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Financial Indicators of Steady Success in Manufacturing Companies: Research on Big Manufacturing Companies in Turkey

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Abstract

Financial indicators (ratios) are calculated from the data found in basic financial statements. Balance sheets, income statements and cash flow statements are used in making different analyses for different information users. These indicators can be used to make inferences about a company's financial condition and its operations and attractiveness as an investment. They also can be used to analyze trends and compare companies' financial performance and situation to other firms. This study empirically examines the common and distinctive financial indicators of steady and unsteady successful big manufacturing companies in Turkey by using data mining methodology. In this framework, the variables that affect the success of the company are identified by using logistic regression analysis. Then the differential values of the indicators are identified by using decision trees. Decision tree analysis is used for checking the logistic regression analysis results. As a result of different tries, the most appropriate decision tree algorithm, C&RT (Classification and Regression Trees) has been selected. According to logistic regression analysis, current ratio, quick ratio, debt ratio, short term debt/total debts, inventory turnover ratio, CFFO/total assets and CFFF/CFFI variables are found to be significant at the 95% confidence level. The results also reveal that quick ratio, debt ratio, short term debt/total debts and inventory turnover ratio variables are found to be distinctive financial indicators for successful companies by using decision trees.

JEL classification number: M41
Keywords: Financial ratios, Data mining, Decision trees, Successful companies, Turkey

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1 Introduction

General purpose financial statements are intended to meet the needs of users who are not in a position to require an entity to prepare reports tailored to their particular information needs. (IAS 1) To fulfill this task, accounting departments have assumed the function of preparation and interpretation of financial statements. The objective of financial statements is to provide information in a structured representation about the financial position, financial performance and cash flows of an entity that is useful to a wide range of users in making economic decisions. Financial statements also show the results of the management's stewardship of the resources entrusted to it [1].

Financial ratio analysis is the calculation and comparison of ratios that are derived from the information in a company's financial statements. These ratios can be used to make inferences about a company's financial condition, its operations and attractiveness as an investment. Financial ratios can be also used to analyze trends and compare companies' financial performance and situation to other firms.

A financial analysis assists in identifying the major strengths and weaknesses of a business enterprise. It indicates whether a firm has enough cash to meet obligations, a reasonable accounts receivable collection period, an efficient inventory policy management policy, sufficient plant, property, and equipment and an adequate capital structure. All of them are necessary if the firm is to achieve the goal of maximizing shareholder wealth. Financial analysis can be also used to assess a firm's viability as an ongoing enterprise and determine whether a satisfactory return is being earned for the risks taken [2].

The basic expectation of all stakeholders is a steady successful company. With the results of this study, stakeholders can observe the financial structure of these companies and can identify their policies and make decisions.

This study empirically examines the common and distinctive financial indicators of steady and unsteady successful big manufacturing companies in Turkey by using data mining methodology.

Several studies have been and are still being realized in the area of financial ratios and data mining separately. However, there was no study found in the existing literature that combines these two areas together. This will be the first study in Turkey about financial ratios using data mining. Therefore, the study is expected to contribute to the literature on accounting ratios and data mining.

This remainder of this study is organized in three sections. In Section 2, the data set, variables employed, research design and methodology are discussed. The empirical findings are presented in Section 3, and Section 4 offers the study conclusions.

2 Data Set and Methodology

To examine the common and distinctive financial indicators of steady and unsteady successful big manufacturing companies in Turkey, this section explains the sample size, data set and variables employed, research design and methodology of the study.

2.1 Sample Size

The sample consists of 174 manufacturing firms that are listed both in the Istanbul Stock Exchange (ISE) and the Istanbul Chamber of Industry (ICI) top 1,000 companies over the past 10 years. The scope of this study is restricted in this way because one of the key success indicators of a company is size (top 1000 companies) and the ability to access the financial data (listed in ISE).

The ICI top 1,000 companies were first selected for the sample. Then it was observed that there were companies in the ICI second top 500 companies section that are listed in the ISE. As a result, the sample consists only of the ICI top 500 companies that are listed in ISE. The financial statements for 2001 to 2009 were collected from the Istanbul Stock Exchange web site. While collecting the data, the companies were divided into 2 categories as steady successful and unsteady successful companies. In this study, the steady successful companies were defined as those that were listed in the ICI top 500 companies list for 10 years continuously (from 2001 to 2009). Unsteady successful companies were defined as the companies that were listed in the ICI top 500 companies list temporarily. Financial statements of 174 companies, 86 steady successful and 88 unsteady successful companies, were gathered as of December 31 for 2001 to 2009. The distribution of these categories is shown in Table 1. The distribution of industries for these companies are shown in Figures 1, 2 and 3.

Table 1: Number of successful companies

	Number	**Percentage**
Steady Successful Companies, coded as “1”	**86**	**49%**
Unsteady Successful Companies, coded as “0”	**88**	**52%**
Total	**174**	**100%**

These types of companies were excluded from the study;

- Non-manufacturing companies (financial institutions are excluded because their financial statements and financial ratios have different aspects).
- Companies that were not listed in the ICI top 100 companies in the past 10 years.
- Companies that were listed in the ICI top 100 companies but not listed in the Istanbul Stock Exchange in the past 10 years.

Also, non-financial ratios that affected the success of the companies were excluded from the study.

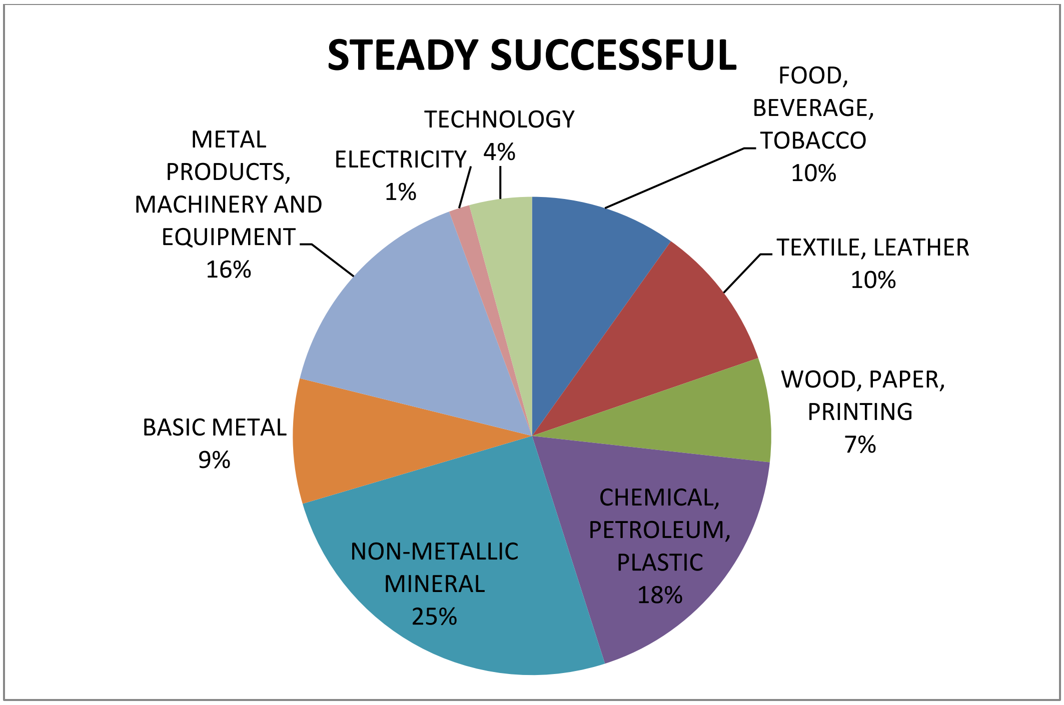


Figure 1: Percentage of steady successful companies by sector

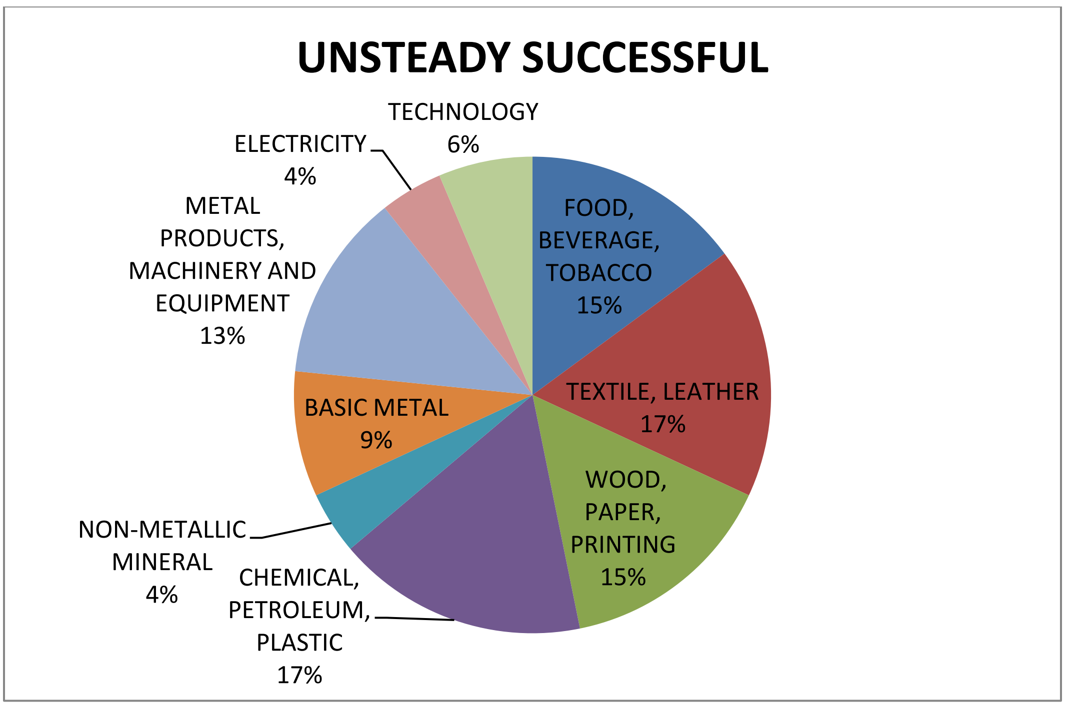


Figure 2: Percentage of unsteady successful companies by sector

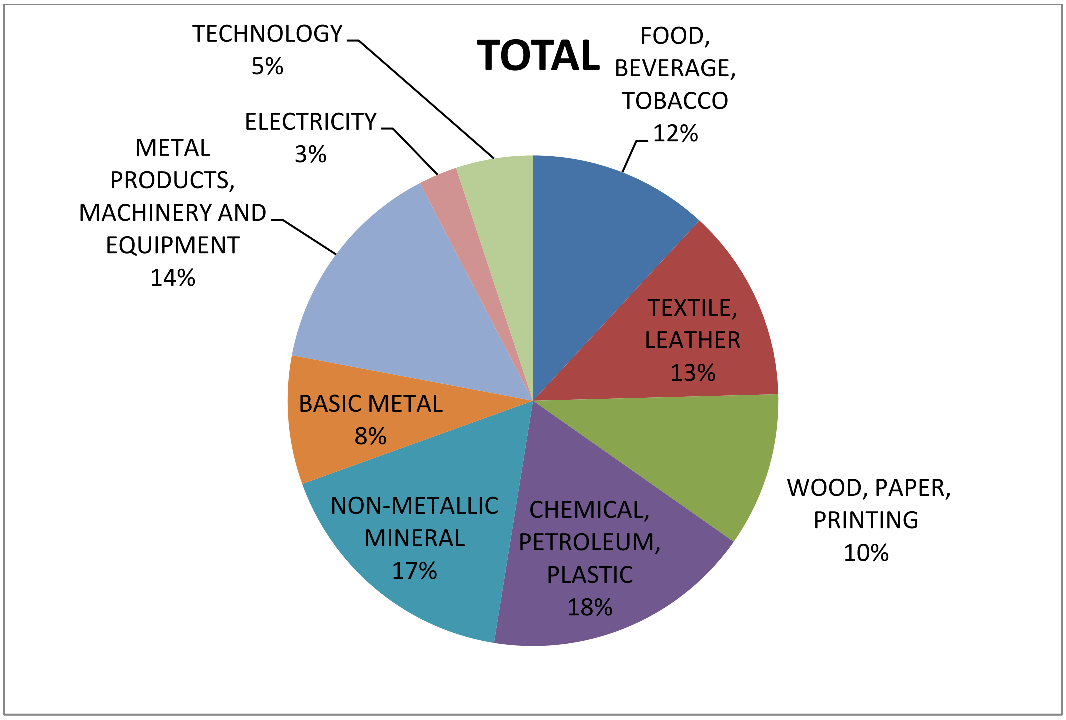


Figure 3: Percentage of successful companies by sector

2.2 Data Set

After collecting the data, thirty one financial indicators (ratios, variables of the study) that are suggested to be important were selected to conduct the empirical research after a detailed literature review. In the literature, there are approximately 70 financial indicators described to define the financial structure, liquidity, profitability, debt payment capability and the value of the companies. These financial indicators are calculated from the data in the basic financial statements. Balance sheets, income statements and cash flow statements were used in making different analyses for different information users.
Data collected for 31 variables that were determined to be important and were used for analyses are displayed in Table 2.

Table 2: Definitions of variables

Name of the financial ratio	**Calculation method**
Current ratio	Current assets/Current liabilities
Quick ratio	(Current assets- inventory)/Current liabilities
Coverage period	((Short term debt-Cash and cash equivalents)/CFFO)*360
Cash conversion cycle	Operating period- (360/ Debt turnover)
Debt ratio	Total debt/Total assets
Short term debt/ Total assets	Short term debt/ Total assets
Short term debt/ Total debt	Short term debt/ Total debt
Fixed assets/ long term debts+ owners' equity	Fixed assets/ long term debt+ owners' equity
Accounts receivables turnover	Sales/Average accounts receivable

Inventory turnover	Cost of goods sold/ Average inventory
Operating period	(360/ Accounts receivables turnover) + (360/ Inventory turnover)
Net working capital turnover	Sales/ Average net working capital
Assets turnover	Sales/ Average total assets
Debt turnover	Cost of goods sold/ Average accounts payable
Return on equity (ROE)	Net Income/ Equity
Return on assets (ROA)	Net Income / Total Assets
EBIT/Total assets	Earnings Before Interest and Taxes/Total assets
Gross profit margin	Gross Profit / Sales
Operating income margin	Earnings Before Interest and Taxes / Sales
Net income margin	Net Income / Sales
Net income/ fixed asset	Net income/ fixed asset
Operating income/Interest expense	Operating income/Interest expense
CFFO/ total debt	Cash flow from operations/ Total debt
CFFO/total sales	Cash flow from operations/ Total sales
CFFO/total assets	Cash flow from operations/ Total assets
CFFO/CFFF	Cash flow from operations/ Cash flow from financing activities
CFFF/CFFI	Cash flow from operations/ Cash flow from financing activities
Increase in sales	(Sales $_t$ – Sales $_{t-1}$)/ Sales $_{t-1}$
Increase in net income	(Net income $_t$ – Net income $_{t-1}$)/ Net income $_{t-1}$
Increase in owners' equity	(Owners' equity $_t$ – Owners' equity $_{t-1}$)/ Owners' equity $_{t-1}$
Increase in assets	(Assets $_t$ – Assets $_{t-1}$)/ Assets $_{t-1}$

After calculating each ratio for each company for 10 years, the data set (without considering the missing data leading to missing observations), the sample consisted of 31 accounting ratios of 174 firms for 10 years leading to a sample size of 53,940, one of the largest data sets used in tests on ISE firms. The average ratio for 10 years was calculated for each ratio and each company. Then the empirical research was conducted.
To illustrate, a small portion of the data set coding is shown in Table 3, The "Success" column represents the success of the company. If the company was steady successful, it was coded as "1"; if it was unsteady it was coded s "0".

Table 3: Data set

	Success	Current_Ratio	Quick_Ratio	Coverage_period	Cash_conversion_cycle	Debt_Ratio	Shorttermdebt_to_Totalassets	Shorttermdebt_to_Totaldebts	Fixedassets_to_Longtermdebts
1	0	1.0708	.4736	.0000	275.5827	.8773	.6687	.7647	.6590
2	0	.7059	.3583	.0000	199.5111	1.6005	1.2483	.8351	.9414
3	0	.6875	.3383	.0000	228.7513	1.7833	1.4653	.8322	.3784
4	0	.8482	.4482	.0000	120.7921	1.2473	.5634	.6197	1.8068
5	0	.8742	.4693	.0000	103.6628	1.2811	.5703	.6069	8.5231
6	0	1.2173	.7270	.0000	112.0626	1.1682	.5278	.6014	.1710
7	0	.9642	.4504	-1098.7869	105.8022	1.2836	.6773	.6295	6.8737
8	0	.9031	.4408	-586.5134	81.9650	1.1230	.6993	.7045	1.9424
9	0	.8501	.4237	-853.8665	77.8028	1.2980	.7235	.6972	1.0116
10	0	.9995	.5878	4205.2702	76.0465	1.1466	.6406	.7229	.7472
11	0	1.8149	.9604	.0000	113.7697	.4883	.3048	.6419	.6856
12	0	1.9763	1.2350	.0000	97.6433	.5767	.3449	.6470	.7125
13	0	2.1922	1.2642	.0000	99.1092	.4871	.2970	.6852	.7291
14	0	2.5286	1.5432	.0000	91.8422	.4110	.2564	.6339	1.0430
15	0	3.0952	1.7955	.0000	127.5120	.3756	.2201	.6181	.9662

2.3 Methodology

This study empirically examines the common and distinctive financial indicators of steady and unsteady successful big manufacturing companies in Turkey by using data mining methodology. The analysis was conducted using the SPSS Clementine program. In this subsection, the methodology used in this study will be briefly explained.

2.3.1 Data mining

There is a huge amount of data stored in real-world databases, and this amount continues to grow exponentially. This creates both an opportunity and a need for semi-automatic and automatic methods that discover the knowledge hidden in such databases. If such discovery activity is successful, discovered knowledge can be used to improve the decision-making process of an organization. *Data mining* is the name often used to refer to an interdisciplinary field that consists of using methods from several research areas to extract knowledge from real-world databases [3].

Data mining deals with the discovery of hidden knowledge, unexpected patterns and new rules from large databases. Data mining is not a single technique. Various different techniques, some of which are listed below, are used for different purposes [4].

- Statistical techniques
- Visualization
- Decision trees
- Association rules
- Neural networks
- Genetic algorithms

In this study, since the dependent variable had two outcomes ("0" and "1"), logistic regression was appropriate and applied for the analysis. Decision Trees Analysis was also used for checking the logistic regression analysis results. As a result of different tries, the most appropriate decision tree algorithm, C&RT (Classification and Regression Trees) was selected.

2.3.2 Logistic Regression Analysis

The simple and multiple linear regression methods were used to model the relationship between a quantitative response variable and one or more explanatory variables. A key assumption for these models was that the deviations from the model fit are normally distributed.

There are many important research topics for which the dependent variable is limited. For example, voting, morbidity or mortality and participation data are not continuous or distributed normally. Binary logistic regression is a type of regression analysis where the dependent variable is a dummy variable: coded 0 or 1. The level 1 usually represents the occurrence of an event of interest, often called a "Success". A logistic regression model is defined in terms of fitted values to be interpreted as probabilities that the event occurs in different subpopulations [5].

Logistic regression has several advantages:

- It is more robust: independent variables don't have to be normally distributed, or have equal variance in each group.
- It does not assume a linear relationship between the independent variables and dependent variable.

- It may handle nonlinear effects.
- Explicit interaction and power terms can be added.
- Dependent variables need not be normally distributed.
- There is no homogeneity of variance assumption.
- Normally distributed error terms are not assumed.
- It does not require that the independent variables be at intervals.
- It does not require that the independent variables be unbounded.

The advantages of logistic regression come at a cost: it requires much more data to achieve stable and meaningful results.

The statistical model for logistic regression is:

$$\text{Log}\left(\frac{p}{1-p}\right) = \beta 0 + \beta 1x$$

where p is a binomial proportion and x is the explanatory variable. The parameters of the logistic model are β0 and β1.

In standard regression, R (or R squared in particular) gives you an idea of how powerful your equation is at predicting the variable of interest. An R close to 1 is a very strong prediction, whereas a small R, closer to zero, indicates a weak relationship. There is no direct equivalent of R for logistic regression.

However, for those who insist on an R value, statisticians have come up with several R-like measures for logistic regression. They are not R itself, R has no meaning in logistic regression. Some of the better known ones are:

- Cox and Snell's R-Square
- Pseudo-R-Square
- Hagle and Mitchell's Pseudo-R-Square

3 Empirical Findings

The data set was analyzed and the following results were obtained by using the SPSS Clementine program. When the case processing summary in Table 4 is reviewed, it can be seen that a total of 174 data were analyzed, with 6 missing data.

Table 4: Case processing summary (logistic regression)

		N	Marginal Percentage
Success	**0.0**	88	50.6%
	1.0	86	49.4%
Valid		174	100.0%
Missing		6	
Total		180	
Subpopulation		174*	

* The dependent variable has only one value observed in 174 (100.0%) subpopulations.

In logistic regression models, Cox-Snell and Nagelkerke R^2 values show the correlation between the dependent variable and independent variables.

The percentage of model description is 64% as can be seen in the pseudo R^2 values in Table 5. The -2 log likelihood statistic is similar to the sum of squares of the regression analysis. In the model fitting information shown in Table 6, this value is getting smaller in the last model. This means that the last (final) model is the best model. The level of significance of the model is Sig. 0.000. When it is compared with 99% and 95% confidence intervals, the value is very small; as a result, one can conclude that the model is significant.

Table 5: Pseudo R^2 Values

Pseudo R-Square	
Cox and Snell	.480
Nagelkerke	.640
McFadden	.472

Table 6: Model fitting criteria and tests

Model Fitting Information				
	Model Fitting Criteria	**Likelihood Ratio Tests**		
Model	**-2 Log Likelihood**	**Chi-Square**	**df**	**Sig.**
Intercept Only	241.192			
Final	127.377	113.815	31	.000

The Wald test is a parametric statistical test with a great variety of uses. Whenever a relationship within or between data items can be expressed as a statistical model with parameters to be estimated from a sample, the Wald test can be used to test the true value of the parameter based on the sample estimate. The Wald test is used to test the statistical significance of each coefficient β in the model. The statistics are used to test the null hypothesis that is H_0= 0, where “0” is a vector with all entries equal to “0”. The Wald statistics rejects the null hypothesis when the significance level is greater than 5% [6].
According to the 95% confidence interval, financial indicators that affect the success of the company are seen in Table 7. The significance of the coefficients of the model were tested using the Wald Statistic, as seen in the Parameter Estimates in Table 8.

Table 7: Wald statistics

	Wald Statistics	Sig.
Current ratio	11.912	.001
Quick ratio	8.137	.004
Debt ratio	5.294	.021
Short term debt/Total debts	20.450	.000
Inventory turnover ratio	4.645	.031
CFFO/total assets	5.204	.023
CFFF/CFFI	5.453	.020

Table 8: Parameter estimates

Parameter Estimates									
		B	**Std. Error**	**Wald**	**df**	**Sig.**	**Exp(B)**	**95% Confidence Interval for Exp(B)**	
Success(a)								**Lower Bound**	**Upper Bound**
1.00	**Intercept**	19.128	3.699	26.742	1	.000			
	Current Ratio	-4.380	1.269	11.912	1	.001	1.25E-002	1.04E-003	.151
	Quick Ratio	3.381	1.185	8.137	1	.004	29.395	2.880	300.004
	Coverage_period	.000	.000	.010	1	.922	1.000	1.000	1.000
	Cash_conv_cycle	.017	.010	2.601	1	.107	1.017	.996	1.037
	Debt Ratio	-10.196	4.432	5.294	1	.021	3.73E-005	6.31E-009	.221
	Short term debt/ Total assets	6.049	6.809	.789	1	.374	423.818	6.78E-004	264908931.520
	Short term debt/ Total debts	-22.437	4.961	20.450	1	.000	1.80E-010	1.08E-014	3.01E-006
	Fixed assets/ long term debts+ owners' equity	-.117	.380	.095	1	.758	.890	.423	1.872
	Accounts receivables turnover	-.013	.018	.511	1	.475	.987	.952	1.023
	Inventory turnover ratio	-.030	.014	4.645	1	.031	.971	.945	.997
	Operating period	.003	.008	.178	1	.673	1.003	.988	1.020
	Net working capital turnover	.004	.009	.194	1	.660	1.004	.986	1.022
	Assets turnover	1.583	.822	3.715	1	.054	4.872	.974	24.376
	Debt turnover	.033	.026	1.679	1	.195	1.034	.983	1.087
	Return on equity (ROE)	.073	.232	.098	1	.754	1.075	.682	1.695
	Return on assets (ROA)	-2.601	9.314	.078	1	.780	7.42E-002	8.77E-010	6282583.138
	EBIT/Total assets	20.791	10.986	3.582	1	.058	1069678223.226	.476	2401313942631783000.000
	Gross profit margin	-1.461	3.403	.184	1	.668	.232	2.95E-004	182.845
	Operating income margin	-14.525	8.598	2.854	1	.091	4.92E-007	2.36E-014	10.246
	Net income margin	6.312	7.630	.684	1	.408	551.284	1.76E-004	1722945840.337
	Net in come/ fixed asset	.655	.981	.445	1	.505	1.924	.281	13.167
	Operating income/Interest expense	.000	.000	.960	1	.327	1.000	.999	1.000
	CFFO/ total debt	.416	.999	.173	1	.677	1.515	.214	10.729
	CFFO/total sales	-8.505	4.616	3.395	1	.065	2.02E-004	2.38E-008	1.720
	CFFO/total	24.976	10.949	5.204	1	.023	70263429040.394	33.662	146661171019584500000.000

Parameter Estimates									
Success(a)		B	Std. Error	Wald	df	Sig.	Exp(B)	95% Confidence Interval for Exp(B)	
								Lower Bound	Upper Bound
	assets								
	CFFO/CFFF	.001	.032	.002	1	.969	1.001	.940	1.067
	CFFF/CFFI	.142	.061	5.453	1	.020	1.153	1.023	1.299
	Increase in sales	-.063	.831	.006	1	.940	.939	.184	4.788
	Increase in net income	-.019	.015	1.491	1	.222	.982	.953	1.011
	Increase in owners' equity	.101	.139	.534	1	.465	1.107	.843	1.452
	Increase in assets	.412	.674	.373	1	.542	1.509	.403	5.659

a. The reference category is: .00.

3.1 Decision Trees

In this study, variables that affect the success of the company were identified by using logistic regression analysis. Then the differential values of the indicators were identified by using decision trees.

Classification is the process of finding a model that best describes and distinguishes data classes or concepts, for the purpose of being able to use the model to predict the class of objects whose class label is unknown. The derived model may be represented in various forms, such as *decision trees*, *IF-THEN rules*, *mathematical formulate* or *neural networks*. A *decision tree is* a flowchart-like tree structure, where each node denotes a test on an attribute value. Each branch represents an outcome of the test, and tree leaves represent classes or class distributions [7].

Decision trees are analytical tools to discover rules and relationships by systematically breaking down and subdividing the information contained in data sets. Decision trees are useful for problems in which the goal is to make broad categorical classifications or predictions [8].

Decision tree methods are a good choice when the data mining task is classification of records or prediction of outcomes. There are two main types of decision trees: [9]

Classification trees label records and assign them to the proper class. Classification trees can also provide the confidence that the classification is correct.

Regression trees estimate the value of a target variable that affects numeric values.

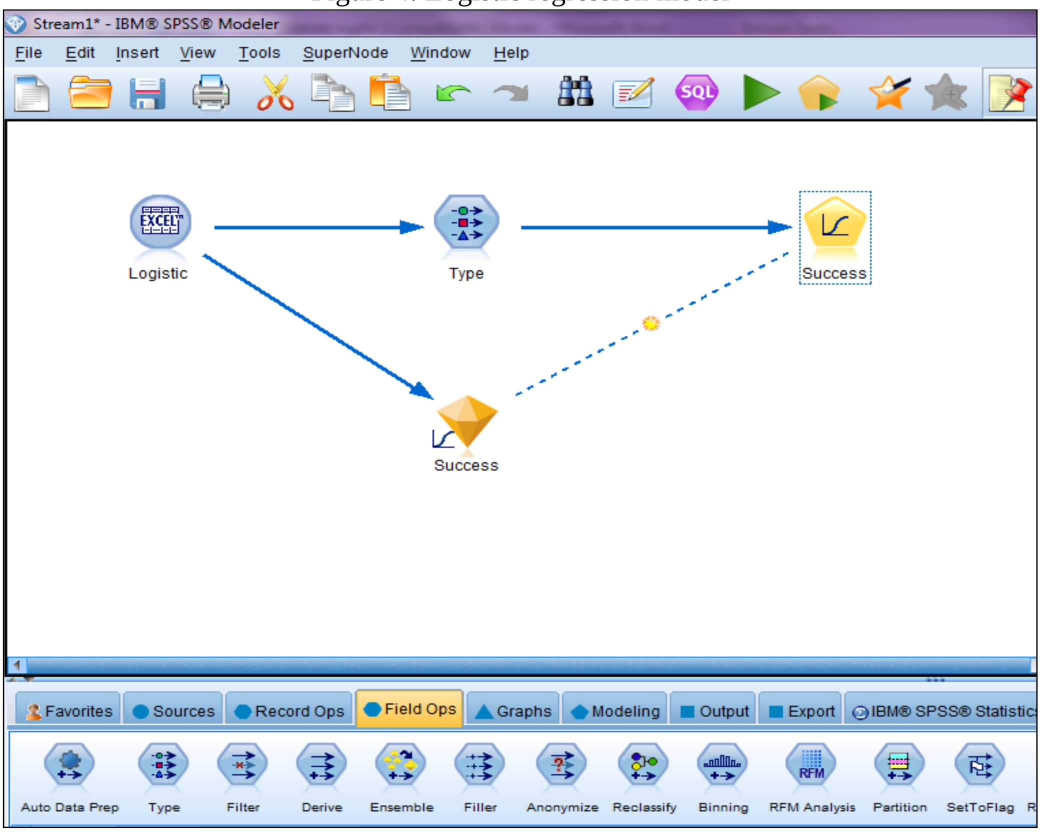
Various decision tree algorithms such as CHAID, C4.5, CART and others produce trees that differ from one another in the number of splits allowed at each level of the tree, how those splits are chosen when the tree is built, and how the tree growth is limited to prevent overfitting.

Among classification and regression trees, C&RT builds classification and regression trees for predicting continuous dependent variables and categorical predictor variables. The classic C&RT algorithm was popularized by Breiman, Friedman, Olshen and Stone. In most general terms, the purpose of the analyses via tree-building algorithms is to determine a set of if-then logical (split) conditions that permit accurate prediction or classification of cases. [10] (Classification and Regression Trees: http://www.statsoft.com/textbook/classification-and-regression-trees/, 10.01.2012)

In most cases, the interpretation of results summarized in a tree is very simple. This simplicity is useful not only for purposes of rapid classification of new observations. It is much easier to evaluate just one or two logical conditions, than to compute classification scores for each possible group, or predicted values, based on all predictors and using possibly some complex nonlinear model equations). It can also often yield a much simpler model for explaining why observations are classified or predicted in a particular manner.

SPSS Clementine and C&RT algorithm were used to analyze the data set. The aim of this study was to determine financial ratios that affected 0-1 coded "Company Success Condition".

Figure 4: Logistic regression model



In Figure 4, the variables that affect the overall success of the company were examined. There were 122 data. The C&RT algorithm chose this data as a "training set". A training set consisting of records whose class labels are known must be provided. The training set was used to build a classification model, which was subsequently applied to the "test set" that consisted of records with unknown class labels.

Evaluation of the performance of a classification model is based on the counts of test records correctly and incorrectly predicted by the model. These counts are tabulated in a table known as a “confusion matrix”.
Although a confusion matrix provides the information needed to determine how well a classification model performs, summarizing this information with a single number would make it more convenient to compare the performance of different models. This can be done using a performance metric such as “accuracy” [11].
Most classification algorithms seek models that attain the highest accuracy, or equivalently, the lowest error rate when applied to the test set. The accuracy of this model was 84.44% and the error rate was 15.56%. It can be seen in Table 9 on the model accuracy.

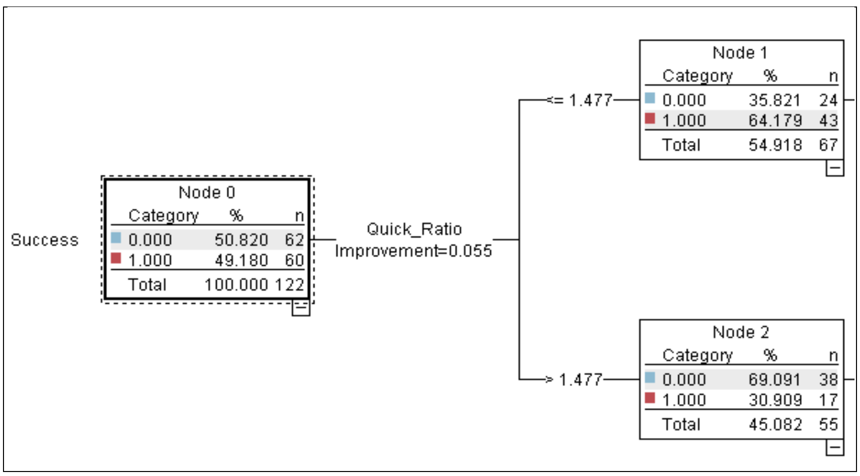
Table 9: Accuracy of the model

Results for output field Success

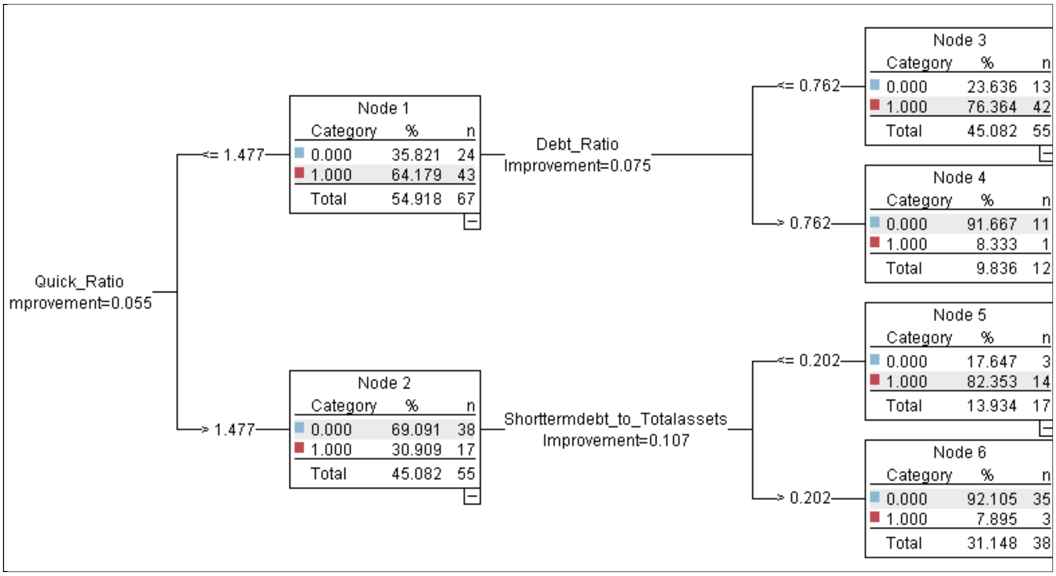
Comparing $R-Success with Success

Correct	152	84.44%
Wrong	28	15.56%
Total	180	

After conducting this model, it was found that the most important variable was quick ratio.

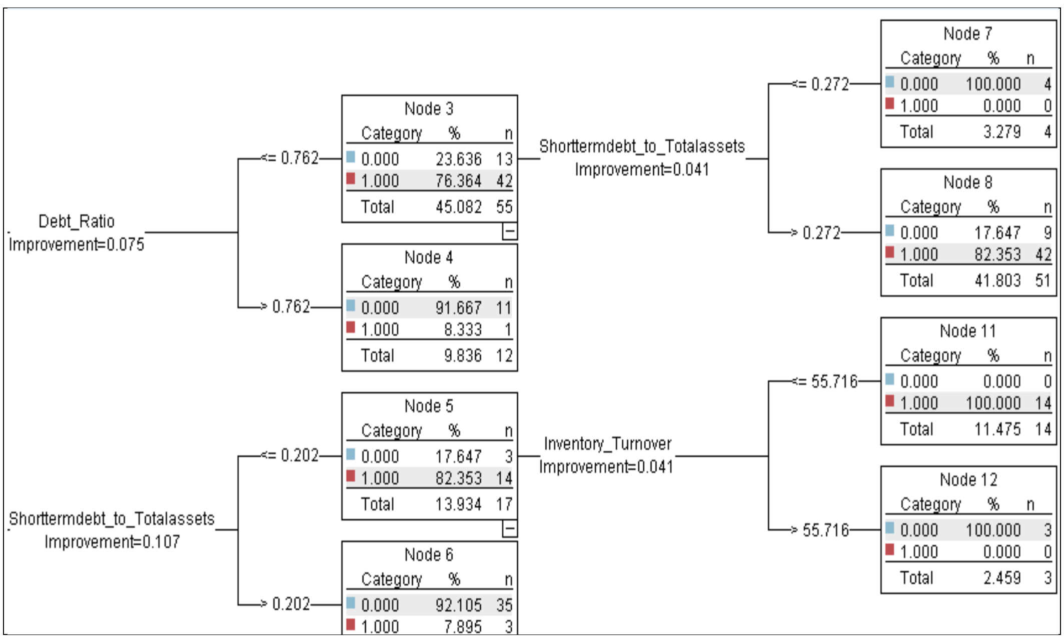


If the quick ratio was less than or equal to1.477, then 64.179% of the firms were steady successful. If the Quick ratio was greater than 1.477, then 69.091% of the firms were unsteady successful.



When this branch was examined again, it was seen that the second most effective variable was debt ratio. If the debt ratio was equal to or less than 0.762, then 76.364% of the companies were steady successful. If the debt ratio was greater than 0.762, then 91.667% of the companies were unsteady successful.

The other variable that was effective in this branch is shorttermdebt_to_totalassets ratio. If shorttermdebt_to_totalassets ratio was equal to or less than 0.202, then 82.353% of the companies were steady successful.



The other important variable was inventory turnover ratio. If this ratio was less than or equal to 55.716, then 100% of the firms were steady successful.

Compared with the results of logistic regression analysis, variables that affected the success of the companies were noteworthy are listed in Table 10.\

Table 10: Effective variables for decision trees

Quick ratio
Debt ratio
Short term debt to Total assets
Inventory turnover ratio

The effective variables for steady successful and unsteady successful companies are shown in Table 11. This presents a brief summary of the decision tree results of the study.

4 Conclusions

The users of financial statements, which include present and potential investors, employees, lenders, suppliers and other trade creditors, customers, governments and their agencies and the public, use financial statements to satisfy some of their different needs for information. For providing information about the financial position, performance and changes in financial position of a company, financial indicators (ratios) are calculated from data in the basic financial statements. These indicators can be used to make inferences about a company's financial condition, its operations and attractiveness as an investment. They can also be used to analyze trends and compare companies' financial performance end situation to other firms. The main desire of the investors is to invest in companies that are steady successful.

This study empirically examines the common and distinctive financial indicators of steady and unsteady successful big manufacturing companies in Turkey by using data mining methodology. In this framework, the variables that affect the success of the company were identified by using logistic regression analysis. Then the differential values of the indicators were identified by using decision trees. Several studies have been and are still being realized in the area of financial ratios and data mining separately. However, there is no study in the literature that combines these two areas together. To our knowledge, this will be the first study in Turkey about financial ratios using data mining. The study is expected to contribute to the literature on accounting ratios and data mining.

According to logistic regression analysis current ratio, quick ratio, debt ratio, short term debt/total debts, inventory turnover ratio, CFFO/total assets and CFFF/CFFI variables are found to be significant at the 95% confidence level. These are the distinctive variables for steady and unsteady successful companies.

Table 11: Summary of the effective variables for steady successful and unsteady successful companies

Quick Ratio		
Less than or equal to 1,477	STEADY	43 Companies
	UNSTEADY	24 Companies
	Total	**67 Companies**

Debt Ratio		
Less than or equal to 0,762	STEADY	42 Companies
	UNSTEADY	13 Companies
	Total	**55 Companies**
Greater than 0,762	STEADY	1 Company
	UNSTEADY	11 Companies
	Total	**12 Companies**
	TOTAL	**67 Companies**

Short term Debt to Total Assets		
Less than or equal to 0,272	STEADY	0 Company
	UNSTEADY	4 Companies
	Total	**4 Companies**
Greater than 0,272	STEADY	42 Companies
	UNSTEADY	9 Companies
	Total	**51 Companies**
	TOTAL	**55 Companies**

Quick Ratio (continued)		
Greater than 1,477	STEADY	17 Companies
	UNSTEADY	38 Companies
	Total	**55 Companies**
	TOTAL	**122 Companies**

Short term Debt to Total Assets		
Less than or equal to 0,202	STEADY	14 Companies
	UNSTEADY	3 Companies
	Total	**17 Companies**
Greater than 0,202	STEADY	3 Companies
	UNSTEADY	35 Companies
	Total	**38 Companies**
	TOTAL	**55 Companies**

Inventory Turnover Ratio		
Less than or equal to 55,7	STEADY	14 Companies
	UNSTEADY	0 Company
	Total	**14 Companies**
Greater than 55,7	STEADY	0 Company
	UNSTEADY	3 Companies
	Total	**3 Companies**
	TOTAL	**17 Companies**

By using decision trees, differential values of the indicators were also identified in this study. Because the C&RT algorithm chose data as a "training set", 122 companies of 174 companies were examined. It was found that the first and most important distinctive variable is *"quick ratio"* for steady successful and unsteady successful companies. This ratio shows that steady successful companies are divided into two groups because of their financial structure. By considering other results of the study, the first group of steady successful companies is defined as *"dynamic companies"* while the second group of steady successful companies is defined as *"cumbersome companies."*

Dynamic Steady Successful Companies

This first group comprised *43 dynamic steady successful companies*, which were 64% of the 67 companies, with a *quick ratio* less than or equal to 1.48. These companies' short term debts were approximately 1.5 times and less of cash and account receivables.

The second distinctive financial indicator for the 67 steady and unsteady successful companies in the first group is the *"debt ratio"*. The third distinctive financial indicator is" *short term debt/ total assets".*

42 companies, 63% of the 67 companies, constitutes the first group, where the *debt ratio* is equal to or less than 0.762. In other words, these steady successful companies' owner's equity was at least about 25% of the total assets.

These 42 companies in the first group had *short term debt/ total assets* greater than 0.27. This also means that these companies' short term debts were approximately 1/3 more than their total assets.

Briefly to summarize dynamic steady successful companies:

Quick ratio was less than or equal to 1.48.

Debt ratio was less than or equal to 0.762.

Short term debt/ total assets was greater than 0.27.

(Too much short term debt, limited cash and short-term receivables to meet short term obligations)

Cumbersome Steady Successful Companies

This second group comprised *17 cumbersome steady successful companies,* which were 31% of the 55 companies, with a *quick ratio* greater than 1.48. These companies' short term debts were more than about 1.5 times cash and receivables.

The second distinctive financial indicator for the 55 steady and unsteady successful companies in the second group was the *"short term debt/ total assets"*. The third distinctive financial indicator was *"inventory turnover ratio".*

14 companies, which was 25 % of the 55 companies with a quick ratio greater than 1.48 in the second group had *short term debt/ total assets* less than or equal to 0,202. This also means that these companies' short term debts were less than about 20% of their total assets.

In 14 companies, which is 82% of the 17 companies with the *short term debt/ total assets* less than or equal to 0.202, had a *inventory turnover ratio* less than or equal to 55.7. These companies had at least about 7 days or more to sell inventory.

Briefly to summarize cumbersome steady successful companies:

Quick ratio was greater than 1.48**.**

Short term debt/ total assets was less than or equal to 0.202.

Inventory turnover ratio was less than or equal to 55.7.

(Less short term debt, more cash and short-term receivables than short term debt, at least 7 days or more to sell inventory)

In this study, empirical research was also conducted to find distinctive financial indicators by sectors. After using this model to categorize companies by sectors, it was observed that the results are not significant in accounting. As they were not interpreted in terms of accounting, the results were excluded from the study. Further research that examines the steady successful companies by sectors should continue to broaden the understanding.

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