Corporate Ratings and a Model Proposition for the Manufacturing Industry at Borsa Istanbul

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Abstract

In this study it is aimed to develop a model using logistic regression analysis for the forecasting the rating grade of a manufacturing firm that form the basis to expert evaluation. Under the scope of this study 35 financial ratios are used as the independent variables, which are calculated on the grounds of annual financial statements and their notes during the period of 2007-2013 which are disclosed by the 206 listed manufacturing firms on Borsa Istanbul, and the status of the firms being "good" or "bad" based on financial capability is used as the dependent variable. Percentage of correct classification of developed model is at acceptable levels. By using the developed model, probability of a firm being "good" or "bad" can be estimated and using the proposed scale rating grade can be appointed of the firm that rating wanted to be performed.

Keywords: corporate rating, logistic regression analysis, rating, financial failure, Borsa Istanbul

1. Introduction

Rating agencies have been criticized severely due to recent bankruptcies and financial crisis. The critics have been focusing on the inadequate regulations at the national and international level and rating agencies have been criticized on losing impartiality, giving better or worse grades than what is deserved. However, taking increment in number of issuers, securitizations and complexity of financial instruments and level of globalization into consideration, it is clear that the importance of rating activities have gradually increased from the point of market and market participants (Öcal, 1997). In this manner, it is thought that the rating agencies will continue to exist and operate in the market.

According to US Securities and Exchange Commission (SEC), credit rating is an opinion of rating agency at a specific date regarding the solvency of a firm or of the security or the bond of the firm (SEC, January 2003).

Capital Markets Board of Turkey (CMB) defined credit rating as *"credit rating an independent, impartial and fair evaluation and classification of the riskiness and solvency of institutions or the ability to pay the capital, interest, and other obligations regarding capital market instruments representing debt, within the specified term by rating agencies."*

According to Banking Regulation and Supervision Agency (BRSA) of Turkey, rating is a process of determining creditworthiness and accordingly credit note, based on the result of studies and analyses to be made depending on the nature of such activities, of customers that are in the scope. Additionally, rating of creditworthiness is defined as operation of an authorized rating agency regarding the independent, impartial and fair evaluation, classification and convenient rating of customer's capability of repaying credits that are to be used or customer's risk of being able to meet obligations of the concerning market instruments which represent their indebtedness such as principal, interest and the likewise.

As seen from the definitions, rating can be done for the firm as a whole or for the particular capital market instruments representing the debt or solvency and the rating activity shall be independent and impartial.

On the other hand, there is no single procedure regarding rating methodology. Each rating agency has its own unique methodology and the methodology can be differentiated in itself by sectors, type of firm and type of financial instrument.

Using statistical methods solely while carrying out rating activities have been criticized. On the other hand, as rating based on solely experts' judgments, can be a waste of time and resource and as they are open to human error and have potential deviation from objectivity, the benefits of using statistical methods come into prominence. However it shall not be assumed that using only statistical methods are adequate. Accordingly, the critique of statistical methods shall be considered as well. Therefore statistical techniques and experts' judgments shall be used jointly in order to remove the limitation of a human, selecting data, processing and concluding with a result from a wide range of data and inadequacy of non-numeric data processing of statistical models shall be eliminated.

In this study it is aimed to develop a model using logistic regression analysis for the forecasting the rating grade of the manufacturing firms that will form basis to Expert evaluation. It should be kept in mind that the rating grade that will be determined by the developed model, is not final.

Furthermore, the rating requires usage of non-public data and/or information besides public data and/or information. In this study, only public data and/or information of the firms are used.

Examining especially some foreign studies, it is understood that rating grades that are given by independent rating agencies are used as dependent variable and therefore dependent variable is considered depending on number of rating grades. In Turkey, since the rating is not compulsory, and optional/voluntary, rating results are not disclosed to public unless they are adequate, usage of rating grades that are determined by rating agencies as dependent variable are not sufficient to run the analysis. Therefore our dependent variable that is used in this study constitutes from two groups (the status of the firms being “good” or “bad” due to financial capability).

Overviewing studies in this area it is seen that discriminant analysis highly used at early times. Afterwards, probit and logit analysis have been started to be used and it is understood that analysis based on “artificial intelligent” have started to be used in some of the latest studies.

In our study, instead of running highly used discriminant analysis which break the assumption of normal distribution, continuity and equality of the deviation matrix, logistic regression analysis is used which gives better results than discriminant analysis and gives opportunity to classify results by producing different probability values for each observation.

Reviewing the rating studies that are conducted in Turkey, no prior study that used same methodology, data and period is found.

Under the scope of this study 35 financial ratios are used as the independent variables, which are calculated on the grounds of annual financial statements and their notes during the period of 2007-2013 which are disclosed by the 206 listed manufacturing firms on Borsa Istanbul equity market.

In this study, the status of the 206 firms being “good” or “bad” based on financial capability is collected by searching news and disclosures at Borsa Istanbul web site for the period of 2007-2009 and Public Disclosure Platform (PDP) web site for the period of 2010-2013. To identify “good” or “bad”, all news and disclosures of sample firms is evaluated by taking into consideration the information about market changes and delisting made by Borsa Istanbul on PDP. Delisted firms or firms those trading activities are held due to financial distress, firms that changed trading market (in negative manner), firms obliged monthly declaration due to financial distress, firms that are warned to take measures by CMB or Borsa Istanbul due to losing capital, or the firms that applied to court by itself due to financial distress are counted as “bad” and crated unique data. This manually created data makes our study original and contributing.

Abstract of the studies regarding the rating activities and methods that are used is stated under the second section of our study, where the data and the method that is used in this study is stated under third and findings that are received and interpretations of them are stated under the fourth section of our study. Finally the conclusion part is stated under the last section.

2. Literature Review

Some of the main studies and methodologies on corporate rating are summarized as follows. The studies which are conducted by using ordinary statistical methods are summarized in Table 1 and the studies which are conducted by using artificial intelligent based analysis are summarized in Table 2 (Hajek, 2010).

Table 1. Prior studies using statistical methods

Studies	Methods	Number of Classes	Data Set	Number of Input Variables	Classification Accuracy on Testing Data (%)
Horrigan (1966)	Linear Regression	9	200	6	56.0
West (1970)	Linear Regression	9	-	4	62.0
Pinches and Mingo (1973 and 1975)	Mult. Discriminant Analy.	5	180	6	64.6
Kaplan and Urwitz (1979)	Ordered Probit Model	6	207	10	66.0
	Linear Regression	6	207	10	55.0
Altman and Katz (1976)	Mult. Discriminant Analy.	2	-	14	77.0
Pogue and Soldofsky (1969)	Linear Regression	2	113	5	80.0
Kamstra, Kennedy and Suan (2001)	Ordered Logistic Regression	6	89	5	58.4
	Ordered Logistic Regression	6	265	5	47.5
	Mult. Discriminant Analy.	6	89	5	62.9
	Mult. Discriminant Analy.	6	265	5	41.9
	Linear Regression	6	89	5	52.8
	Linear Regression	6	265	5	38.9
Hwang and Cheng (2008)	Ordered Logistic Regression	3	736	24	72.8

Table 2. Prior studies using artificial intelligence methods

Studies	Methods	Number of Classes	Data Set	Number of Input Variables.	Classification Accuracy on Testing Data (%)
Moody and Utans (1995)	Feed-Forw. Neu. Netw.	16	196	10	36.2
	Feed-Forw. Neu. Netw.	5	196	10	63.8
	Feed-Forw. Neu. Netw.	3	196	10	85.2
	Mult. Discriminant Analy.	16	196	10	21.4
Dutta and Shekhar (1988)	Feed-Forw. Neu. Netw.	2	47	10	83.3
	Multiple Linear Regr.	2	47	10	64.7
Singleton and Surkan (1990 and 1995)	Feed-Forw. Neu. Netw.	2	18	8	88.0
	Mult. Discriminant Analy.	2	18	8	39.0
Brennan and Brabazon (2004)	Feed-Forw. Neu. Netw.	2	600	8	84.0
	Feed-Forw. Neu. Netw.	5	791	8	52.7
Delahunty and OCallaghan (2004)	Artificial Intel. Systems	2	791	8	72.5
Brabazon and O'Neill (2006)	Grammatical Evolution	2	791	8	84.9
	Feed-Forw. Neu. Netw.	2	791	8	83.3
	Mult. Discriminant Analy.	2	791	8	85.2
Garavagia (1991)	Feed-Forw. Neu. Netw.	3	797	87	84.9
Kim (2005)	Adaptive Learning Netw.	4	1080	26	83.8
Maher and Sen (1997)	Feed-Forw. Neu. Netw.	6	299	5	66.7
	Mult. Discriminant Analy.	6	299	5	61.0
	Ordered Logistic Regr.	6	299	5	61.7
Huang and Chen (2004)	Feed-Forw. Neu. Netw.	5	265	5	80.0
	Feed-Forw. Neu. Netw.	5	265	12	79.3
	Support Vector Machine	5	265	5	78.9
	Support Vector Machine	5	265	12	80.0
Kim (1993)	Feed-Forw. Neu. Netw.	6	228	8	55.2
	Rule Based Expert System	6	228	8	31.0
	Linear Regression	6	228	8	36.2

	Mult. Discriminant Analy.	6	228	8	36.2
	Ordered Logistic Regr.	6	228	8	43.1
	Feed-Forw. Neu. Netw.	6	120	8	56.7
Chaveesuk and Srivaree-Ratana (1999)	Radial Basis Function Neural Network	6	120	8	38.3
	Learning Vector Quant. Neural Network	6	120	8	36.7

The variables and their definitions that used on related previous studies are given in Table 3 (Hajek, 2010).

Table 3. Input variables used for corporate credit ratings in prior studies

Studies	**Input Variables**
Horrigan (1966)	Total Assets, Net Worth/Total Depts, Operating Margin, Working Capital/Sales, Sales/Net Worth, Subordination status
West (1970)	Earnings Variation, Without Loss in Years, Market Value/Total Depts, Market Value
Pinches and Mingo (1973 and 1975)	Years of Consecutive Dividends, Issue Size, ((Net Income+Interest)/Interest, Subordination Status, Long-Term Debts/ Total Assets, Net Income/ Total Assets
Kaplan and Urwitz (1979)	Cash Flow/Interest, Cash Flow/Total Debt, Long-Term Debts/Total Assets, Long-Term Debts/Net Worth, Net Income/Total Assets, Total Assets, Issue Size, Total Assets Variation, Net Income Variation, Subordination Status
Altman and Katz (1976)	Interest Coverage, Interest Coverage Variation, Cash Flow, Earnings Variation, Return on Investment, Depreciation plus Amortization/Operating Revenue
Pogue and Soldofsky (1969)	Total Debt/Total Capital, Net Income/Total Assets, Net Income Variation/Total Assets, Total Assets, (Net income + Interest)/Interest
Kamstra, Kennedy and Suan (2001)	Total Assets, Subordination Status, Return on Total Assets, Total Debts / Total Assets, Interest Coverage
Hwang and Cheng (2008)	KMV-Merton Default Probability, Market Equity Value, Earnings, Total Assets, Total Debts/(EBIT+ Depreciation + Amortization), Total Assets /Equity, Long-Term Debts/Total Capital, Short-Term Debt/Total Capital, Interest Coverage, (EBIT+ Depreciation plus Amortization)/Interest, Cash Flow, Interest, Net Income, Return on Capital, Return on Equity, Return on Total Assets, Operating Margin, Retained Earnings/ Total Assets, Current Ratio, Quick Ratio, Cash Ratio
Dutta and Shekhar (1988)	Total Liabilities/Cash Assets, Total Debt/Total Assets, Sales/Net Worth, Return on Sales, Financial Strength, Earnings/Fixed Cost, Five Years Revenue Growth Rate, Working Capital/Sales, Subjective Prospect of Firm, Total Revenue Ratio,
Singleton and Surkan (1990 and 1995)	Long-Term Debts/Total Capital, Interest Coverage, Return on Equity, Five Years Return on Equity Variation, Total Assets, Construction Costs/Cash Flow
Brennan and Brabazon (2004)	Current Ratio, Retained Earnings/Total Assets, Interest Coverage, Total Debt/Total Assets, Net Margin, Market to Book Value, Total Assets, Return on Total Assets
Delahunty and OCallaghan (2004)	Current Ratio, Retained Earnings/Total Assets, Interest Coverage, Total Debt/Total Assets, Net Margin, Market to Book Value, Total Assets, Return on Total Assets
Brabazon and O'Neill (2006)	Current Ratio, Retained Earnings/Total Assets, Interest Coverage, Total Debt/Total Assets, Net Margin, Market to Book Value, Total Assets, Return on Total Assets
Kim (2005)	Total Assets, Current Ratio, Return on Total Assets, Total Debt/Total Assets, Sales/Fixed Assets, Operating Margin, Interest Coverage, Long-Term Debts/Total Capital, Cash Flow/Current Liabilities
Maher and Sen (1997)	Total Assets, Total Debt /Total Assets, Net Income / Total Assets, Subordination Status, Beta
Huang and Chen (2004)	Total Assets, Total Liabilities, Long-Term Debts / Total Capital, Total Debt /Total Assets, Operating Margin, Return on Equity
Kim (1993)	Total Assets, Total Debt, Long-Term Debts/Total Capital, Current Ratio, (Net Income+ Interest)/ Interest, Preferred Dividends, Stock Price, Subordination Status
Chaveesuk and Srivaree-Ratana (1999)	Total Assets, Total Debt, Long-Term Debts/Total Capital, Short-Term Debt/Total Capital, Current Ratio, (Net Income+ Interest)/Interest, Total Debt /Total Assets, Return on Sales

As the number of variables increase in analysis, the interpretation of model becomes more difficult and applicability of model decreases. Therefore the elimination of insignificant or non-explanatory variables in models should be done. In case of high correlation between variables, it is possible to decrease number of variables by using variable selection methods. On the other hand, this approach may cause excluding important or significant variables from the model due to election criteria (Özdinç, 1999).

Some studies on rating have also conducted in Turkey last decades. The main difference between this domestic and international studies arises from dependent variable of models. Except for rating on banks, as the firm does not have rating or disclosed rating grades in Turkey the rating grades of firms cannot be used as a dependent variable. Some of the related studies on rating in Turkey can be summarized as in Table 4.

Table 4. Related studies carried out in Turkey

Authors (Year)	Methods	Data	Dependent Variables	Independent Variables	Results
Özdinç (1999)	Logistic Regression (Grouping Discriminant and MANOVA at first),	136 firms/ 1993	The result of Discriminant Analysis	9 Financial Ratios	Classification of correctness of Logit is 94.9%
Boyacıoğlu (2003)	Logistic Regression, Artificial Neural Netw., Discriminant Analysis, Cluster Analysis	14 banks/ 1996-2000	Rating grades	24 Financial Ratios	Artificial Neural Network method has better explanatory power than others
Tatlıdil and Ozel (2005)	Discriminant Analysis, Logistic Regression	38 firms/ 2001	Problem in solvency	6 Financial Ratios	The model is not usable
Sezgin (2006)	Logistic Regression, Probit Regression, Discriminant Analysis, Classification and Regression Trees	1649 firms	Problem in solvency		Classification and Regression Trees are better than others
İşman (2009)	Analytic Hierarchy Process	3 car firms		Expert's Opinion	
Yolaş Vurur (2009)	Logistic Regression	4937 firm/ 2005-2007	3 year ave. Profit is over Price Index or not	5* Financial Ratios	Classification of correctness is 64.21%
Hazar (2009)	Factor Analysis Panel Regression	10 banks/ 2004-2007	Rating grades	15* Financial Ratios	Result are consistent with independent rating agencies grades
Yüce (2011)	Ordered Logit, Artificial Neural Network	40 firms/ 1998-2009	Current ratios	4 Financial Ratios	Artificial Neural Network method has better explanatory power than Ordered Logit method.
Budak ve Erpolat (2012)	Logistic Regression Artificial Neural Network	1639 person	Problem in solvency	Loan Amount, Term, Monthly Income, Pledges and Mortgages, Occupation, Age and Marital status	Classification of correctness of Logit is 65.4% and classification of correctness of Artificial Neural Network is 70.3%
Uzunoğlu (2013)	Artificial Neural Network	16 banks/ 2004-2011	Rating grades	Financial Ratios	100% learning success and 80% testing success

Note: (*) Number of variables is used in final model.

In rating activities both quantitative data (financial ratios) and qualitative information shall be taken into consideration. Qualitative informations may enter to the model as a dummy variable or as an expert's judgment. It is argued that using dummy variable for qualitative data is a more appropriate way and it is seen as increasing the success of the model. For example, delay in disclosure of financial reports, independent audit opinion, age of firm, number of employee at managing level, the duration of work of the managers in the firm, the mortgage on the firms' assets may be included to model as the dummy variables. Expert's judgment may include fairness and correctness financial reports and data of the firm, since financial reports and data of the firm had been manipulated (Kadıoğlu, 2014). Keasey and Watson (1997) argues that including qualitative information to model as the dummy variables will increase the success of forecasting financial failure in small and middle sized firms.

3. Data and Methodology

In this study, annual financial statements and their notes of firms that conduct their activities in manufacturing sector and which are prepared according to International Financial Reporting Standards (IFRS) regarding the 2007-2013 period are used. The 206 listed manufacturing firms on Borsa Istanbul equity market have selected as sample and their publicly disclosed balance sheets, income statements and cash flow statements and their notes were collected by using Finnet Analysis Program and from Borsa Istanbul web site (for 2007-2009) and PDP (for 2010-2013) web site.

Due to data prepared, 35 financial ratios in 5 groups were calculated that may have an effect on solvency of the firms. While determining the financial ratios that serve basis to independent variable of this study, the ratios that are used prior studies were also taken into consideration. Additionally, as IFRS was in force during the period of examination, it became possible for us to use the information that obtained from cash flow from operating and investing activities and foreign exchange position which weren't taken into consideration by prior studies conducted in Turkey.

The financial ratios that are prepared to be used within the scope of the study and their definitions are as follows.

Table 5. Financial ratios and their definitions used in the study

Number	Independent Variables	Definitions
Financial ratios using to measure relation between profit and sales		
1	KSA1	Gross Margin / Net Sales
2	KSA2	Operating Profit / Net Sales
3	KSA3	Profit Before Tax / Net Sales
4	KSA4	Net Profit / Net Sales
5	KSA5	Earnings Before Interest and Taxes (EBIT) / Net Sales
6	KSA6	Earnings Before Interest, Taxes, Depreciation and Amortization I / Net Sales
7	KSA7	Earnings Before Interest, Taxes, Depreciation and Amortization II [1] / Net Sales
Financial ratios using to measure relation between profit and equity		
8	KSE1	Profit Before Tax / Total Equity
9	KSE2	Profit After Tax / Total Equity
10	KSE3	Profit After Tax / Total Assets
11	KSE4	Earnings Before Interest and Taxes / Total Assets
12	KSE5	Earnings Before Interest, Taxes, Depreciation and Amortization I / Total Assets
13	KSE6	Earnings Before Interest, Taxes, Depreciation and Amortization II / Total Assets
Financial ratios using to measure debt covering		
14	BK1	Interest Coverage (Earnings Before Interest and Taxes / Interest Expense)
15	BK2	Earnings Before Interest, Taxes, Depreciation and Amortization / (Interest Expense+ Current Portion of Long Term Debts)
16	BK3	Total Liabilities / Earnings Before Interest, Taxes, Depreciation and Amortization II
17	BK4	Assets in Foreign Currency / Liabilities in Foreign Currency
18	BK5	Cash Flows from Operating Activities / Total Liabilities
19	BK6	Cash Flows from Operating Activities / (Total Equity + Total Liabilities)
20	BK7	Cash Flows from Operating and Investment Activities / Total Equity
Financial ratios are using to analyze capital structure		
21	SY1	Total Liabilities / Total Equity
22	SY2	Leverage Ratio (Total Liabilities / Total Assets)

23	SY3	Tangible Fixed Assets (Net) / Total Equity
24	SY4	Equity Structure ((Shareholder's Equity + Capital Reserves + Revenue Restrictive Reserves / Total Equity)
Financial ratios using to analyze liquidity		
25	L1	Current Ratio (Current Assets / Short Term Liabilities)
26	L2	Liquidity Ratio (Liquid Assets + Securities + Short Term Receivable / Short Term Liabilities)
27	L3	Inventory Dependency Rate (Short Term Liabilities - (Liquid Assets + Quick Assets)) / Inventories)
28	L4	Net Sales / Short Term Liabilities
29	L5	Profit After Tax / Short Term Liabilities
30	L6	Receivables Turnover Rate (Net Sales / Trade Receivables)
31	L7	Inventory Turnover Rate (Cost of Sales / Inventories)
32	L8	Effectiveness Rate (1 / ((1+ Receivables Turnover Rate) + (1+ Inventory Turnover Rate))
33	L9	Working Capital Turnover Rate (Net Sales / Current Assets)
34	L10	Assets Turnover Rate (Net Sales / Total Assets)
35	L11	Debts Turnover Rate (Cost of Sales / Trade Debts)

Since there is no rating obligation for Turkish firms except for banks, it is not possible use rating notes as the dependent variable that are given by independent rating agencies. Therefore in this study, the status of the companies being "good" or "bad" based on financial capability is used as the dependent variable. In other words, if the firm is financially in a bad situation or in case of failure then dependent variable takes the value of "0" and otherwise it takes the value of "1".

According to Özdemir (2011), quantitative and qualitative indicators can be used in the determination of financial failure and quantitative indicators can be classified as the book value based indicators and market value based indicators.

In the case of using qualitative indicators, determining the class of the firm is easier and market value based indicators give more fair and accurate results when the market is efficient (Özdemir, 2011). Taking consider Özdemirs' idea into account, we used qualitative indicators to classify bad or good firms[2].

For this manner, the status of the 206 companies being "good" or "bad" based on financial capability is collected by searching news and disclosures at Borsa Istanbul web site for the period of 2007-2009 and KAP web site for the period of 2010-2013. To identify "good" or "bad", we searched all news and disclosures of sample firms by taking into consideration following criteria and the firm, matched following criteria, is classified as "bad" firm.

i) Firms that are delisted by Borsa Istanbul due to financial distress,

ii) Firms those trading activities are held by Borsa Istanbul due to financial distress,

iii) Firms those trading market are lowered by Borsa Istanbul,

iv) Firms that are obliged monthly declaration due to financial distress,

v) Firms that are warned by CMB or Borsa Istanbul to take measures to recover the capital,

vi) Firms that are applied to court by the firm itself due to financial distress.

The firm, being "bad", is checked yearly bases and whenever the information stated above is disseminated we accepted that year as the starting year for "bad" for the firm. If the firm counted as "bad" and if there is new reversal information in following years then we changed the firm as "good".

Depending on financial distress, being "good" or "bad" is constitute our dependent variable and it takes value of "1" for "good" and "0" for "bad".

In our data outliers and having much missing observations have been eliminated by basic sorting and filtering applications. Additionally, since the base of the number is different, all independent variables normalized by subtracting mean and dividing to standard deviation. As result, 88.5 % (1149 observations) of total sample (1298 observations) is classified as "good" and 11.5 % (149 observations) of total sample is classified as "bad".

To avoid weakness and critics on discriminant analysis and least square regression (not fulfilling normal distribution assumptions), we chose logistic regression to run for our model. The studies also show that logistic regression gives better results in case of dependent variable is discrete. Furthermore in our case, logistic regression gives different probability values for each observation depending on the variables in the model and this enable us to determine rating notes depending on tranches of probability.

In our logistic regression analysis, SPSS 18 Portable and SPSS Clementine 11 software packages have been used.

The classification studies on unbalanced data such as an unequal number of “bad” and “good” observation has the disadvantages. Because, it is argued that correct classification success for proportionally high number of observations (in our case being “good”) is higher than correct classification success for proportionally lower number of observations (in our case being “bad”). It is also the case for our sample. In order to overcome this biasness, we run the analysis on balanced sample. In our study, to create balanced sample we took all “bad” observations and randomly selected 15% of “good” observations by using SPSS Clementine 11 software. At the end, our subsample consist of 49% of “bad” observations and 51% of “good” observations and total subsample size became 306 observations. In order to use as much as observations, we designed to our sample consisting 49% “bad” and 51% “good” observations. The descriptive statistics of variables are given Table 6.

Table 6. Descriptive statistics

	Variables	Min.	Max.	Mean	St. Dev.	Skewness	Kurtosis
1	**GOOD1BAD0**	0.00	1.00	0.50	0.50	0.00	-2.02
2	**KSa1**	-1.60	1.00	0.15	0.22	-3.04	23.04
3	**KSa2**	-248.46	2.73	-1.36	16.18	-14.33	214.88
4	**KSa3**	-224.32	3.08	-1.28	14.30	-14.98	232.50
5	**KSa4**	-262.59	2.60	-1.32	16.40	-15.80	252.40
6	**KSa5**	-245.29	2.34	-1.34	15.99	-14.30	213.92
7	**KSa6**	-6.20	2.13	-0.01	0.53	-7.57	82.78
8	**KSa7**	-6.20	0.93	-0.01	0.51	-8.64	93.71
9	**KSe1**	-8.54	42.37	0.14	2.85	12.65	186.88
10	**KSe2**	-8.63	42.93	0.12	2.87	12.82	190.85
11	**KSe3**	-4.45	6.81	-0.03	0.54	5.54	113.58
12	**KSe4**	-2.97	6.80	0.03	0.48	9.70	155.57
13	**KSe5**	-0.96	0.74	0.05	0.12	-1.54	23.28
14	**KSe6**	-0.96	0.78	0.05	0.12	-1.40	23.47
15	**BK1**	-1926.04	65.03	-13.96	138.48	-11.77	151.25
16	**BK2**	-910.75	174.02	-2.58	60.79	-13.08	194.32
17	**BK3**	-997.42	889.69	2.47	124.11	0.38	33.51
18	**BK4**	0.00	1450.20	8.73	94.56	14.74	224.05
19	**BK5**	-2.67	3.76	0.02	0.54	0.07	14.62
20	**BK6**	-1.21	0.72	-0.01	0.20	-2.28	11.44
21	**BK7**	-3.96	3.33	-0.06	0.65	-1.04	10.75
22	**SY1**	-111.11	188.50	1.13	14.59	6.16	117.53
23	**SY2**	0.03	12.56	0.87	1.40	5.36	34.48
24	**SY3**	-15.66	95.84	1.19	6.36	12.59	188.42
25	**SY4**	-214.38	86.94	0.20	15.12	-10.58	160.87
26	**L1**	0.01	28.70	1.86	2.66	5.72	46.72
27	**L2**	0.00	28.21	1.18	2.37	7.76	76.51
28	**L3**	-422.85	158.40	7.65	33.85	-7.10	105.88
29	**L4**	0.00	17.26	2.74	2.58	1.84	4.70
30	**L5**	-20.70	19.40	-0.01	1.92	-0.96	90.75
31	**L6**	0.00	62.98	7.47	8.80	3.48	14.43
32	**L7**	0.00	348.09	11.23	29.53	8.03	77.36
33	**L8**	0.02	0.58	0.17	0.10	1.18	2.21
34	**L9**	0.00	35.22	2.06	2.80	8.05	82.90
35	**L10**	0.00	4.35	0.85	0.62	1.89	6.68
36	**L11**	0.00	237.64	8.96	17.59	9.33	111.91

4. Empirical Results

As it mentioned before, in order to balance our sample we restructured sample by taking all "bad" observations and randomly selected 15% of "good" observations of 1298 observations. In our subsample there are 149 "bad" observations and 157 "good" observations and the subsample is 24% of total sample. 266 observations of subsample are used for estimating the model and 40 observations of subsample are used for testing the model.

Table 7. Logistic regression Wald forward variable selection results

		B	S.S.	Wald	sd	p	Exp(B)
	KSE5 *	1.081	0.263	16.908	1	0	2.947
	BK4 ***	6.941	3.763	3.402	1	0.065	1034.046
	BK5 *	1.058	0.346	9.349	1	0.002	2.882
	BK7 **	-0.379	0.166	5.185	1	0.023	0.685
	SY2 *	-3.332	0.703	22.479	1	0	0.036
Step 12(k)	**L4** *	1.505	0.579	6.749	1	0.009	4.503
	L7 *	-1.241	0.308	16.287	1	0	0.289
	L8 *	0.656	0.159	16.929	1	0	1.927
	L10 *	1.481	0.396	14.01	1	0	4.398
	L11 *	-1.722	0.547	9.902	1	0.002	0.179
	Constant	2.585	0.584	19.616	1	0	13.27

Note: (*) significant at 1%, (**) significant at 5% and (***) significant at 10%

All variables stated under Table 7 are significant. On the other hand, coefficients of *BK7* (*Cash Flows from Operating and Investment Activities / Total Equity*), *L7 (Inventory Turnover Rate (Cost of Sales / Inventories)* and *L11 (Debts Turnover Rate (Cost of Sales / Trade Debts))* are negative and there is an inverse relation between dependent variable and these variables. Besides, coefficients of *L8 (Effectiveness Rate (1 / ((1+ Receivables Turnover Rate) + (1+ Inventory Turnover Rate)))* is positive and there is a same direction relation between *L8* variable and dependent variable. As this is not reasonable on academic/scientific grounds, in other words as same direction relation between *BK7, L7* and *L11* variables and firm success; and inverse relation between *L8* variable; *BK7, L7, L8* and *L11* variables were not included in model study. Additionally, *Exp(B)* (odd) that is calculated for variable *BK4 (Assets in Foreign Currency / Liabilities in Foreign Currency)* is too high, it is decided to excluded from model study.

In logistic regression model that run by exclusion of variables *BK7, L7, L8, L11* and *BK4*, and that run with 5 statistically and academically/scientifically significant variables (*KSE5, BK5, SY2, L4, L10*) it has found out that coefficient of *L10 (Assets Turnover Rate (Net Sales / Total Assets))* is insignificant. Accordingly, a model consisting of variables *KSE5, BK5, SY2* and *L4* and excluded variable *L10*, has formed and the results are stated under Table 8 (See also Appendix 1). All variables are significant which are used in model. As seen from Table 8 all variables have significant coefficient. Both Cox & Snell and Nagelkerke statistics show that explanatory power of the model is 40.2% and 53.6% respectively. It can be concluded that model is significant and valid according to Hosmer and Lemeshow test (p=0.903).

Table 8. Logistic regression final results

	B	S.S.	Wald	sd	p	Exp(B)	Exp(B) Confidence Interval	
KSE5 *	1.084	.239	20.624	1	.000	2.957	1.852	4.720
BK5 *	0.947	.273	12.011	1	.001	2.577	1.509	4.402
SY2 *	-1.772	.428	17.159	1	.000	0.170	0.073	0.393
L4 *	1.244	.340	13.410	1	.000	3.471	1.783	6.755
Constant	1.433	.269	28.322	1	.000	4.190		

Note: (*) significant at 1%,

R^2			Hosmer and Lemeshow Test			
	Cox and Snell	**Nagelkerke**	**Step**	**Chi-square**	**df**	**Sig.**
	0.402	0.536	**1**	3.451	8	0.903

As it is seen from the Table 8 coefficients of variables *KSE5, BK5* and *L4* are positive and the coefficient of variable *SY2* is negative which is corresponded with the theory. Hence, it is expected that financial success has negative relation with variable *SY2* and meanwhile positive relation with variables *KSE5, BK5* and *L4*.

Our estimated logistic regression equation can be stated as follows:

$$Y= 1.433 + 1.084 * KSE5 + 0.947 * BK5 – 1.772 * SY2 + 1.244 * L4$$

Y= 1.433

+ 1.084(Earnings before Interest, Taxes, Depreciation and Amortization I / Total Assets)*

+ 0.947(Cash Flows from Operating Activities / Total Liabilities)*

- 1.772(Leverage Ratio (Total Liabilities / Total Assets))*

+ 1.244(Net Sales / Short Term Liabilities)*

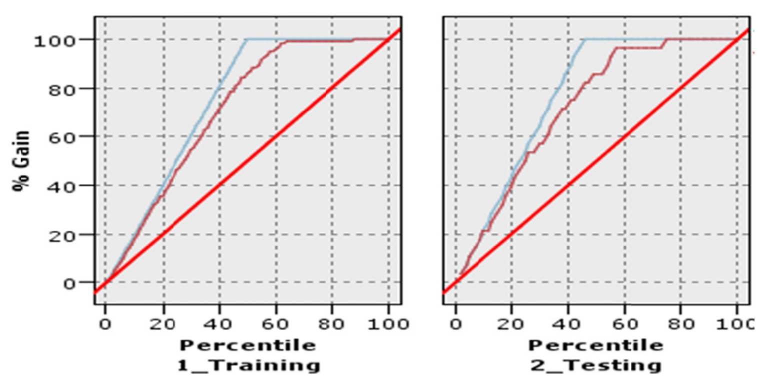
As it known, coefficients of variables calculated in logistic regression do not give accurate information regarding the direct impact of independent variables on dependent variable. To identify impact of independent variables on dependent variable Exp(B)s (odds), that gives proportional result, shall be examined.

As it is seen from the Table 9, our model, which is formed by 4 variables, classifies “bad” firms 77.85% and classifies “good” firms 76.43% correctly which results with an overall 77.12% correct classification.

Table 9. Correct classification percentage of the model that applied subsample

		Predicted Class		Correct classification percentage (%)
		Bad	**Good**	
Observed Class	**Bad**	116	33	77.85
	Good	37	120	76.43
General Correct classification percentage				77.12

Our logistic regression model formed by SPSS 18 Portable Program, is inserted into SPSS Clementine 11.0 and data received have been classified as training sample (266 observations) and testing sample (40 observations). In the graphic below, the uppermost line (blue line) shows correct classification can be made at the most. The area between second graphic line and line which has 45^{o} angle shows the success of the model.



Our logistic regression model run into whole data that contains 1298 observations (149 observations are “bad” and 1149 observations are “good”), *Y* values has calculated for each observation and success probability is calculated via the formula *Exp(Y) /(1-Exp(Y))*. *Y* values that each observation will take, are predicted by accepting the firms which received probability over 0.50 from calculations as successful “good” and firms which received under the mentioned level from calculations as unsuccessful “bad”. Accordingly *Y* values that predicted via this method were compared with observed *Y* and the results of correct classification of the model are given under Table 10.

Table 10. Correct classification percentage of the model that applied to main sample

Observed			Sample	Predicted	
			Total	Bad	Good
Observed Class	Bad	# of obs.	149	116	33
		%	11.5%	**77,85%**	22.15%
	Good	# of obs.	1149	234	915
		%	88.5%	20,36%	**79.64%**

Accordingly, it is seen that, our model classifies “bad” firms 77.85% correctly and classifies “good” firms 79.64% correctly due to application of the model to whole 1298 samples and overall correct classification success is found as 79.42%.

As mentioned before, logistic regression gives different probability values for each observation. This characteristic of the method enables us to make ad libitum classification of firms regarding their success probability.

Within the scope of this study firms are classified as 5 groups based on the probability values for each observation. The group size, rating grades and the probability tranches are given under Table 11.

Table 11. Rating grades and rating grades distribution of firms in the sample

Probability	Grade	# of observations	Percentage (%)
>0.80	A	584	45
0.60-0.80	B	246	19
0.40-0.60	C	217	17
0.20-0.40	D	135	10
<0.20	E	116	9
TOTAL		**1298**	**100**

As it is seen from the table, according to probability tranches of being good, firms were rated as follows where A represents the best grade and where E represents the worst. Firms success probability which are

- greater than 0.80 is “A”,
- greater than 0.60 and less than 0.80 is “B”,
- greater than 0.40 and less than 0.60 is “C”
- greater than 0.20 and less than 0.40 is “D”
- less than 0.20 is “E”

5. Conclusion

There is no single definition and methodology for corporate rating. Each regulative authority or the rating agency has its’ own unique definition and own unique methodology where these are differentiated due to sectors, and regarding the rating of firms or financial instrument. Furthermore, it won’t be possible to use same methodology forever that once formed and the rating methodologies have to be reviewed and improved in time.

In this study a model is developed using logistic regression analysis for the forecasting the rating grades of the manufacturing firms that form the basis to expert evaluation. It should be kept in mind that the appointed rating grades developed by models, are not conclusive and they need to be evaluated by the experts in view of the subjective facts.

The status of the firms being “successful/good” or “unsuccessful/bad” based on financial capability is tried to be determined within the study by using more than one defining variables. In other words, our dependent variable consists of two groups. Accordingly, in our study, logistic regression method is used which is one of the most appropriate model that enables a dependent variable to take two values.

The annual financial statements and their notes prepared according to IFRS regarding the period of 2007-2013 of manufacturing firms that are listed in Borsa Istanbul equity market are used. The 206 listed manufacturing firms that are traded in Borsa Istanbul equity market for the whole examination period or a term of it have been selected for the sample. Accordingly, publicly disclosed balance sheets, income statements and cash flow statements and their notes of 206 listed firms are collected and 35 financial ratio in 5 groups have calculated. Mentioned ratios form independent values of the study and consist of 88.5 % (1149 observations) that are classified as "good" and 11.5 % (149 observations) that are classified as "bad".

While forming the model instead of using whole observations (149 "bad", 1149 "good" of total 1298 observations), 306 (157 "good", 149 "bad") observations which forms circa 24% of the total data were used. In order to balance our sample remaining observations that belong to good firms were excluded. The model is formed by 266 observations chosen from data that consists of 306 observations and the remaining observations were used for test purposes.

The Wald forward variable selection method is used in order to eliminate highly correlated variables and reduce number of variables and accordingly, ten variable has chosen. Following the application of Wald forward variable selection method, four variables which are scientifically/academically insignificant on the grounds of their relation way's, one variable which is statistically insignificant and one variable which have high calculated *Exp(B)* (odd) value are excluded. At the final stage, explanatory model is formed based on four variables (*KSE5, BK5, SY2* and *L4*).

The coefficients of variables *KSE5, BK5* and *L4* are positive and the coefficient of *SY2* is negative which are consistent with the theory. Hence, financial success is expected to have negative relation with *SY2*, meanwhile to have positive relation with *KSE5, BK5* and *L4*.

The logistic regression model of four variables is applied to whole sample of 1298 observations, *Y* values are calculated for each observation and probability of being "good" for each observation has calculated by the formula *Exp(Y)/(1-Exp(Y))*. By accepting calculated probabilities that are greater than 0.5 as "good" (1) and otherwise as "bad" (0) *Y* values are predicted. *Y* values that are predicted and observed were compared and it has found that the model classifies ***"bad" firms 77.85% correctly and classifies "good" firms 79.64% correctly and the classifies overall 79.42% correctly.***

Within the logistic regression model different probability values are calculated for each observation. This feature of the model enabled us to distribute firms depending on tranches of probability. In this study, firms are classified into 5 group based on the probability values for each observation. If the probability of being good is greater than 0.80 then firm's grade is classified as "A", if it is greater than 0.60 and less than 0.80 then firm's grade is classified as "B", if it is greater than 0.40 and less than 0.60 then firm's grade is classified as "C", if it is greater than 0.20 and less than 0.40 then firm's grade is classified as "D" and if it is less than 0.20 then firm's grade is classified as "E", where A group represents the best grade firms and E group represents the worst grade firms.

As a result, by running the four variable logistic regression model to the datas of a selected firm, *Y* value of the chosen firm can be calculated with a success ratio of 78%-80%, by using the formula *Exp(Y)/(1-Exp(Y))*, the probability of being "good"-"bad" of the chosen firm can be determined and rating grade can be given by using a scale that is recommended by us or a scale that will be developped by the users.

It should be kept in mind that the appointed rating grades developed by models, are not final and they need to be evaluated by the expert in view of the facts that are not present in models. Additionally, running model directly to the firm's data may not always result accurately. Users must evaluate the financial reports of the firm on the grounds of fairness and correctness and examine them whether they represent a permanent time-period or not and then give a final rating grade.

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Notes

Note 1. The difference between EBITDA I and EBITDA II is that, EBITDA II consists of termination provisions for severance payment.

Note 2. Although erosion of capital is a quantitative indicators, in our study it is interpreted as whether capital is eroded or not rather than how much eroded.

Appendices

Appendix 1. Results of Logistic Regression

Case Processing Summary

Unweighted Cases(a)		N	Percent
Selected Cases	Included in Analysis	306	100
	Missing Cases	0	0
	Total	306	100
Unselected Cases		0	0
Total		306	100

a If weight is in effect, see classification table for the total number of cases.

Dependent Variable Encoding

Original Value	Internal Value
0	0
1	1

Block 0: Beginning Block

Classification Table(a,b)

Observed			Predicted		
			GOOD1BAD0		Percentage Correct
			0	1	0
Step 0	GOOD1BAD0	0	0	149	0
		1	0	157	1000
	Overall Percentage				513

a Constant is included in the model.

b The cut value is 0.500

Variables in the Equation

		B	S.E.	Wald	df	Sig.	Exp(B)
		Lower	Upper	Lower	Upper	Lower	Upper
Step 0	Constant	.052	.114	.209	1	.647	1.054

Variables not in the Equation

			Score	df	Sig.
Step 0	Variables	KSE5	43.426	1	.000
		BK5	19.649	1	.000
		SY2	24.317	1	.000
		L4	60.695	1	.000
	Overall Statistics		91.576	4	.000

Block 1: Method = Enter

Omnibus Tests of Model Coefficients

		Chi-square	df	Sig.
Step 1	Step	157.178	4	.000
	Block	157.178	4	.000
	Model	157.178	4	.000

Model Summary

Step	-2 Log likelihood	Cox and Snell R Square	Nagelkerke R Square
1	266.819(a)	.402	.536

a Estimation terminated at iteration number 7 because parameter estimates changed by less than .001.

Hosmer and Lemeshow Test

Step	Chi-square	df	Sig.
1	3.451	8	.903

Contingency Table for Hosmer and Lemeshow Test

		GOOD1BAD0 = 0		GOOD1BAD0 = 1		Total
		Observed	Expected	Observed	Expected	Observed
Step 1	1	31	30.396	0	.604	31
	2	27	26.492	4	4.508	31
	3	24	23.714	7	7.286	31
	4	19	20.848	12	10.152	31
	5	15	17.117	16	13.883	31
	6	16	13.721	15	17.279	31
	7	9	9.902	22	21.098	31
	8	7	5.328	24	25.672	31
	9	1	1.337	30	29.663	31
	10	0	.146	27	26.854	27

Classification Table(a)

Observed			Predicted		
			GOOD1BAD0		Percentage Correct
			0	1	0
Step 1	GOOD1BAD0	0	116	33	77.9
		1	37	120	76.4
	Overall Percentage				77.1

a The cut value is ,500

Variables in the Equation

		B	S.E.	Wald	df	Sig.	Exp(B)	95,0% C.I.for EXP(B)	
		Lower	Upper	Lower	Upper	Lower	Upper	Lower	Upper
Step 1(a)	KSE5	1.084	.239	20.624	1	.000	2.957	1.852	4.720
	BK5	.947	.273	12.011	1	.001	2.577	1.509	4.402
	SY2	-1.772	.428	17.159	1	.000	.170	.073	.393
	L4	1.244	.340	13.410	1	.000	3.471	1.783	6.755
	Constant	1.433	.269	28.322	1	.000	4.190		

a Variable(s) entered on step 1: KSE5, BK5, SY2, L4.