INTERNATIONAL JOURNAL OF
CURRENT MULTIDISCIPLINARY STUDIES
Available Online at http://www.journalijcms.com
Vol. 2, Issue,12, pp.536-539, December, 2016
IJCMS

RESEARCH ARTICLE

SURVEY THE ROLE OF NON-FINANCIAL FACTOR IN CREDIT RISK EVALUATION EVIDENCE FROM TEHRAN STOCK EXCHANGE (TSE)

Mojtaba Mortezaee and Majid Govahi

Accounting, Mashhad Branch, Islamic Azad University, Mashhad, Iran

ARTICLE INFO

Received 15th, September, 2016, Received in revised form 5 th, October, 2016, Accepted 24th, November, 2016, Published online 28th, December, 2016

Keywords:

Tehran Stock Exchange (TSE); Credit risk; Data envelopment analysis (DEA); Directional distance functions.

ABSTRACT

This paper is aim to investigate technical efficiency to predict business failures. We use samples of listed companies of Tehran Stock Exchange (TSE) market including;Steel and Metal industry, automotive industriesand Oil, Gas and Petrochemical industriesin order to examine efficiency in each industry. These efficiency evaluationis based on non-parametric Data Envelopment Analysis (DEA) method and logit regression models. Our results show that during sample period (2010-2015) among Steel and Metal industry, automotive industriesand Oil, Gas and Petrochemical industries, 17.76% , 32.29% and 38.54% are respectively at risk of bankruptcy.

INTRODUCTION

Screeningmethod have a great effect on minimizing costs of asymmetric information, thereby it can be useful to promoting the efficiency of the information trend. As emphasized by Stiglitz and Weiss (1992) and Spence (2002)advancements in these methodsleads to reducing credit limitations under asymmetry information.Paradi(2004) noted that importance of credit risk considering market in financial markets. Thus, credit risk is still significant risk in financial markets. This study by consideringcredit risk infinancial institutions and banks to assess their performance. We employ the directional technology distance function Shephard (1970) to measure efficiency.

In this paper weapply a two-phaseresearch methodology to evaluate credit risk. First of all, use non-parametric linear programming methods to measure firm's performance. Second, we use probit and logistic regression analysis to examine the efficiency in predicting corporate failures and bankruptciesby financial variables. For empirical analysis purposes we choose three manufacturing industries including;steel and metal industry,automotive industryproducts and oil and gas and petrochemical industries.

Research Objective

The aim of this paper is to investigate the role of non-financial parameters in credit risk assessment. In particular, we examine whothe result of firm's technical inefficiency measurement can be useful in predicting corporate failures. While much empirical research has emphasized the importance of traditional financial measures in corporate bankruptcy prediction although, the role of non-financial information remains unexplored. Present research suppose that a combination of financial and non-financial factors mayimprove a bank's ability to predict business failures more accurately than the other models which use financial variables.

LITERATURE REVIEW

Altman and Saunders (1997) noted credit-riskanalysis is possible througheconometric methods.Present study has concentrated on financial variables.Financial decision and decision-making techniques can be useful to evaluate the risk of business failures and bankruptcies (Zopounidis, 1992; Diakoulaki et al. 1992; Siskos et al. 1994; Emel et al. 2003). Recently, Data Envelopment Analysis (DEA) was applied to the analysis of credit scoring as in Troutt et al. (1996); Simak (1999), Cielen and Vanhoof (1999) and more recently by Emel et al. (2003) and Paradi et al. (2004).Becchetti and Sierra (2003) have emphasized the importance of non-financial data as predictors of company failures.

Data Analysis

We propose a two stage procedure that can serve as arecent model in examine default risk,for instance in predicting business failure. First stepis aim to measure of firm's performance by

*✉ ***Corresponding author:*** **Mojtaba Mortezaee**
Accounting, Mashhad Branch, Islamic Azad University, Mashhad, Iran

using DEA methods. In second stage we use probity and logistic regression analysis to assess the importance of efficiency in predicting business failures over and above that explained by financial factors. We apply DEA to estimate the directional distance function using a sample of Tehran Stock Exchange (TSE)industries. Following Färe and Grosskopf (2004) and Färe (2007) we assume that firms employ N inputs explain by below equations; to produce M outputs and technology may be characterized by a technology set T, which is the set of all feasible input/output combinations by equation (1).

$x = (x_1, x_n) \in R_+^N$

$y = (y_1, y_m) \in R_+^M$

$T = \{(x, y) : x \text{ can produce } y\}$. (1)

The general case as follows;

$g = (g_x, g_y)$ where $g_x \in R_+^N$ and $g_y \in R_+^M$,

$\vec{D}_T(x, y; g_x, g_y) = \sup \{\beta: (x \quad \beta g_x, y + \beta g_y \in T\}$. (2)

In contrast, the Shephard (1970) distance functions:

$D_o(x, y) = \min \{\theta : (x, y/\theta) \in T\}$ (3)

$D_i(y, x) = \max \{\lambda : (x/\lambda, y) \in T\}$ (4)

Another important property is the representation property, viz.

$\vec{D}_T(x, y; g_x, g_y) \geq 0$ if and only if $(x, y) \in T$ (5)

This says that all feasible bundles (x, y) will have non-negative values of the directional distance function. In turn, an observation is technically efficient when $\vec{D}_T(x, y; g_x, g_y) = 0$. The directional distance function can be estimated using DEA and a VRS (Variable returns to scale) technology as;

$\vec{D}_T(x, y; g_x, g_y) = \max \beta$ (6)

Subject to:

$$\Sigma_{k=1}^{K} z_z x_{kn} \leq x_{kn} - \beta g_x, n = 1,...., N$$

$$\Sigma_{k=1}^{K} z_z y_{km} \leq y_{km} + \beta g_y, m = 1,..., M$$

$$\Sigma_{k=1}^{K} z_z = 1, z_z \geq 0, k = 1,..., K$$

Statistical data used in this paper are extracted from the TSE database. It comprises samples of TSE industries from the Steel and Metal industry, automotive industryproducts, and oil, gas and petrochemical industries operating between 2010 and 2015.

Table 1 gives the descriptive statistics of the variables used in the empirical analysis. We have used data from 33 (198 firm-year observation) firms operating in the Steel and Metal industry, 16 (96 firm-year observation) firms from the automotive industryproducts, and 16 (96 firm-year observation) firms from the oil, gas and petrochemical industry.Table 1 shows that there are considerable differences in capital intensity among the three industries. Oil, gas and petrochemical industries has the lowest physical capital to labor ratio and tangibles to total assets ratio but a higher ratio of intangibles to total assets compared with the other two industries. We estimate that firms in the automotive industry have a better efficiency on average. For all three industries we find considerable efficiency differences between firms in the top efficiency quartile compared to firms in the bottom quartile. Firms in the Steel and Metal industry are on average less leveraged compared to oil and gas and automotive industries and have a higher solvency ratio.

Table 2, 3 and 4 presents the results of the logistic and probit regressions. As it is well known estimated coefficients from binary regression models do not measure the marginal effect of the regression on the dependent variable. For example, the partial regression coefficient estimates in the logit model measure the change in the estimated logit (log of the odds-ratio) for a unit change in the value of a given predictor other things constant.DDF is the firm efficiency measure; size is (log) of total operating revenue; SR is the solvency ratio; PR is profits divided by total assets; tangibles and intangibles are measured as ratios over total assets; GR is the growth in earnings. The dependent variable is a dummy variable (D) indicating if a firm was active (D=0) or is potentially distressed/had left the industry (D=0). Z-statistics are calculated using Huber-White robust standard errors. Prob are p-values of estimated coefficients. R-sq. is the McFadden R-squared computed as one minus the ratio of the unrestricted over the restricted log likelihood values. The LR statistic tests the null that all slope coefficients except the constant are equal to zero.

The marginal effect of a variable on the probability of the response (i.e. firm default) is given by the product of the partial regression coefficient times the odds-ratio.

Table 1 Descriptive Statistics[1]

	Oil, gas and petrochemical industries			**Steel and Metal industries**			**Automotive industries**		
	Mean	**Median**	**St. Dev**	**Mean**	**Median**	**St. Dev**	**Mean**	**Median**	**St. Dev**
Output	127.4	56.7	567.2	287.4	78.4	963.7	136.9	54.6	621.2
Labour	42.7	14.0	176.6	35.4	20.0	106.3	31.6	14.0	119.4
Capital	375.4	54.6	1864.1	449.2	127.8	1946.7	2171.3	166.9	5821.2
DDF	0.336	0.117	0.569	0.345	0.127	0.486	0.174	0.084	0.423
DDF25	0.002	0.000	0.04	0.003	0.000	0.08	0.003	0.000	0.006
DDF75	1.013	0.475	1.002	1.056	0.214	0.375	0.321	0.276	0.544
Profit	0.017	0.037	0.064	0.038	0.036	0.038	0.019	0.018	0.064
TA	0.062	0.027	0.084	0.075	0.052	0.086	0.169	0.049	0.031
Size	3.216	3.114	1.006	3.425	2.364	1.002	3.924	3.111	1.023
SR	0.188	0.115	0.266	0.249	0.264	0.349	0.279	0.115	0.029
INT	0.026	0.003	0.054	0.021	0.004	0.049	0.016	0.004	0.022
DA	0.326	0.412	0.214	0.366	0.297	0.441	0.379	0.416	0.021
Firms	96			198			96		

Table 2 Logit and Probit Regression Analysisfor Steel and Metal industries

	Logit				Probit			
Variable	Coefficient	z-Stat	Prob.	slope	Coefficient	z-Stat	Prob.	slope
DDF	1.235	2.113	0.012	0.261	1.316	1.117	0.013	0.319
PR	-6.442	-3.362	0.000	-0.614	-3.115	-4.326	0.000	-1.017
SR	1.007	3.021	0.003	0.199	0.211	2.978	0.002	0.216
Size	-0.036	-0.215	0.021	-0.012	-0.055	-1.623	0.077	-0.069
INT	-1.111	-0.032	0.014	-0.233	-1.214	-2.119	0.012	-0.364
DDF25	-1.299	-2.365	0.017	-0.144	-0.699	-2.216	0.018	-0.225
Const.	-0.743	-1.715	0.063		-0.456	-1.759	0.216	
LR (4 df)	34.698	R-sq	0.131		LR (4 df)	265.115	R-sq	0.398
P-value	0.000				P-value	0.000		
D=0	178	Total	198					
D=1	35							

In the probit model marginal effects are computed by multiplying the partial regression coefficients times the standard probability density function. Thus unlike partial regression coefficients the value of marginal effects depend on the values of all the regresses. The slope coefficients we report in Table 2 are marginal effects evaluated at the median.

Table 2 shows that efficiency is a significant predictor of default for firms in the Steel and Metal industry. In particular, we find that more efficient firms are less likely to fail. A 0.2 unit increase in the inefficiency score increases the probability of default on average by about 1.65 percent. This probability decreases to about 0.33 percent for the top quartile of the most efficient firms. We also find that a one percentage point fall in profitability increases the probability of default by about 1.03 percent. Similarly, a one percentage point fall in intangibility is expected to increase the probability of default by about 0.26 percent. We find that the solvency ratio is a poor predictor of a company's default. In fact our results suggest that all else equal an increase in SR is expected to increase (albeit by a small amount) rather than decrease the probability of default. This finding suggests that caution needs to be exercised when loan approvals are weighted too heavily on net worth considerations. We conclude that in spite of its simplicity and general appeal SR is a probably a backward rather than forward performance measure and thus it may not be a reliable predictor of a company's future health. Overall, we find from the estimates of the logit model that 27 out of the 198 firms in the Steel and Metal industry sample have a less than five percent probability to fail. Using the forecast values from the probit model we find that 35 firms in this industry have less than five percent probability to fail.

Table 3 presents the regression results for the automotive industry. We find that the effect of profitability on the likelihood of default is similar in terms of both direction and magnitude to that we estimated for the Steel and Metal industry. On the other hand, inefficiency has a smaller albeit still positive and significant effect on default. Again the effect of the solvency ratio on default is positive and significant. We also find that the tangibles to total assets ratio has a positive and significant effect on the default probability. This finding reinforces the caution we raised above with regards to whether some of balance sheet indicators are indeed useful ex-ante indicators of the future health of a company. Overall, the logit model predicts that of the 25 firms in the sample 96 have less than five percent chance to default. According to the probit estimates 31 firms have less than five percent to default.

Table 4 presents logic and probit estimates for the oil, gas and petrochemical industries. We have included a squared term to capture possible non-linearities in the logic and probit effects of efficiency on default. This effect is increasing with inefficiency and remains positive within the range of sample values. The effect of profitability on default is negative although lower in magnitude compared to the estimates for the Steel and Metal industry and automotive industries. We surmise that the positive effect of intangibles on the likelihood of default or financial distress may be a reflection of the Myers (1977) underinvestment problem. The logit model predicts that 34 out of the 96 firms in this industry have less than five percent likelihood to default. The probit model predicts that 37 have less than five percent likelihood to default.

Table 3 Logit and Probit Regression Analysisfor Automotive industries

	Logit				Probit			
Variable	Coefficient	z-Stat	Prob.	slope	Coefficient	z-Stat	Prob.	slope
DDF	0.265	1.302	0.041	0.016	0.128	1.127	0.036	0.033
PR	-6.453	-6.268	0.000	-1.022	-3.023	-4.111	0.000	-1.100
SR	1.203	2.745	0.003	0.052	0.379	2.419	0.007	0.105
Size	-0.39	-1.136	0.176	-0.013	-0.046	-1.129	0.116	-0.016
INT	2.542	3.259	0.000	0.397	1.117	2.697	0.000	0.129
DDF25	-1.459	-2.397	0.012		-0.742	-2.456	0.019	
Const.	216.335	R-sq	0.144		LR (3 df)	218.697	R-sq	0.213
LR (3 df)	0.000				P-value	0.000		
P-value	75	Total	96					
D=0	31							
D=1	0.216	1.298	0.044	0.017	0.127	1.673	0.021	0.021

Table 4 Logit and Probit Regression Analysisfor Oil, gas and petrochemical industries

	Logit				Probit			
Variable	**Coefficient**	**z-Stat**	**Prob.**	**slope**	**Coefficient**	**z-Stat**	**Prob.**	**slope**
DDF	0.289	1.326	0.248	0.056	0.285	1.218	0.213	0.032
PR	-0.056	-1.364	0.056	-0.007	-0.061	-1.155	0.067	-0.012
SR	-1.889	-5.697	0.000	-0.364	-1.545	-3.329	0.000	-0.456
Size	0.215	1.376	0.267	0.015	0.069	1.275	0.133	0.019
INT	1.119	2.457	0.004	0.216	0.800	2.329	0.006	0.059
DDF25	-1.379	-1.116	0.346	-0.297	-0.784	-1.479	0.219	-0.028
Const.	8.246	1.268	0.159	1.222	5.112	1.479	0.077	1.001
LR (5 df)	-1.968	-2.264	0.000		-1.041	-3.321	0.000	
P-value	76.564	R-sq	0.216		LR (5 df)	85.691	R-sq	0.095
D=0	0.000				P-value	0.000		
D=1	76	Total	96					

CONCLUSION

Our results show that during sample period (2010-2015) among Steel and Metal industry, automotive industriesand Oil, Gas and Petrochemical industries, 17.76% (35 firm out of 198), 32.29% (31 firm out of 96) and 38.54% (37 firm out of 96) are respectively at risk of bankruptcy .using samples of firms from three different TSE industries we have been able to corroborate previous results showing that inefficiency may be a significant ex-ante determinant of the likelihood for company failure. We have obtained this performance indicator using the directional distance function which is a generalization of previous approaches used to model technology and measure efficiency. Our results show that profitability is also an important ex-ante predictor of firm default. Our findings also suggest that caution needs to be exercised when using standard balance sheet indicators such as the solvency ratio and the tangibles to assets ratio in credit assessment. The effect of intangibles on the likelihood of default appears to be sample specific so again caution is required when using this information for loan approvals.

References

1. Altman, E.I., and Saunders, A. (1997). *Credit risk measurement developments over the last 20 years*. *Journal of Banking and Finance*, 21, 1721-1742.
2. Becchetti, L. and Sierra, J., (2003). *Bankruptcy Risk and Productive Efficiency in Manufacturing Firms*, *Journal of Banking and Finance*, 27, 2099-2120.
3. Cielen, A. and Vanhoof, K., (1999). *Bankruptcy prediction using a data envelopment analysis*. Manuscript, Limburg University, Diebenpeek.
4. Diakoulaki, D., Mavrotas G. and Papayannakis L., (1992). *A multicriteria approach for evaluating the performance of industrial firms*. Omega, 20(4), 467 –74.
5. Emel, A.B, Oral, M, Reisman, A and Yolalan, R., (2003). *A credit scoring approach for the commercial banking sector*. Socio-Economic Planning Sciences, 37, 103-123.
6. Färe, R. and S. Grosskopf. (2004). *New Directions: Efficiency and Productivity*, Kluwer Academic Publishers, Boston.
7. Paradi, J.C., Asmild, M. and Simak, P.C., (2004). *Using DEA and worst practice DEA in credit risk evaluation*. *Journal of Productivity Analysis*, 21, 153-165.
8. Rajan, R. and L. Zingales, (1995), "*What Do We Know About Capital Structure? Some Evidence from International Data*", *Journal of Finance* 50, pp. 1421-1460.
9. Siskos, Y., Zopounidis, C. and Pouliezos, A., (1994). *An integrated DSS for financing firms by an industrial development bank in Greece*. Decision Support Systems, 12, 151 –68.
10. Simak, P.C., (1999). *DEA based analysis of corporate failure*. Manuscript, University of Toronto, Toronto.
11. Shephard, R. W., (1970).*Theory of cost and production functions* (Princeton University Press, Princeton).
12. Spence, M., (2002) *Signaling in Retrospect and the Informational Structure of Markets*, The American Economic Review, Vol. 92, No. 3, June, pp. 434-459.
13. Stiglitz, J. E., Weiss A. (1992). *Asymmetric information in credit markets and its implications for macro-economics*, Oxford Economic Papers, 44, p. 694-724.
14. Troutt, M.D., Rai, A. and Zhang, A., (1996). *The potential use of DEA for credit applicant acceptance systems*. Computers and Operations Research, 23(4), 405 –8.
15. Zopounidis, C., Pouliezos, A. and Yannacopoulos, D., (1992). *Designing a DSS for the assessment of company performance and viability*. Computer Science in Economics and Management, 5, 41 –56.

****