IFEAMA SPSCP Vol.5 pp.136-145

CORPORATE BANKRUPTCY PREDICTION MODEL IN MONGOLIA

Altan-Erdene Batbayar

MBA, Senior lecturer of Accounting department,

Business school, National University of Mongolia, batalterd@ses.edu.mn

Myagmarsuren Boldbaatar

Ph.D, Lecturer of Economics department,
Science school, National University of Mongolia, myagmarsuren@ses.edu.mn

Tsetsegdelger Enkh-Amgalan

MBA, Lecturer of Accounting department,
Business school, National University of Mongolia, tsetsegdelgeracco@gmail.com

Abstract

A prediction of bankruptcy is the important tool for financiers, shareholders, investors and for any other decision makers. And its importance is now urges the Mongolian economic agents to keep up the present economic situation. Therefore, this study has attempted to propose a bankruptcy prediction model for Mongolian case using the 331 (of which 128 failed and 203 non-failed) companies' financial statement sample from the Ministry of Finance database covering from 2003 to 2014. Our findings show that the proposing M-Score model has achieved the best performing prediction among the comparison models.

Key words: Bankruptcy prediction, Logit Model, Z-score, O-score

Introduction

Bankruptcy is a legal status of an insolvent person or an organization, that is, one who cannot repay the debts that owes to creditors. In most jurisdictions, bankruptcy is imposed by a court order, often initiated by the debtor. When the amount of organization debts is higher than its value of existence assets bankruptcy is occurred (Gitman, 1996). It would be redundant to talk about the consequences of bankruptcy. Therefore, a prediction of bankruptcy is the important tools for financier, shareholders, investors, and for any other decision makers.

Mongolian economic growth rate is slowing for the last three years; therefore, the number of failed companies is rising intensively. For instance, 665 companies failed during last two years and 106 companies are expected to fail[1]. This is the number that is registered in the E-Balance system of Ministry of Finance but in reality many companies are ready to fail. Accounting for those situations, need of bankruptcy prediction model is essential for Mongolia, but we have very limited number of models for bankruptcy prediction for Mongolian case. Practically, we often use Altman's Z-score model which is developed by Edward I. Altman using 66 USA companies' data in 1968 which is not ready to apply this model for our case directly. This is also discussed in previous study (Sodnomdavaa, 2008).

Therefore, there is inevitable demand for developing a bankruptcy econometric model that would be appropriate in Mongolian case. This study is organized as follows. Section 1 reviews the previous studies. Section 2 outlines data, econometric model and estimation methodology. Section 3 presents the empirical results. Finally it concludes.

1. Literature review

Predicting corporate bankruptcy has been discussed invariably for few decades since the work of Beaver (1966, 1968), Altman (1968), Ohlson (1980) and Zmijewski's (1984). Among those methods, the most popular are the Altman and Ohlson's model. Edward I. Altman proposed an analytical technique using financial statement data. He selected 22 financial ratios and analyzed them by using Multivariate Discriminate Analysis (MDA) method; he could produce the function Z which containes 5 financial ratios as independent variables and Z as dependent variable using 66 USA firms' (of which 33 failed firms and the same number of nonfailed firms) financial statement data in 1968. The financial ratios in this model are (i) working capital to total assets; (ii) retained earnings to total assets; (iii) earnings before interest and taxes to total assets; (iv) market value of equity to total debt and (v) sales to total assets. Altman's Z-score remains popular after almost 30 years because it is easy to calculate. Other bankruptcy prediction models exist, some of which are more accurate, especially over a horizon greater than two years. However, they are more complex and most are proprietary (Radha Ganesh Kumar, Kishore Kumar, 2012).

James A. Ohlson developed a new model named "O-score" in 1980. He chose econometric methodology of Conditional Logit Analysis to overcome the problems associated with MDA (Ohlson, 1980). Moreover, he covered 2,163 observations from 105 bankrupt firms and 2,058 nonbankrupt firms. The O-Score consisted from nine variables, namely (i) firm size; (ii) total liabilities to total assets; (iii) working capital to total assets; (iv) current liabilities to current assets; (v) dummy - one if total liabilities exceeds total assets; (vi) net income to total assets; (vii) funds provided by operations to total liabilities; (viii) dummy - one if net income was negative for the last two years and finally (ix) change in net income. The probability of failure is EXP(O-Score) divided by 1+EXP(O-score). Results greater than 0.5 indicate a firm with a high chance of bankruptcy.

It has been argued that the O-Score is a better predictor of bankruptcy than other similar accounting models such as the Altman Z-Score (Radha Ganesh Kumar, Kishore Kumar, 2012), however, researchers may find merits in using both Altman and Ohlson in helping to predict a firm's bankruptcy. Because both Ohlson and Altman use an accounting-based model to help predict bankruptcy, its popularity is stemmed from its simplicity.

The literature regarding to prediction of bankruptcy in Mongolia is quite limited. The most promising work is "Determining a model for bankruptcy risk of companies registered at Mongolian Stock Exchange (MSE)" by researcher Tsolmon Sodnomdavaa in 2008. He hired 217 companies' data, which are registered at MSE, and assigned 30 companies as bankrupted.[2] He developed Z_MGL score model basing on Altman five variables estimated by the probit model. However, Sodnomdavaa have not used real bankrupted data, but it was valuable study.

2. Data and methodology

This study is attempted to propose an alternative model to Z_MGL score model. The four distinguishing features of the present study are the real sample data, the selection of the factor variables, the selection of the model, and the model accuracy. We used real failed and nonfailed companies' financial statements from E-Balance system. Second feature is we chose most appropriate[3] variables from 13 potential variables that are used in the popular models such as Altman Z-score and Ohlson O-score. Third feature is we chose logit model whose variance of the error is $\frac{\pi^2}{3}$ which is greater than probit model (Long, 1997). It is proper to use the model with greater variance of the error, because our collected data has more variance[4]. The last feature is we checked our proposing model using Accurate Prediction Coefficient.

Initially, we collected 439 financial statements, of which 188 were failed between 2003-2014 and 251 were nonfailed companies, from the E-Balance system of Ministry of Finance Mongolia and Mongolian Stock Exchange website. After removing outliers, we had 331 statements of which 128 were failed and 203 were nonfailed companies. The descriptive statistics of the variables are shown in Table 1 along with variable descriptions. We chose 203 nonfailed companies data that covered only 2012 due to the following justification. Why we chose exactly 2012 is the E-Balance system was highly modified in 2013; therefore, it is impossible to compare between before 2012 and 2013 (and thereafter) financial statements. Also Mongolian economic growth accelerated during 2010-2012 and decelerated 2013; hence, there should be less possibility to fail for companies in 2012 which is making reasonable of choosing companies that were not failed by 2012. But we tested our results using companies' data in 2014 that will be discussed later.

Table 1. Descriptive Statistics

Variable	Failed companies				Nonfailed companies			
	Obs.	Mean	Min	Max	Obs.	Mean	Min	Max
year	128	-	2003	2014	203	-	2012	2012
wcta	128	-0.0332	-1.0032	0.9999	203	0.2340	-0.9170	0.8870
reta	128	-0.3029	-3.9991	0.5880	203	0.2456	-1.8643	0.9477
eitta	128	-0.0405	-0.7263	0.6262	203	0.1269	-0.5055	1.0805
mvtb	128	1.0371	-0.4725	10.8119	203	3.6151	-0.2643	18.8852
sta	128	0.8801	0	7.1573	203	1.1552	0	7.2720

size	128	6.1306	1.1986	13.9731	203	10.0048	4.1883	14.0734
tlta	128	0.7193	0.0847	1.8958	203	0.4006	0.0503	1.3592
clca	128	1.7103	0	9.0532	203	0.7467	0	8.9617
oeneg	128	0.2109	0	1	203	0.0148	0	1
nita	128	-0.0599	-0.7263	0.4219	203	0.0957	-0.5055	0.8474
futl	128	-0.0511	-1.7850	1.7257	203	0.6005	-2.7983	8.1901
intwo	128	0.3750	0	1	203	0.1034	0	1
chin	128	0.0077	-1	1	203	-0.0589	-1	1
bnkr	128	1	1	1	203	0	0	0

Note: *wcta* - working capital divided by total assets; *reta* - retained earnings divided by total assets; *eitta* - earnings before interest and taxes divided by total assets; *mvtb* - market value equity divided by book value of total debt; *sta* - sales divided by total assets; *size* - company size, ln(total assets divided by 1000 and GNP price-level index); *tlta* - total liabilities divided by total assets; *clca* - current liabilities divided by current assets; *oeneg* - one if total liabilities exceeds total assets, zero otherwise; *nita* - net income divided by total assets; *futl* - funds provided by operations divided by total liabilities; *intwo* - one if net income was negative for the last two years, zero otherwise; *chin* - change in net income, $\frac{NI_t - NI_{t-1}}{|NI_t| + |NI_{t-1}|}$.

We specify our model as follows. M-score, the bankruptcy predictor, is a latent variable and it linearly depends on the 13 potential variables. If the latent variable, M-score, exceeds some threshold values, we assume that those companies are failed.

$$M\text{-}score = \beta_0 + \beta_1 * wcta + \beta_2 * reta + \beta_3 * eitta + \beta_4 * mvtb + \beta_5 * sta + \beta_6 * size + \beta_7 * tlta + \beta_8 * clca + \beta_9 * oeneg + \beta_{10} * nita + \beta_{11} * futl + \beta_{12} * intwo + \beta_{13} * chin + \varepsilon$$

The M-score (y_i^*) is related to the observed value (y_i)[5] as follows:

$$y_i = \begin{cases} 1 \Rightarrow & if\ y_i^* > 0 \\ 0 \Rightarrow & if\ y_i^* \le 0 \end{cases}$$

Then we assume that the error variable is distributed logistically ($\varepsilon \sim logistic$) and we estimate the model using Stata 11.2.

$$Prob(y_i = 1|x_i) = Prob(y_i^* > 0) = Prob(\beta_i x_i + \varepsilon > 0) = Prob(\varepsilon > -\beta_i x_i) = Prob(\varepsilon \le \beta_i x_i) = F(\beta_i x_i)$$

where $\mathrm{F}(\varepsilon) = \Lambda(\varepsilon) = \frac{\exp(\varepsilon)}{1+\exp(\varepsilon)}$.

Table 2. Correlation matrix

	reta	eitta	mvtb	sta	size	tlta	clca	oeneg	nita	futl	intwo	chin
wcta	0.46 ***	0.42 ***	0.30 ***	0.19 ***	0.34 ***	-0.49 ***	**-0.75** ***	-0.44 ***	0.39 ***	0.28 ***	-0.22 ***	0.01
reta		**0.51**	0.26	0.20	0.46	-0.49	-0.30	-0.48	**0.50**	0.38	-0.45	-0.06

	***	***	***	***	***	***	***	***	***	***	
eitta		0.20 ***	0.34 ***	0.39 ***	-0.32 ***	-0.31 ***	-0.27 ***	**0.97** ***	**0.67** ***	-0.40 ***	0.29 ***
mvtb			-0.05	0.16 ***	**-0.68** ***	-0.25 ***	-0.23 ***	0.21 ***	**0.53** ***	-0.05	0.00
sta				0.01	-0.07	-0.12 **	-0.14 ***	0.31 ***	0.15 ***	-0.23 ***	0.06
size					-0.27 ***	-0.37 ***	-0.24 ***	0.39 ***	0.30 ***	-0.24 ***	-0.02
tlta						0.31 ***	**0.67** ***	-0.34 ***	-0.36 ***	0.14 ***	0.03
clca							0.24 ***	-0.29 ***	-0.21 ***	0.25 ***	-0.04
oeneg								-0.29 ***	-0.13 **	0.23 ***	0.02
nita									**0.66** ***	-0.37 ***	0.33 ***
futl										-0.24 ***	0.13 ***
intwo											0.17 ***

*Note: *, **, and *** represent significance at the 10, 5, and 1 percent levels, respectively*

3. Empirical results

In order to make a reliable estimation, first we controlled the multicollinearity (see Table 2). In the first stage, we dropped *reta*, *eitta*, *tlta*, and *futl* variables due to their highly correlation to other variables. In second stage *clca* and *oeneg* were excluded from the estimation due to its poor performance and multicollinearity problem. In third stage, poor performing variables, *wcta* and *sta*, were excluded from the estimation. After that we developed the model with five variables. The estimation result is presented in Table 3.

$$M\text{-}score = \beta_0 + \beta_1 * mvtb + \beta_2 * size + \beta_3 * nita + \beta_4 * intwo + \beta_5 * chin + \varepsilon$$

Table 3. Logit model estimation[6]

Variables	Coefficients	Std.error	z-statistics	P-value
Intercept	β_0 = 5.7963	0.7465	7.77	0.000
mvtb	β_1 = -0.4839	0.0912	-5.31	0.000
size	β_2 = -0.6793	0.0871	-7.80	0.000
nita	β_3 = -8.2045	2.2506	-3.65	0.000
intwo	β_4 = 1.0809	0.4803	2.25	0.024
chin	β_5 = 0.6805	0.3146	2.16	0.031
LR chi^2	246.94			
Prob > chi^2	0.000		AIC	206.777
Pseudo R^2	0.559		BIC	229.590

All variables are statistically significant at 5 percent level. And the estimated regression is statistically significant at the 1 percent level. A latent variable in our estimation is a proposing *M-score ;* therefore, *mvtb, size* and *nita* have negative effect on *M-score* while *intwo* and *chin* have positive effect on *M-score*. Relationships between variables and bankruptcy are quite logical. For instance, firm size, *size* variable, is related to borrowing capacity. Larger firms are more likely to have raised capital in the past by issuing long-term, unsecured bonds. The assets generated by such borrowing are available to serve as collateral for additional borrowing. (Cornelius J.Casey, Victor E.McGee, Clyde P.Stickney, 1986) Therefore, larger firms are less likely to fail than smaller firms.

Table 4. Measures of fit for Logit model

Log-Lik Intercept only	-220.860	Log-Lik Full Model	-97.389
D(325)	194.777	LR(5)	246.944
		Prob > LR	0.000
McFadden's R^2	0.559	McFadden's Adj. R^2	0.532
ML (Cox-Snell) R^2	0.526	Cragg-Ugler (Nagelkerke) R^2	0.714
McKelvey&Zavoina's R^2	0.820	Efron's R^2	0.627
Variance of y^*	18.271	Variance of error	3.290
Count R^2	0.879	Adj. Count R^2	0.688
AIC	0.625	AIC*n	206.777
BIC	-1,690.911	BIC'	-217.933
BIC used by Stata	229.590	AIC used by Stata	206.777

All types of R-squares are very high, between 0.53-0.88, in this model (see Table 4).

Table 5. Discrete Change in Probability for a Logit model of Bankruptcy

Variable	ΔRange	Δ1	Δσ
mvtb	-0.5391	-0.1175	-0.3015
size	-0.9681	-0.0111	-0.3261
nita	-0.9924	-0.2598	-0.2371
intwo	0.2085	0.2085	0.0724
chin	0.2267	0.1348	0.0695

Note: Δ1 is centered change of 1 around the mean; Δσ is centered change of 1 standard deviation around the mean; ΔRange is change from the minimum to its maximum. All the variables are held at their mean.

From the Table 5, for the *mvtb* variable, each additional ratio of market value equity divided by book value of total debt, the probability of bankruptcy decreases by 11.8 percent, while a firm *size* increases by one unit, the probability of bankruptcy decreases by 1.1 percent holding all other variables at their means. Likewise, net income divided by total assets, *nita*, increases by one unit, the probability of bankruptcy decreases by 25.9 percent and change in net income, *chin*, increases by one unit, probability would increase by 13.5 percent holding all other variables at their means. If the firm's net income was negative for the last two years, *intwo*, the probability of bankruptcy is 20.8 percent greater than the firm whose net income was positive last two years, holding all other variables at their means.

Finally, related tests and statistics are statistically reliable thus we use this model to estimate proposing M-score.

M-score = 5.7963 – 0.4839**mvtb* – 0.6793**size* - 8.2045**nita* + 1.0809**intwo* + 0.6805**chin*

In order to define the degree of bankruptcy risk, we assign probabilities that would discriminate the critical values of the interval. The intervals[7] are as below.

$$Degree\ of\ bankruptcy\ risk = \begin{cases} m_{score} \le -4.595 & No\ risk\ of\ bankruptcy \\ -4.595 < m_{score} \le -2.197 & Low\ risk\ of\ bankruptcy \\ -2.197 < m_{score} \le 0 & Moderate\ risk\ of\ bankruptcy \\ m_{score} > 0 & High\ risk\ of\ bankruptcy \end{cases}$$

We expand sample coverage in order to test our model accuracy. 4,498 companies' financial statements, of which 324 companies were failed during 2003-2014 and 4,174 companies were nonfailed by the 2014, are applied for the analysis. Then we estimated Accurate Prediction Coefficient (APC) for the Altman's Z score, Ohlson's O-score, Sodnomdavaa's Z_MGL score, and our proposing M-score models. APC is calculated by the following formula.

$$APC = \frac{Number\ of\ accurate\ predicted\ failed\ company}{Total\ actual\ failed\ company} + \frac{Number\ of\ accurate\ predicted\ nonfailed\ company}{Total\ actual\ nonfailed\ company}$$

Higher value of APC defines higher accuracy of the model and it is $0 \le APC \le 2$.

Z-score model predicts 225 (out of 324) actual failed and 2,509 (out of 4,174) actually nonfailed companies, accurately. Therefore, APC is $\frac{225}{324} + \frac{2{,}509}{4{,}174} = 1.296$, which is written in parenthesis in bold type after the model name, for the Z-score model (see Table 6).

According to the Table 6, maximum APC among four models is our proposing M-score model. Ordering four models by their prediction accuracy is as below.

$$Z_{MGL} < O_{score} < Z_{score} < M_{score}$$

Table 6. Comparison of accuracy

Actual	Z-score **(1.296)**			O-score **(1.241)**		
	Failed	Nonfailed	Total	Failed	Nonfailed	Total
Failed	225	99	324	238	86	324
Nonfailed	1,665	2,509	4,174	2,059	2,115	4,174
Total	1,890	2,608	4,498	2,297	2,201	4,498
	Z_MGL **(1.160)**			M-score **(1.297)**		
Failed	110	214	324	281	43	324
Nonfailed	749	3,425	4,174	2,380	1,794	4,174
Total	859	3,639	4,498	2,661	1,837	4,498

M-Score performs well comparing to other prediction tools. Consequently, M-score model is capable to predict of bankruptcy for Mongolian companies.

Moreover, every model except Z_MGL has proposed that 50 percent, on average, of nonfailed companies have risk to bankruptcy which indicates that numerous companies are having financial difficulties in Mongolia now. Identifying the source of these difficulties is following open topic for us.

Concluding remarks

This study has attempted to propose a bankruptcy prediction model for Mongolian case. We developed M-score model basing on the 331 companies' financial statements using logit model. M-score is successfully passed the all the statistical tests which provide estimation confidence.

The factors, namely (i) market value equity divided by book value of total debt, (ii) company size, ln(total assets divided by 1000 and GNP price-level index), (iii) net income divided by total assets, (iv) dummy variable, one if net income was negative for the last two years, zero otherwise, and (v) change in net income, $\frac{NI_t - NI_{t-1}}{|NI_t| - |NI_{t-1}|}$, have significant effect on probability to bankruptcy.

Moreover, we compared the performance of the model between M-score, Altman's Z-score, Ohlson's O-score and Sodnomdavaa's Z_MGL score models by calculating Accurate Prediction Coefficients. Our findings show that the proposing M-Score model has achieved the best performing prediction among the comparison models.

Most challenging complications for this study were data problems which are availability of data, incomplete and unbalanced financial statements and poor E-Balance system of Ministry of Finance Mongolia. Accounting all those reasons, further study is widely open.

Reference

Altman, E. I. (1968). Financial Ratios, Discriminant Analysis and the Prediction of Corporate Bankruptcy. *Journal of Finance, 23*(4), 589-608.

Cornelius J.Casey, Victor E.McGee, Clyde P.Stickney. (1986, 4). Discriminating Between Reorganized and Liquidated Firms in Bankruptcy. *The Accounting Review, LXI*(2), 249-261.

Gitman, L. (1996). *Principle of Managerial Finance, 7th edition.* New York, USA: Harper Collins College.

J. Scott Long, Jeremy Freese. (2001). *Regression Models for Categorical Dependent Variables using STATA.* College Station, Texas, USA: Stata Press.

Karamzadeh, M. S. (2013). Application and Comparison of Altman and Ohlson Models to Predict Bankruptcy of Companies. *Research Journal of Applied Sciences, Engineering and Technology, 5*(6), 2007-2011.

Laurel A. Franzen, Kimberly J. Jodfers, Timothy T. Simin. (2007). Measuring Distress Risk: The Effect of R&D Intensity. *The Journal of Finance, 62*(6), 2931-2967.

Long, J. S. (1997). *Regression Models for Categorical and Limited Dependent Variables.* Thousand Oaks, California, USA: SAGE Publications.

Mohammad Jouzbarkand, Farshad Sameni Keivani, Mohsen Khodadadi, Seyed Reza Seyed Nezhad Fahim. (2013). Bankruptcy Prediction Model by Ohlson and Shirata Models in Tehran Stock Exchange. *World Applied Sciences Journal, 21*(2), 152-156.

Ohlson, J. A. (1980). Financial Ratios and the Probabilistic Prediction of Bankruptcy. *Journal of Accounting Research, 18*(1), 109-131.

Radha Ganesh Kumar, Kishore Kumar. (2012, 4). A Comparison of Bankruptcy Models. *International Journal of Marketing, Financial Services and Management Research, 1*(4), 76-86.

Sodnomdavaa, T. (2008). Determining a model for bankruptcy risk of companies registered at Mongolian Stock Exchange. *Conference of School of Economic Studies,NUM* (pp. 1-17). Ulaanbaatar: NUM-Press.

Stewart Jones, David A. Hensher. (2004). Predicting Firm Financial Distress: A Mixed Logit Model. *The Accounting Review, 79*(4), 1011-1038.

Endnotes

[1] Source: E-Balance system of Ministry of Finance Mongolia, http://e-balance.mof.gov.mn
[2] There was no data of bankrupted companies. Therefore he assigned 30 companies as bankrupted basing on their financial ratios and the estimation of five different failure scores including Altman's Z-score.
[3] Statistically significant
[4] Refer to Table 1.
[5] y_i is one if failed and zero otherwise.
[6] Probit model is also estimated (but unreported here) in order to compare the estimates. IC showed Logit model is better.
[7] The probability greater than 50 percent indicates High risk of bankruptcy; greater than 10, lesser than 50 indicates Moderate risk of bankruptcy, greater than 1, lesser than 10 indicates Low risk of bankruptcy; lesser than 1 indicates No risk of bankruptcy.