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ABSTRACT

This paper is prepared to model financial distress cases in Turkey using a non-parametric technique, Multivariate Adaptive Regression Splines (MARS). For this purpose, a sample of 114 firms with 665 annual observations between the years 1994 and 2003 was used to predict financial distress for one year prior failure. Our modeling study on 41 independent variables, 39 financial data-based and 2 non-financial, has resulted in a condensed model including 10 basis functions based on 8 original variables. The final model has an overall rate of correct classification of 81,8 % and is proved to be significantly superior to a naïve model. Its Type I and Type II performances are respectively 91,5 % and 80,9 %. Furthermore, profitability performance, capital structure decisions, and macroeconomic conditions are found to be the major determinants that influence Turkish firms' risk profiles.

Keywords: Financial Distress Prediction, Non-Parametric Modeling, Multivariate Adaptive Regression Splines, Turkey

JEL Codes: G30, G33, C38

KURUMSAL BAŞARISIZLIĞI MODELLEMEK İÇİN TÜRKİYE ÜZERİNE YAPILAN AMPİRİK BİR ÇALIŞMA: ÇOK DEĞİŞKENLİ UYUMLU REGRESYON UZANIMLARI(MARS) TEKNİĞİ KULLANILARAK GELİŞTİRİLEN MODEL ÖNERİSİ

ÖZET

Bu makale, Türkiye'deki finansal başarısızlık örneklerine bir model oluşturmak amacıyla parametrik olmayan MARS tekniği kullanılarak hazırlanmıştır. Finansal başarısızlık durumunu bir yıl önceden tahmin edebilmek amacıyla 1994 ve 2003 yılları arasında 114 firmaya ilişkin 665 adet yıllık gözlem yapılmıştır. 39 u finansal, 2 si finansal olmayan 41 bağımsız değişkenle yapılan çalışma sonucunda, 8 orijinal değişkene dayalı 10 temel fonksiyonlu bir modele ulaşılmıştır. Ortaya konan bu model, %81,8 oranında doğru sınıflandırma başarısına sahiptir ve yalın bir modelden çok daha üstün olduğu kanıtlanmıştır. Modelin Tip I ve Tip II tahmin performansları sırasıyla %91,5 ve %80,9'dur. Buna ilave olarak, Türkiye'deki firmaların risk profillerinde karlılık performanslarının, sermaye yapısı kararlarının ve makroekonomik koşulların çok önemli belirleyici değişkenler olduğu ortaya konmuştur.

Anahtar kelimeler: Kurumsal Başarısızlık Tahmini, Parametrik Olmayan Modelleme, Çok Değişkenli Uyumlu Regresyon Uzanımları

Contents

1. Introduction

Despite the theoretical phenomenon that a business is started assuming it will survive forever, in real life, various factors and conditions might cause some to fail. The financial manager of a failing firm is expected to ward off the collapse of the firm and thereby reduce its losses. A complete understanding of business failures and bankruptcies are also crucial for financial managers of successful firms, because they must know their firms' rights when their customers become insolvent (Brigham and Gapenski, 1997, p.1034).

Financial distress is a concept used for both firms and individuals in order to mean their deficiency in fulfilling existing obligations. In this manner, corporate financial distress is generally defined as a situation where a firm's operating cash flows are not sufficient to satisfy current obligations and the firm is forced to take corrective actions that it would not take, if it had sufficient cash flow (Ross et al, 1999, p.793). This explanation of financial distress from a liquidity view of point mainly emphasizes the incapacity to cover matured liabilities because of the entrepreneurial disability to perform according to the expected returns, which finally result in a delayed or nonexistent fulfillment of an obligation. The persistence of cash flow-based insolvency likely paves the way for bankruptcy as the terminal status of a firm in which the net worth is negative (Altman, 1993, p.4). Furthermore, the situation that total revenues do not cover total costs is called economic failure which is another type of financial distress referring to a less critical circumstance.

Corporate failures bring about some direct and indirect costs which challenge financial stability and ongoing concern. Legal costs, accounting costs, other administrative costs which are associated with financial readjustments and legal proceedings are considered as direct costs. On the other hand, indirect costs include the costs that arise before the legal procedures of bankruptcy, such as lack of financing, hard and costly borrowing, loss of employees and suppliers, and reorganization costs. Andrade and Kaplan (1998) states that a major fixed portion of distress costs are incurred in the period, when firms become distressed before the formal bankruptcy procedures start.

As a result of costing role of financial distress, firm value is very sensitive to the magnitude of perceived financial distress and bankruptcy costs. Since investors know that a highly levered firm has a great potential to fall in financial distress, this inquietude is reflected in the market value of the firm's securities (Clark and Weinstein, 1983). The extent of value change depends on the probability of distress and the magnitude of costs encountered in case of a distress (Brealey and Myers, 1984, p.221)

The findings of the empirical studies conducted on the possible causes of corporate failures show that, such financial factors as issuing too much debt and having insufficient capital are the most relevant determinants of failures while economic factors such as industry conditions and macroeconomic trends are secondarily important. The other factors including firm-specific causes, neglect, disasters, and fraud are considered to be of minor importance (Klapper, 2001, p.3). It is also known that leasing, factoring, hedging, and alike financial techniques may be used as special tools to decrease the probability of insolvency. In theory, hedging is considered as one of the major preventive tools which helps companies reduce the possible damages of a distress event. So, a hedged company may fall in financial distress with a lower probability than an unhedged company (Smithson and Smith, 1992, p.106).

Rarely a firm falls in financial distress because of extraordinary reasons. It is possible to observe the signals of an upcoming failure event in the current accounts of a firm in banks, its relations with the suppliers, and its financial statements. To take proactive actions for the minimization of distress and bankruptcy risk, the early assessment of any deterioration in the firm's financial health is vital. At this point, the past research shows that ratio analysis is regarded as a functional tool in predicting financial distress, if undertaken as integrated with appropriate quantitative techniques. Being motivated by this argument, this paper is aimed at developing a unique model to be used in predicting financial distress cases in Turkey employing the Multivariate Adaptive Regression Splines (MARS) Algorithm with financial ratios.

2. Literature Framework

Over the past 45 years, a vast literature has emerged with the development of statistical models designed to foresee whether the firms will fail or experience some other less severe forms of financial distress. This interest in developing financial distress prediction models seems to be largely motivated by the assumption that an early warning of impending financial distress can confer large benefits to a number of related parties, in terms of avoiding or reducing the costs of any failure event.

The financial distress prediction models previously developed by the researchers differ with respect to the statistical techniques used, nature of variables included, and nature of data collection procedure (use of a single period or multiple periods) implemented.

Considering the modeling techniques undertaken, it is possible to separate the existing models into two groups as parametric and non-parametric. We observe that most of the parametric model proposals have been produced through the application of some traditional econometric techniques such as *Univariate Analysis* (Beaver, 1966), *Discriminant Analysis* (Altman, 1968; Deakin, 1972; Blum, 1974; Casey and Bartzak, 1985), *Logit and Binary Logistic Regression* (Ohlson, 1980; Zavgren, 1985; Gentry, Newbold and Whitford, 1985; Aziz et.al, 1988; Platt and Platt, 1990; Hol et al, 2002), *Probit Analysis* (Zmijewski, 1984; Gentry et al, 2002), and *Multilogit Models*. Among the non-parametric techniques which have been used in the past studies are *Tree Classification* (Frydman et al, 1985), *the Gambler's Ruin Model* (Wilcox, 1971), *Neural Networks and Genetic Algorithm* (Coats and Funt, 1992; Torsun, 1996), *Option-Based Pricing Models* (Merton, 1974; Charitou and Trigeorgis, 1996) *Judgmental Approach* (Libby, 1975; Houghton, 1984), and *Chaos Approach* (Lindsay and Campbell, 1996).

According to the classification to be made respecting the nature of variable used, an initial two-class segmentation can be made: The models based on financial data, and the models based on non financial data. For the financial data-based models, three major categories are available: **Ratio models** in which firm's financial ratios and/or industry averages are used as predictors of failure, **cash-flow models** in which cash flow data are taken into account, and **return variation models** in which security return variations, especially stock returns, are considered to be relevant. In the literature, the weight of ratio models is noticeably higher than those of the models of other types because of their technical simplicity and comprehensibility.

Although ratio models have been widely and successfully implemented, little agreement exists regarding the best accounting ratios to determine the likelihood of financial distress. For example, while Boritz (1991) identifies more than 65 financial ratios that were used as predictors in the previous literature, Karels and Prakash (1995) point out the importance of careful selection of relevant ratios to improve prediction accuracy. However, Hamer (1990) suggests as an opposite argument that the prediction ability of a models is relatively independent of the ratios selected. Unfortunately, no dominant ratio model has emerged, even though some researchers have provided brilliant performance results for their original data sets.

Reilly (1991) reported the summary of the most useful ratios for predicting failure. According to his report, ten accounting ratios were found and proved to be significant in the previous studies. The following table presents these ten ratios and the number of the studies in which each of these ratios was significant.

Table 1: Summary of Most Useful Ratios for Predicting Failure

RATIO	NUMBER OF STUDIES
Cash Flow / Total Liabilities	**7**
Total Debt / Total Assets	**6**
Net Working Capital / Total Assets	**6**
Current Ratio	**6**
Retained Earnings / Total Assets	**5**
Net Income / Total Assets	**5**
Cash / Current Liabilities	**4**
EBIT / Total Assets	**4**
Cash / Sales	**2**
(Current Assets - Inventories) / Sales	**2**

Cash Flow = Net Income + Depreciation

There are some limitations on the use of financial ratios which challenge the accuracy of the analyses based on financial statements data. Those limitations include the following (Reilly and Norton, 1995, p.292):

- Differences in accounting treatments
- Presence of multinational and multi-industrial firms in the sample
- Presence of ratio values not within a reasonable range valid for the industry

In addition to the selection of true predictors, there are some other factors that affect the performance of financial distress prediction models such as, a correct definition of failure event to use in discriminating failing and non-failing firms, ways of sample derivation, choices on modeling techniques and other methodological issues such as cut-off value and prior probabilities, sample size, technique-related restrictive assumptions, multi-period effect, and the assessment of validity (Keasey and Watson, 1991, pp.89 – 102).

3. Empirical Research

This paper presents the results of an inferential study to construct a financial distress prediction model unique to Turkey for one year prior to failure. Financial ratios are taken as independent variables, while explained variable is a dichotomous variable, failing or non-failing. The statistical purpose is to represent the relationships between a set of independent variables and dependent variable with an appropriate equation.

3.1. Data and Model

Our target population is the non-financial firms listed on Istanbul Stock Exchange between the years, 1994 and 2003. To derive a sample to be used, a failed firm is identified with respect to the following two circumstances in confirmation with the failure definition declared in the Turkish Commercial Law:

- The initiation of a legal procedure and lawsuits against a firm falling in difficulty to pay their debts on time
- Having a negative net worth

Finally, a sample of 664 observations for 114 firms has been derived. 59 of the observations have been identified as a failing case. 41 independent variables presented in Table II are used in modeling. 39 of these variables which were previously used also by Muzir (2011) are financial data-based whereas the last two ones are non-financial.

The non-parametric technique we have used in modeling is the Multivariate Adaptive Regression Splines (MARS) developed by Jerome H.Friedman in early 1990s. This technique is based on the use of smoothing splines in determining a possible relationship between a dependent variable and a set of independent variables. A linear line is the final output to be gained through controlling any shifts in presumed relationships. These shifts exist especially on the points called knots and enable passes across regimes. MARS algorithm tries to determine all the knots covering possible interactions among all of the model variables. In this way, the interactions of independent variables among themselves and the effects of these interactions on dependent variable are captured while the relationship of each independent variable with dependent variables is being examined.

Table II: Independent Variables

CODE	**VARIABLE**
X_1	(CURRENT ASSETS-INVENTORIES-OTHER CURRENT ASSETS) / NET SALES
X_2	(CURRENT ASSETS-INVENTORIES-OTHER CURRENT ASSETS) / TOTAL ASSETS
X_3	CURRENT ASSETS / TOTAL ASSETS
X_4	NET WORKING CAPITAL / TOTAL ASSETS
X_5	ACID-TEST RATIO
X_6	CURRENT RATIO
X_7	CHANGE IN CURRENT ASSETS / AVERAGE CURRENT LIABILITIES
X_8	CASH AND CASH EQUIVALENTS / CURRENT ASSETS
X_9	TOTAL LIABILITIES / TOTAL ASSETS
X_{10}	NET SALES / AVERAGE RECEIVABLES
X_{11}	CURRENT ASSETS / NET SALES
X_{12}	NET WORKING CAPITAL TURNOVER
X_{13}	NET WORKING CAPITAL / NET SALES
X_{14}	FIXED ASSETS / EQUITY
X_{15}	TANGIBLE FIXED ASSETS / EQUITY
X_{16}	EQUITY / TOTAL LIABILITIES
X_{17}	CHANGE IN EQUITY / AVERAGE TOTAL LIABILITIES
X_{18}	CHANGE IN EQUITY / AVERAGE TOTAL ASSETS
X_{19}	LONG TERM LIABILITIES / (TOTAL ASSETS - CURRENT LIABILITIES)
X_{20}	RETAINED EARNINGS / TOTAL ASSETS
X_{21}	NET PROFIT / EQUITY
X_{22}	OPERATING PROFIT / TOTAL ASSETS
X_{23}	NET PROFIT / TOTAL ASSETS
X_{24}	NET SALES / (TOTAL ASSETS – CURRENT LIABILITIES)
X_{25}	NET SALES / AVERAGE TOTAL ASSETS
X_{26}	NET SALES / AVERAGE TOTAL EQUITY
X_{27}	(NET PROFIT + DEPRECIATION) / CURRENT LIABILITIES
X_{28}	(NET PROFIT + DEPRECIATION) / TOTAL LIABILITIES
X_{29}	OPERATING PROFIT / (TOTAL ASSETS – CURRENT LIABILITIES)
X_{30}	OPERATING PROFIT / NET SALES
X_{31}	EARNINGS BEFORE INTEREST AND TAX / NET SALES
X_{32}	NET PROFIT MARGIN (NET PROFIT / NET SALES)
X_{33}	MARKET VALUE / NET PROFIT
X_{34}	MARKET VALUE / TOTAL LIABILITIES
X_{35}	MARKET-TO-BOOK RATIO
X_{36}	DUMMY VARIABLE FOR PROFITABILITY (NET PROFIT <0, 1 ; >0, 0)
X_{37}	LOG (TOTAL ASSETS / GNP DEFLATOR)
X_{38}	LOG (TOTAL ASSETS)
X_{39}	LOG (NET SALES)
X_{40}	DUMMY VARIABLE FOR INDUSTRY TYPE (Manufacturing: 0, Other: 1)
X_{41}	DUMMY VARIABLE FOR ECONOMIC CRISIS (Crisis (2000 and 2001): 1, Other: 0)

Determination of each knot is performed by using different variable combinations. Each of the variable combinations to be obtained following the analysis of all model components is called a ***basis function***. After the determination of both the best combination of basis functions and their knots that could yield the highest prediction performance, a least-square regression analysis is undertaken to produce appropriate models (Salford Systems, pp.1-15). A typical MARS model equation can be expressed with the following equation (Tunay, 2001, pp.181 – 182).

$$Y_t = \sum_{k=1}^{N} \varphi_k B_k(x_t) + \varepsilon \qquad (1)$$

In the equation; $B_k(X_t)$ represents k*th* basis function of variable x_t while φ_k symbolizes the regression coefficient of that basis function. Basis functions may be non-linear transformations of x_t. On the other hand, Y_t main function is a linear equation composed of these non-linear basis functions. In other words, predicted values of dependent variable are supposed to be a linear modeling of non-linear relationships associated with independent variables. The final model equation is the one that minimizes the sum of squared errors.

The major advantage of MARS is that both the individual effects of independent variables and their interactions with one another can be captured in modeling. Moreover, the process of knot determination in order to minimize sum of squared errors is one of the different approaches of MARS technique. The technique also allows for using forward and backward variable eliminations. Selection of the most appropriate model is done according to the Generalized Crossvalidation criterion developed by Craven and Wabha (1979).

MARS model results can easily be interpreted using the output of Variance Analysis since the model equation is in a linear form. A higher adjusted R^2 statistic is required for the conclusion on the validity of model equation and results. Furthermore, the changes in adjusted R^2 values during variable elimination process are considered to be a good measure for the significance of each independent variable and each basis function. A penalty factor on the maximum number of basis functions to be included in the model should be assigned especially for the purpose of avoiding any multicollinearity problem.

The decisions on what should be the maximum number of knots for each basis function and whether or not the interactions between independent variables are covered affect model results and validity. Although the number of basis functions can be increased up to 250, regarding the common opinion that an optimal model should contain at most 12 basis functions, it is recommended that the upper limit must be 15 (Salford Systems, pp.39 – 44). As Friedman suggests, the optimum degree of freedom is between 2 and 5. Despite the fact that the decision on learning speed is up to researchers, the most recommended value for that parameter is 4. A higher learning speed value shortens training time but, decreases the possibility of reaching the most optimal solution. Keeping this value as low as possible confronts researcher with serious data and time problems.

In our study, we prefer to assign recommended values to the relevant model parameters. In this context, the maximum number of basis functions is taken as 15 while the maximum knot number is kept at 3. No interactions among variables are assumed.

3.2. Evaluation of Model Performance

Determination of the best cut-off point which will give the highest performance level is done using Receiver Operating Characteristics Curve (ROC) Analysis. In the light of results of that analysis, we test the hypothesis that the model’s prediction performance is superior to a naïve model at 99

% confidence level. We also consider the Type I, Type II, and Overall Performances in assessing model success.

Type I performance refers to model's ability of predicting the failed firms as failed. The percentage of the non-failed firms to be classified by the model as non-failed is known to be Type II performance. Overall true classification rate shows how correctly the model classifies all firms. Finally, in addition to these performance measures, Brier Score, Effron R^2 and Theil's R^2 are other statistics to support our conclusions.

3.3. Empirical Findings

The model results show that, 8 original independent variables are significant at 95 % confidence level and represented with 10 basis functions. As can be seen in Table III, the most significant independent variable is the dummy variable for economic crisis (X41) and this categorical variable is followed by Total Liabilities / Total Assets ratio (X9) that can be considered as a measure of leverage. The other variables found to be statistically significant are, in the order of importance, Operating Profit / Total Assets (X22), Net Working Capital / Total Assets (X4), Net Sales / Average Receivables (X10), Fixed Assets / Equity (X14), Retained Earnings / Total Assets (X20), and Net Profit / Net Sales (X32).

Table III: Relative Variable Importance

Piecewise Cubic Fit on 10 Basis Functions, GCV = 0.06328

Variable	Importance	-gcv
X41	100.00000	0.06416
X9	76.19504	0.06270
X22	71.24625	0.06244
X4	57.06275	0.06181
X10	51.97747	0.06161
X14	46.09988	0.06141
X20	42.04091	0.06129
X32	38.56636	0.06119

The findings summarized in Table IV and the model equation (Equation 2) below suggest that the likelihood of financial distress is a positive function of economic crisis variable (BF3), the ratio of total liabilities to total assets (BF5; in BF6, as the ratio increases until 0,103, decreases in likelihood become limited), Fixed Assets / Equity (BF7) while it is negatively correlated with Operating Profit / Total Assets (BF1 and BF2), Net Sales / Average Receivables (BF9), Net Working Capital / Total Assets (BF11), Net Profit / Net Sales (BF13), and Retained Earnings / Total Assets (BF14). The coefficient of determination for the model is 28,86 %. It can be concluded that the model is accurate and sufficient at 0,001 significance level, because the p-value corresponding to the model's F statistic (27,94) is much below that level.

Table IV: MARS Model Output

N: 665.00 R-SQUARED: 0.29935

MEAN DEP VAR: 0.08872 ADJ R-SQUARED: 0.28864

UNCENTERED R-SQUARED = R-0 SQUARED: 0.36152

PARAMETER	ESTIMATE	S.E.	T-RATIO	P-VALUE
Constant	-0.12299	0.06067	-2.02726	0.04304
Basis Function 1	-0.34915	0.11912	2.93104	0.00350
Basis Function 2	0.42936	0.09383	4.57579	0.00001

Basis Function 3	|	0.15282	0.02351	6.49924	0.00000
Basis Function 5	|	0.23209	0.06854	3.38638	0.00075
Basis Function 6	|	-0.15696	0.04426	-3.54611	0.00042
Basis Function 7	|	0.00868	0.00246	3.52385	0.00045
Basis Function 9	|	0.04194	0.01098	3.82108	0.00015
Basis Function 11	|	-0.36195	0.08857	-4.08663	0.00005
Basis Function 13	|	0.03078	0.00973	3.16259	0.00164
Basis Function 14	|	-0.14372	0.04321	-3.32605	0.00093

F-STATISTIC = 27.94223 S.E. OF REGRESSION = 0.24000

P-VALUE = 0.00000 RESIDUAL SUM OF SQUARES = 37.67060

[MDF,NDF] = [10, 654] REGRESSION SUM OF SQUARES = 16.09481

Basis Functions

===============

BF1 = max(0, X22 - 0.103566);

BF2 = max(0, 0.103566 - X22);

BF3 = (X41 in (1));

BF5 = max(0, X9 - 1.09479);

BF6 = max(0, 1.09479 - X9);

BF7 = max(0, X14 + 18.124);

BF9 = max(0, 3.42047 - X10);

BF11 = max(0, -0.405167 - X4);

BF13 = max(0, 2.55782 - X32);

BF14 = max(0, X20 + 0.369688);

Y = -0.122986 - 0.349151 * BF1 + 0.429356 * BF2 + 0.152824 * BF3 + 0.232093 * BF5

- 0.156964 * BF6 + 0.00867973 * BF7 + 0.0419441 * BF9 - 0.361948 * BF11

+ 0.030776 * BF13 - 0.143722 * BF14

(2)

ROC results and other performance measures indicate that the performance of the model in correctly predicting financial distress cases is satisfactorily high and superior to a naïve model. The best cut-off point has been determined as 0,132, which is a really low value showing high vulnerability of Turkish firms to insolvency factors. While the model classifies correctly 91,5 % of the failed firms, 80,9 % of non-failed firms can be treated by the model as non-failed. The overall correct classification rate is 81,8 %. Table V and Table VI contain details on the ROC statistics and other performance measures. The ROC area statistic is very high (0,922) and statistically significant since the asymptotic significance level is below 0,001, which suggests the accuracy of our MARS model. Our model's Brier score (0,056) is favorably very close and the finding that the Theil's R^2 is much low (0,058) encourages our opinion about the superiority of the model. Additionally, any Effron's R^2 value which is approaching to 1 may be considered to be convincing.

Table V: ROC Results

Case Processing Summary

Y.FAILURE	Valid N (listwise)
Positive[a]	59
Negative	606

Larger values of the test result variable(s) indicate stronger evidence for a positive actual state.

a. The positive actual state is 1,00.

Area Under the Curve

Test Result Variable(s):PROB.MARS

Area	Std. Error[a]	Asymptotic Sig.[b]	Asymptotic 95% Confidence Interval: Lower Bound	Asymptotic 95% Confidence Interval: Upper Bound
,922	,015	,000	,891	,952

The test result variable(s): PROB.MARS has at least one tie between the positive actual state group and the negative actual state group. Statistics may be biased.

a. Under the nonparametric assumption

b. Null hypothesis: true area = 0.5

Table VI: Other Performance Measures

MODEL	BEST CUT-OFF POINT	TYPE I PERFORMANCE	TYPE II PERORMANCE	OVERALL PERFORMANCE	BRIER SCORE	THEIL'S R^2	EFFRON'S R^2
MARS	**0,132**	**91,50%**	**80,90%**	**81,80%**	**0,056**	**0,058**	**0,299**

Brier Score = Sum of Squared Errors / Number of Observations

Theil's R^2 = Sum of Squared Errors / (Number of Observations – Number of Model Variables)

Effron's R^2 = 1 – [Number of All Observations / (Number of Group 1 Observations x Number of Group 2

Observations)] x Sum of Squared Errors

4. Concluding Remarks

Our research findings are convincing enough for us to conclude that the financial distress cases in Turkey can be accurately predicted using a MARS model. MARS as a non-parametric modeling technique helps us produce prediction models ignoring all the restrictive assumptions of such traditional statistical tools as discriminant analysis, logistic regression, and probit technique.

The model results suggest that profitability level and capital structure choices are among the main determinants of corporate sustainability. Highly leveraged firms are expected to be more exposed to financial distress risk but, risk position gets more favorable along with increasing profitability. Moreover, a less liquid position expectedly increases distress probability, whereas better asset turnover performance seems to be supportive in reducing the probability of insolvency. The risk reducing role of profit accumulation (retained earnings) is proved here, just as Altman (1968) did in his original study. Even though no sufficient evidence is obtained about the net effect of industry difference, it is obvious that economic downturns negatively affect corporate risk profile.

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