INDUSTRY SPECIFIC INFORMATION CONTENT OF FINANCIAL RATIOS AND FINANCIAL DISTRESS MODELING

A THESIS SUBMITTED TO
THE GRADUATE SCHOOL OF SOCIAL SCIENCES
OF
MIDDLE EAST TECHNICAL UNIVERSITY

BY

NAZ SAYARI

IN PARTIAL FULFILLMENT OF THE REQUIREMENTS
FOR
THE DEGREE OF DOCTOR OF PHILOSOPHY
IN
THE DEPARTMENT OF BUSINESS ADMINISTRATION

MAY 2013

Approval of the Graduate School of Social Sciences

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ABSTRACT

INDUSTRY SPECIFIC INFORMATION CONTENT OF FINANCIAL RATIOS AND FINANCIAL DISTRESS MODELING

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May 2013, 200 pages

The aim of this study is to investigate uncertainty levels of industries and explore those financial ratios that have the highest information content in determining the set of industry characteristics and use the most informative ratios selected in developing industry specific financial distress models. First, we employ factor analysis to determine the set of ratios that are most informative in specified industries. Second, we use entropy method as a Multiple Attribute Decision Making Model, to measure the level of uncertainty for these industries providing the framework of information theory and further specify those ratios that best reflect the industry specific uncertainty levels. Finally, we conduct logistic analysis and derive industry specific financial distress models to examine the predictive ability of financial ratios selected for each industry. Data for this study are obtained from Datastream for the period 1990-2011. The companies in the sample cover S&P 1500 firms that operate in 9 different industries. We reclassify the sample of firms in 4 industry groups according to their similarity in terms of accounting applications and derive industry specific financial distress models for these industry groups. The results show that financial ratios illustrate industry characteristics and that informativeness of ratios varies among sectors. We further observe that industry specific models predict financial distress better than the benchmark model and most of the ratios selected for each industry significantly contribute to the prediction of financial distress.

Keywords: Entropy, Uncertainty, information theory, financial ratios, industry specific financial distress model

ÖZ

SEKTÖRE ÖZGÜ FİNANSAL RASYOLARIN BİLGİ İÇERİĞİ VE FİNANSAL STRES MODELLEMESİ

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Mayıs 2013, 200 sayfa

Bu çalışmanın amacı, sektör belirsizlik düzeylerinin araştırılması ve sektöre özgü özelliklerin belirlenmesinde en yüksek bilgi içeriğine sahip finansal rasyoları ortaya çıkarmak ve seçilen bu rasyoları kullanarak sektöre özel finansal stres modellerini geliştirmektir. İlk olarak, sektöre özgü finansal rasyoların belirlenmesinde faktör analizi kullandık. İkinci olarak, bilgi teorisi çerçevesinde sektörlerin belirsizlik düzeyini ölçmek ve sektöre özgü belirsizlik düzeyini en fazla yansıtan finansal rasyoları belirlemek için, bir Çoklu Karar Verme Modeli olarak entropi yöntemini kullandık. Son olarak, lojistik analizi yöntemi ile, factor analizi ve entropi modelinden belirlenen sektöre özgü finansal rasyoları kullanarak her sektör için finansal stress modellerini oluşturduk. Bu çalışma için, 1990-2011 dönemini kapsayan veriler Datastream'den elde edilmiştir. Örneklemdeki şirketler 9 farklı sektörde faaliyet gösteren S & P 1500 firmalarını kapsamaktadır. Bu çalışmada 9 farklı sektörü muhasebe uygulamaları açısından benzerlik gösteren 4 sektör grubunda topladık ve bu 4 sektör grubu için sektöre özel finansal stres modelleri elde ettik. Sonuç olarak, finansal rasyoların sanayi özelliklerini yansıttığını ve bu rasyoların bilgi sağlamada sektörler arasında değişiklik gösterdiğini bulduk.

Ayrıca, sektöre özgü finansal stress modellerinin, şirketlerin finansal sıkıntılarını doğru tahmin ettiğini ve bu modellerde kullanılan sektöre özgü finansal rasyoların çoğunun istatistiksel olarak anlamlı olduğunu gözlemledik.

Anahtar Kelimeler: Entropi, belirsizlik, bilgi teorisi, finansal rasyolar, sektöre özgü finansal stress modelleri

To My Mother and Father

ACKNOWLEDGEMENTS

This dissertation would not have been possible without the support of many people. It is the product of a large measure of serendipity, fortuitous encounters with people who have changed the course of my academic career.

First and foremost, I would like to express my deepest appreciation to Prof. Dr. F.N. Can Şımga Mugan for her valuable guidance, advice and encouragement. Her invaluable assistance and inspiration motivated me throughout this challenging process. Without her guidance and persistent help, this dissertation would not have been possible.

I would also like to thank to Assoc. Prof. Dr. Adil Oran and Prof. Dr. Uğur Soytaş for their patient and continuous guidance throughout my study. I am extremely grateful and indebted to them for their sincere help in replying all my questions I had during my thesis. I would like to present my gratitude to Prof. Dr. Ramazan Sarı, Prof. Dr. İsmail Erdem and Prof. Dr. Nalan Akdoğan for their valuable suggestions in revising the study.

I would like to thank to Onur Tekel, Sevgi Eda Tuzcu, Serkan Şahin, Özge Dinç and Bahadır Güler for their technical assistance.

I would also like to present special thanks to my father Mehmet Sayarı and my husband Cengiz Musaoğlu for their valuable suggestions throughout this study and to my mother Sevim Sayarı for her endless support during this process as it always has been.

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GENERAL INTRODUCTION

The use of financial ratio analysis has been a necessity for corporations since 1800s. It first began with the comparison of current assets of a company to its current liabilities in 1890s, followed by return on investment, profit margin and capital turnover ratio in 1920s. In 1930s some researchers started criticizing the use of financial ratios and argue that, since both numerator and denominator of financial ratios vary over time, the time series interpretation of ratios could be problematic. They also argue that the reliability of ratios varies from one another. Following these criticisms, in 1940s the focus is directed to strengthening empirical base of financial ratios analysis. During the period, researchers discussed the predictive power of financial ratios and use of ratios in the prediction of financial failure of firms. The results for the preliminary experiments reveal that net profit to net worth, net worth to debt and net worth to fixed asset ratios were the best indicators that predict financial failure. In 1940s, researchers not only analyzed failed firms, but also analyzed both continuing and discontinuing firms and allow for the comparison of industry mean ratios of discontinuing firms with estimated normal ratios. After 1950s, financial ratio analysis became a popular tool for managerial purposes as well as determination of economic activity. Their usefulness gained acceptance even by small businesses and also by banks for making loan criticisms (Horrigan, 1968).

Following the historical evolution of financial ratio analysis, the purpose of this study is to analyze information content of financial ratios in measuring level of uncertainty of firms in different industries and to determine industry specific financial ratios by exploring which financial ratios possess more information for a specific industry. After determining the industry specific financial ratios, we further aim to generate industry specific financial distress models in predicting financial distress. This study aims to reduce information mass available to financial statement users by mitigating the number of financial ratios that is useful for decision making purposes. In other words, our purpose is to supply industry specific financial ratios to financial statement users that possess the highest information content in particular for that industry. In this respect, we adopt factor analysis method to reduce 51 commonly used financial ratios to determine the most informative and stable ratios between the periods 1990-2011 for each industry group. After determining the most informative and stable ratios in the factor analysis, we further adopt information theory approach and use entropy method to find out which financial ratios provide more information for a particular industry group in verifying the level of uncertainty of firms. Finally, we employ logistic regression analysis to derive industry specific financial distress models and examine the predicting ability of the models. We compare our industry specific models with one of the most reliable financial distress models in the UK, Taffler's Z-score model to evaluate whether industry specific financial distress models predict distress as accurately as other frequently used financial distress models.

There are studies that use entropy method in measuring the loss of information in aggregation process of accounting numbers (Theil, 1967; Lev, 1968) or that employ factor analysis to analyze financial ratio patterns to examine stability of financial ratios over time and across countries (Yli-Olli and Virtanen, 1985; Yli-Olli and Virtanen, 1986). However to our knowledge, no study has specifically analyzed the information content of financial ratios across industries. Moreover, although there are considerable amounts of financial distress models in the accounting literature that predict company failure, none of these models capture industry characteristics and provide prediction of distress in particular for certain industry groups. In this respect, our study serves as the first attempt in distinguishing between distressed companies across industries and in acknowledging financial statement users about the probability of financial distress of firms according to the industry group they belong.

Our dissertation consists of three parts. In the first part, we provide a brief summary of literature on the use of factor analysis in determining more informative financial ratios and conduct factor analysis to determine those financial ratios which are most informative and stable in the long term for each industry group. In this study, our sample consists of S&P 1500 firms for the period 1990-2011, where the related data are obtained from the Datastream. S&P 1500 firms are classified in 9 industries including consumer staples, consumer discretionary, health, industrials, materials, energy, utility, telecommunication and information technology. We reclassified these industries into 4 groups according to their similarity in terms of accounting applications. The first industry group includes consumer staples, consumer discretionary and health sectors - shortened as Cocohe, second group comprises energy and utility sectors - shortened as Enut, third group consists of industrials and materials sectors - shortened as Inma, and finally fourth group includes telecommunication and information technology sectors - shortened as Tein. From the factor analysis conducted for each industry group, we selected 26 ratios for the Cocohe, 24 ratios for the Enut, 30 ratios for the Inma and 29 ratios from the Tein industry groups which are considered as most informative and stable ratios for the 22 years period. We further conduct principal component analysis with the selected ratios from the factor analysis to determine industry specific classification patterns. The analysis reveals that, industry groups demonstrate different classification patterns of financial ratios, indicating companies possess variant industry characteristics.

In the second part, we summarize the studies held so far throughout the accounting and finance literature that employ entropy method in decision making purposes. We further provide a brief summary about Multiple Attribute Decision Making Models (MADM) and discuss the reason of employing entropy method besides other alternatives of MADM. We used entropy method in determining the level of uncertainty of each industry group and select industry specific financial ratios that best informs financial statement users about the uncertainty level of the firms belonging to a particular industry group.

Outcomes of entropy method show that, financial ratios that are most informative in determining the level of uncertainty of a firm vary between industry groups. Consequently, we derive 11 ratios for the Cocohe, 9 ratios for the Enut, 7 ratios for the Inma and 7 ratios for the Tein industry groups that can be demonstrated as industry specific financial ratios.

In the third part, we conduct logistic regression analysis to generate industry specific financial distress models, where the independent variables are those financial ratios derived from the entropy method. Logistic analysis reveals that, all of the industry specific financial distress models classify distressed and non distressed firms, better than our benchmark model - Taffler's (1983) financial distress model - which is cited as the most reliable distress model in the UK (Smith and Graves, 2005). In this section we further checked the generalizability of the logistic outcomes by employing within sample validation test. Validation test results also reveal that, prediction accuracy of the industry specific financial distress models is stable among the training and holdout samples. Overall, the outcomes show that, since industry specific information increases the predictive ability of the financial distress models, industry characteristics have to be taken into account by the financial statement users in evaluating the financial condition of a firm.

CHAPTER I

FINANCIAL RATIO ANALYSIS AND FACTOR ANALYSIS IN DETERMINING MOST INFORMATIVE AND STABLE RATIOS

1.1. Financial Statement Analysis

Financial statement analysis is a technique that provides estimates and inferences to financial statement users, which are useful in making certain business decisions. It is a tool that reduces uncertainty in decision making by providing decision makers a reliable assessment of planning, operating, investing and financing activities of businesses. Financial statement users demand financial statement analysis for a variety of factors. To begin with, creditors lend funds or provide goods and services to companies to be repaid within a reasonable period. In case companies experience losses or adversities, repayment of principal and interest become risky. In this respect, creditors investigate existing capital structure and check for the reliability, timing and stability of future cash flows. Similarly, equity investors provide funds to businesses and bear the uncertainties and risks of ownership in return. As a consequence, they demand financial information about the operations, profitability and financial condition of companies they finance. Notwithstanding, management of companies are responsible for monitoring financial condition as well as possible future investment opportunities. For that reason, they have to stay alert to the ever-changing business circumstances and should react timely to altering business conditions. In addition, auditors employ financial statement analysis in order to avoid potential errors and irregularities occur in operating, investing and financing activities and take necessary precautions against fraudulent actions. Meanwhile, analysts that value companies for purchases or mergers employ financial statement analysis to assess economic value of entities and determine financial and operational conformity of parties which are subject to mergers and acquisitions. Finally, regulators employ tools and techniques of financial statement analysis in the assessment of tax rate and supervisory of entities' tax returns (Bernstein and Wild, 1997).

1.1.1. Techniques Employed in Financial Statement Analysis

In general terms, financial statement users demand financial statement analysis to determine level of uncertainty of an entity, and the effect of uncertainty on decision making process. In this respect, financial statement users revise their beliefs by the insight provided by financial statement analysis.

Financial statement analysis can be examined in two categories. The first category includes cross sectional techniques, where financial statements are analyzed at a point in time. Common size statements and financial ratio analysis are the two options that can be employed within this category. Common size statements are used in comparison of firms that have possible size differences. To avoid this problem, statement of financial position components are expressed as a percentage of total assets and statement of comprehensive income components are expressed as a percentage of total revenues. These statements with percentages are called common size statements (Foster, 1969).

The other technique employed in the cross sectional analysis is financial ratio analysis, which is used in comparing ratios across firms. In the financial ratio analysis, individual financial ratios are categorized in groups for illustrative purposes. In grouping individual ratios, different categorizations exist in the accounting literature depending on the scope of the research. For instance, Foster (1986) uses seven categories that include cash position, liquidity, working capital/cash flow, capital structure, debt service coverage, profitability and turnover. Meanwhile, Horrigan (1965) employs five categories comprising of short term liquidity, long term solvency, capital turnover, profit margin and return on investment ratios.

The second category of financial statement analysis covers time series techniques, where financial statements are analyzed over time. Time series techniques include trend statements and financial ratio analysis. Trend statements are prepared by selecting a base year and expressing other years' statement items relative to the base year value. In this respect, this type of analysis is useful in determining changes in a particular ratio over time and cyclical fluctuations of an industry. Notwithstanding, financial ratio analysis as a time series technique attempts to catch a general trend of a particular financial ratio over a time period. Since financial ratio analysis provides historical data in comparing company performance over a selected period, it is usually employed in forecasting and informing certain future events. In general, we can say that, financial ratio analysis within a time series context is primarily used in identifying past performances, adjusting business practices and in forecasting decisions (Foster, 1969).

In the next section, we will examine the use of financial ratio analysis and principal reasons for employing financial ratio analysis in more detail.

1.2. Financial Ratio Analysis

As discussed in the previous section, financial ratios can be used for several reasons depending on the necessity of the financial statement user. Whittington (1980) investigates the use of financial ratios in two principal categories; normative use and positive use. In the normative use of financial ratios, the ratio analysis summarizes the relation between two accounting numbers in a single number which is then compared with a standard. The standard used in the analysis can be either a theoretical foundation, a past experience of a firm being analyzed or a comparison of the firm analyzed with other firms in the industry. To give an example, Lev (1969) examine the mean reverting properties of financial ratios across firms in a particular industry and employs industry averages as a norm in comparing a firm with other firms in the industry.

In the positive use of financial ratios, a functional relationship is estimated between financial ratios and a dependent variable for prediction purposes. This is mostly used by the investment analysts in estimating future profitability of a firm or by researchers in developing statistical models to predict corporate failure of a company, assessment of potential risks, credit rating and etc.

Barnes (1987) mentions two principal reasons for using financial ratio analysis in terms of methodological aspects. First reason of usage is to control for the size effect and second reason is to control for industry wide factors. Regarding the use of financial ratios in controlling size effect, Horrigan (1966) scales independent variables employed in the bond rating model by total assets to evaluate firms' profitability over time. Similarly, in the bankruptcy prediction studies, Beaver (1966), Altman (1968) and Taffler (1983) control for the size effect by stratifying the selected firms in the sample by mean of total assets. There are also studies that use size control to satisfy the assumptions of statistical models employed in the analysis (Miller and Modigliani, 1966). While a great deal of studies control for the size effect in their statistical analysis, Lev and Sunder (1979) question whether firm size should be controlled on the examined variables in bankruptcy prediction studies. They assert that in order financial ratios to be employed as an instrument for size control, the dependent and independent variables in the analysis should be strictly proportional. To examine the strict proportionality between dependent and independent variables, Lev and Sunder determine three aspects to be considered before starting the analysis. First, if the error term in the relationship is homoscedastic, the comparison of ratios by controlling size effect would not be useful since deviations from the slope of the relationship will be small for large firms and large for small firms. Second, the relation between the variables used in the ratio analysis should not contain an intercept term it would likely to reflect a biased computation of the marginal effect of a change in independent variable on the dependent variable. Third, if there are other dependencies than the size effect on the dependent variable or if the relation between dependent and independent variables is non linear, the use of financial ratios as control for size effect may not be appropriate. In this respect, selection of the proper size variable becomes very important in successfully controlling for the size effect.

Controlling for industry wide factors is the second principal reason for using financial ratios, where the selected ratios are compared between a subject firm and the industry it belongs. The control of industry wide factors provides comparative information about the subject firm's performance relative to the industry mean. To give an example, in his bankruptcy prediction model, Altman (1968) employs only the manufacturing firms where each bankrupt firm is matched with a non bankrupt firm from the same industry. Ohlson (1980), Zmijewski (1984), Aziz et al. (1988), Koh (1992), Mossman et al. (1998), Ugurlu and Aksoy (2006) and Chen and Du (2009) are bankruptcy prediction studies that control for industry wide factors in the financial ratio analysis. Meanwhile, Grice and Dugan (2001) assert that controlling for industry wide factors in bankruptcy prediction models results in sampling bias and accuracy of the outcomes should be evaluated with cautious. They rerun Ohlson's (1980) and Zmijewski's (1984) bankruptcy prediction models by evaluating the models' sensitivity to industry classification. They examine the predictive accuracy of the Ohlson and Zmijewski models as well as the discriminating ability of the financial ratios for different industry classifications. The results reveal that Zmijewski's bankruptcy model is not sensitive to industry classifications since the prediction power of the model does not change between industrial and non industrial firms. However, the results indicate on the other hand that, Ohlson's model is sensitive to industry classifications, because the reliability of the model is greater in industrial firms than in non industrial firms.

The sensitivity of bankruptcy prediction models to industry classifications raises the question of whether a single bankruptcy prediction model is suffice to in evaluate financial condition of firms from different industries. In other words, provided that firms possess industry characteristics, whether using same financial ratios for firms from different industries in the bankruptcy prediction models deteriorate the predicting ability of these models. These are the questions that we will thoroughly discuss in the second chapter of this study. Before all else, we should examine the classification of financial ratios and review the financial ratio analysis literature to clarify the contribution of our study and where we stand among the bankruptcy prediction models.

1.2.1. Classification of Financial Ratios

One of the mostly discussed issues in the financial ratio analysis literature is to find a ratio set that best represents activities of the subject firm. In this respect, four approaches are developed in the literature covering the ratio classification process; pragmatical empiricism, deductive approach, inductive approach and confirmatory approach (Salmi and Martikainen, 1994).

In the pragmatic empiricism, financial ratios are classified mainly in three categories: profitability, long term solvency (capital structure) and short term solvency (liquidity). Many textbooks of financial ratio analysis (i.e. Foster (1978), Brealey and Myers (1988) and Bernstein and Wild (1997)) adopt this approach in classifying financial ratios.

Deductive approach is mainly generated by the du Pont triangle system in 1919 where three basic financial ratios forms the triangle corners; Profits/Total Assets, Profits/Sales and Sales/Total Assets. Courtis (1978), Laitinen (1980) and Bayldon et al. (1984) classify financial ratios used in the literature using this three-step categorical framework.

Although pragmatic empiricism and deductive approaches are theoretical foundations, inductive approach is an empirical foundation where financial ratios are classified according to the empirical outcomes. Factor analysis is a widely used technique in the inductive approach, in which financial ratios are selected from a congested population of initial set of ratios and then classified into factor solutions identified by the factor analysis. Those factors identified by the factor analysis explain a computed percentage of the total variance in the initial ratio sample. Pinches et al. (1973), Johnson (1978), Chen and Shimerda (1981), Gombola and Ketz (1983) and Yli-Olli and Virtanen (1986, 1989) are some of the pioneering studies that use factor analysis in the classification of financial ratios.

Since researchers could not agree on a consistent classification of ratio factors by the inductive approach, later studies adopted confirmatory approach, where researchers hypothesize on a predetermined financial ratio classification factors and try to confirm those classification factors with empirical evidence. Pohlman and Hollinger (1981) use Lev's (1974) and Pinches et al.'s (1975) classification factors and then use redundancy indexes derived from canonical correlation analysis. They observe high correlation between a priori classification factors of Lev and Pinches et al. and conclude using few financial ratios since information they contain is more or less the same. Similarly, Luoma and Ruuhela (1991) evaluate a priori classification of 5 financial ratio factors; profitability, financial leverage, liquidity, working capital and revenue liquidity. They conduct cluster analysis for 15 financial ratios and examine whether the classification of these ratios will conform to a priori classification factor solutions. Results reveal that only profitability and revenue liquidity possess distinct clusters while other factors are significantly interrelated (Salmi and Martikainen, 1994).

Both inductive and confirmatory approaches reveal that a limited number of financial ratios are sufficient in conducting financial ratio analysis since they provide similar information with other financial ratios in the initial ratio sample. Consequently, given that few financial ratios are enough to supply information demanded by the financial statement users, researchers come across with the question of which financial ratios are most useful in providing this information. In this respect, some researchers claim that financial ratios are useful if only the financial information they provide are stable over time (Laurent, 1979; Pohlman and Hollinger, 1981; Yli-Olli and Virtanen, 1985). In addition, some researchers argue that useful financial ratios should be determined by taking industrial variations in to account so that financial ratios would inform financial statement users about industry characteristics of firms (Gupta, 1969; Gupta and Huefner, 1972; Johnson, 1979). Furthermore, some researchers aim to prevent information redundancy in financial ratios and explore most useful financial ratios by obtaining the least multicollinear ratio set (Pinches et al., 1973; Yli-Olli and Virtanen, 1985;

Ezzamel et al., 1987). In the following section, we will examine these studies in detail and summarize their outcomes to determine which financial ratios are selected as most informative.

1.2.2. Literature Review of Financial Ratio Analysis

A common feature of financial ratio analysis research is to derive most useful financial ratios that provide substantial information about future events so that they can be employed in the financial distress/bankruptcy models for prediction purposes. Research on the determination of most useful financial ratios has focused on three main aspects; stability of financial ratios over time, financial ratios possessing industrial variations and obtaining the financial ratio set that does not contain redundant information. To empirically determine the most useful ratios and the best information set, researchers employ factor analysis which is used for data reduction processes in identifying a smaller set of variables from an initial variable set.

Several researchers argue that financial ratios can be used in the financial distress/bankruptcy models if they show stable patterns of factor solutions over time. Pinches et al. (1973) examine the long term stability of financial ratios for the period 1951-1969, by employing R factor analysis where financial ratios are treated as variables and industrial firms are treated as cases. They select 1951, 1957, 1963 and 1969 periods to determine the change in static time positions. The resulting factors analysis provides 7 factors where factor loadings 0.70 or greater in either of the four years are reported. The 7 factors are named as return on investment, capital intensiveness, inventory intensiveness, financial leverage, receivables intensiveness, short term liquidity and cash position. The results indicate that ratios that load to financial leverage factor (Debt/Plant, Debt/Total Capital, Total Liabilities/Net Worth, Total Assets/Net Worth, Debt/Total Assets, Total Liabilities/Total Assets) show the most stable pattern while ratios that load to capital intensiveness factor (Cash Flow/Sales, Total Income/Sales, Net Income/Sales, Current Liabilities/Net Plant, Working Capital/Total Assets, Current Assets/Total Assets, Quick Assets/Total Assets, Current Assets/Sales, Net Worth/Sales, Sales/Total Assets, COGS/Inventory, EBIT/Sales, Sales/Net Plant and Sales/Total Capital) show the least stable pattern.

Similarly, Yli-Olli and Virtanen (1985) employ factor analysis to decide on the "potentially good ratios" and to select those ratios that measure the "same characteristic of the firms' performance" in altering conditions. In this respect, they examined the classification patterns of financial ratios for 42 Finnish firms for the period 1947-1975. To check the reliability of the analysis they compare the outcomes of Finnish firms with US firms for the same period. They select twelve ratios including current ratio, quick ratio, defensive interval measure (DI), debt to equity, long term debt to equity, times interest earned (TIE), earnings to sales, return on assets (ROA), return on equity (ROE), total asset turnover (TAT), inventory turnover and account receivable turnover (ART) ratio. As the researchers examine the aggregated time series of the selected ratios, they compute average values of the ratios by both using equal and value weighted indices. They also compute variables both in levels and in the first difference form. To classify the patterns of financial ratios they use factor analysis and employ Kaiser's orthogonal varimax rotation. They further examine long term stability of financial ratios by dividing the period into two sub periods: 1947-1961 and 1962-1975. The outcomes reveal three factors which they called solvency, profitability efficiency and dynamic liquidity. In the case where value weighted average along with first difference form of variables are used, Finnish firms show similar factor patterns with US firms. Moreover while US firms show high degree of long term stability, they need to conduct transformation analysis for Finnish firms to catch the same long term stability and structural invariance. Along with the outcomes researchers determine the best solvency measures as debt to equity and quick ratio; the best profitability measures as ROA and ROE; the best efficiency ratio as TAT; and the best dynamic liquidity ratio as DI. Meanwhile TIE and ART showed the poorest performance among the 12 financial ratios.

Ezzamel et al. (1987) use factor analysis technique to examine the long term stability of financial ratio patterns for UK manufacturing companies for the period 1973 – 1981. To analyze the long term stability, they classify number of manufacturing companies in three years; 1973, 1977 and 1981. They select 53 ratios according to their popularity in the literature. Researchers both conduct orthogonal and oblique rotation and conclude that oblique rotation provide better clustering of ratios. The study reports 11 factors for 1973, 15 factors for 1977 and 10 factors for 1981. They come up with 10 factors for each year where they select financial ratios that have factor loadings of 0.70 or greater in any of the three years. Those factors are capital intensiveness, profitability I and profitability II, working capital, liquidity I and liquidity II, long term debt, asset turnover I and asset turnover II and inventory. The results show that inventory ratios that include Debtors/Inventory, Sales/Inventory and Current Liabilities/Inventory are most stable among years while asset turnover II ratios that include Sales/Total Assets, Net Profits/Sales, Current Assets/Sales and Cash Flow/Sales and capital intensiveness ratios that cover EBIT/Net Worth, Sales/Net Worth, WC/Net Worth, Fixed Assets/Net Worth, Total Debt/Net Worth, Quick Assets/Net Worth, Current Liabilities/Net Worth, Cash Flow/Net Worth and Long Term Debt/Net Worth show the least stable patterns.

In the financial ratio analysis literature, the second common aspect evaluated by the researchers in selecting the most useful ratios is the determination of industrial variations among the financial ratios and identifying industry specific differences due to industry characteristics. Gupta (1969) examines whether industrial variation, size and growth rate of firms have any effect on financial ratio analysis. He conducts cross sectional analysis for the year 1961, where he determines size of firms by the total assets. First, the researcher classifies ratios in 4 groups including activity, leverage, liquidity and profitability ratios and then compares those ratios by size and growth rate of firms i.e. whether the ratio rises, falls or shows irregular pattern for that particular size and growth rate. Gupta conducts the same procedure for the industrial variation and observes that industrial variation is consistently related to fixed asset composition and organization structure. Primary processing industries such as metal, chemical, stone, glass, paper and allied products tend to have low levels of fixed asset turnover, while advanced processing industries such as food, apparel, furniture and tobacco tend to have higher levels of fixed asset turnover. Similar outcomes are observed for the receivable turnover ratios that, it is positively related to higher product unit value and organizational cost structure of firms. Results reveal that, activity and leverage ratios decrease when the size of the firm increases while the ratios increase with the firm growth. On the contrary, liquidity ratios increase with an increase in the size of firms while they decrease when the firms' growth rate increase. Finally, no regular pattern observed with the profitability ratios that, no association exists between large sized firms and higher profit margins.

In another study, Gupta and Huefner (1972) search for an association between accounting numbers and industry specific attributes. They expect that, certain industries would likely to have higher values for a certain ratio compared with other industries. To analyze this difference, they adopt cluster analysis and classify industries that have similar values of a certain financial ratio. They select 20 manufacturing industries from the Internal Revenue Service that are differentiated according to two-digit industry codes. The financial ratios employed for the grouping of industries are fixed asset turnover, inventory turnover, average collection period and cash velocity. The results show that, fixed asset turnover provided the best results in the classification of industry groupings. However, cash velocity yield less clear findings in the grouping process. Additionally, inventory turnover and average collection period show modest industry characteristics in differentiating between industry groups. Overall, results indicate that, financial ratios are associated with certain industry characteristics and thus ratios may be used as surrogates for determination of industry groupings.

Johnson's (1979) study is another one that uses factor analysis to determine both industry specific differences among the ratios and their long term stability. Using principal component analysis, Johnson examines the cross sectional stability of 61 financial ratios selected from prior studies for two different industries; retailers that include 159 firms and primary manufacturers that include 306 firms. The researcher determines the cross sectional stability of financial ratios by comparing two groups of industries for two years (1972 and 1974). The univariate analysis reveals that 38 of the 61 ratios show significant differences between retail and manufacturing firms in 1974 and similarly 33 of the 61 ratios were also significantly different for the two groups in 1972. In order to improve normality and mitigate outliers, he uses a common logarithmic transformation. The researcher derives 8 factors, which he categorizes as return on investment, financial leverage, capital intensiveness, inventory intensiveness, cash position, receivable intensiveness, short term liquidity and decomposition measures. These eight financial ratio groups show high levels of stability for the years 1972 and 1974. Among these ratio groups, financial leverage and cash position shows the most stable patterns while short term liquidity group shows the least stable pattern. Cross sectional analysis further reveal that, firms in the manufacturing group are more capital intensive, have higher inventory levels, receivables and return on investment and stronger short term liquidity than firms in the retail group.

The third common aspect evaluated in the financial ratio analysis in obtaining the most useful ratio set is the prevention of information redundancy by limiting the level of multicollinearity among the financial ratios. Because of the commonality of financial components within the financial ratios, the degree of overlap between those ratios with same numerator or denominator becomes even greater, so that the additional information they possess might be very small or even equal zero. In order to separate redundant ratios from the others that contain substantial information, Laurent (1979) uses principal component analysis for a total of 45 financial ratios. The researcher lists 10 factors and related financial ratios with the highest loadings. Among the 10 factors, the financial ratios that possess the highest loadings are EBIT/Total Assets, Long Term Debt/Total Assets, Revenue/Working Capital, Shareholders' Funds/Fixed Assets, Revenue/Shareholders' Funds, Quick Assets/Quick Liabilities, Revenue/Inventory, Profit Before Interest and Taxes/Interest, Reserves/Net

Income and Revenue/Debtors. The researcher concludes that, with these 10 ratios that have the highest loadings, 82% of the total variance contained in the original set of 45 financial ratios can be explained. As a check for the reliability of the results, Laurent also reports that the intercorrelations among the 10 ratios are sufficiently low.

Throughout the financial ratio analysis literature, several researchers conclude that, certain sets of financial ratios enclose information that enables us to predict or describe specific attributes of a firm. However, given the fact that, not all sets of financial ratios enclose significant information, Pohlman and Hollinger (1981) examine the information redundancy in financial ratios and explore those sets of ratios that contain significant information. They use 384 firms that have complete data in the Compustat for the period 1969-1978 and employ canonical correlation analysis, which is a more general technique of multiple regression analysis. To recover normality and homoscedasticity, researchers use log transformation. They also compute redundancy indexes from the output obtained from canonical correlation analysis. Redundancy indexes compute the amount of redundant information by analyzing how much information in a certain set of variables is already enclosed in another set of variables. Given that 48 financial ratios were used in the analysis the results reveal that, activity ratios possess the most redundant information given the profitability ratios, while leverage ratios possess similar redundancy indexes as profitability ratios. Specifically speaking, return on investment ratios contain significant information while capital turnover ratios show less significance and higher levels of redundancy index. Since all of the information contained in the inventory turnover ratio is already enclosed with receivable turnover ratio, the greatest amount of redundancy is observed in inventory turnover. However receivable turnover ratios also show 50% redundancy given the short term liquidity ratios. Finally given the cash position ratios, liquidity ratios also show 50% redundancy. Overall results reveal that users of financial ratios should employ minimum number of ratios in order to avoid redundancy and information overload and should select a ratio set that has the highest information content.

To examine the information redundancy among the financial ratios, Chen and Shimerda (1981) combine 7 factors and 39 financial ratios used in the Pinches et al.'s (1975) study with 10 financial ratios that are found important in predicting firm failure in the literature and conduct a principal component analysis to examine whether these 10 financial ratios are overlapping with 39 financial ratios used in the study of Pinches et al.. The 10 important ratios in predicting firm failure cover Net Income/Sales, Net Income/Common Equity, Working Capital/Total Assets, Long Term Debt/Current Assets, Funds Flow/Total Debt, Funds Flow/Current Liabilities, Retained Earnings/Total Assets, No Credit Interval, Quick Flow and Quick Assets/Inventory. They select a total of 1,053 firms in Compustat for the year 1977. The results indicate that among these 10 ratios, Net Income/Sales is highly correlated with EBIT/Sales, Net Income/Common Equity is highly correlated with Net Income/Net Worth, Working Capital/Total Asset is highly correlated with Current Asset/Total Asset, Quick Assets/Inventory ratio is highly correlated with Receivables/Inventory ratio and Funds Flow/Total Debt, Funds Flow/Current Liabilities are highly correlated with Net Worth/Total Debt where the latter ones are used in the Pinches et al.'s study. Overall, Chen and Shimerda conclude that inclusion of these highly correlated ratios results in multicollinearity and mass of information. In this respect, in the financial ratio analysis researchers should pay attention to this multicollinearity problem in order to select the best representative ratios.

Overall, the research on financial ratio analysis reveals that, although some of the ratios show stable patterns over time, are variant among industries and do not cause information redundancy to financial statement users, their usefulness vary from one study to another. To illustrate the most useful ratios that are common for each study that we discussed in the above section, we present a summary of these studies in Table 1, showing the most useful ratios selected in the studies.

From Table 1 we can state that, most useful ratios common for majority of the studies are fixed assets turnover, total debt/net worth and total debt/total assets for financial leverage, net income/total assets and net income/net worth for profitability, receivables/inventory and COGS/inventory for inventory intensiveness, total debt/working capital for working capital, quick assets/total assets, current assets/current liabilities and cash flow/total assets for liquidity ratios. It can be interpreted such that, liquidity and financial leverage ratios dominate other ratio sets in terms of their usefulness and informativeness in the prior studies.

In the following chapters of this study we will empirically define our set of "most useful financial ratios" that are least redundant and most stable over time and also possess financial information specific to particular industry groups. After obtaining our set of most useful ratios, we will compare our findings with the most useful ratios selected in the prior studies. Since prior studies conducted cover the periods 1970s and 1980s, we will be able to evaluate whether the most useful ratios differ between 1970-1980 and 1990-2011 periods.

Table 1. Most Useful Ratios Selected in the Ratio Analysis Literature

Pinches et al. (1973)	Total Income/Total Assets, Cash Flow/Net Worth, Net Income/Total Assets, EBIT/Total Assets, Sales/Total Assets, Sales/Total Capital, Net Worth/Sales, Cash Flow/Total Capital Total Debt/Total Capital, Total Debt/Net Worth, Total Debt/Total Assets, Total Liabilities/Total Assets, Receivables/Inventory, Receivables/Sales
Yli-Olli and Virtanen (1985)	Total Debt/Net Worth, Quick Ratio, Net Income/Total Assets, Net Income/Net Worth, Total Asset Turnover, Defensive Interval Measure
Ezzamel et al. (1987)	Total Debt/Net Worth, Cash Flow/Total Assets, Total Debt/Working Capital, Working Capital/Total Assets, Long Term Debt/Net Capital Employed, Current Liabilities/Inventory, Net Profit/Sales, Quick Assets/Total Assets
Gupta (1969)	Fixed Assets Turnover, Receivables Turnover, Inventory Turnover, Total Debt/Total Assets, Cash Velocity, Average Collection Period, Current Liabilities/Long Term Debt, Bank Loans/Total Assets, Accounts Payable/Total Assets, Current Ratio, Quick Ratio
Gupta and Huefner (1972)	Fixed Assets Turnover, Inventory Turnover, Average Collection Period, Cash Velocity
Johnson (1979)	Net Income/Total Assets, Cash Flow/Total Assets, Cash Flow/Total Capital, Net Income/Total Capital, Long Term Debt/Net Worth, Long Term Debt/Total Capital, Sales/Total Capital, Sales/Property Plan Equipment, COGS/Inventory, Cash/Total Assets, Cash/Funds Expenditures for Operations, Receivables/Inventory
Laurent (1979)	EBIT/Total Assets, Net Income/Total Assets, Cash Flow/Total Assets, Long Term Debt/Total Assets, Long Term Debt/Capital, Revenue/Working Capital , Total Debt/Working Capital, Shareholders’ Funds/Fixed Assets, Quick Assets/Quick Liabilities, Current Ratio, Reserves/Net Income
Chen and Shimerda (1981)	Net Income/Sales, Net Income/Net Worth, Funds Flow/Total Debt, Funds Flow/ Current Liabilities, Current Assets/Total Assets, Receivables/Inventory
Pohlman and Hollinger (1981)	Current Ratio, Quick Assets/Total Assets, Debt/Total Assets, EBIT/Fixed Charges, Sales/Total Assets, COGS/Inventory, Sales/Property Plant Equipment, Sales/Receivables, Total Incomes/Sales, Net Income/Total Assets, Net Income/Net Worth

1.3 Expectations

This study is an exploratory research that has three main purposes. First, it aims to explore most useful and informative financial ratios in the accounting literature in order to reduce the information mass available to financial statement users. Second, it purports to determine the level of uncertainty of firms for different industry groups and examine those ratios which are most informative and industry variant in measuring the uncertainty level of firms. Third aim of this study is to use industry specific financial ratios in predicting financial distress particular for each industry group.

In the previous section we observe that, financial ratios that are least redundant and most stable over time and also those of which embrace industry characteristics are defined as most useful ratios by the prior studies in the accounting literature. Given this definition, first we expect that financial ratios, which contribute most to the explanation of the total variation of the sample and show stable patterns for the sample period would be the ratios with highest information content (Pinches et al., 1973; Yli-Olli and Virtanen, 1985; Ezzamel et al., 1987).

Second, we theorize that, financial ratios with lower entropy scores are more informative than financial ratios with higher entropy scores as they discriminate best between industry groups in determining the uncertainty level of firms (Theil, 1969; Abdel-Khalik, 1974; Gentry et al., 2002; Peng et al., 2009). As depicted in information theory literature, lower entropy leads higher information content. Detailed computations of entropy scores will be explained in the second chapter of this study. From the factor analysis and entropy outcomes covering the first and second chapters, we expect that, most useful and informative financial ratios will vary among the industries, since each industry group exhibits different dynamics in terms of operating, investing, financing and planning activities.

Finally, we believe that financial distress models generated with industry specific financial ratios predict financial distress at least as accurately as other financial distress models, which are popularly employed in the bankruptcy prediction studies (Gupta, 1969; Gupta and Huefner, 1972, Pinches et al., 1975). If this is the case, financial statement users would benefit from employing industry specific financial distress models (FD models) since these models generates financial information enclosing industry characteristics. In the third chapter, as we generate industry specific financial distress models for each industry group and compare the prediction accuracy of our findings with one of the most popularly used financial distress prediction model, Taffler's Z-score model (1983), we expect that, our FD models will outperform Taffler's Z-score model, since Taffler's model does not take into account industrial variations of firms from different industries. In this respect, we aim to contribute to the existing literature by reducing information mass available to financial statement users, since industry specific financial distress models will provide financial information particular for each industry group and will facilitate decision making.

In the following section, we will define our data for this study and demonstrate the methodology that we are going to employ in the selection process of most useful and informative ratios.

1.4. Data and Methodology

Data for this study are obtained from Datastream for the period 1990-2011. The data covers S&P 1500 firms that are active in the market as of March, 2012. S&P 1500 includes S&P 500, S&P Midcap 400 and S&P Smallcap 600 firms that demonstrate approximately 90% of the U.S. market capitalization. 264 firms from the financial sector are excluded from the analysis since there are fundamental accounting differences between financial and industrial firms.

The firms are assigned to the industrial categorization with which they are classified by S&P 1500 that covers information technology, industrials, healthcare, consumer discretionary, consumer staples, energy, materials, telecommunication services and utility sectors. Since some of these sectors show similar characteristics in terms of accounting implications, raw material usage, and production process, we reestablish the categorization of industrial firms in 4 groups. First group covers firms in the consumer staples, consumer discretionary and health care sectors, shortened as "Cocohe". Consumer staples include firms in the foods and staples retailing, beverage and tobacco, household and personal products industries. The consumer discretionary group consists of firms in the automobiles and components, household durables, leisure equipment and products, textiles, apparel and luxury goods, hotels and restaurants, media and retailing industries. Finally the health group covers firms in the health care equipment and supplies, healthcare providers and services, health care technology, pharmaceuticals, biotechnology and life sciences industries.

The second group includes firms in the energy and utility sectors which we shortened as "Enut". Energy sector comprise of firms that produce energy equipment and services, oil, gas and consumable fuels and utility sector consist of firms in the electric, gas and water utilities and further includes independent power producers and energy traders.

The third group present firms in the industrial and material sectors and shortened as "Inma". Industrials sector consists of firms that produce aerospace and defense, building products, construction and engineering, electrical equipment, industrial conglomerates, machinery, commercial and professional services and transportation as well as includes trading companies and distributers, while materials sectors includes firms that produce chemicals, construction materials, containers and packaging, metals and mining, paper and forest products.

The final group comprises firms in the telecommunication services and information technology sectors and shortened as "Tein". Telecommunication sector composes from wireless and diversified telecommunication services and information technology sector includes firms that produce software, communications equipment, computers and peripherals, electronic equipment, instruments and components, office electronics, semiconductors and semiconductor equipment.

From a total of 1236 firms, we exclude 172 firms that have missing data for more than 10 years. The final sample comprises 1064 firms, where Tein includes 228 firms, Enut includes 139 firms, Cocohe includes 414 firms and Inma includes 283 firms. A complete list of firms included in the study is provided in Appendix A.

1.5. Distributional Properties of Financial Ratios in a Factor Analysis Setting

In this study we employ 51 ratios that are selected from the existing literature after completing the two following steps. First, we overview the financial ratio analysis literature, that conduct factor analysis to examine the most informative ratios. Second, we select financial ratios which have 0,70 loadings or higher in these studies and finally we eliminate those ratios that are very similar to each other in order to avoid redundant information and multicollinearity. Financial ratios used in this study are presented in the Appendix B. The ratios are calculated for each 1064 firms for 22 years covering 1990-2011 periods.

Before starting the analysis, we checked whether our data satisfies the necessary assumptions of the factor analysis. Contrary to other multivariate techniques, assumptions of factor analysis are more conceptual rather than statistical. In other words, rather than emphasizing the statistical qualities of variables included, factor analysis centers its concerns on the character and composition of variables. In practical terms, factor analysis assumes normality, homoscedasticity and linearity. However, these assumptions apply only to the extent that they deteriorate the observed correlations between variables. Beyond that, normality is a necessary condition, if only the significance of the factors is going to be determined by a statistical test. Additionally, since one of the objectives of factor analysis is to identify interrelated sets of variables, some degree of multicollinearity is even desirable (Hair et al, 2005).

When we examine the literature regarding distributional properties of financial ratios in a factor analysis setting, as mentioned earlier we observe that, financial ratio analysis can be examined in two parts: a time series analysis where trends in past firm performance are evaluated in order to predict future performance; and a cross sectional analysis where a specific firm is compared against a benchmark i.e. industry averages. For cross sectional analysis, the statistical distribution of financial ratios is important since the ratios are expected to approximate normality. However in time series analysis, there are distinct opinions regarding violation of normality assumption. Some say that, it is not tenable to expect financial accounting ratios to meet assumption of normality (Deakin, 1976) while some argue that financial ratio analysis should continue with the use of normality assumption (Horrigan, 1965; O' Connor, 1973).

Following Deakin's (1976) study, Frecka and Hopwood (1983) examine time series distributional properties of manufacturing companies' financial ratios selected from the Compustat files for the 30 year period, 1950-1979. They use Gamma distribution in detection of outliers and in observation of skewness. They found that, ratio distributions are likely to be right skewed since a unit decrease in the denominator results in a greater absolute change in the value of the ratio than a unit increase in the denominator. They remove outliers from the sample to obtain less skewed distribution and use natural logarithms to transform variables. Then they employ Chi-square test to check normality and observe that WC/TA is normally distributed in 25 of the 30 years and it ensures a high degree of stationarity. Although Deakin (1976) finds that, TD/TA is normally distributed in 15 of the 19 years, Frecka and Hopwood observe that this ratio shows non normal distribution in 22 of the 30 years. The researchers state that, most of the transformed ratios still show non normal distribution and they can only achieve normal distribution when outliers are removed.

Regarding the time series distributional properties of ratios, Richardson and Davidson (1984) mention that when the data do not come from the same period, problems arise due to non stationarity of the times series data. They employ financial ratios used in the Altman's (1968) study of Z-score modeling that include working capital/total assets, retained earnings/total assets, EBIT/total assets, market value of equity/book value of total debt and net sales/total assets. To examine instability in time series data, they factor analyze financial ratios of firms listed in American Stock Exchange (AMEX) for the three years including 1974, 1975 and 1978. The results show that, financial ratios are unstable among the years.

In the literature, there are numerous studies that examine and discuss the effect of cross sectional distributional properties of ratios and the effect of outliers on the financial ratio analysis. Bougen and Drury (1975) conduct cross sectional financial ratio analysis over 700 UK firms for 1975. The ratios used in the analysis include return on invested capital, profit margin, borrowing to shareholders' funds, current ratio, acid test, inventory turnover and debtor turnover. To improve normality, they conduct square root and log normal transformation as well as truncation to minimize the effect of extreme outliers. They employ Chi-square statistics to examine the difference between observed and the expected number of observations. The results reveal that, the ratio distributions are non normal. They conclude that the violation of normality assumption results from varying degrees of skewness and continuation of extreme outliers. Regarding the skewness and normality problem, Barnes (1982) also observes that, when there is lack of strict proportionality among the ratios, skewness and non normal distribution are likely. To avoid this problem, the researcher suggests using transformation analysis.

Similarly, Ezzamel et al. (1987) demonstrates that it is inevitable to avoid the problem of non normally distributed financial ratios because of the skewness and extreme cases of outliers. To them, non normality is even more likely for large samples since large samples lack homogeneity. To examine the normality of financial ratios (total debt/total assets (TD/TA), current assets/current liabilities (CA/CL), working capital/total assets (WC/TA), net income/total assets (NI/TA) and current assets/sales (CA/S), the researchers conduct cross sectional analysis for the period 1980-1981 including 40 firms from the textile, 269 firms from the retail foods and 25 firms from the metal industry. They test normality by employing Kolmogorov-Smirnov Test, Shapiro Wilk Test and Chi-Square Goodness of Fit Test. To obtain a better fit of normality, they transformed data using square roots and natural logarithms. The results show that the researchers obtain lower skewness when transformed data is used, especially for the CA/CL and NI/TA ratios. Industry specific analysis reveals that, no obvious outliers are detected for the retail food industry, while extreme outliers exist for the metal and textile industries. Overall results show that TD/TA and WC/TA are normally distributed while NI/TA is normally distributed only for the textile industry. Similarly, CA/CL and CA/S are normally distributed for some but not all industry groups.

According to Deakin (1976) although assumption of normality for financial ratios is unrealistic, they might show more normally distributed patterns within the same industry group. Following Deakin, in our study, we examined the distributional properties of financial ratios for each of the 4 industry groups. To test normality, we employ visual analyses i.e. stem&leaf plots, P-P plots, histogram and also employ Kolmogorov-Smirnov test for statistical analyses. The results show positive skewness in majority of the variables. Following the literature, positive skewness is an expected outcome in financial ratio analysis since most of the ratios have an effective lower limit of zero while they possess an indefinite upper limit (Horrigan, 1965). Normality tests determine financial ratios with high standard deviations as CF/TD, EBIT/IntExp, QA/CFO, CA/CFO, COGS/AvgInv, CL/Inv, Sales/PPE, TL/WC and Sales/WC for Cocohe group, TD/WC, TL/WC, CF/WC, NI/WC, Inv/WC, Sales/PPE, CL/Inv, Sales/WC, COGS/AvgInv and EBIT/IntExp for Enut group, CF/TD, TD/WC, TL/WC, Sales/WC, COGS/AvgInv, EBIT/IntExp, CA/CFO, QA/CFO and Dividend/NI for Inma group and Sales/WC, Sales/PPE, CL/Inv, COGS/AvgInv, EBIT/IntExp, Rec/Inv, QA/CFO and CA/CFO for Tein group. Our list of ratios with high standard deviations that are common for all industries is also in line with the prior literature findings that observe the financial ratios with extreme standard deviations (Deakin, 1976; Bird and McHugh, 1977).

To handle those variables with high standard deviations and to avoid cases with extreme outliers, we set outlier cut off value to 4 standard deviations and deleted those cases which exceeded that cut off point. In this respect, we had to delete some of the financial ratios with extremely high standard deviations, since more than half of the data would be lost to meet the 4 standard deviations cut off value. Hence, EBIT/IntExp is deleted from

Cocohe, Inma and Tein industries and Sales/WC and TL/WC are deleted from Enut industry group. Consequently, we have 50 ratios in Cocohe, 49 ratios in Enut, 51 ratios in Inma and 50 ratios in Tein industry groups.

As a result of data quality improvement process, although Kolmogorov-Smirnov test exposes rejection of normality assumption, stem&leaf plots, P-P plots and histogram analysis show that financial ratios demonstrate normal distributions around the mean with tolerable standard deviations. Finally, following Hair et al. (2005), when we examine the intercorrelations among the financial variables, we observe that the data matrix has sufficient correlations to justify the implication of factor analysis. Hence, the overall evaluations show that departures from normality do not affect our test results significantly.

1.6. Factor Analysis

Financial ratios provide information that is necessary in decision making. Previous research shows that, reducing uncertainty improves decision making process, which strengthens prediction accuracy of events for decision makers. (Zavgren, 1985; Downey and Slocum, 1975, Abdel-Khalik, 1974 and Ballantine et al., 1997) Hence, in our analysis we aim to explore the uncertainty of each industry using financial ratios. As factor analysis is used in the determination process of a smaller set of variables from a a large set that have special importance to the investigation (Anderson, 1962), we employ factor analysis to decide on which financial ratios have more information content and contribute most to the explanation of the total variation of the sample. We use listwise method to handle missing observations and employ varimax rotation since it maximizes the sum of variances of required loadings of the factor matrix and gives a clearer separation of the factors. To assess the overall significance of the correlation matrix and factorability of the overall set of variables Bartlett's Test of Sphericity and Kayser-Meyer-Olkin (KMO) measure of sampling adequacy (MSA) are conducted respectively. The results are illustrated in Table 2.

Table 2. KMO and Bartlett's Test of Sphericity

	Cocohe	Enut	Inma	Tein
KMO	0,758	0,767	0,754	0,752
Bartlett's Test				
Approx. Chi-Square	268989,579	66582,145	345332,922	127976,109
Df	1225	1176	1225	1225
Sig.	0,000	0,000	0,000	0,000

The results show that MSA values fall in the acceptable range (above 0.50) for all of the four industry groups. Likewise, Bartlett's Test of Sphericity is significant at 0.01% for all of the groups indicating the set of variables are appropriate for factor analysis. Next, to select the most informative ratios, we look at the communalities of the variables in the unrotated factor matrix and eliminate ratios with the communality levels 0.50 or lower. We also derive anti-image correlation matrix of the variables to explore the individual MSAs and eliminate financial ratios that have MSA values under 0.50. Finally we examine the rotated component matrix and remove variables with factor loadings below 0.70 as well as those variables that load more than one factor, since such variables do not have a significant contribution in explaining total variance of the factors. This procedure is conducted for each group of industry.

In factor analysis, our goal is to determine potentially "good" ratios and reselect among those ratios that assess the same characteristics of the companies' performance during changing cyclical conditions. Following the notion that a model is useful for prediction purposes only when the parameters and their association are stable over time (Seay et al., 2004), we examine the long term stability of financial ratios by dividing the sample into two sub periods. First period covers 1990-2000 and second period covers 2001-2011. We compare two periods to determine which ratios have 0.70 or higher factor loadings for both of the sub-periods and eliminate those ratios that do not meet this qualification. To examine whether these ratios change over time, this procedure is also repeated for each group of industry. The resulting set of ratios for each industry group is presented in Table 3.

Table 3. List of Selected Financial Ratios from Factor Analysis

Cocohe	Enut	Inma	Tein
NI/TA	NI/TA	NI/TA	NI/TA
EBIT/TA	EBIT/TA	EBIT/TA	NI/Sales
NI/Sales	NI/NW	NI/Sales	EBIT/TA
NI/NW	NI/TL	EBIT/Sales	EBIT/Sales
NI/TL	FFO/TL	NI/NW	NI/NW
FFO/TA	LTD/TA	NI/TL	NI/TL
TD/NW	TD/NW	FFO/TA	FFO/TA
TL/NW	TL/NW	TA/NW	LTD/TL
TA/NW	TA/NW	TL/NW	LTD/TA
TL/TA	CA/NW	TL/WC	TD/TA
Inv/Sales	TL/TA	Sales/WC	TD/PPE
COGS/Inv	NW/Sales	FFO/WC	TA/NW
TL/WC	Inv/Sales	TD/WC	INV/Sales
Sales/WC	COGS/Inv	Inv/WC	COGS/Inv
FFO/WC	FFO/WC	LTD/TL	Rec/Inv
TD/WC	TD/WC	LTD/TA	CL/Inv
Sales/TA	NI/WC	TD/TA	TL/WC
QA/FEO	Inv/WC	Inv/Sales	Sales/WC
QA/Sales	Sales/TA	COGS/Inv	FFO/WC
CA/Sales	Rec/Sales	Rec/Inv	TD/WC
Cash/TA	Cash/TA	Inv/CA	QA/FEO
Cash/TL	Cash/FEO	Cash/FEO	QA/Sales
CL/PPE	Cash/TL	Cash/TA	CA/Sales
Sales/PPE	Sales/PPE	Cash/TL	Cash/TA
CA/CFO		Sales/TA	Cash/FEO
QA/CFO		CA/TA	CL/PPE
		Sales/PPE	Sales/PPE
		CA/CFO	CA/CFO
		QA/CFO	QA/CFO
		DIV/NI	

After this procedure, in Cocohe group 26 out of 50 financial ratios; in Enut group 24 of the 49 ratios; in Inma group 30 of the 51 ratios; and in Tein group 29 of the 50 financial ratios survived. It can be interpreted that, these ratios contain most of the information in the initial financial ratio sample and they show stable patterns of factor solutions among the 22 years period relative to the remaining ratios in the data set. Results also reveal that, EBIT/TA, NI/TA, NI/NW, TA/NW, NI/TL, Inv/Sales, COGS/Inv, Sales/PPE, Cash/TA, FFO/WC and TD/WC are the common financial ratios that survived in all of the industry groups. Meanwhile, when we examine the industry specific ratios we observe that, FFO/TL, CA/NW, Rec/Sales and NW/Sales survived only for the Enut group, Inv/CA, CA/TA and DIV/NI survived only for the Inma group and TD/PPE survived only for the Tein group. There are also ratios that survived at most for two industry groups. QA/Sales and QA/FEO are the ratios which survived only for the Cocohe and Tein groups, Inv/WC survived only for the Enut and Inma groups, Rec/Inv, LTD/TL and TD/TA survived only for the Inma and Tein groups and finally TD/NW and TL/TA survived only for the Cocohe and Enut groups of industries. These ratios conform the literature that some of the ratios display industry characteristics (Gupta, 1969; Gupta and Huefner, 1972; Pinches et al., 1975).

1.7. Industry Specific Classification Patterns of Financial Ratios

We further conduct principal component analysis for the financial ratios in each group of industries, to classify them into specific dimensions. Fixed factor solution method is employed, where 6 factors account for 80,611%, 84,104%, 77,335% and 81,162% of the total variance in the survived financial ratios in Cocohe, Enut, Inma and Tein industries respectively. The 6 factors identified by the principal component analysis are profitability, liquidity, capital intensiveness, working capital, inventory intensiveness and financial leverage. Since the industries display different characteristics, the composition of these patterns illustrates different groupings. For instance, Cocohe, Inma and Tein industry groups demonstrate 2 different factors for liquidity, while Enut industry group possesses 2 factors for profitability. Moreover, we also observed that fix factor solution method groups capital intensiveness and financial leverage in a single factor in all of the industries. Table 4, Table 5, Table 6 and Table 7 show composition of financial ratio patterns for Cocohe, Enut, Inma and Tein industries respectively. As the total variance explained according to fixed factor solution is low, we demonstrate factor loadings of survived financial ratios that are extracted based on eigenvalues in the initial set of solution. The survived financial ratios are listed from highest to lowest factor loadings under the related dimensions. To illustrate the stability of ratios, the variables are separately listed for periods 1990-2000 and 2001-2011, and are sorted from highest to lowest factor loadings in terms of absolute values based on the first period.

Table 4. Financial Ratios and Factor Loadings Defining 6 Financial Ratio Patterns for Cocohe Industry Group

	1990-2000	2001-2011
Short Term Liquidity-1		
QA/Sales	,893	,867
QA/FEO	,890	,890
CA/Sales	,858	,860
Sales/TA	-,839	-,864
Cash/TA	,828	,839
Cash/TL	,777	,766
Profitability		
NI/TA	,919	,934
EBIT/TA	,894	,894
NI/NW	,888	,847
FFO/TA	,853	,774
NI/Sales	,781	,750
NI/TL	,754	,752
Short Term Liquidity-2		
CL/PPE	,929	,910
CA/CFO	,953	,833
QA/CFO	,876	,797
Sales/PPE	,853	,819
Working Capital		
TL/WC	,921	,926
FFO/WC	,884	,897
Sales/WC	,853	,850
TD/WC	,816	,840
Financial Leverage and Capital Intensiveness		
TD/NW	,930	,856
TL/NW	,880	,933
TA/NW	,874	,925
TL/TA	,863	,879
Inventory Intensiveness		
COGS/Inv	,894	,851
Inv/Sales	-,885	-,900

Table 4 shows that out of short term liquidity ratios 1 and 2, QA/Sales, QA/FEO and CL/PPE and CA/CFO possess the highest factor loadings respectively for both of the periods in Cocohe industry. For profitability, NI/TA and EBIT/TA have the highest loadings for both 1990-2000 and 2001-2011 periods. The working capital factor lists TL/WC and FFO/WC as the financial ratios with the highest loadings, which conserve their stability within the periods. Although the financial leverage-capital intensiveness factor lists TD/NW with the highest factor loading followed by TL/NW for the first period, for the second period TL/NW possesses the highest loading followed by TA/NW. This change in the ranking of financial ratios may be due to structural adjustments for consumer staples, consumer discretionary and health industries i.e. changes in operational or economic procedures (Gupta and Huefner, 1972). Finally inventory intensiveness factor demonstrates COGS/Inv with the highest factor loading in 1990-2000 period and Inv/Sales with the highest loading in 2001-2011 periods.

Table 5. Financial Ratios and Factor Loadings Defining 6 Financial Ratio Patterns for Enut Industry Group

	1990-2000	**2001-2011**
Financial Leverage and Capital Intensiveness		
TD/NW	-,945	-,791
TL/NW	-,900	-,932
TA/NW	-,886	-,925
TL/TA	-,848	-,906
FFO/TL	,741	,754
LTD/TA	-,735	,864
Profitability-1		
NI/TA	,913	,900
EBIT/TA	,909	,891
NI/NW	,896	,859
NI/TL	,812	,806
Working Capital		
FFO/WC	,953	,929
NI/WC	,924	,902
Inv/WC	,897	,785
TD/WC	,824	,847
Profitability-2		
NW/Sales	-,830	-,738
Sales/TA	,808	,749
Sales/PPE	,798	,793
CA/NW	,769	,816
Short Term Liquidity		
Cash/FEO	,936	,840
Cash/TA	,922	,886
Cash/TL	,884	,826
Rec/Sales	,766	,829
Inventory Intensiveness		
Inv/Sales	-,884	-,831
COGS/Inv	,835	,782

Table 5 illustrates energy and utility (Enut) industry group where we observe that factor patterns are substantially different from other industry groups, since they display 2 liquidity factors while Enut industry group demonstrate 2 profitability factors. The first factor is the financial leverage-capital intensiveness, in which TD/NW has the highest loading for the first period and TL/NW for the second period. Profitability-1 factor demonstrates NI/TA and EBIT/TA with the highest loadings for both of the periods, while profitability-2 factor displays NW/sales and Sales/TA as the ratios with the highest loadings for the first period and CA/NW followed by Sales/PPE for the second period. It indicates that PPE becomes the determining factor between 2001 and 2011 for energy and utility industry group. The reason of the change is most probably due to increase in necessity of PPE procurement for the investments in new districts as a consequence of high customer demands and growing industrialization. For working capital factor, FFO/WC and NI/WC possess the highest factor loadings and conserve their stability within the periods. When we examine the short term liquidity factor, we observe that Cash/FEO has the highest loading followed by Cash/TA, which are stable for both of the periods. Finally, inventory intensiveness factor displays Inv/Sales having the highest loading followed by COGS/Inv for both 1990-2000 and 2001-2011 periods.

When we analyze the industrials and materials (Inma) sectors in Table 6, the patterns show two short term liquidity ratio dimensions, as in the case of Cocohe and Tein industry groups. Although DIV/NI, EBIT/TA and NI/TA have the highest loadings for the period 1990-2000, EBIT/TA, NI/TA and NI/Sales possess the highest factor loadings for the second period. The change in the factor loadings among the periods may result from dividend policy changes of firms in the last decade. Financial leverage-capital intensiveness demonstrates that, LTD/TA and TD/TA have the highest loading for the first period while LTD/TL, TA/NW and TL/NW have the highest loadings for the second period. The outcomes show that, although financial leverage ratios contribute most in explaining the total variation in the first period, for the second period, capital intensiveness ratios also strongly contribute to the explanation of the total variation. This change in factor loading patterns over the periods may arise from the changes in general conditions facing these industries i.e. new trade associations undertaken among firms, changes in market structure or regulatory environment (Hrebiniak and Snow, 1980).

Table 6. Financial Ratios and Factor Loadings Defining 6 Financial Ratio Patterns for Inma Industry Group

	1990-2000	2001-2011
Profitability		
Div/NI	,937	-,877
EBIT/TA	,930	,940
NI/TA	,931	,942
NI/Sales	,891	,907
NI/NW	,861	,871
EBIT/Sales	,857	,887
NI/TL	,812	,862
FFO/TA	,768	,826
Financial Leverage and Capital Intensiveness		
LTD/TA	,885	,868
TD/TA	,883	,811
LTD/TL	,869	,941
TA/NW	,816	,919
TL/NW	,810	,919
Inventory Intensiveness		
Inv/Sales	-,901	-,908
COGS/Inv	,860	,871
Rec/Inv	,847	,848
Inv/CA	-,834	-,802
Working Capital		
TL/WC	,929	,923
Sales/WC	,915	,888
FFO/WC	,872	,850
TD/WC	,835	,827
Inv/WC	,783	,765
Short Term Liquidity-1		
Cash/FEO	,916	,962
Cash/TA	,909	,920
Cash/TL	,862	,862
Short Term Liquidity-2		
CA/CFO	,954	,952
QA/CFO	,946	,940
Sales/PPE	,904	,833
CA/TA	,796	,730
Sales/TA	,765	,764

Unlike Cocohe and Enut, in the Inma group, there are 4 ratios in the inventory intensiveness factor, indicating the importance and informativeness of inventory ratios for this particular industry. In this factor, Inv/Sales and COGS/Inv possess the highest factor loadings followed by Rec/Inv and Inv/CA, which are stable throughout the periods. In working capital factor, TL/WC has the highest loading followed by Sales WC for both of the periods. For short term liquidity-1 and liquidity-2, Cash/FEO, Cash TA and CA/CFO, QA/CFO ratios have the highest factor loadings and they show stable patterns among the periods. The overall liquidity patterns reveal that, rather than liquidity ratios that include sales or expenditures accounts, liquidity ratios that render information about asset structure and operating activities are more determining factors in industrials and materials sectors.

In Table 7 it is observed that, telecommunication services and information technology industry group (Tein) also show similar factor patterns with Inma industry group in terms of inventory intensiveness. Meanwhile, in terms of short term liquidity, this industry group also displays two factors like Inma and Enut industry groups. Profitability factor shows NI/TA, NI/Sales and EBIT/TA possessing the highest factor loadings for both of the periods.

For short term liquidity patterns 1 and 2, QA/Sales, Cash FEO and CA/CFO, QA/CFO have the highest loadings respectively and are stable among the periods. Financial leverage-capital intensiveness factor displays LTD/TA and LTD/TL as the ratios with the highest loadings for both of the periods. Similarly, working capital patterns are also stable among the periods, showing TL/WC and FFO/WC as the highest loadings. Finally, inventory intensiveness factor displays Inv/Sales, Rec/Inv with the highest loadings followed by CL/Inv and COGS/Inv for both of the periods. Rather than asset structure, sales volume becomes the most determining factor for these sectors. As both of the sectors in Tein industry group are technology intensive, the stability in the factor loading in both periods indicate that the informativeness of those ratios with the highest factor loadings do not vary due to technological developments.

Table 7. Financial Ratios and Factor Loadings Defining 6 Financial Ratio Patterns for Tein Industry Group

	1990-2000	2001-2011
Profitability		
NI/TA	,947	,959
NI/Sales	,930	,921
EBIT/TA	,921	,924
NI/NW	,895	,902
EBIT/Sales	,893	,904
FFO/TA	,866	,789
NI/TL	,831	,834
Short Term Liquidity-1		
QA/Sales	,953	,973
Cash/FEO	,934	,960
CA/Sales	,924	,949
QA/FEO	,908	,958
Cash/TA	890	,848
Financial Leverage and Capital Intensiveness		
LTD/TL	,928	,911
LTD/TA	,922	,937
TD/TA	,879	,906
TD/PPE	,780	,772
TA/NW	,741	,838
Working Capital		
TL/WC	,964	,965
FFO/WC	,931	,939
TD/WC	,921	,902
Sales/WC	,907	,884
Inventory Intensiveness		
Inv/Sales	-,876	-,870
Rec/Inv	,843	,842
CL/Inv	,775	,774
COGS/Inv	,770	,860
Short Term Liquidity-2		
CA/CFO	,981	,944
QA/CFO	,969	,940
Sales/PPE	,893	,891
CL/PPE	,796	,851

In the financial ratio analysis literature, many studies employ factor analysis as an empirical evidence of deriving most useful ratios from a larger initial set (Pinches et al., 1975; Laurent, 1979; Chen and Shimerda, 1981; Pohlman and Hollinger, 1981; Yli-Olli and Virtanen, 1985; Ezzamel et al., 1987). To strengthen the selection process and refinement of most useful and informative ratios, we further employ entropy method as an information theory approach. In the next section, we will introduce entropy method, where those survived ratios in each industry group from the factor analysis will be used in the measurement of entropy. Given the survived ratios, entropy measures will be computed for each industry by determining the entropy of each financial ratio.

CHAPTER II

FURTHER ELIMINATION OF FINANCIAL RATIOS BY ENTROPY METHOD AND DETERMINING UNCERTAINTY LEVEL OF INDUSTRY GROUPS

2.1. Entropy Method in Accounting and Finance Literature

In information theory, the method used to calculate the amount of uncertainty contained in a message is called entropy, which is first introduced by Shannon (1948) with the following equation:

$$H = \sum_{i=1}^{n} p_i \, h(p_i) = -\sum_{i=1}^{n} p_i \log p_i$$

where H represents the expected information or entropy of a message and p is the probability of a particular event. This equation also tells us that, as the uncertainty increases, the amount of information contained in the message also increases. Since entropy of the probability distribution p_i also represents the uncertainty, when all p_i's are equal, the entropy value reaches its maximum value, so does uncertainty.

Vetschera (2000) defines the value of information in decision analysis as perfect and imperfect information, where the value of perfect information (VPI) is the case if information system provides the true state of nature in a certain manner, while the value of imperfect information (VII) is the case if information system supplies only stochastic information on the true state of nature. Since entropy is an information source which does not depend on the alternatives and does not take into account the opportunity costs of alternatives, it stochastically determines the information system by taking into account only the probabilities. Thus, the predicting ability of entropy depends heavily on the value of information system selected for decision making purposes.

Given the above explanation, Belkaui (1975) measures asset, liability and balance sheet information using entropy method. The researcher aggregates asset side of the statement of financial position under current assets and fixed assets and liabilities side under current liabilities, long term liabilities and equity. He extends Shannon's entropy with the following equation:

$$\mathrm{I} = \sum_{i=1}^{n} \mathrm{q_i} \log\left(\frac{\mathrm{qi}}{\mathrm{pi}}\right)$$

where q_i are the fractions of current assets, current liabilities, fixed assets, long term liabilities and equity and p_i are the corresponding fractions in the earlier statement of financial position.

The researcher's aim is to examine the predictive ability of the information contained in these accounting numbers in case of a takeover event. In this respect, Belkaui forms a control group and measures the informational diversity via comparing taken over companies with the control group. The results reveal that, information contained in the taken over firms are greater than the firms in the control group for both assets and liabilities information measures. In addition, information contained in the liability group of accounts has higher prediction power than the asset group of accounts. This is because of the less stable nature of liability accounts compared with the asset accounts and the unstableness becomes even greater incase of takeovers. Overall outcomes indicate that, accounting numbers have predictive ability of the information measures when company takeover is the case.

Similarly, Peng et al. (2009) examine whether changes of financial status of listed companies can be predicted using entropy method. They select 11 financial indexes which are proved to be correlated with financial crises in the literature, including current and quick ratios, debt-to-asset ratio, capital accumulation ratio, growth in total assets, earnings per share, net assets per share, cash flow from operations per share, ROA and ROE. They also select ownership structure indexes, character of directorate indexes and investor protection indexes as non-financial corporate governance indexes. The researchers then classify each index as positive, negative or moderate according to their contribution to the promotion of financial status. Finally, they calculate the entropy value of indexes and assign weights to each index in the entropy method. The sample comprises of metal and non metal companies in Shanghai Stock Exchange for the year 2006. 121 loss firms are specially treated and others without loss for that particular year are treated as normal companies. The researchers ranked companies according to their entropy values where a higher ranking means a better financial status. The results show that, companies with special treatment have lower ranking than normal companies in most of the cases, indicating financial status of companies can be predicted with entropy method.

As the entropy method is used in measuring uncertainty conveyed by the information that is being analyzed, it is also preferred in bankruptcy prediction studies. Zavgren (1985) employs entropy method to assess the exposure of American industrial firms to bankruptcy. He employs financial ratios which are determined by Pinches et al. (1973) as strongest ratios that have the highest factor loadings within 7 factors obtained in their study. The researcher uses logit model for a five year period to obtain the probability estimates of the financial ratios and then conducts Shanon's entropy to compute the information content of the predictions from the logit model. Zavgren employs Shanon's entropy as an ex-post measure where the uncertainty of the occurrence of an event is computed before and after the delivery of a message. This implies that, the higher the entropy in the probability distribution, the higher the surprise of occurrence of an event. He measures the total decrease in entropy by taking difference between the first and the fifth periods. The results show that, the logit model significantly predicts bankruptcy even five years prior to failure. However, not all of the ratios provide significant information in the prediction model. For instance, profitability ratios do not provide information in any of the years while turnover ratios provide information only for the 4^{th} and 5^{th} period. Contrarily, liquidity ratios are significant only for the first 3 years. Meanwhile, entropy outcomes reveal that uncertainty of healthy firms decrease along the 5 years period. Similarly, it is also observed that entropy of the failure firms also decreases, but with a higher amount of bits than the healthy firms. The outcomes indicate that, in case of bankruptcy, the degree of surprise is greater for healthy firms than for failure firms.

Another bankruptcy study held by Keasey and McGuinness (1990) examines the failure of UK industrial firms for the period 1976-1984 via entropy method and logistic analysis. They extend Zavgren's (1985) work by evaluating whether the entropy measure predicts firm failure when it is not known that potentially bankrupt firms are going to fail. That is, contrary to Zavgren's ex post method they use ex ante method as a check for the reliability of the Zavgren's findings. The researchers matched each failed firm with a non failed firm, making a total of 86 companies. They developed logit function by employing 16 financial ratios in order to analyze financial behavior. Those financial ratios are return on shareholders' equity (RSE), return on capital employed (RCE), trading profit margin (TPM), pre-tax profit margin (PPM), turnover/net plant (TAE), stock turnover (ST), debtors turnover (DT), creditors turnover (CT), capital gearing (CG), income gearing (IG), borrowing ratio (BR), working capital ratio (WC), quick asset ratio (QAR), cash/assets (CA), inventory/sales (INS) and ST×1/DT. Employing entropy method, they examine the amount of information conveyed by the predicted probabilities given that which firms have failed is known. The ex post results show that, profitability (PPM and RCE) and efficiency ratios (INS, CT, TAE) significantly predicts bankruptcy 3 years prior to failure. On the contrary, ex ante results reveal that, as the time of failure approaches, the fate of failed firms becomes clear, however they cannot make this clear cut conclusion for the fate of non failed firms.

Gentry et al. (2002) uses cash flow information to determine the value of a firm as well as the management performance and to predict bankruptcy via entropy method. First they categorize cash flow components as cash inflow and outflow amounts and then compute relative cash flow (CFC*) as the percentage of cash flow component to the total cash flow. They hypothesized that, patterns of CFC* is closely associated with the credit risk rating of a firm. Other important cash flow variables used in the study are net cash flow (NCF), net operating cash flow (NOF), investment cash flow (NIF and ΔNWC for change in net working capital) and financing cash flow (FCE and DIV for dividend flow). The most important variable that determines the financial success or failure of a firm is NOF, where other components of cash flows depend on the performance of NOF. The researchers select 99 failed and 99 non-failed companies for the period 1971-1987. Gentry et al. use inductive learning approach to examine decision making process via cash flow patterns. Next, they determine the most important cash flow components with the entropy method and finally come up with a decision tree, in which they observe the three most important cash flow components (NOF, DIV and NIF) in predicting bankruptcy. From the analysis of those cash flow components, they observed three important characteristics of failed firms that significantly separate them from non failed firms. These characteristics of failed firms include firms that do not pay dividend, do not invest in new PPE and do not have positive NOF. Results also show that, DIV has the highest information content among other CFC in predicting bankruptcy.

Entropy method is also used in evaluating construct validity of a given diversification strategy. Hoskisson et al. (1993) examine construct validity including convergent, discriminant and criterion related validity where convergent validity refers to whether different measures of the same construct with different methods conforms to each other, and discriminant validity refers to assessing the extent of difference between construct of interest and other concepts. They measure discriminant validity with firm size, leverage and R&D intensity and diversification strategy via entropy method. To measure diversification performance of firms, they include accounting performance measures such as ROA, ROE and return on sales (ROS) and market based performance measures such as Sharpe and Treynor measures of market return. The results demonstrate a strong support for the construct validity of diversification strategy via entropy measure. The outcomes also reveal that, a significant negative relation exists between diversification strategy and accounting performance.

Horowitz and Horowitz (1968) use entropy method in marketing research to analyze concentration of US firms in the brewing industry for the period 1944-1964. They first compute concentration ratios for the leading 25 firms and then measure the relative entropy of each firm which is the "ratio of actual to the maximum entropy in a system". They hypothesize that, the degree of competition increases with the degree of uncertainty. In this respect, entropy is used as a measure of degree of competition and relative entropy is used as the maximum level of competitiveness of a particular industry, which in this case is the brewing industry. The results indicate that, although the number of firms is continuously declining in the brewing industry, relative competition among the survivors is still at considerable levels. This outcome is most probably resulted from mergers which increases the competitive atmosphere. The outcomes also show that, industry performance is more important than concentration ratios.

There are various studies that use entropy method in evaluating accounting data. Theil (1969) uses entropy in determining information content of accounting numbers and how accounting numbers can be transformed into prior and posterior probabilities for a particular accounting period. Theil also examines whether information content of aggregate versus disaggregate accounting numbers illustrate significant differences. For a specific company, Theil uses two-periods aggregated statement of financial position where the individual assets i.e. current assets, noncurrent receivables, property, plant and equipment and taxes and other prepaid expenses are measured as fraction of total assets in that year which makes up the prior probabilities. Same procedure is repeated for the liabilities accounts.

Assets	**Year t**	**Year (t-1)**	**Liabilities**	**Year t**	**Year (t-1)**
Current Assets	X_{t1}	$Y_{1(t-1)}$	Current Liabilities	M_{t1}	$N_{1(t-1)}$
Noncurrent Receivables	X_{t2}	$Y_{2(t-1)}$	Long Term Debt	M_{t2}	$N_{2(t-1)}$
PPE	X_{t3}	$Y_{3(t-1)}$	Other Liabilities	M_{t3}	$N_{3(t-1)}$
Tax, Prepaid Expense	X_{t4}	$Y_{4(t-1)}$	Shareholder's Equity	M_{t4}	$N_{4(t-1)}$
Total Assets	X_{Tt}	$Y_{T(t-1)}$	Total Liabilities	M_{Tt}	$N_{T(t-1)}$

Prior probabilities for the year (t-1): $\frac{Y_{1(t-1)}}{Y_{T(t-1)}} \times \frac{Y_{2(t-1)}}{Y_{T(t-1)}} \times \frac{Y_{3(t-1)}}{Y_{T(t-1)}} \times \frac{Y_{4(t-1)}}{Y_{T(t-1)}}$

Given the fractions of (t-1), the following year's corresponding asset fractions composes the posterior probabilities.

Posterior probabilities for the year t: $\frac{X_{t1}}{X_{Tt}} \times \frac{X_{t2}}{X_{Tt}} \times \frac{X_{t3}}{X_{Tt}} \times \frac{X_{t4}}{X_{Tt}}$

Then the researcher computes the information contained in this message in terms of bits by the following equation:

$$\frac{X_{t1}}{X_{Tt}} \times \log \frac{X_{t1}/X_{Tt}}{Y_{1(t-1)}/Y_{T(t-1)}} + \cdots + \frac{X_{t4}}{X_{Tt}} \log \frac{X_{t4}/X_{Tt}}{Y_{4(t-1)}/Y_{T(t-1)}} \quad = \quad \text{N bits}$$

This N bits is called the asset information of t given (t-1). Same procedure is also conducted for the liability accounts. From the above equation we can interpret that, as the discrepancy between the t and (t-1) fractions increase, asset information of year t will also increase.

Next, the researcher uses disaggregated statement of financial position where he decomposes current asset account into cash, marketable securities, receivables, inventories and other current assets and repeats this disaggregation process for all of the other accounts. Theil then calculates the expected information for the items that fall under each aggregate account and sum them up to obtain the new information contained in total assets and total liabilities. The outcomes of disaggregation process reveal that, decomposing accounts into subgroups provide more information to financial statement users than aggregated accounts. Meanwhile, the researcher also concludes that, behavior of the aggregate group of assets is much closer to proportionality than the disaggregated group of individual assets.

To examine the change in the value of information, Theil conducts another analysis, where he first computes sales information by regions breakdown only and then computes the sales information by including both region and product information. The results again shows that, the information value, when both region and product information provided, exceeds the information value when only the region information is provided.

Lev (1969) discusses the information loss caused by aggregation of accounting numbers and shows how the entropy of probability distribution of disaggregated accounts is greater than the entropy of probability distribution of aggregated accounts. For that reason Lev states that, accountants should aggregate the pair of accounting numbers which causes the smallest loss first and then should aggregate the numbers with the second smallest loss and keep the aggregation procedure with this logic. A cut off point should be determined by the management for each account so that the sensitivity of aggregation procedure will be improved by placing emphasis on the qualitative characteristics of the accounting numbers.

Lev further examines whether informational measures discriminate between failure and non failure firms. The researcher selects 37 pair of firms from Moody's Industrial Manual that operate 26 different industries so that the industry effect will be eliminated. He computes assets information, liabilities information, and balance sheet information as it is computed in Theil. He then compares the information measures of failed firms with the non failed firms. The results show that information contained in the failed firms is greater than the non failed firms in more than 50% of the cases. Moreover, it is also observed that discriminating power of balance sheet information is greater than the asset and liability information measures since it captures the information contained in these items. Finally, the results further reveal that, information content of liabilities measure is greater than the assets measure for both failed and non failed firms, and the difference is even greater for failing firms. The reason of this difference arises from the fact that, liabilities are less stable than assets leading to higher entropy values for liabilities for all firms and this difference is even greater for failed firms.

Lev additionally computes time horizon information, where he tests whether balance sheet information measure increases with an increase in the time interval. The outcomes show that, the greater the time interval between two balance sheet dates, the greater the discriminating power of the balance sheet measures. This is also because of the fact that, larger deviations are more likely for broader time intervals in the financial statement items.

Abdel-Khalik (1974) employs entropy method in decision making, particularly in business loan granting decision of commercial banks where the amount of information is related to the credit granting decision. First, the author questions whether the amount of information measured by the entropy method influences users' expectations or their decision making. Second, he questions whether there is a significant relation between loss in entropy and mean decision due to aggregation of accounting numbers. In this respect, the researcher conducts a field study where business loan officers of commercial banks from 36 states of US are selected. A total of 207 responses are collected which contains loan recommendation and estimate making of the probability of default on each loan for every borrower. Since entropy method cannot compute negative numbers in the financial statements, Abdel-Khalik equates net sales to 1 and takes proportions for the other accounting numbers. Furthermore, if there is net loss for a particular period, the author decreases net sales by the amount of net loss. In order to avoid negative numbers of depreciation, he treats this amount as a liability account. The outcomes of Spearman and Pearson rank correlation show that, the change in the means of decisions does not move in the same direction with entropy changes, while ranking of entropy and the mean estimates of the probability of default on loans goes hand in hand. Moreover, it is observed that, entropy index calculated for aggregate accounting numbers decreases along with the operational needs of the subjects. Hence they conclude that since loss in entropy due to aggregation of accounting numbers do not change decision makers' expectations significantly, the level of aggregation is not relevant to subjects' decision making process.

The literature of entropy method in accounting research reveals that, although there are studies that employ this method in determining information content of accounting numbers or in deciding aggregation/disaggregation of financial statement items, no study use entropy method in examining the information content of financial ratios and in measuring the uncertainty level of industries. In this respect, we will introduce multiple attribute decision making model in the following section, as a weight determination process of financial ratios. Furthermore, we will measure the level of uncertainty of firms and total entropy of industries to evaluate which industry group possesses more uncertainty than the others.

2.2. Multiple Attribute Decision Making Models and Use of Entropy Method

Multiple Attribute Decision Making (MADM) is a statistical method which is used in making preference decisions from available alternatives that are differentiated by conflicting attributes. MADM is mainly used in determination of appropriate weights for each criterion in the decision matrix. Subjective weighting and objective weighting are the two categories found in the literature for weight determination processes. If the decision makers possess a priori weights for their preferences, we use subjective weighting in the MADM analysis. Analytical Hierarchy Process (AHP) method (Saaty, 1980), Weighted Least Squares (WLS) method (Chu et al., 1979) and Delphi method (Hwang and Lin, 1987) can be classified in this group. To give an example, Yang et al. (2010) use MADM model in evaluating the management performance, where they employ Balanced Score Card (BSC) technique in determining subjective weights for each attribute. In this respect they use process capability index (Cp), where the weights of attributes are assigned by the experts. Similarly, Zavadskas et al., (2010) use expert judgment method by conducting interviews with the construction specialists and derive weights of the attributes according to those experts' opinions. In a case study setting, the authors examine which of the investment projects selected by the stakeholders are less risky than the alternatives. The study ranks attributes according to subjective weighting and derived dispersion of experts ranking values as well as rank of concordance accordingly. Another study conducted by Liu (2012) examined how expert judgment can be used as subjective weights when there is uncertain linguistic information in the problem in a

MADM setting. The author computes relative similarity degree of decision making information of the experts and derives the comprehensive weight of each attribute according to the experts' evaluation information. In order to calculate attribute weights, Liu employs maximizing deviations method where each deviation value of alternatives are divided by the total deviation value.

Subjective attribute weights can be also derived using game theory approach. Zhou et al. (2011) compute attribute weights by integrating static strategic game theory in MADM model, where each attribute is treated as a player in the game. They compute weight arithmetic averages in the aggregation process of attribute values which correspond to each alternative. After computing attribute values, all the alternatives are ranked according to the information obtained by those attribute values.

Contrary to the subjective weighting, if the decision makers do not possess a priori weights and the weights are computed by the help of mathematical models without considering the preferences of decision makers, we use objective weighting in the MADM analysis. In this respect, entropy method is one of the mathematical models used in the determination of objective weights, especially when it is difficult to obtain reliable subjective weights. Shannon's entropy is the most widely used technique in information theory that measures uncertainty, where the weight of an attribute decreases as the degree of entropy for that particular attribute increases (Lotfi and Fallahnejad, 2010). The logic behind this model is that, for higher levels of entropy, the discriminating ability of the attribute declines. Hence, the weight of that particular attribute should be smaller, since decision makers would likely prefer those attributes with higher levels of discriminating power. In this manner, entropy measures the diversity of attribute values (Vetschera, 2000).

2.2.1. Methods for Evaluating the Objective Weights

Before explaining why we choose to use entropy method in the weight determination process, it is necessary to evaluate other methods of objective weighting and their area of use in the literature. To begin with, Relative Ratio method is one of the newly developed methods used in MADM problems. In case there are multiple conflicting attributes in an environment, this method ranks those conflicting attributes and selects best alternatives by determining the ideal solution set. The ideal solution set is selected according to the distance of the alternatives from the positive ideal solution as well as the negative ideal solution. In other words, those attributes which are farther from the negative ideal solution and which are closer to the positive ideal solution are chosen for the ideal solution set. In this respect, the attributes are divided into two data sets, which can be classified as benefit attributes and cost attributes. For the benefit attributes, attribute values are computed as follows (Li, 2009):

$$\mu_{ij} = \frac{f_{ij} - f_{min}}{f_{max} - f_{min}}$$

where f_{max} is the greatest value among the attributes f_i (i=1, 2,……m) and f_{min} is the smallest value among the attributes f_i, for all n alternatives f_j (j=1, 2, ……….n). Contrarily, for the cost attributes, attribute values are calculated by the following equation:

$$\mu_{ij} = \frac{f_{max} - f_{ij}}{f_{max} - f_{min}}$$

According to the above calculations, the alternative with the greatest normalized attribute value is selected as the positive ideal solution (x^+), while the alternative with the smallest normalized attribute value is selected as the negative ideal solution (x^-). Then, a distance measure is employed (i.e. Minkowski, Euclidean or Chebyshev distance measures) to obtain the ranking order of alternatives. Finally the "satisfactory level $\varepsilon_p(x_j)$" is derived, which both satisfies the criteria of the shortest distance from the positive ideal solution and farthest distance from the negative ideal solution among the ranking order of alternatives.

In case substitution method, rate of attributes are different and the decision maker puts different importance weights for different interval values of the same attribute, where Simple Additive Weighting (SAW) technique could be used to determine objective criteria weights. In this method, attribute values are normalized by separating the attributes as maximized and minimized attributes by the following formulae respectively (Zavadskas et al., 2007; Tang, 2012; Vaduva, 2012):

$$x_{ij} = \frac{a_{ij}}{a_i^{max}}$$

$$x_{ij} = \frac{a_i^{min}}{a_{ij}}$$

Another method used in the evaluation process of the objective weighting is the "Technique for Order Preference by Similarity to the Ideal Solution" (TOPSIS) method. The method ranks competing firms according to their performance computed from financial ratios. The method is first developed by Hwang and Yoon (1981) and the normalized attribute values (r_{ij}) are calculated by the following equation:

$$r_{ij} = \frac{f_{ij}}{\sqrt{\sum_{j=1}^{n} f_{ij}^2}}$$

Then, the weights of the normalized attribute values -which is denoted by v_{ij}- are computed by multiplying normalized attribute values with the weights obtained from the ideal solution set. As an extended version of TOPSIS method, Deng et al. (2000) develop modified TOPSIS method that attempts to solve the problem of subjective weighting in relative importance of financial ratios. Instead of using weighted decision matrix used in the original TOPSIS method, modified TOPSIS method employs weighted Euclidean distance measure in determining the overall performance index for each alternative decision. Moreover, different from the original TOPSIS method, the degree of divergence (d_j) for each criterion is calculated by the Entropy method in the modified version, where the overall performance index is derived from the following formula:

$$P_i = \frac{d_i^-}{d_i^+ + d_i^-}$$

where d_i^+ is the sum of all distance of probabilities from the positive ideal solution and d_i^- is the sum of all distance of probabilities from the negative ideal solution. The equation states that as the value of P_i increases the performance of the j^{th} alternative increases.

To examine the effectiveness of the modified TOPSIS method, Deng et al. (2000) compare Entropy method with other methods, i.e. CRICIC (Criteria Importance through Intercriteria Correlation), SD (Standard Deviation Method) and MW (Mean Weight Method) methods. The findings show that, objective weights obtained from Entropy method are more capable of reflecting average intrinsic information provided by the financial ratios in the comparison of firm performance.

Another extension to the TOPSIS method is developed by Liu and Jinan (2011), where the objective weights are determined by the variation coefficient method for continuous random variables on the bounded intervals. First, the authors compute the average value of each attribute and then calculate the mean square deviation of the attributes. Variation coefficient of each attribute is obtained by dividing the average value of the attributes by the mean square deviations. The variation coefficient of attributes is demonstrated by the symbol E_j and the weights of attributes are calculated by the following equation:

$$w_j = \frac{E_j}{\sum_{j=1}^{n} E_j}$$

TOPSIS method is further used in decision making problems with fuzzy data sets (Lotfi et al., 2007). Same procedures in evaluating continuous random variables are also applied for the fuzzy numbers (i.e. normalizing fuzzy numbers, weighting the normalized fuzzy numbers) according to the derivation of distance measures from the ideal solution set and ranking order of alternatives by the performance index.

For attribute values that are classified as continuous random variables on bounded intervals, Jin et al. (2010) uses a rank approach based on projection model, where attribute weights are computed by projection pursuit model and genetic algorithm. According to the model, weighted correlation coefficients are computed between each alternative and the ideal solution. Then, grey correlation coefficients are derived for the corresponding alternatives. Finally the optimal projection direction is determined using genetic algorithm to generate value intervals for every decision variable.

2.2.2. Entropy Method

Entropy method is one of the models used in MADM, which ranks the alternative values that are derived from objective weighting. In entropy method, there are several techniques are used in the literature for the normalization of attribute values. However, the most frequently used normalization formula is first developed by Zeleny (1974), where the attributes are classified as maximized and minimized attributes:

$$r_{ij} = \frac{a_j^{max} - a_{ij}}{a_j^{max} - a_j^{min}} \quad ; \quad for\ all\ maximized\ attributes$$

$$r_{ij} = \frac{a_{ij} - a_j^{min}}{a_j^{max} - a_j^{min}} \quad ; \quad for\ all\ minimized\ attributes$$

In the above formula, attributes that would probably affect entropy negatively are classified as maximized attributes, and those attributes that would probably affect entropy positively are classified as minimized attributes.

In order to assign objective weights, Zeleny normalizes attribute values by computing a probability value for each entry in the decision making matrix by the following equation:

$$p_{ij} = \frac{r_{ij}}{\sum_{j=1}^{m} r_i}$$

where p_{ij} refers to the probability value for each entry and r_{ij}'s are the solution alternatives. Then, Zeleny computes entropy of each attribute (E_j) and obtains the degree of diversification (d_j) by the below equation:

$$d_j = 1 - E_j$$

Provided that the decision maker does not have prior subjective weights and any reason to prefer one attribute to another, each attribute should be equally treated according to the principle of insufficient reasoning (Starr and Greenwood, 1977). However, since attributes with low entropies are preferred to attributes with high entropies as they possess more information, rather than assigning equal weights to each attribute, Zeleny (1974) uses below formula in determining the best weight set:

$$w_j = \frac{d_j}{\sum_{j=1}^{m} d_j}$$

Given the above explanations about the implications of the entropy method, we choose to use entropy as a method for evaluating the importance weights of financial ratios, because its weight determination process is more objective than similar methods, when investigating the contrast between attribute values i.e. financial ratios in this case. Moreover, entropy method is attractive in determining the importance weights of ratios because it requires no distributional assumptions like the other output models that use objective measuring techniques (Sobehart, 2001).

2.2.3. Entropy Method in Evaluating the Importance Weights

It is now clear that, an attribute does not contain much information when all the alternatives have similar outcomes for that attribute, and hence we can eliminate that attribute from the model. Therefore, before conducting the entropy method, we need a set of solution alternatives in the decision matrix, which will show the set of outcomes of values of decision attributes (Aomar, 2002).

In our analysis, after obtaining the set of financial ratios from the factor analysis, we are ready to use this data set as the decision matrix of the entropy model. In this study, the decision matrix of the entropy model $D_{m\times n}$ with m alternatives and n attributes can be illustrated as follows:

$$D = \begin{bmatrix} x_{11} \dots & x_{1j} \dots & x_{1n} \\ . & . & . \\ x_{i1} \dots & x_{ij} \dots & x_{in} \\ . & . & . \\ x_{m1} \dots & x_{mj} \dots & x_{mn} \end{bmatrix}$$

where m is the number of companies and n is the number of financial ratios for one industry per year. In addition, i takes the values from 1 to m and j takes the values from 1 to n, so that x_{ij} demonstrates company i's value of financial ratio j.

In information theory, entropy method is used to measure the level of uncertainty, demonstrated by a distinct probability distribution, p_i, which is first developed by Shannon (1947) as

$$H = \sum_{i=1}^{n} p_i \, h(p_i) = -\sum_{i=1}^{n} p_i \ln p_i \qquad (1)$$

where H represents the expected information or entropy of a message and p is the probability of a particular event. According to Shannon's entropy measure when all p_i's except one equal 0, and one of them equals 1, then H has the minimum value that equal 0, which is the case of certainty. Contrarily, when all p_i's are probabilistically equal, say 1/m, H reaches its maximum value, H_{max} and equals lnm.

As stated in the previous section, the probabilistic outcomes of financial ratios can be defined as p_{ij}, and is computed by the following equation developed by Zeleny (1974):

$$P_{ij} = \frac{r_{ij}}{\sum_{i=1}^{m} r_{ij}} \qquad (2)$$

where r_{ij} measures closeness to the ideal solution. We also mentioned that, Zeleny separates the attributes into two categories, where the first category includes those attributes that negatively affect the entropy level and the second category includes those attributes that positively affect the entropy level. In the literature, attributes that negatively affect entropy level are also classified as "cost type index" and those attributes that positively affect entropy level are categorized as "benefit type index" (Wang and Wang, 2012). However, in our study, where the attributes are financial ratios, we are unable to distinguish them either as ratios that positively or negatively affect entropy level, or as ratios that possess benefit or cost characteristic on entropy level of industries. It is because, up to a point, an increase in a financial ratio may be treated as a positive outcome while after an indeterminate limit, the ongoing increase of that ratio might have negative effects. Moreover, this indeterminate level changes from company to company and from industry to industry, and hence, it is not possible to treat a financial ratio as a positive attribute to a certain point and negative afterwards. For reasons mentioned so far, we use the following formula in the normalization process of attribute values:

$$r_{ij} = \frac{x_{ij-} x_j^{min}}{x_j^{*} - x_j^{min}} \qquad (3)$$

where x_j* = max x_{ij} and x_j^{min} = min X_{ij} and $r_{ij} \geq 0$ for every j. This is a one sided formula where all of the financial ratios are equally treated in terms of their effect on entropy level. In other words, r_{ij} measures the distance of attribute values for every company from the minimum attribute level, given the range of each attribute. Consequently, this one sided normalization method provides consistency among the outcomes in determining the entropy measure of importance.

Provided that p_{ij} determines the weights of importance for every attribute (financial ratio) and $p_{ij} \geq 0$ for every j, the entropy E_j of the probabilistic outcomes of financial ratios is computed by the following equation:

$$\mathrm{E_j} = \sum\nolimits_{i=1}^{m} \mathrm{p_{ij}}\, \mathrm{h}(\mathrm{p}_{\mathrm{ij}}) = -k \sum\nolimits_{i=1}^{m} \mathrm{p_{ij}} \ln \mathrm{p_{ij}} \qquad (4)$$

where E_j represents the uncertainty or entropy of the message and k is a positive constant and is equal to 1/lnm, which guarantees that $0 \leq E_j \leq 1$. Given that entropy of an information system is the measure of quantity of information, we obtained financial ratios as the information source to compute the sum of all information values that are weighted by their level of uncertainty. Since entropy and uncertainty express the same concept, entropy of the probability distribution p_i also represents the uncertainty of that probability distribution. According to the information theory, probability estimates generated by financial ratio analyses are messages from an information system, and the amount of information in each message is computed by its ability to reduce uncertainty (Zavgren, 1985). In this respect, entropy is a decreasing function of the probability of an event.

The total entropy or uncertainty of a particular industry for a period is calculated by the following equation:

$$E = \sum_{j=1}^{n} e(p_j)$$

This equation shows that, uncertainty increases with the increase in $e(p_j)$ since the j^{th} financial ratio transfers less information for a given company. If $e(p_j)$ reaches its maximum point, lnm, then j^{th} financial ratio would not transfer any information for that company.

We further compute weight for each financial ratio according to how much information they transfer in determining uncertainty of a company. Diversification degree of each financial ratio is computed as follows (Zeleny, 1982):

$$d_j = 1 - E_j \qquad (6)$$

where d_j is the degree of diversification of the information obtained from financial ratio j and E_j is the entropy of the financial ratio. After calculating the degree of diversification, the objective weight of each financial ratio is computed by the following equation:

$$w_j = \frac{d_j}{\sum_{j=1}^{n} d_j} \qquad (7)$$

Equations (6) and (7) illustrate that, weights of financial ratios (w_j) are negatively related to entropy (E_j) such that, when financial ratios transfer less uncertain information they display higher weights. The reason they carry higher weights than more uncertain ratios is that, they become more preferable by the decision makers because of related lower uncertainty levels.

2.3. Results of Entropy Method

After conducting the normalization method stated in the previous section and computing the entropy of each financial ratio that are selected from the factor analysis for every industry separately, we obtained the resulting entropy levels and organize them from lowest to highest entropy values as shown in Table 8. The outcomes show that, Cash/TL has the lowest entropy level for three of the four industries, indicating this liquidity ratio has the highest information content for consumer staples, consumer discretionary, health, energy, utility, industrials and materials sectors for decision making purposes.

Table. 8 Entropy of Financial Ratios and Total Entropy of Industries

Cocohe	Entropy	Enut	Entropy	Inma	Entropy	Tein	Entropy
Cash/TL	0,897316	Cash/TL	0,901488	Cash/TL	0,913486	CL/Inv	0,835161
Cash/TA	0,926043	TD/WC	0,908195	Cash/TA	0,93085	TD/PPE	0,849962
COGS/Inv	0,936037	Cash/FEO	0,912239	Rec/Inv	0,931053	TD/TA	0,872553
CL/PPE	0,938509	Cash/TA	0,918672	COGS/Inv	0,948376	COGS/Inv	0,910145
QA/Sales	0,938644	Sales/PPE	0,922827	Sales/PPE	0,954332	CL/PPE	0,911791
QA/FEO	0,942041	COGS/Inv	0,93211	LTD/TA	0,955314	QA/FEO	0,932323
Inv/Sales	0,946571	Inv/Sales	0,947269	Inv/Sales	0,956694	QA/Sales	0,954667
Sales/PPE	0,947751	TD/NW	0,957328	TD/TA	0,961387	LTD/TA	0,960121
Sales/WC	0,952786	Sales/TA	0,959155	Inv/CA	0,962573	Rec/Inv	0,960252
CA/Sales	0,959063	TA/NW	0,96331	LTD/TL	0,962647	LTD/TL	0,960312
TL/WC	0,959851	TL/NW	0,966309	Sales/WC	0,974277	CA/Sales	0,960448
Sales/TA	0,964833	LTD/TA	0,972025	Sales/TA	0,978005	Sales/PPE	0,962093
CA/CFO	0,975954	CA/NW	0,974611	Cash/FEO	0,979375	Inv/Sales	0,963186
FFO/TA	0,976096	FFO/TL	0,976068	TL/WC	0,98037	Cash/TA	0,964932
EBIT/TA	0,976376	Rec/Sales	0,976746	CA/TA	0,981282	CA/CFO	0,968288
NI/TA	0,976898	FFO/WC	0,977496	NI/TL	0,983893	QA/CFO	0,968348
TD/WC	0,977637	EBIT/TA	0,978345	CA/CFO	0,9844	NI/TA	0,969161
TL/TA	0,978221	NW/Sales	0,978389	NI/NW	0,985282	EBIT/TA	0,969412
NI/NW	0,980026	NI/TL	0,979347	EBIT/TA	0,98576	FFO/TA	0,972045
FFO/WC	0,980029	NI/TA	0,979369	TL/NW	0,985991	Cash/FEO	0,972385
TA/NW	0,980218	TL/TA	0,981458	TA/NW	0,986078	Sales/WC	0,975156
TL/NW	0,980223	NI/NW	0,985657	FFO/WC	0,986869	FFO/WC	0,976211
TD/NW	0,980227	NI/WC	0,985688	QA/CFO	0,987084	NI/TL	0,976391
QA/CFO	0,981177	Inv/WC	0,987352	TD/WC	0,987302	TL/WC	0,976487
NI/TL	0,984345			EBIT/Sales	0,987465	EBIT/Sales	0,977241
NI/Sales	0,985182			Inv/WC	0,987895	NI/NW	0,977293
				FFO/TA	0,987938	TD/WC	0,97733
				NI/Sales	0,987992	NI/Sales	0,977549
				NI/TA	0,98829	TA/NW	0,977979
				DIV/NI	0,989147		
Total Entropy	*0,949827*	*Total Entropy*	*0,941275*	*Total Entropy*	*0,957885*	*Total Entropy*	*0,919293*

Meanwhile for telecommunications and information technology sectors, CL/Inv and COGS/Inv possesses the first and fourth lowest entropy levels, which are classified as inventory intensiveness ratios in the factor analysis. The importance of inventory intensiveness ratios in Tein industry may be related to the idea that, technology dependent firms attract customers and fight against competitors by improving their just in time inventory management and by providing strong integration between sales and production planning. Although the inventory accounts in the statement of financial position may not amount to a significant percentage of total assets, inventory ratios provide information to financial statement users about whether inventory management systems work effectively in these sectors. To give an example, by looking at the inventory intensiveness ratios, a financial statement user can examine whether the company uses traditional "build to stock model" or consumer driven "build to order business model" which guarantees just in time inventory management (Brynjolfsson and Hitt, 2000).

The second ratio with the lowest entropy level and highest information content is the Cash/TA for both consumer staples-consumer discretionary-health and industrials-materials sectors. Likewise, for energy and utility sectors Cash/FEO and Cash/TA are the ratios that possess the third and fourth lowest entropy levels, indicating the importance of liquidity factor for Cocohe, Enut and Inma industry groups. Not surprisingly, in the accounting literature it is argued that, financial statement users and regulators necessitate detailed information regarding the cash flow items of companies since disclosure of these items provide more timely information as well as information about uncertainty of firms (Casey and Bartczak, 1985). Moreover, it is strikingly evident that, recent studies which examine financial failure predicting ability of financial ratios, predominantly employ ratios based on cash position among industrial, natural resources production and manufacturing firms (Jones and Hensher, 2004). Other ratios that have the lowest entropy levels following cash related ratios are the inventory intensiveness ratios for Cocohe and Inma industry groups. In line with the literature, since these sectors possess both raw materials, work in process and finished goods in the inventory accounts, understanding the determinants of inventory behavior (i.e. inventory turnover and sales policies) plays an important role. Especially in industrials and materials sectors, a low level of inventory turnover could possibly cause future sales to decline if the customer requires immediate delivery (Courchene, 1967). For that reason, the inventory behavior of these firms and their direct effect on sales would supply material information to financial statement users in decision making process.

Meanwhile, in telecommunications and information technology industry group, rather than ratios related to cash position, financial leverage ratios possess the second and third lowest entropy levels, which are TD/PPE and TD/TA respectively. The reason why entropy outcome of these sectors differ from the others lies in the fact that these sectors necessitate huge amounts of financial support in order to stay competitive in the market. The technology intensive sectors should sustain competitive advantage and fight against "bigger and better" responses from competitors in terms of newly developed technologies. Hence, to preserve competitive advantage, technology intensive firms have to initiate their business to leverage newly found products (Kettinger et al., 1994). In this respect, it is not surprising that, information content of financial leverage ratios is greater than liquidity and profitability ratios for this industry group.

Finally, it is important to note that, Sales/PPE ratio possesses lower levels of entropy scores for most of the industries. Sales/PPE ratio is mostly used as a proxy for capacity utilization in the literature and it informs financial statement users about how much revenue a firm can generate per dollar of PPE. Hence, the ratio serves as a resource deployment and operating efficiency indicator, which provides material information about whether the firm allocates its resources and future investment projects effectively and turn their operations into profit (Raturi et al., 2009).

When we look at the total entropy scores of industry groups we observe that, telecommunication and information technology industry group has the lowest level of entropy, indicating uncertainty in this group is lower than Cocohe, Inma and Enut industry groups. Contrary to Tein industry group, Cocohe, Enut and Inma industry groups show quite similar levels of entropy, which are 0,949827, 0,941275 and 0,957885 respectively. One of the reasons of low level of uncertainty for Tein industry group would arise from the lack of resource dependency compared to other sectors. For instance, energy and utility sectors heavily depend on natural resources such as gas, petroleum, coal, wind and solar power. Likewise, industrials and materials sectors depend on purchases of raw materials. For that reason, these sectors become vulnerable to increases in general price levels or shortages in natural resources (Antonelli, 2003). Second, telecommunication and information technology industries have the power of reducing cost of coordination, communication and information processing as well as increasing complementary innovations, which in turn accelerates productivity. Since these sectors facilitate complementary organizational investments and enable reduction in cost of production, the level of uncertainty turns out to stay at tolerable degrees in this industry group compared to other groups. Third, technology intensive firms produce or utilize "difficult to imitate" assets while firms in the consumer staples, consumer discretionary and materials sectors produce or utilize assets that can be easily imitated which brings considerable risk to these industries (Teece, 2000).

Hence, from the entropy model, we derived and ranked industry specific financial ratios, which possess more information in determining the uncertainty level of the industry groups. Eventually, we conduct logistic regression analysis to predict financial distress and derive a financial distress model for each industry group. In the logistic regression, we use financial ratios as exogenous variables which are below 0,96 entropy level, illustrated in Table 8. We choose the cut off value as 0,96, since after that level, the entropy values of financial ratios do not change considerably. Moreover, including too much exogenous variables in the financial distress model deteriorates the power of the model as well as stability of the regression coefficients. In addition, using up too many degrees of freedom with respect to number of observations is another problem in regression analysis. If number of unknowns converges too much to the number of observations, we come across with the problem of "over fitting the model", which results in unrealistically large R^2 values (Babyak, 2004). In this respect, setting the cut off value of entropy at 0,96 prevents this over-fitting problem and brings us adequate amount of exogenous variables for each industry group. Ultimately, the final set of financial ratios with lowest entropy levels for each industry group, that will be used in the logistic regression analysis are illustrated in Table 9.

Table 9. Financial Variables Selected for Logistic Regression Analysis

Cocohe	Entropy	Enut	Entropy	Inma	Entropy	Tein	Entropy
Cash/TL	0,897316	Cash/TL	0,901488	Cash/TL	0,913486	CL/Inv	0,835161
Cash/TA	0,898043	TD/WC	0,908195	Cash/TA	0,930851	TD/PPE	0,849962
CL/PPE	0,938509	Cash/FEO	0,912239	Rec/Inv	0,931053	TD/TA	0,872553
QA/Sales	0,938644	Cash/TA	0,918672	COGS/Inv	0,948376	COGS/Inv	0,910145
QA/FEO	0,942041	Sales/PPE	0,922827	Sales/PPE	0,954332	CL/PPE	0,911791
Inv/Sales	0,946571	COGS/Inv	0,93211	LTD/TA	0,955314	QA/FEO	0,932323
Sales/PPE	0,947751	Inv/Sales	0,947269	Inv/Sales	0,956694	QA/Sales	0,954667
Sales/WC	0,952786	TD/NW	0,957328				
CA/Sales	0,959063	Sales/TA	0,959155				
TL/WC	0,959851						

Before conducting logistic regression analysis, we will overview the existing literature about financial distress models in the next section, where financial ratios are employed for bankruptcy prediction purposes. Reviewing earlier studies on bankruptcy prediction models will convey our contribution to the existing literature better, and will provide financial statement users about the benefits of using our financial distress model among the most popular ones in decision making purposes.

CHAPTER III

LOGISTIC REGRESSION ANALYSIS AND GENERATING INDUSTRY SPECIFIC FINANCIAL DISTRESS MODELS

3.1. Literature of Financial Distress Models

In the early 1960s, a necessity emerged in the accounting literature regarding the assessment of business performances and determination of financially distressed firms by generating financial distress/bankruptcy prediction models. In this section, we review prior literature and present the financial distress/bankruptcy prediction models, and examine how studies define financial distress/bankruptcy; which financial ratios are preferred and included in the models throughout the history; and whether the models are powerful enough in predicting financial distress/bankruptcy. Since the literature regarding the financial distress/bankruptcy prediction models is quite large, we are going to pursue a two step procedure. First, we will discuss the most popular financial distress models, which are also used for comparison purposes in our analysis. Second, we will provide a chronological table of other studies that are carried out, including definition of financial distress/bankruptcy, estimation procedures, variables employed and resulting outcomes.

One of the pioneering studies, Beaver (1966) conducts univariate analysis to predict firm failure by financial ratios. He selects 79 failed and non failed firms by using paired sample design for the period 1954-1964, where failed and non failed firms are matched according to asset size and industry classification. First, Beaver employs 30 ratios according to their popularity in the literature, their definition covering the "cash flow" concept and their good performance in the prior studies. Second, these 30 ratios are divided into 6 categories including cash flow ratios, net income ratios, debt to total asset ratios, liquid-asset to total asset ratios, liquid asset to current debt ratios and turnover ratios. Third, from each category one ratio is selected as a representative of that category. Final ratios derived to be used in the analysis are cash flow/total debt, net income/total assets, total debt/total assets, working capital/total assets, current ratio and no credit interval [(defensive assets-current liabilities)/funds expenditures for operations]. In the next step, Beaver compares mean values of ratios between failed and non failed firms and observes a significant difference between the groups for all of the ratios. When he compares the mean asset size of two groups he finds that, asset size of the non failed firms continue to grow, while asset size of the failed firms decline one year prior to failure. He further conducts dichotomous classification test in which the failed and non failed firms are classified according to an optimal cut off score determined for each financial ratio. The classification test results show that, misclassification error is 13% in the first year prior to failure, while the error rate increases to 22% in the fifth year prior to failure. The outcomes indicate that, the correct classification accuracy of the test deteriorates as the time period before failure increases. Moreover, Beaver also observes that, the ability of the financial ratios in predicting bankruptcy varies. For instance, cash flow/total debt ratio possesses the greatest prediction ability among the others, while current ratio has the worst performance. Results further indicate that, failed and non failed firms cannot be classified with equal success such that, type 1 error (failed firms classified as non failed) is always greater than type 2 error (non failed firms classified as failed) for all of the periods before failure.

Altman's (1968) bankruptcy prediction model is the most popular one among the others. He defines firms from manufacturing industry in the US stock markets as bankrupt if they filed a bankruptcy petition under Chapter 10 of the National Bankruptcy Act for the period 1945-1965. The study uses matched sampling method, where 33 bankrupt firms are matched with 33 non bankrupt firms in terms of asset sizes. The ratios are selected according to their popularity in literature, including Working Capital/Total Assets (X_1), Retained Earnings/Total Assets (X_2), Earnings Before Interest and Taxes/Total Assets (X_3), Market Value of Equity/Book Value of Total Debt (X_4) and Sales/Total Assets (X_5). The author employs multiple discriminant analysis (MDA) and derives the following discriminant function:

$Z_{Altman} = 0.012X_1 + 0.014X_2 + 0.033X_3 + 0.006X_4 + 0.999X_5$

Altman conducts F-Ratio test to examine group mean differences between bankrupt and non bankrupt firms and observe that, all of the mean differences of variables are significantly different except X_4. He further ranks variables according to their relative contribution to the model and reveals that, X_3 contributes most to the discriminating ability of the model, while X_1 has the lowest contribution among the variables. To examine the classification accuracy of the model, Altman computes Type I and Type II errors. Type I error refers to cases where firms are misclassified as non bankrupt when they are actually bankrupt and Type II error refers to cases where firms are misclassified as bankrupt when they are actually non bankrupt. The results show that, the model predicts 95% of the total sample correctly for one year prior to bankruptcy, while the accuracy rate falls to 72% for two years prior to bankruptcy. To testify the strength of the model, Altman uses a secondary sample where he separates firms as healthy and financially distressed. Financially distressed firms are defined as firms suffered from negative income from two to three consecutive years between 1958 and 1961. He runs the same model for the financially distressed firms and observed that, the model totally classifies 79% of the sample firms correctly. Consequently, a Z score for each firm is computed from the discriminant function which shows that, firms having a Z score greater than 2.99 can be exactly classified as non bankrupt and firms having a Z score below 1.81 clearly fall into the bankrupt group. Firms that have Z score between 1.81 and 2.99 fall into the "grey area" where classification accuracy is susceptible.

Ohlson (1980) derives a bankruptcy prediction model as an alternative to Altman's Z score model. The study employs logistic regression to examine the probability of a firm being bankrupt or non bankrupt for a pre specified time period. He defines bankrupt firms according to Chapter 10, Chapter 11 and any other declaration indicating bankruptcy in the National Bankruptcy Act for the period 1970-1976 covering industrial firms in the NYSE, AMEX and other US stock markets. Apart from Altman's matched sampling method, Ohlson selects

105 bankrupt firms and 2,058 non bankrupt firms in which the asset sizes also vary between groups. The ratios used in the model are SIZE (logarithm of Total Assets/GNP Price Level Index), TLTA (Total Liabilities/Total Assets), WCTA (Working Capital/Total Assets), CLCA (Current Liabilities/Current Assets), OENEG (equals 1 if TL>TA and 0 otherwise), NITA (Net Income/Total Assets), FFOTL (Funds from Operations/Total Liabilities), INTWO (equals 1 if Net Income<0 for the last two years and 0 otherwise) and CHIN (change in Net Income) which are selected according to their frequent use in the literature. Ohlson's bankruptcy prediction model is illustrated by the following equation:

$$Z_{Ohslon} = -1.32 - 0.407*SIZE + 6.03*TLTA - 1.43*WCTA + 0.0757*CLCA - 2.37*NITA - 1.83*FFOTL + 0.285*INTWO - 1.72*OENEG - 0.521*CHIN$$

Ohlson determines a cutoff score of 0.038, which minimizes the sum of Type I and Type II errors. At this cutoff point, the model correctly classifies 82.6% of the non bankrupt firms and 87.6% of the bankrupt firms for one year prior to bankruptcy. It is important to note that although Ohlson's accuracy rates are lower than Altman's, Ohlson asserts that, this outcome may arise from several factors. First, the time period used in the analysis is completely different that, Ohlson's data covers 1970s, while Altman's data cover 1950s and 1960s. Second, the predictors, definition of bankruptcy as well as the choice of estimation procedures are also different from Altman's, which may affect the accuracy of the outcomes.

Taffler (1983) formulates a bankruptcy prediction model for the manufacturing firms that are quoted in London Stock Exchange for the period 1969-1976. Following Altman, he uses matched sampling by size and industry covering 46 bankrupt and 46 non bankrupt firms. Bankruptcy definition includes filing for bankruptcy petition, entry into creditors' voluntary liquidation, winding up by Order of the Court and clear action on part of the government. The variables employed in the model are selected by conducting a factor analysis on 80 potentially useful ratios which resulted in 4 ratios that captures 91.6% of the total variance in the data set. Those ratios are PBT/AVCL (Profit

Before Tax/Average Current Liabilities=X_1), CA/TL (Current Assets/Total Liabilities=X_2), CL/TA (Current Liabilities/Total Assets=X_3) and No-Credit Interval ((Current Assets-Inventory-Current Liabilities)/(Sales-Profit Before Tax+Depreciation) =X_4). Taffler runs a MDA model and obtained the following Z score model:

$Z_{Taffler} = 3.20 + 12.18X_1 + 2.50X_2 – 10.68X_3 + 0.0289X_4$

He determines Z score cutoff point as -1.95 in case constant term is not included in the model and zero otherwise. The results show that predictive accuracy of the Taffler's Z score model is 95.7% for the bankrupt firms and 100% for the non bankrupt firms. Taffler reveals that these high classification accuracy rates arise from the careful selection of the sample by paying attention to the distinction between solvent and failed firms and avoidance of collinearity among the variables.

Another popular financial distress prediction model is proposed by Zmijewski (1984) for the period 1972-1978, in which all industrial firms possessing SIC codes less than 6000 in the NYSE and AMEX are included. The author defines financial distress as "the act of filing a petition for bankruptcy" where out of 2,241 firms, 129 firms satisfies this condition. A probit analysis employed where financial ratios included in the model are ROA (Net Income/Total Assets), FINL(Total Debt/Total Assets) and LIQ (Current Assets/Current Liabilities). The resulting financial distress model is as follows:

$Z_{Zmijewski} = -4.336 - 4.513*ROA +5.679*FINL + 0.004*LIQ$

When Zmijewski uses matched sampling with unweighted probit analysis, the model classifies 92,5% of the bankrupt firms and 100% of the non bankrupt firms correctly. Contrarily, when he doesn't use matched sampling, the classification accuracy falls to 62,5% for bankrupt firms and 99,5% for non bankrupt firms. Meanwhile, when he employs WESML probit analysis, the classification accuracy rates even falls substantially to 52,5% with matched sampling and to 42,5% with unmatched sampling for the bankrupt firms.

Additionally, with WESML probit analysis, the accuracy rates do not discriminate between matched and unmatched sampling in the prediction of non bankrupt firms. Zmijewski further examines the effect choice based sample selection and complete data sample selection on the model estimation process. Since both of the sample selection processes significantly affect the correct classification and prediction rates, the author reveals that, WESML techniques should be employed in conducting probit analysis in order to eliminate the effects of choice based sample bias. To eliminate complete data sample selection bias, Zmijewski employs bivariate porbit analysis. However, the outcomes show that, neither simple probit assessment nor bivariate probit analysis improves the estimation results.

Other studies, which develop or reestimate existing financial distress/bankruptcy prediction models, are illustrated chronologically in Table 10.

In reviewing the prior literature of financial distress/bankruptcy prediction models, we observe that, although there are studies that predict financial distress/bankruptcy of firms, no study specifically addresses the question of how to predict financial distress of firms for different industries. In this respect, we propose industry specific financial distress models by using most informative industry specific financial ratios that we derived from the factor analysis and entropy measures. In generating industry specific financial distress models, we employ logistic regression analysis for each industry group. In the following section, we will explain the properties of logistic regression analysis and the reasons of selecting this method in spite of the other methods used in the financial distress/bankruptcy prediction studies.

Table 10. Researches on Financial Distress/Bankruptcy Prediction

Author (s)	Definition of Financial Distress/Bankruptcy	Estimation Procedure	Variables in the Model	Results
Frydman et al. (1985)	Companies filed for bankruptcy petition under Chapter 11	Recursive Partitioning Algorithm (RPA) used and compared with Discriminant Analysis (DA). For DA, 58 bankrupt and 142 non bankrupt industrial firms selected for the period 1971-1981. For RPA, a classification tree built for 200 firms, considering prior probabilities and stated misclassification costs in distributing the firms as bankrupt/non bankrupt.	20 financial variables selected which are found significant in predicting bankruptcy by the studies of Altman (1968), Deakin (1972) and Altman et al. (1977).	The classification accuracy of RPA model is greater than DA model. In RPA, CashFlow/TotalDebt has the highest discriminating ability among the other ratios while in DA the discriminating power is greatest for CurrentAssets/CurrentLiabilities
Casey and Bartczak (1985)	Firms listed as bankrupt on Wall Street Journal Index for the 1971-82 period	Multiple Discriminant Analysis (MDA) constructed for 60 bankrupt and 230 non bankrupt industrial firms for the period 1971-1982. Logit Analysis also conducted for the same sample of firms.	Two cash flow variables (CFO/CL and CFO/TL) and six accrual based ratios (Cash/TA, CA/TA, CA/CL, Sales/CA, NI/TA and TL/NW) used in the analysis to examine whether cash flow based data predicts bankruptcy better than accrual based data.	Neither in MDA nor in LA an increase determined in the marginal classification accuracy by including cash flow data.

Table 10 (continued)

Author(s)	Definition of Financial Distress/Bankruptcy	Estimation Procedure	Variables in the Model	Results
Lau (1987)	Financial distress examined in five states: State 0: financial stability, State 1: omitting or reducing dividend payments, State 2: technical default and default on loan payments, State 3: protection under Chapter 10 and 11 of the Bankruptcy Act, State 4: bankruptcy and liquidation	350 firms for state 0, 20 firms for state 1, 12 firms for state 2 and 5 firms for state 3 and state 4 selected. Multinomial Logit Analysis (MLA) conducted for generating the financial distress prediction model and the results are compared with MDA	A total of 10 variables selected for measuring borrowing capacity, stock flexibility, cost flexibility, dividend flexibility and asset disposability, which overall identify "financial flexibility".	In state 0, classification accuracy of MLA model is 99.4%, 98.9% and 99.1% for 1, 2 and 3 years prior to bankruptcy. In state 1 corresponding outcomes are 65%, 15%, 10%, in state 2 86.7%, 66.7%, 46.7%, in state 3 70%, 40%, 30% and in state 4 60%, 100%, 80% respectively. In all of the states MLA models outperforms MDA in terms of classification accuracy.
Aziz et al. (1988)	Companies filed for bankruptcy petition under Chapter 10 and 11 or otherwise declared bankruptcy	Lawson's identity components are checked for the suitability in discriminating between bankrupt/non bankrupt firms by MDA and LA. 50 bankrupt firms are matched with 50 non bankrupt firms in terms of industry and asset size for the period 1971-82. Results are compared with Altman's Z Score Model	Variables used in the Lawson's identity include Funds from Operations (FFO), Cash and Marketable Securities (CMS), Current Liabilities (CL), Short Term Debt (STD), Common and Preferred Stock (CPS), Long Term Debt (LTD) and Tax Liability (TL). Aziz et al.'s model is called Cash Flow Based (CFB) Model.	Taxes assessed and actually paid in cash variable has the highest contribution followed by CFO in MDA. Classification accuracy rate of MDA ranges from 72.5% to 88.8% for 1 to 5 years prior to bankruptcy while LA accuracy rates ranges between 78.6% to 91.8%, indicating superiority of LA model. CFB model outperforms Altman's Z Score model.
DeAngelo and DeAngelo (1990)	Firms classified as financially distressed if they experience negative income (or negative pre-tax operating income) at least 3 consecutive years	A final sample of 80 healthy and 80 financially distressed industrial firms selected according to complete data criterion for the period 1980-85. Dividend analysis conducted where normalized cash dividend payments compared between healthy and distressed firms.	Normalized dividend payments d(t) equals total cash dividend paid per split-adjusted share of common stock in year t relative to year 0.	Firms are likely to increase dividend payments before the distress period and reduce them in the distress period. Mean % change in dividend payments significantly differ between healthy and distress firms. An initial reduction in dividend payments followed by larger reductions in consecutive periods.

Table 10 (continued)

Author(s)	Definition of Financial Distress/Bankruptcy	Estimation Procedure	Variables in the Model	Results
Gilbert et al. (1990)	Firms classified in three groups; bankrupt group (US firms filed a Chapter 11 bankruptcy petition), random group (non financial firms that have complete data) and distressed group (firms that have negative earnings for any three consecutive years)	Bankrupt group, random group and distressed group consist of 76, 304 and 304 firms respectively for the period 1974-83. Stepwise logistic regression used.	Variables used in the model: Cash/TA, CFO/CL, CFO/TA, CFO/TL, CA/CL, CA/TA, EBIT/TA, NW/TD, NW/TL, NI/TA, Retained Earnings/Total Assets (RE/TA), Sales/CA, Sales/TA, WC/TA	Opposing to the findings of Casey and Bartczak (1985), cash flow variables discriminate best between bankrupt/non bankrupt firms. Overall classification accuracy rate is 66.7% for bankrupt/random group while for bankrupt/distressed group 70% of the bankrupt firms are misclassified as non bankrupt leading to a poor performance.
Koh (1992)	Firms classified as going concern and non going concern. Going concern group consists of firms that filed for bankruptcy and non going concern firms consist of non bankrupt firms for the same period.	165 going concern firms are matched with 165 non going concern firms in terms of industry and asset size for the period 1980-85. Logit Analysis (LA) used in estimation process and optimal cutoff points are determined which minimizes the total misclassification cost	Variables included in the model: Quick Assets/Current Liabilities (QA/CL), Market Value of Equity/Total Assets (MV/TA), TL/TA, Interest Payments to Earnings Before Interest and Tax (IEBT), NI/TA and RE/TA	Overall accuracy of the model ranges between 99.9% to 88.5% for different cutoff points, indicating robustness of optimal cutoff points to different misclassification costs.
Ward (1994)	Financial distress examined in four states: state 0 financially healthy, state 1 cash dividend reduction (if dividend per share is reduced by 40% after a successive dividend per share history), state 2 loan principal, interest default or debt accommodation, state 3 firms file for Chapter 11 protection.	Ordinal Logistic Model used where number of firms in the four state model meets the requirement regarding minimum sample size of 10(S+1), S as the number of independent variables. The overall sample comprises of 227 US non financial firms for the period 1984-88. Rank Probability Score (RPS) also generated to strengthen the outcomes.	Variables in the model: NI/TA, Sales/CA, NW/TL, CA/CL, CA/TA, Cash/TA, CFO/TL, NOF/TL (Net Income + depreciation and amortization over total liabilities).	NOF/TL, CFO/TL and NI/TA are the significant predictors of financial distress both 1 and 2 years prior to financial distress. Cash flow based variables (NOF/TL and CFO/TL) are better measures of economic income than NI/TA. RPS outcomes also support strong predictive power of cash flow based model.

Table 10 (continued)

Author(s)	Definition of Financial Distress/Bankruptcy	Estimation Procedure	Variables in the Model	Results
Begley et al. (1996)	Companies filed for bankruptcy petition under Chapter 11	Reestimate Altman's and Ohlson's bankruptcy prediction models for the period 1980-1989. 165 bankrupt and 3,300 non bankrupt firms selected from NYSE, AMEX and NASDAQ.	Include all variables used in Altman and Ohlson models.	Ohlson model outperforms Altman model in terms of classification accuracy. Overall classification accuracy is 81.3% for Ohlson and 78.2% for Altman model.
Ward and Foster (1997)	Two models developed: First model compares healthy and bankrupt firms where bankruptcy is defined as firms filed for bankruptcy petition under Chapter 11. Second model compares healthy firms and firms experiencing loan default/debt accommodation.	Logistic Regression employed for a total of 317 firms in which 253 are healthy 29 are bankrupt and 35 experiencing loan default/debt accommodation for the period 1988-1989.	Both models employ 10 ratios, including six accrual ratios, three cash flow ratios and one ratio to control firm size; NI/TA, Sales/CA, CA/CL, NW/TL, CA/TA, Cash/TA, log(TA), CFO/TL, CFI/TL and CFF/TL.	For healthy/bankruptcy model only NI/TA and NW/TL are significant in predicting failure while for healthy/loan default/debt accommodation model NI/TA, Sales/CA, NW/TL, CA/TA, log(TA), CFO/TL and CFI/TL are significant indicating loan default/debt accommodation model predicts future financial distress better than bankruptcy model.
Etheridge and Sriram (1997)	Failed banks are defined according to FDIC categorization including failure, assisted merger and liquidated banks	Compares MDA, LA and Artificial Neural Network (ANN) models in terms of predicting ability of bank failure. 148 failed banks and 992 healthy banks are selected for the period 1986-88. Relative cost of type I and type II errors are estimated according to different probabilities of error rates.	Starting with 55 ratios, the ratios that have greater than 0.10 level of significance are eliminated using a stepwise method in LA and MDA. The final model includes 16 ratios in MDA and 13 ratios in LA.	LA and MDA perform better than ANN in terms of overall accuracy rates. However when relative error costs are included in the models ANN outperforms LA and MDA in correctly classifying failed/non failed banks. ANN also performs better than LA and MDA when time period before failure is extended.

Table 10 (continued)

Author(s)	Definition of Financial Distress/Bankruptcy	Estimation Procedure	Variables in the Model	Results
Mossman et al. (1998)	US industrial firms that declared bankruptcy under Chapter 7 or Chapter 11.	Four bankruptcy prediction models compared; Altman, 1968 (financial ratio model), Aziz et al., 1988 (cash flow model), Clark and Weinstein, 1983 (market return model) and Aharony et al., 1980 (market return variation model) for the period 1980-1991.Matched sampling used between 190 bankrupt/non bankrupt firms in terms of size and industry.	Market return model includes variables of 12 and 60 month compound return, market adjusted return with value weighted and equal weighted index. Return variation model includes variables of 12 and 60 month standard deviation of returns.	Correct classification rate is lowest for the return variation model while financial ratio model has the highest classification accuracy. Ratio (83.9%) and cash flow models (82.6%) discriminates best between bankrupt/non bankrupt firms however market return (74.1%) and variation models (65.4%) have the poorest performance for both one and two years prior to failure.
Kahya and Theodossiou (1999)	Failed firms that declared bankruptcy under Chapter 7 or Chapter 11.	Time Series Cumulative Sums (CUSUM) model employed which ascertains serial correlation, includes information for more than one period and stationary independent variables. 72 failed and 117 non failed firms are selected from NYSE and AMEX manufacturing and retailing sectors for the period 1974-1991.	27 financial ratios and their first differences are included in the model. These ratios cover liquidity, profitability, long term profitability, financial leverage, market structure, size, management efficiency, operating leverage and activity.	CUSUM model that captures best stationary level includes four independent variables: log of deflated total assets, change in the ratio of inventory to sales, change in the ratio of fixed assets to total assets and change in the ratio of operating income to sales. The results show that these ratios are stable over time indicating their high classification performance.
McLeay and Omar (2000)	Firms are classified as failed either; 1) filed for bankruptcy 2) shares sold off to private investors 3) entered into capital restructuring or reorganization 4) experienced negative shareholders' funds for three consecutive years 5) incurred accumulated losses for three consecutive years.	LA and MDA conducted for a total of 648 failed and 767 non failed Malaysian firms for the period 1980-91. Transformation analysis further conducted to specify the most and least normal ratio sets. To examine sensitivity of failure prediction models to normality of ratios, classification accuracy of untransformed and transformed models are compared.	28 financial ratios selected according to their frequent use in the literature. Ratios divided into two groups: 1) ratios with both numerator and denominator are bounded at zero so that the ratio takes only positive values 2) ratios with either numerator or denominator are bounded at zero.	The most normal ratio set includes one bounded (Sales/TA) and one unbounded ratio (EBIT/TA). However the least normal ratio set includes only unbounded ratios i.e. EBIT/Sales, Sales/Shareholders' funds, TD/WC. Transformed model of MDA outperforms untransformed model with 7.9% improvement in terms of classification accuracy. However no improvement detected when LA model used, indicating insensitivity to normality.

Table 10 (continued)

Author(s)	Definition of Financial Distress/Bankruptcy	Estimation Procedure	Variables in the Model	Results
Laitinen and Laitinen (2000)	Bankrupt US industrial firms filed under Chapter 11.	285 bankrupt and non bankrupt firms selected for 1985-1993. Stepwise LA used in the estimation process of variables where second-order and interaction terms are included. Taylor's model determines the difference between first order and second order variables.	To examine insolvency risk Cash Flow/TA, NW/TA and Cash/TA ratios used including their second-order and interaction terms.	In the first-order model only NW/TA and Cash/TA are statistically significant for one year prior to bankruptcy. However, when the Taylor's expansion applied, all of the first-order and second-order variables become significant, indicating the nonlinear relation of Cash flow data to insolvency risk.
Shumway (2001)	Firms classified as bankrupt if they filed for any bankruptcy within five years of delisting.	Conducts both hazard model and static model forecasts to compare the out of sample accuracy of the models. The sample contains 300 bankrupt firms listed in NYSE and AMEX for the period 1962-1992.	Employed Altman’s (1968) and Zmijewski’s (1984) variables in addition to market capitalization, age, excess return and standard deviation of firms’ stock returns.	Market driven variables outperform accounting based variables of Altman’s and Zmijewski’s in predicting failure. Although model coefficients of Hazard model are close to MDA and Logit models, they are overestimated.
Grice and Ingram (2001)	Distressed firm definition includes Chapter 11 bankruptcy, Chapter 7 liquidation, bonds vulnerable to default and low stock ratings.	148 distress and 824 non distressed manufacturing and non manufacturing firms are included for the period 1988-1991. Examined the classification accuracy of Altman's Z score when the time period is different. Calculated the accuracy of the model by dividing number of correctly predicted firms to total number of firms.	Variables in the Altman's Z score model are reestimated.	Classification accuracy of the 1988-1991 sample drops significantly relative to the Altman's original sample, indicating application of Altman's Z score model to more recent data is not as accurate as the model applied to 1960s data set in predicting bankruptcy.
Foreman (2003)	Competitive Local Exchange Carriers (CLECs) defined as bankrupt if a CLEC filed for reorganization and protection from creditors to the SEC.	14 bankrupt and 63 non bankrupt CLECs selected cross sectionally for 2000-2001 period. Applied binomial LA and a case study conducted afterwards.	Variables in the model are Earnings per Share, number of employees, Federal Communication Commission/Sales, Market-to-Book, RE/TA, ROA, Total Debt Proportion and WC/sales	96% of the CLECs are correctly classified in the LA model. Decrease in EPS and ROA results in higher probabilities of bankruptcy. Higher values of RE/TA and Total Debt Proportion also increase the bankruptcy risk.

Table 10 (continued)

Author(s)	Definition of Financial Distress/Bankruptcy	Estimation Procedure	Variables in the Model	Results
Grice and Dugan (2003)	Distressed firm definition includes Chapter 11 bankruptcy, Chapter 7 liquidation, bonds vulnerable to default and low stock ratings.	Reestimate Zimjeswki's (X score model) and Ohlson's (Y score model) bankruptcy prediction models for the period 1992-1999. 183 distressed and 841 non distressed firms are selected for X score model and 154 distressed and 889 non distressed firms are selected for the Y score model.	Variables in the Zmijeski's and Ohlson's original models are used. Sensitivity of the coefficient of variables to various distress situations and industry classifications are examined.	Both X and Y score models' coefficients are not stable across time periods and they are not sensitive to different distress situations. Ohlson's model is sensitive to industry classifications while Zmijewski's model is not. Classification accuracy of the Y score model (88.7%) is greater than the X score model (86.1%)
Agarwal and Taffler (2003)	Companies with Z scores (Taffler, 1983) smaller than 0 possess the risk of bankruptcy and companies with Z scores greater than 0 do not possess the risk of bankruptcy.	Fama McBeth's (1973) cross sectional regression conducted for 2,356 UK companies listed on LSE for the period 1979-2000. Companies are ranked on z scores, market capitalization and B/M ratio.	In addition to variables used in Taffler's Z score model, market return, risk free rate, stock return, size, book-to-market (B/M), beta and GDP growth rate are included in the multifactorial model.	Firms with lower z scores are likely to earn lower stock returns than firms with higher z scores. Beta, size and B/M ratios are significant in determining performance of stock returns. No common variation observed between size, B/M, Z scores and returns.
Jones and Hensher (2004)	Financial distress categorized as: state 0 non failed firms, state 1 insolvent firms that fail to pay Australian Stock Exchage annual listing fees, raise capital to produce sufficient working capital to finance continuing operations, default on loan and restructure debt/equity to make loan repayments, state 2 firms declared bankruptcy after the appointment of liquidators, insolvency administrators receivers.	7,818 firm years for state 0, 197 firm years for state 1 and 226 firm years for state 2 selected from manufacturing, resources and financial sector in ASE for the period 1996-2003. Mixed Logit Model used to determine the significant variables on the probability of firm failure which also captures the effect of mean and variance of a particular variable on the estimated parameters. The distribution of parameters in the mixed logit model can be normal, lognormal or triangular.	Variables in the study are Net CFO/TA, Cash Resources/TA, Net CFO/Annual Interest Payments (Cash Flow Cover), Sales Revenue/TA, TD/NW, TD/Gross CFO, WC/TA.	Cash Resources/TA, Net CFO/TA, WC/TA and Cash Flow Cover significantly affect the probability of all three states of financial distress. Increase in Net CFO/TA increases the probability of non failure while increases in Gross CFO/TD lead to a decrease in the probability of non failure. Cash flow based variables generate consistent information in predicting financial distress for each distress category.

Table 10 (continued)

Autho r(s)	Definition of Financial Distress/Bankruptcy	Estimation Procedure	Variables in the Model	Results
Chava and Jarrow (2004)	Bankruptcy is defined as the firms filed either for Chapter 7 or Chapter 11petition.	Hazard rate estimation procedure is conducted for 1461 bankrupt US firms where number of non bankrupt firms vary between 1962-1999. Industry effects are examined for selected industry groups	Altman's (1968), Zmijewski's (1984) and Shumway's variables are employed. The forecasting ability of these bankruptcy models is compared.	Shumway's model performs better than Altman's and Zmijewski's models in predicting company failure. Industry effects has a significant influence on both intercept and slope of the bankruptcy model coefficients.
Smith and Graves (2005)	Distressed firms in the "turnaround process" are divided into two phases: decline stemming phase and recovery phase. 4 year turnaround cycle determined where firms that experience successful turnaround possess negative z scores for two consecutive years followed by two years of positive z scores. Failed firms are those that do not experience a recovery period.	Employed Taffler's (1983) Z score model and conducted MDA for the turnaround model where 83 failed and 40 recovered firms selected from LSE excluding manufacturing sector for the period 1991-1992.	In addition to variables used in Taffler's Z score model, (ln(TA)) used as a measures of size, change in total tangible assets used as a measure of efficiency total tangible assets minus secured loans divided by total tangible assets used as a measure of free assets and change in CEO or chairman in a financial year used as a measure of internal climate and board stability.	Significant relation exists between severity of financial distress and failed/recovered status of firms. EBIT/CL, CL/TA and NCI variables from the Taffler's Z score model are significantly related to severity of financial distress. The turnaround model classifies 78 of the 83 failed firms and 30 of the 40 recovered firms correctly. There is also a significant relation between free assets, size and recovered firms while no significant difference observed for the CEO turnover rate between the failed/recovered group of firms.
Pompe and Bilder beek (2005)	Firms categorized as bankrupt if legal status of the firm is "bankrupt" under Belgian Law. These firms have delayed payments against creditors and have lost all credits.	Both MDA and Neural Network (NN) conducted for 238 bankrupt and 750 non bankrupt industrial firms covering the period 1986-1994. Optimal cut off score for bankrupt/non bankrupt classification determined by dichotomous classification test.	Employed 45 ratios in the analysis covering profitability, activity, liquidity and solvency. Ranked standard deviations and first differences of ratios and reduced total number of ratios included in the study to 25.	In line with Beaver's (1966) findings, CF/TD has the highest predictive power while Turnover/TA, CA/TA and Trade Debtors/Turnover ratios performed poorly against the other ratios. Overall classification accuracy of the MDA model is 79% and 72% for one and two years prior to bankruptcy respectively. NN results are also similar to MDA outcomes.

Table 10 (continued)

Author (s)	Definition of Financial Distress/Bankruptcy	Estimation Procedure	Variables in the Model	Results
Beaver et al. (2005)	Firms declared bankruptcy in either of the sources: 2003 Compustat Annual Industrials file, 2003 CRSP Monthly Stock file, website bankruptcy.com and Capital Change Reporter.	Hazar model used for 544 bankrupt and 4,237 non bankrupt industrial firms (excluding utility and financial firms) covering the period 1962-2002, which predicts the probability of bankruptcy at time t conditional upon the survival of the firm until time t. To examine whether predictors are robust over time the period divided into two subperiods: 1962-1993 and 1994-2002.	Three explanatory variables used in the analysis are ROA as a measure of profitability, Net Income Before Interest, Taxes, Depreciation, Depletion and Amortization divided by Total Assets (ETL) as a measure of cash flow and Total Liabilities/Total Assets (LTA) as a measure of leverage.	In the financial ratios based model ROA, ETL and LTA are significant predictors of bankruptcy and prediction accuracy of the variables are robust over the periods. In the market based model, size, LERET (lagged cumulative security residual returns) and LSIGMA (lagged std. dev. of security residual returns) are significant and the prediction accuracy of the model is stable over time. However incremental power of market based variables is greater in the second sub period than financial ratios.
Ugurlu and Aksoy (2006)	Manufacturing firms delisted from the ISE for either of the following reasons; accumulated losses greater than shareholder's equity, forced for liquidation, difficulty in repaying financial obligations, financial problems or filed for bankruptcy, firms that used up 2/3 of shareholders' equity and facing difficulty in retiring outstanding bonds, payments of interests or principal on financial obligations.	27 distressed firms are matched with 27 non distressed firms in terms of size and industry for the period 1996-2003. First, factor analysis used to determine most important predictors for a total of 22. Second, MDA used to develop a failure prediction model in which 10 variables are included by stepwise selection. Third, logistic regression conducted which includes a total of 11 variables as a result of stepwise selection method.	10 variables identified by MDA are NW/TA, (accounts payable + notes payable)/TA (APNPTA), Sales/Tangible Assets (STFA), QA/Sales, LTD/TD, WC/LTD, MVE/TL, (Cash+ Marketable Securities)/CL, EBIT/Paid Capital and EBITDA/TA. 11 variables identified by the LA are EBITDA/TA, EBIT/Sales, APNPTA, Sales/CA, MVE/BVTL, STFA, ROE, WC/LTD, Other Income Before Taxes/Other Income After Taxes (OIBOIA), (TA/1000)/World Price Index and Sales/WC.	Overall, MDA model classifies 85.9% of the firms correctly while classification accuracy of the logistic regression model is 95.6% indicating LA outperforms MDA in financial distress prediction models. Z score model is developed by MDA in which six of the ratios are from LA. ROE and OIBOIA discriminates best between distressed - non distressed firms. EBIT/Paid Capital and LTD/TD are also significant predictors of the model.

Table 10 (continued)

Author(s)	Definition of Financial Distress/Bankruptcy	Estimation Procedure	Variables in the Model	Results
Sohn and Kim (2007)	Small and Medium Sized firms (SMEs) grouped as default and non default. Default firms include those that delayed payback, issued bad-check, failed product commercialization, had bad credit of manager, closed business or corporate reorganization procedure in three years after receiving technology fund.	1,458 defaulted and 330 non defaulted firms are selected for the period 1997-2002. Both fixed effects and random effects logistic regression model constructed to compare the performance of two models.	For fixed effects model 19 financial and non financial variables selected out of which 9 become significant in prediction of failure. The significant ratios are NI/NW, NW Turnover, Growth Rate of NW, NI/TA, TA Turnover, Growth Rate of TA, Growth Rate of Sales, dummy variable equals 1 if SME is listed in the stock market, otherwise -0- and technology experience score.	Fixed effects LA classifies 60.5% of the firms correctly while overall classification accuracy of the random effects LA is 64.5%. Out of 9 significant variables derived from fixed effects model, NW Turnover, Growth Rate of NW and Growth Rate of Sales become insignificant in the random effects model. Results show that random effects model is superior than fixed effects model in default prediction of SMEs.
Hua et al. (2007)	Two groups identified: distressed firms and non distressed firms. Firms defined as financially distressed if they are announced as special treatment share by Shangai Stock Exchange (SSE) indicating that these firms become insolvent since their liabilities are disproportionate to their assets.	Integrated Binary Discriminant Rule (IBDR) and conventional Support Vector Machine (SVM) analysis employed for 60 distressed and 60 non distressed manufacturing firms in predicting financial distress for the period 1999-2004. IBDR is predicted to be superior to conventional SVM since it employs structural risk minimization principal which in turn minimizes the misclassification risk.	Out of 22 variables 10 variables are selected according to paired-samples t test. These 10 ratios are also reduced to 7 by deleting intercorrelated variables. 7 variables used in the analysis are Sales/TA, Cash Flow Ratio, Growth Ratio of Sales, Growth Ratio of TA, NI/TA, Gross Profit/COGS, Cash and Cash Equivalents/CL.	Prediction accuracy of IBDR is superior than conventional SVM. All of the 7 variables are significant in discriminating between distressed and non distressed firms.

Table 10 (continued)

Author(s)	Definition of Financial Distress/Bankruptcy	Estimation Procedure	Variables in the Model	Results
Pindado et al. (2008)	Definition of bankrupt firms include not only bankrupt firms but also firms that have financial expenses exceeding their EBITDA for two consecutive years and firms experiencing decrease in market value for two consecutive years.	Unbalanced panel data analysis conducted for 17,439 non distressed and 721 distressed US firms as well as for 14,514 non distressed and 1188 distressed firms in the G-7 countries for the period 1990-2002.Both fixed and random effects Logistic Regression used to estimate financial distress model.	Variables used in the analysis are EBIT/ROA, Financial Expenses/ROA and Retained Earnings/ROA. A dummy variable to measure time effect also included in the model to examine the time effect.	All of the variables are significant in both fixed and random effects models. Significance of time variable shows that financial distress fluctuates according to changing macroeconomic conditions. Classification accuracy of the model for US firms is 87% and for firms that belong to G-7 countries is 83%.
Li and Sun (2008)	Firms are classified as distressed if they experience negative net income for two consecutive years.	Used Ranking-Order Case Base Reasoning (ROCBR) in predicting 153 distressed and non distressed firms in Shangai and Shenzhen Stock Exchange for the period 2000-2005. The outcomes of ROCBR are compared with MDA and LA.	31 financial ratios used in the analysis that cover profitability, activity, growth, liability, per share items and yields and structure ratios.	ROCBR has the highest prediction accuracy among the other models. 91.7% of the firms correctly classified within ROCBR model while classification accuracy drops to 87.04% and 87.93% for Logit and MDA models respectively.
Chen and Du (2009)	Firms classified as bankrupt if they have any indication of financial distress in the auditors' reports, financial and taxation databases or in the Taiwan Stock Exchange (TSEC).	Factor Analysis conducted to reduce number of ratios from 37 to 18. Then, Back Propagation Network (BPN)as an ANN method and Clustering Analysis as a Data Mining (DM) technique employed for predicting 34 matched bankrupt and non bankrupt firms listed in the TSEC for the period 1999-2006.	37 ratios included in the study are earnings ability, financial structure ability, management efficiency ability, management performance, debt repaying ability and non financial factors i.e. Dividend payout ratio, price/book ratio, insider holding ratio and the proportion of collaterized shares by the BOD.	The classification accuracy of BPN is greater than clustering analysis over 1, 2, 3 and 4 years prior to failure. However the accuracy rate of the BPN model falls as the time period before failure is extended. Classification accuracy of the BPN model is 82.14% for 1 year prior to failure while the accuracy falls to 60% for 4 years prior to failure.

Table 10 (continued)

Author(s)	Definition of Financial Distress/Bankruptcy	Estimation Procedure	Variables in the Model	Results
Li et al. (2010)	No definition provided for failure and distress firms.	Two samples drawn from Shenzhen and Shangai Stock Exchanges; sample 1 comprising of 135 failure and healthy firms and sample 2 comprising of 153 distressed and healthy firms. Classification and Regression Tree (CART) method used.	Four variables are selected from the stepwise method of MDA are Total Asset Turnover, TA/TL, Growth Rate of TA and Earnings per Share.	CART method outperforms all other methods in terms of predictive accuracy. The strength of the CART method arises from its inclusion of misclassification cost and variance of variables in implementation process of algorithms.
Hill et al. (2011)	Firms' financial status are classified as stable, financially distressed or bankrupt. Financial distressed is defined as firms having negative income for any three consecutive years between the period 1977-1987.	The sample includes 257 firms from the manufacturing, wholesale, retail and service sectors in which 75 are classified as bankrupt. Event history methodology conducted which uses time varying independent variables and allows for censoring.	Variables selected for the analysis cover Cash/TA, Income Before Extraordinary Items/TA, TL/TA, log of Sales and a dummy variable coded as 1 if firms possess qualified opinion in audit reports and 0 otherwise.	The means of three groups are significantly different at 5% level. Cash/TA significantly identifies distressed firms but it is not significant in identifying bankrupt firms. Like other varibles in the model, "Qualified Opinion" variable is also statistically significant.
Terzi et al. (2012)	Firms classified as failed if their Z score computed according to Altman's model (1968) are below 1.81 and non failed otherwise.	LA, ANN and Decision Tree models compared in terms of classification accuracy. 167 firms selected from Istanbul Stock Exchange (ISE) in manufacturing industry for the period 2009-2010.	27 financial ratios are selected representing management efficiency, liquidity, financial structure and profitability.	LA classifies 94.6% of the firms and ANN classifies 95.7% of the firms correctly while the classification accuracy drops down to 86.8% in the Decision Tree model.
Hamdi and Karaa (2012)	No definition provided for bankrupt/ non bankrupt discrimination.	528 Tunisian firms selected for the period 1999-2006.ANN compared with financial analysis. Financial analysis includes detection of risk points in the financial statements, analysis of working capital and capital need and examination of insolvency risk.	26 ratios included in the model representing profitability, financial leverage, liquidity and working capital.	ANN outperforms financial analysis in terms of objectivity and time consumption. ANN classifies up to 98% of the cases correctly indicating superiority of data mining techniques to traditional analysis of bankruptcy prediction.

3.2. Logistic Regression Analysis

As seen from earlier research, various financial failure prediction models have been developed and numerous modeling techniques have been employed since 1960s. Although the most popular technique in failure prediction models was Multiple Discriminant Analysis (MDA) in 1960s, Logistic Analysis (LA) become more preferable in 1980s, because of the drawbacks of MDA in dealing with non normally distributed data. To deal with non normally distributed data, LA follows a non linear maximum likelihood estimation procedure in determining parameter estimates of the model by the following equation:

$$P(X_i) = \frac{1}{[1+\exp-(b_0+b_1X_{i1}+b_2X_{i2}+\cdots+b_n X_{in})]} \qquad (8)$$

where $P(X_i)$ is the probability of financial distress/bankruptcy given the X_i attribute, X_i is the value of the attribute for firm i and b_n is the coefficient of the attributes X_{in}. In this respect, LA model provides information about diverging firm attributes that are combined in a "multivariate probability score" which specifies probability of failure or vulnerability of firms to failure (Balcaen and Ooghe, 2006). The interval for the $P(X_i)$ score is [0,1], where probability scores that are close to zero indicate financial health, while probability scores that are close to 1 indicate financial distress of firms. In a logistic function, the probability of financial health or financial distress of a particular firm can be understood through analyzing deterioration or amelioration of financial ratios as exogenous variables. After the estimation of exogenous variables, firms are classified into groups as distressed or non distressed, according to a cut off score determined by the analyst. In the next step, logistic regression weights the independent variables and computes a Z-score for each firm in the sample in a form of financial distress probability (Back et al., 1996). Given the brief summary regarding the logistic analysis, we are now ready to examine the third part of our analysis by investigating each step of the logistic analysis procedures in detail.

3.1.1. Definition of Financial Distress and Sample Selection

In the literature, there are mainly two types of definitions regarding financially distressed firms. The first type of financial distress definition includes those firms that actually experience financial failure and are classified as failed by legal declaration according to bankruptcy law of the countries they belong. The second type of financial distress definition includes those firms that do not declare bankruptcy yet, but experience financial difficulties which may arise from firm specific, industry specific or even country specific factors. Since our sample comprises of S&P 1500 firms that are active in the market as of march, 2011 in which none of them experience bankruptcy yet, we define financial distress as the firms that experience financial difficulty. Following the prior literature, firms experiencing financial difficulty are identified as firms that possess negative net income for at least 3 or 5 consecutive years depending on the sample size between the periods 1990-2011. The identification of financially distressed firms for each sample of industry is illustrated in Table 11.

Table 11. Number of Financially Distressed Firms per Industry

	Cocohe	Enut	Inma	Tein
Financially Distressed Firms (a least 3 consecutive years)	103	16	46	93
Financially Distressed Firms (a least 5 consecutive years)	53	2	10	33
Total Number of Firms	414	139	283	228

Table 11 shows that, if we define financial distress as firms having negative net income for at least 5 consecutive years, 53 firms in Cocohe, 2 firms in Enut, 10 firms in Inma and 33 firms in Tein industries are classified as financially distressed out of 414, 139, 283 and 228 firms respectively. Notwithstanding, if we define financial distress as firms having negative net income for at least 3 consecutive years, 103 firms in Cocohe, 16 firms in Enut, 46 firms in Inma and 93 firms in Tein industries are categorized in the financially distressed group. Provided that the study covers 22 years of period, the distressed group of firms with at least 5 consecutive years of negative net income will provide more accurate outcomes. However, there are only two firms that abide this requirement in the energy and utility sector (Enut) and hence the sample size is not sufficient to conduct logistic analysis. In this respect, we chose to use the sample that covers distressed firms with at least 3 consecutive years of negative income for this particular industry group.

3.1.2. Methodological Design

In the literature, several studies reveal that financial ratios do not follow normal distribution because of several factors mentioned in the first part of our study (Deakin 1976; Barnes 1982; Frecka and Hopwood 1983; Ezzamel et al. 1987). Since we observe significant but tolerable departures from normality in the factor analysis section of our study, we chose to use Logistic Analysis in developing a financial distress prediction model to avoid the problems of non normally distributed data. As the error term in the logistic regression follows a binary distribution, invalidation of the normality assumption will not affect the statistical testing.

In the two group logistic analysis, financial distress variable is set to be the binary dependent variable that takes the value 1, if the firm is financially distressed and zero otherwise. In other words, the group assigned by value 1 generates the distressed group and the group assigned by the value 0 generates the non distressed group. The independent variables are those selected by the entropy method that possess 0,95 or lower entropy levels. Since the aim of the study is to generate industry specific financial distress prediction models by using industry specific financial ratios, we conduct logistic analysis for each industry group separately. The research question in the current state of the analysis is to determine whether industry specific financial ratios that we obtained from the entropy method have any discriminating ability between the distressed and non distressed group of firms.

3.1.3. Independent Sample Tests

Before starting the estimation process of logistic analysis, the Levene's Test for equality of variances and t test for equality of means are conducted to examine whether mean of industry specific financial ratios differentiate between distressed and non distressed firms. Table 12 shows the group statistics of financial ratios including mean, standard deviation and standard error mean of individual variables and Table 13 shows the variance equality mean differences between distressed and non distressed groups of firms that belong to consumer staples, consumer discretionary and health sectors. Since outliers that are greater than 4 standard deviations are deleted case by case from each variable in the financial distress models, number of firm year observations of distressed and non distressed firms differs for each financial ratio illustrated in the group statistics. In Table 12 number of distressed firms is represented by "1" and number of non distressed firms is represented by "0".

Table 12. Group Statistics of Cocohe Industry Group

Fiveyrsfull		N	Mean	Std. Deviation	Std. Error Mean
CashTL	1	782	,57456	,67697	,02421
	0	6873	,33297	,48845	,00589
CashTA	1	728	,17977	,16775	,00622
	0	6995	,11630	,12370	,00148
COGSInv	1	679	3,72103	3,43594	,13186
	0	5740	5,29980	3,75298	,04954
CLPPE	1	781	1,65484	1,64724	,05894
	0	6731	1,36447	1,31852	,01607
QASales	1	794	,49442	,42897	,01522
	0	7053	,23167	,22909	,00273
QAFEO	1	726	,43193	,29750	,01104
	0	6883	,25810	,23100	,00278
InvSales	1	846	,09045	,08806	,00303
	0	6893	,11155	,08149	,00098
SalesPPE	1	742	4,61894	4,37802	,16072
	0	6290	6,12603	4,01359	,05061
SalesWC	1	891	2,19569	3,83807	,12858
	0	5253	4,74610	4,83720	,06674
CASales	1	798	,72082	,46660	,01652
	0	7072	,38626	,26260	,00312
TLWC	1	877	1,34713	3,58877	,12118
	0	6186	1,94094	4,29926	,05466

In Table 13, EV stands for the assumption of equality of variances and EVN stands for no assumption of equality of variances. Levene's Test for equality of variances shows that, all of the financial ratios have significantly different variances, indicating the spread of the data is different between distressed and non distressed group. When we look at the observed differences between the variable means, we notice that all of the mean differences are significant at 1%, indicating the distressed and non distressed group means differ from each other for financial ratios in the Cocohe industry group.

Table 13. Independent Sample Test for Cocohe Industry Group

		Levene's Test for Equality of Variances		t-test for Equality of Means				
		F	Sig.	t	Df	Sig. (2-tailed)	Mean Difference	Std. Error Difference
CashTL	EV	231,869	,000	12,530	7653	,000	,2416	,0193
	EVN			9,697	875,913	,000	,2416	,0249
CashTA	EV	238,533	,000	12,683	7721	,000	,0635	,0050
	EVN			9,931	811,345	,000	,0635	,0064
COGSInv	EV	8,404	,004	-10,455	6417	,000	-1,5788	,1510
	EVN			-11,208	880,804	,000	-1,5788	,1409
CLPPE	EV	87,649	,000	5,663	7510	,000	,2904	,0513
	EVN			4,753	899,709	,000	,2904	,0611
QASales	EV	724,484	,000	27,369	7845	,000	,2628	,0096
	EVN			16,989	844,642	,000	,2628	,0155
QAFEO	EV	134,395	,000	18,706	7607	,000	,1738	,0093
	EVN			15,266	819,799	,000	,1738	,0114
InvSales	EV	15,736	,000	-7,044	7737	,000	-,0211	,0030
	EVN			-6,630	1030,554	,000	-,0211	,0032
SalesPPE	EV	13,837	,000	-9,578	7030	,000	-1,5071	,1573
	EVN			-8,944	894,179	,000	-1,5071	,1685
SalesWC	EV	38,701	,000	-14,959	6142	,000	-2,5504	,1705
	EVN			-17,605	1416,748	,000	-2,5504	,1449
CASales	EV	621,107	,000	30,907	7868	,000	,3346	,0108
	EVN			19,902	854,864	,000	,3346	,0168
TLWC	EV	25,728	,000	-3,902	7061	,000	-,5938	,1522
	EVN			-4,467	1261,336	,000	-,5938	,1329

Table 14 shows the group statistics and Table 15 shows the Levene's test for equality of variances as well as t-test for equality of means for Enut industry group. For the energy and utility sectors, Cash/TL, TD/WC, Cash/FEO, Cash/TA, TD/NW and Sales/TA ratios have different means at 1% significance level among the distressed and non distressed groups, while Sales/PPE, COGS/Inv and Inv/Sales have different means only at 10% significance level. Moreover, Cash/TL and Cash/TA ratios possess equal variances with unequal means, while Inv/Sales ratio possesses unequal variances with equal means. It indicates that, the distressed and non distressed group differs either in terms of mean values or in terms of spread of the data.

Table 14. Group Statistics of Enut Industry Group

Threeyrsfull		N	Mean	Std. Deviation	Std. Error Mean
CashTL	1	309	,08376	,09385	,00534
	0	2405	,06538	,08952	,00183
TDWC	1	200	1,37235	4,47622	,31652
	0	1481	-,30019	4,82674	,12542
CashFEO	1	301	,15944	,13230	,00763
	0	2386	,09361	,11489	,00235
CashTA	1	308	,04280	,03898	,00222
	0	2398	,03266	,03762	,00077
SalesPPE	1	320	,98438	1,40008	,07827
	0	2454	1,10149	1,12749	,02276
COGSInv	1	244	7,98250	4,97259	,31834
	0	1867	8,62556	4,96331	,11487
InvSales	1	290	,04963	,04660	,00274
	0	2401	,05373	,03868	,00079
TDNW	1	291	1,11385	,87724	,05142
	0	2462	,96839	,62457	,01259
SalesTA	1	328	,44825	,28091	,01551
	0	2379	,53699	,29229	,00599

Table 15. Independent Sample Test for Enut Industry Group

		Levene's Test for Equality of Variances		t-test for Equality of Means				
		F	Sig.	t	df	Sig. (2-tailed)	Mean Difference	Std. Error Difference
CashTL	EV	2,198	,138	3,379	2712	,001	,01838	,00544
	EVN			3,258	383,559	,001	,01838	,00564
TDWC	EV	7,287	,007	4,638	1679	,000	1,67254	,36059
	EVN			4,913	265,521	,000	1,67254	,34046
CashFEO	EV	21,254	,000	9,201	2685	,000	,06583	,00715
	EVN			8,249	359,381	,000	,06583	,00798
CashTA	EV	2,240	,135	4,434	2704	,000	,01014	,00229
	EVN			4,314	384,135	,000	,01014	,00235
SalesPPE	EV	2,360	,125	-1,695	2772	,090	-,11710	,06907
	EVN			-1,437	374,886	,152	-,11710	,08151
COGSInv	EV	,000	,996	-1,903	2109	,057	-,64306	,33794
	EVN			-1,900	309,715	,058	-,64306	,33843
InvSales	EV	12,312	,000	-1,666	2689	,096	-,00410	,00246
	EVN			-1,440	338,812	,151	-,00410	,00285
TDNW	EV	75,515	,000	3,578	2751	,000	,14546	,04065
	EVN			2,747	325,654	,006	,14546	,05294
SalesTA	EV	8,291	,004	-5,178	2705	,000	-,08873	,01714
	EVN			-5,336	430,585	,000	-,08873	,01663

When we examine mean and variance analysis of the industrials and materials sectors, we observe that Rec/Inv, COGS/Inv, LTD/TA and Inv/Sales ratios possess different means between distressed and non distressed group of firms at 1% level of significance. Additionally, the mean values of Sales/PPE and Cash/TL ratios also differ between groups at 5% and 10% significance level respectively. Meanwhile, for Cash/TA ratio, both Levene's Test for equality of variances and t-test for equality of means shows that, neither the spread of the data nor the mean differs between the groups. Group statistics and independent sample test of Inma industry group are illustrated in Table 16 and Table 17.

Table 16. Group Statistics of Inma Industry Group

Fiveyrsfull		N	Mean	Std. Deviation	Std. Error Mean
CashTL	1	176	,18271	,22144	,01669
	0	5322	,15300	,19787	,00271
CashTA	1	180	,08465	,08278	,00617
	0	5486	,07534	,08245	,00111
RecInv	1	171	1,17270	2,02481	,15484
	0	4741	1,74950	1,85149	,02689
COGSInv	1	163	4,62278	2,92885	,22941
	0	4463	5,94617	3,51433	,05261
SalesPPE	1	180	4,50742	4,02736	,30018
	0	5282	5,28368	4,23650	,05829
LTDTA	1	180	,22903	,16494	,01229
	0	5557	,18988	,13789	,00185
InvSales	1	153	,17868	,10861	,00878
	0	5578	,11299	,07944	,00106

Table 17. Independent Sample Test for Inma Industry Group

		Levene's Test for Equality of Variances		t-test for Equality of Means				
		F	Sig.	T	df	Sig. (2-tailed)	Mean Difference	Std. Error Difference
CashTL	EV	5,699	,017	1,952	5496	,051	,02971	,01522
	EVN			1,757	184,360	,081	,02971	,01691
CashTA	EV	,730	,393	1,491	5664	,136	,00931	,00625
	EVN			1,486	190,836	,139	,00931	,00627
RecInv	EV	1,773	,183	-3,989	4910	,000	-,57680	,14461
	EVN			-3,670	180,402	,000	-,57680	,15716
COGSInv	EV	,011	,915	-4,748	4624	,000	-1,32339	,27874
	EVN			-5,623	179,467	,000	-1,32339	,23536
SalesPPE	EV	1,774	,183	-2,421	5460	,015	-,77626	,32060
	EVN			-2,539	192,745	,012	-,77626	,30579
LTDTA	EV	17,574	,000	3,724	5735	,000	,03915	,01051
	EVN			3,149	187,193	,002	,03915	,01243
InvSales	EV	51,774	,000	9,976	5729	,000	,06568	,00658
	EVN			7,426	156,492	,000	,06568	,00884

Finally, the independent sample test for telecommunication and information technology sectors reveals that, CL/Inv, TD/PPE, QA/FEO and QA/Sales ratios have different means between groups at 1% significance level, while CL/PPE and COGS/Inv have different means between groups at 5% and 10% level of significance respectively. Moreover, TD/TA ratio possesses equal mean with unequal variances, while COGS/Inv and CL/Inv ratios possess unequal means with equal variances. Results indicate that distressed and non distressed groups differ at least in terms of group means or group variances. Group statistics and independent sample test of Tein industry group are illustrated in Table 18 and Table 19.

Table 18. Group Statistics of Tein Industry Group

fiveyrsfull		N	Mean	Std. Deviation	Std. Error Mean
CLInv	1	296	3,9909	3,9307	0,2285
	0	2648	3,2776	4,3954	0,0854
TDPPE	1	479	0,5423	0,9190	0,0420
	0	3481	0,7863	1,1228	0,0190
TDTA	1	495	0,1063	0,1429	0,0064
	0	3600	0,1116	0,1282	0,0021
COGSInv	1	289	5,9479	4,2645	0,2509
	0	2654	5,4555	4,2069	0,0817
QAFEO	1	502	0,9404	0,6002	0,0268
	0	3650	0,6934	0,4812	0,0080
QASales	1	469	0,7553	0,4272	0,0197
	0	3661	0,5480	0,3551	0,0059
CLPPE	1	497	2,3903	2,1362	0,0958
	0	3470	2,1563	1,8830	0,0320

Table 19. Independent Sample Test for Tein Industry Group

		Levene's Test for Equality of Variances		t-test for Equality of Means				
		F	Sig.	t	df	Sig. (2-tailed)	Mean Difference	Std. Error Difference
CLInv	EV	,147	,701	2,675	2942	,008	,71326	,26666
	EVN			2,924	382,398	,004	,71326	,24391
TDPPE	EV	37,169	,000	-4,550	3958	,000	-,24394	,05362
	EVN			-5,291	690,549	,000	-,24394	,04610
TDTA	EV	18,449	,000	-,850	4093	,395	-,00530	,00623
	EVN			-,783	608,412	,434	-,00530	,00677
COGSInv	EV	,649	,420	1,887	2941	,059	,49244	,26094
	EVN			1,867	351,843	,063	,49244	,26381
QAFEO	EV	47,761	,000	10,438	4150	,000	,24699	,02366
	EVN			8,838	592,879	,000	,24699	,02795
QASales	EV	35,447	,000	11,616	4128	,000	,20737	,01785
	EVN			10,076	553,964	,000	,20737	,02058
CLPPE	EV	32,617	,000	2,546	3965	,011	,23405	,09192
	EVN			2,317	611,447	,021	,23405	,10101

3.1.4. Model Estimation Process

After conducting preliminary analysis of group means and variance statistics, we estimate a proposed model by logistic analysis for each industry group separately in order to examine whether most informative financial ratios selected by the entropy method have any ability in predicting financial distress. We further analyze whether we can form industry specific financial distress prediction models (FD models) by employing these most informative financial ratios as independent variables.

To start with, Logistic Analysis provide us two basic outcomes; predictive accuracy of the overall model and significance of coefficients used in the model. Predictive accuracy of the model is determined by a classification matrix, where classification accuracy of the individual groups (distressed and non distressed firms), classification accuracy of the overall model, type I and type II errors are illustrated. In our logistic regression model, type I error corresponds to number of non distressed firms classified as distressed and type II error corresponds to number of distressed firms classified as non distressed.

In investigating the accuracy of the classification matrix and the overall model fit, there are basically three tests that have to be analyzed. First, Hosmer and Lemeshow (2000) classification test provides comparison between observed and predicted events by chi-square statistics. In the Hosmer and Lemeshow χ^2 Test, it is expected that no significant difference exists between the actual and predicted values of the dependent variable so that we can make sure of the goodness of the overall model fit. It is also important to note that, the test requires a sample of at least 50 cases, with each having at least 5 observations for the accuracy of the test results. Another measure for testing the overall model fit is the pseudo-R statistics, which includes Cox and Snell R^2 and Nagelkerke R^2 statistics. Pseudo R statistics tells us similarly but not exactly what OLS R^2 explains in linear regression models. Higher values of pseudo R^2 indicates higher values of the overall model fit. In analyzing R^2 values it is evident that, the values for Cox and Snell R^2 will always be smaller than Nagelkerke R^2 since Cox and Snell R^2 is an adjustment of Nagelkerke R^2, where maximum value for Nagelkerke R^2 equals 1 and maximum value for Cox and Snell R^2 equals 0,75. Third measure for the goodness of the overall model fit is the -2 log likelihood (-2LL) value, where smaller values for -2LL is preferable. To determine a good fitting model, we should compare -2LL value of "constant only" model with the actual model where all variables are included. If -2LL value is smaller in the actual model than in the constant only model, then it can be interpreted as a sign for a potential gain in terms of variables included in the model and a better model fit.

In the estimation process of logistic coefficients, we use Wald Statistics in assessing the significance of each independent variable. Significant values of test statistics for a particular variable indicate that, the variable has a considerable effect on the estimated probability and prediction of group membership. Unlike linear regression, logistic regression coefficients measure the change in the ratio of probabilities rather than the magnitudes. The ratio of probabilities is expressed as odds which are calculated as follows:

Odds Value = $Prob_i$ / (1 – $Prob_i$)

where odds greater than 1,0 corresponds to a probability of higher than 0,50, while odds lower than 1,0 corresponds to a probability of lower than 0,50.

As logistic regression coefficients are expressed in terms of logarithms, it is difficult to interpret them in their original form. Hence SPSS outcomes also provides exponentiated logistic coefficients, illustrated by Exp(B), which are the transformations of the original coefficients. In this respect, original coefficients reflect changes in the logged odds, while exponentiated coefficients reflect changes in the original odds values. If we interpret the original coefficients, illustrated by B, we should notice that logit values of coefficients greater than 0,0 corresponds to a positive effect on the estimated probability, while logit values of coefficients less than 0,0 corresponds to a negative effect on the estimated probability. In interpreting the exponentiated coefficients, it is important to note that, odds value equating 1,0 provides no information about the direction of the independent-dependent variable relationship. Meanwhile, exponentiated coefficients greater than 1,0 corresponds to a positive relation and exponentiated coefficients smaller than 1,0 corresponds to a negative relation among the variables.

After giving a brief summary about important factors in interpretation of the logistic analysis, in the next section we will provide outcomes of logistic regression for each industry group and evaluation of the findings.

3.2. Results of Logistic Analysis

3.2.1. Logistic Regression Outcomes of Cocohe Industry Group

In the consumer staples, consumer discretionary and health industry group, Cash/TL, Cash/TA, COGS/Inv, CL/PPE, QA/Sales, QA/FEO, Inv/Sales, Sales/PPE, Sales/WC, CA/Sales and TL/WC ratios are included as exogenous variables in the financial distress prediction model. In order to determine whether variables included in the estimated model are overall appropriate for discrimination between groups, we should check for several criteria. First criterion is to examine the log likelihood value for the overall model fit. Table 20 shows the base model iteration history that only contains the constant term.

Table 20. Iteration History of the Base Model of Cocohe Industry Group

Iteration		-2 Log likelihood	Coefficients Constant
	1	2259,486	-1,723
	2	2020,976	-2,362
	3	2005,899	-2,576
	4	2005,776	-2,597
Step 0	5	2005,776	-2,597

a. Constant is included in the model.

b. Initial -2 Log Likelihood: 2005,776

c. Estimation terminated at iteration number 5 because parameter estimates changed by less than ,001.

At step 0, the log likelihood value (-2LL) is 2005,776. This value is important in examining whether log likelihood ratio will be reduced after including the exogenous variables into the model. A reduction in the -2LL value is one of the criteria in determining the overall model fit. Table 21 shows the iteration history of the estimated model when the exogenous variables are included in the estimation process. After the inclusion of exogenous variables, -2LL value is reduced from the base model of 2005,776 to 1673,718 at step 1, indicating a considerable increase in the model fit.

Table 21. Iteration History of the Estimated Model of Cocohe Industry Group

Iteration		-2 Log likelihood	Coefficients											
			Constant	CashTL	CashTA	COGSInv	CLPPE	QASales	QAFEO	InvSales	SalesPPE	SalesWC	CASales	TLWC
Step 1	1	2093,823	-1,907	-,101	-,559	-,013	,000	1,544	-2,387	-3,537	-,008	,004	3,047	-,029
	2	1738,042	-2,496	-,209	-1,369	-,035	,023	3,490	-4,214	-6,432	-,021	-,011	4,854	-,040
	3	1678,378	-2,476	-,258	-2,369	-,063	,050	5,083	-5,290	-8,567	-,036	-,048	5,603	-,020
	4	1673,764	-2,399	-,250	-2,901	-,076	,061	5,657	-5,589	-9,272	-,043	-,069	5,757	-,003
	5	1673,718	-2,392	-,247	-2,969	-,078	,063	5,714	-5,614	-9,333	-,044	-,072	5,771	-,001
	6	1673,718	-2,392	-,247	-2,970	-,078	,063	5,715	-5,614	-9,333	-,044	-,072	5,771	-,001

a. Method: Enter

b. Constant is included in the model.

c. Initial -2 Log Likelihood: 2005,776

d. Estimation terminated at iteration number 6 because parameter estimates changed by less than ,001.

Second criterion is to look at the Omnibus Test of Model Coefficients to find out whether the model that contains exogenous variables selected for estimation process predicts financial distress better than by chance alone. In other words, the "Model" tests whether a significant difference exists between the "constant only model" and the model with independent variables. Table 22 shows that, estimated model with 11 exogenous variables significantly predicts financial distress at 1% with a Chi-square value of 332,058 better than the constant only model. The significance of the model further supports that, a significant relation exists between financial distress and financial ratios selected in the Cocohe industry group.

Table 22. Omnibus Tests of Model Coefficients of Cocohe Industry Group

		Chi-square	df	Sig.
	Step	332,058	11	,000
	Block	332,058	11	,000
Step 1	Model	332,058	11	,000

Third, we should check for the pseudo R statistics. Table 23 contains Cox and Snell R^2 and Nagelkerke R^2 with the -2LL value of the estimated model. The proportion of the variation in the financial distress variable that can be explained by the predictive power of 11 exogenous variables is 0,080 for Cox and Snell R^2 and 0,202 for Nagelkerke R^2. The higher the pseudo R statistics the better the overall model fit. It can be interpreted that, for this particular industry group, the logistic regression model accounts for at least one-fifth of the total variation between the distressed and non distressed group of firms.

Table 23. Model Summary of Cocohe Industry Group

Step	-2 Log likelihood	Cox & Snell R Square	Nagelkerke R Square
1	1673,718[a]	,080	,202

a. Estimation terminated at iteration number 6 because parameter estimates changed by less than ,001.

As a fourth criterion, we should also investigate the Hosmer and Lemeshow Test to determine the goodness of fit between the observed and predicted probabilities in classifying the distressed and non distressed group of firms. Table 24 shows that Hosmer and Lemeshow test statistics is 0,141 with 12,224 Chi-Square value, indicating no significant difference exists between observed and predicted values and the model fit is acceptable.

Table 24. Hosmer and Lemeshow Test for the Cocohe Industry Group

Step	Chi-square	df	Sig.
1	12,224	8	,141

The last examination of the overall model fit is to determine classification accuracy of the model, illustrated with a classification matrix in Table 25. The results show that, for a cut of ratio 0,059 (which minimizes both type I and type II error rates), the overall percentage of cases correctly classified is 67,2%. As the cases illustrated by one shows the distressed firms and cases illustrated by zero shows non distressed firms, the outcomes reveal that, cases of firms misclassified as distressed when they are actually non distressed is 1247 and the cases of firms misclassified as non distressed when they are actually distressed is 59 for a total of 2459 and 217 cases respectively. In other words, the percentage of cases correctly classified is 66,4% for the non distressed group and 78,6% for the distressed group of firms, where the type I and type II errors are 33,6% and 21,4% respectively.

Table 25. Classification Table of the Cocohe Industry Group

Observed			Predicted		
			Fiveyrsfull		Percentage Correct
			0	1	
Step 1	Fiveyrsfull	0	2459	1247	66,4
		1	59	217	78,6
	Overall Percentage				67,2

a. The cut value is ,059

The analysis reveals that, for both distressed and non distressed groups, prediction accuracy of the model is considerably better than chance which is 50% for each group. Additionally, the analysis also shows that, the model correctly predicts distressed group of firms more accurately than non distressed group of firms.

Variables included in the analysis, their statistical significance, the direction of the relationship and their effect on the predicted probabilities are illustrated in Table 26. To evaluate the statistical significance of the exogenous variables, we employed Wald Test statistics.

Table 26. Variables in the Equation in Cocohe Industry Group

		B	S.E.	Wald	df	Sig.	Exp(B)
Step 1[a]	CashTL	-,247	,222	1,237	1	,266	,781
	CashTA	-2,970	1,177	6,366	1	,012	,051
	COGSInv	-,078	,031	6,131	1	,013	,925
	CLPPE	,063	,106	,351	1	,553	1,065
	QASales	5,715	1,774	10,374	1	,001	303,332
	QAFEO	-5,614	,961	34,158	1	,000	,004
	InvSales	-9,333	1,693	30,387	1	,000	,000
	SalesPPE	-,044	,031	2,065	1	,151	,957
	SalesWC	-,072	,032	4,971	1	,026	,931
	CASales	5,771	1,192	23,449	1	,000	320,971
	TLWC	-,001	,040	,001	1	,974	,999
	Constant	-2,392	,401	35,514	1	,000	,091

a. Variable(s) entered on step 1: CashTL, CashTA, COGSInv, CLPPE, QASales, QAFEO, InvSales, SalesPPE, SalesWC, CASales, TLWC.

Wald Test statistics reveals that, QA/Sales, QA/FEO, Inv/Sales, CA/Sales and the constant term are statistically significant at 1%, while Cash/TA, COGS/Inv and Sales/WC are statistically significant at 5%. Contrarily, Cash/TL, CL/PPE, Sales/PPE and TL/WC are not statistically significant in explaining the predicted probability of financial distress. For the insignificant variables, we checked whether dropping them out of the model ameliorate the prediction accuracy or improve overall fit of the model. However, results reveal that, deleting one of the variables neither increases the prediction accuracy of the model nor provides an improvement in the overall model fit. Additionally, when we dropped the insignificant variables out of the model, we observe that Hosmer and Lemeshow test become significant, indicating a significant difference exists between the observed and the predicted values of the financial distress variable and hence the model fit is not acceptable. Moreover, Cox and Snell R^2 and Nagelkerke R^2 values are also decreased in the reduced model, indicating that the total variance in the financial distress variable explained by the independent variables deteriorated relative to the actual model. Hence, we conclude that although some of the variables in the actual model are not statistically significant, overall accuracy of the model is greater than the reduced model in predicting financial distress.

When we look at the direction of the relationship between statistically significant ratios and financial distress, we observe that some of the ratios possess negative sign (their Exp(B) values are below 1) and some of the ratios possess positive sign (their Exp(B) values are above 1). For the Cocohe industry group the results show that, Cash/TA, COGS/Inv, QA/FEO, Sales/WC and Inv/Sales are negatively related while CA/Sales and QA/Sales are positively related to financial distress. In other words, as the values of either CA/Sales or QA/Sales increase, the predicted probability of financial distress will also increase, which will increase the likelihood that a firm is classified as distressed. Meanwhile, as the values of Cash/TA, COGS/Inv, QA/FEO, Sales/WC and Inv/Sales increase, the likelihood that a firm is classified as distressed will decrease.

First, we examine the inventory behavior of Cocohe industry group and its effect on financial distress. COGS/Inv is a turnover ratio which is mostly affected from inventory valuation rules such as increasing raw material prices and inventory levels. Higher the COGS/Inv ratio, higher the stock turnover, indicating inventory policies are efficient, production cycle becomes shorter as a consequence of lower work-in-process inventory or high turnover resulting accounting valuation methods are preferred. COGS/Inv ratios should be evaluated with Inv/Sales Ratio, since they complement to each other. Inv/Sales ratio shows companies’ ability to manage inventories, so that an increase in this ratio is generally interpreted as ineffective inventory management and low inventory turnover. In the literature of industrial management, inventory behavior is associated with two important factors; cost of production and cost of being away from some target level of inventory. In order to stay in equilibrium between these factors, several inventory production systems are developed throughout the history. One of the frequently used production systems is called Just-in-Time production (JIT), where items are produced to meet demand rather than creating surplus or in advance of need. In the prior studies, it is observed that firms which adopt JIT production experience lower levels of Inv/Sales ratio and high inventory turnover rates (Biggart and Gargeya, 2002). However, this is not the case for all industry groups, especially for the industries that produce luxury goods or high-tech equipment, where cost of changing production is substantially expensive. Robert Morris Associates (1983) states that, industries with high cost of changing production possess the lowest industry median inventory turnover ratios relative to industries with low cost of changing production. In this respect, in the consumer discretionary and health sectors, JIT production could even reduce profitability of firms if forecasted demands do not meet the actual demand levels or coordination strategy between producers and distributers does not work effectively (Donohue, 2000).

Another reason of the negative association between inventory behavior and financial distress in the Cocohe industry can be explained with production smoothing model of inventory behavior when the production cost function is non-convex. According to the model, at low levels of output, the production function is convex, while at higher levels of output it becomes concave as a consequence of technological progress. In this type of production cost function, any small change in the demand level causes substantial shifts in the production, which results in more volatile production volumes than sales. Moreover, if firms use inventories as buffer stocks in case of a demand shock, then it is likely for these industries to experience inventory reductions when sales increase and inventory explosions when sales decrease. Especially in the consumer staples sector, where most of the firms produce non durable goods, the variance of production is greater than variance of sales. In other words, this sector tolerates a substantial departure of actual inventories from the optimum level and do not attempt to adjust inventory level immediately to future market conditions (Lovell, 1962). Moreover, for these particular industries, reduction in inventory turnover (increase in Inv/Sales) indicates that the production cost function is smoothed relative to sales, which decrease the unfavorable outcomes of demand shocks (Blinder, 1986). Hence, we can state that, unlike other sectors, decrease in Inv/Sales ratio would reduce financial distress in the Cocohe industry group.

Second, we examine QA/Sales, QA/FEO and CA/Sales ratios and their effect on financial distress. As noted earlier, logistic analysis reveals that, increase in the QA/Sales and CA/Sales ratios increase financial distress, while increase in QA/FEO ratio reduces financial distress. To understand the relationship, we should notice that quick assets include cash and cash equivalents as well as accounts receivable. The reason why QA/Sales and CA/Sales ratios increase the probability of financial distress lies in the fact that, increase in the amount of quick assets and currents assets most probably arise from the increase in the accounts receivables, indicating a problem in the collection of receivables and deterioration in the receivable turnover. Substantial increase in these accounts would also imply that, these firms with increasing levels of QA/Sales and CA/Sales ratios are inefficient in transforming excess funds for investment purposes, which would create financial distress in the long term. Notwithstanding, decrease in funds expenditures for operations relative to quick asset would imply that, the firm is capable of generating funds for investing activities, as it creates enough excess liquid assets after deducting payments for expenses.

Finally, when we look at the behavior of Cash/TA ratio for the Cocohe industry group we observe that, increase in the cash position reduces the financial distress probability of firms. We can interpret that, because of the supply contracts made between manufacturers and dealers, this industry group necessitates more liquid assets in order to circumvent bottleneck periods. Similarly, the increase in the Sales/WC ratio implies that companies effectively generate enough capital in capturing projected sales volume. In this respect, for the Cocohe industry group, increase in the effectiveness of companies' use of working capital in generating sales decreases the probability of financial distress.

In order to examine the magnitude of the relationship between the financial ratios and financial distress, we have to look at the exponentiated coefficients, Exp(B). Table 26 shows that CA/Sales and QA/Sales have the greatest magnitude in affecting the predicted probability of financial distress. In addition, among the ratios that decrease the prediction probability of distress, Inv/Sales ratio has the greatest magnitude, where its Exp(B) value is close to zero.

3.2.2. Logistic Regression Outcomes of Enut Industry Group

In the energy and utility industry group, we include Cash/TL, TD/WC, Cash/FEO, Cash/TA, Sales/PPE, COGS/Inv, Inv/Sales, TD/NW and Sales/TA ratios as independent variables in the financial distress prediction model. To examine the discriminating ability of independent variables between distressed and non distressed group of firms, we evaluate the base model iteration history, containing only the constant term in the model.

Table 27. Iteration History of the Base Model of the Enut Industry Group

Iteration		-2 Log likelihood	Coefficients
			Constant
Step 0	1	577,126	-1,599
	2	546,662	-2,084
	3	545,719	-2,190
	4	545,717	-2,195
	5	545,717	-2,195

a. Constant is included in the model.

b. Initial -2 Log Likelihood: 545,717

c. Estimation terminated at iteration number 5 because parameter estimates changed by less than ,001.

Table 27 shows that, when only the constant term is included in the model, the log likelihood ratio (-2LL) is 545,717. To examine, whether the -2LL value is reduced after the inclusion of the independent variables we should also look at the iteration history of the estimated model, illustrated in Table 28. The outcomes demonstrate a reduction in the -2LL value, from 545,717 to 473,529, indicating an improvement in the model fit when independent variables are included.

Table 28. Iteration History of the Estimated Model of Enut Industry Group

Iteration		-2 Log likelihood	Coefficients									
			Constant	CashTL	TDWC	CashFEO	CashTA	SalesPPE	COGSInv	InvSales	TDNW	SalesTA
Step 1	1	540,794	-2,450	4,126	,019	2,118	-11,715	,286	,051	6,318	,217	-1,117
	2	482,688	-3,849	7,796	,044	3,543	-21,665	,609	,112	13,607	,454	-2,654
	3	473,946	-4,494	9,960	,062	3,856	-26,816	,849	,155	18,316	,606	-4,011
	4	473,531	-4,587	10,485	,067	3,810	-27,837	,919	,165	19,362	,639	-4,457
	5	473,529	-4,588	10,513	,067	3,801	-27,874	,924	,166	19,411	,641	-4,488
	6	473,529	-4,588	10,513	,067	3,801	-27,874	,924	,166	19,411	,641	-4,488

a. Method: Enter

b. Constant is included in the model.

c. Initial -2 Log Likelihood: 545,717

d. Estimation terminated at iteration number 6 because parameter estimates changed by less than ,001.

To test whether the estimated model with the independent variables predicts financial distress better than by chance, we investigate the Omnibus Test of Model Coefficients, illustrated in Table 29.

Table 29. Omnibus Test of Model Coefficients of Enut Industry Group

		Chi-square	df	Sig.
	Step	72,188	9	,000
	Block	72,188	9	,000
Step 1	Model	72,188	9	,000

The estimated model with 9 independent variables significantly predicts financial distress at 1% with 72,188 Chi-square value. Following the overall test of model coefficients, we checked for the pseudo R statistics, illustrated in Table 30. Cox and Snell R^2 and Nagelkerke R^2 are 0,083 and 0,172 respectively. The outcomes indicate that, although the proportion of variation in the financial distress variable that can be explained by the 9 independent variables in Enut industry group is lower than Cocohe industry group, the logistic regression model accounts for a considerable amount of the total variation among distressed and non distressed groups.

Table 30. Model Summary of Enut Industry Group

Step	-2 Log likelihood	Cox & Snell R Square	Nagelkerke R Square
1	473,529[a]	,083	,172

a. Estimation terminated at iteration number 6 because parameter estimates changed by less than ,001.

We further conduct Hosmer and Lemeshow Test, as a goodness of fit measure of the model. In Table 31, it is evident that, the test statistics are insignificant with 12,926 Chi-Square level. The results indicate that, the difference between the observed and predicted values is not significant and the model fit is acceptable.

Table 31. Hosmer and Lemeshow Test for Enut Industry Group

Step	Chi-square	df	Sig.
1	12,926	8	,114

When we look at the classification matrix of Enut industry group in Table 32, we observe that the overall percentage of correctly classified cases is 62,5%. The model correctly classifies 60,5% of the non distressed firms and 81% of the distressed firms, given a cut of score of 0,077. Similar to the outcomes of Cocohe industry group, classification accuracy of the model for Enut industry group is greater in the distressed group than in the non distressed group. When we consider the issue from the lenders' point of view, higher prediction accuracy of distressed group can be interpreted as an advantage, since misclassification cost of distressed firms would be greater in terms of failing repayments of obligations.

Table 32. Classification Table of Enut Industry Group

Observed			Predicted		
			Threeyrsfull		Percentage Correct
			0	1	
Step 1	Threeyrsfull	0	456	298	60,5
		1	16	68	81,0
	Overall Percentage				62,5

a. The cut value is ,077

Table 33 illustrates variables in the equation and their test statistics. According to Wald Test statistics, Cash/TL, Cash/TA, Sales/PPE, COGS/Inv, Inv/Sales, TD/NW, Sales/TA and the constant term are statistically significant at 1%, while TD/WC and Cash/FEO are statistically significant at 5% and 10% respectively.

Table 33. Variables in the Equation in Enut Industry Group

		B	S.E.	Wald	Df	Sig.	Exp(B)
	CashTL	10,513	3,269	10,340	1	,001	36789
	TDWC	,067	,027	5,999	1	,014	1,069
	CashFEO	3,801	2,055	3,422	1	,064	44,744
	CashTA	-27,874	9,536	8,543	1	,003	,000
	SalesPPE	,924	,211	19,248	1	,000	2,519
	COGSInv	,166	,043	14,944	1	,000	1,180
	InvSales	19,411	4,913	15,612	1	,000	269295256
	TDNW	,641	,233	7,561	1	,006	1,898
	SalesTA	-4,488	1,044	18,473	1	,000	,011
Step 1[a]	Constant	-4,588	,869	27,902	1	,000	,010

a. Variable(s) entered on step 1: CashTL, TDWC, CashFEO, CashTA, SalesPPE, COGSInv, InvSales, TDNW, SalesTA.

B and Exp(B) values reveal that, Cash/TA and Sales/TA are negatively related to financial distress, while Cash/TL, TD/WC, Cash/FEO, Sales/PPE, COGS/Inv, Inv/Sales and TD/NW are positively related to financial distress. The results show that, the likelihood that a firm is classified as distressed increases as the financial ratios with positive sign increases. Notwithstanding, the likelihood that a firm is classified as distressed decreases as the financial ratios with negative sign increases.

To give a brief summary about the energy and utility industry group, the firms included in these sectors take place in the exploration, transportation and power generation of natural resources as well as transmission, distribution of electricity, water, gas, crude oil etc.. The firms which involved in the exploration and development of natural resources have primarily two options in the accounting of operating expenses. Statement of Financial Accounting Standards (SFAS) 19 introduced by FASB accepts "Successful Efforts Method" which requires capitalization of operation expenses that are successfully discovered new reserves (FASB, 1977). On the contrary, Securities and Exchange Commission (SEC), which is responsible for the regulation of the financial reporting of publicly traded firms in the US financial market, accepts "Full Cost Method" that requires capitalization of operating expenses no matter the attempt of discovery of new reserves are successful or not. In the light of these explanations, any reduction in the operating expenses and increase in long term assets would imply that the firms apply full cost method. At this point it is important to note that, one of the drawbacks of applying full cost method is the increase in amortization cost and tax obligations, thereby reduction in long term profitability. In this respect, an increase in the Cash/FEO ratio as a result of decrease in FEO would contribute to the deterioration of financial health. Along with the increase in Cash/TL ratio can also be interpreted as the firms' slowdown in appraising new investment opportunities and holding of idle cash. On the contrary, increase in the Cash/TA ratio would indicate that, firms which are conservative would likely to apply successful efforts method and thereby slow down the increase of long term assets and improve short term solvency (Machek, 2011). Consequently, increase in the Cash/TA ratio results in a reduction of financial distress for this particular industry group.

Contrary to the outcomes of Cocohe industry group, an increase in the Inv/Sales and COGS/Inv ratios results in an increase in the probability of financial distress in the Enut industry group. In order to examine the relationship, we should look at the content of inventory for the energy and utility sector. To illustrate, inventory accounts of power generation companies include raw materials (natural gas, coal-lignite, fuel oil, chemicals, etc.), spare parts (turbines, valves, transformers etc.) and operating materials (maintenance materials etc.). Meanwhile, inventory accounts of electricity distribution companies include spare parts, consumables, electrical materials, and disassembled materials. Additionally, in the utility sector, recognized allowances, certified emission reductions (CERs) not held for sale in the entities' ordinary course of business, products owned by the entities which are stored in PPE of third parties and natural resources (i.e. oil, gas, nuclear fuel etc.) purchased for storage purposes are classified as inventory. Inventory accounts include both physical and non physical inventories such that, for a nuclear fuel production company, nuclear materials (i.e. fuel rods), fuel components in the warehouse or in the reactor and allowances as a part of intangible assets are all classified as inventory. Companies in the energy and utility sectors determine cost of inventories either according to first-in-first out method or weighted average method (Wiegand and Schwieters, 2011). In these sectors, inventory behavior is primarily determined by the optimal level of production and non-storability of the inventory produced and it necessitates compensation of high demand level with just in time production. Unlike Cocohe industry group, in order energy and utility sectors to tolerate operating and construction costs (resulting from building new facilities) and political pressures that push companies to minimize profits, they have to meet the demand of customers "just in time" not to bear any extra cost (Joskow, 2003). Consequently, for the energy and utility industries, we can state that, any reduction in the inventory turnover or any increase in the cost of production would likely to increase financial distress.

When we examine the asset turnover of these industries we observe that, increase in the asset turnover ratio (Sales/TA) implies improvement in the asset utilization as well as profitability of these industries, thereby its effect on the financial distress is negative. Additionally, as the PPE stands for the value of firms' fixed assets, an increase in the Sales/PPE ratio would imply inability of the energy and utility sectors of transforming the excess fund generated from the value of services sold to the investments on long term assets, which would aggravate financial distress in these industries. Another reason of the positive association between Sales/PPE ratio and financial distress might arise from the fact that, unlike Cocohe and Inma industry groups, the productivity of energy and utility sectors heavily depends on natural resources, weather conditions and seasonality. To give an example, in cases of extreme weather conditions such as heat waves and ice and snow, short term electricity and natural gas consumption increases substantially which in turn exploits sales figures. However, in the long run those sales figures could not be captured, since the weather conditions return to average levels. Similarly, substantial changes in wind speed and cloudiness results in a considerable increase/decrease in the wind and solar generation output level. In addition, the operations of fossil fuel and nuclear power stations considerably affected from drought and elevated cooling water temperatures (Hirschberg and Abrams, 2011). For that reason, in order to sustain energy production and sales growth, companies should invest on a portfolio of energy generating assets. For instance, a company which only invests on solar power would suffer in cloudy weather. Similarly, a company which only invests on wind power plants would likely to experience a slowdown in sales figures when the weather is stagnant. On the contrary, if a company invests on an optimized generation mix, it will be able to sustain its production and sales regardless of the weather conditions (Russo, 2003). Generally speaking, since capturing sustainable sales growth is more desirable than sudden increases in the sales figure relative to PPE, it can be stated that, decrease in Sales/PPE ratio as a consequence of accelerated long term investments with a diversity of PPE portfolio would likely to reduce financial distress for this particular industry group.

In the energy and utility sector, a high level of debt is acceptable if only it is compensated by stable income. However, positive relation between financial distress and TD/WC ratio reveals that, if firms accumulate debt when their liquidity is low, they will be unable to manage their costs, which in turn will lead to an increase in their financial risk and deterioration in their short term solvency. Similarly, an increase in the TD/NW ratio also triggers reduction in return on equity and increases financial distress.

Finally, the magnitude of the variables reveals that, Inv/Sales, Cash/TL and Cash/FEO ratios have the greatest impact on increasing the probability of financial distress for Enut industry group. Meanwhile Cash/TA and Sales/TA also possess high Exp(B) values, which contributes to reduction in the probability of financial distress.

3.2.3. Logistic Regression Outcomes of Inma Industry Group

In the industrials and materials sectors, the independent variables included in the study covers Inv/Sales, Rec/Inv, LTD/TA, Cash/TA, COGS/Inv, Cash/TL and Sales/PPE. To determine the appropriateness of the overall model, we checked for the reduction in the -2LL value from the base model to the estimated model. The iteration history of the base model and the estimated model are illustrated in Table 34 and Table 35 respectively:

Table 34. Iteration History of the Base Model in Inma Industry Group

	Iteration	-2 Log likelihood	Coefficients
			Constant
	1	1783,772	-1,864
	2	1341,216	-2,727
	3	1277,855	-3,203
	4	1274,765	-3,339
	5	1274,753	-3,348
Step 0	6	1274,753	-3,348

Table 35. Iteration History of the Estimated Model of Inma Industry Group

	Iteration	-2 Log likelihood	Coefficients							
			Constant	InvSales	RecInv	LTDTA	CashTA	COGSInv	CashTL	SalesPPE
	1	1725,072	-2,752	3,438	-,018	,611	2,074	,038	-,386	-,001
	2	1196,728	-5,026	8,541	-,076	1,643	5,435	,104	-1,019	-,002
	3	1060,266	-7,175	13,812	-,237	3,044	9,578	,194	-1,810	-,006
	4	1031,932	-8,220	16,278	-,505	4,000	11,901	,260	-2,268	-,013
	5	1028,017	-8,274	16,485	-,748	4,265	12,363	,283	-2,399	-,017
	6	1027,801	-8,190	16,335	-,829	4,276	12,396	,285	-2,427	-,017
	7	1027,800	-8,183	16,321	-,835	4,276	12,397	,285	-2,429	-,017
Step 1	8	1027,800	-8,183	16,321	-,835	4,276	12,397	,285	-2,429	-,017

a. Method: Enter

b. Constant is included in the model.

c. Initial -2 Log Likelihood: 1274,753

d. Estimation terminated at iteration number 8 because parameter estimates changed by less than ,001.

Table 34 shows that, the log likelihood value for the base model when only the constant term is included in the financial distress model is 1274,753. When we look at the iteration history of the estimated model in Table 35, we observe that -2LL value is reduced from 1274,753 to 1027,800, indicating the goodness of the model fit.

The Omnibus Test of Model Coefficients, illustrated in Table 36, reveals that at 1% significance level, the model containing 7 independent variables predicts financial distress better than by chance.

Table 36. Omnibus Test of Model Coefficients in Inma Industry Group

		Chi-square	df	Sig.
	Step	246,953	7	,000
	Block	246,953	7	,000
Step 1	Model	246,953	7	,000

Table 37 illustrates the pseudo R statistics, where Cox and Snell R^2 is 0,056 and Nagelkerke R^2 is 0,218, indicating the logistic regression model accounts for more than one-fifth of the total variation between the distressed and non distressed group of firms. It is important to note that, the proportion of variation in the financial distress variable that can be explained by the 7 independent variables in Inma group is greatest among the other industry groups.

Table 37. Model Summary of Inma Industry Group

Step	-2 Log likelihood	Cox & Snell R Square	Nagelkerke R Square
1	1027,800[a]	,056	,218

a. Estimation terminated at iteration number 8 because parameter estimates changed by less than ,001.

In Table 38, Hosmer and Lemeshow Test statistics are demonstrated for Inma industry group. The insignificance of Hosmer and Lemeshow test reveals that, no significant difference exists between the observed and predicted probabilities, indicating the model fit is acceptable in classifying the group of firms as distressed and non distressed.

Table 38. Hosmer and Lemeshow Test for the Inma Industry Group

Step	Chi-square	df	Sig.
1	11,412	8	,179

In order to examine the overall model fit, we further compute the classification accuracy of the model, illustrated in Table 39.

Table 39. Classification Table of the Inma Industry Group

			Predicted		
			fiveyrsfull		Percentage Correct
Observed			0	1	
Step 1	fiveyrsfull	0	3289	865	79.2
		1	47	99	67.8
	Overall Percentage				78.8

a. The cut value is ,038

The outcomes show that, overall classification accuracy of the model is 78,8% which is the greatest overall accuracy rate among the other industry groups. When we look at the accuracy rate of individual groups, we observe that the model correctly classifies 79,2% of the non distressed firms and 67,8% of the distressed firms. Contrary to Cocohe and Enut industry groups, classification accuracy rate is higher in the non distressed group than in the distressed group, which may be due to industry specific factors.

Finally, we investigate the Wald Test statistics of independent variables included in the distress model which is illustrated in Table 40.

Table 40. Variables in the Equation in Inma Industry Group

		B	S.E.	Wald	df	Sig.	Exp(B)
	InvSales	16,321	1,625	100,898	1	,000	12249183
	RecInv	-,835	,205	16,568	1	,000	,434
	LTDTA	4,276	,702	37,126	1	,000	71,926
	CashTA	12,397	2,928	17,929	1	,000	242098
	COGSInv	,285	,039	53,678	1	,000	1,330
	CashTL	-2,429	1,326	3,354	1	,067	,088
	SalesPPE	-,017	,025	,487	1	,485	,983
Step 1[a]	Constant	-8,183	,598	187,096	1	,000	,000

a. Variable(s) entered on step 1: InvSales, RecInv, LTDTA, CashTA, COGSInv, CashTL, SalesPPE.

Wald test statistics show that, Inv/Sales, Rec/Inv, LTD/TA, Cash/TA, COGS/Inv ratios and the constant term are statistically significant at 1% and Cash/TL is statistically significant at 10%. Meanwhile, Sales/PPE ratio is not significant in predicting financial distress for Inma industry group. We conduct a logistic regression by excluding the Sales/PPE ratio to examine whether the reduced model renders any improvement in the overall model fit relative to the actual model. The outcomes show that, Hosmer and Lemeshow test become significant indicating a significant difference exists between the observed and the predicted values of financial distress and hence the model fit is not acceptable. Additionally, we further observe that, both the R^2 values and the classification accuracy rates declined relative to the actual model, indicating overall fit of the actual model is more acceptable than the reduced model.

When we look at the direction of the independent variables, B and Exp(B) values reveal that, increase in Inv/Sales, LTD/TA, Cash/TA and COGS/Inv ratios increase the probability of financial distress, while increase in Rec/Inv and Cash/TL decrease the probability of financial distress for this particular industry group. When we compare the outcomes of Industrials and materials sectors with other industry groups we observe that, the direction of the variables are in line with energy and utility sectors, but they are in opposite direction with consumer staples, consumer discretionary and health sectors. Unlike Cocohe industry group, industrials and materials sectors produce durable goods rather than non durable goods. As Blinder (1986) mentions in his article that variance of sales is greater than variance of production in the manufacturing firms that produce durable goods. For that reason, in the industrials and materials sector, decrease in the output and inventory variance leads to a reduction in the Inv/Sales ratio which can be interpreted as an improvement of inventory management techniques (Irvine and Schuh, 2005). In consequence, any upward movement in the Inv/Sales and COGS/Inv ratios would indicate increase in financial distress for the Inma industry group. Strengthening the adverse effect of low inventory turnover on financial distress, Rec/Inv ratio further shows that, increase in the receivable turnover relative to inventory can be interpreted as an improvement in the firms' short term solvency which in turn decreases the probability of financial distress.

To continue with the asset and liquidity structure of the industrials and materials sectors, we observe that the relation between Cash/TA, Cash/TL ratios and financial distress is completely different from the other industry groups. For this particular industry group, increase in the Cash/TA ratio increases the probability of financial distress, while increase in the Cash/TL ratio decreases the probability of financial distress. First, the reason of the relationship between Cash/TA ratio and financial distress might lie in the fact that, although possessing a liquid asset structure is interpreted as an evidence of financial strength, this may not be the case when firms accumulate too much cash holdings in lieu of appraising certain investment opportunities. Second, the relation between Cash/TA and financial distress might arise from the fact that, although increase in the liquidity position of the firms compensate the short term financial obligations and reduce financial distress, neglecting the opportunity of directing available cash resources to building new PPE, downgrades the affirmative impact of short term solvency.

Table 41. Comparison of Industry Groups in Processing Long-Term Investment Opportunities

	N	Minimum	Maximum	Mean	Std. Deviation
CASHTA_Tein	4214	0	.83355	.27674	.20331
PPETA_Tein	4229	0	.70792	.17062	.14682
CASHTA_Inma	5666	0	.40226	.07563	.08247
PPETA_Inma	5783	0	.92449	.31032	.18968
CASHTA_Enut	2706	0	.17244	.03381	.03791
PPETA_Enut	2849	0	.95074	.64828	.19194
CASHTA_Cocohe	7723	0	.57075	.12229	.12982
PPETA_Cocohe	8085	0	.93313	.26096	.19535

To examine understand why cash/TA have negative coefficient in the Inma industry group, we compare the maximum and mean Cash/TA and PPE/TA ratios of each industry group and question whether Inma industry group do not process available cash resources into long term investment opportunities as much as other industry groups. We use the PPE/TA ratio as an indicator of long term investments processed by the firms as a percentage of total assets. In Table 41 it is observed that, Enut industry group possess the lowest cash holdings while Tein industry group possess the highest cash holdings available for long term investment opportunities. Additionally, Cocohe and Inma industry groups hold cash resources 12,2% and 7,5% of their total assets respectively. When we compare PPE/TA ratios, we detect that mean values of PPE/TA are 26% for the Cocohe, 31% for the Inma, 17% for the Tein and 65% in the Enut industry groups. We further observe that, the maximum levels of PPE/TA ratios are quite similar between industry groups, excluding Tein in which maximum level of PPE encloses 70% of the total assets. For the Inma industry group, given the mean and maximum values of PPE/TA and Cash/TA ratios, we cannot find any evidence regarding the inefficient use of cash resources or poor processing of long term investment opportunities. (See also descriptive statistics of financial statement accounts for Cocohe, Enut, Inma and Tein industry groups in the Appendix C). We also compare Cash/TA and PPE/TA ratios of Inma industry group with the industry averages of industrials and materials sectors to examine whether above average industry level of Cash/TA ratio results in an increase in the financial distress. However, the outcomes reveal that, both Cash/TA and PPE/TA ratios of Inma industry group are at industry averages. In addition, we compare Cash/CL and TD/NW ratios of Inma with the industry averages as well as with the other industry groups to investigate whether a problem exists in firms' ability of paying short term obligations or whether the proportion of debt to equity is too high in financing assets. However, we again could not find any evidence regarding an unnatural business activity of Inma industry group that could explain the relation between Cash/TA and financial distress. Consequently, the reason of the positive association between Cash/TA and financial distress for this particular industry group is left as a future research subject to be discussed and examined in more detail.

To continue with the Sales/PPE ratio of Inma industry group, the inverse relation between this ratio and financial distress might indicate that firms efficiently process long term investment opportunities when sales volume increases more than PPE. In this respect, increase in sales more than the increase in long term investments ameliorates long term profitability for the Inma industry group. Finally, when we examine the relation between LTD/TA and financial distress, we observe that increase in the long term borrowings relative to total assets deteriorates the short term solvency of firms, thereby precipitating the probability of financial distress.

In terms of magnitude, Inv/Sales, Cash/TA and LTD/TA dominate other financial ratios in affecting the prediction probability of financial distress model. Additionally, among the ratios that decrease the prediction probability of distress, Cash/TL ratio has the greatest magnitude, where the Exp(B) value is close to zero.

3.2.4. Logistic Regression Outcomes of Tein Industry Group

In the telecommunication and information technology industry group, CL/Inv, TD/PPE, TD/TA, COGS/Inv, QA/FEO, QA/Sales and CL/PPE are included as exogenous variables into the financial distress prediction model. First, we compare the base model and estimated model iteration histories to find out whether any reduction occurred in the log likelihood ratio as a consequence of inclusion of 7 variables in the model.

Table 42. Iteration History of the Base Model of Tein Industry Group

	Iteration	-2 Log likelihood	Coefficients Constant
	1	1629,227	-1,639
	2	1522,072	-2,170
	3	1517,892	-2,302
	4	1517,880	-2,310
Step 0	5	1517,880	-2,310

a. Constant is included in the model.

b. Initial -2 Log Likelihood: 1517,880

c. Estimation terminated at iteration number 5 because parameter estimates changed by less than ,001.

In Table 42, when the model contains only the constant term at step 0, -2LL value is 1517,880 while at step 1, when the model contains both the constant term and the 7 exogenous variables, -2LL value is reduced by 135,083 and decreased down to 1382,797. The reduction of the -2LL value shows a considerable improvement in the model fit. Iteration history of the estimated model is illustrated in Table 43.

Table 43. Iteration History of the Estimated Model of Tein Industry Group

Iteration		-2 Log likelihood	Coefficients							
			Constant	CLInv	TDPPE	TDTA	COGSInv	QAFEO	QASales	CLPPE
Step 1	1	1557,830	-2,281	-,010	-,274	2,161	,025	-,824	1,622	,086
	2	1399,889	-3,507	-,024	-,618	4,731	,052	-1,481	2,972	,184
	3	1383,297	-4,069	-,035	-,889	6,512	,067	-1,769	3,589	,243
	4	1382,798	-4,154	-,037	-,967	6,913	,070	-1,821	3,692	,253
	5	1382,797	-4,155	-,037	-,971	6,931	,070	-1,822	3,695	,253
	6	1382,797	-4,155	-,037	-,971	6,931	,070	-1,822	3,695	,253

a, Method: Enter

b, Constant is included in the model,

c, Initial -2 Log Likelihood: 1517,880

d, Estimation terminated at iteration number 6 because parameter estimates changed by less than ,001, When we analyze the overall test of the model illustrated in Table 44, we observe that the prediction of financial distress model with 7 exogenous variables possesses a higher performance than predicting by chance. The Chi-square test statistics shows that, at 1% significance level the estimated model accurately predicts financial distress.

Table 44. Omnibus Test of Model Coefficients of Tein Industry Group

		Chi-square	df	Sig.
	Step	135,083	7	,000
	Block	135,083	7	,000
Step 1	Model	135,083	7	,000

Pseudo R statistics are further investigated for the overall model fit. Table 45 shows that, the proportion of variation in the financial distress variable that can be explained by the predictive power of 7 exogenous variables is 0,053 for Cox and Snell R^2 and 0,116 for the Nagelkerke R^2 statistics. The outcomes reveal that, although Tein industry group possesses the lowest variance proportion explained among the other industry groups, the logistic regression model accounts for more than one-tenth of the total variation between distress and non distress group of firms.

Table 45. Model Summary of Tein Industry Group

Step	-2 Log likelihood	Cox & Snell R Square	Nagelkerke R Square
1	1382,797[a]	,053	,116

a. Estimation terminated at iteration number 6 because parameter estimates changed by less than ,001.

Next, we examine Hosmer and Lemeshow test statistics to observe whether there is a significant difference between observed and predicted probabilities in classifying distressed and non distressed groups. In Table 46, Hosmer and Lemeshow test results reveal that, the difference between observed and predicted probabilities are not statistically significant, indicating the model fit is acceptable.

Table 46. Hosmer and Lemeshow Test for the Tein Industry Group

Step	Chi-square	df	Sig.
1	12,490	8	,131

Finally we checked for the classification accuracy of the overall model as well as the individual group accuracies to determine the predictive power of the financial distress model in Tein industry group. The classification matrix illustrated in Table 47 shows that, 69,7% of the overall model is correctly classified for a 0,088 cut of score. Classification accuracy of the non distressed group is 70,1%, while classification accuracy of the distressed group is 65%, indicating the financial distress model predicts non distressed firms more accurately than distressed firms. When we compare classification accuracy rates of Tein industry group with other industry groups we observe that, misclassified cases in the distressed group of firms are highest among the others. The results indicate that, the model of Tein industry group is not as powerful as other industry groups in predicting financial distress.

Table 47. Classification Table of Tein Industry Group

			Predicted		
			fiveyrsfull		Percentage Correct
Observed			0	1	
Step 1	Fiveyrsfull	0	1597	680	70,1
		1	79	147	65,0
	Overall Percentage				69,7

a. The cut value is ,088

When we look at the Wald test statistics of the exogenous variables in Table 48, we observe that all of the variables, except CL/Inv, are statistically significant at 1% in predicting financial distress. To examine whether a reduced model better predicts financial distress than the actual model, we rerun a logistic regression by dropping CL/Inv out of the model. However, the outcomes of Hosmer and Lemeshow test and Pseudo R statistics reveal that, the prediction accuracy of the actual model is greater than the reduced model.

The sign of the financial ratio coefficients show that, TD/PPE, QA/FEO and the constant term are negatively related to financial distress, while TD/TA, COGS/Inv, QA/Sales and CL/PPE are positively related to financial distress. In other words, increase in financial ratios with the negative coefficients reduces the probability of financial distress, while increase in financial ratios with positive coefficients increases the probability of financial distress. If we examine the magnitude of the independent variables, we observe that TD/TA and QA/Sales contributes most to the predicted probability of financial distress.

Table 48. Variables in the Equation in Tein Industry Group

		B	S.E.	Wald	df	Sig.	Exp(B)
	CLInv	-,037	,023	2,494	1	,114	,964
	TDPPE	-,971	,156	38,572	1	,000	,379
	TDTA	6,931	1,004	47,632	1	,000	1023
	COGSInv	,070	,020	12,189	1	,000	1,072
	QAFEO	-1,822	,445	16,772	1	,000	,162
	QASales	3,695	,525	49,451	1	,000	40,240
	CLPPE	,253	,048	27,864	1	,000	1,288
Step 1[a]	Constant	-4,155	,242	293,901	1	,000	,016

a. Variable(s) entered on step 1: CLInv, TDPPE, TDTA, COGSInv, QAFEO, QASales, CLPPE.

To begin with, we should clarify the reason of the inverse relation between TD/PPE and CL/PPE in terms of their effect on financial distress. Keeping the long term investments constant, increase in the short term portion of the total liabilities increases financial distress, while increase in the long term borrowings decreases financial distress. In order to understand this outcome, we have to examine the financial needs of high tech firms along with the market structure of these industries. First, in the telecommunication and information technology industries, there are high barriers to entry, since innovative activities necessitates substantial market power. Second, marketing and R&D expenditures are so expensive that, in order to compete with big competitors high volumes of external financing is inevitable. Third, since it is almost the greatest capital intensive industry group, telecommunication and information technology sectors should stay alert and continuously replace old technologies with new ones to cope with the instantly changing environment and technology patterns (Giudici and Paleari, 2000). Because of the above mentioned facts, these high tech industries require long term borrowings in processing long term investment opportunities in order to survive in the market. Additionally, if high tech firms pay off long term investments with short term obligations, cost of financing will increase which unfavorably affects short term solvency and increase financial distress.

Similarly, the reason why TD/TA ratio possess the greatest magnitude in increasing financial distress lies in the fact that, the high tech industries are open to risk of failure in developing new technologies as well as the risk of investing in obsolete projects. In this respect, SFAS 2 requires immediate expensing most of the R&D expenditures especially in the high tech firms where the risk of failure in developing new technologies is high (FASB, 1974). Consequently, for this particular industry group, if increases in R&D costs and financing cannot be compensated with successful asset management, increase in the probability of financial distress becomes unavoidable.

When we look at the short term asset structure we observe that, QA/FEO reduces the probability of financial distress, while QA/Sales increases the probability of financial distress. Given that quick assets include receivable account, an upward movement in the receivables relative to sales indicates that, firms experience problems in the collection of receivables or the collection periods are too long. In addition, increase in the accounts receivable would also indicate that, firms dominantly generate sales on account, which would create liquidity problems in the long run and increase the probability of financial distress. Contrarily, increase in the quick assets relative to funds expenditures for operations shows that, firms are able to cover operating expenses with short term assets and improve their short term solvency.

Finally, unlike the inventory behavior of manufacturing sector, in order high tech firms to survive in the market and compete with the competitors, they have to minimize the gap between actual and optimum level of inventories and adjust their stocks due to anticipated price changes. Moreover, high tech firms necessitate a higher degree of accounting conservatism in order to stay competitive in the market and to overcome bottleneck periods. In this respect, it expected that high tech firms adopt LIFO method, which is more conservative than the other inventory methods. However the study of Kwon et al. (2006) reveals that, only 3% of the high tech firms adopt LIFO method, while rest of them prefer using FIFO or average cost method (Kwon et al., 2006). In light of the findings, if cost of inventory sold continues to rise despite of adopting the least conservative FIFO method, increase in the gap between actual and optimum level of output will be fatal, which in turn will aggravate over-valuation of inventories and precipitate the probability of financial distress.

Overall, the results of logistic analysis reveal that, the effect of financial ratios on the probability of financial distress varies due to industry characteristics. Although an increase in a particular ratio may precipitate financial distress for a certain industry group, it may reduce the probability of financial distress for another industry group. To give an example, Cash/TA and Cash/TL ratios have the opposite sign between Enut and Inma industry groups. Similarly, the sign of the Sales/PPE ratio is negative in Cocohe and Inma industry groups, while it is positive in Enut industry group. Moreover, COGS/Inv and Inv/Sales ratios are negatively related to financial distress in the Cocohe industry group, while they are positively related to financial distress in the Enut and Inma industry groups. The reason of the change in the sign of the coefficients between industries would arise from three factors. First, coefficients with unexpected signs would indicate multicollinearity among the predictor variables (Gunst, 1983). In order to clarify whether the sign of the coefficients are affected from multicollinearity, we dropped the predictor variables which are significantly correlated with the other predictor variables. We rerun a logistic regression to examine whether sign of the coefficients differ between the actual and the reduced model. However, the outcomes reveal that, although significantly correlated variables are excluded from the model, the sign of the remaining variables did not change. In this respect, the results indicate that, the difference in the sign of the coefficients among different industry groups does not arise from multicollinearity between the predictor variables.

Second, the reason of the different signs for the same predictor variables between industry groups might arise from industry characteristics. For instance, inventory behavior of the energy and utility sectors are completely different from manufacturing sector, since most of the inventories of energy and utility sectors consist of spare parts, while the inventories of manufacturing sector include raw materials, work in process and finished goods. Similarly, the inventory behavior of durable and non durable goods also varies in terms of length of production and stock turnover period, output-stock equilibrium level, volume of fabrication of purchased materials, goods in process and finished goods as well as sales volume and expectations (Lovell, 1961). Notwithstanding, fixed asset composition (plant size, level of mechanization, vertical integration, nature of the production process and etc.) and sales behavior are also completely different between utility sector and manufacturing sector. In order to examine the relation of Sales/PPE ratio with financial distress between these industry groups, we should consider production characteristics of the industries such as capacity utilization, structure of the leased assets (whether they are owned or leased for a certain period), age of the plants and managerial efficiency. We should further consider economic characteristics of the industries as well, since they directly affect the level of fixed asset turnover. To give an example, industries that produce apparel, leather, tobacco, furniture and food possess the greatest fixed asset turnover among other industries, since their composition of asset structure are directly related to manufacturing operations. On the contrary industries such as primary metal and petroleum possess lower levels of fixed assets since they hold higher volumes of natural resources, which are indirectly related to manufacturing operations (Gupta and Huefner, 1972). Hence, the sign of the ratios would likely to differ between industry groups as a result of varying industry and economic characteristics.

Third, the sign of the coefficients for the same predictor variables would vary between industry groups since the optimum level of each financial ratio differs not only for each industry group but also for each firm, depending on the firm structure. In this respect, the effect of financial ratios on the financial distress of firms is nonlinear, since increase/decrease in the financial ratios up to an optimum level would likely to reduce financial distress, but after the optimum level, increase/decrease in the financial ratios would precipitate financial distress. To give an example, increase in the level of Cash/TA can be interpreted as a sign of short term liquidity, since high levels of cash holdings would likely to reduce transaction costs and serves as a buffer in meeting highly volatile input prices (Baum et al., 2006). On the other hand, after a certain level of liquidity, ongoing increase in the cash holdings can be regarded as a slowdown in the evaluation process of long term investment opportunities. Provided that firms' liquidity decisions are taken by the management depending on future profit perceptions, capital investment needs and uncertainty level of the industry that the firm belongs, an increase in the Cash/TA ratio to a certain level can be interpreted as a sign of financial health, while after that level its positive effect on financial health would likely to disappear. Such an outcome can be extended for all financial ratios that provide information about the optimum asset and capital structure of a firm. For that reason, we can state that, since financial ratios are nonlinearly related to financial distress variable, sign of the coefficients of predictor variables would likely to vary between industry groups.

In this respect, the outcomes once again demonstrate the importance of using industry specific financial ratios in determining the level of financial distress. Since industry specific financial distress models provide detailed information about sector specific risks along with industry characteristics, financial statement users would benefit from employing them in decision making purposes.

In the next section as a robustness test, we will conduct split sample validation test for each financial distress model to examine whether the prediction accuracy of the models are robust and holds for a restricted sample of data as well.

3.3. Split-Sample Validation Results of Logistic Analysis

In this section, we conduct split-sample validation test for each industry group to examine whether prediction accuracy of the financial distress model developed by the logistic analysis holds for a restricted sample of data as well. In this respect, we performed 80-20 split-sample validation, where 80% of the sample data is randomly selected as the training sample and 20% as the hold out sample. We employed "Uniform" function to generate random values in SPSS, where the minimum value is set to 0 and maximum value is set to 1. The random values generated which are less than 0,80 are classified in the training sample and the rest is classified in the hold out sample. In order to make sure that the accuracy of the financial distress models hold for the restricted sample of data we have to check two subjects. First, we should check whether the difference of total accuracy rates between the training and the hold out sample exceeds 10%. Second, we should examine whether the overall accuracy rate is greater than 50% for both the training and the hold out sample. If the difference of the accuracy rates between the samples exceeds 10%, then we can conclude that the prediction accuracy of the model varies between subsamples (James et al., 2005). Additionally, if the overall accuracy rate is below 50%, we can state that the model predicts financial distress not any better than predicting by chance (Hair et al, 2005).

Table 49 shows the classification accuracy table of the validation sample for the Cocohe industry group. The results reveal that, overall classification accuracy of the training sample is 76,9% and the overall classification accuracy of the holdout sample is 74,5%. Since the difference between the overall accuracy rates of training and holdout samples is less than 10% and both of the rates exceed by chance criterion, we can support the previous findings of logistic analysis that, the financial distress model of the Cocohe industry group accurately classifies firms as distressed and non distressed.

Table 49. Classification Table of Validation Sample for Cocohe Industry Group

Observed			Predicted					
			Selected Cases[b]			Unselected Cases[c,d]		
			Fiveyrsfull		Percentage Correct	Fiveyrsfull		Percentage Correct
			0	1		0	1	
Step 1	Fiveyrsfull	0	2281	648	77,9	582	195	74,9
		1	78	140	64,2	18	40	69,0
	Overall Percentage				76,9			74,5

a. The cut value is ,059

b. Selected cases split LT 0,80

c. Unselected cases split GE 0,20

d. Some of the unselected cases are not classified due to either missing values in the independent variables or categorical variables with values out of the range of the selected cases.

In table 50, we demonstrate the split-sample validation outcomes of the Enut industry group. Classification table shows that, the overall accuracy rate of the training and the hold out samples are 63% and 65,7% respectively. As split sample validation supports the prior findings of logistic analysis, we can state that, the financial distress model of Enut industry group accurately predicts distressed and non distressed firms for different subsamples.

Table 50. Classification Table of Validation Sample for Enut Industry Group

Observed			Predicted: Selected Cases[b] Threeyrsfull 0	1	Percentage Correct	Unselected Cases[c,d] Threeyrsfull 0	1	Percentage Correct
Step 1	Threeyrsfull	0	362	242	59,9	93	57	62,0
		1	12	53	81,5	1	18	94,7
	Overall Percentage				62,0			65,7

a. The cut value is ,077

b. Selected cases Split LT 0,80

c. Unselected cases Split GE 0,20

d. Some of the unselected cases are not classified due to either missing values in the independent variables or categorical variables with values out of the range of the selected cases.

Table 51 shows the classification table of validation sample in Inma industry group where overall accuracy of the training and holdout sample are 78,7% and 76,7% respectively. Since the difference of overall accuracy rates are below 10% and the prediction accuracy of the overall model is greater than by chance criterion, we can conclude that the prediction accuracy of the financial distress model for the Inma industry group is true for different subsamples.

Table 51. Classification Table of Validation Sample for Inma Industry Group

Observed			Predicted: Selected Cases[b] fiveyrsfull 0	1	Percentage Correct	Unselected Cases[c,d] fiveyrsfull 0	1	Percentage Correct
Step 1	fiveyrsfull	0	2629	698	79,0	638	189	77,1
		1	35	84	70,6	10	17	63,0
	Overall Percentage				78,7			76,7

a. The cut value is ,038

b. Selected cases split LT 0,80

c. Unselected cases split GE 0,20

d. Some of the unselected cases are not classified due to either missing values in the independent variables or categorical variables with values out of the range of the selected cases.

Finally, Table 52 illustrates the split sample validation outcomes for the Tein industry group. The overall accuracy rate of training and holdout samples are 70,8% and 68,2% respectively. We can confirm previous outcomes of logistic analysis that, the prediction accuracy of the financial distress model for Tein industry group can be supported for different subsamples.

Table 52. Classification Table of the Validation Sample for Tein Industry Group

			Predicted					
			Selected Cases[b]			Unselected Cases[c,d]		
			fiveyrsfull		Percentage Correct	fiveyrsfull		Percentage Correct
Observed			0	1		0	1	
Step 1	fiveyrsfull	0	1301	528	71.1	311	137	69.4
		1	59	122	67.4	20	25	55.6
	Overall Percentage				70.8			68.2

a. The cut value is ,088

b. Selected cases Split LT 0,80

c. Unselected cases Split GE 0,20

d. Some of the unselected cases are not classified due to either missing values in the independent variables or categorical variables with values out of the range of the selected cases.

To sum up, for each industry specific financial distress model, split-sample validation test reveals that, even if we draw different subsets of data from the same sample set, the predictive accuracy of the overall models stay considerably stable. Although it is likely that the holdout samples are less consistent in classifying the dependent variables, we observe that the selection of variables is substantially consistent among the samples. Following the outcomes, we can assert that the strength of the financial distress models developed by logistic analysis can be supported even with a smaller sample set.

In Table 53, we further illustrate the financial ratios used in our industry specific financial distress models with the classification accuracy rates of each industry group as well as the financial ratios employed in Altman's, Ohlson's, Taffler's and Zmijewski's models. The table shows that, except TD/TA and Sales/TA, financial ratios employed by the industry specific financial distress models and the four most popular models in the literature are quite different. The usage of different financial ratios from the literature might arise from the fact that, the ratios selected in our models aim to reflect industrial variations, while those ratios employed in the prior studies aim to reflect general performance of firms without considering the industry characteristics. Moreover, the table also reveals that, none of the four most popular models employ cash based ratios. Contrarily in our industry specific financial distress models we employ several cash related ratios as they possess more timely information. Consequently, although our industry specific financial distress models are significantly correlated with Altman's, Ohlson's, Taffler's and Zmijewski's models in terms of measuring financial distress, the content of independent variables employed in the formulation of the models is completely different.

Table 53. Financial Ratios Employed in FD Models and Other Most Popular Studies

Classification Rates	FD_{Cocohe}	FD_{Enut}	FD_{Inma}	FD_{Tein}
0	66,4	60,5	79,2	70,1
1	78,6	81,0	67,8	65,0
Overall	67,2	62,5	78,8	69,7
Ratios	Cash/TL	Cash/TL	Cash/TL	CL/Inv
	Cash/TA	Cash/TA	Cash/TA	TD/PPE
	COGS/Inv	COGS/Inv	COGS/Inv	COGS/Inv
	CL/PPE	Cash/FEO	LTD/TA	CL/PPE
	Sales/PPE	Sales/PPE	Sales/PPE	QA/FEO
	QA/FEO	TD/WC	Rec/Inv	QA/Sales
	Inv/Sales	Inv/Sales	Inv/Sales	TD/TA
	QA/Sales	TD/NW		
	Sales/WC	Sales/TA		
	CA/Sales			
	TL/WC			

Ratios in Well Known Studies	Altman (1968)	Ohlson (1980)	Taffler (1983)	Zmijewski (1984)
	WC/TA	SIZE	EBIT/CL	NI/TA
	RE/TA	TL/TA	CA/TL	TD/TA
	EBIT/TA	WC/TA	CL/TA	CA/CL
	MVE/BVTD	CL/CA	NCI	
	Sales/TA	OENEG		
		NI/TA		
		FFO/TL		
		INTWO		
		CHIN		

3.4. Industry Specific FD Models

In this section, we construct industry specific FD models for Cocohe, Enut, Inma and Tein industry groups using the output obtained from logistic analysis. Then, we compare the predictive ability of our FD models with Taffler's (1983) Z-score model to demonstrate whether our industry specific FD models are as powerful as a Z-score model which is recognized as "one of the most reliable model in predicting company failure in the UK” (Smith and Graves, 2005).

As previously stated in the previous sections of the study, Taffler’s Z-score model is demonstrated by the following equation:

$$Z_{Taffler} = 3.20 + 12.18X_1 + 2.50X_2 - 10.68X_3 + 0.0289X_4$$

where X_1 refers to Profit Before Tax/Average Current Liabilities, X_2 refers to Current Assets/Total Liabilities, X_3 refers to Current Liabilities/Total Assets and X_4 refers to No Credit Interval which is calculated as (Current Assets – Inventory – Current Liabilities)/(Sales – Profit Before Tax + Depreciation).

Taffler’s Z-score model is not only used in prediction of failure but also in identification and selection of financially distressed companies. In this respect, firms that possess negative Z-scores are classified as financially distressed and firms with positive Z-scores are classified as non distressed. The reason why we prefer to compare our model with Taffler’s Z-score model rather than comparing it with other bankruptcy or bankruptcy based financial distress studies i.e. Altman’s (1968), Ohlson’s (1980) or Zmijewski’s (1984) Z-score models lies in the fact that, our model includes distressed firms rather than bankrupt firms. When we run Altman’s, Ohlson’s and Zmijewski’s Z-score models with the sample of firms we use in the current study, we observe that all of the firms are classified as non bankrupt since these models are only used in predicting bankruptcy rather than predicting financial distress. On the contrary, when we run Taffler’s Z-score model with the current sample used in this study, we obtain comparable outcomes with our industry specific distress models.

To start with, in the Cocohe industry group, we run the following FD model that we find from logistic regression analysis:

FD_{Cocohe} = -2.392 - 0.247*CashTL - 2.970*CashTA - 0.078*COGSInv + 0.063*CLPPE + 5.715*QASales - 5.614*QAFEO - 9.333*InvSales - 0.044*SalesPPE - 0.072*SalesWC + 5.771*CASales

The outcomes show that, from a total of 4011 cases (only the number of cases excluding missing data are counted), FD model for the Cocohe industry group misclassifies 663 of the cases, while for the same sample of firms, Taffler's Z-score model misclassifies 756 of the cases. In other words, classification accuracy of the overall FD_{Cocohe} model is 83,5%, while classification accuracy of the $Z_{Taffler}$ model is 81,2%. The outcomes indicate that, the industry specific FD model performs slightly better than Taffler's financial distress model for the consumer staple, consumer discretionary and health industry group of firms.

When we look at the other industry groups, we observe similar findings. For the energy and utility industry group of firms we derived the following model from the logistic analysis:

FD_{Enut} = -4.588 + 10.513*CashTL + 0.067*TDWC + 3.801*CashFEO - 27.874*CashTA + 0.924*SalesPPE + 0.166*COGSInv + 19.411*InvSales + 0.641*TDNW - 4.488*SalesTA

After we run the FD_{Enut} model we observe that, from 838 of the cases only 88 cases are misclassified. On the contrary, for the same industry group of firms Taffler's model misclassifies 307 of the cases. The results show that, for the energy and utility industry group of firms the industry specific FD model performs substantially better than Taffler's Z-score model where classification accuracy of the FD_{Enut} model is 89,5%, while classification accuracy of the $Z_{Taffler}$ model is 63,4%.

Continuing with the industrials and materials industry group of firms, logistic regression analysis constructs the following FD model in predicting financial distress:

FD_{Inma} = -8.183 + 16.321*InvSales - 0.835*RecInv + 4.276*LTDTA + 12.397*CashTA + 0.285*COGSInv - 2.429*CashTL - 0.017*SalesPPE

Running the FD model for the Inma industry group the outcomes reveal that, out of 4300 cases, FD_{Inma} Model misclassifies only 135 of cases while, Taffler's Z-score model misclassifies 313 of the cases. In other words, classification accuracy of the industry specific FD model is 96,9%, while classification accuracy of the Taffler's financial distress model is 92,7%, indicating FD_{Inma} model outperforms $Z_{Taffler}$ for the industrials and materials group of firms.

Finally, for the telecommunication and information technology industry group, we derive the following FD model from the logistic regression analysis:

FD_{Tein} = -4.155 - 0.037*CLInv - 0.971*TDPPE + 6.931*TDTA + 0.070*COGSInv - 1.822*QAFEO + 3.695*QASales + 0.253*CLPPE

The outcomes show that, out of 2503 cases, FD model for Tein industry group misclassifies 228 of the cases, whereas Taffler's Z-score model misclassifies 586 of the cases. To put it in another way, the industry specific FD model classifies 90,9% of the firm year observations correctly, while Taffler's Z-score model classifies only 76,6% of the cases correctly. The outcomes indicate that, FD_{Tein} model performs substantially better than $Z_{Taffler}$ model in predicting financial distress.

To sum up, in all of the industry groups, the FD models developed by industry specific financial ratios performs better than the most popular and frequently used financial distress model in UK, Taffler's Z-score model. We can state that, when we employ industry specific financial ratios and develop industry specific financial distress models, we improve the predicting accuracy of the distress models so that they become more informative for the financial statement users.

Finally, for comparison purposes, we examine whether our industry specific FD models are correlated with other most popular distress models.

First, in addition to Taffler's Z-score model, we compute Altman's (1968) and Ohlson's (1980) Z-score models for each industry group covering the 1990-2011 period. Then, we derive Spearman's Correlation to observe whether the industry specific financial distress models have any statistical dependence with other distress models. Spearman' Correlation Test outcomes are illustrated in Table 54, Table 55, Table 56 and Table 57 for Cocohe, Enut, Inma and Tein industry groups respectively.

Table 54. Spearman Correlation Test of Cocohe Industry Group

			Z_{Ohlson}	$Z_{Taffler}$	$Z_{Zmijewski}$	FD_{Cocohe}
Spearman's rho						
	Z_{Ohlson}	Correlation Coefficient	1,000	-,637**	,779**	-,075**
		Sig, (2-tailed)		0,000	0,000	,000
	$Z_{Taffler}$	Correlation Coefficient	-,637**	1,000	-,437**	,054**
		Sig, (2-tailed)	0,000		,000	,004
	$Z_{Zmijewski}$	Correlation Coefficient	,779**	-,437**	1,000	-,040*
		Sig, (2-tailed)	0,000	,000		,033
	FD_{Cocohe}	Correlation Coefficient	-,075**	,054**	-,040*	1,000
		Sig, (2-tailed)	,000	,004	,033	

**, Correlation is significant at the 0,01 level (2-tailed),

*, Correlation is significant at the 0,05 level (2-tailed),

c, Listwise N = 2817

Table 55. Spearman Correlation Test of Enut Industry Group

			$Z_{Taffler}$	$Z_{Zmijewski}$	Z_{Ohlson}	FD_{Enut}
Spearman's rho	$Z_{Taffler}$	Correlation Coefficient	1,000	-,422**	-,596**	,181**
		Sig, (2-tailed)		,000	,000	,000
	$Z_{Zmijewski}$	Correlation Coefficient	-,422**	1,000	,719**	,241**
		Sig, (2-tailed)	,000		,000	,000
	Z_{Ohlson}	Correlation Coefficient	-,596**	,719**	1,000	-,106**
		Sig, (2-tailed)	,000	,000		,004
	FD_{Enut}	Correlation Coefficient	,181**	,241**	-,106**	1,000
		Sig, (2-tailed)	,000	,000	,004	

**, Correlation is significant at the 0,01 level (2-tailed),

b, Listwise N = 729

Table 56. Spearman Correlation Test of Inma Industry Group

			$Z_{Taffler}$	$Z_{Zmijewski}$	Z_{Ohlson}	FD_{Inma}
Spearman's rho	$Z_{Taffler}$	Correlation Coefficient	1,000	-,375**	-,617**	-,180**
		Sig, (2-tailed)		,000	0,000	,000
	$Z_{Zmijewski}$	Correlation Coefficient	-,375**	1,000	,751**	,185**
		Sig, (2-tailed)	,000		0,000	,000
	Z_{Ohlson}	Correlation Coefficient	-,617**	,751**	1,000	,243**
		Sig, (2-tailed)	0,000	0,000		,000
	FD_{Inma}	Correlation Coefficient	-,180**	,185**	,243**	1,000
		Sig, (2-tailed)	,000	,000	,000	

**, Correlation is significant at the 0,01 level (2-tailed),
b, Listwise N = 4000

Table 57. Spearman Correlation Test of Tein Industry Group

			$Z_{Taffler}$	$Z_{Zmijewski}$	Z_{Ohlson}	FD_{Tein}
Spearman's rho	$Z_{Taffler}$	Correlation Coefficient	1,000	-,674**	-,775**	-,184**
		Sig, (2-tailed)		,000	0,000	,000
	$Z_{Zmijewski}$	Correlation Coefficient	-,674**	1,000	,783**	,275**
		Sig, (2-tailed)	,000		0,000	,000
	Z_{Ohlson}	Correlation Coefficient	-,775**	,783**	1,000	,202**
		Sig, (2-tailed)	0,000	0,000		,000
	FD_{Tein}	Correlation Coefficient	-,184**	,275**	,202**	1,000
		Sig, (2-tailed)	,000	,000	,000	

**, Correlation is significant at the 0,01 level (2-tailed),

b, Listwise N = 1711

There are two reasons why we prefer Spearman's Correlation to other correlation tests (i.e. Pearson's and Kendall's Correlation Test). First, the financial distress model derived in this study is a monotonic and non linear function which fits best with the Spearman non parametric correlation test. Second, Spearman Rank Correlation does not require normality assumption, so that non normality of the financial ratios would not create any problem in deriving the correlation matrix.

The outcomes of Spearman Correlation show that, in all of the industry groups, correlation exists between Altman's, Ohlson's, Zmijewski's, Taffler's and industry specific FD models at 1% significance level. The existence of the negative correlation between some of the models depends on the nature of the financial ratios selected in prediction of financial distress so that the sign of the financial distress variable changes in each of the model. Overall, we can interpret that, there is a strong association between the models in terms of measuring financial distress.

3.5. Concluding Remarks

This study attempts to formulate industry specific financial distress models to reduce the information mass available to financial statements users. Following Yli-Olli and Virtanen (1984), we conduct factor analysis for the S&P 1500 firms that are active in the market as of March, 2011 and derived the most informative financial ratios for each industry group, which show stable patterns between the 1990-2011 periods. We further conduct principal component analysis to compose industry specific classification patterns of financial ratios selected from the factor analysis. After obtaining the initial ratio set for each industry group from the factor analysis, we conduct entropy method to verify industry specific financial ratios that possess the highest information content in determining uncertainty level of industry groups. We use industry specific financial ratios derived from the entropy method as independent variables in the logistic regression analysis and attempt to generate industry specific financial distress models. The results show that, industry specific financial distress models for all of the industry groups accurately predict financial distress, while classification accuracy rates diverge between the industry groups. For instance, energy and utility industry group possess the highest prediction accuracy in classifying distress firms (81%), while industrials and materials sector have the highest prediction accuracy in classifying non distressed firms (79,2%). To check the robustness of the outcomes, we conduct split sample validation test for each industry group to examine whether prediction accuracy of the industry specific financial distress models also holds for a restricted sample of data as well. The results show that, the prediction accuracy of the models shows stable patterns between different subsamples.

After obtaining the industry specific financial distress models we derived FD-score of each firm and compare the prediction outcomes of our models with the Z-score model of Taffler's (1986), which is cited as the most reliable financial distress model used in the UK. The outcomes reveal that, prediction accuracy of the industry specific FD models is greater than the prediction accuracy of Taffler's Z-score model for all of the industry groups.

Our results could have several direct applications. First the results show those financial ratios which are going to be used for a particular industry. Since industry characteristics are very difficult to be quantified in themselves, it is important to observe the financial ratios that correspond to a certain set of industry characteristics. In this respect, financial ratios serve as surrogates in specifying the set of industry characteristics. Second, since there are numerous amounts of financial ratios, financial statement users face with the problem of selecting irrelevant information. Our results would also contribute to the literature by providing the optimum information set. In other words, rather than using all ratios available in the literature, the researchers will be able to use financial ratios that have the highest information content and those ratios that will demonstrate the characteristics of that particular industry. Third, our results would further find applicability in certain phases of planning at the firm, industry and even at the microeconomic level. At the firm level, if we adjust financial ratios to industry averages, we will also be able to adjust uncertainty of individual firms according to industry averages derived from entropy measures. It will become easy for a firm to evaluate its own ratios by referencing to a group average. At the microeconomic level, ascertaining the uncertainty of industries will provide information in planning and forecasting definite future investment needs of a particular industry. Consequently, governments would supply incentives by determining benefit-cost as well as capital-output relations and by assessing the tolerable levels of uncertainty for industries. Finally, our study provides useful insight to financial statement users in determining the financial distress of firms.

Although there are considerable amounts of financial distress models in the accounting literature, they lack industry related information and treat all firms equally, as if they are from the same industry groups. On the contrary, since we use industry specific financial ratios in generating financial distress models for each industry group separately, prediction accuracy of our models reflect industry related information as well. As a consequence, industry specific financial distress models would find applicability in notifying financial statement users regarding reasons of financial distress for different industry groups.

For future research, industry specific financial ratios can be analyzed in detail and mean values of distressed firms' financial ratios for each industry group could be compared to actual industry averages to examine whether firms classified as distressed by the industry specific FD models possess financial ratio levels below industry averages. In generating financial distress models, it is noted that we either use matched sample design or determine a range for mean asset size of distressed and non distressed firms. In this respect, as a future research subject, distressed and non distressed s&p 1500 firms could be matched in terms of asset size to evaluate whether an improvemenet in the prediction accuracy rate of FD models would be observed.

We could also conduct industry specific financial distress models for firms other than S&P 1500 firms to investigate whether prediction accuracy of the models could be generalized. As noted earlier, it is observed that, although some of the coefficients of predictor variables possess positive sign for one industry group, they turn out to be negative for another industry group. We concluded that, the reason of the changing signs would arise either from industry characteristics or from the non linear relation between financial distress and predictor variables. For future research, to examine the precision of these findings, industry specific financial distress models could be regenerated by different sample of firms. In this respect, we can compare the coefficient signs of the predictor variables in the actual model and the regenerated model to examine whether sign of the coefficients show stable patterns for different sample of firms.

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APPENDICES

A. LIST OF S&P FIRMS INCLUDED IN THE STUDY

3D SYSTEMS CORP
3M COMPANY
AAON, INC.
AAR CORP
AARON'S, INC.
ABAXIS INC
ABBOTT LABORATORIES
ABERCROMBIE & FITCH
ABM INDUSTRIES INC
ACCENTURE PLC
ACI WORLDWIDE INC
ACTUANT CORPORATION
ACXIOM (R) CORP
ADOBE SYSTEMS INC
ADTRAN INC
ADVANCED ENERGY INDS
ADVANCED MICRO
ADVENT SOFTWARE, INC
AEGION CORP
AEROPOSTALE, INC.
AES CORP (THE)
AETNA INC
AFFYMETRIX, INC.
AGCO CORP
AGILENT TECHNOLOGIES
AGILYSYS INC
AGL RESOURCES INC
AIR METHODS CORP
AIR PRODUCTS & CHEMS
AIRGAS INC
AK STEEL HOLDING
AKAMAI TECHNOLOGIES
AKORN, INC.
ALASKA AIR GROUP INC
ALBANY INTERNATIONAL
ALBEMARLE CORP
ALCOA INC
ALEXANDER & BALDWIN
ALIGN TECHNOLOGY INC
ALLEGHENY TECHNOLOGS
ALLERGAN INC
ALLETE, INC.
ALLIANCE DATA SYSTEM
ALLIANCE ONE INTL
ALLIANT ENERGY CORP
ALLIANT TECHSYSTEMS
ALLSCRIPTS HEALTH
ALMOST FAMILY, INC.
ALTERA CORPORATION
ALTRIA GROUP INC
AMAZON.COM INC
AMCOL INTL CORP
AMEDISYS, INC.
AMEREN CORPORATION
AMERICAN EAGLE
AMERICAN ELECTRIC
AMERICAN GREETINGS
AMERICAN SCIENCE
AMERICAN STATES WATE
AMERICAN VANGUARD
AMERISOURCEBERGEN
AMETEK INC
AMGEN INC
AMN HEALTHCARE
AMPHENOL CORP
AMSURG CORP.
ANADARKO PETROLEUM
ANALOG DEVICES, INC.
ANALOGIC CORPORATION
ANDERSONS INC
ANIXTER INT'L
ANN INC
ANSYS, INC.
APACHE CORPORATION
APOGEE ENTERPRISES
APOLLO GROUP, INC.
APPLE INC
APPLIED IND'L TECH
APPLIED MATERIALS
APTARGROUP, INC.
AQUA AMERICA, INC.
ARBITRON INC
ARCH COAL, INC.
ARCHER DANIELS MIDL.
ARCTIC CAT INC.
ARKANSAS BEST CORP
ARQULE, INC.
ARRIS GROUP INC.
ARROW ELECTRONICS
ASCENA RETAIL
ASHLAND INC
ASTEC INDUSTRIES INC
AT&T INC
ATLANTIC TELE-NET
ATMEL CORPORATION
ATMI INC
ATMOS ENERGY CORP
ATWOOD OCEANICS INC
AUTODESK INC
AUTOMATIC DATA PROC
AUTONATION INC
AUTOZONE INC
AVERY DENNISON CORP
AVID TECHNOLOGY INC
AVISTA CORPORATION
AVNET INC
AVON PRODUCTS INC
AZZ INCORPORATED
BADGER METER, INC.
BAKER HUGHES INC
BALCHEM CORPORATION
BALL CORPORATION
BALLY TECHNOLOGIES
BARD, (C.R.) INC.
BARNES & NOBLE
BARNES GROUP INC
BAXTER INTERNATIONAL
BE AEROSPACE, INC.
BEAM INC
BECTON, DICKINSON
BED BATH & BEYOND
BEL FUSE
BELDEN INC.
BEMIS COMPANY INC
BENCHMARK ELECTRONIC
BEST BUY CO INC
BIG 5 SPORTING GOODS
BIG LOTS, INC.
BIGLARI HOLDING
BIOGEN IDEC INC.
BIO-RAD LABORATORIES
BIO-REFERENCE LABS
BJ'S RESTAURANTS INC
BLACK BOX CORP
BLACK HILLS CORP

CARPENTER
BLYTH INC
BMC SOFTWARE INC
BOB EVANS FARMS, INC
BOEING COMPANY (THE)
BORGWARNER INC
BOSTON BEER COMPANY
BOSTON SCIENTIFIC
BOTTOMLINE TECH
BOYD GAMING CORP
BRADY CORP
BRIGGS & STRATTON
BRIGHTPOINT INC
BRINKER INT'L
BRINK'S COMPANY
BRISTOL-MYERS SQUIBB
BRISTOW GROUP INC.
BROADCOM CORPORATION
BROOKS AUTOMATION
BROWN FORMAN CORP
BROWN SHOE CO
BRUNSWICK CORP
BUCKEYE TECHNOLOGIES
BUCKLE, INC. (THE)
BUFFALO WILD WINGS
CA INC
CABLEVISION SYSTEMS
CABOT CORPORATION
CABOT MICROELECTRON
CABOT OIL & GAS CORP
CACI INTERNATIONAL
CADENCE DESIGN SYST
CALAVO GROWERS INC
CALGON CARBON CORP
CALLAWAY GOLF CO
CAL-MAIN FOODS INC
CAMBREX CORPORATION
CAMERON INTL CORP
CAMPBELL SOUP CO
CANTEL MEDICAL CORP.
CARBO CERAMICS INC.
CARDINAL HEALTH, INC
CAREER EDUCATION CO
CARLISLE COMPANIES
CARMAX INC

COCA-COLA
CARNIVAL CORPORATION
TECHNOLOGY
CARTER'S, INC.
CASCADE CORPORATION
CASEY'S GEN STORES
CASTLE (A.M.) & CO
CATALYST HEALTH
CATERPILLAR INC
CATO CORPORATION
CBS CORPORATION
CDI CORP
CEC ENTERTAINMENT
CELGENE CORPORATION
CENTERPOINT ENERGY
CENTRAL GARDEN & PET
CENTRAL VERMONT PUB
CENTURY ALUMINUM CO
CENTURYLINK
CERADYNE, INC.
CERNER CORPORATION
CH ENERGY GROUP, INC
CH ROBINSON WORLD
CHARLES RIVER LAB
CHECKPOINT SYSTEMS
CHEESECAKE FACTORY
CHEMED CORPORATION
CHESAPEAKE ENERGY
CHEVRON CORPORATION
CHICO'S FAS INC
CHILDREN'S PLACE
CHRISTOPHER & BANKS
CHURCH & DWIGHT CO
CIBER, INC.
CIENA CORPORATION
CIGNA CORP
CINCINNATI BELL
CINTAS CORPORATION
CIRCOR INTERNATIONAL
CIRRUS LOGIC, INC.
CISCO SYSTEMS, INC.
CITRIX SYSTEMS INC
CLARCOR INC
CLEAN HARBORS, INC.
CLECO CORPORATION
CLIFFS NATURAL

CLOROX COMPANY (THE)
CMS ENERGY CORP
COACH INC
COMPANY
COCA-COLA ENTERPR
COGNEX CORP
COGNIZANT TECHNOLOGY
COHU, INC.
COINSTAR INC
COLDWATER CREEK INC
COLGATE-PALMOLIVE
COLLECTIVE BRAND
COMCAST CORPORATION
COMFORT SYSTEMS USA
COMMERCIAL METALS CO
COMMUNITY HEALTH
COMPASS MINERALS
COMPUTER PROGRAMS &
COMPUTER SCIENCES
COMPUWARE CORP
COMSTOCK RESOURCES
COMTECH TELECOM
CONAGRA FOODS INC
CONCUR TECHNOLOGIES
CONMED CORPORATION
CONOCOPHILLIPS
CONSOL ENERGY INC.
CONSOLIDATED EDISON
CONSOLIDATED GRAPHIC
CONSTELLATION BRANDS
CONVERGYS CORP
CON-WAY INC
COOPER COMPANIES INC
COOPER INDUSTRIES
COPART INC
CORELOGIC, INC
CORINTHIAN COLLEGES
CORN PRODUCTS INT'L
CORNING INCORPORATED
CORPORATE EXEC BOARD
CORRECTIONS CORPORTN
CORVEL CORPORATION
COSTCO WHOLESALE
COVANCE INC

COVENTRY HEALTH CAR
CRACKER BARREL
CRANE CO
CREE, INC.
CROSS COUNTRY HEALTI
CROWN CASTLE INT'L
CRYOLIFE, INC.
CSG SYSTEMS INT'L
CSX CORPORATION
CTS CORP
CUBIC CORPORATION
CUBIST PHARMA
CUMMINS INC.
CURTISS-WRIGHT CORP
CVS CAREMARK
CYBERONICS, INC.
CYMER INC
CYPRESS SEMICONDUCTI
CYTEC INDUSTRIES INC
D.R. HORTON, INC.
DAKTRONICS, INC.
DANAHER CORP
DARDEN RESTAURANTS
DARLING INT'L INC.
DAVITA, INC.
DEAN FOODS CO.
DECKERS OUTDOOR COR
DEERE & COMPANY
DELL INC.
DELTIC TIMBER CORP
DELUXE CORPORATION
DENTSPLY INTL INC
DEVON ENERGY CORP
DEVRY INC.
DIAMOND OFFSHR DRILL
DIEBOLD, INC.
DIGI INTERNATIONAL
DIGITAL GEN
DIGITAL RIVER, INC.
DINEEQUITY, INC
DIODES INCORPORATED
DIRECTV
DOLLAR TREE, INC
DOMINION RESOURCES
DONALDSON CO INC
DOVER CORP
DOW CHEMICAL COMPAN
DREW INDUSTRIES INC
DRIL-QUIP, INC
DSP GROUP INC
DST SYSTEMS, INC.
DTE ENERGY CO
DU PONT DE NEMOURS
DUKE ENERGY CORP
DYCOM INDUSTRIES INC
EAGLE MATERIALS, INC
EASTMAN CHEMICAL CO
EATON CORPORATION
EBAY INC.
EBIX, INC.
ECOLAB INC
EDISON INTERNATIONAL
EDWARDS LIFESCIENCES
EL PASO CORPORATION
EL PASO ELECTRIC CO
ELECTRO SCIENTIFIC
ELECTRONIC ARTS, INC
EMC CORP
EMCOR GROUP, INC.
EMERSON ELECTRIC CO.
ENCORE CAPITAL GRP
ENCORE WIRE CORP
ENERGEN CORP
ENTERGY CORPORATION
ENZO BIOCHEM INC
EOG RESOURCES, INC.
EPIQ SYSTEMS, INC.
EQT CORPORATION
EQUIFAX INC.
EQUINIX, INC.
ERESEARCHTECH
ESCO TECHNOLOGIES
ESTEE LAUDER CO
ESTERLINE TECH CORP
ETHAN ALLEN INTERIOR
EXAR CORPORATION
EXELON CORPORATION
EXPEDITORS INTL WASH
EXPONENT, INC.
EXPRESS SCRIPTS
EXTERRAN HOLD
EXXON MOBIL CORP
F5 NETWORKS INC
FACTSET RESEARCH SYS
FAIR ISAAC CORP.
FAIRCHILD SEMICOND
FAMILY DOLLAR STORES
FARO TECHNOLOGIES
FASTENAL COMPANY
FEDERAL SIGNAL CORP
FEDEX CORP
FEI COMPANY
FIFTH & PACIFIC COS
FINISH LINE, INC THE
FIRSTENERGY CORP
FISERV INC
FLIR SYSTEMS INC
FLOWERS FOODS INC
FLOWSERVE CORP
FLUOR CORPORATION
FMC CORPORATION
FMC TECHNOLOGIES
FOOT LOCKER, INC
FORD MOTOR COMPANY
FOREST LABS INC
FOREST OIL CORP
FORRESTER RESEARCH
FORWARD AIR CORP
FOSSIL INC
FRANKLIN ELECTRIC CO
FRED'S, INC.
FREEPORT-MCMORAN
FRONTIER COMMUN
FTI CONSULTING INC
FULLER (H B) CO
G&K SERVICES INC
GAMESTOP CORPORATIO
GANNETT CO INC
GAP, INC (THE)
GARDNER DENVER INC
GARTNER INC
GATX CORP
GENCORP INC.
GENERAL CABLE CORP
GENERAL COMMN INC

GENERAL DYNAMICS
GENERAL ELECTRIC CO.
GENERAL MILLS, INC.
GENESCO INC.
GEN-PROBE INC
GENTEX CORPORATION
GENTIVA HEALTH SERVI
GENUINE PARTS CO
GEO GROUP, INC.
GEORESOURCES, INC.
GIBRALTAR INDUSTRIES
GILEAD SCIENCES, INC
GLOBAL PAYMENTS INC
GOODRICH CORPORATION
GOODYEAR TIRE&RUBBEI
GRACO INC
GRAINGER (W.W.), INC
GRANITE CONSTRUCTION
GREAT PLAINS ENERGY
GREATBATCH INC
GREEN MOUNTAIN
GREIF INC
GRIFFON CORPORATION
GROUP 1 AUTOMOTIVE
GUESS ?, INC.
GULF ISLAND
GULFPORT ENERGY CORP
H&R BLOCK INC
H.J. HEINZ COMPANY
HAEMONETICS CORP
HAIN CELESTIAL GROUP
HALLIBURTON COMPANY
HANGER ORTHOPEDIC
HARLEY-DAVIDSON INC
HARMAN INT'L INDUST
HARMONIC INC.
HARRIS CORPORATION
HARRIS TEETER SUPER
HARSCO CORPORATION
HARTE-HANKS, INC.
HASBRO INC
HAVERTY FURNITURE
HAWAIIAN ELECTRIC
HAWKINS, INC.
HAYNES INTERNATIONAL
HEADWATERS, INC.
HEALTH MGMT ASSOC
HEALTH NET INC
HEALTHCARE SVCS
HEALTHWAYS INC
HEARTLAND EXPRESS
HEIDRICK & STRUGGLES
HELEN OF TROY LTD
HELIX ENERGY
HELMERICH & PAYNE
HENRY, (JACK) & ASSC
HERMAN MILLER INC
HERSHEY CO (THE)
HESS CORPORATION
HEWLETT-PACKARD CO.
HIBBETT SPORTS INC.
HILL-ROM HOLDINGS
HI-TECH PHARMACAL CO.
HMS HOLDINGS CORP
HNI CORPORATION
HOLLYFRONTIER
HOLOGIC INC
HOME DEPOT, INC.
HONEYWELL INTERNATN
HORMEL FOODS CORP
HOT TOPIC, INC.
HUB GROUP, INC.
HUBBELL INC
HUMANA INC.
HUNT (J.B.) TRANSPRT
ICONIX BRAND GROUP
ICU MEDICAL, INC.
IDACORP, INC.
IDEX CORP
IDEXX LABORATORIES
IGATE CORPORATION
II-CI INCORPORATED
ILLINOIS TOOL WORKS
INFORMATICA CORP
INFOSPACE, INC.
INGERSOLL-RAND
INGRAM MICRO INC.
INSIGHT ENTERPRISES
INSPERITY, INC.
INTEGRA LIFESCI
INTEGRA LIFESCI
INTEGRATED DEVICE
INTEGRYS ENGY GRP
INTEL CORPORATION
INTEL CORPORATION
INTER PARFUMS, INC.
INTERACTIVE
INTERFACE, INC.
INTERMEC INC
INTERNATIONAL PAPER
INTERPUBLIC GROUP
INTERSIL CORPORATION
INTEVAC, INC.
INT'L BUSINESS MACHS
INTL FLAVORS&FRAGRAI
INT'L GAME TECH
INT'L RECTIFIER
INT'L SPEEDWAY CORP
INTUIT INC
INTUITIVE SURGICAL
INVACARE CORPORATIOI
ION GEOPHYSICAL
IRON MOUNTAIN INC
ITRON INC
ITT CORPORATION
ITT EDUCATIONAL SVCS
J & J SNACK FOODS
J.M. SMUCKER CO
J2 GLOBAL INC
JABIL CIRCUIT INC
JACK IN THE BOX INC
JACOBS ENG GROUP INC
JAKKS PACIFIC, INC.
JDA SOFTWARE GROUP
JDS UNIPHASE CORP
JOHNSON & JOHNSON
JOHNSON CONTROLS
JOS A BANK CLOTH
JOY GLOBAL, INC.
JUNIPER NETWORKS INC
KAISER ALUMINUM CORI
KAMAN CORPORATION
KANSAS CITY SOUTHERN
KAYDON CORP
KB HOME

KELLOGG COMPANY
KELLY SERVICES, INC.
KENNAMETAL INC
KENSEY NASH CORP
KIMBERLY-CLARK CORP
KINDRED HEALTHCARE
KIRBY CORP
KIRKLAND'S, INC.
KLA-TENCOR CORP
KNIGHT TRANSPORT
KOHLS CORPORATION
KOPIN CORP
KORN/FERRY INT'L
KRAFT FOODS INC
KROGER CO. (THE)
K-SWISS INC
KULICKE AND SOFFA
L-3 COMMUNICATIONS
LAB CORP OF AMERICA
LACLEDE GROUP INC
LAM RESEARCH CORP
LAMAR ADVERTISING CO
LANCASTER COLONY
LANDAUER INC
LANDSTAR SYSTEM INC.
LAWSON PRODUCTS, INC
LA-Z-BOY INCORP
LEGGETT & PLATT INC
LENNAR CORP
LENNOX INTERNATIONA
LEXMARK INTERNATL
LIFE TECHN
LIFEPOINT HOSPITALS
LILLY (ELI) AND CO.
LIMITED BRANDS INC
LINCARE HOLDINGS INC
LINCOLN ELECTRIC
LINDSAY CORPORATION
LINEAR TECHNOLOGY
LITHIA MOTORS INC
LITTELFUSE INC
LIVEPERSON, INC.
LKQ CORPORATION
LOCKHEED MARTIN COR
LOUISIANA-PACIFIC
LOWE'S COMPANIES INC
LSB INDUSTRIES INC
LSI CORPORATION
LUFKIN INDUSTRIES
LYDALL, INC.
M.D.C. HOLDINGS, INC
M/I HOMES, INC.
MACY'S, INC.
MAGELLAN HEALTH INC
MANHATTAN ASSOCIATE
MANPOWER
MANTECH INTL
MARATHON OIL CORP.
MARCUS CORP
MARINEMAX, INC.
MARRIOTT INT'L
MARTIN MARIETTA MAT
MASCO CORP
MATERION CORP
MATRIX SERVICE CO
MATTEL, INC.
MATTHEWS INT'L CORP
MAXIMUS INC
MCCORMICK & CO INC
MCDONALD'S CORP
MCGRAW-HILLS COS
MCKESSON CORPORATIO
MDU RESOURCES GROUP
MEADWESTVACO CORP
MEASUREMENT SPECIAL
MEDICINES COMPANY
MEDICIS PHARMA CORP
MEDIFAST INC
MEDNAX, INC.
MEDTRONIC, INC.
MEMC ELECTRONIC
MEN'S WEARHOUSE INC
MENTOR GRAPHICS CORP
MERCK & CO INC
MERCURY COMPUTER SY
MEREDITH CORP
MERIDIAN BIOSCIENCE
MERIT MEDICAL SYSTEM
MERITAGE HOMES CORP
METHODE ELECTRONICS
METTLER-TOLEDO INT'L
MICREL, INCORPORATED
MICROCHIP TECHNOLOGY
MICRON TECHNOLOGY
MICROS SYSTEMS INC
MICROSEMI CORP
MICROSOFT CORP
MICROSTRATEGY INC
MINE SAFETY
MINERALS TECHNO
MKS INSTRUMENTS, INC
MOBILE MINI INC
MOHAWK INDUSTRIES
MOLEX INCORPORATED
MOLSON COORS BREW
MONARCH CASINO
MONRO MUFFLER BRAKE
MONSANTO COMPANY
MONSTER BEVERAGE
MONSTER WORLDWIDE
MOOG INC.
MOTOROLA SOLUTIONS
MOVADO GROUP INC
MSC INDUSTRIAL
MTS SYSTEMS CORP
MUELLER INDUSTRIES
MULTIMEDIA GAMES
MURPHY OIL CORP
MYERS INDUSTRIES
MYLAN INC
NABORS INDUSTRIES
NANOMETRICS, INC.
NASHFINCH COMPANY
NATIONAL FUEL GAS CO
NATIONAL INSTRUMENTS
NATIONAL PRESTO IND
NATL OILWELL VARCO
NATUS MEDICAL
NAVIGANT CONSULTING
NCI BUILDING SYSTEMS
NCR CORPORATION
NEOGEN CORPORATION
NETAPP INC.
NETFLIX INC
NETGEAR, INC.

NETSCOUT SYSTEMS INC
NEW JERSEY RESOURCES
NEW YORK TIMES CO.
NEWELL RUBBERMAID
NEWFIELD EXPLORATION
NEWMARKET CORP
NEWMONT MINING CORP
NEWPORT CORPORATION
NEWS CORPORATION
NEXTERA ENERGY
NIKE INC.
NISOURCE INC
NOBLE CORPORATION
NOBLE ENERGY, INC.
NORDSON CORPORATION
NORDSTROM, INC.
NORFOLK SOUTHERN
NORTHEAST UTILITIES
NORTHROP GRUMMAN
NORTHWEST NAT. GAS
NORTHWESTERN CORP
NOVATEL WIRELESS INC
NOVELLUS SYSTEMS INC
NRG ENERGY INC.
NUCOR CORPORATION
NUTRISYSTEM INC
NV ENERGY INC.
NVIDIA CORPORATION
NVR, INC.
O REILLY AUTOMOTIVE
OCCIDENTAL PETROLEUM
OCEANEERING INTL
OFFICE DEPOT, INC.
OFFICEMAX INC
OGE ENERGY CORP
OIL STATES INTL
OLD DOMINION FREIGHT
OLIN CORP
OLYMPIC STEEL, INC.
OM GROUP, INC.
OMNICARE, INC.
OMNICELL, INC.
OMNICOM GROUP INC
ON ASSIGNMENT, INC.
ONEOK, INC.
OPLINK COMM INC
OPNET TECHNOLOGIE
ORACLE CORPORATION
ORBITAL SCIENCES
OSHKOSH CORPORATION
OSI SYSTEMS, INC.
OVERSEAS SHIPHOLDING
OWENS & MINOR, INC.
OWENS-ILLINOI, INC.
OXFORD INDUSTRIES
OYO GEOSPACE CORP
P.F. CHANG'S CHINA
PACCAR INC.
PACKAGING CORP
PALL CORPORATION
PALOMAR MEDICAL TECH
PANERA BREAD CO
PAPA JOHN'S INT'L
PAR PHARMACEUTICAL
PARAMETRIC TECH CORP
PAREXEL INT'L CORP
PARK ELECTROCHEMICAL
PARKER-HANNIFIN CORP
PATTERSON CO INC
PATTERSON-UTI ENGY
PAYCHEX INC
PCTEL, INC.
PEABODY ENERGY CORP
PEET'S COFFEE
PENN VIRGINIA CORP
PENNEY (J.C.) CO.
PENTAIR INC
PEP BOYS-MANNY
PEPCO HOLDINGS, INC.
PEPSICO, INC.
PERICOM SEMICOND
PERKINELMER INC
PERRIGO CO
PERRY ELLIS
PETROLEUM
PETROQUEST ENERGY
PETSMART INC
PFIZER INC
PG&E CORPORATION
PIEDMONT NATURAL GAS
PINNACLE ENTERTAINMT
PINNACLE WEST CAPTL
PIONEER DRILLING
PIONEER NATURAL RES
PITNEY BOWES INC.
PLAINS EXPLOR & PROD
PLANTRONICS, INC.
PLEXUS CORP
PNM RESOURCES, INC.
POLARIS INDUSTRIES
POLYCOM INC
POLYONE CORP
POOL CORPORATION
POWELL INDUSTRIES
POWER INTEGRATIONS
PPG INDUSTRIES INC
PPL CORP
PRAXAIR, INC.
PRECISION CASTPARTS
PRICELINE.COM INC
PROCTER & GAMBLE CO
PROGRESS ENERGY INC
PROGRESS SOFTWARE
PSS WORLD MEDICAL,
PUBLIC SVC ENTRPR GR
PULSE ELECTRONIC
PULTEGROUP
PVH
QLOGIC CORP
QUAKER CHEMICAL COR
QUALCOMM INC
QUALITY SYSTEMS, INC
QUANEX BUILDING
QUANTA SERVICES, INC
QUEST DIAGNOSTICS
QUEST SOFTWARE INC
QUESTAR CORPORATION
QUESTCOR PHARM.
QUICKSILVER RESOURCE
QUIKSILVER, INC.
R R DONNELLEY & SONS
RADIOSHACK CORP
RADISYS CORP
RALCORP HOLDINGS INC
RALPH LAUREN

RANGE RESOURCES CORI
RAYTHEON COMPANY
RED HAT, INC.
RED ROBIN GOURMET
REGAL
REGENERON PHARMA
REGIS CORP
RELIANCE STEEL
RENT-A-CENTER, INC.
REPUBLIC SERVICES
RESMED INC.
RESOURCES CONNECTIOI
REYNOLDS AMERICAN
RF MICRO DEVICES INC
ROBBINS & MYERS, INC
ROBERT HALF INTL INC
ROCK-TENN COMPANY
ROCKWELL AUTOMATIOI
ROCKWELL COLLINS INC
ROFIN-SINAR TECHNO
ROGERS CORPORATION
ROLLINS, INC.
ROPER INDUSTRIES INC
ROSS STORES, INC.
ROVI CORPORATION
ROWAN COMPANIES PLC
RPM INTERNATIONAL
RTI INT'L METALS
RUBY TUESDAY INC
RUDOLPH TECHNOLOGIE
RYDER SYSTEM, INC.
RYLAND GROUP, INC
SAFEWAY INC
SAKS INCORPORATED
SALIX PHARMACEUTICAI
SANDERSON FARMS INC
SANDISK CORP
SARA LEE CORPORATION
SAVIENT PHARMATCLS
SCANA CORPORATION
SCANSOURCE, INC.
SCHEIN (HENRY) INC
SCHLUMBERGER LIMITEI
SCHOLASTIC CORP
SCHULMAN (A) INC
SCHWEITZER-MAUDUIT
SCIENTIFIC GAMES
SCOTTS MIRACLE-GRO
SCRIPPS (E.W.) CO
SEACOR HOLDINGS INC.
SEALED AIR CORP
SEARS HOLDINGS CORP
SELECT COMFORT CORF
SEMPRA ENERGY
SEMTECH CORP
SENECA FOODS CORP.
SENSIENT TECHLG CORI
SERVICE CORP INT'L
SHAW GROUP INC
SHERWIN-WILLIAMS CO
SHUFFLE MASTER, INC
SIGMA DESIGNS, INC.
SIGMA-ALDRICH CORP
SILGAN HOLDINGS INC.
SILICON LABORATORIES
SIMPSON MFG
SKECHERS U.S.A., INC
SKYWEST, INC.
SKYWORKS SOLUTIONS
SM ENERGY COMPANY
SMITH (A.O.) CORP
SMITHFIELD FOODS INC
SNAP-ON INC
SNYDER'S-LANCE, INC
SONIC AUTOMOTIVE INC
SONIC CORP
SONOCO PRODUCTS CO
SOTHEBY'S
SOUTH JERSEY INDS
SOUTHERN CO (THE)
SOUTHWEST AIRLINES
SOUTHWEST ENERGY CO
SOUTHWEST GAS CORP
SPARTAN MOTORS, INC.
SPARTAN STORES INC
SPECTRUM PHARMACTI
SPRINT NEXTEL CORP
SPX CORPORATION
ST JUDE MEDICAL INC
STAGE STORES INC
STAMPS.COM INC.
STANDARD MICROSYSTEM
STANDARD MOTOR
STANDARD PACIFIC
STANDEX INT'L CORP
STANLEY BLACK
STAPLES INC
STARBUCKS CORP
STARWOOD HOTELS
STEEL DYNAMICS, INC.
STEIN MART, INC.
STEPAN COMPANY
STERICYCLE, INC.
STERIS CORPORATION
STEVEN MADDEN LTD
STONE ENERGY CORP
STRATASYS, INC.
STRAYER EDUCATION
STRYKER CORPORATION
STURM, RUGER & CO
SUNOCO INC
SUPERIOR ENERGY SVCS
SUPERIOR INDUSTRIES
SUPERTEX INC
SUPERVALU INC.
SURMODICS, INC.
SWIFT ENERGY COMPANY
SYKES ENTERPRISES
SYMANTEC CORP
SYMMETRICOM INC
SYNAPTICS INC
SYNOPSYS INC
SYSCO CORPORATION
TAKE-TWO INTERACTIVE
TARGET CORP
TECH DATA CORP
TECHNE CORP
TECO ENERGY INC
TELEDYNE TECH.
TELEFLEX INC
TELEPHONE & DATA SYS
TELETECH HOLDINGS
TELLABS INC
TENET HEALTHCARE
TENNANT COMPANY

TERADYNE INC
TEREX CORPORATION
TESORO CORPORATION
TETRA TECH INC
TETRA TECHNOLOGIES
TEXAS INDUSTRIES
TEXAS INSTRUMENTS
TEXTRON INC
THERMO FISHER
THOR INDUSTRIES, INC
THORATEC CORP
TIBCO SOFTWARE INC.
TIDEWATER INC.
TIFFANY & CO.
TIME WARNER INC
TIMKEN COMPANY (THE)
TITANIUM METALS CORP
TJX COMPANIES, INC.
TOLL BROTHERS, INC.
TOOTSIE ROLL IND
TORO COMPANY (THE)
TOTAL SYSTEM SERVICE
TOWERS WATSON
TRACTOR SUPPLY CO
TREDEGAR CORP
TRIMBLE NAVIGATION
TRINITY INDUSTRIES
TRIQUINT SEMICONDUCT
TRIUMPH GROUP INC
TRUEBLUE, INC.
TTM TECHNOLOGIES
TUESDAY MORNING COR
TUPPERWARE BRANDS
TW TELECOM INC
TYCO INTERNATIONAL
TYLER TECHNOLOGIES
TYSON FOODS, INC.
UGI CORPORATION
UIL HOLDINGS CORP
ULTRATECH, INC.
UNIFIRST CORPORATION
UNION PACIFIC CORP
UNIT CORPORATION
UNITED NATURAL FOODS
UNITED ONLINE INC
UNITED PARCEL SVCS
UNITED RENTALS INC
UNITED STATES STEEL
UNITED STATIONERS
UNITED TECHNOLOGIES
UNITED THERAPEUTICS
UNITEDHEALTH GROUP
UNIVERSAL CORP
UNIVERSAL ELEC
UNIVERSAL FOREST PR
UNIVERSAL HEALTH SVC
UNS ENERGY CORP
URBAN OUTFITTERS
URS CORPORATION
V F CORPORATION
VALASSIS COMM.
VALERO ENERGY CORP
VALMONT INDUSTRIES
VALSPAR CORPORATION
VALUECLICK, INC.
VARIAN MEDICAL SYST
VASCO DATA SECURITY
VECTREN CORP
VEECO INSTRUMENTS
VERISIGN, INC.
VERIZON COMMUNICATN
VERTEX PHARMA INC
VIAD CORP
VIASAT, INC.
VICOR CORPORATION
VIROPHARMA INC
VISHAY INTERTECH
VOXX INTERN
VULCAN MATERIALS CO
WABTEC CORP
WALGREEN CO.
WAL-MART STORES INC
WALT DISNEY
WARNACO GROUP, INC.
WASHINGTON POST CO
WASTE CONNECTIONS
WASTE MANAGEMENT
WATERS CORPORATION
WATSCO INC
WATSON PHARMCL INC
WATTS WATER TECH
WAUSAU PAPER CORP
WD-40 COMPANY
WEBSENSE INC
WELLPOINT INC
WENDYS
WERNER ENTERPRISES
WEST PHARMACEUTICAL
WESTAR ENERGY, INC.
WESTERN DIGITAL CORP
WGL HOLDINGS, INC.
WHIRLPOOL CORP
WHOLE FOODS MKT
WILEY (JOHN) & SONS
WILLIAMS COMPANIES
WILLIAMS-SONOMA
WINNEBAGO INDUSTRIES
WISCONSIN ENERGY
WMS INDUSTRIES INC.
WOLVERINE WORLD WIDE
WOODWARD GOVERNOR C
WORLD FUEL SERVICES
WORTHINGTON INDS
XCEL ENERGY INC
XEROX CORPORATION
XILINX INC
XO GROUP
YAHOO! INC
YUM! BRANDS INC
ZALE CORP
ZEBRA TECHNOLOGIES
ZIMMER HOLDINGS INC

B. LIST OF FINANCIAL RATIOS

1. Earnings Before Interest and Taxes / Total Assets (EBIT/TA)
2. Net Income / Total Assets (NI/TA)
3. Funds Flow from Operations / Total Assets (FFO/TA)
4. Net Income / Total Liabilities (NI/TL)
5. Funds Flow from Operations / Total Liabilities (FFO/TL)
6. Net Income / Net Worth (NI/NW)
7. Funds Flow from Operations / Net Worth (FFO/NW)
8. Earnings Before Interest and Taxes / Net Sales (EBIT/Sales)
9. Long Term Debt / Total Assets (LTD/TA)
10. Long Term Debt / Total Liabilities (LTD/TL)
11. Total Assets / Net Worth (TA/NW)
12. Total Liabilities / Total Assets (TL/TA)
13. Total Debt / Property, Plant and Equipment (TD/PPE)
14. Total Liabilities / Net Worth (TL/NW)
15. Total Debt / Net Worth (TD/NW)
16. Total Debt / Total Assets (TD/TA)
17. Funds Flow from Operations /Total Debt (FFO/TD)
18. Total Debt / Working Capital (TD/WC)
19. Total Liabilities / Working Capital (TL/WC)
20. Funds Flow from Operations/ Working Capital (FFO/WC)
21. Net Income / Working Capital (NI/WC)
22. Inventory / Working Capital (Inv/WC)
23. Current Assets / Total Assets (CA/TA)
24. Funds Flow from Operations/ Net Sales (FFO/Sales)
25. Net Income / Net Sales (NI/Sales)
26. Current Liabilities / Property, Plant and Equipment (CL/PPE)
27. Quick Assets / Total Assets (QA/TA)
28. Net Worth / Net Sales (NW/Sales)
29. Net Sales / Total Assets (Sales/TA)
30. Net Sales / Property, Plant and Equipment (Sales/PPE)
31. Inventory / Net Sales (Inv/Sales)
32. Current Liabilities / Inventory (CL/Inv)
33. Working Capital / Total Assets (WC/TA)
34. Current Assets / Net Sales (CA/Sales)

35. Net Sales / Working Capital (Sales/WC)
36. Cost of Goods Sold / Inventory (COGS/Inv)
37. Earnings Before Interest and Taxes / Interest Expense (EBIT/IntExp)
38. Current Assets / Net Worth (CA/NW)
39. Dividend / Net Income (Div/NI)
40. Current Assets / Current Liabilities (CA/CL)
41. Quick Assets / Current Liabilities (QA/CL)
42. Cash and Cash Equivalents / Total Assets (Cash/TA)
43. Cash and Cash Equivalents / Total Liabilities (Cash/TL)
44. Quick Assets / Funds Expenditures for Operations (QA/FEO)
45. Cash and Cash Equivalents/Funds Expenditures for Operations (Cash/FEO)
46. Net Receivables / Inventory (Rec/Inv)
47. Inventory / Current Assets (Inv/CA)
48. Receivables / Net Sales (Rec/Sales)
49. Quick Assets /Net Sales (QA/Sales)
50. Quick Assets / Cash Flow from Operations (QA/CFO)
51. Current Assets / Cash Flow from Operations (CA/CFO)

C. DESCRIPTIVE STATISTICS OF FINANCIAL STATEMENT ACCOUNTS

Descriptive Statistics of Financial Statement Accounts of Cocohe Industry Group

	N	Minimum	Maximum	Mean	Std. Deviation
Cash	9086	0	55.622.000	443.135	2.089.246
Shareholders' Equity	9108	-17.311.000	152.071.000	1.869.759	5.981.450
Common Stock	9086	0	30.296.000	142.903	1.030.078
Current Assets	9108	0	151.019.000	1.741.308	6.417.263
Current Liabilities	9108	0	124.703.000	1.305.074	5.746.422
Total Inventories	9108	0	40.714.000	584.166	1.755.193
Long Term Debt	9108	0	125.806.000	1.135.642	5.031.592
Preferred Stock	9107	0	5.275.000	16.140	137.198
Property Plant Equipment	9108	0	112.324.000	1.270.049	4.656.876
Receivables	9108	0	83.824.000	558.140	3.235.282
Total Assets	9108	0	303.828.000	5.134.487	17.760.598
Total Debt	9108	0	179.804.000	1.469.965	7.796.433
Total Liabilities	9100	0	291.518.000	3.207.076	13.617.429
Cost of Goods Sold	9108	0	326.997.000	3.409.978	12.976.276
Depreciation Depletion Amortization	9106	0	16.519.000	190.561	774.836
Earnings Before Interest and Taxes	9108	-41.907.000	34.299.000	507.587	1.793.133
Interest Expense	9108	0	10.927.000	89.482	468.828
Net Income	9108	-44.461.000	22.048.000	281.857	1.237.075
Operating Expense	9108	0	420.392.000	4.925.062	16.518.947
Net Sales	9106	0	446.950.000	5.482.746	17.796.652
Dividends	9108	0	8.541.000	105.222	470.759
Funds from Operations	9108	-917.000	32.384.000	548.651	1.734.555
Cash Flow from Operations	9108	-3.204.000	33.764.000	522.580	1.741.607
Valid N (listwise)	9051				

Descriptive Statistics of Financial Statement Accounts of Enut Industry Group

	N	Minimum	Maximum	Mean	Std. Deviation
Cash	3058	0	34.500.000	390.560	1.634.389
Shareholders' Equity	3058	-696.199	154.396.000	3.305.996	9.691.961
Common Stock	3058	0	11.920.000	507.572	1.299.782
Current Assets	3058	0	85.963.000	1.750.509	5.077.791
Current Liabilities	3058	0	77.505.000	1.665.465	4.352.779
Total Inventories	3058	0	15.024.000	329.365	938.727
Long Term Debt	3058	0	27.085.000	2.290.268	3.582.714
Preferred Stock	3058	0	3.065.000	98.862	259.764
Property Plant Equipment	3058	0	214.664.000	5.887.332	12.645.863
Receivables	3058	0	38.642.000	777.240	2.343.364
Total Assets	3058	0	326.834.000	9.424.471	20.918.026
Total Debt	3058	0	28.653.000	2.660.973	4.146.325
Total Liabilities	3057	0	166.090.000	5.940.073	11.549.162
Cost of Goods Sold	3058	0	308.752.000	4.281.096	17.783.152
Depreciation Depletion Amortization	3058	0	15.583.000	445.181	1.110.204
Earnings Before Interest and Taxes	3058	-9.061.000	72.989.000	876.817	3.513.406
Interest Expense	3058	0	2.333.000	176.601	284.040
Net Income	3058	-16.998.000	45.220.000	463.760	2.326.457
Operating Expense	3058	0	379.291.000	5.719.686	22.349.200
Net Sales	3058	0	433.526.000	6.610.594	25.462.489
Dividends	3058	0	9.020.000	187.168	620.935
Funds from Operations	3058	-955.591	61.560.000	1.018.559	3.375.416
Cash Flow from Operations	3058	-1.045.221	59.725.000	981.992	3.337.974
Valid N (listwise)	3057				

Descriptive Statistics of Financial Statement Accounts of Inma Industry Group

	N	Minimum	Maximum	Mean	Std. Deviation
Cash	6226	0	150.864.000	527.538	5.397.459
Shareholders' Equity	6226	-3.141.200	118.936.000	1.536.641	5.179.149
Common Stock	6226	0	13.445.000	122.600	573.344
Current Assets	6205	0	174.875.000	1.716.135	7.292.062
Current Liabilities	6205	0	248.610.000	1.489.241	10.159.896
Total Inventories	6226	0	32.240.000	414.762	1.155.144
Long Term Debt	6226	0	377.138.000	1.347.391	11.615.827
Preferred Stock	6226	0	4.000.000	20.229	158.729
Property Plant Equipment	6226	0	78.530.000	1.377.533	4.268.087
Receivables	6226	0	38.759.000	630.184	1.717.760
Total Assets	6226	0	797.769.000	5.383.888	32.631.996
Total Debt	6226	0	523.762.000	1.936.003	18.539.237
Total Liabilities	6224	0	684.157.000	3.775.855	27.487.856
Cost of Goods Sold	6205	0	72.280.000	2.545.989	5.674.226
Depreciation Depletion Amortization	6226	0	11.492.000	172.900	520.045
Earnings Before Interest and Taxes	6226	-12.725.000	50.630.000	433.886	1.904.177
Interest Expense	6226	0	26.209.000	106.676	796.616
Net Income	6226	-11.341.000	22.468.000	222.074	911.777
Operating Expense	6226	0	136.524.000	3.442.080	8.249.986
Net Sales	6226	0	180.929.000	3.901.247	9.876.546
Dividends	6226	0	12.408.000	86.409	429.506
Funds from Operations	6226	-1.328.000	47.595.000	452.900	1.680.516
Cash Flow from Operations	6226	-3.991.000	48.601.000	442.961	1.811.519
Valid N (listwise)	6203				

Descriptive Statistics of Financial Statement Accounts of Tein Industry Group

	N	Minimum	Maximum	Mean	Std. Deviation
Cash	5016	0	60.592.000	713.188	2.863.564
Shareholders' Equity	5016	-2.703.600	115.540.000	1.839.137	6.708.848
Common Stock	4994	0	63.415.000	257.069	2.684.051
Current Assets	5016	0	74.918.000	1.640.342	5.566.994
Current Liabilities	5016	0	52.939.000	1.031.174	4.150.591
Total Inventories	5016	0	10.108.000	183.143	653.923
Long Term Debt	5016	0	64.720.000	642.906	3.486.913
Preferred Stock	5016	0	1.419.000	9.697	76.114
Property Plant Equipment	5016	0	107.087.000	1.017.064	6.067.258
Receivables	5016	0	30.726.000	574.809	2.354.250
Total Assets	5016	0	275.644.000	4.165.122	17.302.802
Total Debt	5016	0	74.991.000	803.653	4.276.659
Total Liabilities	5003	0	168.898.000	2.228.574	10.594.271
Cost of Goods Sold	5016	0	94.152.000	1.644.815	6.291.592
Depreciation Depletion Amortization	5016	0	21.577.000	238.795	1.198.868
Earnings Before Interest and Taxes	5016	-28.509.000	34.205.000	399.217	2.022.050
Interest Expense	5016	0	4.096.000	43.613	235.569
Net Income	5016	-56.121.900	25.922.000	231.793	1.647.591
Operating Expense	5015	0	115.856.000	2.663.955	9.489.703
Net Sales	5016	0	127.245.000	3.111.475	11.089.058
Dividends	5016	0	36.112.000	75.740	702.572
Funds from Operations	5016	-1.029.000	39.813.000	576.702	2.555.690
Cash Flow from Operations	5016	-1.164.000	37.529.000	566.611	2.501.459
Valid N (listwise)	4980				

D. TURKISH SUMMARY

TURKISH SUMMARY

Bu çalışmanın amacı, sektör belirsizlik düzeylerinin araştırılması ve sektöre özgü özelliklerin belirlenmesinde en yüksek bilgi içeriğine sahip finansal rasyoları ortaya çıkarmak ve seçilen bu rasyoları kullanarak sektöre özel finansal stres modellerini geliştirmektir. İlk olarak, sektöre özgü finansal rasyoların belirlenmesinde faktör analizi kullandık. İkinci olarak, bilgi teorisi çerçevesinde sektörlerin belirsizlik düzeyini ölçmek ve sektöre özgü belirsizlik düzeyini en fazla yansıtan finansal rasyoları belirlemek için, bir Çoklu Karar Verme Modeli olarak entropi yöntemini kullandık. Son olarak, lojistik analizi yöntemi ile, factor analizi ve entropi modelinden belirlenen sektöre özgü finansal rasyoları kullanarak her sektör için finansal stress modellerini oluşturduk. İlerleyen bölümlerde sözü geçen üç analize daha detaylı olarak değinilecektir.

Genel Değerlendirme

Finansal oran analizinin kullanımı 1800'lerden beri şirketler için bir zorunluluk olmuştur. İlk olarak finansal oran analizi dönen varlıklarla kısa vadeli yabancı kaynakların karşılaştırılması ile başlamıştır. 1920' lerde ise kar marjı ve sermaye devir hızı getiri hesaplamaları ile devam etti. 1930'larda bazı araştırmacılar finansal oranların kullanımını eleştirerek, finansal oranların pay ve paydalarının zaman içinde değişmesine bağlı olarak, oranların zaman serisi yorumunun sorunlu olabileceğini savundu. Ayrıca oranları güvenilirliğinin birbirinden farklılık arz ettiğini iddia ettiler. Bu eleştiriler sonrasında, 1940'larda odak noktası finansal oran analizinin ampirik temelini güçlendirmeye yönlendirildi. Yine bu dönemde, araştırmacılar finansal oran analizinin, firmaların mali başarısızlık tahmininde kullanılıp kullanılamayacağını tartışmaya başladı. İlk deneyler sonucunda, net karın sermayeye oranının, sermayenin toplam borçlara oranının ve sabit kıymetlerin sermayeye oranının şirketlerin başarısızlık tahmininde en çok bilgi içeren rasyolar olduğu ortaya çıktı. 1940'larda, araştırmacılar sadece başarısız firmaları değil, aynı zamanda hem faaliyetleri devam eden ve durdurulan firmaları da inceleyerek, faaliyetleri durdurulan firmaların sektör ortalamasının ne kadar gerisinde kaldığını hesapladılar. 1950'lerden sonra, finansal oran analizi, hem şirket yönetiminde, hem de ekonomik faaliyetlerin belirlenmesinde popüler bir araç haline geldi. Finansal rasyon analizleri, küçük işletmeler de dahil olmak üzere bankalarda kredi kullandırma kriterlerinin belirlenmesinde önemli hale geldi.

Bu tarihsel evrimin ardından kendi çalışmamıza dönecek olursak, bu çalışmanın amacı farklı sektörlerde firmaların belirsizlik düzeyini ölçmek, finansal oranların bilgi içeriğini analiz etmek ve hangi finansal rasyoların hangi sektörler için daha fazla bilgi içerdiğini belirleyerek, sektöre özel finansal oranları tespit etmektir. Sektöre özel bilgi içeren finansal oranlar belirlendikten sonra, yine bu oranları kullanarak sektöre özel finansal stres modelleri oluşturmayı hedefliyoruz. Bu çalışma, finansal tablo kullanıcılarının karar alma süreçlerine finansal rasyoların sayısını azaltarak yardımcı olmayı hedeflemektedir. Diğer bir deyişle, bizim amacımız bu sanayi için özellikle en yüksek bilgi içeriğine sahip finansal rasyoları, finansal tablo kullanıcılarına sağlamaktır. Bu bağlamda, her sanayi grubu için 1990-2011 dönemini kapsayan S&P 1500 firmalarına ait finansal tablolar Datastream veri tabanından indirilmiş, literatürde en yaygın şekilde kullanılan 51 finansal rasyo tespit edilmiş ve faktör analizi yöntemi ile bu rasyolardan en çok bilgi içeriğine sahip olanları belirlenmiştir. S&P 1500'de yer alan sektörler bilgi teknolojisi, sanayiciler, sağlık, tüketici ihtiyaç malzemeleri, tüketici lüks malzemeleri, enerj ve enerji hizmet sektörü, telekomünikasyon hizmetleri ve yardımcı malzeme olarak sınıflandırılmıştır. Muhasebe uygulamaları açısından benzerlik gösteren sektörler birleştirilerek dört sektör grubu meydana getirilmiştir.

Birinci grup "Cocohe" olarak kısaltılmış tüketici lüx malzemeleri, tüketici ihtiyaç malzemeleri ve sağlık sektörlerini kapsar. Tüketici ihtiyaç malzemeleri yiyecek ve perakende, içecek ve tütün, ev ve kişisel ürün firmalarını içerir.

Tüketici lüx malzemeleri grubu ise otomobil ve yedek parçaları, dayanıklı tüketim mallari, eğlence, ekipman ve ürünleri, tekstil, giyim ve lüks eşya, otel, restoranlar ve medya şirketlerinden oluşur. Son olarak sağlık grubu sağlık ekipmanları ve sarf malzemeleri, sağlık hizmeti, sağlık teknolojisi, ilaç, biyoteknoloji ve yaşam bilimleri sanayi firmalarını kapsar.

İkinci grup "Enut" olarak kısaltılmış olup enerji ve hizmet sektöründeki firmaların içerir. Enerji sektörü enerji ekipman ve hizmet üreten firmalar, petrol, gaz ve sarf yakıtlar ve enerji hizmet sektörünü oluşturan elektrik, gaz ve su araçları firmalarından oluşur.

Sanayi ve malzeme sektörler grubu "Inma" olarak kısaltılmış olup, malzeme sektörü kimyasallar üreten firmaları, sanayi sektörü ise, havacılık ve savunma, yapı ürünleri, inşaat ve mühendislik, elektrik ekipmanları, endüstriyel holdingler, makine, ticari ve profesyonel hizmetler ve ulaşım gibi ticaret şirketleri ve dağıtıcılar, inşaat malzemeleri, ambalaj ve paketleme, metal ve madencilik, kağıt ve orman ürünleri firmalarını içerir.

Son grup telekomünikasyon hizmetleri ve bilgi teknolojileri sektörlerinde ise "Tein" olarak kısaltılmış olup, telekomünikasyon sektörü kablosuz ve çeşitli telekomünikasyon hizmetlerinden oluşan firmaları, bilgi teknolojileri sektörün ise yazılım üreten firmaları, haberleşme cihazları, bilgisayar ve çevre birimleri, elektronik ekipman, alet ve parçaları, ofis elektronik eşya üreticileri ile yarı iletkenler ve yarı iletken ekipman üreten firmaları içerir.

S&P 1500 şirketlerinin içinden verileri eksik olanlar ile finans sektöründeki şirketler analize dahil edilmemiştir. Bunun sonucunda toplam 1064 şirket dört sektör grubunun toplamını oluşturmaktadır. Bu 1064 şirketten 414 şirket Cocohe grubuna, 283 şirket Inma grubuna, 228 şirket Tein grubunua ve 139 şirket Enut grubuna dahil edilmiştir. Çalışmaya dahil edilen firmaların tam listesi Ek A'da verilmiştir.

Faktör Analizi

Faktör analizinde en bilgilendirici ve istikrarlı finansal rasyolar belirlenmiştir. En bilgilendirici rasyolar 0,70 ve üzeri faktör yüküne sahip olan rasyolar olarak belirlenmiştir. İstikrarlı rasyolar ise, hem 1990-2000 hem 2000-2011 örneklem periodunda en fazla bilgi içeren yani faktör yükü 0,70 ve üzerinde olan rasyolar olarak belirlenmiştir. Faktör analizi sonucunda elde edilen en fazla bilgi içeren rasyolar sektör grupları bazında Tablo 1, Tablo 2, Tablo 3 ve Tablo 4'te gösterilmektedir. Bu rasyolar ingilizce kısaltmalarıyla gösterilmiş olup türkçe karşılıkları EK-B de verilmiştir.

Tablo 1. 6 Finansal Rasyo Şablonu ile Finansal Rasyolar ve Factor Yükleri - Cocohe Sektör Grubu

	1990-2000	2001-2011
Kısa Vadeli Likidite Rasyoları-1		
QA / Sales	,893	,867
QA / FEO	,890	,890
CA / Sales	,858	,860
Sales / TA	-,839	-,864
Cash / TA	,828	,839
Cash / TL	,777	,766
Karlılık Rasyoları		
NI / TA	,919	,934
EBIT / TA	,894	,894
NI / NW	,888	,847
FFO / TA	,853	,774
NI / Sales	,781	,750
NI / TL	,754	,752
Kısa Vadeli Likidite Rasyoları-2		
CL / PPE	,929	,910
CA / CFO	,953	,833
QA / CFO	,876	,797
Sales / PPE	,853	,819
İşletme Sermayesi Rasyoları		
TL / WC	,921	,926
FFO / WC	,884	,897
Sales / WC	,853	,850
TD / WC	,816	,840
Finansal Kaldıraç ve Sermaye Duyarlılık Rasyoları		
TD / NW	,930	,856
TL / NW	,880	,933
TA / NW	,874	,925
TL / TA	,863	,879
Stok Duyarlılık Rasyoları		
COGS / Inv	,894	,851
Inv / Sales	-,885	-,900

Tablo 2. 6 Finansal Rasyo Şablonu ile Finansal Rasyolar ve Factor Yükleri - Enut Sektör Grubu

	1990-2000	2001-2011
Finansal Kaldıraç ve Sermaye Duyarlılık Rasyoları		
TD / NW	-,945	-,791
TL / NW	-,900	-,932
TA / NW	-,886	-,925
TL/TA	-,848	-,906
FFO / TL	,741	,754
LTD / TA	-,735	,864
Karlılık Rasyoları-1		
NI / TA	,913	,900
EBIT / TA	,909	,891
NI / NW	,896	,859
NI / TL	,812	,806
İşletme Sermayesi Rasyoları		
FFO / WC	,953	,929
NI / WC	,924	,902
Inv / WC	,897	,785
TD / WC	,824	,847
Karlılık Rasyoları-2		
NW / Sales	-,830	-,738
Sales / TA	,808	,749
Sales / PPE	,798	,793
CA / NW	,769	,816
Kısa Vadeli Likidite Rasyoları		
Cash / FEO	,936	,840
Cash / TA	,922	,886
Cash / TL	,884	,826
Rec / Sales	,766	,829
Stok Duyarlılık Rasyoları		
Inv / Sales	-,884	-,831
COGS / Inv	,835	,782

Tablo 3. 6 Finansal Rasyo Şablonu ile Finansal Rasyolar ve Factor Yükleri - Inma Sektör Grubu

	1990-2000	2001-2011
Karılılık Rasyoları		
Dıv / NI	,937	-,877
EBIT / TA	,930	,940
NI / TA	,931	,942
NI / Sales	,891	,907
NI/NW	,861	,871
EBIT / Sales	,857	,887
NI / TL	,812	,862
FFO / TA	,768	,826
Finansal Kaldıraç ve Sermay		
Duyarlılık Rasyoları		
LTD / TA	,885	,868
TD / TA	,883	,811
LTD / TL	,869	,941
TA / NW	,816	,919
TL / NW	,810	,919
Stok Duyarlılık Rasyoları		
Inv / Sales	-,901	-,908
COGS / Inv	,860	,871
Rec / Inv	,847	,848
Inv / CA	-,834	-,802
İşletme Sermayesi Rasyoları		
TL / WC	,929	,923
Sales / WC	,915	,888
FFO / WC	,872	,850
TD / WC	,835	,827
Inv / WC	,783	,765
Kısa Vadeli Likidite Rasyolar		
1		
Cash / FEO	,916	,962
Cash / TA	,909	,920
Cash / TL	,862	,862
Kısa Vadeli Likidite Rasyolar		
2		
CA / CFO	,954	,952
QA / CFO	,946	,940
Sales / PPE	,904	,833
CA / TA	,796	,730
Sales / TA	,765	,764

Tablo 4. 6 Finansal Rasyo Şablonu ile Finansal Rasyolar ve Factor Yükleri - Tein Sektör Grubu

	1990-2000	2001-2011
Karlılık Rasyoları		
NI / TA	,947	,959
NI / Sales	,930	,921
EBIT / TA	,921	,924
NI / NW	,895	,902
EBIT / Sales	,893	,904
FFO / TA	,866	,789
NI / TL	,831	,834
Kısa Vadeli Likidite Rasyoları-1		
QA / Sales	,953	,973
Cash / FEO	,934	,960
CA / Sales	,924	,949
QA / FEO	,908	,958
Cash / TA	890	,848
Finansal Kaldıraç ve Sermaye Duyarlılık Rasyoları		
LTD / TL	,928	,911
LTD / TA	,922	,937
TD / TA	,879	,906
TD / PPE	,780	,772
TA / NW	,741	,838
İşletme Sermayesi Rasyoları		
TL / WC	,964	,965
FFO / WC	,931	,939
TD / WC	,921	,902
Sales / WC	,907	,884
Stok Duyarlılık Rasyoları		
Inv / Sales	-,876	-,870
Rec / Inv	,843	,842
CL / Inv	,775	,774
COGS / Inv	,770	,860
Kısa Vadeli Likidite Rasyoları-2		
CA / CFO	,981	,944
QA / CFO	,969	,940
Sales / PPE	,893	,891
CL / PPE	,796	,851

Faktör analizinde en bilgilendirici ve istikrarlı oranları belirlendikten sonra, bilgi kuramı yaklaşımını benimsemek suretiyle, firmaların belirsizlik düzeyini gösteren en bilgilendirici rasyoları bir kez de entropi metodu ile her bir sektör grubu için ayrı ayrı hesapladık. Finansal rasyoların ve şirketlerin belirsizlik düzeyini hesaplamak için kullanılan entropi denklemi aşağıdaki gibidir.

$$H = \sum_{i=1}^{n} p_i \, h(p_i) = -\sum_{i=1}^{n} p_i \ln p_i$$

Bu denklemde H entropi finansal rasyoların ve şirketlerin belirsizlik düzeyini bildiriken p herhangi bir olayın olasılığını hesaplamaktadır. Bu çalışmada olayların olasılığı finansal rasyolar aracılığı ile bulunmaktadır. Sektör grupları bazında finansal rasyoların ve sektör gruplarının belirsizlik düzeyi (entropisi) en düşük belirsizlik düzeyinden en yüksek belirsizlik düzeyine göre sıralanmak suretiyle aşağıdaki tabloda verilmiştir.

Tablo 5: Finansal Rasyoların Entropi Değerleri

Cocohe	Entropy	Enut	Entropy	Inma	Entropy	Tein	Entropy
Cash / TL	0,897316	Cash / TL	0,901488	Cash / TL	0,913486	CL / Inv	0,835161
Cash / TA	0,926043	TD / WC	0,908195	Cash / TA	0,93085	TD / PPE	0,849962
COGS/Inv	0,936037	Cash FEO	0,912239	Rec / Inv	0,931053	TD / TA	0,872553
CL / PPE	0,938509	Cash /TA	0,918672	COGS /Inv	0,948376	COGS/ Inv	0,910145
QA / Sales	0,938644	Sales /PPE	0,922827	Sales /PPE	0,954332	CL / PPE	0,911791
QA / FEO	0,942041	COGS/Inv	0,93211	LTD / TA	0,955314	QA / FEO	0,932323
Inv / Sales	0,946571	Inv /Sales	0,947269	Inv / Sales	0,956694	QA / Sales	0,954667
Sales /PPE	0,947751	TD / NW	0,957328	TD / TA	0,961387	LTD / TA	0,960121
Sales /WC	0,952786	Sales / TA	0,959155	Inv / CA	0,962573	Rec / Inv	0,960252
CA / Sales	0,959063	TA / NW	0,96331	LTD / TL	0,962647	LTD / TL	0,960312
TL / WC	0,959851	TL / NW	0,966309	Sales / WC	0,974277	CA / Sales	0,960448
Sales / TA	0,964833	LTD / TA	0,972025	Sales / TA	0,978005	Sales / PPE	0,962093
CA / CFO	0,975954	CA / NW	0,974611	Cash /FEO	0,979375	Inv / Sales	0,963186
FFO / TA	0,976096	FFO / TL	0,976068	TL / WC	0,98037	Cash / TA	0,964932
EBIT /TA	0,976376	Rec /Sales	0,976746	CA / TA	0,981282	CA / CFO	0,968288
NI / TA	0,976898	FFO / WC	0,977496	NI / TL	0,983893	QA / CFO	0,968348
TD / WC	0,977637	EBIT / TA	0,978345	CA / CFO	0,9844	NI / TA	0,969161
TL / TA	0,978221	NW/ Sales	0,978389	NI / NW	0,985282	EBIT / TA	0,969412
NI / NW	0,980026	NI / TL	0,979347	EBIT / TA	0,98576	FFO / TA	0,972045
FFO / WC	0,980029	NI / TA	0,979369	TL / NW	0,985991	Cash /FEO	0,972385
TA / NW	0,980218	TL / TA	0,981458	TA / NW	0,986078	Sales / WC	0,975156
TL / NW	0,980223	NI / NW	0,985657	FFO / WC	0,986869	FFO / WC	0,976211
TD / NW	0,980227	NI / WC	0,985688	QA / CFO	0,987084	NI / TL	0,976391
QA / CFO	0,981177	Inv / WC	0,987352	TD / WC	0,987302	TL / WC	0,976487
NI / TL	0,984345			EBIT/Sales	0,987465	EBIT/Sales	0,977241
NI / Sales	0,985182			Inv / WC	0,987895	NI / NW	0,977293
				FFO / TA	0,987938	TD / WC	0,97733
				NI / Sales	0,987992	NI / Sales	0,977549
				NI / TA	0,98829	TA / NW	0,977979
				DIV / NI	0,989147		
Total Entropy	*0,949827*	*Total Entropy*	*0,941275*	*Total Entropy*	*0,957885*	*Total Entropy*	*0,919293*

Entropi metodundan elde edilen belirsizlik düzeyi en düşük yani bilgi seviyesi en yüksek finansal rasyolar lojistik regresyon analizinde finansal stres modellerinde kullanılmak üzere seçilmiştir. Bu seçimi yaparken 0,96 entropi derecesi kesme noktası olarak alınmış ve bu noktanın altındaki entropi değerine sahip finansal rasyolar finansa stres modellerinde kullanılmak üzere belirlenmiştir.

Lojistik Regresyon Analizi

Bu çalışmada son olarak, sektöre özel finansal stres modellerini elde etmek ve modellerin tahmin yeteneğini incelemek için lojistik regresyon analizi kullanılmıştır. Lojistik regresyon analizinden elde edilen sektöre özel finansal stres modelleri ve bu modellerde kullanılan rasyolar aşağıdaki gibidir.

FD_{Cocohe} = -2.392 - 0.247*CashTL - 2.970*CashTA - 0.078*COGSInv + 0.063*CLPPE + 5.715*QASales - 5.614*QAFEO - 9.333*InvSales - 0.044*SalesPPE - 0.072*SalesWC + 5.771*CASales

FD_{Enut} = -4.588 + 10.513*CashTL + 0.067*TDWC + 3.801*CashFEO - 27.874*CashTA + 0.924*SalesPPE + 0.166*COGSInv + 19.411*InvSales + 0.641*TDNW - 4.488*SalesTA

FD_{Inma} = -8.183 + 16.321*InvSales - 0.835*RecInv + 4.276*LTDTA + 12.397*CashTA + 0.285*COGSInv - 2.429*CashTL - 0.017*SalesPPE

FD_{Tein} = -4.155 - 0.037*CLInv - 0.971*TDPPE + 6.931*TDTA + 0.070*COGSInv - 1.822*QAFEO + 3.695*QASales + 0.253*CLPPE

Sonuç

Sonuç olarak, faktör analizi ve entropi metodu verileri dahilinde, finansal rasyoların sanayi özelliklerini yansıttığını ve bu rasyoların bilgi sağlamada sektörler arasında değişiklik gösterdiğini bulduk. Ayrıca, lojistik regresyon analizi sonucunda ise sektöre özgü finansal stress modellerinin, şirketlerin finansal sıkıntılarını doğru tahmin ettiğini ve bu modellerde kullanılan sektöre özgü finansal rasyoların çoğunun istatistiksel olarak anlamlı olduğunu gözlemledik.

EKLER

A. Çalışmada Kullanılan S&P Firmalarının Listesi

3D SYSTEMS CORP
3M COMPANY
AAON, INC.
AAR CORP
AARON'S, INC.
ABAXIS INC
ABBOTT LABORATORIES
ABERCROMBIE & FITCH
ABM INDUSTRIES INC
ACCENTURE PLC
ACI WORLDWIDE INC
ACTUANT CORPORATION
ACXIOM (R) CORP
ADOBE SYSTEMS INC
ADTRAN INC
ADVANCED ENERGY INDS
ADVANCED MICRO
ADVENT SOFTWARE, INC
AEGION CORP
AEROPOSTALE, INC.
AES CORP (THE)
AETNA INC
AFFYMETRIX, INC.
AGCO CORP
AGILENT TECHNOLOGIES
AGILYSYS INC
AGL RESOURCES INC
AIR METHODS CORP
AIR PRODUCTS & CHEMS
AIRGAS INC
AK STEEL HOLDING
AKAMAI TECHNOLOGIES
AKORN, INC.
ALASKA AIR GROUP INC
ALBANY INTERNATIONAL
ALBEMARLE CORP
ALCOA INC
ALEXANDER & BALDWIN
ALIGN TECHNOLOGY INC
ALLEGHENY TECHNOLOGS
ALLERGAN INC
ALLETE, INC.
ALLIANCE DATA SYSTEM
ALLIANCE ONE INTL
ALLIANT ENERGY CORP
ALLIANT TECHSYSTEMS
ALLSCRIPTS HEALTH
ALMOST FAMILY, INC.
ALTERA CORPORATION
ALTRIA GROUP INC
AMAZON.COM INC
AMCOL INTL CORP
AMEDISYS, INC.
AMEREN CORPORATION
AMERICAN EAGLE
AMERICAN ELECTRIC
AMERICAN GREETINGS
AMERICAN SCIENCE
AMERICAN STATES WATE
AMERICAN VANGUARD
AMERISOURCEBERGEN
AMETEK INC
AMGEN INC
AMN HEALTHCARE
AMPHENOL CORP
AMSURG CORP.
ANADARKO PETROLEUM
ANALOG DEVICES, INC.
ANALOGIC CORPORATION
ANDERSONS INC
ANIXTER INT'L
ANN INC
ANSYS, INC.
APACHE CORPORATION
APOGEE ENTERPRISES
APOLLO GROUP, INC.
APPLE INC
APPLIED IND'L TECH
APPLIED MATERIALS
APTARGROUP, INC.
AQUA AMERICA, INC.
ARBITRON INC
ARCH COAL, INC.
ARCHER DANIELS MIDL.
ARCTIC CAT INC.
ARKANSAS BEST CORP
ARQULE, INC.
ARRIS GROUP INC.
ARROW ELECTRONICS
ASCENA RETAIL
ASHLAND INC
ASTEC INDUSTRIES INC
AT&T INC
ATLANTIC TELE-NET
ATMEL CORPORATION
ATMI INC
ATMOS ENERGY CORP
ATWOOD OCEANICS INC
AUTODESK INC
AUTOMATIC DATA PROC
AUTONATION INC
AUTOZONE INC
AVERY DENNISON CORP
AVID TECHNOLOGY INC
AVISTA CORPORATION
AVNET INC
AVON PRODUCTS INC
AZZ INCORPORATED
BADGER METER, INC.
BAKER HUGHES INC
BALCHEM CORPORATION
BALL CORPORATION
BALLY TECHNOLOGIES
BARD, (C.R.) INC.
BARNES & NOBLE
BARNES GROUP INC
BAXTER INTERNATIONAL
BE AEROSPACE, INC.
BEAM INC
BECTON, DICKINSON
BED BATH & BEYOND
BEL FUSE
BELDEN INC.
BEMIS COMPANY INC
BENCHMARK ELECTRONIC
BEST BUY CO INC
BIG 5 SPORTING GOODS
BIG LOTS, INC.
BIGLARI HOLDING
BIOGEN IDEC INC.
BIO-RAD LABRATORIES
BIO-REFERENCE LABS
BJ'S RESTAURANTS INC
BLACK BOX CORP

BLACK HILLS CORP
BLYTH INC
BMC SOFTWARE INC
BOB EVANS FARMS, INC
BOEING COMPANY (THE)
BORGWARNER INC
BOSTON BEER COMPANY
BOSTON SCIENTIFIC
BOTTOMLINE TECH
BOYD GAMING CORP
BRADY CORP
BRIGGS & STRATTON
BRIGHTPOINT INC
BRINKER INT'L
BRINK'S COMPANY
BRISTOL-MYERS SQUIBB
BRISTOW GROUP INC.
BROADCOM CORPORATION
BROOKS AUTOMATION
BROWN FORMAN CORP
BROWN SHOE CO
BRUNSWICK CORP
BUCKEYE TECHNOLOGIES
BUCKLE, INC. (THE)
BUFFALO WILD WINGS
CA INC
CABLEVISION SYSTEMS
CABOT CORPORATION
CABOT MICROELECTRON
CABOT OIL & GAS CORP
CACI INTERNATIONAL
CADENCE DESIGN SYST
CALAVO GROWERS INC
CALGON CARBON CORP
CALLAWAY GOLF CO
CAL-MAIN FOODS INC
CAMBREX CORPORATION
CAMERON INTL CORP
CAMPBELL SOUP CO
CANTEL MEDICAL CORP.
CARBO CERAMICS INC.
CARDINAL HEALTH, INC
CAREER EDUCATION CO
CARLISLE COMPANIES
CARMAX INC
CARNIVAL CORPORATION
CARPENTER TECHNOLOGY
CARTER'S, INC.
CASCADE CORPORATION
CASEY'S GEN STORES
CASTLE (A.M.) & CO
CATALYST HEALTH
CATERPILLAR INC
CATO CORPORATION
CBS CORPORATION
CDI CORP
CEC ENTERTAINMENT
CELGENE CORPORATION
CENTERPOINT ENERGY
CENTRAL GARDEN & PET
CENTRAL VERMONT PUB
CENTURY ALUMINUM CO
CENTURYLINK
CERADYNE, INC.
CERNER CORPORATION
CH ENERGY GROUP, INC
CH ROBINSON WORLD
CHARLES RIVER LAB
CHECKPOINT SYSTEMS
CHEESECAKE FACTORY
CHEMED CORPORATION
CHESAPEAKE ENERGY
CHEVRON CORPORATION
CHICO'S FAS INC
CHILDREN'S PLACE
CHRISTOPHER & BANKS
CHURCH & DWIGHT CO
CIBER, INC.
CIENA CORPORATION
CIGNA CORP
CINCINNATI BELL
CINTAS CORPORATION
CIRCOR INTERNATIONAL
CIRRUS LOGIC, INC.
CISCO SYSTEMS, INC.
CITRIX SYSTEMS INC
CLARCOR INC
CLEAN HARBORS, INC.
CLECO CORPORATION
CLIFFS NATURAL
CLOROX COMPANY (THE)
CMS ENERGY CORP
COACH INC
COCA-COLA COMPANY
COCA-COLA ENTERPR
COGNEX CORP
COGNIZANT TECHNOLOGY
COHU, INC.
COINSTAR INC
COLDWATER CREEK INC
COLGATE-PALMOLIVE
COLLECTIVE BRAND
COMCAST CORPORATION
COMFORT SYSTEMS USA
COMMERCIAL METALS CO
COMMUNITY HEALTH
COMPASS MINERALS
COMPUTER PROGRAMS &
COMPUTER SCIENCES
COMPUWARE CORP
COMSTOCK RESOURCES
COMTECH TELECOM
CONAGRA FOODS INC
CONCUR TECHNOLOGIES
CONMED CORPORATION
CONOCOPHILLIPS
CONSOL ENERGY INC.
CONSOLIDATED EDISON
CONSOLIDATED GRAPHIC
CONSTELLATION BRANDS
CONVERGYS CORP
CON-WAY INC
COOPER COMPANIES INC
COOPER INDUSTRIES
COPART INC
CORELOGIC, INC
CORINTHIAN COLLEGES
CORN PRODUCTS INT'L
CORNING INCORPORATED
CORPORATE EXEC BOARD
CORRECTIONS CORPORTN
CORVEL CORPORATION
COSTCO WHOLESALE
COVANCE INC

COVENTRY HEALTH CAR
CRACKER BARREL
CRANE CO
CREE, INC.
CROSS COUNTRY HEALTI
CROWN CASTLE INT'L
CRYOLIFE, INC.
CSG SYSTEMS INT'L
CSX CORPORATION
CTS CORP
CUBIC CORPORATION
CUBIST PHARMA
CUMMINS INC.
CURTISS-WRIGHT CORP
CVS CAREMARK
CYBERONICS, INC.
CYMER INC
CYPRESS SEMICONDUCTI
CYTEC INDUSTRIES INC
D.R. HORTON, INC.
DAKTRONICS, INC.
DANAHER CORP
DARDEN RESTAURANTS
DARLING INT'L INC.
DAVITA, INC.
DEAN FOODS CO.
DECKERS OUTDOOR COR
DEERE & COMPANY
DELL INC.
DELTIC TIMBER CORP
DELUXE CORPORATION
DENTSPLY INTL INC
DEVON ENERGY CORP
DEVRY INC.
DIAMOND OFFSHR DRILL
DIEBOLD, INC.
DIGI INTERNATIONAL
DIGITAL GEN
DIGITAL RIVER, INC.
DINEEQUITY, INC
DIODES INCORPORATED
DIRECTV
DOLLAR TREE, INC
DOMINION RESOURCES
DONALDSON CO INC
DOVER CORP
DOW CHEMICAL COMPAN
DREW INDUSTRIES INC
DRIL-QUIP, INC
DSP GROUP INC
DST SYSTEMS, INC.
DTE ENERGY CO
DU PONT DE NEMOURS
DUKE ENERGY CORP
DYCOM INDUSTRIES INC
EAGLE MATERIALS, INC
EASTMAN CHEMICAL CO
EATON CORPORATION
EBAY INC.
EBIX, INC.
ECOLAB INC
EDISON INTERNATIONAL
EDWARDS LIFESCIENCES
EL PASO CORPORATION
EL PASO ELECTRIC CO
ELECTRO SCIENTIFIC
ELECTRONIC ARTS, INC
EMC CORP
EMCOR GROUP, INC.
EMERSON ELECTRIC CO.
ENCORE CAPITAL GRP
ENCORE WIRE CORP
ENERGEN CORP
ENTERGY CORPORATION
ENZO BIOCHEM INC
EOG RESOURCES, INC.
EPIQ SYSTEMS, INC.
EQT CORPORATION
EQUIFAX INC.
EQUINIX, INC.
ERESEARCHTECH
ESCO TECHNOLOGIES
ESTEE LAUDER CO
ESTERLINE TECH CORP
ETHAN ALLEN INTERIOR
EXAR CORPORATION
EXELON CORPORATION
EXPEDITORS INTL WASH
EXPONENT, INC.
EXPRESS SCRIPTS
EXTERRAN HOLD
EXXON MOBIL CORP
F5 NETWORKS INC
FACTSET RESEARCH SYS
FAIR ISAAC CORP.
FAIRCHILD SEMICOND
FAMILY DOLLAR STORES
FARO TECHNOLOGIES
FASTENAL COMPANY
FEDERAL SIGNAL CORP
FEDEX CORP
FEI COMPANY
FIFTH & PACIFIC COS
FINISH LINE, INC THE
FIRSTENERGY CORP
FISERV INC
FLIR SYSTEMS INC
FLOWERS FOODS INC
FLOWSERVE CORP
FLUOR CORPORATION
FMC CORPORATION
FMC TECHNOLOGIES
FOOT LOCKER, INC
FORD MOTOR COMPANY
FOREST LABS INC
FOREST OIL CORP
FORRESTER RESEARCH
FORWARD AIR CORP
FOSSIL INC
FRANKLIN ELECTRIC CO
FRED'S, INC.
FREEPORT-MCMORAN
FRONTIER COMMUN
FTI CONSULTING INC
FULLER (H B) CO
G&K SERVICES INC
GAMESTOP CORPORATIOI
GANNETT CO INC
GAP, INC (THE)
GARDNER DENVER INC
GARTNER INC
GATX CORP
GENCORP INC.
GENERAL CABLE CORP
GENERAL COMMN INC

GENERAL DYNAMICS
GENERAL ELECTRIC CO.
GENERAL MILLS, INC.
GENESCO INC.
GEN-PROBE INC
GENTEX CORPORATION
GENTIVA HEALTH SERVI
GENUINE PARTS CO
GEO GROUP, INC.
GEORESOURCES, INC.
GIBRALTAR INDUSTRIES
GILEAD SCIENCES, INC
GLOBAL PAYMENTS INC
GOODRICH CORPORATIO
GOODYEAR TIRE&RUBBE
GRACO INC
GRAINGER (W.W.), INC
GRANITE CONSTRUCTION
GREAT PLAINS ENERGY
GREATBATCH INC
GREEN MOUNTAIN
GREIF INC
GRIFFON CORPORATION
GROUP 1 AUTOMOTIVE
GUESS ?, INC.
GULF ISLAND
GULFPORT ENERGY CORP
H&R BLOCK INC
H.J. HEINZ COMPANY
HAEMONETICS CORP
HAIN CELESTIAL GROUP
HALLIBURTON COMPANY
HANGER ORTHOPEDIC
HARLEY-DAVIDSON INC
HARMAN INT'L INDUST
HARMONIC INC.
HARRIS CORPORATION
HARRIS TEETER SUPER
HARSCO CORPORATION
HARTE-HANKS, INC.
HASBRO INC
HAVERTY FURNITURE
HAWAIIAN ELECTRIC
HAWKINS, INC.
HAYNES INTERNATIONAL

HEADWATERS, INC.
HEALTH MGMT ASSOC
HEALTH NET INC
HEALTHCARE SVCS
HEALTHWAYS INC
HEARTLAND EXPRESS
HEIDRICK & STRUGGLES
HELEN OF TROY LTD
HELIX ENERGY
HELMERICH & PAYNE
HENRY, (JACK) & ASSC
HERMAN MILLER INC
HERSHEY CO (THE)
HESS CORPORATION
HEWLETT-PACKARD CO.
HIBBETT SPORTS INC.
HILL-ROM HOLDINGS
HI-TECH PHARMACAL CO.
HMS HOLDINGS CORP
HNI CORPORATION
HOLLYFRONTIER
HOLOGIC INC
HOME DEPOT, INC.
HONEYWELL INTERNATN
HORMEL FOODS CORP
HOT TOPIC, INC.
HUB GROUP, INC.
HUBBELL INC
HUMANA INC.
HUNT (J.B.) TRANSPRT
ICONIX BRAND GROUP
ICU MEDICAL, INC.
IDACORP, INC.
IDEX CORP
IDEXX LABORATORIES
IGATE CORPORATION
II-CI INCORPORATED
ILLINOIS TOOL WORKS
INFORMATICA CORP
INFOSPACE, INC.
INGERSOLL-RAND
INGRAM MICRO INC.
INSIGHT ENTERPRISES
INSPERITY, INC.
INTEGRA LIFESCI

INTEGRA LIFESCI
INTEGRATED DEVICE
INTEGRYS ENGY GRP
INTEL CORPORATION
INTEL CORPORATION
INTER PARFUMS, INC.
INTERACTIVE
INTERFACE, INC.
INTERMEC INC
INTERNATIONAL PAPER
INTERPUBLIC GROUP
INTERSIL CORPORATION
INTEVAC, INC.
INT'L BUSINESS MACHS
INTL FLAVORS&FRAGRA
INT'L GAME TECH
INT'L RECTIFIER
INT'L SPEEDWAY CORP
INTUIT INC
INTUITIVE SURGICAL
INVACARE CORPORATIO
ION GEOPHYSICAL
IRON MOUNTAIN INC
ITRON INC
ITT CORPORATION
ITT EDUCATIONAL SVCS
J & J SNACK FOODS
J.M. SMUCKER CO
J2 GLOBAL INC
JABIL CIRCUIT INC
JACK IN THE BOX INC
JACOBS ENG GROUP INC
JAKKS PACIFIC, INC.
JDA SOFTWARE GROUP
JDS UNIPHASE CORP
JOHNSON & JOHNSON
JOHNSON CONTROLS
JOS A BANK CLOTH
JOY GLOBAL, INC.
JUNIPER NETWORKS INC
KAISER ALUMINUM COR
KAMAN CORPORATION
KANSAS CITY SOUTHERN
KAYDON CORP
KB HOME

KELLOGG COMPANY
KELLY SERVICES, INC.
KENNAMETAL INC
KENSEY NASH CORP
KIMBERLY-CLARK CORP
KINDRED HEALTHCARE
KIRBY CORP
KIRKLAND'S, INC.
KLA-TENCOR CORP
KNIGHT TRANSPORT
KOHLS CORPORATION
KOPIN CORP
KORN/FERRY INT'L
KRAFT FOODS INC
KROGER CO. (THE)
K-SWISS INC
KULICKE AND SOFFA
L-3 COMMUNICATIONS
LAB CORP OF AMERICA
LACLEDE GROUP INC
LAM RESEARCH CORP
LAMAR ADVERTISING C
LANCASTER COLONY
LANDAUER INC
LANDSTAR SYSTEM INC.
LAWSON PRODUCTS, INC
LA-Z-BOY INCORP
LEGGETT & PLATT INC
LENNAR CORP
LENNOX INTERNATIONA
LEXMARK INTERNATL
LIFE TECHN
LIFEPOINT HOSPITALS
LILLY (ELI) AND CO.
LIMITED BRANDS INC
LINCARE HOLDINGS INC
LINCOLN ELECTRIC
LINDSAY CORPORATION
LINEAR TECHNOLOGY
LITHIA MOTORS INC
LITTELFUSE INC
LIVEPERSON, INC.
LKQ CORPORATION
LOCKHEED MARTIN COR
LOUISIANA-PACIFIC
LOWE'S COMPANIES INC
LSB INDUSTRIES INC
LSI CORPORATION
LUFKIN INDUSTRIES
LYDALL, INC.
M.D.C. HOLDINGS, INC
M/I HOMES, INC.
MACY'S, INC.
MAGELLAN HEALTH INC
MANHATTAN ASSOCIATE
MANPOWER
MANTECH INTL
MARATHON OIL CORP.
MARCUS CORP
MARINEMAX, INC.
MARRIOTT INT'L
MARTIN MARIETTA MAT
MASCO CORP
MATERION CORP
MATRIX SERVICE CO
MATTEL, INC.
MATTHEWS INT'L CORP
MAXIMUS INC
MCCORMICK & CO INC
MCDONALD'S CORP
MCGRAW-HILLS COS
MCKESSON CORPORATIO
MDU RESOURCES GROUP
MEADWESTVACO CORP
MEASUREMENT SPECIAL
MEDICINES COMPANY
MEDICIS PHARMA CORP
MEDIFAST INC
MEDNAX, INC.
MEDTRONIC, INC.
MEMC ELECTRONIC
MEN'S WEARHOUSE INC
MENTOR GRAPHICS CORP
MERCK & CO INC
MERCURY COMPUTER SY
MEREDITH CORP
MERIDIAN BIOSCIENCE
MERIT MEDICAL SYSTEM
MERITAGE HOMES CORP
METHODE ELECTRONICS
METTLER-TOLEDO INT'L
MICREL, INCORPORATED
MICROCHIP TECHNOLOG
MICRON TECHNOLOGY
MICROS SYSTEMS INC
MICROSEMI CORP
MICROSOFT CORP
MICROSTRATEGY INC
MINE SAFETY
MINERALS TECHNO
MKS INSTRUMENTS, INC
MOBILE MINI INC
MOHAWK INDUSTRIES
MOLEX INCORPORATED
MOLSON COORS BREW
MONARCH CASINO
MONRO MUFFLER BRAKE
MONSANTO COMPANY
MONSTER BEVERAGE
MONSTER WORLDWIDE
MOOG INC.
MOTOROLA SOLUTIONS
MOVADO GROUP INC
MSC INDUSTRIAL
MTS SYSTEMS CORP
MUELLER INDUSTRIES
MULTIMEDIA GAMES
MURPHY OIL CORP
MYERS INDUSTRIES
MYLAN INC
NABORS INDUSTRIES
NANOMETRICS, INC.
NASHFINCH COMPANY
NATIONAL FUEL GAS CO
NATIONAL INSTRUMENT
NATIONAL PRESTO IND
NATL OILWELL VARCO
NATUS MEDICAL
NAVIGANT CONSULTING
NCI BUILDING SYSTEMS
NCR CORPORATION
NEOGEN CORPORATION
NETAPP INC.
NETFLIX INC
NETGEAR, INC.

NETSCOUT SYSTEMS INC
NEW JERSEY RESOURCES
NEW YORK TIMES CO.
NEWELL RUBBERMAID
NEWFIELD EXPLORATION
NEWMARKET CORP
NEWMONT MINING CORP
NEWPORT CORPORATION
NEWS CORPORATION
NEXTERA ENERGY
NIKE INC.
NISOURCE INC
NOBLE CORPORATION
NOBLE ENERGY, INC.
NORDSON CORPORATION
NORDSTROM, INC.
NORFOLK SOUTHERN
NORTHEAST UTILITIES
NORTHROP GRUMMAN
NORTHWEST NAT. GAS
NORTHWESTERN CORP
NOVATEL WIRELESS INC
NOVELLUS SYSTEMS INC
NRG ENERGY INC.
NUCOR CORPORATION
NUTRISYSTEM INC
NV ENERGY INC.
NVIDIA CORPORATION
NVR, INC.
O REILLY AUTOMOTIVE
OCCIDENTAL PETROLEUM
OCEANEERING INTL
OFFICE DEPOT, INC.
OFFICEMAX INC
OGE ENERGY CORP
OIL STATES INTL
OLD DOMINION FREIGHT
OLIN CORP
OLYMPIC STEEL, INC.
OM GROUP, INC.
OMNICARE, INC.
OMNICELL, INC.
OMNICOM GROUP INC
ON ASSIGNMENT, INC.
ONEOK, INC.
OPLINK COMM INC
OPNET TECHNOLOGIE
ORACLE CORPORATION
ORBITAL SCIENCES
OSHKOSH CORPORATION
OSI SYSTEMS, INC.
OVERSEAS SHIPHOLDING
OWENS & MINOR, INC.
OWENS-ILLINOI, INC.
OXFORD INDUSTRIES
OYO GEOSPACE CORP
P.F. CHANG'S CHINA
PACCAR INC.
PACKAGING CORP
PALL CORPORATION
PALOMAR MEDICAL TECH
PANERA BREAD CO
PAPA JOHN'S INT'L
PAR PHARMACEUTICAL
PARAMETRIC TECH CORP
PAREXEL INT'L CORP
PARK ELECTROCHEMICAL
PARKER-HANNIFIN CORP
PATTERSON CO INC
PATTERSON-UTI ENGY
PAYCHEX INC
PCTEL, INC.
PEABODY ENERGY CORP
PEET'S COFFEE
PENN VIRGINIA CORP
PENNEY (J.C.) CO.
PENTAIR INC
PEP BOYS-MANNY
PEPCO HOLDINGS, INC.
PEPSICO, INC.
PERICOM SEMICOND
PERKINELMER INC
PERRIGO CO
PERRY ELLIS
PETROLEUM
PETROQUEST ENERGY
PETSMART INC
PFIZER INC
PG&E CORPORATION
PIEDMONT NATURAL GAS
PINNACLE ENTERTAINMT
PINNACLE WEST CAPTL
PIONEER DRILLING
PIONEER NATURAL RES
PITNEY BOWES INC.
PLAINS EXPLOR & PROD
PLANTRONICS, INC.
PLEXUS CORP
PNM RESOURCES, INC.
POLARIS INDUSTRIES
POLYCOM INC
POLYONE CORP
POOL CORPORATION
POWELL INDUSTRIES
POWER INTEGRATIONS
PPG INDUSTRIES INC
PPL CORP
PRAXAIR, INC.
PRECISION CASTPARTS
PRICELINE.COM INC
PROCTER & GAMBLE CO
PROGRESS ENERGY INC
PROGRESS SOFTWARE
PSS WORLD MEDICAL,
PUBLIC SVC ENTRPR GR
PULSE ELECTRONIC
PULTEGROUP
PVH
QLOGIC CORP
QUAKER CHEMICAL COR
QUALCOMM INC
QUALITY SYSTEMS, INC
QUANEX BUILDING
QUANTA SERVICES, INC
QUEST DIAGNOSTICS
QUEST SOFTWARE INC
QUESTAR CORPORATION
QUESTCOR PHARM.
QUICKSILVER RESOURCE
QUIKSILVER, INC.
R R DONNELLEY & SONS
RADIOSHACK CORP
RADISYS CORP
RALCORP HOLDINGS INC
RALPH LAUREN

RANGE RESOURCES CORI	SCHWEITZER-MAUDUIT	STAMPS.COM INC.
RAYTHEON COMPANY	SCIENTIFIC GAMES	STANDARD MICROSYSTEI
RED HAT, INC.	SCOTTS MIRACLE-GRO	STANDARD MOTOR
RED ROBIN GOURMET	SCRIPPS (E.W.) CO	STANDARD PACIFIC
REGAL	SEACOR HOLDINGS INC.	STANDEX INT'L CORP
REGENERON PHARMA	SEALED AIR CORP	STANLEY BLACK
REGIS CORP	SEARS HOLDINGS CORP	STAPLES INC
RELIANCE STEEL	SELECT COMFORT CORI	STARBUCKS CORP
RENT-A-CENTER, INC.	SEMPRA ENERGY	STARWOOD HOTELS
REPUBLIC SERVICES	SEMTECH CORP	STEEL DYNAMICS, INC.
RESMED INC.	SENECA FOODS CORP.	STEIN MART, INC.
RESOURCES CONNECTIOI	SENSIENT TECHLG CORI	STEPAN COMPANY
REYNOLDS AMERICAN	SERVICE CORP INT'L	STERICYCLE, INC.
RF MICRO DEVICES INC	SHAW GROUP INC	STERIS CORPORATION
ROBBINS & MYERS, INC	SHERWIN-WILLIAMS CO	STEVEN MADDEN LTD
ROBERT HALF INTL INC	SHUFFLE MASTER, INC	STONE ENERGY CORP
ROCK-TENN COMPANY	SIGMA DESIGNS, INC.	STRATASYS, INC.
ROCKWELL AUTOMATIOI	SIGMA-ALDRICH CORP	STRAYER EDUCATION
ROCKWELL COLLINS INC	SILGAN HOLDINGS INC.	STRYKER CORPORATION
ROFIN-SINAR TECHNO	SILICON LABORATORIES	STURM, RUGER & CO
ROGERS CORPORATION	SIMPSON MFG	SUNOCO INC
ROLLINS, INC.	SKECHERS U.S.A., INC	SUPERIOR ENERGY SVCS
ROPER INDUSTRIES INC	SKYWEST, INC.	SUPERIOR INDUSTRIES
ROSS STORES, INC.	SKYWORKS SOLUTIONS	SUPERTEX INC
ROVI CORPORATION	SM ENERGY COMPANY	SUPERVALU INC.
ROWAN COMPANIES PLC	SMITH (A.O.) CORP	SURMODICS, INC.
RPM INTERNATIONAL	SMITHFIELD FOODS INC	SWIFT ENERGY COMPANY
RTI INT'L METALS	SNAP-ON INC	SYKES ENTERPRISES
RUBY TUESDAY INC	SNYDER'S-LANCE, INC	SYMANTEC CORP
RUDOLPH TECHNOLOGIE	SONIC AUTOMOTIVE IN	SYMMETRICOM INC
RYDER SYSTEM, INC.	SONIC CORP	SYNAPTICS INC
RYLAND GROUP, INC	SONOCO PRODUCTS CO	SYNOPSYS INC
SAFEWAY INC	SOTHEBY'S	SYSCO CORPORATION
SAKS INCORPORATED	SOUTH JERSEY INDS	TAKE-TWO INTERACTIVE
SALIX PHARMACEUTICAI	SOUTHERN CO (THE)	TARGET CORP
SANDERSON FARMS INC	SOUTHWEST AIRLINES	TECH DATA CORP
SANDISK CORP	SOUTHWEST ENERGY C	TECHNE CORP
SARA LEE CORPORATION	SOUTHWEST GAS CORP	TECO ENERGY INC
SAVIENT PHARMATCLS	SPARTAN MOTORS, INC.	TELEDYNE TECH.
SCANA CORPORATION	SPARTAN STORES INC	TELEFLEX INC
SCANSOURCE, INC.	SPECTRUM PHARMACTI	TELEPHONE & DATA SYS
SCHEIN (HENRY) INC	SPRINT NEXTEL CORP	TELETECH HOLDINGS
SCHLUMBERGER LIMITEI	SPX CORPORATION	TELLABS INC
SCHOLASTIC CORP	ST JUDE MEDICAL INC	TENET HEALTHCARE
SCHULMAN (A) INC	STAGE STORES INC	TENNANT COMPANY

TERADYNE INC
TEREX CORPORATION
TESORO CORPORATION
TETRA TECH INC
TETRA TECHNOLOGIES
TEXAS INDUSTRIES
TEXAS INSTRUMENTS
TEXTRON INC
THERMO FISHER
THOR INDUSTRIES, INC
THORATEC CORP
TIBCO SOFTWARE INC.
TIDEWATER INC.
TIFFANY & CO.
TIME WARNER INC
TIMKEN COMPANY (THE)
TITANIUM METALS CORP
TJX COMPANIES, INC.
TOLL BROTHERS, INC.
TOOTSIE ROLL IND
TORO COMPANY (THE)
TOTAL SYSTEM SERVICE
TOWERS WATSON
TRACTOR SUPPLY CO
TREDEGAR CORP
TRIMBLE NAVIGATION
TRINITY INDUSTRIES
TRIQUINT SEMICONDUCT
TRIUMPH GROUP INC
TRUEBLUE, INC.
TTM TECHNOLOGIES
TUESDAY MORNING COR
TUPPERWARE BRANDS
TW TELECOM INC
TYCO INTERNATIONAL
TYLER TECHNOLOGIES
TYSON FOODS, INC.
UGI CORPORATION
UIL HOLDINGS CORP
ULTRATECH, INC.
UNIFIRST CORPORATION
UNION PACIFIC CORP
UNIT CORPORATION
UNITED NATURAL FOODS
UNITED ONLINE INC
UNITED PARCEL SVCS
UNITED RENTALS INC
UNITED STATES STEEL
UNITED STATIONERS
UNITED TECHNOLOGIES
UNITED THERAPEUTICS
UNITEDHEALTH GROUP
UNIVERSAL CORP
UNIVERSAL ELEC
UNIVERSAL FOREST PR
UNIVERSAL HEALTH SVC
UNS ENERGY CORP
URBAN OUTFITTERS
URS CORPORATION
V F CORPORATION
VALASSIS COMM.
VALERO ENERGY CORP
VALMONT INDUSTRIES
VALSPAR CORPORATION
VALUECLICK, INC.
VARIAN MEDICAL SYST
VASCO DATA SECURITY
VECTREN CORP
VEECO INSTRUMENTS
VERISIGN, INC.
VERIZON COMMUNICATN
VERTEX PHARMA INC
VIAD CORP
VIASAT, INC.
VICOR CORPORATION
VIROPHARMA INC
VISHAY INTERTECH
VOXX INTERN
VULCAN MATERIALS CO
WABTEC CORP
WALGREEN CO.
WAL-MART STORES INC
WALT DISNEY
WARNACO GROUP, INC.
WASHINGTON POST CO
WASTE CONNECTIONS
WASTE MANAGEMENT
WATERS CORPORATION
WATSCO INC
WATSON PHARMCL INC
WATTS WATER TECH
WAUSAU PAPER CORP
WD-40 COMPANY
WEBSENSE INC
WELLPOINT INC
WENDYS
WERNER ENTERPRISES
WEST PHARMACEUTICAL
WESTAR ENERGY, INC.
WESTERN DIGITAL CORP
WGL HOLDINGS, INC.
WHIRLPOOL CORP
WHOLE FOODS MKT
WILEY (JOHN) & SONS
WILLIAMS COMPANIES
WILLIAMS-SONOMA
WINNEBAGO INDUSTRIES
WISCONSIN ENERGY
WMS INDUSTRIES INC.
WOLVERINE WORLD WIDE
WOODWARD GOVERNOR C
WORLD FUEL SERVICES
WORTHINGTON INDS
XCEL ENERGY INC
XEROX CORPORATION
XILINX INC
XO GROUP
YAHOO! INC
YUM! BRANDS INC
ZALE CORP
ZEBRA TECHNOLOGIES
ZIMMER HOLDINGS INC

B. Faktör Analizinin Sonucunda Elde Edilen Finansal Rasyolar ve Türkçe Karşılıkları

NI / TA : Net gelirlerin toplam varlıklara oranı

EBIT / TA: Faiz ve vergi öncesi gelirlerin toplam varlıklara oranı

EBIT / Sales : Faiz ve vergi öncesi gelirlerin satışlara oranı

NI / Sales: Net gelirlerin satışlara oranı

NI / NW : Net gelirlerin özkaynaklara oranı

NI / TL : Net gelirlerin toplam yabancı kaynaklara oranı

FFO / TL : Operasyonlardan sağlanan fonların toplam yabancı kaynaklara oranı

FFO / TA : Operasyonlardan sağlanan fonların toplam varlıklara oranı

LTD / TA : Uzun vadeli yabancı kaynakların toplam varlıklara oranı

LTD / TL : Uzun vadeli yabancı kaynakların toplam yabancı kaynaklara oranı

TD / NW : Toplam borcun özkaynaklara oranı

TL / NW : Toplam yabancı kaynakların özkaynaklara oranı

TA / NW : Toplam varlıkların özkaynaklara oranı

CA / NW : Dönen varlıkların özkaynaklara oranı

NW / Sales: Özkaynakların satışlara oranı

TL / TA : Toplam yabancı kaynakların toplam varlıklara oranı

TD / TA : Toplam borçların toplam varlıklara oranı

Inv / Sales: Stokların satışlara oranı

COGS / Inv : Satışların maliyetinin stoklara oranı

CL / Inv : Kısa vadeli yabancı kaynakların stoklara oranı

TL / WC : Toplam yabancı kaynakların işletme sermayesine oranı

Sales / WC : Satışların işletme sermayesine oranı

FFO / WC : Operasyonlardan sağlanan fonları işletme sermayesine oranı

TD / WC : Toplam borçların işletme sermayesine oranı

Inv / WC : Stokların işletme sermayesine oranı

NI / WC : Net gelirlerin işletme sermayesine oranı

Sales / TA : Satışların toplam varlıklara oranı

QA / Sales : Hemen nakite dönüştürülebilir varlıkların satışlara oranı

CA / Sales : Dönen varlıkların satışlara oranı

CA / TA : Dönen varlıkların toplam varlıklara oranı

QA / FEO : Hemen nakite dönüştürülebilir varlıkların operasyonlarda harcanan fonlara oranı

Cash / FEO : Nakit değerlerin operasyonlarda harcanan fonlara oranı

Cash / TA : Nakit değerlerin toplam varlıklara oranı

Cash / TL : Nakit değerlerin toplam yabancı kaynaklara oranı

CL / PPE : Kısa vadeli yabancı kaynakların maddi duran varlıklara oranı

Sales / PPE : Satışların maddi duran varlıklara oranı

TD / PPE : Toplam borçların maddi duran varlıklara oranı

CA / CFO : Dönen Varlıkların operasyonlardan sağlanan nakit akışına oranı

QA / CFO : Hemen nakite dönüştürülebilir varlıkların operasyonlardan sağlanan nakit akışına oranı

Rec / Sales : Alacakların satışlara oranı

DIV / NI : Temettülerin net gelirlere oranı

E. CURRICULUM VITAE

CURRICULUM VITAE

PERSONAL INFORMATION

Surname, Name: Sayarı Musaoğlu, Naz

Nationality: Turkish (TC)

Date and Place of Birth: 24 September 1982 , Ankara

Marital Status: Married

Phone: +90 312 286 60 86

email: nsayari@metu.edu.tr

EDUCATION

Degree	Institution	Year of Graduation
PHD	METU Department of Business Administration	2013
MS	Başkent University	2008
BS	Bilkent University	2004
High School	TED Ankara Collage	2000

WORK EXPERIENCE

Year	Place	Enrollment
2010-Present	METU Department of Business Administration	Research Assistant
2008-2010	Baskent University Department of Accounting and Financial Management	Research Assistant
2006-2008	TEPAV	Research Assistant
2004-2005	PriceWaterhouseCoopers	Auditor

FOREIGN LANGUAGES

Advanced English, Fluent German

PUBLICATIONS

1. Sayari, N. "Implications of Socieatas Europaea in Member States of European Union", World of Accounting Science, 5(12), 293-305 (2011)
2. Sayari, N. and Mugan, F. N. C. "Comparison of Book Income and Taxable Income in terms of Value Relevance of Earnings", GBATA, 14th Annual International Conference, NY, USA (2012)

HOBBIES

Sports, Movies, Philosophy

F. TEZ FOTOKOPİSİ İZİN FORMU

TEZ FOTOKOPİSİ İZİN FORMU

ENSTİTÜ

Fen Bilimleri Enstitüsü ☐

Sosyal Bilimler Enstitüsü ☑

Uygulamalı Matematik Enstitüsü ☐

Enformatik Enstitüsü ☐

Deniz Bilimleri Enstitüsü ☐

YAZARIN

Soyadı : Sayarı

Adı : Naz

Bölümü : İşletme

TEZİN ADI (İngilizce) :Industry Specific Information Content of Financial Ratios and Financial Distress Modeling

TEZİN TÜRÜ : Yüksek Lisans ☐ Doktora ☑

1. Tezimin tamamından kaynak gösterilmek şartıyla fotokopi alınabilir. ☐

2. Tezimin içindekiler sayfası, özet, indeks sayfalarından ve/veya bir bölümünden kaynak gösterilmek şartıyla fotokopi alınabilir. ☐

3. Tezimden bir (1) yıl süreyle fotokopi alınamaz. ☑

TEZİN KÜTÜPHANEYE TESLİM TARİHİ: