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Seref Kalayci
*Suleyman Demirel University*

Abdulmecit Karatas
*Bogazici University*

Ali Coskun
*Bogazici University*

Ayhan Kirtas
*Bogazici University*

# Financial Ratio Classification and Sub-Sector Discrimination of Manufacturing Firms Evidence from an Emerging Market

**Şeref Kalayci***
**Süleyman Demirel University, Isparta**

**Abdülmecit Karataş****
**Boğaziçi University, Istanbul**

**Ali Coşkun*****
**Boğaziçi University, Istanbul**

**and**

**Ayhan Kirtaş******
**Boğaziçi University, Istanbul**

This article aims to develop an empirically-based classification of financial ratios for manufacturing firms and to examine whether or not these ratios can be used in differentiating sub-sectors of manufacturing industry. The article involves 160 manufacturing firms which are traded in the emerging Istanbul Stock Exchange (ISE). It covers the period between December

* Şeref Kalayci is an assistant professor of finance at the Department of Management, Süleyman Demirel University, Turkey. His research interests include corporate finance, market micro structure, and multivariate data analysis.

** Abdülmecit Karataş is an assistant professor of finance at the Department of International Trade, Boğaziçi University, Turkey. His research interests include corporate finance, investments, and multivariate data analysis.

*** Ali Coşkun has graduated from Boğaziçi University, Turkey and is now a Ph.D. student in Accounting at the University of Texas at Dallas.

**** Ayhan Kirtaş has graduated from Boğaziçi University, and is now working as a director in the food industry in Turkey.

1992 and June 1999, and financial ratios of those companies have been calculated for 14 terms. Factor analysis was applied, both to isolate the independent patterns of financial ratios and to create an empirical classification for them. Factor analysis revealed four common factors, namely profitability, solvency/leverage, liquidity, and activity. The discriminating ability of the independent patterns of the financial ratios has been evaluated by means of the discriminant analysis. The eight sub-sectors of the manufacturing firms were included in the analysis, and it was concluded that those common factors are statistically significant in differentiating the sub-sectors of manufacturing firms of an emerging market.

**Introduction**

Since the late 1800s, ratio analysis has been the major decision-making tool used in the interpretation and evaluation of financial statements. Generally, such an analysis involves the breakdown of the examined financial reports into components (e.g., fixed and current assets) which are then evaluated in relation to each other and to exogenous standards. The major users of these ratios are: investors, for making portfolio decisions; management, for evaluating the operational and financial efficiency of the firm as a whole and sub-units (e.g., departments); lenders, for determining the credit worthiness of loan applicants; labor unions, for establishing an economic basis for collective bargaining; regulatory agencies, for controlling the activities of subordinated units; and researchers in economics and business administration, for studying firms. Most of the financial ratios are positively correlated with one another. In addition, some ratios, especially those with relatively stable components, are correlated over time. This means that only a small number of financial ratios are needed to capture most of the information ratios can provide, but it also means that this small number must be selected very carefully. Using a small subset of ratios to represent the whole set requires choosing ratios that are both highly correlated with those ratios excluded, and not correlated with the other ratios in the subset. Several academic studies have attempted to identify ratio subsets that meet these conditions. In this respect, this article provides a scientific approach to classifying financial ratios of manufacturing companies whose shares are actively traded in Istanbul Stock Exchange, and extent current literature by discriminating sub-sectors of manufacturing industry based on financial ratios. After this general introduction, a brief explanation of the earlier studies specifically concentrated on empirically based classifications of financial ratios and / or containing the discrimination of the companies according to their financial structure will be given. The research design section of the article includes data and its examination, variables, model, methodology, factor and Discriminant analyses. Results are summarized under the empirical findings part. The article ends with a conclusion.

**I. Literature Review**

The question of classifying financial ratios has been a subject of much research. Different approaches have been applied on the problem of classification of financial ratios. The first approach could be called a pragmatic or an authoritative approach, in which the classifications of financial ratios largely develop from established business practises and personal views of eminent financial analysts. Many standard text-books present material from this approach. The second approach has been more deductive, in which the classification of the financial ratios is based on the technical relationships between the different financial ratios. The "Du Pont triangle" is a classic example of this approach. Around 1919, the Du Pont Company began to use its famous ratio triangle system to evaluate its operating results. The papers using this approach include Courtis (1978), Laitinen (1983), and Bayldon & Woods & Zafiris (1984). The third approach is an inductive, empirical classification of financial ratios using statistical techniques, factor analysis in particular. This paper falls into the third category.

The first users of an inductive approach for classifying financial ratios were George E. Pinches, Kent A. Mingo and J. Kent Caruthers (1974), who performed R- type factor analysis in order to empirically classify financial ratios, and measured the long-term stability and change in these classifications between 1951 and 1969. According to these authors, meaningful empirically-based classifications of financial ratios can be determined, and the composition of these groups is reasonably stable over time, even when the magnitude of the financial ratios is undergoing change. Gombala and Ketz (1983) also reported considerable time series stability of the factors for the period 1971-1980. One insight from their research is that cash flow and cash position ratios have different correlation structures than do the ratios traditionally grouped under the liquidity category. A second insight is that the turnover ratio category is a relatively heterogeneous one. Salmi, Virtanen and Yli-Olli (1990) used factor and transformation analyses to find stable categories of financial ratios for Finnish data covering 1974-84. They observed six stable factors. Dahlstedt, Salmi, Luoma, and Laakonen (1994) indicated that the official industry classification is not homogeneous in terms of central financial ratios. Aktaş, Karacaer, and Karacabey (2001) searched the differences between failed and non-failed firms, and found that while there were differences between non-failed and failed firms according to nature of financial ratios, there was no need to work on a large number of financial ratios to reflect the financial positions of firms.

Studies using financial ratios to discriminate companies according to their financial structure mostly focus on determining failed and non-failed firms. Discriminant analysis is the most widely-used technique (see Dimitras, Zanakis, and Zoponunidis 1996). For this purpose, the first study was conducted by Beaver (1966), who matched a sample of failed firms with a sample of non-failed firms and studied their financial ratios for a period of up to five years before failure, and found that they had high predictive ability. This technique was to become known as classification analysis and was essentially univariate. Altman (1968) improved on Beaver's univariate method of analysis by introducing the multivariate approach, which allows the simultaneous consideration of several variables in the prediction of failure. The approach is that of multiple discriminant analysis. Altman's model was extremely accurate in predicting bankruptcy. This model failed to predict only two of the thirty-three large bankrupt firms 1 year prior to bankruptcy. Taking into account the latest financial reporting standards, Altman expanded his studies with new variables in following years (1977 - 1983).

In 1972 Robert Edmister, using at least three consecutive financial statements of small businesses, correctly discriminated failed and non-failed firms. Dambolena and Khoury (1980) classified firms into failed and non-failed groups with 78 percent accuracy five years prior to failure. McGurr and DeVaney (1998) proposed using single industry samples to enhance the predictive accuracy of multivariate methods.

## II. Data and Methodology

In this study, analysis is done on the manufacturing industry of an emerging market; the balance sheets and the income statements of 160 manufacturing firms traded in the Istanbul Stock Exchange (ISE) have been investigated from December 1992 to June 1999; the distributions of the firms according to sectors are indicated below. This study started from the year 1992, since the number of companies that were traded in ISE before that year was limited.

For instance, seventeen of the present twenty-seven food companies, five of the ten manufacturers of paper and paper products, printing and publishing, and six of thirteen basic metal industry companies were absent before the year 1992.

Manufacturing industry consists of the following eight sub-sectors as classified by ISE:

1. Food, beverage, tobacco (27 companies)
2. Manufacture of paper and paper products, printing and publishing (10 companies)
3. Manufacture of chemical and of chemical petroleum, rubber and plastics (21 companies)
4. Manufacture of fabricated metal products, machinery, equipment (28 companies)
5. Basic metal industries (13 companies)
6. Product of woods (3 companies)
7. Manufacture of non-metallic mineral products (23 companies)
8. Textile, wearing apparel, leather industries (35 companies)

One of the crucial parts of the data examination is to detect the outliers (observations having distinct differences from the others). In the literature, there are plenty of methods available to identify the outliers. One of the most straightforward methods for large sample sizes is to determine a threshold-value of standard scores after standardization of the variables. Using that method for the data set used in this study would result in huge loss of information and that might result in insufficient data or unrepresentative results for the whole sample. Although visual examination of the data was preferred, descriptive statistics of financial ratios containing standard deviations, maximum and minimum values, and range were also considered in catching the outliers (Hair et al., 1995, 66). One of the important benefits of close examination of the data is to assure the assessment of the outliers in multivariate perspective.

In order to understand the nature of nineteen financial ratios, their methods of distribution are examined. For this purpose, histograms, Kolmogorov-Smirnov test, and skewness and kurtosis statistics are checked. The results showed that neither of the nineteen financial ratios except financial leverage, gross margin, and operating margin, are normally distributed. Foster (1986) points out that there is considerable evidence that specific financial ratios are not well described by a normal distribution. In this article, we do not need to normalize the non-normality distributed initial variables, since we apply Factor analysis (which normalizes the new variables obtained). This will serve as the input for further Discriminant analysis.

The basic financial ratios that are commonly used to measure the company performance are used in this article, too. These financial ratios are the variables for the subsequent Factor Analysis.

- **The Current Ratio** = Current Assets / Current Liabilities
- **The Liquidity or "Acid Test" Ratio** = (Cash + Marketable Securities + Receivables) / Current Liabilities
- **Cash Ratio** = (Cash + Marketable Securities) / Current Liabilities
- **Return on Assets** = Net Profit / Total Assets
- **Profit Before Tax / Total Equity**
- **Short Term Financial Debt / Total Equity**

- **Equity Turnover** = Net Sales / Equity
- **Fixed Assets Turnover** = Net Sales / Fixed Assets
- **Total Assets Turnover** = Net Sales / Total Assets
- **Financial Debt Turnover** = Net Sales / Financial Debts
- **Short Term Financial Debt / Working Capital**
- **Financial Leverage** = Total Debts / Total Assets
- **Total Financial Debt / Working Capital**
- **Gross Margin** = Gross Profit / Net Sales
- **Operating Margin** = Operating Profit / Net Sales
- **Margin Before Interest and Taxes** = Earning Before Interest and Taxes / Net Profit
- **Margin Before Taxes** = Earning Before Taxes / Net Profit
- **Net Profit Margin** = Net Profit / Net Sales
- **Debt / Equity**

As financial ratios calculated from yearly data and six-month income statement tables are not comparable, some transformations have been made in the income statement table values to acheive comparable ratios. Since the values in the income statements are periodic, in order to get the corrected values for six-month income statement tables, values of semi annual income statements were first multiplied by two. Thus, the values in the semi-annual and annual income statements became comparable. Because the balance sheet is the instant photograph of the companies' financial statement, no transformation has been made on six-month yearly data of the balance sheet. Through these transformations, the financial ratios calculated from yearly and six-month data became comparable. Descriptive statistics of financial ratios is given in the table below.

The main objectives of this article are to form empirical classifications of the financial ratios for the manufacturing companies, and to examine whether financial ratios can be used for differentiating sub-sectors of the manufacturing industry or not in ISE. In order to form the orthogonal factors of basic financial ratios, R-type factor analysis has been employed. Besides, factor analysis will also serve to constitute the required data for the subsequent discriminant analysis, which is used to differentiate sub-sectors of manufacturing industry. For that purposes, the hypothesis will be as follows:

$H_a$: There is a difference between the sub-sectors of the manufacturing industry regarding their financial structures. (*Alternate hypothesis*)

## III. Empirical Findings

### A. Factor Analysis

All of the nineteen financial ratios are used in the analysis, and financial ratios are the variables in the analysis. The aim is to create a new set of factors that are orthogonal, and sequentially extract a maximal variance from the variables using the original variables by means of factor analysis.

The first step in factor analysis is to visually examine the correlation matrix for the 19 variables in order to assess appropriateness of data for the factor analysis. The correlation matrix for the 19 variables showed that all variables have a large correlation with at least one of the other variables in the set having coefficients with an abosulte value greater than 0,30.

The second method for checking the appropriateness of data for factor analysis is known as "**Kaiser-Meyer-Olkin (KMO)** measure of overall sampling adequacy".This is an index for comparing the magnitudes of the observed correlation coefficients to the magnitudes of the partial correlation coefficients. **KMO** value for the data set used in this article is 0.725, which by far meets the requirements of **KMO**.

Bartlett's test of sphericity is another test to assess whether the correlation matrix is appropriate for factor analysis. In Bartlett's test the null hypothesis is that correlation matrix which comes from a population of variables that are independent. If the null hypothesis can be rejected, then a factor analysis can be conducted. For our data set, Barlett Test of Sphericity is equal to 42.812, and it is significant for the $p < 0,0000$. So, the sample is suitable for the factor analysis.

The three methods used for checking the appropriateness of data for factor analysis proved our data set to be suitable for performing this analysis.

The principal factor model is used in prediction of model parameters of Factor Analysis. In order to determine the number of common factors to be extracted, the talent root criterion was used. According to this rule, the number of common factors is equal to the number of factors having eigenvalue of greater than 1. In Table 2, it is seen that the number of factors having eigenvalue greater than 1 is four, so the number of common factors is four. Using the first four factors, 77.4 % of variance can be explained.

Communality can be defined as the proportion of the total variance of a variable accounted for and the common factors in a factor analysis. If the entire variance of a variable is explained by the common factors, the communality is equal to 1. Low communality for a variable indicates that that specific variable cannot be explained well using the common factors with respect to other financial ratios. However, looking at Table 3, communalities seem extremely high which means that common factors are successful in representing the financial ratios.

Table 4 presents the factor-loading matrix. Factor loading represents the correlation between the common factors and the financial ratios. The factor-loading matrix can be considered the beta weights of a multiple regression analysis. Thus, the empirical classification of the financial ratios was done using the loading in Table 4. Inspection of the matrix will show that certain variables have a high correlation, or high loading on a factor, whereas other variables do not. It then becomes possible to determine which financial ratios are best represented by the common factors. The financial ratios are generally placed under the factor having the highest factor loading for that variable. In this article, the factor-loading matrix was examined to classify the financial ratios.

In this step, each common factor is labeled to reflect the common characteristics of financial ratios having high loading on factors. The following financial ratios have high loading on factor one. All of them are profitability ratios and factor one can be named as **Profitability Factor**.

| | Loading |
|---|---|
| Margin Before Interest and Tax | .91 |
| Operating Margin | .89 |
| Pretax Margin | .80 |
| Gross Margin | .78 |
| Net Profit Margin | .77 |
| Return on Assets | .77 |
| Profit Before Taxes / Shareholder's Equity | .61 |

Debt Equity and Financial Leverage ratios have the highest loading on factor two, and the ratios under factor two are all related to solvency and leverage, so it was named as **Solvency / Leverage Factor**.

| | Loading |
|---|---|
| Debt / Equity | .87 |
| Financial Leverage | .77 |
| Net Sales / Equity | .65 |
| Short Term Financial Debt / Total Equity | .64 |
| Short Term Financial Debt / Working Capital | .54 |
| Total Financial Debt / Working Capital | .53 |

The current, acid and cash ratios are the most popular liquidity ratios and highly loaded on the third factor. The third factor was named **Liquidity Factor**. The ratios under solvency / leverage factor all have negative loading on Liquidity Ratios. This means that the companies having high debt loads face liquidity problem, as expected.

| | Loading |
|---|---|
| Acid Test Ratio | .89 |
| Current Ratio | .87 |
| Cash Ratio | .80 |

Total Assets, Fixed Assets and Financial Debt Turnover are all highly loaded on factor four. These are the turnover ratios, and the fourth factor was named **Activity Factor**.

| | Loading |
|---|---|
| Net Sales / Total Assets | .91 |
| Net Sales / Fixed Assets | .76 |
| Net Sales / Financial Debt | .65 |

Employing R type factor analysis to the nineteen financial ratios of 160 manufacturing companies listed in ISE, the following four factors are handled: *profitability, financial leverage / solvency, liquidity* and *activity (turnover)* factors. The results of the factor analysis are consistent with the classification of the financial ratios in the literature (Lev (1989), Altman

(1968), Foster (1980), Weston and Brigham (1981). As a result, in this study, the nineteen financial ratios were explained successfully, using four common factors which are very consistent to categories used in explaining the content of the ratios in the literature.

### B. Discriminant Analysis

Discriminant Analysis attempts to derive the linear combination of two or more independent variables that will discriminate best between a priori defined groups. This is achieved by maximising the 'between group variance' relative to the 'within group variance'. This relationship is expressed as the ratio of beetween-group to within- group variance. The discriminant analysis derives the linear combinations from an equation that takes the following form:

$$Z = w1x1 + w2\,x2 + \ldots\ldots wnxn$$

Where

Z = Discriminant Score

Wi (i = 1, 2, 3, ............., n) = Discriminant Weights

Xi = (i = 1, 2, 3, ............., n) = Independent variables, the financial ratios

Thus, each firm receives a single composite discriminant score which is then compared to a cut-off value, which determines to which group the company belongs.

The two most frequently used methods in deriving the discriminant models have been the simultaneous (direct) method and the stepwise method. The stepwise method that we used begins with no variables in the model. In each step, if the variable that contributes least to the discriminatory power of the model measured by Wilks' Lambda fails to meet the criterion, it is removed, and is replaced by the variable not existing in the model that contributes most to the discriminatory power of the model. When all variables in the model meet the criterion to stay and none of the other variables meets the criterion to enter, the stepwise selection process stops. In this section, to assess whether or not there are significant differences in terms of financial structures between sub-sectors of manufacturing industry, discriminant analysis is employed (Hair et al., 1998).

The sub-sectors of manufacturing industry are the categorical dependent variables of the discriminant analysis and common factors obtained from factor analysis are the independent variables.

Discriminant analysis is quite sensitive to the ratio of the sample size to the number of predictor variables. Many studies suggest a ratio of twenty observations for each predictor variable. Our observations meet this requirement.

In order to derive a discriminant function, the simultaneous method was employed. We wanted to include all the independent variables in the analysis and are not interested in seeing intermediate results based only on the most discriminating variables.

Examining group differences is helpful to see the prominent differentiating factors before starting a detailed analysis. In Table 5, group statistics for the following eight sub-sectors are presented:

1. Food, beverage, tobacco
2. Manufacture of paper and paper products, printing and publishing
3. Manufacture of chemical and of chemical petroleum, rubber and plastics
4. Manufacture of fabricated metal products, machinery, equipment
5. Basic metal industries
6. Product of woods
7. Manufacture of non-metallic mineral products
8. Textile, wearing apparel, leather industries

As it is seen in Table 5 above, products of wood and manufacture of non-metallic products sectors have the highest profitability scores. Basic metal industries and textile, wearing apparel, and leather industries definitely have the lowest profitability scores. Having a high profitability score is the desired property for the companies; a high profitability score is probably the result of the high operating performance.

For the leverage/solvency factor, the smaller scores indicate the stronger capital structure. According to that criterion, *basic metal industries, manufacture of non-metallic mineral products* and *manufacture of paper* and *publishing* sectors have a stronger capital structure.

*Manufacture of paper* and *paper products, printing and publishing* sector has the highest liquidity scores. This means that firms in that sector have the highest ability to meet their short-term financial obligations. *Food, beverage, tobacco* and *textile, wearing appeals, leather industries* have the lowest liquidity scores.

*Manufacture of chemical and of chemical petroleum, rubber and plastics* and *manufacture of fabricated metal products, machinery, equipment* sectors have the highest activity scores.

At the bottom of the Table 5, factor scores for the total are presented. If there were no missing values, the averages would be equal to zero, and the standard deviations would be equal to one, since the factor scores were normalized in the factor analysis.

To test whether the selected discriminating variables (calculated factor scores) differ significantly among the sub sectors of manufacturing industry in ISE, we used the Wilks' Lambda (U-statistic) test statistic.

In order to assess statistical significance of the Wilks' Lambda, it can be converted to either F test or Chi-Square test. Table 6 shows that all the discriminant functions are statistically significant, which means that in terms of ratio classification, there are differences among the sub sectors of manufacturing industry in ISE. These functions are created in order to provide discrimination between sets of groups.

The Canonical discriminant function is a linear combination of the discriminating variables that are formed to succeed the optimum classification of the groups.

When the sign is ignored, each weight represents the relative contribution of its associated variable to that function. Loadings in Table 7 provide an interpretation of the four functions. Discriminate functions handled at the end of multiple discriminant analysis can be expressed by the following equations. Profitability and liquidity have high loadings on the first function.

Function 1 = -0,033 + 0,814 Profitability *Factor* – 0,293 *Solvency / Leverage Factor* + 0,671 *Liquidity Factor* – 0,014 Activity Factor

Function 2 = 0,013 + 0,391 Profitability *Factor* + 0,509 *Solvency / Leverage Factor* – 0,245 *Liquidity Factor* + 0,819 Activity Factor

Function 3 = -0,011 – 0,578 *Profitability Factor* – 0,129 *Solvency / Leverage Factor* + 0,649 *Liquidity Factor* + 0,542 Activity Factor

Function 4 = 0,035 – 0,089 *Profitability Factor* + 0,913 *Solvency / Leverage Factor* + 0,400 *Liquidity Factor* – 0,352 Activity Factor

There are eight groups and four factors available, so four canonical discriminant functions can be used at most.

The canonical correlation measures the association between the discriminant scores and the groups. Table 8 shows the explained part of the variances by group differences. It also shows that the first discriminant function explains the maximum amount of the variance as it is defined in the basic model of the multiple discriminant analysis.

Functions at group centroids are presented in Table 9. The method included taking the original value for a case on each variable, multiplying it by the coefficient for that variable, and then adding these products along with the constant term compute group Centroids. For instance, the group centroids of the food, beverage and tobacco sector which is seen in the first row of the first function of table 9 is calculated by the following equation:

Group Centroid of Food, Beverage, Tobacco Sectors for Function 1 = - 0,033 + 0,814 * (-0,09) – 0,293 * (- 0,10) + 0,671 * (- 0,40) – 0,014 * (- 0,03) = -0,3449

As can be seen in Table 9, the first factor does the best discrimination between the food, beverage, tobacco sector (first sector) and product of woods sector (sixth sector). However, the first function is not able to discriminate the food, beverage, tobacco sector (first sector) and textile, wearing apparel, leather industries (eigth sector) etc.

The classification results are shown in Table 10. In the table, the bold values are correctly classified by the analysis. Correctly classified cases are 656 out of 1899, and the overall classification rate is 34.5 %. Certainly, the classification accuracy would be higher if the number of the sectors used in the analysis decreased. Using the same factors, only the pre-determined years or pre-determined sectors can be investigated. To demonstrate, two-group discriminant analysis was employed using the same factors as when using factor analysis. Since the basic objective of the study is to do discrimination for the whole sub-sectors of the manufacturing industry, the results of the two-group discriminant analysis is not shown in detail and only the final classification statistics are displayed. Prior probability for each group is equal to 50 %.

Classification accuracy is equal to 78.3% for the food, beverage, tobacco and manufacture of paper and paper products, printing and publishing sectors.

Classification accuracy is equal to 70.2% companies in manufacture of chemical and of chemical petroleum, rubber, plastics and manufacture of paper and paper products, printing and publishing

The percentage of correctly-classified grouped cases is only 50.1% for the manufacture of chemical and of chemical petroleum, rubber, plastics and manufacture of fabricated metal products, machinery, and equipment sectors, so the canonical discrimination functions are unsuccessful in distinguishing these two sectors. Group statistics in Table 5 also indicates that neither of the factor scores are different for the companies of these two sectors.

Classification accuracy is 73.0% for the basic metal industries and manufacture of fabricated metal products, machinery, and equipment sector.

Classification accuracy for the basic metal industries and product of woods sector, presented in Table 10, is equal to 82.3%.

Classification accuracy for the product of woods and manufacture of non-metallic mineral products is equal to 69.2%.

Lastly, the classification accuracy for the textile, wearing apparel, leather industries and manufacture of non-metallic mineral products is 66.6%.

One of the important points is that if the principle objective was to investigate the differences between two specific sectors, for instance textile and basic metal industries, then handling the factors using only the financial ratio information of these two specific sectors and then applying two-group discriminant analysis would give better classification results. However, in this study rather than concentrating on two specific sectors, doing an empirical classification comprising the whole sub-sectors companies of manufacturing industry was aimed.

The matter of classification accuracy is very important. Classification can be viewed as the division of the total variable space into mutually exclusive and exhaustive regions. Any given observation is classified into groups in the variable space.

When the sample sizes of the groups are equal, the determination of the chance classification is rather simple, obtained by dividing one by the number of the groups. The determination of chance classifications where the group sizes are unequal is more complex. If there were two groups, one of which would contain 75% of the subjects without the aid of discriminant analysis, arbitrarily assigning all subjects to the larger group, a 75% classification accuracy could be achieved, so classification accuracy lower than 75% would not be helpful.

If the percentage of correct classifications is significantly larger than what would be expected by chance, an attempt can be made to interpret the discriminant functions in the hope of developing group profiles. If not, there will be no interpretation. In the light of all information presented so far, the classification accuracy should be greater than that achieved by chance.

The classification accuracy should be at least one-fourth greater than that achieved by chance. This criterion provides only a rough estimate of the acceptable level of predictive accuracy. According to this criterion, the classification accuracy should be at least greater than 12.5% by 1.25, which is equal to 15.6%. In this study, the classification accuracy, which is also called hit ratio, is 34.5%, and the classification performance is much higher than the expected classification accuracy achieved by chance.

Another statistically based measure of classification accuracy relative to chance is Press's Q statistics. In our case, Press's Q value is equal to 843.7, which is highly significant.

## IV. Conclusion

The objectives of this article were to develop empirically-based classification of financial ratios for the manufacturing firms and to evaluate classification accuracy of financial ratios in differentiating sub-sectors of manufacturing industry in an emerging market. Multivariate data analysis techniques- R type factor analysis and Discriminant analysis-, financial ratios and financial statements, namely balance sheets and income statements, were used to reach these objectives.

Using R type factor analysis, four factors were handled; these are **profitability**, *covering margin before interest and taxes, operating margin, pretax margin, gross margin, net profit margin, return on assets, profit before taxes over shareholder's equity ratios*, **financial leverage / solvency**, *covering debt over equity, financial leverage, net sales over equity, short term financial debt over total equity, short term financial debt over working capital, total financial debt over working capital ratios*, **liquidity** *covering acid-test ratio, current ratio, cash ratio,* and finally **activity** *covering net sales over total assets, net sales over fixed assets and net sales over financial debt ratios*. It is important that all factors be orthogonal to each other as a peculiarity of factor analysis, which means that all four factors represent different dimensions for the companies. Clear clustering of financial ratios in four factors gives us the chance to examine financial performance of the manufacturing companies.

As a result of factor analysis, the nineteen financial ratios were explained successfully using four common factors, which are also very consistent with categories used to explain the content of ratios in the literature. Besides, this study presents an empirically found evidence for an emerging market, though the literature gives evidence concerning developed markets.

In this article, the second analysis that has been used to examine data was multiple discriminant analysis. In the result, it has been shown that eight sub-sectors in the manufacturing firms have different financial structures according to the calculated financial ratios in the article. This means that the sub-sectors are affected in different ways by the economic factors. This result is also validating that using sector averages for financial ratios is an appropriate tool in benchmarking operational and financial performance of ISE companies. On the other hand, evaluating performance of a firm according to performance of all manufacturing firms can mislead long-term investors and creditors.

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## Table 1

## Descriptive Statistics of Financial Ratios

| FINANCIAL RATIOS | N | RANGE | MEAN | STD. DEVIATION | SKEWNESS | | KURTOSIS | |
|---|---|---|---|---|---|---|---|---|
| | Statistics | Statistics | Statistics | Statistics | Statistics | Std. Error | Statistics | Std. Error |
| Return On Assets | 1977 | 1.80 | ,29 | ,18 | .41 | .06 | 2.38 | .11 |
| Profit Before Tax/Total Equity | 1950 | 8.47 | ,37 | ,47 | -2.61 | .06 | 26.98 | .11 |
| Net Sales/Equity | 1936 | 55.16 | 3,49 | 2,75 | 3.97 | .06 | 38.22 | .11 |
| Net Sales/ Fixed Assets | 1948 | 38.25 | 5,15 | 4,30 | 2.24 | .06 | 7.93 | .11 |
| Net Sales/ Total Assets | 1966 | 6.58 | 1,34 | ,61 | 1.75 | .06 | 7.16 | .11 |
| Net Sales / Financial Debt | 1966 | 13.16 | 2,82 | 1,69 | 1.68 | .06 | 4.48 | .11 |
| Gross Margin | 1974 | 1.07 | ,32 | ,13 | -.06 | .06 | .45 | .11 |
| Operating Margin | 1974 | 1.15 | ,18 | ,12 | -.19 | .06 | 1.97 | .11 |
| Margin Before Interest and Tax | 1964 | 1.72 | ,23 | ,14 | .26 | .06 | 3.64 | .11 |
| Pretax Margin | 1969 | 1.89 | ,13 | ,16 | -.34 | .06 | 5.35 | .11 |
| Net Profit Margin | 1973 | 2.26 | ,09 | ,13 | -.80 | .06 | 12.22 | .11 |
| Current Ratio | 1978 | 6.67 | 1,73 | ,74 | 1.89 | .06 | 6.33 | .11 |
| Acid-Test Ratio | 1978 | 4.81 | 1,14 | ,59 | 1.40 | .06 | 3.26 | .11 |
| Cash Ratio | 1977 | 2.70 | ,27 | ,39 | 2.38 | .06 | 6.46 | .11 |
| Short Term Fin. Debt / Working Cap | 1977 | 1.59 | ,25 | ,25 | 1.21 | .06 | 1.73 | .11 |
| Total Fin. Debt / Working Capital | 1976 | 2.80 | ,37 | ,36 | 1.71 | .06 | 4.95 | .11 |
| Financial Leverage | 1978 | 1.52 | ,54 | ,19 | .52 | .06 | 1.13 | .11 |
| Debt / Equity | 1935 | 21.68 | 1,60 | 1,65 | 3.09 | .06 | 16.48 | .11 |
| Short Term Fin. Debt / Total Equity | 1975 | 1.21 | ,42 | ,18 | .64 | .06 | .29 | .11 |

**Table 2**

**Eigenvalues**

| COMPONENT | INITIAL EIGEN VALUES | | | ROTATION SUMS OF SQUARED LOADINGS | | |
|---|---|---|---|---|---|---|
| | Total | % of Variance | Cumulative % | Total | % of Variance | Cumulative % |
| 1 | 6,988 | 36,777 | 36,777 | 4,662 | 24,537 | 24,537 |
| 2 | 3,555 | 18,711 | 55,488 | 3,572 | 18,801 | 43,338 |
| 3 | 2,860 | 15,054 | 70,542 | 3,436 | 18,086 | 61,424 |
| 4 | 1,297 | 6,827 | 77,369 | 3,030 | 15,945 | 77,369 |
| 5 | ,889 | 4,677 | 82,046 | | | |
| 6 | ,699 | 3,676 | 85,722 | | | |
| 7 | ,660 | 3,471 | 89,194 | | | |
| 8 | ,416 | 2,190 | 91,384 | | | |
| 9 | ,377 | 1,985 | 93,368 | | | |
| 10 | ,279 | 1,467 | 94,836 | | | |
| 11 | ,256 | 1,347 | 96,183 | | | |
| 12 | ,185 | ,971 | 97,154 | | | |
| 13 | ,154 | ,811 | 97,965 | | | |
| 14 | ,123 | ,648 | 98,613 | | | |
| 15 | 9,732E-02 | ,512 | 99,125 | | | |
| 16 | 8,802E-02 | ,463 | 99,588 | | | |
| 17 | 4,020E-02 | ,212 | 99,800 | | | |
| 18 | 2,274E-02 | ,120 | 99,919 | | | |
| 19 | 1,534E-02 | 8,074E-02 | 100,00 | | | |

**Table 3**

**Communalities**

| FİNANCİAL RATIOS | INITIAL | EXTRACTION |
|---|---|---|
| Return On Assets | 1,000 | ,800 |
| Profit Before Tax/Total Equity | 1,000 | ,652 |
| Net Sales/Equity | 1,000 | ,811 |
| Net Sales/ Fixed Assets | 1,000 | ,691 |
| Net Sales/ Total Assets | 1,000 | ,843 |
| Net Sales / Financial Debt | 1,000 | ,767 |
| Gross Margin | 1,000 | ,631 |
| Operating Margin | 1,000 | ,794 |
| Margin Before Interest and Tax | 1,000 | ,868 |
| Pretax Margin | 1,000 | ,866 |
| Net Profit Margin | 1,000 | ,803 |
| Current Ratio | 1,000 | ,859 |
| Acid-Test Ratio | 1,000 | ,859 |
| Cash Ratio | 1,000 | ,687 |
| Short Term Fin. Debt / Working Cap. | 1,000 | ,671 |
| Total Fin. Debt / Working Capital | 1,000 | ,666 |
| Financial Leverage | 1,000 | ,846 |
| Debt / Equity | 1,000 | ,787 |
| Short Term Fin. Debt / Total Equity | 1,000 | ,798 |

**Table 4**

**Factor Loading Matrix**

| FINANCIAL RATIOS | COMPONENT | | | |
|---|---|---|---|---|
| | 1 | 2 | 3 | 4 |
| **Return On Assets** | ,77 | ,06 | ,15 | ,43 |
| **Profit Before Tax/Total Equity** | ,61 | -,25 | -,05 | ,46 |
| **Net Sales/Equity** | -,12 | ,71 | -,11 | ,53 |
| **Net Sales/ Fixed Assets** | ,14 | ,32 | -,03 | ,76 |
| **Net Sales/ Total Assets** | -,13 | -,02 | -,01 | ,91 |
| **Net Sales / Financial Debt** | -,11 | -,43 | ,39 | ,65 |
| **Gross Margin** | ,78 | ,00 | -,02 | -,17 |
| **Operating Margin** | ,89 | -,02 | ,00 | -,07 |
| **Margin Before Interest and Tax** | ,91 | ,06 | ,14 | -,14 |
| **Pretax Margin** | ,80 | -,36 | ,29 | ,13 |
| **Net Profit Margin** | ,77 | -,35 | ,28 | ,10 |
| **Current Ratio** | ,06 | -,30 | ,87 | ,09 |
| **Acid-Test Ratio** | ,13 | -,19 | ,89 | ,09 |
| **Cash Ratio** | ,20 | -,10 | ,80 | ,00 |
| **Short Term Fin. Debt / Working Cap** | -,20 | ,54 | -,43 | -,39 |
| **Total Fin. Debt / Working Capital** | -,26 | ,53 | -,23 | -,52 |
| **Financial Leverage** | -,11 | ,77 | -,50 | -,03 |
| **Debt / Equity** | -,08 | ,87 | -,14 | -,03 |
| **Short Term Fin. Debt / Total Equity** | ,02 | ,64 | -,60 | ,15 |

## Table 5

## Group Statistics

| SECTOR CODE | FACTOR SCORE | MEAN | STD. DEVIATION | VALID N (LISTWISE) Unweighted | Weighted |
|---|---|---|---|---|---|
| 1 | Pprofitability factor | -,09 | ,98 | 306 | 306 |
| | Solvency/leverage factor | -,10 | 1,00 | 306 | 306 |
| | Liquidity factor | -,40 | ,76 | 306 | 306 |
| | Activity factor | -,03 | 1,23 | 306 | 306 |
| 2 | Profitability factor | -,07 | 1,20 | 117 | 117 |
| | Solvency/leverage factor | -,29 | ,88 | 117 | 117 |
| | Liquidity factor | ,62 | 1,22 | 117 | 117 |
| | Activity factor | -,16 | ,64 | 117 | 117 |
| 3 | Profitability factor | ,11 | ,74 | 255 | 255 |
| | Solvency/leverage factor | ,16 | ,94 | 255 | 255 |
| | Liquidity factor | -,05 | ,81 | 255 | 255 |
| | Activity factor | ,37 | 1,03 | 255 | 255 |
| 4 | Profitability factor | ,15 | ,77 | 314 | 314 |
| | Solvency/leverage factor | ,20 | ,78 | 314 | 314 |
| | Liquidity factor | ,00 | ,77 | 314 | 314 |
| | Activity factor | ,36 | ,95 | 314 | 314 |
| 5 | Profitability factor | -,46 | ,76 | 164 | 164 |
| | Solvency/leverage factor | -,33 | ,71 | 164 | 164 |
| | Liquidity factor | ,07 | ,97 | 164 | 164 |
| | Activity factor | ,11 | 1,01 | 164 | 164 |
| 6 | profitability factor | ,99 | 1,12 | 39 | 39 |
| | Solvency/leverage factor | -,17 | ,50 | 39 | 39 |
| | Liquidity factor | ,45 | ,83 | 39 | 39 |
| | Activity factor | ,28 | 1,00 | 39 | 39 |
| 7 | profitability factor | ,44 | 1,00 | 305 | 305 |
| | Solvency/leverage factor | -,27 | ,91 | 305 | 305 |
| | Liquidity factor | ,33 | 1,08 | 305 | 305 |
| | Activity factor | -,26 | ,94 | 305 | 305 |
| 8 | Profitability factor | -,28 | 1,01 | 399 | 399 |
| | Solvency/leverage factor | ,07 | 1,05 | 399 | 399 |
| | Liquidity factor | -,10 | 1,12 | 399 | 399 |
| | Activity factor | -,29 | ,72 | 399 | 399 |
| Total | Profitability factor | ,01 | ,98 | 1899 | 1899 |
| | Solvency/leverage factor | -,04 | ,93 | 1899 | 1899 |
| | Liquidity factor | ,01 | ,99 | 1899 | 1899 |
| | Activity factor | ,01 | ,99 | 1899 | 1899 |

**Table 6**

**Wilks' Lambda Statistics for the Canonical Discriminant Functions**

| TEST OF FUNCTION (S) | WILKS' LAMBDA | CHI-SQUARE | SIG |
|---|---|---|---|
| 1 | ,739 | 572,948 | ,000 |
| 2 | ,850 | 306,900 | ,000 |
| 3 | ,944 | 109,515 | ,000 |
| 4 | ,980 | 38,015 | ,000 |

**Table 7**

**Canonical Discriminant Function Coefficients**

| | FUNCTION | | | |
|---|---|---|---|---|
| | 1 | 2 | 3 | 4 |
| profitability factor | ,814 | ,391 | -,578 | -,089 |
| solvency / leverage factor | -,293 | ,509 | -,129 | ,913 |
| liquidity factor | ,671 | -,245 | ,649 | ,400 |
| activity factor | -,014 | ,819 | ,542 | -,352 |
| ( Constant) | -,033 | ,013 | -,011 | ,035 |

**Table 8**

**Explained Variance by the Canonical Discriminant Functions**

| FUNCTION | EIGENVALUE | % OF VARIANCE | CUMULATIVE % | CANONICAL CORRELATION |
|---|---|---|---|---|
| 1 | ,151 | 47,2 | 47,2 | ,362 |
| 2 | ,110 | 34,4 | 81,6 | ,315 |
| 3 | ,039 | 12,0 | 93,7 | ,193 |
| 4 | ,020 | 6,3 | 100,0 | ,141 |

**Table 9**

**Functions at Group Centroids**

| **SECTOR CODE** | **FUNCTION** | | | |
|---|---|---|---|---|
| | **1** | **2** | **3** | **4** |
| **1** | -,34 | ,00 | -,22 | -,20 |
| **2** | ,42 | -,45 | ,38 | ,08 |
| **3** | -,03 | ,45 | ,07 | ,02 |
| **4** | ,03 | ,46 | ,07 | ,08 |
| **5** | -,27 | -,26 | ,41 | -,23 |
| **6** | 1,12 | ,43 | -,12 | -,12 |
| **7** | ,63 | -,24 | -,16 | -,03 |
| **8** | -,34 | -,27 | -,08 | ,18 |

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**on Results**

| UP MEMBERSHIP | | | | TOTAL |
|---|---|---|---|---|
| **5** | **6** | **7** | **8** | |
| 8 | 4 | 34 | 91 | 306 |
| 9 | 1 | 27 | 42 | 117 |
| 8 | 0 | 32 | 51 | 255 |
| 10 | 1 | 28 | 65 | 314 |
| **6** | 0 | 3 | 60 | 164 |
| 0 | **2** | 18 | 2 | 39 |
| 7 | 5 | **130** | 75 | 305 |
| 9 | 0 | 28 | **198** | 399 |
| 2,6 | 1,3 | 11,1 | 29,7 | 100,0 |
| 7,7 | ,9 | 23,1 | 35,9 | 100,0 |
| 3,1 | ,0 | 12,5 | 20,0 | 100,0 |
| 3,2 | ,3 | 8,9 | 20,7 | 100,0 |
| 3,7 | ,0 | 1,8 | 36,6 | 100,0 |
| ,0 | 5,1 | 46,2 | 5,1 | 100,0 |
| 2,3 | 1,6 | 42,6 | 24,6 | 100,0 |
| 2,3 | ,0 | 7,0 | 49,6 | 100,0 |