Paper Title: ***The Importance of Qualitative Factors in Firm Default: Evidences from Turkey***

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The Importance of Qualitative Factors in Firm Default: Evidences from Turkey

Abstract

One of the main criticisms to be made of the existing credit risk management practices is that these latter include very limited use of the qualitative information about the counterparties. The undervaluation of the qualitative information's importance in the existing credit risk models, based largely on quantitative inputs like financial ratios, will undoubtedly have to be reconsidered in the near future. From this perspective, the most notable contribution of this study is the inclusion of qualitative information to credit risk modeling. This paper investigates the determinants of firm defaults for Turkish companies. Data are collected from the database of a commercial bank operating in Turkey and consist of 1772 firms (*observations*) for 32 variables (*qualitative and quantitative*). All the observations are drawn from Turkish manufacturing sector during the period between 15.03.2001 and 21.09.2005. Multivariate logistic regression is employed for constructing the predictive models. The results of this study reveal that the inclusion of qualitative and quantitative variables to the regression equation, at the same time, not only improves the R^2 value but also modifies the composition of predictive variables.

EFM Classification Codes: 130

I. Introduction

Although there is an abundant literature on credit risk modeling, since the pioneering studies of Beaver (1966) and Altman (1968), the recent global financial crisis has demonstrated the need for new tools to predict corporate failure. It is obvious that the paradigms about the counterparty default risk (*commonly called, credit risk*) prediction have changed due to the recent global financial crisis. Prominently, in many studies reviewed (e.g. Wang, 2009), it is observed that finance professionals, academicians and policy makers have begun to scrutinize and criticize the existing credit risk management practices. It seems that the one of the main criticisms to be made of the existing credit risk management practices is that these latter include very limited use of the qualitative information about the counterparties. The undervaluation of the qualitative information's importance in the existing credit risk models, based largely on quantitative inputs like financial ratios, will undoubtedly have to be reconsidered in the near future. From this perspective, the most notable contribution of this study is the inclusion of qualitative information to credit risk modeling. By using qualitative and quantitative data obtained from the records of a commercial bank operating in Turkey, a default prediction model is generated. Another contribution of this study is its focus on an emerging country. The inherently volatile nature of emerging markets

(Mody, 2004) and their different characteristics in terms of political, economic and institutional factors would help to observe whether the credit risk models, developed generally by using data from developed markets, have a widespread applicability or not. In that sense, Turkey as a developing country experiencing financial and economic crises since 1960 provides a very prominent setting for this study.

The program adopted by Turkish government in 1980 was, as a whole, a new program aiming not only the stabilization with export-led recovery but also the liberalization of the Turkish economy. Especially, after 1984, external capital movements have begun to liberalize substantially. Then, in 1989, the biggest change was occurred with the Decree No: 32 (regarding the protection of the value of the Turkish currency). This decree was a very important step toward financial liberalization, since due to this decree the following permissions were realized (Esen, 2000): (1) Turkish residents are allowed not only to buy foreign exchange from financial institutions including banks, but also to buy securities abroad and to transfer the foreign exchange required to purchase such securities abroad. (2) Non-residents are allowed not only to buy and sell Turkish securities, but also to transfer income and sales proceeds of these securities abroad through financial institutions including banks. (3) Turkish commercial banks are permitted to extend credits denominated in foreign currency to foreign trade companies.

In such a liberalized economic environment, the firms became more prone to crises in relatively less regulated conditions. Moreover, like many other developing countries, Turkey has experienced a surge in capital inflows in the 1990's. These inflows were massively short term, speculative, and destabilizing. As a result, Turkey experienced two severe economic crises in 1994 and 2001. Current account deficit financed by short-term inflows brought about one of

the most serious depressions of Turkish economic history in 1994, which was resulted in the liquidation of three commercial banks by the government. Though their reasons were similar, the intensity of the consequences of 1994 and 2001 crises were not the same. The heavy impact of 2001 crisis was not only on the financial sector but also on the real sector. The pressure of the high level of indebtedness on several firms created a real insolvency problem. The financing of long-term investments with short-term funding (6 months-1 year) produced an inevitable credit crunch.

The remainder of the paper proceeds as follows. The following section briefly describes the relevant theoretical framework. Section III describes data and methodology used in this study. The results are reported in section IV. Section V concludes the paper.

II. Theoretical Framework

As it is stated by Miyake and Inoue (2009), the approaches in credit risk modeling can be classified as follows: traditional approach, structural approach, inductive approach.

Saunders (1999, p. 7-16) views three classes of models as comprising the traditional approach, expert systems, rating systems and credit scoring systems. In an expert system, the credit granting decision depends largely on the subjective judgment of lending officer. One of the most common expert systems involves the analysis of the following key characteristics about the customer and granting the credit according to subjectively weighted averages of these factors: character, capital, capacity, collateral and cycle (or economic conditions). In rating systems, the loan portfolio is divided in different risk categories and the required loss reserves for the financial institution are determined accordingly. The international accord

developed by the Basel Committee on Banking Supervision, Basel II, aims to establish a global standard for financial institutions in terms of risk measurement and provides an opportunity for improving internal rating systems. On the other hand, in credit scoring systems, certain key factors that determine the probability of default are pre-identified and all of them are combined and weighted into a quantitative score. The common characteristic of the traditional approaches is the use of past data (mostly quantitative) about the customer.

Structural approach involves the models which use the evolution of firms' structural variables in order to determine the time of default. Asset and debt values are considered as the major structural variables. Though the roots of structural approach date back to the ends of 1950's (Modigliani and Miller, 1958), Black and Scholes (1973) and Merton (1974) have revolutionized this approach by rendering the firm valuation, contingent on the firm's cash flows. In Merton's model, a firm defaults when the value of the firm's assets fall below the face value of the outstanding debt, at maturity. Just after the study of Merton (1974), Black and Cox (1976) claimed that a default occurs when a firm's asset value falls below a certain threshold. In contrast to the Merton's model, Black and Cox claim that default can occur at any time.

Finally, inductive approach refers to the probabilistic models where the default probability is exogenously given (e.g. neural network applications). Neural networks are based on a black-box and they try to imitate the learning mechanism of human knowledge and memory by capturing some features that cannot be incorporated in a simple calculation algorithm (Resti and Sironi, 2007, p. 302).

Following the overview of the extensive body of literature on the credit risk modeling, we will focus particularly on the researches concerning the credit scoring with the use of logistic regression analysis, since this method is used in this study. The use of regression based methods dates back to 1970's. During the period 1970-1980, the use of linear regression, discriminant analysis and the probit regression was widespread in the studies on credit scoring. Nevertheless, because of the strong multivariate normality assumptions, these methods were abandoned in course of time. The relaxation of the normality assumption led the researchers to use logistic regression. This method is introduced by Ohlson (1980) to the "default prediction" research area. Ohlson's paper presents the empirical results of a study aiming to predict corporate failure as evidenced by the event of bankruptcy. The dataset covers the years 1970-1976. By using traditional financial ratios and the firm size as the predictors, Ohlson calculated "type I" and "type II" errors in different cut points. In another study, Pantalone and Platt (1987) used the logit model for distinguishing healthy banks from the failed ones. In pursuit of these studies, many researchers have continued to use logistic regression with which, significant and robust estimations can be obtained in credit scoring, by avoiding the problems of linear regression and discriminant analysis (e.g. Gilbert *et al*., 1990; Hayden, 2003). It is useful to revise the study of Altman and Saunders (1998) in order to understand the key developments in credit risk measurement between 1980-2000.

III. Data and Methodology

Data

Data used in this study are collected from the database of a commercial bank operating in Turkey and consist of 1772 firms (*observations*) for 32 variables. All the observations are

drawn from Turkish manufacturing sector during the period between 15.03.2001 and 21.09.2005. The size of the sample, which is 1772, is highly sufficient for discriminating the defaulted firms from the non-defaulted ones by the use of logistic regression, as the method of analysis.

Variables

The goal of an analysis using logistic regression is to find a model for describing the relationship between an outcome (*dependent* or *response*) variable and a set of independent (*predictor* or *explanatory*) variables. These independent variables are often called *covariates* (Hosmer and Lemeshow, 2000, p:1). The dependent variable, used in this study, is called "state" and indicates the default state of the credit user. "State" takes on the values 0 and 1, referring to the non-default and default case, respectively. For purposes of this study, two groups of predicting variables are used for discriminating the defaulted firms from the non-defaulted ones. The first group composes of the qualitative variables and the second group consists of the quantitative variables.

13 variables are in the category of so called "qualitative variables" (Table 1). These qualitative variables represent most of the traditional "criteria of 6 C's" that commercial loan lenders consider in deciding to lend or not. These criteria are the followings: **c**haracter (PH-IBC, CRFS), **c**apability to manage the business (NPLV, RAI, FR-MR, MSFL, MMPS, RCU), **c**apacity (PHFS), **c**ollateral and guarantees (OSHO), **c**ontext of the business (DCP), **c**onditions or terms of loans (RBFI, WCBFI).

Table 1

List of qualitative variables

QUALITATIVE VARIABLE	ABBREVIATED NAME OF THE VARIABLE
non-performing loan volume	NPLV
rediscounts of accrued interest	RAI
paying habits / issuing of bad cheques	PH – IBC
credibility and reputation of the firm and its shareholders	CRFS
relationships with other banks and financial institutions	RBFI
property holdings of the firm and its shareholders	PHFS
financial risks and managerial risks	FR - MR
ownership and situation of head office and other offices	OSHO
working conditions with banks and other financial institutions	WCBFI
maturity structure of financial liabilities	MSFL
demand conditions for the products	DCP
maturity matching of purchases and sales	MMPS
rates of capacity utilization	RCU

The scores for these qualitative variables are basically obtained from a questionnaire conducted by bank representatives who pay periodical visits to applicant firm and its facilities. There are 4 answers to each question, and they take on the values from 1 to 4. 4 is given to the most likely condition that generally causes the default of firms and 1 is given to firms in good condition in terms of the corresponding question. These values are ordinal and complete each other. In table 2, each qualitative variable is explained briefly. Further details are available upon request.

Table 2

Descriptions of qualitative variables

VARIABLE	DESCRIPTION
NPLV	Measures the level of loans on which the firm***** has already defaulted.
RAI	Measures the level of rediscount balance, which is not proportional with cash risk incurred by the firm.
PH – IBC	Measures to what extent the owners are reliable and responsible in repayment of borrowed funds.
CRFS	Measures how the firm and its shareholders are perceived by their stakeholders (*customers, suppliers, competitors, etc.*), in terms of trustworthiness and meeting the monetary and non-monetary promises.
RBFI	Measures the strength and the continuity of the relationship between the firm and other banks and financial institutions.
PHFS	Measures the total tangible wealth level of the shareholders besides the invested capital to the firm.
FR – MR	Measures the level of risks (*resulting from current operations, speculative operations, financial operations, etc.*) incurred by the firms' owners and managers.
OSHO	Measures to what extent the owners invest to the firm.
WCBFI	Evaluates how the other banks and financial institutions perceive the credibility of the firm. The collateral and other conditions that other banks and financial institutions require from the firm can be considered as the criteria.
MSFL	Measures the quality of management of maturity-match between the current liabilities and the working capital and incomes.
DCP	Measures whether or not there is a demand for the products produced by the firm.
MMPS	Measures the quality of management of maturity-match between the purchases and sales.
RCU	Measures to what extent the firm's capacity is used efficiently.

***** : "firm" refers to the "applicant firm"

The second group of variables consists of financial ratios, in other words, "quantitative variables", which represent liquidity, efficiency, leverage, profitability and growth levels of 1772 firms (Table 3).

Table 3

List of quantitative variables

QUANTITATIVE VARIABLE	ABBREVIATED NAME OF THE VARIABLE
Liquidity ratios	
current ratio	CR
liquidity ratio	LR
adequacy of net working capital	ANWC
Efficiency ratios	
net sales / total assets	NS/TA
turnover rate of tangible fixed assets	TTFA
Leverage ratios	
total liabilities / total shareholders' equity	TL/TSE
short-term liabilities / total assets	STL/TA
short-term bank loans / total liabilities	STBL/TL
tangible long-term assets / shareholders' equity	TLTA/SE
short-term liabilities / net sales	STL/NS
total bank loans / shareholders' equity	TBL/SE
Profitability ratios	
operating income / net sales	OI/NS
return on sales	ROS
return on assets	ROA
ratio of financial expenses to net profit plus financial expenses	FE/NPPFE
net income / shareholders' equity	NI/SE
Growth ratios	
growth rate of net sales	GRNS
growth rate of total assets	GRTA

Financial ratios are mapped into 4 categories following the same logic as for the qualitative variables. There are 4 states for each quantitative variable and take on the values from 1 to 4. 4 is given to the most likely condition that generally causes the default of firms and 1 is given to firms in good condition. Threshold values for quantitative variables are given in table 4. Thresholds are chosen together with the financial credit analysts and the credit experts of the bank. We have interviewed 30 analysts and experts together, and took a weighted average of thresholds. Weights are determined by their experiences. For some of the ratios, especially for the ones having some debt measure as nominator and shareholders' equity as denominator, negative values are mapped to fourth category. In such a case, the

lower the ratio's value, the less likely the firm would be defaulted, but for negative values, the more likely the firm would go bankrupt.

Table 4

Threshold values for quantitative variables

	Cut-off points			
	1	2	3	4
LIQUIDITY RATIOS				
CR	X ≥ 1,75	1,75 > X ≥ 1,25	1,25 > X ≥ 0,75	X < 0,75
LR	X ≥ 1,25	1,25 > X ≥ 0,80	0,80 > X ≥ 0,50	X < 0,50
ANWC	X ≥ 6,00	6,00 > X ≥ 4,00	4,00 > X ≥ 2,00	X < 2,00
EFFICIENCY RATIOS				
NS/TA	X > 2,50	2,50 ≥ X > 1,50	1,50 ≥ X > 1,00	X ≤ 1,00
TTFA	X ≥ 8,00	8,00 > X ≥ 6,00	6,00 > X ≥ 3,00	X < 3,00
LEVERAGE RATIOS				
TL/TSE	0,00 ≤ X < 1,00	1,00 ≤ X < 3,00	3,00 ≤ X < 5,00	0,00> X > 5,00
STL/TA	X < 0,40	0,40 ≤ X < 0,50	0,50 ≤ X < 0,60	X ≥ 0,60
STBL/TL	X < 0,15	0,15 ≤ X < 0,30	0,30 ≤ X < 0,50	X ≥ 0,50
TLTA/SE	0,00 ≤ X < 0,75	0,75 ≤ X < 1,10	1,10 ≤ X < 1,50	0,00 > X ≥ 1,50
STL/NS	X ≤ 0,25	0,25 < X ≤ 0,50	0,50 < X ≤0,75	X > 0,75
TBL/SE	0,00 ≤ X < 1,00	1,00 ≤ X < 2,00	2,00 ≤ X < 3,00	0,00> X ≥ 3,00
PROFITABILITY RATIOS				
OI/NS	X ≥ 0,08	0,08 > X ≥ 0,04	0,04 > X ≥ 0,01	X < 0,01
ROS	X ≥ 0,05	0,05 > X ≥ 0,02	0,02 > X ≥ 0,00	X < 0,00
ROA	X ≥ 0,08	0,08 > X ≥ 0,04	0,04 > X ≥ 0,02	X < 0,02
FE/NPPFE	0,00 ≤ X < 0,40	0,40 ≤ X < 0,60	0,60 ≤ X < 0,80	0,00> X ≥ 0,80
NI/SE	X > 0,30	0,30 ≥ X > 0,15	0,15 ≥ X > 0,05	X ≤ 0,05
GROWTH RATIOS				
GRNS	X ≥ 0,12	0,12 > X ≥ 0,05	0,05 > X ≥ -0,05	X < -0,05
GRTA	X ≥ 0,08	0,08 > X ≥ 0,03	0,03 > X ≥ -0,05	X < -0,05

Methodology

Multivariate logistic regression is employed in this study for constructing the predictive models. Regression analyses are expressed in terms of odd ratio and 90% confidence interval and performed using Matlab software. Firstly, the "state" variable is regressed on each predicting variable separately by making use of logistic regression. Demand conditions for the products (DCP), and turnover rate of tangible fixed assets (TTFA) are dropped from qualitative and quantitative variables respectively, due to high p-values. Then, backward stepwise regression is employed on qualitative and quantitative variables separately

(table 5, table 6). Finally, we run stepwise regression on the entire data set covering both qualitative and quantitative variables (table 7).

IV. Empirical Results

The results of backward stepwise regression ran on the qualitative variables, more specifically the estimated odd ratios are presented in table 5. Significance threshold for the regression is chosen to be 0.10. The parameter estimates suggest that the following independent variables bring up more information for explaining the state of default: relationships with other banks and financial institutions (RBFI), maturity structure of financial liabilities (MSFL), maturity matching of purchases and sales (MMPS), credibility and reputation of the firm and its shareholders (CRFS), non-performing loan volume (NPLV) and rates of capacity utilization (RCU). Based on the values of odd ratios, the relationship between the probability of default and the maturity structure of financial liabilities can be considered as the strongest. A unit change for the worse in the maturity-match between the current liabilities and the working capital and incomes results in an increase in log of the odds ratio of default by 2,49. It is also noteworthy that the significant independent variables fall into the following groups of the traditional "criteria of 6 C's": **c**haracter (CRFS), **c**apability to manage the business (NPLV, MSFL, MMPS, RCU) and **c**onditions or terms of loans (RBFI).

Table 5

Stepwise regression results for qualitative model

Variables	Odds ratio	Std. Err.	Z	P	lower interval	upper interval
RBFI	1.6644	0.2821	3.01	0.003	1.1939	2.3203
MSFL	2.4993	0.2539	9.02	0.000	2.0481	3.0499
MMPS	1.4535	0.1618	3.36	0.001	1.1685	1.8080
CRFS	1.8863	0.4048	2.96	0.003	1.2386	2.8726
NPLV	1.4522	0.2155	2.51	0.012	1.0857	1.9425
RCU	1.4543	0.2540	2.14	0.032	1.0328	2.0480
Number of obs = 1772 LR chi2(9) = 454.17 Prob > chi2 = 0.0000 Log likelihood = -363.76175 Pseudo R2 = 0.3843						

The results of backward stepwise regression ran on the quantitative variables are shown in table 6. The results of analysis indicate that the following independent variables lead to a significant increase in the probability of default: net sales / total assets (NS/TA), total bank loans / shareholders' equity (TBL/SE), short-term liabilities / total assets (STL/TA), growth rate of total assets (GRTA), current ratio (CR), ratio of financial expenses to net profit plus financial expenses (FE/NPPFE) and total liabilities / total shareholders' equity (TL/TSE). The estimated odd ratios in table 6 show that the relationship between the probability of default and the current ratio is the most significant. More specifically, a unit change for the worse in current ratio of the firm lead to an increase in the odds ratio of default by 2,59 times. This result is very consistent with the results of stepwise regression for qualitative model which is previously reported. The significant independent variables fall into almost all of the categories of financial ratios with the dominance of leverage ratios. These later are as follows: liquidity ratios (CR), efficiency ratios (NS/TA), leverage ratios (TL/TSE, STL/TA, TBL/SE), profitability ratios (FE/NPPFE) and growth ratios (GRTA).

Table 6

Stepwise regression results for quantitative model

Variables	Odds ratio	Std. Err.	Z	P	lower interval	upper interval
NS/TA	4.48e+08	9.98e+07	89.56	0.000	2.90e+08	6.94e+08
TBL/SE	1.3802	0.2486	1.79	0.074	0.9697	1.9645
STL/TA	1.9372	0.2838	4.51	0.000	1.4537	2.5816
GRTA	1.5924	0.1878	3.95	0.000	1.2638	2.0064
CR	2.5874	0.6149	4.00	0.000	1.6239	4.1225
FE/NPPFE	1.5306	0.2322	2.81	0.005	1.1369	2.0606
TL/TSE	1.4539	0.2496	2.18	0.029	1.0386	2.0354
Number of obs = 1772 LR chi2(7) = 896.41 Prob > chi2 = 0.0000 Log likelihood = -142.64055 Pseudo R2 = 0.7586						
Note: 1238 failures and 0 successes completely determined.						

Since the aim of this study is to bring up the importance of the qualitative information in default prediction, the following step is to run a stepwise regression on the entire data set covering both qualitative and quantitative variables (table 7). The inclusion of qualitative and quantitative variables to the regression equation, at the same time, not only improves the R2 value from 0.7586 to 0.7963 (from table 6 to table 7) but also modifies the composition of predictive variables. The joint contribution of qualitative and quantitative variables provides the results displayed in table 7. According to the final estimated model, the predictors (*qualitative and quantitative*) of state of default are related with the following dimensions of qualitative and quantitative predictors: **c**onditions or terms of loans (RBFI), **c**ollateral and guarantees (OSHO), **c**apability to manage the business (NPLV), efficiency (NS/TA), leverage (TL/TSE, STL/TA), growth (GRTA), liquidity (CR), profitability (FE/NPPFE, OI/NS). Especially the **c**onditions or terms of loans, efficiency, leverage and growth related predictive variables are the most significant ones.

Table 7

Stepwise regression results for the entire model (*qualitative* + *quantitative*)

Variables	Odds ratio	Std. Err.	Z	P	lower interval	upper interval
NS/TA	4.76e+08	1.74e+08	54.63	0.000	2.32e+08	9.74e+08
TL/TSE	1.4966	0.2234	2.70	0.007	1.1170	2.0053
STL/TA	2.2028	0.4131	4.21	0.000	1.5253	3.1813
RBFI	2.6781	0.6385	4.13	0.000	1.6784	4.2733
GRTA	1.8010	0.2370	4.47	0.000	1.3916	2.3309
CR	2.2864	0.6297	3.00	0.003	1.3327	3.9226
OSHO	2.0117	0.4572	3.08	0.002	1.2886	3.1406
FE/NPPFE	1.3898	0.2342	1.95	0.051	0.9988	1.9337
NPLV	1.9616	0.6183	2.14	0.033	1.0576	3.6385
OI/NS	1.3864	0.3034	1.49	0.135	0.9029	2.1288
Number of obs = 1772 LR chi2(10) = 940.95 Prob > chi2 = 0.0000 Log likelihood = -120.36904 Pseudo R2 = 0.7963						
Note: 1238 failures and 0 successes completely determined.						

Finally, how the inclusion of qualitative predictive variables changed the rating and default probability structure is displayed in table 8. First raw is the number of firms with decreased ratings in default and non-default cases after adding qualitative variables to regression (This is a rating system with 4 classes and thresholds are 0.5, 0.1 and 0.01). For 184 default cases, ratings of 12 firms are downgraded and none of them is upgraded. For non-default case, ratings of 134 firms are upgraded and ratings of 21 of them are downgraded. Raw 3 and raw 4 show the share within the corresponding samples. Raw 5 and raw 6 present the average changes in rating degrees (mapped into integer values such as 1, 2, 3, and 4). For instance, number -1.333 is computed as the average of the vector [-1, -2, -1, -1, -1, -1, -1, -1, -2, -2, -1, -2]. As seen, total of 12 firms is downgraded in default state and 4 of them is downgraded by 2 classes. Finally last raw shows the average change in probability of default (This is computed by extracting probability of default computed in the model with qualitative variables from the probability of default values computed in financial ratios only model).

Table 8

Change in Rating and Default Probability Structure in Stepwise Model

	1	0
Decreasing	12.0000	21.0000
Increasing	0.0000	134.0000
%Decreasing	0.0652	0.0132
%Increasing	0.0000	0.0844
Avg. Dec. R	-1.3333	1.1418
Avg. Inc. R	0.0000	-1.0476
Avg. Pr. Diff	-0.0574	0.0010

V. Conclusion

Prediction of firm default is an important topic for both finance researchers and decision makers in business, especially in credit institutions. Though there is an extensive literature and numerous studies examining the default prediction, there is no a clear conclusion for the best model. The underestimation of the predictive variables in qualitative nature in the existing default prediction models can be considered as one of the main weaknesses of the existing models. This study takes a fairly uncommon perspective by focusing not only on the quantitative but also qualitative predictors of firm default. The aim of this paper is to investigate the qualitative and quantitative determinants of firm defaults for 1772 Turkish companies over the time period 2000 – 2006. The multivariate logistic regression is conducted firstly on qualitative and quantitative variables separately, then on all of the variables simultaneously. The results of this study reveal that the inclusion of qualitative and quantitative variables to the regression equation, at the same time, not only improves the R2 value but also modifies the composition of predictive variables. According to the final estimated model, the predictors (*in qualitative and quantitative nature*) of state of default are the followings: relationships with other banks and financial institutions, ownership and situation of head office and other offices, non-performing loan volume, net sales / total assets, total liabilities / total shareholders' equity, short-term liabilities / total assets, growth rate of total assets, current ratio, ratio of financial expenses to net profit plus financial

expenses, operating income / net sales. More specifically, a unit change for the worse in these predictive variables lead to an increase in the odds ratio of default.

The main contribution of this study to the literature is the consideration of predictive variables in qualitative nature in the bankruptcy prediction modeling. The very large size of data set and the research setting (*an emerging country, Turkey*) which is prone to economic crises can be considered as the points that render this study interesting. The significant predictive variables determined in this study may guide the policy makers or users of the bankruptcy models to develop early warning systems. Moreover, these bankruptcy predictors may be useful for managers, rating agencies and auditors.

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