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Financial failure forecast by option pricing method: a Turkish case

Abstract

The main purpose of this study is to develop a financial failure prediction model that can be utilized by all actors in the economy. As financial failure criteria, Turkish Bankruptcy Law article 179 pursuant to Turkish Trade Law articles 324 and 434, and net loss in each of the preceding three years are used. The study applies market based default risk estimation model with three different statistical distribution assumptions to 180 industrial firms listed on ISE (Istanbul Stock Exchange) and follows two main steps. In the first step, KMV-Merton default probability measures are calculated according to normal distribution, student's t and asymmetric student's t-distributions assumptions for each firm. In the second step, for the evaluation purpose, pair of information content tests and estimation accuracy test are conducted to the different KMV-Merton models and compared with the results of accounting based models. Test findings indicate that KMV-Merton models are not superior to accounting based models, and in the end market based and accounting based models are combined to construct a robust and objective early warning system.

Keywords: failure prediction, option pricing model, accounting based default measures, normal distribution, student's t-distribution, asymmetric student's t-distribution.
JEL Classification: C13, C16, C52, G10, G32, G33.

Introduction

Nowadays, business enterprises operate in a rapid changing trade-economic, technological, psycho-social, and ecologic environment. This changing environment brings some sort of uncertainties. Under these uncertainties, sustaining operations and overcoming those conditions are an integral part of management. The crises that the businesses encounter are inevitable and unpredictable; and prevention of them requires special managerial attentions and interventions. As a matter of fact, at the end of 20th century and at the beginning of the current century a number of business enterprises in both developing countries and developed ones met with economic based crises.

November 2000 and February 2001 crises, arisen from Turkish own structural problems, and current global economic crises had a great impact on Turkish economy. Lots of firms came to the point of bankruptcy, shut down of operations and so on… In the past, after the crisis, in order to rescue distressed firms, most of the banks and major finance companies constituted a moratorium, which was coordinated by Banking and Regulation and Supervision Agency. This moratorium aimed to reconsolidate the debts of the distressed firms via guarantee of government authorization, which also pronounced as Istanbul Approach. This approach was also supported by World Bank and IMF in order to resolve economic crisis. Istanbul approach concerned 304 firms, 96 of which were medium-sized enterprises and restructuring agreements were concluded with 66 of medium-sized enterprises (OECD, 2004). Like in previous economic crisis Turkish government authorities aimed to constitute a moratorium like Istanbul approach to reconsolidate the debts of distressed firms and declared some series of solution packages to overcome vitiating factors of current global economic crisis and put them into force under four main headlines that are interest rate changes, adjustment of required reserve ratio, foreign exchange intervention and liquidity injection (Erdönmez, 2009).

In the light of brief information above, insolvency, default and in advance bankruptcy trigger the economic losses of stockholders, labors, customers, vendors and other stakeholders. Those losses cause social and economic losses in national and global dimension (Aktaş, 1993). Therefore, the recent default and bankruptcies of many companies have underlined the importance of failure prediction both in academia and industry. It now seems more necessary ever to develop early warning systems that can help prevent or avert corporate default, and facilitate the selection of firms to collaborate with or invest in.

In bankruptcy prediction studies two main approaches can be distinguished: The first and the most often used one is the empirical search for predictors that lead to lowest misclassification rates. The second approach concentrates on the search for statistical and structural methods that would also lead to improved prediction accuracy (Back et al., 1996).

The pioneering study in the field of bankruptcy prediction was conducted by Beaver in 1966. Beaver made the first study in bankruptcies and estimating failure risk of companies. The only point where Beaver was mostly criticized was that his study was dependent on univariate analysis and considered certain groups (a limited number) of financial ratios. In 1968, Altman expanded this analysis to multivariate discriminant analysis. Until the 1980s Discriminant Analysis (DA) was the dominant method in failure prediction. Meyer and Pifer (1970) established a financial failure estimation model based on linear regression analysis in which 0 and 1 (y = 1;

Failed) were taken as dependent variables. In 1972, Deakin tried to combine the studies of Beaver and Altman in a rationalist manner and utilized Beaver's 14 variables with application of series of multivariate discriminant models. In 1975, Libby tried to develop Deakin's model. Moyer (1977) brought forward the idea that the model developed by Altman (1968) had a poor predictive power and Moyer obtained higher classification success via utilizing stepwise DA. A number of other studies were conducted to develop DA to obtain better estimation results. Joy and Tofelson (1975) criticized the estimation power of DA, discriminating power of used variables and classification success. Taffler (1983) made some changes in DA and calculated performance scores for companies; also he proposed another z-score model that performed better than Altman's model for British companies. Ohlson (1980) was the first to practise logit analysis in the failure prediction. Most of the studies conducted after 1981 used logit analysis to mitigate the constraints of DA (Zavgren, 1985; Lau, 1987; Keasey and McGuinness, 1990; Tennyson et al., 1990).

Dichev (1998), Griffin and Lemmon (2002), and Ferguson and Shockley (2003) examined relation between the stock returns and bankruptcy risk of insolvent and risky companies by using Altman's (1968) Z-score and Ohlson's (1980) conditional logit model. Blume et al. (1998) and Molina (2005) emphasized that accounting based variables were used as expert decision in firm ratings. Avramov et al. (2007) underlined the strong link between credit ratings and stock returns. Shumway (2001) criticized traditional ratio analysis being static and the bankruptcy probabilities were biased and inconsistent by ignoring the fact that the firms change through time and overlooked the causative indicators of bankruptcy. Therefore, Shumway established a dynamic logit based model that uses both accounting based and market driven variables to forecast bankruptcy more accurately. Among the other recent studies followed Shumway's approach is Chava and Jarrow's (2004) study that considers industry effects and monthly observation intervals to validate the superior forecasting performance of Shumway's hazard model. Also, Beaver et al. (2005) investigated robustness of predictive force of financial ratios through time.

These mentioned studies have focused heavily on classification accuracy and compensation of decreasing predictive force of the models rather than causal indicators of financial failure. Beaver et al. (2005) stated that several forces over the last forty years potentially affect the ability of financial ratios to predict bankruptcy. Those factors could be summarized as development of accounting standards which has a positive effect on predictive ability of financial ratios; on the contrary, increase in relative importance of financial derivatives and intangible assets in financial statements, and increase in the degree of discretion entering financial statements impaired the financial statements' quality. So, this phenomenon underlined the importance of market driven data in financial failure prediction literature.

According to Beaver et al. (2005), the spread of financial derivatives and corporate debt products in economy attracted academics' and practitioners' interest in structural models that forecast corporate defaults. Because, data limitation is the disadvantage of accounting based models and explanatory variables are primarily limited to financial statements data which are updated infrequently and are determined by accounting procedures that rely on book value rather than market valuation. And there is often limited economic theory as to why particular financial ratio would be useful in default forecast. In contrast, modern structural default risk measurement models are more firmly grounded in financial theory. One of the popular innovative forecasting structural models stems from Black-Scholes' (1973) and Merton's (1974) seminal works on pricing options; this method was further developed by KMV corporation which was later acquired by Moody's. Consistent with Bharath and Shumway (2004) we refer to this model as the KMV-Merton model. This model is applied to various sectors by Vassalou and Xing (2004), Chan-Lau et al. (2004), Van den End and Tabbea (2005) among others.

1. The KMV-Merton model

Black and Scholes (1973) and Merton (1974) have developed an option pricing model that is also used for computing corporate default measures. An important observation in Merton's (1974) model is that the equity of a firm is viewed as a call option on the value of firm's assets. The strike price of the call option is equal to the face value of the firm's debts and the option expires at time T when the debt matures. Principally, the liability side of the balance sheet of a firm is composed of debt and equity. The equity holders have the right but not the obligation to pay back the debts to the creditors. When the debts of the firm mature the equity holders would pay the debts to the creditors if the market value of the firm's assets is greater than the face value of the debts. Otherwise, the equity holders would not pay the debts when the value of the firm's assets is not enough to fully pay back the firm's debts. Then the firm files for bankruptcy and is assumed to transfer the ownership of the firm to the creditors without cost. Therefore, equity holders are the residual claimants on the firm's assets after all other obligations have been met and have limited liability when the firm goes bankrupt. Consequently, the payoffs to equity are similar to payoffs to call option.

The Merton model has two important assumptions. The first assumption is that the market value (V_A) of a firm's underlying assets follows a Geometric Brownian Motion with an instantaneous drift (μ) and volatility (σ). W is a standard Wiener process.

$$dV_A = \mu V_A dt + \sigma_A V_A dW. \quad (1)$$

The second assumption is that the firm has issued just one discount bond maturing in T periods. Under these assumptions, as stated above, the equity of the firm is a call option on the underlying value of the firm's asset with a strike price equal to face value of the firm's debts expired at time T. The face value of debt at time t is denoted by X which will mature at time T. The market value of firm's equity (V_E) is a call option on V_A, and according to the Black-Scholes-Merton option valuation model, their relationship is defined by the following equation:

$$V_E = V_A N(d_1) - Xe^{-rT} N(d_2), \quad (2)$$

where $N(.)$ is the cumulative standard normal distribution, r is the risk free rate and the parameters d_1 and d_2 are related through the following equations:

$$d_1 = \frac{\ln(V_A / X) + (r + 0{,}5\sigma_A^2)T}{\sigma_A \sqrt{T}}, \quad (3)$$

$$d_2 = d_1 - \sigma_A \sqrt{T}. \quad (4)$$

As stated in Crosbie and Bohn (2003), default occurs when the market value of the firm's assets is less than the face value of debt (X) at the time of maturity. Alternatively, default happens when the ratio of market value of assets to book value of debt is less than one. Hence, the probability of default (PD) is the probability that market value falls below the face value of debt at time T.

The BSM model assumes that the natural log of future asset values is distributed normally so the probability of default at t could be presented as follows:

$$PD_t = N(-DD) = N\left[-\frac{\ln \frac{V_{A,t}}{X_t} + (\mu - 0{,}5\sigma_A^2)T}{\sigma_A \sqrt{T}} \right], \quad (5)$$

where distance-to-default (DD)

$$DD = \frac{\ln \frac{V_{A,t}}{X_t} + (\mu - 0{,}5\sigma_A^2)T}{\sigma_A \sqrt{T}}, \quad (6)$$

shows how many standard deviations further from the mean are required for default to materialize.

Crosbie and Bohn (2003) state that, the weak point of the model hangs on normal distribution assumption of the model. Hence, result of Moody's KMV model's empirical distribution of default rates has much wider tail than the normal distribution. Unfortunately, we do not have the opportunity to employ an empirical distribution on default occurrences for Turkish firms.

Financial data generally have leptokurtosis, volatility clustering and leverage effects. For this reason, in the study normality assumption of the model is also replaced with heavy-tailed alternatives which are student's t-distribution and asymmetric student's t-distribution. So in this way two additional models are established.

For estimation purposes, this study follows a procedure similar to the one used by Hillegeist et al. (2004) in order to obtain the unobserved parameters of the model. First, the initial values are determined by setting V_A equal to the book value of liabilities plus the market value of equity and $\sigma_A = \sigma_E V_E / (V_E + X)$. σ_E is defined by calculation of standard deviation of log changes of daily stock prices. Then by using equations (2) through (4), new values for V_A are estimated and based on new V_A values new σ_A is computed. The new σ_A is used as a new input in equations to estimate new V_A. This iterative procedure is repeated until the new σ_A converges to the previous one. The applied tolerance level for convergence is 10^{-6}. Values satisfying this condition give us the estimated values of market asset value and asset volatility. The mean log changes in implied asset values (V_A) will be used as an estimate of drift term (μ) in equation (1), since Crosbie and Bohn (2003) provide no description of how to estimate drift term. In the calculations consistent with the similar studies term structure of debts assumed mature in one year (T = 1).

The above estimation process is repeated two more times by substitution of normality assumption of the model with student's t- and asymmetric student's t-distributions. Asymmetric student's t-distribution could be summarized as follows:

$$t(x|\gamma) = \frac{2}{\gamma + \frac{1}{\gamma}} \left[t\left(\frac{x}{\gamma}\right) I_{\{X \geq 0\}} + t(x\gamma) I_{\{X<0\}} \right], \quad (7)$$

where $I_{\{X \geq 0\}}$ is 1 if X ≥ 0 and 0 if X < 0 (Rachev et al., 2008).

2. Data and sample selection

The study sample is composed of 188 industrial firms listed on the ISE in 2000, of which 150 are non-distressed, 30 are financially distressed, and 8 have no sufficient market data, thus they are omitted from the analysis.

Financially distressed firms are defined by two criteria:

1. Turkish Bankruptcy Law article 179 pursuant to Turkish Trade Law articles 324 and 434; business enterprises incurring 2/3 loss in capital stock could be defined as bankrupt.

Bankruptcy is a legal procedure, even though those companies selected according to these criteria were not officially bankrupt, they could be classified as financially distressed.

2. Firms with net loss in each of the preceding three years.

In this study, for the initial sample, the ratios are derived from financial statements dated one annual reporting period prior to financial distress occurrence. The data (financial statements and daily stock prices) were derived from Istanbul Stock Exchange (www.imkb.gov.tr).

Table 1 provides a summary statistics for industry failure rates based on number of individual firms for year 2000.

Consistent with Vassalou and Xing (2004), short-term debt plus one half of long-term debt are considered as book value of firm's debt (*X*). As risk free rate (*r*), yearly compounded interest rate of treasury discounted auctions figures for 2000, which is about 36%, is taken into analysis.

According to Table 1, 16,7% of industrial firms listed on ISE were defined as financially distressed. The failure rates vary considerably among industry groups. The iron and steel (50%); chemistry, plastic and dye (50%); paper and packaging (37,5%); cotton and wool (36,84%); synthetic (33,33%); home textile and carpet (33,33%); electronics, telecom and technology (28,57%); durable consumer goods (14,29%); food and beverage (13,79%); ready to wear and leather (12,5%); construction products (11,11%); and metal processing (10%) have experienced the highest rates of failure, measured as the percentage of firms in the industry that are defined as financially distressed according to the above criteria for study period 2000. On the contrary, none of the firms in the auto spare parts, automotive, cement, ceramics, fertilizer and pesticides, furniture, glass, media, petroleum products, pharmacy and health, stationary products, and tire and cords industries were defined as financially distressed for the study period.

Table 1. Summary statistics of industry failure rates

Industry	Number of firms	Number of distressed firms	Percent of distressed firms
Auto spare parts	7	0	0,00
Automotive	7	0	0,00
Cement	16	0	0,00
Ceramics	5	0	0,00
Chemistry, plastic and dye	8	4	50,00
Construction products	9	1	11,11
Cotton and wool	19	7	36,84
Durable consumer goods	7	1	14,29
Electronics, telecom and technology	7	2	28,57
Fertilizer and pesticides	4	0	0,00
Food and beverage	29	4	13,79
Furniture	2	0	0,00
Glass	3	0	0,00
Home textile and carpet	3	1	33,33
Iron and steel	4	2	50,00
Media (press)	3	0	0,00
Metal processing	10	1	10,00
Paper and packaging	8	3	37,50
Petroleum products	5	0	0,00
Pharmacy and health	2	0	0,00
Ready to wear and leather	8	1	12,50
Stationary products	2	0	0,00
Synthetic	9	3	33,33
Tire and cord	3	0	0,00
Total	180	30	16,67

In order to evaluate the performances of KMV-Merton probability (KMV-Prob) methods, in the next section the three different assumption based KMV-Prob (Norm Dist), KMV-Prob (T-Dist) and KMV-Prob (Asym. T-Dist) measures are to be compared with two traditional accounting based methods of discriminant analysis, Z-Score and Logistic cumulative probability function that were constructed in the preceding study of the author (see Aktan, 2009). The coefficients of the models are updated for this study for the period 2000. Two accounting based models are presented below:

Table 2. Discriminant model weights

Characteristics	Weights
Lq1 (Current ratio)	0,241
Lv7 (Long-term debts to equity ratio)	0,018
Fs2 (Equity to fixed assets)	0,14
P10 (Return on assets)	3,903
P11 (Financial expenses to inventories ratio)	0,009
Constant	-0,519

Table 2 presents the estimated weights of the discriminant function (8). Discriminant model is obtained by putting the estimated weights into related places and the outcome of the model takes the form below:

$$Z_a = 0{,}519+0{,}241Lq1_a+0{,}018Lv7_a+0{,}14Fs2_a$$
$$+3{,}903P10_a+0{,}009P11_a. \quad (8)$$

All of the discriminant coefficients are positive; hence increases in selected characteristics (ratios) of a firm reduce its probability of failure.

Table 3. Logit model weights

Characteristics	Weights
Lq2 (Quick ratio)	-3,354
Fs2 (Equity to fixed assets ratio)	-2,022
P9 (Return on long-term debts)	-0,523
Constant	1,869

Table 3 presents the estimated weights of the logistic cumulative probability function (9). Cumulative probability function is obtained by substituting the estimated weights into related places and the outcome of the model takes the form below:

$$P_i = \frac{1}{1+e^{-(1{,}869-3{,}354Lq2-2{,}022Fs2-0{,}523P9)}}\,. \quad (9)$$

All of the function's coefficients are negative; therefore, increases in selected characteristics (ratios) of a firm reduce its probability of failure.

3. Comparison of performances of five different models

Comparison of the five different models begins with presenting their average financial failure probability rates for solvent and distressed firms. Results are tabulated below.

Table 4. Average financial failure probability rate of models

Model	Solvent (%)	Distressed (%)	Total (%)
KMV-Prob (Normal Dist)	5,6	43,9	12
KMV-Prob (T-Dist)	5,6	44	12,1
KMV-Prob (Asym. T-Dist)	8,3	52,6	15,7
DA-Prob	17	63,1	24,7
Logit-Prob	7,5	62,4	16,7

According to Table 4, failure probability rates of solvent firms are much closer to zero as compared to failure probability rates of distressed firms. For the classification purpose, the cut-off value for the probabilities is set to 50%, and KMV-Prob (Normal Dist) and KMV-Prob (T-Dist)'s average rates for distressed firms are 43,9% and 44%, respectively. These values are close to each other and moderately lover than 50%; on the other hand, KMV-Prob (Asym. T-Dist)'s average rate for distressed firms is 52,6% that is slightly higher than 50%. These figures could be interpreted as KMV-Prob (Normal Dist) and KMV-Prob (T-Dist) and estimate (classify) distressed firms as solvent. Therefore, produced type I error by KMV-Prob (Normal Dist) and KMV-Prob (T-Dist) would be high as compared to KMV-Prob (Asym. T-Dist) and accounting based models. On the other hand, produced type II errors by these five models would be more or less closer to each other.

If results of accounting based models left aside and concentrated on KMV-Prob models, asym. t-distribution assumption based KMV-Merton model's figures are significantly different and better than other assumption based KMV-Merton models. This difference could indicate that substitution of normal assumption with asym. t-distribution assumption strengthens KMV-Merton model.

Table 5. Correlation matrix

	Distressed	KMV-Prob (Normal Dist)	KMV-Prob (T-Dist)	KMV-Prob (Asym. T-Dist)	DA-Prob	Logit-Prob
Distressed		0,495	0,492	0,523	0,712	0,743
KMV-Prob (Normal Dist)	0,404		0,999	0,965	0,543	0,540
KMV-Prob (T-Dist)	0,409	0,981		0,965	0,538	0,538
KMV-Prob (Asym. T-Dist)	0,433	0,800	0,822		0,561	0,540
DA-Prob	0,569	0,449	0,437	0,415		0,901
Logit-Prob	0,570	0,419	0,403	0,399	0,905	

In the correlation summary of Table 5, Pearson correlations are presented above the diagonal and Spearman correlations are presented below the diagonal. All of the correlations are significant at the 1% level (2-tailed). Distressed is an indicator variable equal to 1 if the firm is defined as financially distressed, and 0 otherwise. Spearman correlation is a non-parametric version of Pearson correlation.

According to correlation matrix, Pearson correlations and Spearman correlations show that all of the probability measures are positively correlated. KMV-Prob (Asym. t-Dist) has the highest correlation coefficient of 0,561 with DA-Prob among other KMV-Prob measures and has the same correlation coefficient of KMV-Prob (Normal Dist) 0,540 with Logit-Prob. KMV-Prob (Normal Dist) and KMV-Prob (t-Dist) have the highest correlation coefficients of 0,999 with each other and 0,995 with KMV-Prob (Asym t-Dist). These higher correlation coefficients among KMV-Prob measures are foreseeable because all of the variables of the models are derived from the same data basket; only the distribution assumptions of the models differ from each other and this difference shows itself by 0,004 below deviance produced by asymmetric t-distribution assumption. Besides, DA-Prob and Logit-Prob also have higher correlation value of 0,901. These five models correlation coefficients with distressed indicator could be ranked from higher to lower as Logit-Prob, DA-Prob, KMV-Prob (Asmy T-Dist), KMV-Prob (Normal Dist) and KMV-Prob (T-Dist) according to their coefficients of 0,743, 0,712, 0,523, 0,495, and 0,492, respectively. While the market based KMV-Prob measures and accounting based traditional ratio models of DA-Prob and Logit-Prob have positive correlations, the moderate magnitudes of the correlations suggest that KMV-Prob measures may be reflecting different information content about the probability of financial failure. On the other hand, higher correlation values of DA-Prob and Logit-Prob could refer that these two accounting based models represent the same information content; their initial dissimilarity from KMV-Prob is that they don't include a measure of volatility which is a key component of KMV-Prob measures.

In order to compare the performances of five models, consistent with Hillegeist et al. (2004) pair of relative information tests were to be conducted and classification accuracies of these five models are presented.

Relative information test examines whether one model provides more information as compared to other models. The tests are based on how well each failure probability measure explains the variation in the actual failure probability using a logit based discrete hazard model proposed by Shumway (2001) but differs in terms of time horizon. Contrary to Shumway, single period observations are used in this study that is the criticized point of being static; however, the aim is to compare a dynamic KMV probability model with static discriminant and logit models, hence single firm year observations are used. Mentioned discrete hazard model has the following form:

$$P_i = \frac{1}{1+e^{-(\alpha+\beta_i X_i)}}, \tag{10}$$

where P stands for probability of failure; α stands for system wide variable that captures the baseline hazard rate, in the study as baseline hazard rate the natural log of firm's time span in the ISE is used as a proxy for firm's age because this study covers one-year period and using another macro-economic or economy-wide variable instead of time span in ISE would be same for each firm, therefore that variable would add nothing to the hazard model. In order to have a well performing hazard model, using time span of a company in ISE as a proxy for company's age would be a good choice, since organizational lifecycle correlated with failure; most of the failed firms went bankrupt in early years of operation (Thornhill and Amit, 2003). β stands for coefficients of explanatory variables and X stands for explanatory variables. To get reliable results from discrete hazard model, the independent variables need to be in a form that is consistent with the model's underlying assumptions. Since KMV probabilities of individual firms are in the form of probabilities that need to be transformed into a score using the inverse logistic function (11) below. As KMV probabilities approach zero (one) KMV scores approach negative (positive) infinity. To overcome this problem, the maximum and minimum values of KMV probabilities are bounded between 10^{-10} and $1\text{-}10^{-10}$ values.

$$\text{Score}_{KMV} = \ln\left(\frac{KMVprob}{1-KMVprob}\right). \tag{11}$$

Scores for discriminant analysis and logit analysis are provided by SPSS 15, therefore probability figures of these models are not necessary to be transformed into scores.

To compare the relative information content analysis for market based KMV-Scores and the two accounting based DA-Score and Logit-Score models, five separate hazard models are estimated using the log of time span of the firms listed on the ISE. The log of time span is the proxy for firm's age that is the baseline hazard rate. Dependent variable is an indicator variable that equals 1 if the firm is defined as distressed, and 0 otherwise. The results of the analyses are summarized in Table 6 below.

Table 6. Relative information content of models

Variable	KMV-Score (Normal Dist)	KMV-Score (T-Dist)	KMV-Score (Asym. T-Dist)	DA-Score	Logit-Score
Constant	1,186	1,099	0,474	1,554	1,474
Log of Time-Span	-0,794	-0,773	-0,695	-0,853	-0,779
KMV-Score (Normal Dist)	0,195				
KMV-Score (T-Dist)		0,191			
KMV-Score (Asym. T-Dist)			0,181		
DA-Score				2,000	
Logit-Score					0,998
Log Likelihood	-253,512	-254,766	-248,928	-151,304	-144,077
Nagelkerke R Square	0,301	0,296	0,318	0,643	0,663

In all five models, log of time span is significant at 10% level. This finding shows that baseline hazard rate provides moderate incremental information to that provided by each of the models. In addition, Constant variables and Score variables are significant at 10% and 1% levels, respectively.

According to Table 6, accounting based measures provide more information about the probability of failure than the market based KMV-Score measures. This inference is drawn from the log likelihood and pseudo-R^2 statistics of the models: Logit-Score has the largest log likelihood statistics of -144,077 and pseudo-R^2 of 0,663; Logit-Score model is followed by DA-Score with closer log likelihood of -151,304 and pseudo-R^2 of 0,643. In contrast to accounting based measures, market based KMV-Scores measures have the smaller log likelihood statistics and pseudo-R^2. Among them, KMV-Score (Asym. T-Dist) is the best performer with -248,928 log likelihood statistics and 0,318 pseudo-R^2 compared to KMV-Score (Normal Dist) and KMV-Score (T-Dist)'s log likelihood of -253,512; -254,766 and pseudo-R^2 of 0,301, and 0,296, respectively.

Next, to see which model performs better solely with regard to classification accuracy and error types, the estimation accuracies of these five different models are presented in Table 7. In the table, type I error rate stands for estimating a distressed firm as solvent and type II error rate stands for estimating a solvent firm as distressed.

Table 7. Classification matrix

Model	Type I error (%)	Type II error (%)	Overall accuracy (%)
KMV-Prob (Normal Dist)	56,67	4,67	86,67
KMV-Prob (T-Dist)	53,33	4,67	87,22
KMV-Prob (Asym. T-Dist)	46,67	4,67	88,33
DA-Prob	40	2,67	91,11
Logit-Prob	36,67	2,67	91,67

Table 7 demonstrates that Logit-Prob model outperforms DA-Prob model and KMV-Prob models. Logit-Prob model produces 36,67% type I errors and 2,67% type II errors, while DA-Prob model produces 40% type I errors and the same amount, 2,67%, of type II errors of Logit-Prob model. The overall estimation accuracies of Logit-Prob model and DA-Prob model are close to each other by 91,67% and 91,11%, respectively. On the other hand, KMV-Prob models produce a little bit much error than the other two accounting based models. KMV-Prob (Asym. T-Dist) model produces 46,67% type I errors and 4,67% type II errors, and the followers KMV-Prob (T-Dist) and KMV-Prob (Normal Dist) produce 53,33% and 56,67% type I errors, respectively; their produced type II errors are equal to 4,67%, three market based models produce the equal amount of type II errors. With regard to overall accuracy, Logit model outperforms all of the models with 91,67% followed by DA model with 91,11%. On the other hand, KMV-Prob (Asym. T-Dist) is the best performer among the market based models with 88,33% of overall accuracy. Then come KMV-Prob (T-Dist) and KMV-Prob (Normal Dist) models with 87,22% and 86,67% of overall accuracy, respectively. This demonstration proved that substitution of normal assumption of market based model with fat-tailed alternatives increases the power of the model.

According to information content test results and above estimation accuracies, these analyses suggest that KMV-Prob has no superiority over accounting based models unlike the suggestion in Hillegeist et al. (2004) to increase the power of estimating bankruptcy by using KMV-Prob instead of accounting based models as a proxy for probability of bankruptcy. However, the performance of the market based model is correlated with the employed statistical distribution assumption. In this study, asymmetric t-distribution assumption increased the performance of the model compared to normal and t-distribution assumptions.

To take this study further, KMV-Prob (Asym. T-Dist) model is combined with DA-Prob model and Logit-Prob model separately to increase the own information content of the model and to increase the overall estimation accuracy. A small note, the better performance of the asym. t-distribution assumption is the reason why it is used in this additional information content test. Since the results presented in Table 5 show that the correlation between KMV-Prob models and accounting based models are positive and moderate in magnitude, low correlations imply that these models possibly capture different information about financial failure. Table 8 summarizes the combined KMV-DA models' and KMV-Logit models' regression results. In both combined models KMV-Score (Asym. t-Dist) is positive and significant at the 5% level, and its coefficient figures are similar in both models. Both accounting based Score variables are significant at the 1% level, Constant and Log Time-Span variables are significant at the 10% level.

Table 8. Additive information content

Variable	KMV-Score (Asym. T-Dist) and DA-Score	KMV-Score (Asym. T-Dist) and Logit-Score
Constant	2,401	2,344
Log of Time-Span	-1,098	-1,057
KMV-Score (Asym. T-Dist)	0,112	0,111
DA-Score	1,903	

Table 8 (cont.). Additive information content

Variable	KMV-Score (Asym. T-Dist) and DA-Score	KMV-Score (Asym. T-Dist) and Logit-Score
Logit-Score		0,966
Log Likelihood	-136,490	-128,574
Nagelkerke R Square	0,685	0,706
Type I Error (%)	36,67	26,67
Type II Error (%)	2,67	2,67
Overall Accuracy (%)	91,67	93,33

Comparison of above log likelihood and pseudo-R^2 figures with those presented in Table 6, shows that both accounting based models provide a significant amount of additional information about the probability of failure beyond that contained in KMV-Score (Asym. T-Dist) model. Combination of KMV-Score and Logit-Score models produces the largest log likelihood statistics (-128,574) and pseudo-R^2 (0,706). Combination of KMV-Score and DA-Score model produces moderately smaller log likelihood statistics and pseudo-R^2 (-136,490 and 0,685, respectively). Hence, Logit-Score adds moderately more information to KMV-Score.

KMV-Logit-Score model produces 26,67% type I errors and 2,67% type II errors, while KMV-DA-Score model produces 36,67% type I errors and 2,67% type II errors. The overall estimation accuracy amounts to 93,33% for KMV-Logit-Score model and 91,67% for KMV-DA-Score model.

The findings in Table 8 and Table 6 imply that KMV-Scores fail to reflect as much information as contained in accounting based models. The lower performance of the market based KMV-Score models could come from the factors that drive failure outside the KMV model. As Bharath and Shumway (2004) state, the most important inputs of the model are market value of equity, book value of debt, and the volatility of equity. When market value of equity declines, the probability of failure increases, which is the strong and weak point of the model. In addition, amount of book value of debt is another aspect of the model. In the study, it is implicitly assumed that all of the firm's debts mature in one year. This assumption is violated in practice. Book value of debt (X) is set to current debts and one half of long-term debts, which is the assumption of Vassalou and Xing (2004). The amount of long-term debt in book value of debt is arbitrary; hence, lowering the default point (X) reduces the probability of failure. In Turkey, relative high level of indebtedness of industrial firms, debt term structure and heavy foreign borrowing make firms fragile to global financial shocks (Özmen and Yalcin, 2007). This high level of indebtedness indicates that the amount of book value of debt should be considered carefully. In order for the model to perform better, as Bharath and Shumway (2004) state, both the Merton model assumptions must be met and markets must be efficient and well informed.

Conclusion

Companies should be considered as living organisms. Throughout their life cycle they could also become ill and financial distress is the terrible disease for them. Best method to cure this disease is defining the symptoms and taking remedial actions. As Ackoff (1999) initiates, a symptom either indicates the presence of a threat or an opportunity; variables used as symptoms are properties of the behavior of the organization or its environment. Such variables can also be used dynamically as pre-symptoms or omens, as indicators of future opportunities or problems.

The targets of the prediction models could be summarized as letting analyst or any of the stakeholders to act due to the results of the model and pre-intervene to the variables in order to affect the prediction results. In this sense, combining multivariate statistical analyses and structural models and considering them as a whole, it is possible to construct a multidimensional and objective early warning system that allows an analyst to act according to the results and pre-intervene to the variables to assess organizational strategies.

On the other hand, the efficiency of the early warning system, whether it is market based or accounting based, depends on two main aspects. One is the preparation of financial statements in accordance with accounting standards consistent with legal regulations and the second is the existence of well informed and efficient market. In other terms, the efficiency of the early warning system increases with transparency of the financial statements and available information about the company in the market. Consequently, early warning system is a worthwhile technique in prediction of financial failure, perfection of the system is dependent on proper work of accounting and auditing firms in the economic system.

Recent studies proved that market based structural model could be used in estimating default risk. Thus, financial failure estimation models are grounded on a theoretical model for the first time. In addition, theory grounded market based structural models have some superior attributes as compared to traditional accounting based models. These attributes could be summarized with regard to the initial model of this study. KMV-Merton model has definite variables and these variables never change. On the contrary, in the traditional accounting based models, variables vary according to a researcher.

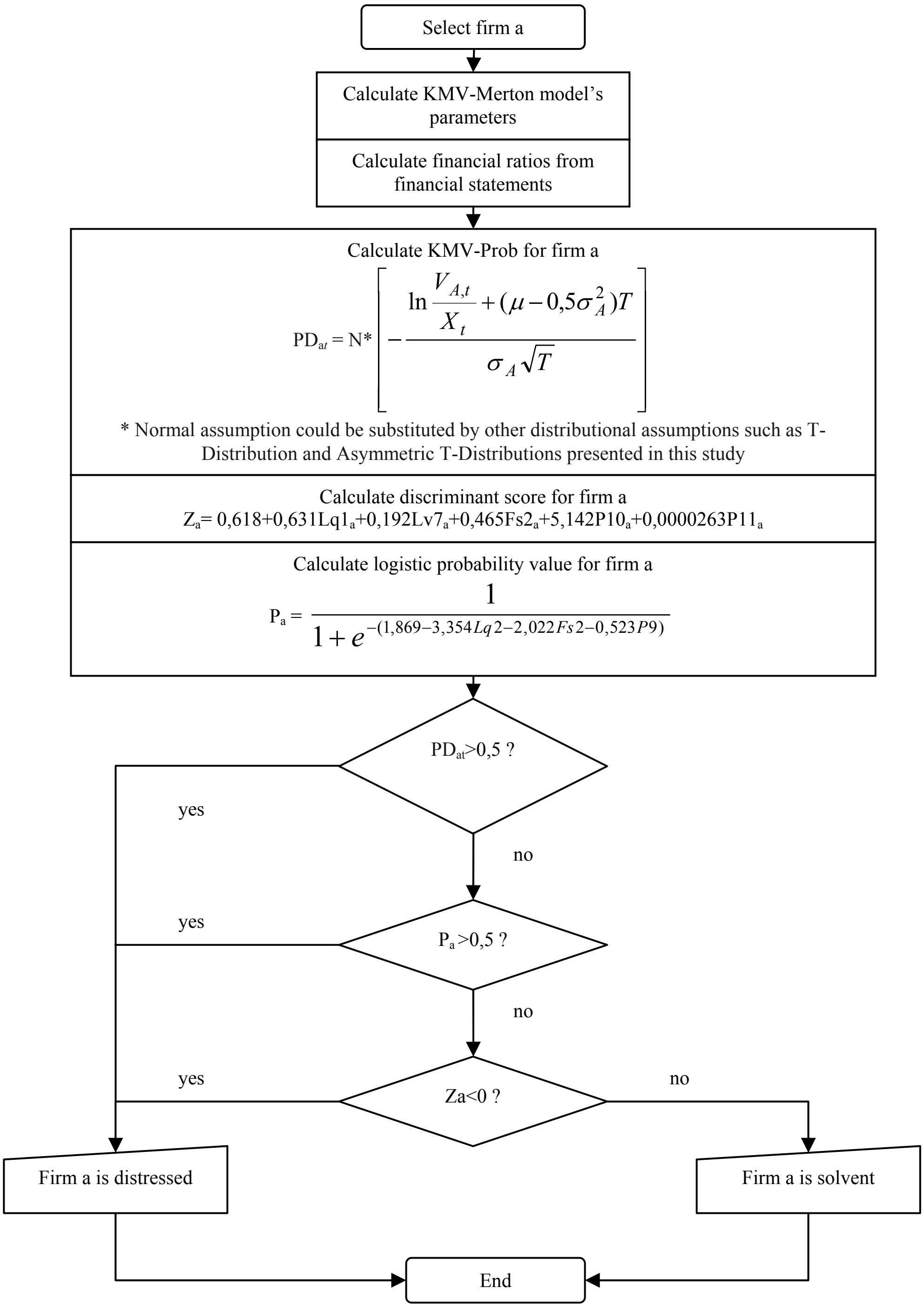

Fig. 1. General flow diagram of early warning system

Next, in an efficient market equity prices are valued according to future expectations, in other words, any new information in the market immediately dysplays in equity prices. But in traditional accounting based models, the data resources are based on historical data.

This study included in its scope industrial companies quoted to ISE for the period 2000. It further applied the KMV-Merton model based on three statistical distribution assumptions to estimate probability of failure. Also, to evaluate the models' performance, pair of information content tests were applied and results were compared with accounting based models of DA and Logit analyses. According to information content of the models and the produced amount of errors, traditional accounting based models outperformed KMV-Merton model with a narrow margin. On the other hand, combined models contained much information related to probability of failure and their produced amount of errors was moderately lower than their individual figures. Best combined-model was KMV-Score and Logit-Score model. Moderately lower performance of KMV-Merton model could be caused by arbitrary determination book value of debt, statistical distribution assumption of the asset returns and violation of efficient market assumption of the theory. Therefore, in the light of the analysis findings, it is hard to recommend KMV-Merton model solely. In contrast to Hillegeist et al.'s (2004) suggestion of using KMV-Merton model solely as a proxy for probability of bankruptcy, market based models should make contribution to traditional accounting based models until Turkish stock market matures some more; hence, there is some evidence of stock price manipulations on the ISE (see Hürriyet, 02.04.2009).

To sum up, the differences between alternative methods affect information contents of the models that differ due to the variables measuring different corporate characteristics. Therefore, combining multivariate statistical analyses models and considering them as a whole, it is possible to construct a multidimensional and objective early warning system. This system is summarized in Figure 1, which represents a general flow diagram of constructed models to be used as an early warning system.

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