Faculty Working Papers

Financial Characteristics of Merged Firms:
A Multivariate Analysis

Donald L. Stevens

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College of Commerce and Business Administration
University of Illinois at Urbana-Champaign

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August 3, 1972

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Introduction

The FTC reported 22,517 corporate acquisitions during the 1960's, compared to 7200 for the twenty year period, 1940-1959.[1] The increased employment of this method of corporate growth has generated a number of studies explaining certain segments of the merger movement. Attempts to explain why firms merge have resulted in a wide range of motives and goals being associated with merger-active firms. Various segments of this population have been isolated and mergers in these strata described as consummated to avoid bankruptcy (for the acquired firm), capitalize upon managerial inefficiencies, for synergistic purposes, gain from valuation discrepancies, to diversify in a portfolio sense, and many others.[2] All of these have been shown to be consistent with shareholder wealth maximization goals in theory and a large number of empirical studies have attempted to demonstrate wealth increases from mergers. In these cases, merger active firms were compared to indexes of performance for industrial firms in general. These same performance studies have been used to support hypotheses that mergers often occur for other than shareholder wealth maximization reasons. Included here are attempts to establish management behavior which seeks maximization of "power" and wealth of management rather than shareholders.

While numerous motives have been established for growth through merger,

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[1]Federal Trade Commission, Economic Report on Corporate Mergers, Hearings on Antitrust and Monopoly, Committee of the Judiciary, US Senate, 91st Congress, 1st session; Part 8A, USGPP, 1969.

[2]For an extended general collection of recent merger articles, see Conglomerate Mergers and Acquisitions: Opinions and Analysis, 44 St. Johns Law Review (Special Edition, 1970).

For a specific discussion of the recent literature relating to this area see Stevens, Donald L. "A Multivariate Analysis of Financial Characteristics of Acquired Firms in Industrial Mergers." Unpuplished PhD Dissertation, Michigan State University, 1972.

conclusions must be qualified such that alternative reasons for merger must be associated with certain segments of the merger movement. If there exists a common basis for decision making with respect to prospective mergers, it is not apparent in the current literature. There are in fact few attempts to relate specific merger motives to a generalized framework.

The recent papers by Lintner and Lewellen,[3] however, are theoretical discussions of a specific financial rationale for merger. Both authors argue that mergers could produce gains for their stockholders due to resultant increased debt capacity for the merged firm and that this financial leverage consideration would justify merger independent of other operational gains.

Another existing study which included some empirical testing was that by Monroe and Simkowitz.[4] These authors investigated a sample of conglomerate takeover targets and noted that acquired firms were smaller, had lower PE ratios, unused debt capacity, and observed that non-financial characteristics appeared to be important. However, their use of a stepwise discriminant analysis procedure with a set of highly correlated variables raises some doubts as to which financial characteristics were significant.

The Study of Acquired Firms

The purpose of this study was to determine if a consistent financial

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[3] Lintner, John. "Expectations, Mergers and Equilibrium in Purely Competitive Securities Markets," American Economic Review, LXI, No. 2 (May, 1971) 109-114.

Lewellen, Wilbur G. "A Pure Financial Rationale for the Conglomerate Merger." The Journal of Finance, XXVI (May, 1971) 521-537.

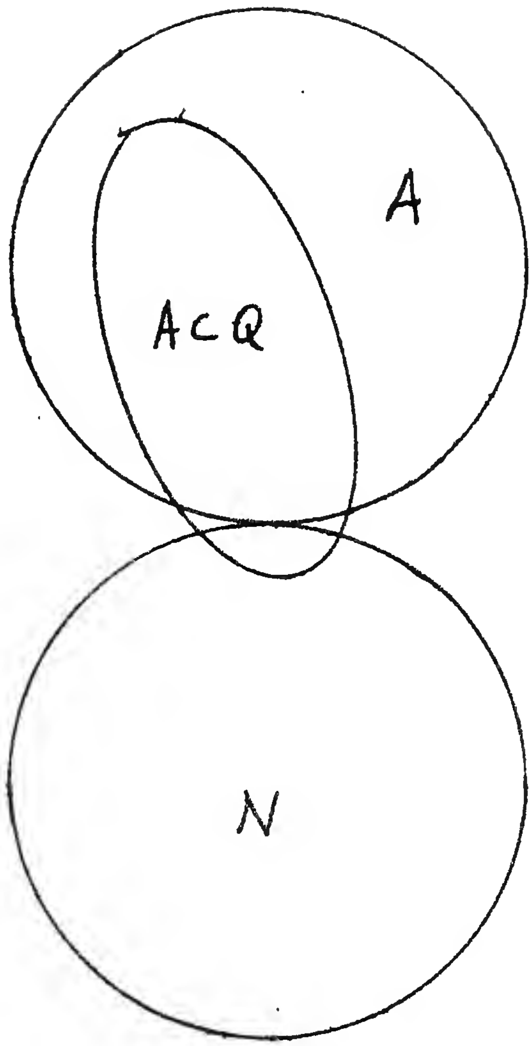
[4] Monroe, Robert J. and Simkowitz, Michael A. "Investment Characteristics of Conglomerate Targets: A Discriminant Analysis." Paper read before the Southern Finance Association, (No. V, 1970) (mimeo).

basis for merger exists as measured by pre-merger financial characteristics of the acquired firms in the merger. Specifically, qualities such as profitability, liquidity, degree of financial leverage, and dividend payout were measured for acquired firms to see if profiles exist which systematically differentiate acquired from others.

In attempting to differentiate firms acquired and non-acquired, based upon financial characteristics, one must first recognize and deal with an essential grouping problem and its direct consequences. A sample design aimed solely at acquired and non-acquired firms implies that these are self-contained, mutually exclusive groups and that these groups will systematically differ in their financial characteristics. It is not at all convincing, however, to argue that no firms exist which have the same financial characteristics as acquired firms. One can argue that there are certain combinations of financial characteristics which make firms attractive for acquisition. Of all firms which possess these financial profiles, some will be acquired and others will not. Acquired firms would be expected to possess certain financial qualities different from firms which would not be attractive acquisition candidates but perhaps not much different from other firms not acquired at one point in time but certainly attractive for acquisition as measured by their financial profile.

Figure 1 illustrates the grouping problem. If a decision maker examined the set of all firms with respect to financial characteristics he could find two essentially self-contained subsets labelled attractive and not-attractive (A and N in Figure 1). Further if the decision maker were considering a search for acquisition candidates, he could immediately exclude the not-attractive subset and limit his search to the attractive group of firms for potential acquisition targets. It follows that if other decision makers consider the same financial characteristics and if these remain important

Figure 1



A: attractive

N: not attractive

ACQ: ACQUIRED

over time, this should be reflected in the acquisition decision itself. Therefore, firms acquired should come from the attractive group and will form a subset of that group (ACQ in Fig. 1).

For analysis purposes sampling can be done of acquired firms with confidence that the ACQ group is a subset of the set of attractive firms (A). The most precise statement of the goal of the analysis would be to develop a model to differentiate attractive from not-attractive firms. Sampling acquired firms is an acceptable surrogate for an attractive group. The problem is that, a priori, there is no not-attractive identity to firms, nor is there an attractive identity to attractive-but-not-acquired firms. When sampling is made on an acquired-non-acquired basis, the non-acquired group will be composed of both attractive and not-attractive firms. This will lessen the group differences to the extent that this occurs. One way to reduce this liklihood of including attractive firms in the non-acquired sample was to stratify the sample.

Sample

The initial sample was composed of eighty firms with forty firms in each of the two groups. The acquired firms were merged during the calendar year 1966 and were taken from the annual listing published by the FTC.[5] One barrier to empirical research in this area is the problem of obtaining financial data. The FTC provides the most complete listing of mergers but these include only acquired firms with $10 million assets or more at the time of acquisition. This cut-off accounts for only 12% of the total reported mergers but the great majority of the total acquired assets.

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[5]Federal Trade Commission, Large Mergers in Manufacturing and Mining, 1948-1969. Statistical Report #5. Bureau of Economics

However, even for acquisition in this size class, published financial information is not always available. Thus, of the sixty-nine reported acquisitions for the sample year 1966 only forty were retained in the sample when the data requirements were imposed.

The second sample group also included forty firms chosen randomly from Moody's Industrials, but subject to several restrictions. First, the firms must have been in existence for five years prior to 1966 and still not acquired as of January 1970. This would exclude firms in the process of being acquired in the sample year and reduce the number of presumably attractive firms in the non-acquired sample. Second, if the firm had any large minority or majority stockholders it was excluded. It was felt that for closely held firms, the financial attractiveness criterion could easily be subordinated to the "willingness of the majority stockholder" criterion. Thus attractive firms might never be acquired due to the opposition of a controlling stockholder. Third, the samples were matched by size distribution of assets. Size is an important consideration in mergers. Acquired firms tend to be smaller than their buyers. This could have been used as a predictor variable in the model as was the case in the Monroe and Simkowitz study.[6] However, there are other considerations. Financial data such as that in Moody's is not representative of all firms but only of the largest firms. A sample therefore of firms taken from Moody's would contain firms larger in size not only with respect to acquired firms but with respect to all firms. Another size consideration is most relevant in the merger area and that is the anti-trust implications which increase in importance as size increases. Thus many attractive large firms could not be acquired. Finally it was

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[6] op. cit. Monroe & Simkowitz.

felt that a more comparable set of financial characteristics could be derived if the samples were composed of firms with similar size distribution of assets.

Once the sample groups were determined, financial statement data was collected from Moody's Industrials and a group of financial ratios were calculated for each of the firms. The two prior reporting periods were used for data and the ratios were averaged to minimize random fluctuations. Traditional ratio analysis as a tool for financial measurement has been widely used historically and needs no review here. At the same time most studies using ratio analysis employed a univariate methodology in which ratios were analyzed one at a time (and often in large numbers). The shortcomings of this approach are significant whenever more than one variable is interacting to produce differences. For example, acquired firms may exhibit little difference with respect to other firms in their levels of profitability and liquidity. However, these measures when considered with the level of unused debt capacity might produce quite large differences. In short, most problems for which ratios are relevant are multivariate in nature and a univariate approach could lead to misinterpretation and faulty conclusions.

Multicollinearity in Financial Data

A second problem is coincident not only with ratio analysis but with most research methodologies in finance and is generally labelled the multicollinearity problem. An assumption of most statistical techniques derived from the general linear model is that the set of predictor variables is mutually uncorrelated. Although moderate departures from this do not significantly impair the results, when the variables are highly collinear the weights in the resulting model are highly unstable, the model tends to

be highly sample sensitive and interpretation becomes very difficult.

This problem is quite evident in any large set of financial ratio data. Given the large set of financial data items, the potential number of ratios increases almost without bound. At the same time the level of redundancy is increasing almost at the same rate and no significant information is added. The reason is that ratios are simple combinations of financial data items which represent a limited number of financial dimensions. Often financial dimensions are implied by the qualities of profitability, liquidity, leverage, and measures of activity. However, there exists no single measure of these qualities which is widely accepted. This partially explains the reliance upon groups of ratios to measure these qualities (see Foulke, for example).[7] However, to include these groups together in a linear model would result in a high level of multicollinearity among the predictors and its inherent problems. This problem was evident in both the bankruptcy study by Altman[8] and the merger study by Monroe and Simkowitz.[9] Altman employed a set of financial ratios in a discriminant model to predict liklihood of bankruptcy. Altman noted the high multicollinearity in the ratio set and emphasized that variables should be carefully chosen. His selection technique was basically achieved through a large number of trial computer runs.

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[7] Foulke, Roy A. Practical Financial Statement Analysis, 5th Ed. (New York, McGraw Hill, 1961).

[8] Edward I. Altman. "Financial Ratios, Discriminant Analysis and the Prediction of Corporate Bankruptcy," Journal of Finance (September 1968), 589-609.

[9] Monroe and Simkowitz, op. cit.

Monroe and Simkowitz also employed a set of financial ratios with discriminant analysis to study characteristics of conglomerate takeover targets. They experienced the multicollinearity problem and neither liquidity, profitability, nor leverage entered the final step-wise discriminant functions. They explained the omission was due to multicollinearity in the case of leverage and lack of group differences in the case of liquidity and profitability. Despite the difficulties with highly correlated ratios within the predictor set, both of these studies recognized the weakness of traditional univariate ratio analysis and successfully attempted a multivariate approach with ratios.

Factor Analysis in This Study

The problem of multicollinearity faced by Altman and Monroe and Simkowitz was also present in this study. The data collected for the original sample of eighty firms was used to generate the data matrix $X_{(20X80)}$. The ratios included were all widely used and represented measures associated with each of the financial qualities previously mentioned as well as dividend policy and price-earnings ratio. These ratios are listed by group in Table 3.1 and Table 3.2 lists means and standard deviation. Table 3.3 is the correlation matrix for the twenty ratios aggregated over the eighty firms sample and indicates the high correlations among the variables.

The data matrix X represents the total information set for the subsequent analysis. However it contains a large number of measures for a fewer number of financial qualities. What is needed is a smaller set with a maximum retention of the information available in X, but represented by a smaller set of variables with minimum inter-correlations. This problem can be approached with factor analysis.

TABLE 3.1

SUMMARY OF FINANCIAL RATIOS EMPLOYED

Class	Number	Ratio
Liquidity	11	net working capital/total assets
	17	net working capital/sales
Profitability	1	EBIT/total assets
	5	gross profit/sales
	6	EBIT/sales
	7	net income/sales
	8	EBIT/sales
	9	net income/net stockholders equity
	10	net income/total assets
Leverage	4	long term debt/market value equity
	18	LT liabilities/mkt. value equity
	13	LT debt/net stockholders equity
	19	LT debt/total assets
	20	total liabilities/total assets
Activity	16	sales/total assets
	15	cost of goods sold/inventory
	14	sales/(current assets-inventory)
"Other"	12*	interest/(cash + marketable securities)
	2	cash dividends/net income
	3	price/earnings

NOTE: The distinction between LT debt and LT liabilities was that LT debt included only long term bonds and similar obligations whereas LT liabilities included all entries of a long term nature.

*This ratio behaves similarly to LIQ and LEV.

TABLE 3.2

MEANS AND STANDARD DEVIATIONS FOR TWENTY RATIOS IN THREE FIRM GROUPINGS

Non-Acquired Firms			Acquired Firms		
Ratio	Mean	Standard Deviation	Ratio	Mean	Standard Deviation
1	10.47	7.69	1	11.87	7.81
2	34.33	29.89	2	37.03	22.11
3	17.47	16.47	3	14.99	10.93
4	30.08	28.67	4	19.28	23.00
5	26.79	18.46	5	25.76	15.16
6	9.30	10.53	6	8.07	6.22
7	6.22	9.13	7	4.52	4.12
8	10.39	10.30	8	8.82	6.16
9	8.08	15.35	9	9.45	7.27
10	5.39	4.80	10	6.04	4.67
11	34.59	18.60	11	40.65	13.79
12	15.02	15.29	12	14.55	20.59
13	44.14	41.17	13	25.13	37.19
14	4.67	2.09	14	4.79	2.10
15	10.33	21.54	15	4.47	3.01
16	1.36	.65	16	1.41	.52
17	29.85	23.87	17	31.46	12.05
18	18.31	12.98	18	12.22	11.23
19	22.31	14.97	19	13.76	11.21
20	44.58	18.54	20	34.50	15.13
n=40			n=40		

Aggregated Firms		
Ratio	Mean	Standard Deviation
1	11.17	7.73
2	35.68	26.16
3	16.23	13.94
4	24.68	26.39
5	26.28	16.79
6	8.68	8.61
7	5.37	7.09
8	9.61	8.47
9	8.77	11.95
10	5.72	4.72
11	37.62	16.55
12	14.78	18.02
13	34.64	40.14
14	4.73	2.08
15	7.40	15.56
16	1.38	.59
17	30.66	18.80
18	15.26	12.44
19	18.03	13.83
20	39.54	17.56
n=80		

TABLE 3.3

CORRELATION MATRIX FOR TWENTY RATIOS ON EIGHTY FIRMS

	Correlation Matrix									
	1	2	3	4	5	6	7	8	9	10
1	1.000									
2	0.163	1.000								
3	-0.083	-0.025	1.000							
4	-0.232	-0.066	-0.056	1.000						
5	0.262	-0.070	0.186	-0.211	1.000					
6	0.633	-0.017	-0.034	-0.268	0.612	1.000				
7	0.422	-0.077	-0.022	-0.189	0.622	0.950	1.000			
8	0.605	-0.058	0.008	-0.205	0.629	0.992	0.954	1.000		
9	0.678	0.145	-0.008	0.039	0.243	0.454	0.362	0.454	1.000	
10	0.952	0.168	-0.087	-0.239	0.338	0.733	0.577	0.707	0.758	1.000
11	0.271	0.118	-0.157	-0.187	-0.208	-0.005	-0.126	-0.068	0.173	0.190
12	-0.206	-0.276	-0.013	0.587	-0.179	-0.229	-0.173	-0.159	-0.083	-0.252
13	-0.212	-0.209	0.000	0.792	-0.105	-0.245	-0.187	-0.178	0.055	-0.251
14	0.042	0.069	-0.332	0.095	-0.300	-0.341	-0.348	-0.364	-0.009	-0.025
15	-0.053	-0.005	-0.107	0.004	0.023	-0.086	-0.072	-0.076	-0.005	-0.028
16	0.139	0.116	-0.266	-0.001	-0.435	-0.374	-0.413	-0.430	-0.121	0.021
17	0.076	-0.067	0.030	-0.229	0.223	0.501	0.485	0.477	0.104	0.147
18	-0.210	-0.191	-0.068	0.779	-0.137	-0.294	-0.238	-0.229	0.087	-0.243
19	-0.247	-0.177	-0.022	0.757	-0.017	-0.248	-0.170	-0.169	0.099	-0.245
20	-0.231	-0.313	0.038	0.723	-0.244	-0.378	-0.326	-0.306	-0.137	-0.307

	11	12	13	14	15	16	17	18	19	20
11	1.000									
12	-0.137	1.000								
13	-0.197	0.455	1.000							
14	0.002	0.109	0.075	1.000						
15	-0.351	-0.067	0.075	0.080	1.000					
16	0.346	-0.088	-0.026	0.623	0.068	1.000				
17	0.508	-0.196	-0.230	-0.531	-0.319	-0.428	1.000			
18	-0.167	0.478	0.914	0.179	0.155	-0.016	-0.252	1.000		
19	-0.299	0.486	0.869	0.122	0.136	-0.133	-0.323	0.900	1.000	
20	-0.287	0.642	0.783	0.190	0.060	0.164	-0.490	0.745	0.786	1.000

Factor analysis is a multivariate method which enables the researcher to simplify and summarize a large data matrix into a smaller one without appreciable loss of information. This technique is primarily concerned with the resolution of a set of observed variables with a linear transformation, to form new derived variables (factors), and considerable simplification is attained.[10] In this study, the specific problem was a large number of intercorrelated ratios with information about a group of firms. The task was to reduce the number of variables without loss of information. The simplification in factor analysis is based upon the amount of linear dependence, or redundancy, that exists in the data matrix, X. If a set of vectors, A, is linearly dependent upon another set of vectors, B, then it is possible to describe the first set of vectors in terms of the second set. In this context, the twenty linearly dependent vectors in A are the correlated ratios, and this set may be described in terms of r new vectors (r less than n) which are themselves, linearly independent (uncorrelated). Only the linearly independent vectors need be retained because the vectors in A (the n-space) are linear combinations of those in the r-space. The first set of n vectors may explicitly be described by stating their relationship (dependence) to the subset of r. This is called the factor loadings matrix.

Hopefully the number of linearly independent vectors (r-space) will be considerably smaller than the original s-space and a great deal of simplification will be attained.

Principal components analysis was the specific factor analysis solution employed in this study. This is probably the most widely used technique in factor analysis and its purpose is to extract maximum variance from the

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[10]Jagdish Sheth and Douglas Tigert, "Factor Analysis in Marketing," unpublished paper presented at AMA Workshop in Multivariate Methods in Marketing, January, 1970, 41 pages.

observed variables. In this problem the principal components solution seeks to extract the greatest amount of variance from the data matrix, X, of twenty ratios and express this in the fewest dimensions (factors) as possible. Harman noted that this specific technique is especially useful when a large body of data requires simplification.[11]

Analysis of Merger Data

The original data matrix $X_{(20x80)}$, was the basic source for analysis. The matrix of correlations among the variables $R_{(20x20)}$, served as the input for factor analysis. The R matrix, as shown in Table 3.3, summarized the information inherent in X while presenting this in a standardized form. Table 3.4 summarized the output of the original factor analysis, a factor loadings matrix $A_{(20x20)}$. Table 3.4 indicates the re-allocation of variance from twenty variables into a minimum number of uncorrelated factors. The characteristic roots (or eigenvalues) are in column one and labeled variance. Columns two and three, respectively, indicate the percentage of the total variance explained by the individual factors, and the cumulative reduction of variance as the number of factors increase.

It is apparent from Table 3.4 that considerable redundancy existed in the original data set. The first three factors accounted for over 63% of the variance in X, and the first ten factors accounted for over 94% of the total variance. The relevant decision at this stage, relative to Table 3.4, was how many factors to preserve for further analysis. Several procedures are noted in the literature[12] including retaining factors with corresponding eigenvalues greater than unity, and retaining enough factors to account for

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[11]For a rigorous and extensive treatment of factor analysis, see Harman, H. H. Modern Factor Analysis, Chicago: University of Chicago Presss, 1967.

[12]Tatsuoka, Maurice, M. Multivariate Analysis, New York: John Wiley & Sons, Inc., 1971, chapter 5.

TABLE 3.4

SUMMARY OF FACTOR ANALYSIS: TWENTY RATIOS ON EIGHTY FIRMS

Factor	Variance	Percent Variance	Cumulative Percent
1	6.46	32.32	32.32
2	3.72	18.60	50.92
3	2.49	12.47	63.40
4	1.67	8.38	71.78
5	1.15	5.75	77.54
6	0.99	4.95	82.49
7	0.79	3.97	86.47
8	0.65	3.26	89.74
9	0.52	2.64	92.39
10	0.44	2.24	94.63
11	0.36	1.84	96.47
12	0.23	1.16	97.64
13	0.16	0.83	98.47
14	0.11	0.55	99.03
15	0.07	0.37	99.41
16	0.05	0.26	99.68
17	0.03	0.16	99.85
18	0.02	0.11	99.96
19	0.00	0.02	99.99
20	0.00	0.00	99.99

some pre-determined amount of total variance such as 80% or 90%. In applying several of these tests to the results in Table 3.4, six factors were retained for further analysis and these accounted for 82.49% of the original variance in X. The implicit assumption here is that the space include six independent dimensions and the remaining 17.51% of the variance was essentially error variance.

The next step in the analysis was a rotation of the principal axes of the space to impose simple structure upon the new factor loadings matrix $A_{(20x6)}$ which is shown in Table 3.8. A varimax rotation procedure was employed, and its purpose was to alter the axes of the space so as to maximize the association of each variable with one factor to the exclusion of the others. This facilitates research interpretation of the A matrix while preserving the orthogonality of the space. (A more rigorous discussion of the rotation principles and procedures can be found in Harman).[13]

Interpretation was made of the six factors in A by identifying the ratios which loaded highest on each of the factors. For example, factor one had high loadings for ratios 4, 12, 13, 18, 19, and 20 which all were leverage ratios (see Table 3.1). The remaining ratios had loadings close to zero for factor one. Thus factor one was labelled the leverage factor and that financial quality included as an essential dimension in the sample space. Factor two contained the group of profitability ratios, followed successively by factors with liquidity, turnover, dividend policy and price earnings. The actual labeling of the factors is arbitrary in a statistical sense, but widely used for research interpretation and quite clear in this instance because the ratios clearly grouped together by

[13]Harman, op. cit.

TABLE 3.8

VARIMAX ROTATION INTO SIX SPACE: SUMMARY OF FACTORS AND ROTATED FACTOR MATRIX

Summary			
Factor	Variance	Percent Variance	Cumulative Percent
1	4.76	28.89	28.89
2	4.32	26.19	55.08
3	3.15	19.09	74.18
4	1.78	10.84	85.02
5	1.29	7.86	92.89
6	1.17	7.10	99.99

Ratio	1	2	3	4	5	6
1	-0.157	0.908	-0.185	0.134	0.104	-0.018
2	-0.157	0.074	-0.083	-0.001	0.811-	-0.039
3	-0.028	-0.056	0.232	-0.008	0.028	-0.896-
4	0.888	-0.095	-0.032	0.021	0.007	0.027
5	-0.127	0.458-	0.509	-0.304	-0.131	-0.124
6	-0.227	0.787-	0.492	-0.023	-0.161	0.141
7	-0.174	0.667-	0.570	-0.103	-0.235	0.167
8	-0.151	0.781-	0.525	-0.056	-0.196	0.097
9	0.176	0.784-	0.009	0.108	0.320	-0.059
10	-0.176	0.951-	-0.052	0.067	0.121	0.018
11	-0.169	0.079	-0.135	0.842-	0.206	0.218
12	0.609-	-0.116	-0.098	0.098	-0.433	-0.100
13	0.933-	-0.072	0.008	-0.053	-0.017	0.018
14	0.080	0.017	-0.794-	-0.122	-0.056	0.214
15	0.044	-0.045	-0.078	-0.717-	0.214	0.263
16	-0.088	-0.032	-0.850-	0.137	0.039	0.177
17	-0.022	0.108	0.693-	0.564-	-0.002	0.231
18	0.937	-0.079	-0.047	-0.079	0.030	0.096
19	0.927-	-0.058	0.021	-0.195	-0.006	0.002
20	0.815-	-0.145	-0.272	-0.111	-0.300	-0.145

financial quality. Thus the factor analysis has reduced the data matrix X to a derived set of six factors which identified the essential financial dimensions as well as the relationship between each of the original ratios and the factors as shown by the factor loadings matrix. These loadings are similar to correlation coefficients which is of assistance is a subsequent stage of the analysis.

At this juncture the data from the original sample has been refined and expressed in six derived variables which are linear combinations of the original twenty ratios. These may be used in the subsequent discriminant model for factor score inputs, or individual ratios from each of the factors may be used to represent the factors themselves. For example, if one ratio such as ratio 13 in factor 1 were substituted for the factor itself, very little information would be sacrificed due to the high loading of .933 indicating that $(.933)^2$ or about 85% of the variance of the factor will be associated with the variance of ratio 13. Similarly, a high loading ratio can be used from each factor as a factor surrogate generating a set of six ratios which form an approximation of the factor analysis solution itself. The advantage of this procedure is that financial data is required for only six ratios whereas if the factor scores were used the entire twenty ratio set would be needed to generate the six factor scores. In that financial data problems have already been discussed, it is apparent that to the extent data requirements could be reduced, the model would increase in usefulness. (Actually the factor scores were subsequently used in the discriminant analysis to analyze the differences in the model and no significant information was sacrificed when the individual ratios were substituted for the factors).

Multiple Discriminant Analysis

The result of the factor analysis performed upon the original data was to summarize and simplify the data for further use. The reduced data set, in the form of ratios taken from each of the factors, was the basic input into a discriminant analysis which tested for group differences between acquired and non-acquired firms and generated a linear function which best separated the groups.

Given objects with know a priori group membership, the primary objective of MDA is to correctly classify entities into mutually exclusive groups by the statistical decision rule of maximizing the ratio of among-group to within-groups variance-covariances on the profile developed by the independent variables. In addition, the discriminant analysis reveals which of the specific variables employed accounted for the largest portions of the intergroup differences.

MDA has had increasing use in finance research problems in recent years, notably the previously cited studies by Altman and Monroe and Simkowitz. MDA is an alternative when research problems must deal with nonmetric dependent variables. It should be noted however that in the two-group case (which applies to this study as well as the two others cited above) the discriminant solution is the same as that generated by using a zero-one multiple regression.[14]

The reduced set of ratios determined by the factor analysis was used to generate the discriminant model of the form

$$Z_1 = b_1X_1 + b_2X_2 + \cdots + b_iX_i$$

where the b_i are discriminant coefficients, the X_i are the independent

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[14]Tatsuoka, op. cit.

variables (ratios) and Z_i is the discriminant score of the i^{th} firm.

It should be emphasized at this point that the financial dimensions derived from the factor analysis and the financial dimensions which best discriminate among groups are not necessarily the same. The purpose of the principal components solution was, with each stage of the solution, to extract maximum remaining variance from the total variable set. There exists no dependent variable in factor analysis, only a single set of interdependent variables. Thus the first principal axis will be selected without regard to its effect upon groups within the total set. On the other hand, discriminant analysis begins with a priori groups and finds the variable profile which maximally differentiates among these groups. Thus, while the factor analysis procedure allowed the derivation of six dimensions for input into MDA, it in no way suggested which combination, if any, would discriminate among groups.

The MDA stage involved a series of test runs using alternative inputs from the six factors. In that several of the factors had two or three ratios with very high loadings, little statistical difference resulted from varying the choice. The final discriminant function was chosen on the basis of four ratios in the following model:

$$Z_i = 0.108\ X_1 - 0.033\ X_2 + 0.987\ X_3 + 0.111\ X_4$$

X_1 earnings before interest & tax/sales
X_2 net working capital/total assets
X_3 sales/total assets
X_4 long term liabilities/ total assets

As can be seen, the financial dimensions which best differentiated the groups were profitability, liquidity, a gross activity measure (total asset turnover), and a financial leverage measure.

Group Differences and Interpretation of MDA

For purposes of comparison, an analysis was made as to how the groups

differed with respect to each of the above ratios, and how well any of the ratios would have separated the groups on a univariate basis. Table 4.1 presents the group means for each of the ratios in the discriminant function and also presents the F-statistic from a one-way analysis of variance test of the difference of the group means on a univariate basis. First, from a univariate point of view, only the leverage variable indicated a difference between the two samples which was statistically significant. If a univariate methodology had been employed, the only conclusion which could have been statistically valid was that acquired firms had lower levels of leverage. None of the other observed differences were significant.

Table 4.2 presents the statistics of the multivariate discriminant function. The centroid is the multivariate equivalent of the mean and the Wilks lambda is the distance measure between the centroids. The significance of the distance is approximated by the F-statistic. For the two groups, F = 2.936 was significant at the 0.025 level. Thus the hypothesis that the differences were attributable to chance was rejected.

Analysis of the independent variables was of interest to indicate their individual influence upon the discriminant function. This was not directly apparent from the discriminant coefficients due to differing measurement scales. The scale factors were removed and Table 4.3 indicates the relative importance of the four ratios. The most significant of the ratios was the ratio measuring leverage. This finding was consistent with the conclusions of the univariate tests. Profitability was the second most important variable in group discrimination. Although not significant in a univariate context, it was second only to leverage as a contributor to group discrimination. The turnover variables and the liquidity variable were third and fourth respectively. It should be

TABLE 4.1

UNIVARIATE TESTS OF SIGNIFICANCE FOR
GROUP MEANS: ORIGINAL SAMPLE

Variable	Ratio	Group Means NON-ACQ	Group Means ACQ	F
X_1	EBIT/sales	10.40	8.83	.68
X_2	NWC/total assets	34.59	40.66	2.74
X_3	sales/total assets	1.36	1.41	0.15
X_4	LT liabilities/total assets	22.31	13.77	8.35
$F_{(1,60)(.01)} = 7.08$		n=40	n=40	
$F_{(1,60)(.10)} = 2.79$				

TABLE 4.2

MDA: GROUP DIFFERENCES

Group		Centroid
1 non-acquired		3.792
2 acquired		2.524
	Wilks lambda	0.8646
	$F_{(4,75)}$	2.936
$F_{(4,75)(.05)} = 2.48$		
$F_{(4,75)(.025)} = 2.94$		

noted that while the dividend payout ratio and price earnings ratios were both input into the MDA model, neither improved the discriminant function.

TABLE 4.3

MDA: SCALED VECTORS AND DISCRIMINANT FUNCTION, ORIGINAL SAMPLE

Variable	Ratio	Discriminant Coefficient	Scaled Vector	Rank
X_1	EBIT/sales	0.108	8.085	2
X_2	NWC/total assets	-0.033	-4.800	4
X_3	sales/total assets	0.987	5.196	3
X_4	LT liabilities/total assets	0.111	12.953	1

However, the joint effect on the four variable profile with respect to the two groups indicated that the groups could be differentiated. One further observation is appropriate at this point in that Altman observed the same relationship with the same ratio in his bankruptcy study.[15] Although the sales/total assets ratio produced very little group differences with respect to the means, it was an important component of the discriminant function and excluding that variable reduced both the significance of the centroid separation and the classification ability of the model. Again, this is a further indication that a univariate analysis can often miss the nature of differences in financial problems.

[15] Altman, op. cit.

Classification of the MDA Model

To further test the ability of the discriminant function to discriminate between the groups, the individual firms were then subjected to a classification into one of the two groups based upon their individual discriminant scores. The classification procedure employed in this study is discussed in Tatsuoka (chapter 8) and is based upon a chi-square statistic which allows probability assessment for group membership liklihood based upon that statistic. The discriminant function produced the following classification results when applied to the original sample and these are in Table 4.4

TABLE 4.4

MDA: CLASSIFICATION MATRIX, ORIGINAL SAMPLE

PREDICTED	ACTUAL NON-ACQ (%)	#	ACQ (%)	#	
NON-ACQ	(55)	22	(14)	6	28
ACQ	(45)	18	(85)	34	52
$t = 3.58$		40		40	

$t_{(60)(.0005)} = 3.46$

$$t = \frac{p-.5}{\left(\frac{.5(1-.5)}{n}\right)^{\frac{1}{2}}}$$

p = proportion correct (70%)

n = 80

A t-test was employed to test the null hypothesis that 56/80 or 70% classification accuracy could be attributed to chance. The t statistic of 3.58 allowed rejection of the null hypothesis at the .0005 level of signifi-

cance. Thus the discriminant function did have the power to classify acquired and non-acquired firms.

However, examination of the classification results for the individual groups reveals that while the acquired firms were very accurately classified, the non-acquired firms were more evenly split between the acquired and non-acquired samples. The explanation of this result is that offered by the earlier discussion concerning sampling and Figure 1. The real research interest centers around the A and N groupings in Figure 1 but the sampling was made with ACQ as a surrogate for A and a non-acquired group as a surrogate for group N. It was recognized at that time that this second sample would include both group A and group N members.

If one accepts this configuration, another interpretation of the classification results is possible. That is the eighteen non-acquired firms which were classified acquired were likely members of the attractive (A) group in Figure 1, while the twenty-two non-acquired firms which were correctly classified as non-acquired were from the not-attractive (N) group in Figure 1. In that the acquired firms are no longer available for acquisition it is the eighteen attractive firms which should be of interest as primary acquisition targets. Thus if a model such as this could be shown to be consistent and validated over time, and owing to the lack of a priori A and N groupings, the primary interest would be in the mis-classified non-acquired firms.

Validation of Results

It has been noted by Morrison and others that designs of this sort tend to include an upward bias in the classification because the same firms used in the derivation of the model are also used for classification.[16]

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[16] D. G. Morrison. "On the Interpretation of Discriminant Analysis," Journal of Marketing Research, Vol. 6 (May, 1969), 156-163.

One method of avoiding this bias is to fit a discriminant function to part of the data and then use this function to classify the remaining firms. To accomplish this each of the a priori groups were divided into two subgroups of size twenty. A discriminant function was derived using one sub group from each of the acquired and non-acquired samples. This model was used with the same classification procedure to classify the two other subsets. The results in Table 4.5 indicate that little shrinkage took place and offer evidence in support of the original model.

TABLE 4.5

MDA: CLASSIFICATION MATRIX, VALIDATION SAMPLE

	Actual		
Predicted	NON-ACQ	ACQ	
NON-ACQ	13	6	19
ACQ	7	14	21
	20	20	
$t = 2.213$	percent correct = 67.5%		
$t_{(40)(.025)} = 2.021$			

A second type of validation was attempted to determine if the variables in the discriminant model and their coefficients remained stable over other time periods. If this could be accepted, it could be argued that the financial profile for attractiveness for acquisition is stable and its components are those variables in the model. Historically models developed in financial research (notably stock price models) have had little stability over time.

Just as the a priori groups in the original sample could not be generated

from attractive and not-attractive firms, neither could the validation sample. The only available alternative to offer evidence in support of the model's stability over time was to sample acquired firms for other time periods and classify them with the original model. This was accomplished with samples of firms acquired in the years 1967 and 1968. Twenty firms were sampled for each year and the financial data was collected to generate the four ratios used in the discriminant function. Each of the firms was classified in the same way except that all of the firms would be expected to be classified as acquired. Table 4.6 indicates the results.

TABLE 4.6

MDA: CLASSIFICATION MATRIX, VALIDATION SAMPLE
ACQUIRED FIRMS 1967 and 1968

Predicted		Actual (ACQ) 1967	Actual (ACQ) 1968
NON-ACQ		6	6
ACQ		14	14
	%accuracy	70%	70%

Both validation groups were classified with 70% accuracy lending support to the contention that the financial profile of the discriminant model remained applicable in periods other than the period used to develop the model. This would also increase the level of confidence for accepting firms in these years which, although not acquired, were classified as acquired by the model. These firms, in that they possess similar financial profiles to acquired firms, should stand as more attractive takeover targets.

Summary & Conclusions

The purpose of this study was to analyze financial characteristics of acquired firms for the period immediately prior to acquisition. A multivariate framework was developed to determine which financial qualities best distinguished firms acquired in mergers from similar firms not acquired.

A discriminant model was developed using six financial dimensions derived from a factor analysis of a much larger data source. The factor analysis was applied because of the high degree of multicollinearity present in the original data set and as an analytical substitute for other more judgemental approaches used in similar studies. A discriminant function was derived employing ratios from the financial dimensions of leverage, profitability, turnover and liquidity. The model demonstrated significant differences between the samples and an ability to classify firms not used in the derivation of the model. Further subsequent samples from other time periods offered evidence in support of the stability over time of the discriminant model. These findings were consistent with the belief that a financial basis was common to the merger decision and similar to other capital asset acquisition decisions.

This study also demonstrated the usefulness of a multivariate framework in financial analysis. The multivariate profile in the model included financial qualities which indicated no group differences in univariate testing. Further a procedure was offered for dealing with the multicollinearity problem so often faced in empirical research of this kind. Factor analysis was shown to be a useful device to summarize the total data set without significant loss of information, such that the remaining variables minimized the inter-correlation problem. MDA proved to be a useful technique for detecting group differences and indicating which variables best distinguished

the groups. This application of these tools should provide incentive for their future application in research in finance.

A number of questions have been raised by this study which merit future inquiry. First, general replication of this study, perhaps introducing new variables or additional financial qualities, appears justified. It is apparent that the original twenty ratio data set is by no means exhaustive. To the extent that new measures can be introduced which measure an essentially new financial dimension, it would provide another factor coming out of the factor analysis and an additional input into the MDA. This addition could include non-financial as well as financial qualities. It should be recalled at this point that an assumption was implicit that if all relevant decision variables were not expressed by the financial ratios, at least they were indirectly reflected in the ratios. However, the observation of several mis-classified acquired firms in both the original and validation samples is testimony that the model does not completely specify all the relevant variables. One specific addition might be to augment the original data matrix with the Monroe and Simkowitz variables prior to the factor analysis and see if additional dimensions are derived. Another important extension would be to sample small firms to the extent data is available. Here it would be interesting to see if the same criteria were applied to these companies.

Finally, the areas of factor analysis and related multivariate techniques merits further investigation by researchers in finance. Factor analysis particularly has not seen many applications in published financial research. Its potential as a data simplification tool, and as a tool to identify structure in data should offer encouragement and increase the refinement of the multivariate approach to ratio analysis.

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