Will Stocks be Posted DS After Listing?

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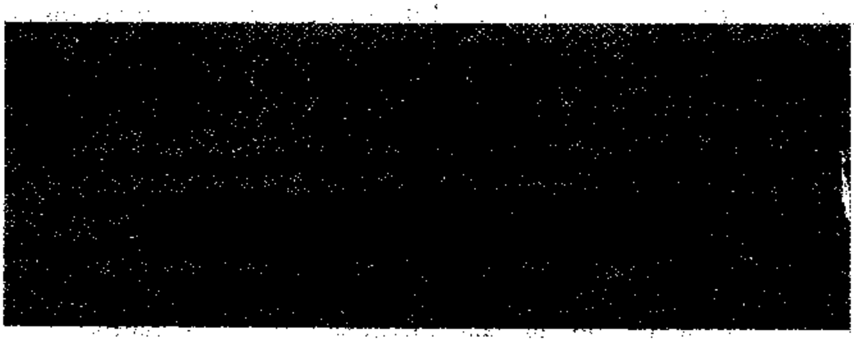

ABSTRACT

The study attempts to provide a set of objectively established discriminatory roles that can be used to differentiated sets of designated securities (DS) from sets of not designated securities (NDS) when evoluating their applications for listing on the SET.

FORCED ENTRY, RAO's V, MAHALANOBIS (MAHAL) and MINIMUM RESIDUAL (MINRESID) methods are each examined in order to determine which techniques minimizes the probablity of misclassification. After the discriminant function was derived a factor analytic solution, using the Principal Component method, (PC) with various rotations techniques including VARIMAX, OBLIMIN and SKIPPED ROTATE, was used to identity underlying characteristics. Financial information was obtained from securities' prospectus, issued during 1990-1992, before the securities were listed. The historical designated security anouncements, issued by the SECURITY EXCHANGE OF THAILAND (SET) served as our guideline for DS.

In summary, the linear discriminant function derived from RAO's V method yields the most satisfactory results, with 100 percent (pct) acuracy in classitication of the analysis samples and 80.53 percent classifiation accuracy for the holdout groups. FORCED ENTRY, or DIRECT method, was the least promising, while the MAHALANOBIS (MAHAL) and MINIMUM RESIDUAL (MINRESID) were not clearly distinct. In factor analysis, Principle Component analysis with VARIMAX ROTATION best identities the seven solitary attributes used as discriminants.

The major conclusions of this research are that about 50% of potential DS behevior can be explained by either the over or understated profitability for the past two years or by their forecasts, as presented in their prospectus at the time of listing. An additional 21.2 percent of the deviation could be attributed to its financial strength, the underwriter's price per book value and the percentage of minor shareholders. Surprisingly, the percentage of major shareholder and the market capitalization are not statistically significant from our 3 selected newly approved as listing companies in 1992 and by using our discriminant rules, one was classified as a potential DS, while the other two are classified as NDS. Several recommendations are then presented for the SET's consideration, which were developed to help avoid listing troublesome DS and to help appropriately classify NDS.

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BACKGROUND

Preventive measurement is usually better than corrective measurement. DSs, all of which have been well publiczed with regard to their 'unusual price and trading volume movement' ought to be discriminated against be SET, if possible, approval for listing process. Widely used in the credit cardholder approval process to eduate applicants for good vs bad credit risk, Discriminant Function Analysis (DFA) is based on statistical, not functional relationships. Its use allows DS and NDS to be classified using rules to specify a linear discriminant combination. Then a simple accepted or rejected decision can be made based on numerically differentiating group membership. In addition a factor analysis helps provide insights in to the typical attributes of a DS, which facilitates verification to group membership. This should minimize the probability of SET listing a DS.

For example, the function could be derived as follows:

[redacted]

Z be the i th security's discriminant score.

b be the discriminant coefficient for the n independent variable.

x be the i th security's independent variable.

The classification procedure could be described as follows:

if Z > cutting score, classify security i as belonging to DS.

if Z < cutting score, classify security i as belonging to NDS.

OBJECTIVES

1. To discriminate, and to describe, DS amd NDS into two classes, by minimizing the probability of DS, being misclassified.

2. To distinctly identify brief attributes of DSs, and NDSs, with a minimum lot of information, in order to develop DS checklists.

3. To recommend areas for further research on this topic matters.

MAJOR ASSUMPTIONS

1. The data are normally distributed.

2. The dispersion and covariance structures are unknown, but equal, for both groups.

3. Any errors are assumed to be randomly distributed.

4. The informations provided by the prospectus, or the SET, are the same sets which are used during the listing approval process.

5. Because the time reference for each security is at the listed date, the external environment factors are assumed constant, despite the presence of several major environment, during 1990-1992.

COMMENTS : There is evidence that discriminant analysis is not very sensitive to violations of multivariate normality of the distribution as suggested by Hair, Anderson and Tatham (1) ... The common covariance matrix is somewhat critical, although it is violated in practice. Some cautions and tests are recommended by Johnson and Wichern (2) ... For the case of unequal covariance matrices, the quadractic function has performed sligtly better than the linear decision rule, according to Morrison (3).

FOUR MAJOR STAGES FOR APPLICATION OF DISCRIMINANT AND FACTOR ANALYSIS STAGE

ONE : DERIVATION

1.1 Variable Selection : Based on the researchers' observation and intuition, research questions, directed toward distinguishing the behaviors of DS from NDS are outlined below.

a) Are the Ds firms small or large in term of paid up capital registration and number of employee?

b) Do the DS firms have a large concentration of small or major shareholders of (% ownership/no. of major sharehoder)?

c) Do the DS firms have a past record, or future projection, of rapid capital increase?

d) Do the Ds firms have high or low leverage (debt/equity) ratio, current (asset/liability) ratio and dividend payout?

e) Do the DS firms have high or low profitability as measured by past, present, and projected earning per share and net income per net total sale?

f) Do the DS firms have high or low growth in terms of historical, present and projected performance ratios, such as return on assets, return on shareholders' equity and earning per share?

g) Do the Ds firms have high or low investment utilization in terms of past, present, and projected sale per total assets?

These financial ratios obtained from each securities prospectus just before listing are our metric predictor variables. (see APPENDIX I) The past records of SET declaration for DS are our nonmetric criterion variables, categoried as either DS or NDS. All the input data are given in APPENDIX II.

COMMENTS : Although we were able to identity more than 19 idependent mátric variables, several were eleminated. Because they proved redundant. Many of the financial ratios were mathematically similiar, even though the exact nature of their measurements were different. Number of employee and size of capital register, for instance, both indicate the relative magnitude of the firm. In performance example profitability and the total sale of the company were highly correlate. The major implication is that to improve this study in the future, one may need to include extra dimension in non-financial data such as the type of business, financial underwriter characteristics and the background (eg age, education, etc.) of management teams and major shareholders.

1.2 SAMPLE SELECTION : 126 observations, during Janaury 1990 to April 1992, are included as our samples. For purposes of Discriminant Analysis, the samples was divided randomly into analysis sample and holdout sample on the basis of 20, 50 and 80 pct. The analysis sample was used to calculate the discriminant function, and the hold out sample to validate the function.

COMMENTS : Out of 132 companies listed during January 1990 to April 1992, 26 firms are DS. Some DS are given more than once, but we have not taken this into account on the DS frequency. Six observations are discarded mainly owing to incompleted data *(TABLE 3)*. Moreover, THAI AIRWAYS INTERNATIONAL Ltd. was excluded because they were listed before a public offering and the nature of fund management without financial projection was the reason Patana was excluded.

Fund. Most of the missing values in the sample were extraprolated after several simulated run. Interestedly, the smaller the analysis sample, the better the results in terms of properly classified the holdout sample. Presumably, because most of the computation methods (discussed in next sections) represent polar extremes, such as the maximization or minimization of statistical distance, the smaller sample may give larger deviation than the larger analysis sample. When equally stratified sample sizes are used for the analysis and holdout samples, the results are more or less similar to the DIRECT method. Futhermore, the larger hold out sample ought to give higher were statistical confidence than the smaller one in validation *(TABLE 1)*. The main implication would be for future research to run different sample sizes for analysis and holdout in order to optimize the solution.

1.3 **COMPUTATION METHOD** : The FORCED ENTRY or DIRECT method and the various STEPWISE METHODs : MAHAL, RAO's V AND MINRESID are used for comparison. The **DIRECT method** is simultaneously computed, using the entire set of independent variables. On the other hand, in **STEPWISE METHODS**, the computation is sytematically based as follows (5) :

a) RAO's V method : The criteria is to maximize ROA's V number defined as :

[redacted]

where p is the number of variables in the model, g is the number of groups, N_k is the sample size in the k th group, X_{ik} is the mean of the i th variable for the kth group, X_i is the mean of the i th variable for all groups combined, and Wij is an element of the inverse of the within-groups covariance matrix.

b) MAHALANOBIS method : The criteria is to maximize MAHALANOBIS' distance, D^2, a generalized measure of the distance between two groups, the distance between groups a and b is defined as :

[redacted]

where p is the number of variables in the model, Xia is the mean for the i th variable in group a, and Wil is an element from the inverse of the within-group covariance matrix.

c) MINIMUM RESIDUAL METHOD : the criteria is to minimize the sum of unexplained variation between groups. Two-group discriminant analysis is analogous to multiple regression in which the dependent variable is either O or 1, depending on the group to which a case belongs. In fact, the MAHALANOBIS' distance and R^2 are proportional. Thus, $R^2 = cD^2$. For each pair or groups, a and b, the unexplained variation from the regression is $1\text{-}R^2$ ab' where R^2 ab is the square of the multiple correlation coefficient when a variable coded as 0 or 1 is considered the dependent variable.

COMMENTS : Direct Method depicted the least promising result, while various stepwise methods, generally indicated reasonably acceptable solutions. In short, RAO's V method, also kown as the Lawley-Hotelling trace, which maximizing RAO's V number, give us the best discriminant function with 100 pct. and 80.53 pct correctness in the 20 percentage analysis sample and the 80 percentage holdout sample *(TABLE 2)*. It seems that the larger the differences between group means, the larger is RAO's V. Perhaps because the sampling distribution of V number is approximately an asymmetric chi-square distribution with p (g-1) degree of freedom (df), the cúrve are positively skewed, becoming less so as df increases corresponding to DS two polar extreme behaviors. (6)...The MAHAL and MINRESIS result are similar to mediorce explanation because, maybe, due to the proportional relationship of R^2 and D^2. (7)... It remains to be proved whether or not RAO's V method would consistently outperform MAHAL and MINRESID in the similar cases where two out of proportional sample size groups like 26 DS vs 100 NDS samples are tested.

1.4 STATISTICAL SIGNIFICANCE: All STEPWISE methods give a very impressive statistical significance level = 0.000 (almost 100 pct). They also have Chi-square statistics greater than 30.

The Analysis of variance has F Statistic score of 8,374 which is statistically significant at the 0.0045 level. Consequently, at the 0.05 pct. level the statistical inference accept the difference between the two groups, DS and NDS. It is important to note that these statistical test doesn't tell how well the function predicts.

STAGE TWO : VALIDATION

CUTTING SCORE DETERMINATION: The cuttion score is the criterion (score) against which each security's discriminant score is judged to determine into which group the security should be classified. In constructing classification matrices, we use three basic alternatives to achieve the determination objectives of the optimum cutting score (also referred to as a critical Z value) which give us the highest score in predicting DS at the minimum misclassification of NDS. (8) The basic calculations are as follows :

a) THE SIMPLE CUTTING SCORE : is the average between the DS and NDS group centroids.

b) THE WEIGHTED AVERAGE CUTTING SCORE : as the name implied, is the weighted average of the group centriod.

c) 'THE JACK KNIFE SCORE' : is to find the best cutting score arbitrary, after simulating all securities' discriminant scores. The most satisfactory prediction of a 70 pct hit ratio for DS and 81.55 pct hit ratio for NDS was achieved by an interval for the Jack Knife score in RAO's method discriminate output *(TABLE 3)* between 8.5 and -26.5 score for NDS and DS setting.

COMMENTS : The test discrimination data, reflectual in a histogram to DS in all STEPWISE METHODS, displays the formation of two separated distributions. At the same time, the NDS distribution appears to be normal in shape (FIGURE I & II). Furthermore, after several run most discriminant scores for DS were in two different extreme polars *(TABLE 4)*. Consequently, it is possible that most DSs either significantly overstated or understated their operating performance, when they applied to the SET for listing

STAGE THREE : INTERPRETATION

3.1 DISCRIMINANT COEFFICIENT : From the standardized discriminant function coefficient generated by RAO's METHOD, we have found that only 7 out of 19 explanatory variables are nontrivial. The weight on FSG and P _ EPS2 has the outstanding first and second highest weights of 30.94310 and 28.76034. The other five explanatory variables : PN _ PROF2 P _ EPS3, LEV1 and LEV2 are at least one fifth of the FSG. The rest of independent variables such CAP _ IN and PMJ _ SH are neglectfuly less than 0.5 *(TABLE 5)*.

COMMENTS : The interpretation of discriminant weight is analogous to the interpretation of beta weights in regression. Consequently, instability, degree of multicollinearity and relevant relationship are among some of the cautions that ought to be exercised. One of the implication of this finding is useful to SET, at least in terms of inhibiting DS, from fabricating financial data, by verifying the key discriminant variable, such as P __ EPS2 and FSG.

3.2 DISCRIMINANT LOADINGS : From RAO' V, the discriminant function is as : DS = -28.67273 - 1.6887 PN __ PROF2 + 1.0810 P __ EPS3 + 2.6307 P __ EPS2 + 38.5818 FSG - 16.6945 FEPSG + 0.1533 LEV1 – 0.5789 LEV2 .....(equation 1)

The equation has 7 ranks and log determinant of 1.031827. The NDS and DS group centriod centriod are -4.2944 and 204.9145 respectively. FIGURE 2 depicts the data graphichly for the entire population of DS, and NDS and provides statistical summarirs.

COMMENTS : Though the RAO's V derived discriminant function with interval cutting score from Jackknife method is the best uncovered in our research, the researcher would recommend that others try non-linear combination or two stages DS and NDS groups for clear separation in the two extreme of DS sample for improvement.

STAGE FOUR : FACTOR ANALYSIS FOR PROFILING GROUP DIFFERENCE

We selected principal component as our factor analysis technique because we assume that the latent effects are not easily observed in a large set of variables transforming. The initial data matrix was transformed to facilitate interpretation by providing a simple structure. Three different rotation methods were applied as follows (4) :

a) VARIMAX : is to orthogonally rotate to maximize the number of dependent variables that have high loading on a factor

b) OBLIMIN : is to flexibly rotate to minimize the parameter delta, controls the extent of obliqueness.

c) SKIPPED OR NO ROTATION : is a straight forward principal component analysis

Regardless of rotation method, Kaiser-Meyer-Olikin Measure (KMO) of Sample Adequacy, as 0.53490, is acceptable. This range is not spectacular eventhough our 126 observations is greater than the five time the 19 dependant variables, as suggested by Hair, Anderson and Tatham. (9) Furthermore, after standardized data for the analysis, seven principal components, namely ZCAP __ IN, ZPMJ __ SH, ZPMR __ SH, ZUP __ BV, ZP __ TSAL3, ZP __ TSAL2, and ZP __ PRO3, which have the variance greater than 1 (the eigenvalue > 1), explained 76.6 pct. of total variance of the dependant variable matrix. With as eigenvalue of about 3.0, the ZCAP __ IN, ZPMJ __ SH and ZPMR __ SH give unexceptional about 15 pct. explaination each, whereas the remaining four components which has eigen value between 1-1.5 describe other 26 pct. *(FIGURE 3).*

Different rotations give different profiles of the matrix. No ROTATION give us the weakest link among with-in group variable, but the VARIMAX give us more insight of the factors. For example, Factors, 1 and 2 are obviously last and planned forecast year operation performance in term of sale, profit and earning per share, before listing.

COMMENTS : The KMO of 0.534 seems to indicate that our weakest drawback in sample adequacy comparing the magnitudes of the abserved correlation coeffcients to the magnitudes of the partial correlation coefficient. Though mor observations do not genrally give higher KMO, the researcher failed to and more observation because DS system was commenced in 1989. For further study, additional variables are strongly recommended, especially in non-financial figures such as type of business and the management and ownership profile to enhance KMO... It is interesting to note that the relative important principle components are different from the relative important dependent variable in RAO discriminant functions. Different variables accounted for high eigen value or factor loading than those that were prominent discriminant variables. Nevertheless, both factor analysis and discriminant function are essentially summed up as the focus of past, future performance and financial gearing of the firm.

CONCLUSION :

In the past two years, between Jan. 1990-April 1992, SET has approved 26 DS out of 136 firms for listing implying the 20 pct. chance for DS to approve. By using simple linear discriminant combination as a tool, as stated in equation 1, SET may be able to differentiate up to 80 pct. of all potential DS. If the discriminant function had been applied only two applicates, HANA And B-GRIMM would have been approved *(TABLE 6)*. Hence, NTS may be future DS or troublesome securities in the future as per our studies. To enhance the chance of misclassification of DS, SET authority should particularly try best to validate the financial statement on prospectus of the incoming security. 'Over or understated' financial facts are simply the tools for future 'unusual price and trading volume movement'.

THE SHORT LISTS FOR SET TO CONSIDER ARE AS FOLLOWS :

1. SET ought to implement the use to objective statistical methods as a tool to assist the authority during the evaluation and decision processes. In short, this paper has demonstrated that even the simple linear discriminant function could improve the performance of classifying DS and NDS.

2. Past and planned forecast financial data, especially on operating performance, must be verified carefully. SET ought to pay closed attention to the firm that 'Under or Overstation' financial performance.

3. One of the primary reasons to be listed in SET is for the firm with good potential to raise capital for future expansion. Thus, the mislevel of market capitalization and the percentage of major shareholder concentration as indicators of DS could discriminant against the small or family owned firm in which violated SET's aim.

4. SET may look at the leverage of the companies does have some explanation in DS and NDS behavior after listed.

FINAL WORDS :

According to one leading English newspaper in Thailand, 'The sigma of being 'Cowboy Market' will remain for as long as authorities are relaxed about allowing the SET to become a part time casino.'

FOOTNOTES

[1] Hair, Anderson and Tatham, **MULTIVARIATE DATA ANALYSIS**, second edition, 1984, page 76.

[2] Johnson and Wichern, **APPLIED MULTIVARIATE STATISTICAL ANALYSIS**, second edition, 1988, page 472-9.

[3] Morrison, Donald F., **MULTIVARIATE STATISTICAL METHOD**, second edition, 1990, page 275-278.

[4] The rank of a matrix is defined to be the maximum number of linear independent column or row in the matrix.

[5] Norusis, J. Marija, **SPSS/PC + ADVANCED STATISITICS 4.0.**, 1990, page B21-33.

[6] Lehman, **STATISTIC AND RESEARCH DESIGN IN THE BEHAVIRAL SCIENCE**, 1988, page 284-285.

[7] Norusis, page B-22.

[8] The researchers feel strongly that at present SET has more concern on the quality of listed security than on the quatitity of the securities. Consequently our objective is to identify the DS at maximum level eventhough some sacrifices for misclassified NDS are incurred at minimum level.

[9] Hair, Anderson and Tatham, page 237.

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TABLE 1

Comparison of different methods (RAO, MAHAL, MINRESID) with different GT Values

[redacted]

		GT Value		
		.20	.50	.80
DS	RAO	40	85.7	100
	MAHAL	39.1	42.9	42.9
	MINRESID	35	26.7	100.0
	DIRECT	91.3	63.6	100.0
NDS	RAO	98.8	98.0	100.0
	MAHAL	100.0	100.0	90.5
	MINRESID	100.0	96.4	100.0
	DIRECT	100.0	100.0	100.0
CORRECTLY CLASSIFIED	RAO	87.25	96.49	100.0
	MAHAL	87.25	87.69	78.57
	MINRESID	86.73	81.43	100.0
	DIRECT	84.85	92.16	100.0

[redacted]

		GT Value		
		.20	.50	.80
DS	RAO	16.7	10.5	36.0
	MAHAL	0	16.7	21.1
	MINRESID	16.7	27.3	22.7
	DIRECT	25.0	33.3	50.0
NDS	RAO	94.4	92	93.2
	MAHAL	84.6	91.8	91.1
	MINRESID	86.4	91.1	91.0
	DIRECT	91.3	85.0	76.8
CORRECTLY CLASSIFIED	RAO	75	69.57	80.53
	MAHAL	68.75	77.05	77.55
	MINRESID	71.43	78.57	76.0
	DIRECT	81.48	74.67	71.57

Remark : 1. RAO Method clearly gives us a dominate solution to all other methods.
2. GT Value * refers to percentage of for hold out sample, random sampling

TABLE 2

RDA 80% Classification Result

[redacted]

Classification Results for cases selected for use in the analysis

Actual Group	No. of Cases	Predicted Group Membership	
		0	1
Group 0 NDS	12	12 100.0%	0 .0%
Group 1 DS	1	0 .0%	1 100.0%
Percent of "grouped" cases correctly classified: 100.00%			

[redacted]

Classification Results for cases not selected for use in the analysis

Actual Group	No. of Cases	Predicted Group Membership	
		0	1
Group 0 NDS	88	82 93.2%	6 6.8%
Group 1 DS	25	16 64.0%	9 36.0%
Percent of "grouped" cases correctly classified: 80.53%			

TABLE 3

COMPARISON OF DIFFERENT CUTTING SCORE WITH THE THREE METHODS

METHOD OF CUTTING SCORE	RAO 0.80 % OF CORRECTNESS			MAHAL 0.80 % OF CORRECTNESS			MINRESID 0.80 % OF CORRECTNESS		
	SCORE	DS	NDS	SCORE	DS	NDS	SCORE	DS	NDS
SIMPLE	100.31	11.54	98.0	1.8037	26.92	94.0	7.7289	23.0	97.0
WEIGHTED AVE.	38.8758	19.23	95.0	0.5615	26.92	88.0	1.9929	34.6	89.0
JACK KNIFE	8.5 TO -26.5	70.0	81.55	0.425 TO -1.216	42.31	82.0	5.5 TO -3.5	57.6	77.0

FORMULA

SIMPLE CUTTING SCORE = (MEAN DS + MEAN NDS) / 2

WEIGHTED AVE. CUTTING SCORE =

$$\frac{\text{(MEAN DS) * SAMPLE SIZE OF DS + (MEAN NDS) * SAMPLE SIZE OF NDS}}{\text{TOTAL SAMPLE}}$$

TABLE 4

ROA 80% Calcuated

NAME	DS	Disc.Scor
SUNTEC	1	3559.0784
SUSCO	1	446.1726
FTX	0	338.0376
APRINT	1	196.3494
STECON	0	119.1790
SURAT	1	81.8172
SHIN	0	55.2021
KKI	0	50.2377
SH	0	44.7634
B-LAND	1	40.0590
FORTUN	0	36.3107
IEC	0	27.3983
ROBINS	0	25.1504
TCB	0	23.6530
INSURE	0	21.3312
RR	1	20.5587
TPIPL	0	17.5347
JCT	0	17.1219
SE-ED	1	13.4570
TNPC	0	12.2382
TAF	1	9.3520
KMC	1	8.6217
HEMRAJ07	1	8.5125
MK	0	8.2132
TOPP	0	6.7561
AHC	0	6.5665
API	0	6.3442
STANLEY	0	6.1362
MANRIN	0	5.8699
HTX	0	4.6637
MORKOT	0	4.2004
SMPC	0	3.8139
TATL	0	2.7361
VIBHA	0	2.6390
PCM	0	2.5561
PIZZA	0	2.1978
MFC	0	1.2533
MODERN	0	0.9141
SMK	0	0.5430
YCI	0	0.1099
PP	0	-0.0423
SK	0	-0.2291
TCCC	0	-0.2865
CASTLE	1	-0.3994
UNITED	0	-0.6654
TONHUA	1	-0.7514
INFILE	0	-0.7821
SHANG	0	-0.9327
STA	0	-1.3000
BSI	0	-1.4461

NAME	DS	Disc.Scor
PRANDA	0	-1.4558
ESSEX	0	-1.5267
GEL	0	-1.6948
APO	1	-1.9006
CHOTI	0	-2.1475
CWT	1	-2.2184
UPOIC	0	-2.2831
KARAT	0	-2.8873
PPC	0	-3.0322
METCO	0	-3.1151
TFS	1	-3.2447
ASL	0	-3.5225
GRANIT	0	-3.6254
IBC	1	-3.6937
UNI	0	-3.8017
KKC	0	-3.9245
SDF	0	-4.2926
SUN	0	-4.3968
TTF	0	-4.6199
TASCO	0	-4.7128
EWC	0	-4.7529
HT	0	-4.9516
P-FCB	0	-4.9770
DTCI	0	-4.9812
TPP	0	-5.0504
TSTE	0	-5.1641
QH	0	-5.1717
SVH	0	-5.3192
BIJOUX	0	-5.3249
TEIC	0	-5.5392
LEE	1	-5.6294
DCC	0	-5.6778
EFS	0	-5.8926
UMW	0	-5.9940
DVS	0	-6.1164
TSI	0	-6.2741
TCFI	0	-6.7034
SAWANG	0	-6.7739
AFL	0	-6.9080
SITHAI	0	-6.9392
S-CHEM	0	-6.9846
TDT	0	-7.0088
PATKOL	0	-7.0653
KG	0	-7.1124
ADVANCE	0	-7.4737
NSTAR	0	-7.7593
NKI	0	-8.0384
T-RUBB	0	-10.0632
RHC	0	-10.2144
TCI	0	-12.4711
PE	0	-12.4721

NAME	DS	Disc.Scor
RENOWN	0	-12.7367
CENTEL	0	-12.788
MALEE	0	-12.8662
WAT	1	-16.2553
TVO	0	-16.3858
SCI	0	-16.9297
MDX	0	-17.1334
THECO	0	-17.5115
TFD	0	-19.8644
CNT	0	-26.0208
UCT	1	-26.7379
VARO	1	-27.3988
GFPT	1	-28.0130
TTT	0	-28.2844
TFC	0	-28.8531
JULDIS	0	-35.6419
TC	1	-38.0664
FAS	0	-42.3684
SCP	0	-44.2675
SOMPR	1	-45.4322
PIC	0	-50.8053
MGR	1	-118.0553
TYONG	1	-288.4350
IMF	1	-329.1919
AJ	1	-671.1726

TABLE 5

Standardized Canonical Discriminant Function Coefficients

PN_PROF2	-3.03338
P_EPS3	1.62381
P_EPS2	28.76034
FSG	30.94310
FEPSG	-8.70193
LEV1	2.82557
LEV2	-1.77461
CONSTANT	0

for comparison of the relative strength of each discriminatory variables

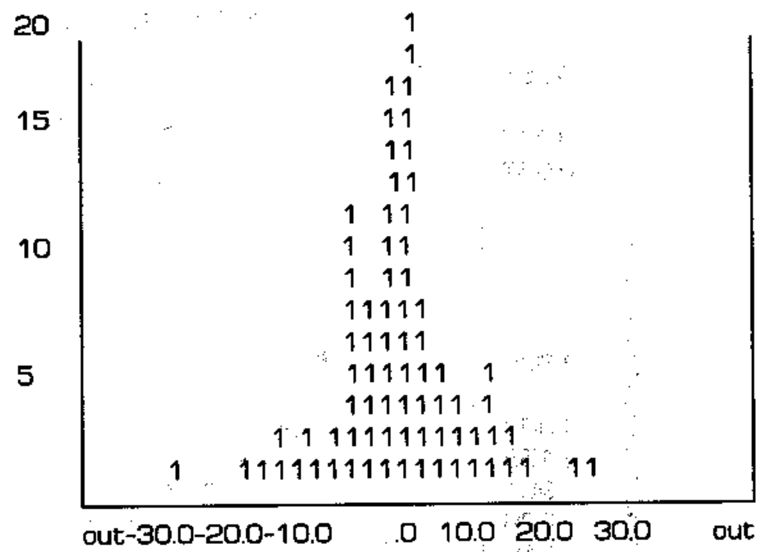
Unstandardized canonical Discriminant Function Coefficients

PN_PROF2	-1.688791
P_EPS3	1.081069
P_EPS2	2.630729
FSG	38.58180
FEPSG	-16.69448
LEV1	.1533107
LEV2	-.5789350
CONSTANT	-28.67273

for calculation of the discriminant score for each observations.

Figure I
Test Discrimination (All Data × 0.80 RAO)
Histogram for Group 0 Not DS

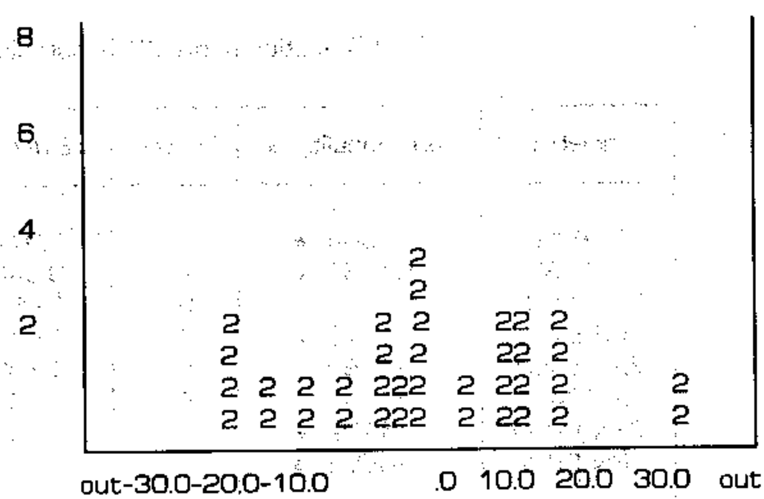
canonical Discriminant Function 1



NDS centroids = -2.483

Figure II
Test Discrimination (All Data × 0.80 RAO)
Histogram for Group 1 DS

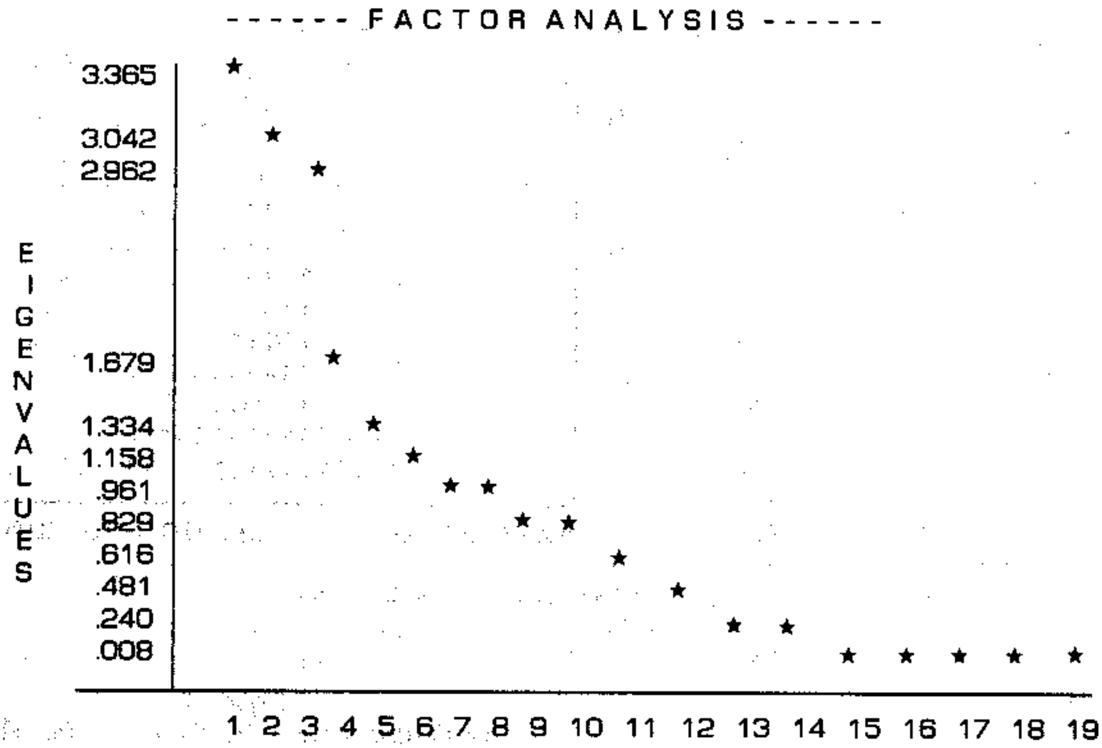
canonical Discriminant Function 1



DS Centroids = 29.7984

Figure III
Accumulated Eigen-value of each factors

Test Factor for All data Standard



Final Statistics show 76 % cumulative % for factor

Variable	Communality ★	Factor	Eigenvalue	Pct of Var	Cum Pct
ZCAP_IN	.42504 ★	1	3.34465	17.6	17.6
ZPMJ_SH	.61262 ★	2	3.04213	16.0	33.6
ZPMR_SH	.67613 ★	3	2.96174	15.6	49.2
ZUP_BV	.71118 ★	4	1.67879	8.8	58.0
ZP_TSAL3	.88982 ★	5	1.33354	7.0	65.1
ZP_TSAL2	.41437 ★	6	1.15805	6.1	71.2
ZPN_PRO3	.75479 ★	7	1.03252	5.4	76.6
ZPN_PRO2	.96653 ★				

APPENDIX 1

VARIABLE LIST USED IN FORMULA

NAME	DESCRIPTION	EXPLANATION
DS	Discriminant Score	
CAP_IN	CAP-REG2	
PMJ_SH	$\frac{\text{MJ-SH}}{\text{ERS-1000-M}}$	Concentration of major own (average for each)
PMR_SH	$\frac{\text{OTHER-SH}}{\text{ERS-1000-L}}$	Concentration of minor own
UP_BV	$\frac{\text{V-Price}}{\text{BV3}}$	Ratio of Underwrite Value to Book Value
P_TSALE3	$\frac{\text{TSALE 3}}{\text{TSALE 2}}$	Sales Growth the year before listed year
P_TSALE2	$\frac{\text{TSALE 2}}{\text{TSALE 1}}$	Sales Growth 2 years fore listed year
PN_PROF3	$\frac{\text{N-PROF 3}}{\text{N-PROF 2}}$	Net profit growth the year before listed year
PN_PROF2	$\frac{\text{N-PROF 2}}{\text{N-PROF 1}}$	Net profit growth 2 years before listed year
P_EPS3	$\frac{\text{EPS 3}}{\text{EPS 2}}$	Earning Per Share growth the year before listed year
P_EPS2	$\frac{\text{EPS 2}}{\text{EPS 1}}$	Earning Per Share growth 2 years before listed year
P_ROE3	$\frac{\frac{\text{EPS3}}{\text{BV3}} - \frac{\text{EPS2}}{\text{BV2}}}{\text{EPS2/BV2}}$	Return on Equity growth the year before listed year
P_ROE2	$\frac{\frac{\text{EPS2}}{\text{BV2}} - \frac{\text{EPS1}}{\text{BV1}}}{\text{EPS1/BV1}}$	Return on Equity growth 2 years before listed year
LEV2	$\frac{\text{TA2}}{\text{CAP-REG2}}$	Leverage the year before listed
LEV1	$\frac{\text{TA1}}{\text{CAP-RE}}$	Leverage 2 years before listed
FSG	$\frac{\text{FTSALE 2}}{\text{FTSALE 1}}$	Forecasted Sales growth the year after listed
FPG	$\frac{\text{FN-PROF 2}}{\text{FN-PROF 1}}$	Forecasted Net profit growth the year after listed
FEPSG	$\frac{\text{FEPS 2}}{\text{FEPS 1}}$	Forecasted earning per share growth the year after listed
FBVG	$\frac{\text{FBV2}}{\text{FBV1}}$	Forecasted book value growth the year after listed
FCRG	$\frac{\text{FCAP-REG2}}{\text{FCAP-REG1}}$	Forecasted Capital Registered growth the year after listed