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A Study on Estimation of Financial Liquidity Risk Prediction Model Using Financial Analysis

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Abstract

In this study we conducted a static financial analysis of the financial ratios of the manufacturing, information service, and financial and insurance industries to propose a model for predicting the financial liquidity risk, and performed ANOVA to select the significant variables affecting the healthy liquidity firms and the poor liquidity firms. Using the results of ANOVA, the linear discriminant model, the secondary discriminant model, the probit model, and the logit discriminant model were estimated and tested to propose a predictive model. The results of the test are as follows. The variables selected by ANOVA were all significant in the significance test of all models. And the fitness and the explanatory power of the estimated model were evaluated by the Apparent Error Rate (APER) which is the misclassification rate of the confusion matrix which is the classification matrix of the observation result and the prediction result. As the result, the misclassification rate of the logit discriminant model was the lowest, and the next lowest model was the probit model. Therefore, in order to compare the predictive power of the probit and logit discriminant models, the association analysis between the prediction probability and the observation response was analyzed and the predictive power was compared using rank correlation coefficients. As the result, the predictive power of the logit discriminant model is higher than that of the probit model. Therefore, the logit discrimination model, which has the lowest misclassification rate of all data and has the highest forecasting power, is proposed as the final model for predicting the financial liquidity risk.

Keywords: ANOVA, Probit model, Logit discriminant model, Misclassification rate, Rank correlation coefficients

INTRODUCTION

Korean economy has cut its base rate several times in order to escape the economic crisis that started with the global financial crisis and has been maintaining its low interest rate policy. This is because there is a strong will and belief that the economy can be recovered only when money is released on the market. However, the rapid increase in market liquidity due to low interest rates should never be ignored. The sharp rise in liquidity can lead to a bubble problem by raising the market value too much, and the short-termed shortfall of market funds, which is released to the financial sector, may become serious. Such speculative short-term funds are likely to lead to another problem called the liquidity crisis, since there is a substantial amount of money but no substantial flow. Therefore, as the strategy to avoid the second economic crisis, some carefully express to raise interest rates. The international community believes that Korean economy is at risk of financial liquidity due to the continued low interest rates. In particular, the IMF points out that all Korean companies are facing corporate debt problems, and that all industries need to be restructured because of the increase in household debts and the problem of soundness of corporate debts, which are represented by insolvent companies. Recently the Federal Reserve Board (FRB) of the US raised its base interest rate as the first step for normalizing its monetary policy. If the US raises the interest rate, the increase in the risk is inevitable as the management condition deteriorates due to the rapid leaking of investment funds that has flowed into Korea and emerging countries. Therefore, it is necessary to continually study the forecasting models needed to manage the liquidity risk of companies, considering the sluggish sales of companies due to the slowdown in economic growth, low interest rate policy, interest rate hikes in the US, and uncertainties in overseas markets. Similar previous studies of the financial liquidity forecasting model are as follows. In 1985, West analyzed bank failures using factor analysis and logit analysis [1], and in 1991, Tam analyzed the banking industry using neural network analysis [2]. In 1994, Cho developed a logistic model predicting in the service industry [3], and in 1996, Lee et al. confirmed the predictive power of hybrid neural network models using 57 financial ratios [4]. In 1999, Davalos et al. predicted the risk of airlines by using neural network method, and in 1997, Altman and Narayanan suggested that the predictive power of each country varies according to the economic environment. In 2007, Davalos et al. suggested that activity indicators are important variables for risk prediction [7], and in 2009, Boyacioglu et al. used logit model and discriminant model to test the predictive power using 20 financial ratios [8]. In 2011, Kim emphasized that the growth indicators are important variables for risk prediction [9]. In 2015, Iturriaga and Sanz compared and analyzed the predictive power between models by performing discriminant analysis, logit analysis and neural network analysis on US commercial banks [10]. In 2016, An analyzed the ratios of unlisted companies and proposed a predicting model using multiple regression model [11]. As a previous research using logit and multiple regression models in other fields, in 2017, Kim used the multiple regression model to test the identity effect of body shape recognition and body shape management [12], and in 2017, Hwang and Kim analyzed the potential risk of infection using logistic analysis [13]. And in 2006, Tabachnick and Fidell found that in multivariate discriminant analysis the assumption of multivariate normality did not seem to be a big problem as far as it was not violated by extreme values, if the number of predictive variables was small and the number of cases in the smallest group was 20 or more, even though the numbers of cases in groups were different [14].

RESEARCH METHODS

Data and research model

The data used in this study are the financial statements of the manufacturing, information service, and financial and insurance industries in 2016. The total number of enterprises is 165; the healthy liquidity companies are 89, and the bad liquidity companies 76. The financial liquidity analysis variables used are Current ratio (CUR), Cash ratio (CR), Quick ratio (QR), Net working capital ratio (NR), Debt ratio (DR), Total borrowings and bonds payable to total assets (TA), Interest coverage ratio (IR), EBITDA to interest cost ratio (EIR), stockholders equity to total assets (SA), and Interest expenses to total borrowings and bonds payable (IP). As a research model, when $f_1(\mathbf{x})$ and $f_2(\mathbf{x})$ are probability density functions of healthy liquidity companies and bad liquidity companies respectively, the logit model considered is as follows:

$$\log\frac{f_1(\mathbf{x})}{f_2(\mathbf{x})} = \beta_0 + \boldsymbol{\beta}'\mathbf{x} \qquad (2\text{-}1)$$

The probabilities $P_1(\boldsymbol{x})$ and $P_2(\boldsymbol{x})$ belonging to two firms are estimated as follows:

$$P_1(\mathbf{x}) = \frac{\exp(\beta_0+\boldsymbol{\beta}'\mathbf{x})}{1+\exp(\beta_0+\boldsymbol{\beta}'\mathbf{x})} \qquad (2\text{-}2)$$

$$P_2(\boldsymbol{x}) = 1 - P_1(\boldsymbol{x})$$

Then, the prediction result is classified as follows using the classification reference value $d = 0.5$

$$\beta_0 + \boldsymbol{\beta}'\mathbf{x_0} \geq d \rightarrow \text{Healthy liquidity} \qquad (2\text{-}3)$$

$$\beta_0 + \boldsymbol{\beta}'\mathbf{x_0} < d \rightarrow \text{Bad liquidity}$$

Assessment of the fit of the model

The Apparent Error Rate (APER), which evaluates the model fit, is the ratio of misclassified data when the data is reclassified by using the estimated classification function. It is a measure of the misclassification rate of any classification function regardless of the distribution pattern of the group and is calculated as follows using the correct classification rate (CCR),

$$\mathrm{APER} = 1 - \mathrm{CCR} \qquad (2\text{-}4)$$

where $\mathrm{CCR} = \left(\frac{n_{ii}+n_{i+}}{n}\right) \times 100\%$, n is the total number of observations, n_{ii} is the diagonal element regularly stored in the classification matrix, and n_{i+} is the sum of ith row.

Estimation of predictive power of the model

The rank correlation coefficients, which is the statistic that evaluates the predictive power of probit and logit discriminant models, are calculated as follows. In the comparative model, a model with large values of rank correlation coefficients is judged as a model with good predictive power.

$$\text{Somer's}\ \ D = \frac{1}{t}(n_c - n_d) \qquad (2\text{-}5)$$

$$\text{Goodman} - \text{Kruskal Gamma} = \frac{n_c-n_d}{n_c+n_d}$$

$$\text{Kendall's Tau} - a = \frac{n_c-n_d}{n(n-1)/2}$$

$$C = \frac{1}{t}\left\{n_c + \frac{1}{2}(t - n_c - n_d)\right\}$$

where n is the total number of observations, t is the total number of pairs having different response value, n_c is the number of matched pairs, and n_d is the number of mismatched pairs.

RESULTS AND DISCUSSION

The prior probability and classification reference value used in the comparative analysis model was 0.5, and it was confirmed that the misclassification rate in the linear discriminant model was 27.62%, higher than that in the secondary discriminant model. Therefore, a prediction model was proposed by comparatively analyzing the secondary discriminant model, the probit model, and the logit discriminant model. The comparison results are shown in Table 1 to Table 5.

Variable selection and significance test

Table 1 shows the results of ANOVA of identity test between two companies. Based on the F-test with the significance level of 5%, the variables CUR, CR, QR, NR, TA, and SA were selected as statistically significant variables for discriminating

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between healthy liquidity companies and bad liquidity companies. The remaining variables were excluded from the independent variables of the estimation model.

Table 1. ANOVA

	Healthy liquidity		Bad liquidity		Statistics	
Variables	Mean	Std. dev.	Mean	Std. dev.	F	p-value
CUR	226.79	353.96	570.69	947.92	18.59	0.0001
CR	59.14	108.45	227.39	400.23	14.49	0.0002
QR	211.85	343.20	440.38	529.62	11.11	0.0011
NR	19.06	23.17	34.62	26.76	16.02	0.0001
DR	26.86	31.06	28.80	26.16	0.18	0.6687
TA	9.63	12.85	2.41	3.87	22.23	0.0001
IR	18.03	29.16	11.10	23.07	2.79	0.0966
EIR	21.33	52.94	17.69	96.72	0.09	0.7601
SA	45.52	34.02	73.60	21.16	38.89	0.0001
IP	4.87	11.75	7.83	15.22	1.98	0.1615

Table 2 shows the results of testing the significance of the discriminant coefficients in the probit and logit discriminant models. Since, using the Wald chi-square statistic at the significance level of 5%, the significance probability of all the discriminant coefficients including the intercept are small, it is confirmed that the discriminant coefficients are very significant variables to distinguish the two groups in the probit and logit discriminant model.

Table 2. The significance test of the model

Analysis of Maximum Likelihood Estimates (Probit Model and Logit Discriminant Model)				
Variables	Wald - χ^2	Pr > ChiSq	Wald - χ^2	Pr > ChiSq
Intercept	13.3764	0.0003	12.4134	0.0004
CUR	9.1012	0.0026	10.1406	0.0015
CR	0.8970	0.0436	0.6500	0.0201
QR	9.9888	0.0016	10.6698	0.0011
NR	6.4539	0.0111	8.6473	0.0033
TA	17.9250	0.0001	16.1608	0.0001
SA	23.0162	0.0001	22.4956	0.0001

Secondary discriminant model

The confusion matrix by the secondary discriminant function is shown in Table 3. 64 out of 89 companies belonging to healthy liquidity companies were correctly classified, and 63 out of 76 companies belonging to bad liquidity companies were correctly classified. Therefore, the misclassification rate for the total data is 23.03%, and the misclassification rate is 22.60% if the prior probability is equal.

Table 3. Confusion matrix

Quadratic Discriminant Function			
From G	Healthy liquidity	Bad liquidity	Total
Healthy liquidity	64	25	89
Bad liquidity	13	63	76
Total	77	88	165
Error Count Estimates for G			
Rate	0.2809	0.1711	0.2260

Probit model and logit discriminant model

Table 4 is the confusion matrix of the probit model and the logit discriminant model for evaluating the fit of the model. By the probit model, 71 out of 89 companies belonging to healthy liquidity companies were correctly classified, and 61 out of 76 companies belonging to bad liquidity companies were correctly classified. By the logit discriminant model, 71 out of 89 companies belonging to healthy liquidity companies were correctly classified, and 63 out of 76 companies belonging to bad liquidity companies were correctly classified. Therefore, the misclassification rates for the total data are 20% and 18.78% respectively, and the misclassification rates are 19.95% and 18.65% respectively when the classification reference value is 0.5.

Table 4. Confusion matrix

Probit Model			
From G	Healthy liquidity	Bad liquidity	Total
Healthy liquidity	71	18	89
Bad liquidity	15	61	76
Total	86	79	165
Error Count Estimates for G			
Rate	0.2023	0.1974	0.1995
Logit Discriminant Model			
From G	Healthy liquidity	Bad liquidity	Total
Healthy liquidity	71	18	89
Bad liquidity	13	63	76
Total	84	81	165
Error Count Estimates for G			
Rate	0.2024	0.1711	18.65

Association of Predicted Probabilities and Observed Responses

Table 5 is statistics for evaluating the predictive power of the probit model and the logit discriminant model. The result of comparison between the two models shows that the values of the rank correlation coefficients of the logit discriminant model are higher overall than those of the probit model. Therefore, the estimated research model that predicts the financial liquidity risk is as follows.

$$\log\left(\frac{\widehat{p}_1}{1-\widehat{p}_1}\right) = 1.7337 - 0.0186\ \mathrm{CUR} - 0.0017\ \mathrm{CR} - 0.0181\ \mathrm{QR} + 0.0511\ \mathrm{NR} + 0.1533\ \mathrm{TA} - 0.0467\ \mathrm{SA}$$

Table 5. Analysis of association of predicted probabilities and observed responses

Probit Model		Logit Discriminant Model	
Rank correlation coefficients			
Somer' D	0.770	Somer' D	0.776
Gamma	0.761	Gamma	0.777
Tau-a	0.380	Tau-a	0.388
C	0.880	C	0.888

This study derived a scientific model that predicts the financial liquidity risk of a firm. The results are summarized as follows. When the prior probability and the classification reference value are 0.5, the misclassification rate of the secondary discrimination model is 22.6%, the probit model 19.95%, and the logit discriminant model 18.65%. The logit discriminant model is the most suitable model to identify the financial liquidity risk, and its predictive power is also high as 88.8%. The results of this study are based on empirical data. Therefore, we expect that it will be used to establish the management strategy to secure financial liquidity of medium-sized enterprises as well as large corporations in the situation that asset quality of corporate loans is expected to be pressured due to sluggish sales following sluggish economic growth and market interest rate hike. And it will be meaningful for companies that are trapped in the financial risk due to US interest rate hikes to reduce debt and manage liquidity through financial risk management. However, the liquidity forecasting model through static analysis of financial ratios is insufficient to reflect the rapid change of business environment and has a limitation that can not grasp the strategic behavior of the company. Therefore, for the accuracy and usefulness of the forecasting model, dynamic analysis such as cash flow analysis, non-financial information analysis which can reflect the change of management environment, and studies of causal relationship model, AHP model (Analytical Hierarchy Process Model), data mining, and hybrid model etc. will be needed.

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