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QUALITATIVE DETERMINANTS AND CREDIT-DEFAULT RISK: EVIDENCE FROM TURKEY

This paper investigates the qualitative and quantitative determinants of firm defaults for Turkish manufacturing companies over the time period 2001—2005 by using yearly observation intervals. The paper uses a multivariate logistic regression on the sample of 1772 firms to construct a predictive model. According to the results of this study, the most significant predictors of default are short-term financial leverage, profitability, nonperforming loan volume, and the levels of collateral and guarantees. The qualitative variables significantly increase the power of the model to predict firm default.

Keywords: *credit-default risk, default probability estimation, qualitative risk predictors, risk management, emerging markets.*

JEL classification: G33, G21.

Касірга Їлдірак, Омюр Сюер

ЧИННИКИ ЯКОСТІ І КРЕДІТНО-ДЕФОЛТНІ РИЗИКИ (ЗА ДАНИМИ ТУРЕЧЧИНИ)

У статті за допомогою щорічних інтервалів спостереження досліджено якісні і кількісні чинники дефолту турецьких компаній-виробників за 2001—2005 роки. У дослідженні використано багатофакторну логістичну регресію на вибірці з 1772 фірм для побудови прогнозної моделі. За результатами цього дослідження, найбільш значущі ознаки майбутнього дефолту — короткостроковий фінансовий левеDидж, рентабельність, обсяг кредитів, що не обслуговуються, рівні забезпечення і гарантій. Якісні змінні значно збільшують ефективність моделі для прогнозування дефолтів.

Ключові слова: *кредітно-дефолтні ризики, оцінка вірогідності дефолту, якісні предиктори ризику, управління ризиком, ринки, що розвиваються.*

Табл. 6. Літ. 14.

Касирга Йилдирак, Омюр Сюэр

ФАКТОРЫ КАЧЕСТВА И КРЕДИТНО-ДЕФОЛТНЫЕ РИСКИ (ПО ДАННЫМ ТУРЦИИ)

В статье с помощью ежегодных интервалов наблюдения исследуются качественные и количественные факторы дефолта турецких компаний-производителей за 2001—2005 годы. В работе используется многофакторная логистическая регрессия на выборке 1772 фирм для построения прогнозной модели. По результатам этого исследования, наиболее значимые признаки будущего дефолта — краткосрочный финансовый левеDидж, рентабельность, объем необслуживаемых кредитов, уровни обеспечения и гарантий. Качественные переменные значительно увеличивают эффективность модели для прогнозирования дефолтов.

Ключевые слова: *кредитно-дефолтные риски, оценка вероятности дефолта, качественные предикторы риска, управление риском, развивающиеся рынки.*

1. Introduction. Although there has been an abundant amount of 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

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predict corporate failure. Due to the recent global financial crisis, the paradigms for counterparty default risk prediction have changed. As a result, many finance professionals, academicians and policy makers have begun to scrutinize and criticize the existing credit-risk management practices. One of the main criticisms in the studies (e.g., Klein et al., 2009) is that these practices include very limited use of the qualitative information on counterparties. From this perspective, the most notable contribution of this study is the inclusion of qualitative information in credit-risk modeling. By using qualitative and quantitative data in the records of a commercial bank operating in Turkey, this study generates a default prediction model. The inherently volatile nature of emerging markets and their different characteristics in terms of political, economical and institutional factors 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 the 1970s provides a very prominent setting. Furthermore, we conjecture that the importance of qualitative variables in default prediction may be more pronounced in emerging economies like Turkey.

The remainder of the paper proceeds as follows. The next section briefly describes the relevant theoretical framework. Section 3 describes the data and the method used in this study. The results are reported in Section 4 and 5 concludes the paper.

2. The theoretical framework. As Miyake and Inoue (2009) stated, the approaches in credit risk modeling can be classified as follows: the traditional approach, the structural approach, or the inductive approach. Saunders (1999: 7—16) viewed 3 classes of models that comprise the traditional approach: expert systems, rating systems, and credit scoring systems. This study focused on the research that concerns credit scoring[3] through the use of a logistic regression analysis. The use of regression-based methods dates back to the 1970s. During that period, the use of the linear regression, the discriminant analysis and the probit regression were widespread. Altman (1968) used linear discriminant analysis to find discriminating variables for bankruptcy prediction. Altman's model is based on the initial sample composed of 66 corporations with 33 firms in each of the 2 groups (bankrupt vs. non-bankrupt). Altman's well-known Z-Score model, which uses only 5 financial ratios[4] to determine the financial health of a firm, is the output of this study. Zmijewski (1984) developed a bankruptcy prediction model by adopting a probit approach. The financial distress model estimations reported in this study indicated that the probability of bankruptcy is a decreasing function of return on assets and an increasing function of financial leverage. Nevertheless, because of the strong multivariate normality assumptions, these methods were abandoned over the course of time. The relaxation of the normality assumption led to the use of the logistic regression. This method was introduced by Ohlson (1980). Ohlson's paper presented the empirical results of a study aiming to predict corporate failure as evidenced by bankruptcy. His dataset covered

[3] 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.

[4] X1: working capital/total assets, X2: retained earnings/total assets, X3: earnings before interest and taxes/total assets, X4: market value equity/book value of total debt, X5: sales/total assets.

the years 1970—1976. By using traditional financial ratios and firm size as 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 failed ones. In pursuit of these studies, many researchers have continued to use the logistic regression from which significant and robust estimations can be obtained for credit scoring by avoiding the problems of the linear regression and the discriminant analysis (e.g., Gilbert et al., 1990; Hayden, 2003).

These regression-based bankruptcy forecasting models have also been subject to criticism, most notably by Queen and Roll (1987), Theodossiou (1993) and Shumway (2001). Starting from the disadvantages of the use of accounting data in bankruptcy prediction, Queen and Roll (1987) relied solely on market information to predict the survival of firms. Theodossiou (1993) presented a dynamic model based on CUSUM analysis for predicting financial distress. The study of Shumway (2001) was built upon the studies of Queen and Roll (1987) and Theodossiou (1993). The author initially explained the deficiencies of static models in forecasting bankruptcy; he then proposed a hazard model using both accounting ratios and market-driven variables.

As stated above, in the existing credit-risk models, the qualitative information's importance is underestimated. One of the rare studies that considers the role of nonfinancial factors in default prediction belongs to Grunert et al. (2005). As the authors affirmed, this study constituted a first attempt to explore the role of non-financial factors in credit ratings. They analyzed the credit-file data of 4 major German banks for the period of January 1992 — December 1996 and found evidence that the joint utilization of financial and nonfinancial factors more accurately predicts future default events than the single use of each of these factors. Grunert et al. used the definition of default by the Basel Committee on Banking Supervision. They used management quality and market position as the non-financial determinants of default. The main differences of the present study from the study of Grunert et al. (2005) lie in the sample size, sample characteristics and the qualitative variables used in the analysis.

3. Data and method.

3.1. Data description. The data used in this study are collected from the database of a commercial bank operating in Turkey and consist of 1,772 firm observations for 31 variables. All the observations are drawn from Turkish manufacturing during the period of March 15, 2001 and September 21, 2005. The data about the financial ratios of the firms are obtained from the records of the bank. With regard to qualitative information about the firms, the procedure is more complex. Upon the request of the bank's top management, one of the world's leading global management consulting firms provides the procedures and guidelines regarding credit rating. The guidelines that the consulting firm provided include not only quantitative, but also qualitative information (Tables 1 & 2). Qualitative information is obtained through a questionnaire filled out by bank representatives who paid periodical visits to the firms.

The size of the sample is sufficient enough for discriminating the defaulted firms from the non-defaulted ones with the use of the logistic regression. Out of 1,772 firms, 184 have defaulted. More specifically, these 184 firms failed to make loan repayments within 90 days after the due date. All other debtor firms make the repayments on time.

Table 1. **List of qualitative variables**

QUALITATIVE VARIABLE	ABBREVIATED NAME OF THE VARIABLE
Character	
Paying habits / issuing of bad checks	**PH – IBC**
Credibility and reputation of the firm and its shareholders	**CRFS**
Capability to manage the business	
Non-performing loan volume	**NPLV**
Rediscounts of accrued interest	**RAI**
Financial risks and managerial risks	**FR – MR**
Maturity structure of financial liabilities	**MSFL**
Maturity matching of purchases and sales	**MMPS**
Rates of capacity utilization	**RCU**
Capacity	
Property holdings of the firm and its shareholders	**PHFS**
Collateral and guarantees	
Ownership and situation of head office and other offices	**OSHO**
Context of the business	
Demand conditions for the products	**DCP**
Conditions or terms of loans	
Relationships with other banks and financial institutions	**RBFI**
Working conditions with banks and other financial institutions	**WCBFI**

Table 2. **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**

3.2. Variables. The dependent variable used in this study is called "state" and indicates the default state of the credit user. State takes on the values of zero and one in the non-default and default case respectively. For purposes of this study, 2 groups of predicting variables are used for discriminating the defaulted firms from the non-defaulted ones. The first group comprises the qualitative variables and the second group comprises the quantitative variables.

13 variables are in the category called qualitative variables (Table 1). These qualitative variables represent the traditional criteria of 6 C's that commercial loan lenders consider in deciding to lend or not. As mentioned above, the scores for these qualitative variables are basically obtained from the questionnaire conducted by bank representatives who pay periodical visits the applicant firms and their facilities. There are 4 answers to each question and they take 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 the firms in good condition in terms of the corresponding question.

The second group of variables consists of financial ratios, in other words, quantitative variables that represent liquidity, efficiency, leverage, profitability, and growth levels of the 1,772 firms (Table 2).

3.3. Method. This study uses a multivariate logistic regression to construct the predictive model. The logistic regression analyses are expressed in terms of an odds ratio and are performed using Stata software. Firstly, the "state" variable is regressed on each predicting variable separately. The results show that all the variables have a statistically significant relation with the state variable in these individual regressions. Because there are many variables that represent the same behaviors of a firm, we select representative variable(s) for each category of both qualitative and quantitative variables in order to avoid the problem of multicollinearity. The objective for the selection is to find the least collinear group of variables that satisfy the best fit. The variance inflation factor (VIF) and the covariance matrix of estimated coefficients (VCE) are used for this purpose.

From among the qualitative variables, PH-IBC for the character, MSFL for the capability to manage the business, PHFS for the capacity, OSHO for collateral and guarantees, DCP for context of the business, and WCBFI for the conditions or terms of loans are selected. Moreover, NPLV is retained as a control variable representing "bad credit," which is a crucial indicator for default. As a matter of fact, in most of the expert-based hierarchical rating systems, NPLV is used as a barrier variable while deciding to continue to rate a firm or not. The related statistics indicate the absence of multicollinearity.

For most of the categories of quantitative variables, it is not that easy to find a representative variable, as the variables display almost the same importance. The current ratio is the single dominating variable in the latent factor that is constructed for the liquidity ratios category and thus is selected to be the representative variable. For the efficiency, leverage, and profitability ratios, factor analysis is applied. Table 3 shows the predictions of 2 factors for efficiency ratios, 3 factors for leverage ratios and 2 factors for profitability ratios. It is important to note that these factors are latent factors that satisfy orthogonality conditions. Regarding the growth ratios category, the predicted latent factor introduces collinearity into the model and does not perform a good fit. Thus, the growth rate of net sales is selected as the representative variable for that category. The GRNS also brings in no collinearity to the model with a VIF value of 1 and low covariance with other variables. Moreover, the use of LVRG3 and PRF1 together in the model is problematic in terms of multicollinearity. The selection is made in favor of LVRG3 as it has a smaller value for VIF.

Table 3. **Results of factor analyses**

Factor analysis for efficiency ratios (by PCA)				
Factor	**Eigen value**	**Difference**	**Proportion**	**Cumulative**
EFF1	1.1964	0.3928	0.5982	0.5982
EFF2	0.8036		0.4018	1.0000
Variable	**EFF1**		**Uniqueness**	
NS/TA	0.7734		0.4018	
TTFA	0.7734		0.4018	
Factor analysis for leverage ratios				
Factor	**Eigen value**	**Difference**	**Proportion**	**Cumulative**
LVRG1	1.7994	1.3232	0.5300	0.5300
LVRG2	0.4761	-0.6431	0.1403	0.6703
LVRG3	1.1192		0.3297	1.0000
Variable	**LVRG1**	**LVRG2**	**LVRG3**	**Uniqueness**
TL/TSE	0.9991	-0.0417	-0.0000	0.0000
STL/TA	0.0724	0.0064	0.8786	0.2228
STBL/TL	-0.0380	0.1756	0.3888	0.8166
TLTA/SE	0.4758	-0.1021	-0.0838	0.7561
STL/NS	0.0325	0.0056	0.4349	0.8098
TBL/SE	0.7530	0.6581	-0.0000	0.0000
Factor analysis for profitability ratios				
Factor	**Eigen value**	**Difference**	**Proportion**	**Cumulative**
PRF1	1.7228	0.2453	0.5383	0.5383
PRF2	1.4775		0.4617	1.0000
Variable	**PRF1**	**PRF2**	**Uniqueness**	
OI/NS	0.6229	0.7729	0.0147	
ROS	0.6247	0.7809	0.0000	
ROA	0.8921	-0.4518	0.0000	
FE/NPPFE	0.3310	-0.2358	0.8389	
NI/SE	0.1980	-0.1034	0.9501	

4. Empirical Results. Table 4 presents the results of the logistic regression run on the (1) quantitative variables, (2) qualitative variables and, (3) entire dataset covering both quantitative and qualitative variables. The estimated odds ratios in the first column of Table 4 show that an increase in the current ratio, the first factor of efficiency, the second factor of leverage and the growth rate of net sales decrease the probability of default. On the other hand, an increase in the third factor of leverage and the second factor of profitability increases the probability of default and stands as the predictor with the highest statistical significance. These results not only support some of the findings of previous studies (Altman, 1968; Ohlson, 1980; Zmijewski, 1984) but also provide original evidence regarding the unique characteristics of Turkish companies. When the factor loadings are analyzed (Table 3) for the second and third factors of leverage, it is observed that LVRG2 is strongly positively loaded by the ratio of total bank loans to shareholders' equity. On the other hand, the variables that load significantly and positively on the third factor of leverage include the ratio of short-term total liabilities to total assets, the ratio of short-term liabilities to net sales and, the ratio of short-term bank loans to total liabilities. These findings imply that the use of short-term debt increases the probability of default, as expected, whereas the increase in the ratio of bank loans relative to equity decreases the probability of default. The empirical findings are striking and may imply that firms in Turkey should borrow from banks at longer maturities to avoid default risks. These results are not surprising considering the characteristics of SMEs. Most of the empirical researches' findings denote that SMEs in Turkey have difficulties in obtaining credits from banks, particularly long-term credits due to their relatively weaker financial structures. In addition, considering the facts that: (1) the refinancing risk increases with the amount of short-term borrowing and, (2) the ability to borrow from banks is a sign of credibility, our findings are not only statistically but also economically significant. Another significant variable increasing the probability of default is the second factor of profitability. This factor is positively loaded by the ratio of operating income to net sales and the return on sales and, negatively loaded by the return on assets. Although the signs of OI/NS and ROS appear economically inexplicable, the association of the decrease in ROA with the increase in default probability is an anticipated finding. To sum up, it can be stated that the significant independent variables fall into almost all of the categories of financial ratios but with the dominance of the leverage ratios. Specifically, a unit change for the worse in the short-term financial leverage of the firm leads to an increase in the odds ratio of default by 12.3059 times. The other important predictor appears to be the factor for profitability. Thus, for Turkish firms, one of the key issues in reducing the probability of default is to focus on optimum capital structure.

When the results of the logistic regression including qualitative variables only are examined (Table 4), the parameter estimates suggest that the following independent variables give more information for explaining the state of default: paying habits / issuing of bad checks, non-performing loan volume, maturity structure of financial liabilities, the property holdings of the firm and its shareholders, ownership and situation of the head office and other offices, demand conditions for the products, and working conditions with banks and other financial institutions. Based on the values of the odds ratios, the relation between the probability of default and the maturity structure of financial liabilities is the strongest. A unit of change for the worse in the maturity match between the current liabilities and the working capital and incomes results in an increase in the log of the odds ratio of default by 3.2163. The strong relation between MSFL and the default probability appears to be supportive to our previous finding indicating that the use of short-term debt increases the probability of default. The second strongest explanatory variable is NPLV. As expected, a unit of change for the worse in the non-performing loan volume results in an increase in default probability by 1.7473 unit. Another variable which increases default probability significantly is the working conditions with banks and other financial institutions. This finding reinforces our earlier result indicating that the increase in the ratio of bank loans relative to equity decreases the probability of default. Although relatively less significant, the results point out that the paying habits / issuing of bad checks and the ownership and situation of the head office and other offices impact default probability as well. Specifically, a unit change for the worse in PH-IBC and OSHO leads to an increase in the odds ratio of default by 1.4443 and 1.3936 times, respectively. These findings are also consistent with the fact that in Turkish banking sector where the relationship banking is a widely used lending decision-making method, the moral values of shareholders and the asset-based collateral, despite its paucity, are important factors in credit approval.

Table 4. **Logistic regression results**

Logistic regression results for quantitative model		**Logistic regression results for qualitative model**		**Logistic regression results for the entire model (quantitative+qualitative)**	
Variables	Odds ratio (p-value)	Variables	Odds ratio (p-value)	Variables	Odds ratio (p-value)
CR	0.4867	**PH-IBC**	1.4443	**NPLV**	2.4504
	(0.086)*		(0.007)***		(0.000)***
EFF1	0.0262	**NPLV**	1.7473	**MSFL**	1.4920
	(0.000)***		(0.000)***		(0.004)***
LVRG2	0.7402	**MSFL**	3.2163	**PHFS**	0.7337
	(0.001)***		(0.000)***		(0.046)**
LVRG3	12.3059	**PHFS**	0.7760	**OSHO**	1.6739
	(0.000)***		(0.024)**		(0.001)***
PRF2	8.7311	**OSHO**	1.3936	**DCP**	0.4878
	(0.000)***		(0.005)***		(0.000)***
GRNS	0.2834	**DCP**	0.7141	**WCBFI**	1.3613
	(0.000)***		(0.003)***		(0.054)**
		WCBFI	1.7011	**EFF1**	0.0328
			(0.000)***		(0.000)***
				LVRG2	0.7377
					(0.000)***
				LVRG3	15.2966
					(0.000)***
				PRF2	9.0769
					(0.000)***
				GRNS	0.2560
					(0.000)***
Number of obs	1768	Number of obs	1768	Number of obs	1768
Pseudo R^2	0.5530	Pseudo R^2	0.3676	Pseudo R^2	0.6202
AIC	541.7883	AIC	762.7528	AIC	472.4586
BIC	580.1315	BIC	806.5736	BIC	538.1899
Hosmer-Lemeshow		Hosmer-Lemeshow		Hosmer-Lemeshow	
Prob > chi²	0.1066	Prob > chi²	0.0000	Prob > chi²	0.1573

***, **,* Significant at the 0.01, 0.05, and 0.10 levels.

Because the aim of this study is to show the importance of the qualitative information in default prediction, we run a stepwise regression on the entire dataset covering both quantitative and qualitative variables (Table 4). The inclusion of quantitative and qualitative variables in the regression equation, simultaneously, not only improves the R^2 value from 0.5530 to 0.6202, but also modifies the composition of the predictive variables. Hosmer-Lemeshow Chi-square test results are obtained as goodness of fit measures and the statistics show an improvement as the probability is increased from 0.1066 to 0.1573. Likewise, AIC and BIC statistics are lower for the latter model. According to the final estimated model, the predictors (quantitative and qualitative) of the state of default are related with the following dimensions of quantitative and qualitative predictors: capability to manage the business (NPLV, MSFL), capacity (PHFS), collateral and guarantees (OSHO), context of the business (DCP), conditions or terms of loans (WCBFI), efficiency (EFF1), leverage (LVRG2, LVRG3), profitability (PRF2), growth (GRNS). Contradictory to the results obtained from "quantitative only" and "qualitative only" models, the current ratio (CR) and the paying habits / issuing of bad checks (PH-IBC) are not found as significant predictors of firm default in the logistic regression for the entire model. All other variables remain significant with the same signs. The leverage and profitability predictive variables are the most significant ones, as expected.

Next, Table 5 displays how the inclusion of qualitative predictive variables changes the rating and default probability structure of the defaulted firms. The inclusion of the qualitative variables might have an important role in catching the big loans that default. Assuming that the firms with smaller PD can use bigger amounts of loans, one should also analyze the behavior of the tail where the PD is smaller than some certain threshold. In this study, an arbitrary threshold value (0.3) is used. It is important to note that this is not a real PD value, but just the outcome of the logistic regression model. In order to compute the real-time PD values, the credit rating migration matrices over the years are needed.

The first column of Table 5 represents the PD estimates generated from the regression run with all of the variables (quantitative and qualitative). The second column represents the PD estimates generated from the regression run with only quantitative variables. It is assumed that if the bank used the quantitative only model, PD estimates would be below 0.3 for these 44 firms represented in Table 5 and the loan application would be approved. Moreover, as PD estimate gets lower, the amount of the loan granted gets higher and the interest gets lower or both. Finally, the last column is the difference between the PD estimates from both regressions. For instance, the firm represented at the last row has a PD estimate of only 0.029, if the quantitative only model is employed. Adding qualitative variables, the PD estimate improves to 0.401. Out of 44 defaults that are located under the 0.3 threshold, there are only 3 cases where the quantitative regression model produces greater PD values. The smallest PD value with a negative difference is 0.245, which can be considered as an important value compared to the rest. It is worthy to note that this comparison is done only among the defaulted firms having a state value of one. Thus, it can be concluded that the inclusion of qualitative variables significantly increases the power of the system to predict firm default that the quantitative only regression indicates are safe.

The receiver operating characteristics (ROC) curve analysis is also used because it is one of the most widely used validation tools for diagnostic analysis. 30 different thresholds are selected to distinguish the model's defaulted firms from the non-defaulted ones and to check whether there is any improvement in terms of the area under the ROC curve in all of the cases (Table 6). For all of the threshold values up to 0.19, the area under ROC curve gets larger in favor of the quantitative and qualitative regression model. If we assume that the optimal model is selected based upon the largest area criterion under the ROC curve, then the quantitative model reaches its maximum at the threshold value of 0.13 (0.8920); but for the same threshold, the quantitative and qualitative model produces the area of 0.9152. Moreover, going back to the analyses discussed in Table 5, for this same threshold value and smaller, there is always an improvement switching from the quantitative model to the quantitative and qualitative model in terms of PD values. This is also true for the case where the quantitative and qualitative model reaches its maximum. For this case, the threshold is 0.08 and the ROC values are 0.8639 and 0.9263 for the quantitative and the quantitative and qualitative models respectively.

Table 5. **PD differences between 2 regression models for the defaulted firms with the PD of 0.3 and less**

total PD	quan PD	diff (.3)
0.198	0.012	0.186
0.392	0.287	0.105
0.384	0.136	0.248
0.100	0.064	0.036
0.582	0.159	0.423
0.042	0.005	0.037
0.587	0.268	0.319
0.136	0.245	-0.109
0.448	0.155	0.293
0.156	0.072	0.084
0.427	0.036	0.391
0.213	0.014	0.199
0.415	0.028	0.387
0.403	0.138	0.265
0.104	0.067	0.037
0.586	0.162	0.424
0.048	0.014	0.034
0.592	0.269	0.323
0.210	0.252	-0.042
0.459	0.162	0.297
0.175	0.076	0.099
0.422	0.035	0.387
0.203	0.018	0.185
0.403	0.287	0.116
0.396	0.140	0.256
0.119	0.073	0.046
0.592	0.163	0.429
0.046	0.011	0.035
0.593	0.273	0.320
0.101	0.073	0.028
0.462	0.158	0.304
0.174	0.077	0.097
0.424	0.035	0.389
0.217	0.021	0.196
0.405	0.290	0.115
0.391	0.136	0.255
0.196	0.299	-0.103
0.587	0.167	0.420
0.043	0.013	0.030
0.591	0.270	0.321
0.255	0.142	0.113
0.449	0.155	0.294
0.159	0.077	0.082
0.430	0.029	0.401

Table 6. **Comparison of areas under ROC curves for different thresholds**

PD Thresholds	Quantitative ROC	Quantitative & Qualitative ROC
0.01	0.7653	0.8052
0.02	0.8012	0.8567
0.03	0.8203	0.8829
0.04	0.8380	0.9018
0.05	0.8531	0.9014
0.06	0.8648	0.9124
0.07	0.8656	0.9194
0.08	0.8639	0.9263
0.09	0.8737	0.9233
0.10	0.8809	0.9159
0.11	0.8847	0.9194
0.12	0.8879	0.9117
0.13	0.8920	0.9152
0.14	0.8846	0.9068
0.15	0.8884	0.9094
0.16	0.8698	0.9004
0.17	0.8726	0.9026
0.18	0.8752	0.9045
0.19	0.8790	0.8942
0.20	0.8802	0.8747
0.21	0.8818	0.8747
0.22	0.8840	0.8757
0.23	0.8862	0.8769
0.24	0.8881	0.8673
0.25	0.8788	0.8676
0.26	0.8802	0.8687
0.27	0.8704	0.8695
0.28	0.8711	0.8719
0.29	0.8610	0.8723
0.30	0.8621	0.8730

5. Conclusion. Although there are different models for default prediction in the literature, no clear consensus exists on which is the best model. The underutilization of the qualitative predictive variables in these models can be considered as one of their main weaknesses. This study takes a fairly uncommon perspective by focusing not only on the quantitative but also the qualitative predictors of firm default. The aim of this paper is to investigate the qualitative and quantitative determinants of firm defaults for 1,772 Turkish companies over the time period of 2001–2005. The multivariate logistic regression is conducted firstly on quantitative and qualitative variables separately, then on all of the variables simultaneously. The results of this study show that the inclusion of qualitative variables to the regression equation not only improves the R^2 value but also modifies the composition of the predictive variables. Moreover, the inclusion of qualitative variables significantly increases the power of the system for predicting defaulted firms that the quantitative only regression indicates are safe. According to the results of this study, the most significant predictors of the state of default are related with the short-term financial leverage, profitability, nonperforming loan volume, and the level of collateral and guarantees. More specifically, a unit change for the worse in these predictive variables leads to an increase in the odds ratio of default.

The present results are novel and important in 3 important aspects. Firstly, to our knowledge, this is the first study in which the role of qualitative factors in default prediction is explored in a developing country. It is believed that the findings of this study may be of stronger relevance for other emerging economies. Secondly, the survey results used in this study provide not only extensive but also unique information from a large dataset, thus making it easy to generalize the results at least on Turkish banking sector. Finally, it is worth noting that the results of this study are not only statistically but also economically significant. As such, the importance of the variable OSHO, the proxy of collateral and guarantees, in explaining the credit default is very meaningful when the prevailing conditions of the real economy in Turkey is considered. It is well known that in Turkey one of the most important factors complicating the access of SMEs to financial resources is the difficulties encountered in finding sufficient collateral.

Using the insights gained from this analysis, some recommendations can be provided on analyzing a firm before granting a loan. The recommendations would be helpful, especially for creditors at emerging markets where relationship banking is a very common practice. The significant predictive variables determined in this study might guide policy makers or users of the bankruptcy models to develop early warning systems. Moreover, these bankruptcy predictors might be useful for managers, rating agencies and auditors.

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