Usefulness of Financial Ratios in a Single Industry

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This paper reports the findings of a study on the relationship and ratio grouping of a well-published set of financial ratios within the context of a single, homogeneous industry. The findings provide some insight into the validity of using single-industry ratio averages as standards to evaluate individual firm performance. Factor analysis was used to study the interrelationship among the ratios and to determine whether these ratios group in the "traditional" category of ratios suggested in the financial statement analysis literature. This analysis was followed by a cluster analysis of the composite ratios derived from the factor analysis to determine whether any consistent and stable statistical grouping of firms developed over time within the industry. These analyses were done for 72 companies for the period 1966–1975 using Dunn and Bradstreet ratios and Compustat data.

The traditional approach to the evaluation and interpretation of a firm's financial ratios involves the use of trend and/or cross-sectional analyses. In the former, a firm's ratios are plotted over time and external statement users analyze the ratio patterns to identify downward or undesirable trends so an evaluation of performance can be made. The framework for evaluation is often the past year's performance and the standard of evaluation is the direction of the ratio trend and the magnitude of change in the trend line. In contrast, cross-sectional analysis involves making comparisons between the firm's ratios and industry averages or ratios of similar firms. The implicit assumption underlying cross-sectional analysis is that these industry averages are a valid benchmark against which to evaluate individual firm performance.

Lev [12] and others [7, 16] have criticized the use of trend and cross-sectional analysis in interpreting and evaluating a firm's ratios. The issues raised relate to the following:

1. possible intercorrelation of financial ratios,
2. desirability of industry averages as performance targets,
3. the nature and stability of ratio groupings in the context of a single industry,

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4. proper measures of central tendency for ratios.

These issues are still debatable and open to research. The published literature in recent years in accounting and finance has provided insight into issues 1 and 4 [1, 16], while questions related to issues 2 and 3 still remain unanswered.

In an article exploring the effects of size, growth, and industry on the financial ratios of manufacturing companies, Gupta [7] found that interindustry variations in ratios do exist and that these differences relate, for the most part, to characteristics of the different industries. In a related study, Gupta and Huefner [8] indicated that financial ratios correspond to sets of industry characteristics. The closeness of this correspondence is a function of the ratio being utilized, with the more aggregate ratios (e.g., total asset turnover) being less helpful in explaining interindustry differences. The authors imply that as industry classifications become less descriptive of the activities of a firm, subindustry group ratio averages may be better targets in evaluating firm performance than are the industry averages.

Firms desire to adjust their ratios to some predetermined standards based on industry averages [12]. Lev [12] provided empirical evidence to support this observation that firms do appear to adjust their financial ratios to industry averages.

Questions similar to those suggested by Gupta and Huefner [8] and Lev [12] are explored in this paper. An extension is made of the work by Pinches et al. [15, 16, 17] into the hierarchical classification of financial ratios and the stability of ratio groupings over time.

Methodolgy

Selection of Industry The source of data for this study was Standard and Poor's Compustat tapes, which contain key financial statement data for approximately 2,400 industrial companies for a period of between 10 and 20 years. All companies on the tapes are also identified by 4-digit SIC code as assigned by the U.S. Department of Commerce.

The industry selected for analysis was the oil-crude industry, SIC Code 1311, because it satisfied the two following criteria:

1. there were at least 30 companies in the industry with nine years of data for the period 1966–1975;
2. the industry evidenced a high degree of homogeneity.

The first criterion was necessary for statistical reasons. Seventy-two of the approximately 90 companies listed in Compustat under the 1311 SIC code were selected for inclusion in the study. These 72 companies are a subset of the entire industry but the only companies for which usable, published data could be acquired.

The second criterion was included to minimize the number of factors that could influence the variability of the financial ratios. To satisfy the last criterion, homogeneity was defined in terms of specialization and coverage ratios often used in marketing to determine industry concentration [10]. The coverage ratio measures the extent to which a product is produced by companies classified in that product's industry. In contrast, the specialization ratio measures the extent to which firms classified in a given industry produce products primary to it. The higher the values of these ratios, in particular, the specialization ratio, the more homogeneous the industry. Although these ratios are not published for the oil-crude industry, a personal conversation with the Chief of the Minerals Branch—Industry Division, U.S. Department of Commerce, provided evidence that ratios of 90 percent or better for coverage and specialization would be likely.

Two caveats are associated with the use of this industry in the analysis. First, the oil and gas industry, while homogeneous in some respects, is not homogeneous with regard to accounting practices. Until recently, there were two diverse accounting approaches used in the industry in the preparation of published financial satements—full costing and successful efforts. Therefore the differences in accounting methods may affect the underlying structure of the ratios studied. Despite the fact that this issue is not specifically addressed in the research, and analysis of the results for the full costing companies versus the successful efforts companies indicated it was not a significant factor in explaining group differences.

The second caveat relates to the fact that financial ratios are just one of the two primary information sets used by analysts to evaluate industry and firm performance in the oil-crude industry. The other factor that is closely monitored and evaluated is an estimate of the value of reserves held. An analysis of this information was not included in the study because it was not available through Compustat or other published public reports. This omission is not considered serious in that the purpose of the paper is to propose an approach to the study of the interrelationship and stability of a standard set of well-publicized ratios in the context of a single industry with the intent of assessing the appropriateness of these ratios as measures of performance. To the extent that analysts use other nonratio data in performance evaluation does not mitigate the importance or necessity of studying the nature of financial ratios.

Data For each of the companies in the industry subset, 13 of Dunn and

Bradstreet's (D & B) 14 key ratios [5] were calculated from the raw data on the S & P tapes; the collection period could not be computed because of missing data on the files. D & B ratios were utilized because they are normally recognized as being the most widely accepted and used set of ratios in evaluating firm performance by parties external to the company [18]. The ratio set could have been expanded to include other ratios often cited in the literature but not widely available to external users of financial statements. D & B ratios, despite their narrowness, are accessible to professional analysts as well as others i.e., existing or potential stockholders and creditors, and used as broad benchmarks in evaluating firm performance. The total assets of each company were included in the data base as a size variable. Table 1 contains a listing of all the variables used in the analysis with their corresponding labels. Each ratio has been classified into one of four ratio categories —profitability, liquidity, leverage, turnover—indicating what the ratio is attempting to measure. The selection of the ratio categories and the classification of individual ratios is based on the literature on financial statement analysis [13, 18].

The last value added to the data base for each company was the number of SIC codes assigned to it by the Department of Commerce. The D & B Million Dollar Directory [4] contains a listing of the 1,000 largest companies with their accompanying SIC classification. A review of this directory indicated that 28 of the 72 companies analyzed had a single SIC Code with the remainder of the companies having multiple SIC codes. The factor analysis, described later, indicated that the number of SIC classifications for each company did not significantly account for any of the variability in the ratios.

Data Analysis

Factor Analysis A principal components factor analysis with a varimax rotation was performed on the data using SPSS [14] to determine whether consistent and stable ratio groupings existed, and to reduce the data set for subsequent analysis. The data were factor analyzed for each year, and for all companies and years together. Principal components analysis was used because it has the objective of portraying a set of associated variables in terms of a set of orthogonal linear combinations of those variables. The combinations are selected so that each set of component scores accounts for a decreasing proportion of variance in the original variable. Thus the first factor will account for the most variability with each successive factor explaining less. Factor analysis can be used for many purposes including data reduction and to

Table 1: Variables Analyzed

Variable	Label	Measure of
Current assets to current debt	(CASSCDB)	Liquidity
Net profits on net sales	(NPRONSAL)	Profitability
Net profits on tangible net worth	(NPROTNW)	Profitability
Net profits on net working capital	(NPRONWC)	Profitability
Net sales to tangible net worth	(NSALTNW)	Turnover
Net sales to net working capital	(NSALNWC)	Turnover
Net sales to inventory	(NSALINV)	Turnover
Fixed assets to tangible net worth	(FASSTNW)	Leverage
Current debt to tangible net worth	(CDBTNEW)	Leverage
Total debt to tangible net worth	(TDBTNW)	Leverage
Inventory to net working capital	(INVNWC)	Liquidity
Current debt to inventory	(CDBINV)	Liquidity
Funded debt to net working capital	(FDBNWC)	Leverage
Total assets	(TASS)	Size

determine the underlying structure of a set of variables. The fact that some of the variables factor analyzed are linearly dependent on one another could lead to a data instability problem. However, a detailed review of the factor analysis output indicated that this potential problem did not occur in the data set.

Factor analysis is particularly useful in analyzing financial ratios since the technique minimizes the intercorrelation between factors and, therefore, identifies the information redundancy of ratios. The varimax rotation maximizes the sum of variance of squared factor loadings in the columns of the factor matrix. This rotation assists in data interpretation because it forces high and low factor loadings for the variable in each factor.

The results of this analysis are summarized in Table 2. The table lists the two to four highest loading variables on each factor for the years 1967 through 1975, and for all the years together. The listing of just the two to four highest loading variable does not have any particular significance other than to provide insight into the mix and nature of the ratios loading on each factor. The typical exposition of the results of a factor analysis is to show variables under a given factor when those variables have their highest loading under that factor. This display approach was not used because the contents of Table 2 (and Table 3, which will be discussed later) convey information more useful for the analysis at hand. The notation in parentheses following each variable indicates what the variable is intended to measure, as shown in Table 1.

Table 2: Factor Loadings Using Raw Data Factors

Year	1		2		3		4		5	
1967	NSALTNW(T)	0.95	FASSTNW(Lev)	0.90	CDBINV(L)	0.86	NPRONWC(P)	0.78	CASSCDB(L)	−0.77
	NSALNWC(T)	0.83	TDBTNW(Lev)	0.98	NSALINV(T)	0.80	FDBNWC(Lev)	0.74		
1968	INVNWC(L)	0.96	TDBTNW(Lev)	0.93	CDBINV(L)	0.95	CASSCDB(L)	−0.85	NASLTNW(T)	0.61
	NPRONWC(P)	0.84	CDBTNW(Lev)	0.81	NSALINV(T)	0.88				
	FDBNWC(Lev)	0.83								
1969	NSALNWC(T)	0.86	CDBINV(L)	0.97	TDBTNW(Lev)	0.89	FDBNWC(Lev)	0.77	TASS(S)	−0.56
	INVNWC(L)	0.71	NSALINV(T)	0.82	CDBTNW(Lev)	0.87	FASSTNW(Lev)	−0.70		
			NPROSAL(P)	0.76						
1970	INVNWC(L)	0.99	CDBINV(L)	0.98	TDBTNW(Lev)	0.81	NSALINV(T)	0.77		
	NPRONWC(P)	0.99	NSALINV(T)	0.86	CDBTNV(Lev)	0.80				
	FDBNWC(Lev)	0.99	NPROSAL(P)	0.85						
	NSALNWC(T)	0.98								
1971	NSALTNW(T)	0.93	NSALINV(T)	0.96	NPRONWC(P)	0.96	CASSCDB(L)	−0.84	FASSTNW(Lev)	0.78
	NSALNWC(T)	0.79	CDBINV(L)	0.93	FDBNWC(Lev)	0.75	NPROSAL(P)	−0.60	TDBTNW(Lev)	0.76
1972	NSALINV(T)	0.96	NSALNWC(T)	0.87	TDBTNW(Lev)	0.92	FDBNWC(Lev)	0.90	NSALTNW(T)	0.68
	CDBINV(L)	0.93	INVNWC(L)	0.80	CDBTNW(Lev)	0.69	NPRONWC(P)	0.84		
	NPROSAL(P)	0.84								
1973	NSALINV(T)	0.91	TDBTNW(Lev)	0.87	INVNWC(L)	0.86	NPROTNW(P)	0.82	TASS(S)	−0.53
	CDBINV(L)	0.91	CDBTNW(Lev)	0.76	NSALNWC(T)	0.84				
	NPROSAL(P)	0.79								
1974	NSALNWC(T)	0.92	TDBTNW(Lev)	0.88	CDBINV(L)	0.96	NPROTNW(P)	0.80	FDBNWC(Lev)	0.76
	NSALTNW(T)	0.87	CDBTNW(Lev)	0.79	NSALINV(T)	0.85	NPRONWC(P)	0.71		
1975	CDBINV(L)	0.77	NSALINV(T)	0.86	FDBNWC(Lev)	0.91	INVNWC(L)	0.81	CDBTNW(Lev)	0.61
	NPROSAL(P)	0.76	NSALTNW(T)	0.76	FASSTNW(Lev)	0.83				
	NPRONWC(T)	0.71	NSALNWC(T)	0.78						
All years	NPRONWC(T)	0.95	CDBINV(L)	0.95	TDBTNW(Lev)	0.74	CASSCDB(L)	−0.76	NSALTNW(T)	0.73
	FDBNWC(Lev)	0.93	NSALINV(T)	0.82			CDBTNW(Lev)	0.75		
	INVNWC(L)	0.93	NPROSAL(P)	0.74						
	NSALNWC(T)	0.93								

A visual analysis of this table indicates that there was little consistency and stability in the factor loadings across all years, though there appears to be some stability in the loading and movement of certain variables over short time spans. For example, in 1967 and 1968 the same two ratios—CDBINV and NSALINV—consistently loaded together as factor three. In addition, the TDBTNW ratio loaded quite high on either factor 2 or 3 in years 1967–1972. The other interesting observation illustrated in the table is that the ratio groupings formed were also inconsistent with what is anticipated on the basis of previous research [16]. The factors did not conform in any consistent manner to the predetermined ratio categories of profitability, liquidity, leverage, and turnover. The Pinches et al. [16] study found that ratios could be classified into seven broad categories and that these groupings remain relatively stable through time. However, the Pinches study was based on an analysis of 28 ratios across 211 industrial firms with different SIC classifications for the years 1966–1969. The results of our analysis using the D & B ratios for 72 companies within a relatively homogeneous industry do no substantiate the findings of Pinches et al.. In the context of a single industry there was neither stability in the factor loadings through time nor in the loading of ratios within the factors. The only discernible commonality among the factors is the ratios with similar denominators appear to lead together. The classification of ratios into four categories may overshadow the fact that the same ratio can be used to measure different aspects of a company's financial well-being. Certain categories of ratios do tend to move together. For example, some consistency in the movement of the liquidity and turnover ratios occurs, and with the profitability and leverage ratios. This observation is consistent with the findings of Pinches et al. [16], which indicated a hierarchical relationship among ratios with profitability and leverage ratios moving together as do the liquidity and certain turnover ratios.

In an effort to determine whether these results (i.e., unstable relationships) were due simply to first-order nonlinear data relationships and/or some outlying data points, the raw data were transformed and the factor analysis repeated. The transformation was the natural logarithm of the absolute value of the miminum variable over all the companies plus three plus the variable value. That is, the value for variable i in year t for firm j (V_{itj}) was transformed using

$$V_{itj} = \ln\left[3 + ABS\left(\min_{j} V_{itj}\right) + V_{itj}\right].$$

This approach included normalizing all values to be positive and minimized the effects of outliers without changing the relative position

Table 3: Factor Loadings Using Transformed Data Factors

Year	1		2		3		4		5	
1967	NSALNWD(T)	0.86	NSALTNW(T)	0.83	TDBTNW(Lev)	0.89	NSALINV(T)	0.95	CASSCDB(L)	−0.69
	FDBNWC(Lev)	0.85	CDBTNW(Lev)	0.80	FASSTNW(Lev)	0.82				
	INVNWC(L)	0.85	NPROSAL(P)	−0.78						
1968	INVNWC(L)	0.97	TDBTNW(Lev)	0.95	NPROSAL(P)	0.93	NSALINV(T)	0.87	TASS(S)	−0.46
	NSALNWC(T)	0.96	CDBTNW(Lev)	0.79	CDBINV(L)	0.82				
	NPROMWC(P)	0.87								
1969	NSALNWC(T)	0.90	TDBTNW(Lev)	0.93	NPROSAL(P)	0.91	NSALINV(T)	0.89	TASS(S)	−0.54
	INVNWC(L)	0.82	CDBTNW(Lev)	0.89	CDBINV(L)	0.89				
	FDBNWC(Lev)	0.82								
1970	FDBNWC(Lev)	0.94	CDBTNW(Lev)	0.85	CDBINV(L)	0.95	NSALTNW(T)	0.78		
	INVNWC(L)	0.92	TDBTNW(Lev)	0.83	NPROSAL(P)	0.79				
	NPRONWC(P)	0.92			NSALINV(T)	0.78				
	NSALNWC(T)	0.71								

1971	TDBTNW(Lev)	0.88	NPRONWC(P)	0.94	CDBINV(L)	0.89	NSALTNW(T)	0.85	NPROTNW(P)	0.87
	CASSCDB(L)	−0.78	FDBNWC(Lev)	0.93	NSALINV(T)	0.86				
	CDBTNW(Lev)	0.76	NSALNWC(T)	0.73						
1972	CDBINV(L)	0.93	FASSINV(Lev)	0.80	NSALTNW(T)	0.73	NSALNWC(T)	0.92	NPRONWC(P)	0.69
	NSALINV(T)	0.85	TDBTNW(Lev)	0.79			INVNWC(L)	0.85		
	NPROSAL(P)	0.78	FDBNWC(Lev)	0.71						
1973	TDBTNW(Lev)	0.86	NSALNWC(T)	0.97	NSALINV(T)	0.90	NPROTNW(P)	0.83	TASS(S)	−0.55
	CASSCDB(L)	0.82	INVNWC(L)	0.84	CDBINV(L)	0.88			NSALTNW(T)	0.53
	CDBTNW(Lev)	0.81								
1974	NPRONWC(P)	0.83	NSALNWC(T)	0.90	CASSCDB(L)	−0.78	NSALINV(T)	0.77		
	CDBINV(L)	0.71	INVNWC(L)	0.88	TDBTNW(Lev)	0.77				
	NPROSAL(P)	0.73			FASSTNW(Lev)	0.74				
					CDBTNW(Lev)	0.73				
1975	NPROSAL(P)	0.80	FDBNWC(Lev)	0.94	NSALINV(T)	0.88	CDBINV(L)	0.64		
	TDBTNW(Lev)	−0.76	FASSTNW(Lev)	0.78	NSALNWC(T)	0.82				
	CDBTNW(Lev)	−0.76								
All years	INVNWC(L)	0.95	CDBTNW(Lev)	0.93	CDBINV(L)	0.99	NSALTNW(T)	0.74	NPROTNW(P)	0.67
	FDBNWC(Lev)	0.94	TDBTNW(Lev)	0.75						
	NSALNWC(T)	0.86								
	NPRONWC(P)	0.84								

of firm ratios, the latter being a necessity of any transformation in this context. The results of the subsequent factor analysis are contained in Table 3. These results indicate more consistency in the loadings during specific subperiods but still evidence instability over all the years. Furthermore, as in the analysis of the raw data, there is no indication that four ratio sets exist.

During the period 1967–1969, which is similar to the period used by Pinches et al. [16], five variables consistently loaded the highest on the five factors: total assets, net sales to net working capital, total debt to tangible net worth, net sales to inventory, and net profits on net sales. In contrast, in 1970 through 1972 five different variables appeared frequently—net profits on tangible net worth or net working capital, current debt to inventory, net sales to tangible net worth, and total debt to tangible net worth. Finally, little consistency occurs in how the ratios loaded during the last three years, 1973–1975. The stability of the loadings in each of the first two 3-year subperiods but yet not between these periods is difficult to explain. Perhaps circumstances affected this industry or the economy during these different time periods that had a structural effect on the underlying ratios of companies within the industry. For example, the oil embargo in 1974 created turmoil in the industry, so even with homogeneity across companies and a uniform and reasonable accounting method, the data are not likely to be stable over the1973—1975 period. However, to the best of our knowledge, there were no other major shocks or contaminations on the industry over the period examined other than the previously memtioned oil embargo. Of course, it is also possible that the D & B ratios do not clearly group into the "traditional" family of ratios cited in the literature because of the uniqueness of the ratios used or the sample studied. However, despite the fact that the ratios did not group consistently into four sets, there was once again consistency in the movement of certain ratios (e.g., leverage and profitability). This observation indicates that there may be a critical interrelationship between these ratios and that, in certain circumstances, they provide similar insight into explaining firm performance. The possible validity of this observation comes into focus when analyzing a ratio such as return on total assets, a profitability ratio. If one divides this ratio by one minus the total debt/total asset ratio (a leverage ratio), one gets the return on net worth (a profitability ratio).

One last test of the temporal stability of the loadings and classifications was conducted by 1) calculating and comparing the correlation coefficients of the factor loadings of all variables for all factors in adjacent years (Table 4), and 2) comparing factor loadings from the factor analysis for 1967—1975 combined versus those for each in-

Table 4: Correlations of Factor Loadings between Years for Each Factor (Transformed data)

Year	One	Two	Three	Four	Five
67/68	0.94[a]	0.57	0.16	0.94[a]	−0.72[a]
	0.94[a]	0.57	0.16	0.94[a]	−0.72[a]
68/69	0.97[a]	0.97[a]	0.97[a]	0.91[a]	0.91[a]
	0.95[a]	0.97[a]	0.97[a]	0.91[a]	0.91[a]
69/70	0.69[a]	0.91[a]	0.70[a]	0.65[a]	*b*
	0.57	0.91[a]	0.83[a]	0.66[a]	*b*
70/71	0.54	−0.53	0.50	0.83[a]	*b*
	0.52	0.79[a]	0.50	0.83[a]	*b*
71/72	−0.60[a]	−0.03	0.14	0.07	0.28
	−0.63	−0.60[a]	0.14	0.06	0.28
72/73	−0.47	0.29	−0.17	−0.45	−0.21
	−0.29	−0.47	−0.17	0.22	0.81[a]
73/74	−0.66[a]	0.98[a]	−0.13	−0.38	*b*
	0.98	−0.66[a]	0.46	0.12	*b*
74/75	0.97[a]	0.50	0.58	−0.45	*b*
	−0.44	0.02[a]	0.69[a]	0.41	*b*

[a] Significant at the 0.01 level.
[b] No factor five appeared in 1970 and 1974.

dividual year of the analysis (Table 5). This analysis was conducted in two different ways. The first approach was to calculate and compare the correlation coefficients of the factor loadings as they appeared in the factor analysis output. That is, factor 1 for 1967 was compared with factor 1 for 1968. The results of this analysis appear in the first rows of Tables 4 and 5. The second approach involved calculating and comparing the correlation coefficients of similar factor loadings, regardless of the factor number in the factor analysis output. For example, in the period 1974—1975, the correlation coefficient of −0.44 under factor one in Table 4 indicates the relationship between factor 2 in 1974 and factor 1 in 1975 because the loadings for these two factors indicated that variables were brought into each factor in approximately the same order (consequently, this logical factor, although present in both years, was more influential in 1975 than in 1974 since it was factor 1 in 1975). These latter relationships were formed to see if there was more commonality in the factor loadings despite the order in which they appeared each year.

All of these analyses basically supported the previously made observations that there was little consistency in the classifications over

Table 5: Correlations of the Factor Loadings for 1967–1975, Combined versus Each Year (Transformed data)

Year	One	Two	Three	Four	Five
1967	0.83[a]	0.77[a]	0.08	0.71[a]	−0.01
	0.84[a]	0.77[a]	0.08	0.71[a]	−0.01
1968	0.81[a]	0.84[a]	0.90[a]	0.66[a]	0.30
	0.82[a]	0.84[a]	0.90[a]	0.66[a]	0.30
1969	0.81[a]	0.91[a]	0.85[a]	0.77[a]	0.26
	0.69[a]	0.91[a]	0.85[a]	0.77[a]	0.26
1970	0.93[a]	0.96[a]	0.87[a]	0.94[a]	[b]
	0.94[a]	0.96[a]	0.98[a]	0.94[a]	[b]
1971	0.58	−0.60[a]	0.52	0.83[a]	0.72[a]
	0.44	0.73[a]	0.52	0.79[a]	0.72[a]
1972	−0.05	0.57	−0.30	0.46	0.17
	0.47	−0.51	−0.29	0.46	0.17
1973	−0.00	0.17	0.92[a]	−0.34	0.08
	0.84[a]	0.93[a]	0.92[a]	0.80	0.46
1974	−0.05	0.29	−0.07	0.89[a]	[b]
	0.80[a]	−0.66[a]	0.22	0.20	[b]
1975	−0.07	0.24	0.08	−0.54	[b]
	−0.08	0.24	0.09	−0.54	[b]

[a] Significant at the 0.01 level.
[b] No factor five appeared in 1970 and 1974.

all the years. Any recognized consistencies occurred during certain subperiods or when the combined years' factor loadings were compared with each year's factor loadings. In the latter case, there was several significant relationships between the combined factor loadings and the individual years 1967 through 1970, once again supporting the observation that the most stability and consistency in the ratio groupings occurred during the subperiod 1967—1969.

As with any other statistical technique, caution must be exercised by the researcher when using any factor analysis method. In particular, problems may occur if the variables used are poorly distributed (i.e., badly skewed or bimodal, or the variables included in the analysis are linearly dependent [2, 6, 9]). Furthermore, the results of the factor analysis or most any other multivariate technique may be influenced by the nature and size of the sample, expecially if there are too few data observations for the number of variables being analyzed. In our study with 648 observations and only 14 variables, this was not an issue.

Cluster Analysis Cluster analysis was performed to address the question of industry subgroups. In this situation, the purpose of cluster analysis is to find (and characterize) subindustry groups for which firms in the same subgroup have similar ratios while firms in different subgroups have dissimilar ratios. Normally, the five factors resulting from the factor analysis above would have been used in the cluster analysis instead of using the 13 individual ratios. However, since these loadings were neither consistent nor stable, it was decided not to use the factors, but rather to use a reduced set of 13 ratios. The eight ratios selected for the cluster analysis were the current ratio (CASSCDB), net profits to tangible net worth (NPROTNW), net profits to net working capital (NPRONWC), net sales to tangible net worth (NSALTNW), net sales to net working capital (NSALNWC), total debt to tangible net worth (TDBTNW), current debt to inventory (CDBINV), and funded debt to net working capital (FDBNWC). These transformed ratios were selected because they consistently loaded the highest in the factor analysis and an inspection of the coefficient correlation matrix indicated that there was no significant interrelationships among these variables. In addition, five of these variables loaded the highest when the factor analysis was done for all the years together. The combined years' factor loadings were the only ones consistently related to the factor loadings for each year. See Table 5.

The BMDP program P2M [3] for case clustering was used for each year individually. A case was the set of selected transformed ratio values for one firm for one year. Similarity between observations (cases) was defined by the Euclidian distance metric.

The output from each cluster analysis run is a clustering tree that indicates the amalgamation (grouping) for cases and groups of cases. Figure 1, the clustering tree for 1971, indicates, for example, that companies 77 and 42 were grouped together (i.e., had a similar set of ratios), and subsequently these companies grouped with companies 13, 58, 80, 14, and 79 at a higher level of amalgamation. This clustering configuration indicates that companies 13 through 79 are similar but that companies 77 and 42 more closely resemble each other.

A complete display of clustering for all nine runs is not necessary because the interpretation of this output was not subsequently different from the results for 1971. A visual comparative analysis of the nine clustering trees indicated there was no consistent statistical grouping of firms across all the years or even within certain subperiods. Therefore within the context of the industry analyzed in this research, there were no consistent and stable grouping of firms over time.

Cluster analysis was used in this study as an exploratory device to determine whether consistent and stable groupings of firms existed. As

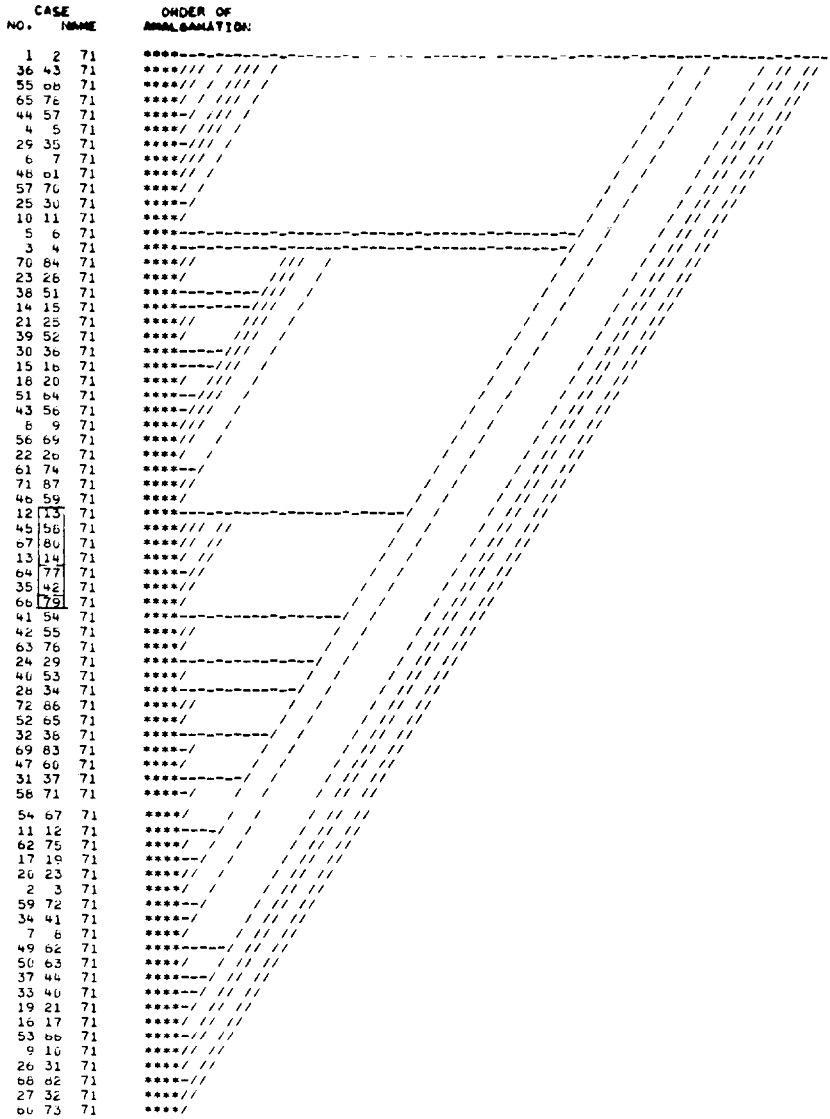

FIGURE 1. Cluster Analysis Tree for Transformed 1971 Data.

such, the cluster analysis results could be used in future research to generate hypotheses about how firms in a particular industry group.

Even though the application of this technique in accounting and finance is relatively new, it does appear to have potential usefulness in financial analysis other than ratio analysis. For example, it would be possible to use cluster analysis in 1) capital budgeting, 2) portfolio and stock investment analysis, and 3) profitability studies. In fact, the technique has wide applicability in the general area of corporate financial performance. In addition to being used as an exploratory method, cluster analysis can be used to develop classification schemes, inductive generalizations, and in discovering ''natural classes'' of variables [1]. Problems can occur with this technique. many of these relate to the distance, or similarity, measure used, how the researcher defines and interprets a cluster, what is being clustered, and determining the statistical reliability of clusters [1].

Conclusions

On a micro basis, consistent and logical ratio groupings may not exist. However, despite the lack of formation of consistent and stable groups, different sets of ratios do tend to move together, which does confirm previous observations in certain macro studies [15, 16, 17]. Thus it is unreasonable to believe that a single ratio measures only one dimension of a firm's financial well-being as sometimes implied in the ''traditional'' ratio analysis literature. The tendency in the literature to group ratios may be valid on a macro basis but not necessarily in a micro context. This has important implications for industry analysts who use a reduced set of ratios, as suggested in the macro study findings, to evaluate firm performance. The appropriate set of ratios to use in an industry context will be defined by the nature of the companies that make up that industry group. It is also interesting to note that within the context of a single industry, it may be unrealistic to assume that ratio groupings, whatever they may be, will remain consistent and stable over time.

Consistent and stable statistical groupings of firms over time may not exist. Therefore, using subindustry ratio averages, based on seemingly ''similar'' firms within the same industry, as standards in which to evaluate individual firm performance may not be valid or particularly useful. Thus our tentative findings do not support the previously made observation by Gupta and Huefner [8] that subindustry group ratio averages may be better targets in evaluating firm performance than are industry averages. Consistent subindustry groupings of firms simply did not exist in the context of our analysis.

The inconsistencies of our findings and those of previously cited macro studies suggest that the abstraction of macro study findings to individual industries and ratios may be inappropriate. More research is needed at the industry level to improve the tools and standards used to evaluate individual firm performance.

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