni |
| Pulp & Paper | Kohjin | 1975 | Nippon Pulp Industry |
| | Nippon Paper Mfg. | 1963 | Mishima Paper Manufacturing |
| | Taio Seishi | 1962 | Nippon Kakoh Seishi |
| | Dainippon Transparent Paper Mfg. | 1968 | Tokyo Cellophane |
| Iron & Steel | Japan Special Steel | 1964 | Nippon Stainless Steel |
| | Sanyo Special Steel | 1965 | Nippon Yakin Kogyo |
| | Teikoku Charcoal Pigiron Mfg. | 1966 | Kawaguchi Metal Industries |
| Machinery | Sansei MFG | 1974 | OSG Mfg. |
| | Yoshida Machine Tool | 1975 | Okamoto Machine Tool Works |
| | Nippon Card Clothing | 1969 | Nippon Spindle Mfg. |
| | Satoh Agricaltural Machine Mfg. | 1971 | Iseki |
| | Asahi Sangyo | 1963 | Tsukishima Kikai |
| | HAYAKAWA IRON WORKS | 1972 | Meiji Machine |
| | Iwate-Fuji Industrial | 1971 | Tanaka Machinery Mfg. |
| | Nihon Joryu Kogyo | 1966 | Nikkiso |
| | Matsuoka Tool | 1965 | Suzuki Iron Works |
| | Kansai Koki | 1964 | Yutani Heavy Industries |
| Transportation Equipment | Yokohama Shipbuilding | 1965 | The Hakodate Dock |
| | Tokyu Kurogane Motor | 1962 | Aichi Machine Industry |
| | Tokyo Hatsudoki | 1964 | Yamaha Motor |
| | Yamaguchi Bicycle Manufacture | 1963 | Nichibei Fuji Cycle |
| Precision Instrument | Shinagawa Seisakusho | 1964 | Aichi clock and Electric Implement |
| | Tokyo Tokei Seizo Kaisha | 1974 | Orient Watch |
| Other Products | The Necos | 1964 | Nissan Norin Kogyo |

**Appendix 6 Sample Firms for Verification Purpose (Secondary Sample)**

| Industry | Failed Firm's Name | Date of Fail-ure | Nonfailed Firm's Name |
|---|---|---|---|
| Glass & Ceramics Product | Osaka Yogyo | 1977 | Nippon Crucible<br>Tokai Konetsu Kogyo |
| Iron & Steel | Nippon Satetsu Steel | 1977 | Toshin Steel |
| Electrical Machinery | Nippon Ferrite Industrial | 1977 | Sansui Electric<br>Foster Electric<br>The Weston<br>Clarion<br>Showa Musen Kogyo |
| Transpor-tation Equipment | Hashihama Shipbuilding | 1977 | Nitchitsu Industries |
| Mining | | | Mitsui Mining<br>Sumitomo Coal Mining<br>Hokkaido Colliery & Steamship |
| Foods | | | Takara Shuzo |
| Textiles | | | The Japan Wool Textile<br>Daito Woolen Spinning & Weaving<br>Daido Worsted Mills<br>The Chuo Woollen<br>Miyuki Keori |
| Pulp & Paper | | | Sanyo-Kokusaku Pulp<br>Tokai Pulp<br>Toyo Pulp<br>Oji Paper<br>Honshu Paper<br>Jujo Paper Mfg.<br>Mitsubishi Paper Mills<br>Kanzaki Paper Mfg. |
| Machinery | | | Nippei Industrial<br>Sonoike Mfg.<br>Wasino Machine<br>Shoun Machine Tool<br>Ishii Precision Tool<br>Takisawa Machine Tool<br>Toyama Machine Works<br>Koike Sanso Kogyo<br>Nippon Gear<br>Dengyosha Machine Works<br>Sanko Engineering & Construction<br>Iwata Air Compressor Mfg.<br>Yamada Yuki Seizo<br>Oye Kogyo |
| Precision Instrument | | | Citizen Watch<br>Ricoh Watch<br>Jeco<br>RHYTHM WATCH |