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Comparison of Binary Logit Model and Multinomial Logit Model in Predicting Corporate Failure

Bi-Huei Tsai

Department of Management Science, National Chiao Tung University
1001 Ta-Hsueh Road, Hsinchu 300, TAIWAN
Tel: +886 3 5712121 ext 57111 Fax: +886 3 5733062
E-mail: bhtsai@faculty.nctu.edu.tw

Abstract: A critical issue in the prediction of corporate failures is, whether to categorize sample firms in a binary fashion into failed firms and non-failed firms or to classify failed firms according to multiple financial difficulties. As most previous studies only employ the binary approach in their forecast, this work compares both the binary logit model and the multinomial logit model to determine whether or not the accuracy of forecasting corporate failures can be improved by further classifying financially-failed firms. The binary logit model recognizes slightly-distressed events and bankruptcy-and-reorganizations events both as corporate failure, while the multinomial logit model distinguishes between levels of corporate failure events as slightly-distressed firms and bankruptcy-and-reorganization firms. The empirical results show that the misclassification errors and error costs of the binary logit model are smaller than those of the multinomial logit model, suggesting that the binary logit model performs superior to the multinomial logit model in predicting corporate failure. The comparison results imply that the slightly-distressed firms and bankruptcy-and-reorganization firms are similar in characteristics. The occurrence of slightly-distressed events is already on the verge of bankruptcy, signifying major financial failure in the company operations. In such case, investors and debtors should be especially alert to withdraw their investments or terminate their loans to prevent loss.

JEL Classifications: G01, G32, G34
Keywords: Binary logit model; Multinomial logit model; Misclassification errors; Corporate failure

1. Introduction

This work compares both the binary logit model and the multinomial logit model to determine whether or not the accuracy of forecasting corporate failures can be improved by further classifying financially-failed firms. Previous articles choose the conventional failing and non-failing dichotomy to categorize firms' financial conditions; the binary logit model is employed to predict the occurrence of financial distress events (Beaver, 1966; Ohlson, 1989; Shumway, 2001). However, according to Balse Committee on Banking Supervision (2001), not only bankruptcy but also many different financial distress events resulting in credit loss of stake-holders may lead to the financial failing of a firm. Particularly, different factors signal the occurrence of different financial distress events since the disclosure quality of financial statement varies with the financial conditions of firms. It is worthwhile to separate the slight financial difficulties from serious corporate failures to capture the different critical factors in explaining these different types of corporate failure events. Johnsen and Ronald (1994) once used multinomial logit models to predict corporate bankruptcy and financial distress, proving that the financial conditions predicted by this model are value-added. Based on this conclusion, this investigation for the first time includes a new type, "slightly-distressed", as financial distress events, in addition to the "reorganizations and bankruptcy" events, so that the differences of the financial ratios in explaining the occurrence of these two types of financial events can be explored. In our research, "slightly-distressed" firms are defined as firms which undergo the reclassification from publicly listed firms to delisted firms[1], bailed out by government, suffering termination of operations because of economic recession, or experiencing bounced checks due to "non-sufficient funds" (NSF). Since previous binary logit model cannot approximate the three statuses of corporate financial conditions ("non-failed", "slightly-distressed", and "reorganization and bankruptcy"), this study utilizes the multinomial logit model to explore the different critical factors that explain the two different extents of financial distress: "slightly-distressed" and "reorganization and bankruptcy". Thus, we can distinguish which factors are suitable to foresee the occurrence of different failed events and to further estimate the probabilities that a firm will encounter "slightly-distressed" or "reorganization and bankruptcy" events. Furthermore, the forecast accuracy of binary logit model and multinomial logit model can be compared.

The unique contribution of this paper is to statistically test the difference in predictive ability between binary logit model and multinomial logit model based on various levels of cut-off points. Previous research chooses "a single cut-off point" to distinguish failing firms from non-failing ones (e.g., Begley, Ming and Watts, 1996; Kalotychou and Fuertes, 2006). Although they have chosen the optimal cut-off point which minimizes the errors in their samples to distinguish failed firms (including "slightly-distressed firms" and "reorganization and bankruptcy firms") from non-failed ones, it is arbitrary for the prior research to compare the predictive ability among various alternative models based on "a single" cut-off point. To overcome this problem, this work adopts a range of cut-off points from 0.01 to 0.5 to evaluate the predictive ability between the binary and multinomial logit models in the forecast window. The criteria of error rates and estimated misclassification costs (EMCs) are employed to compare predictive ability of the two models in our research. Bootstrapping simulation is iterated 1,000 times to estimate the empirical distributions of misclassification error rates and EMCs to determine the critical values for hypotheses testing. This work then illustrates statistical error comparisons of these 1,000 resamples at various cut-off points ranging from 0.01 to 0.5 between binary and multinomial logit models.

In addition to considering various financial conditions, the contribution of this study also includes applying corporate governance factors to capture the characteristics of "non-failed", "slightly-distressed", "reorganization and bankruptcy" events. This investigation examines whether different financial distress predictions are related to corporate governance, financial ratios, and market variables to different extents. The corporate governance factors have been previously verified to provide incremental explanatory power in predicting credit risk of Asian firms which do not truthfully express operational performance in financial statements (e.g., Johnson et al., 2000; Iturriaga and Crisostomo, 2010), so this paper employs corporate governance factors to examine their usefulness in predicting financial distress events. The corporate governance variables include ownership ratio of the insiders, pledge ownership ratio of the insiders, and deviation ratio between voting and cash flow rights. Insiders are directors, supervisors, managers and large shareholders (that own 10 percent or more of a company's outstanding share).

This study employs data of publicly listed companies that traded on the Taiwan Stock Exchange. The results show that prediction accuracy does not improve as we classify the credit risk events in detail. Generally speaking, the probability density functions (PDFs) of misclassification error rates of multinomial logit model is larger than those of binary logit model in 2007. This once again supports the usefulness of binary logit model in predicting financial distress, particularly in the emerging markets where the firms with financial distress have similar characteristics since the

[1] The stock of a firm with deteriorating operations whose equity value per share reduced to below five dollars might be classified as "full-deal stock" by Taiwan Stock Exchange. Investors should take "full-deal stocks" and cash to brokers to perform physical transaction, so full-deal stocks are not as liquid as original stocks.

occurrence of slightly-distressed events is already on the verge of bankruptcy, signifying major corporate failure in the company operations.

2. Logit Models

2.1 Binary Logit Model

Both Constand and Yazdipour (2011) and Zhu and Li (2010) express that in terms of the logistic regression model the predicted rate of corporate financial failure can indicate that the credit risk of corporate has more economic significance than the z-score values estimated by discriminant analysis; therefore, this study employs logistic regression model to predict corporate failure. The probability that firms suffer events of financial distress can be expressed as equation (1).

$$P_i = E(Z_i) = F(\omega' x_i) = \frac{1}{1+e^{-\omega' x_i}} = \frac{e^{\omega' x_i}}{1+e^{\omega' x_i}} \qquad (1)$$

where Z_i is a dummy variable, which is set to one only in the year in which a financial distress occurred; otherwise Z_i is equal to zero. Under binary logit model, the probability that firms suffer financial distress can be expressed as equations (2).

$$\ln\left(\frac{P_i}{1-P_i}\right) = \omega' x_i \qquad (2)$$

where P_i is the probability that the ith firm suffers financial distress. The variables x_i are the explainers of financial distress conditions. This work follows Teng et al. (2011) and Wang et al. (2010) to apply financial ratios, market variables and corporate governance variables in detecting corporate failure. Financial ratio variables are working capital to total assets, retained earnings to total assets, earnings before interest and taxes to total assets, market equity to total liabilities, sales to total assets, net income to total assets, total liabilities to total assets, and current assets to current liabilities. Three market variables adopted by this work are excess returns, logarithm of size of each firm relative to the total size of the Taiwan Stock Exchange, and idiosyncratic standard deviation of the stock return of each firm. Furthermore, firm age is defined as the number of calendar years that the firm has existed in Taiwan. This article applies the logarithm of the number of calendar years that sample firms have been existed in Taiwan as firm age variable. The corporate governance variables include ownership ratio of the insiders, pledge ownership ratio of the insiders, and deviation ratio between voting and cash flow rights. Insiders are directors, supervisors, managers and large shareholders (that own 10 percent or more of a company’s outstanding share).

2.2 Multinomial Logit Model

Multi-period multinomial logit model is used to estimate parameters based on data from each observation as if they constituted a separate observation. Unlike the binary Logit model, this paper distinguishes the financial conditions Y of the sample firms into three types: “non-failed” (j=1), “slightly-distressed” (j=2) and “reorganized and bankrupt” (j=3). Under multinomial logit model, the probability that firms suffer “slightly-distressed” events and “reorganization and bankruptcy” events can be expressed as following equations.

$$\text{Prob}(Y = j) = \frac{e^{\beta'_j x_i}}{1+\sum_{k=1}^{J} e^{\beta'_k x_i}} \qquad (j=1, 2, 3) \qquad (3)$$

$$\text{Prob}(Y = 0) = \frac{1}{1+\sum_{k=1}^{J} e^{\beta'_k x_i}} \qquad (4)$$

This work follows Nerlove and Press (1973) to apply multinomial logit model and then utilizes time-varying corporate variables x_i, to predict different extents of corporate failures. Parameters are estimated using the maximum likelihood estimation method in the training period sample.

3. Tests of Predictive Accuracy

3.1 Probability Forecast

The probability forecasts from the binary and multinomial logit models. Thus, the "slightly-distressed" and "reorganization and bankruptcy" firms are combined together as the failed firms, so the estimated probability of the failed firm ρ for the sample firm is the sum of the estimated probability of "slightly-distressed" events and that of "reorganization and bankruptcy" events.

$$\rho = \text{Prob}(Y=2) + \text{Prob}(Y=3) \tag{5}$$

Then, this study defines a cut-off point λ as the threshold which distinguishes failed firms from non-failed firms. If the estimated probability of failed firms exceeds cut-off point, then the firm is classified as failed; otherwise the firm is classified as non-failed.

3.2 Bootstrapping Simulation

The criteria employed to compare predictive ability of alternative models in our research is the misclassification errors, namely, the loss amount which are derived from the misjudging non-failed firms into failed firms or the other way around. If the firm suffers from financial distress but its forecasted probability of financial distress is smaller than the cut-off rate and is erroneously categorized as non-failed, a type I error occurs and the economic loss of the type I error is θ_1. If firm is non-failed but is erroneously categorized as failed, a type II error occurs and the economic loss of the type II error is θ_0. Bootstrapping is iterated 1,000 times to estimate the empirical distributions of misclassification error rates to determine the critical values for hypotheses testing (Hopwood et al. 1994). The estimated misclassification cost (EMC) can be computed as equation (6)

$$EMC = \rho_i \times \theta_1 \times p(\hat{\rho}_i < \lambda \mid Y = 2,3) + (1-\rho_i) \times \theta_0 \times p(\hat{\rho}_i > \lambda \mid Y = 1) \tag{6}$$

Here, $p(\hat{\rho}_i < \lambda \mid Y = 2,3)$ is the rate of type I error and $p(\hat{\rho}_i > \lambda \mid Y = 1)$ is the rate of type II error. Hopwood *et al.* (1994) assumes the optimal cut-off point should be chosen with the condition that the expected costs of missed crises are equal to those of false alarms. We follows the work of Hopwood *et al.* (1994) to choose the optimal cut-off point with the condition that the expected cost of misclassifying distressed companies as non-distressed ones ($\lambda\times\theta_1$) is equal to that of misjudging non-distressed companies as distressed ones ($(1-\lambda)\times\theta_0$).

From the above relations, we can rewrite $\lambda = \dfrac{\theta_0}{\theta_1 + \theta_0} = \dfrac{1}{(\theta_1/\theta_0)+1}$, where $\dfrac{\theta_1}{\theta_0}$ is the cost ratio. This means that the cutoff probability will decrease as the cost ratio increases. In practice, risk-averse decision makers view the loss generated by missed crises to be much more daunting than the loss generated by false alarm. For completeness, we simulate the cost-ratio (θ_1/θ_0) from 1 to 99, so the cut-off-points of financial distress λ ranging from 0.01 to 0.5 is examined in our research. EMC is an ex post measure, so (1-ρ) and ρ, are the actual population proportions of failed and non-failed firms, respectively. We utilize EMC values to investigate the predictive ability of the proposed models.

4. Results

The study sample comprises Taiwan-listed companies excluding the financial industry due to its different nature, and firms without sufficient data. Data in 2003 to 2006 is the training sample, while data in 2007 and 2008 is the test sample. Information used to predict financial distress (including financial ratios variables, market variables, and corporate governance) is collected from the previous year of the event year. Company financial distress event and prediction information are collected from various sources in the Taiwan Economic Journal (TEJ) database.

4.1 Estimation of Logit Models

The results of binary logit model and multinomial logit models are listed in Panel A and Panel B of Table 1, respectively. As for the corporate governance variables in the binary logit model, the coefficients of corporate governance variables, pledge ownership ratios of the insiders, are significant for “failed” firms at the 1% significance level, while the coefficients of financial ratios, except for the ratio of net income to total assets and total liabilities to total assets, are insignificant. Financial ratios, compared with corporate governance variables, are less relevant to the occurrence of “failed” events. This indicates that the mangers have incentives to manipulate financial ratios in accounting reports to cover up financial difficulties (Rosner, 2003). Thus, financial ratios reveal limited information, so corporate governance signal incremental information concerning “failed” events.

Table 1. Parameter estimation results of binary logit model and multinomial logit model

Panel A: Results of binary logit model

	Coefficient	**t-value**
Constant	-5.9833	-5.5256 ***
Natural logarithm of age	-0.1031	-0.5743
Current asset to current liability	-0.2464	-1.3104
Total liabilities to total assets	3.4290	4.7657 ***
Working capital to total assets	0.7692	1.1944
Retained earnings to total assets	0.2073	0.5723
Sales to total assets	-0.3140	-1.6443
Net income to total assets	-5.0417	-7.2496 ***
Market equity to total liabilities	0.0000	-0.2380
Abnormal returns	-0.3195	-1.8157
Firm's relative size	-0.0812	-1.0279
Idiosyncratic standard deviation of each firm's stock returns	0.2597	3.0722 ***
Ownership ratio of the insiders	-0.0093	-1.4692
Pledge ownership ratio of the insiders	0.0110	3.0347 ***
Deviation ratio between voting and cash flow rights	0.0094	0.9438

Note: *, ** and *** indicate significance at the level of 10%, 5% and 1%, respectively.

Panel B: Results of multinomial logit model

	Slightly Distressed			Reorganization and Bankruptcy		
	Coefficient	t-value		Coefficient	t-value	
Constant	-6.589781	-5.689523	***	-1.743341	-0.706249	
Natural logarithm of age	-0.170037	-0.883758		-0.095181	-0.255896	
Current asset to current liability	-0.174919	-1.014280		-1.880085	-2.273120	**
Total liabilities to total assets	2.904149	3.915618	***	4.577164	3.172012	***
Working capital to total assets	0.781368	1.192265		2.535851	1.781165	*
Retained earnings to total assets	0.089373	0.242431		0.297887	0.456194	
Sales to total assets	-0.256715	-1.263602		-0.461491	-1.134300	
Net income to total assets	-4.771801	-6.735008	***	-5.268047	-5.205522	***
Market equity to total liabilities	-0.000011	-0.134864		-0.001165	-1.609344	
Abnormal returns	-0.218845	-1.303680		-0.817389	-2.019665	**
Firm’s relative size	-0.150893	-1.760573	*	0.285454	1.969602	**
Idiosyncratic standard deviation of each firm’s stock returns	0.288657	3.282692	***	0.017213	0.100328	
Ownership ratio of the insiders	-1.169583	-1.680263	*	0.625347	0.526286	
Pledge ownership ratio of the insiders	1.291637	3.335938	***	0.240756	0.370956	
Deviation ratio between voting and cash flow rights	1.658059	1.597590		-4.558555	-1.677001	

Note: *, ** and *** indicate significance at the level of 10%, 5% and 1%, respectively.

Regarding multinomial Logit model, we can decide which factors are crucial for “slightly-distressed” and “reorganization or bankruptcy” firms. This study has discovered that "total liabilities to total assets" is significantly related to the company's financial conditions. This result coincides with Pasaribu's (2011) capital structure and the related conclusion of corporate failure. As for the corporate governance variables of “slightly-distressed” firms in the multinomial logit model, the coefficients of corporate governance variables, including ownership ratios of the insiders and pledge ownership ratio of the insiders, are significant for “slightly-distressed” firms at the 10% significance level, while the coefficients of financial ratios, except for the ratio of net income to total assets and total liabilities to total assets, are insignificant. Financial ratios, compared with corporate governance variables, are less relevant to the occurrence of “slightly-distressed” events. This indicates that the mangers have incentives to manipulate financial ratios in accounting reports to cover up slightly-distressed difficulties. Thus, financial ratios reveal limited information, so corporate governance signal incremental information concerning “slightly-distressed” events.

As for binary logit model, two of the six financial ratios are substantially significant for “failed” events, while one of the coefficients of the three corporate governance variable, pledge ownership ratios of the insiders, is statistically significant at the 5% significance level. The coefficient of pledge ownership ratios of the insiders are significant both in binary and multinomial logit models. At the 5% significance level, one of the three market variables is statistically related to “failed” events. This suggests that binary logit model hardly separate the explanatory factors for interpreting “slightly-distressed” events and “reorganization and bankruptcy” events. Because the reorganized and bankrupt firms truly express the operational difficulties in their financial statements, investors timely react to their devaluation of the reorganized and bankrupt firms, inducing the negative association between “bankruptcy and reorganization” events and abnormal returns. Regarding multinomial logit model, financial ratios and market variables dominate corporate governance information in predicting “reorganization and bankruptcy” events. The empirical results that illustrate the correlation between company performance and financial distress condition (Choy et al. 2011). Coefficients of financial ratios and market variables in binary logit model are not as obvious as those in multinomial logit model.

4.2 Comparison of Misclassification Errors between Binary Logit and Multinomial Logit Models

In multinominal model, 0.02 is the most optimal cut-off point at which can accurately distinguish the “non-failed” from the other firms. Meanwhile, the most optimal cut-off point to distinguish “reorganization and bankruptcy” firms from the other firms, in our training sample firms, is 0.17. The accuracy rate of multinomial logit model at these two specific cut-off points 0.02 and 0.17 in 2007 and 2008 are listed in Table 2. Because 0.05 is the most optimal cut-off point at which the classification between “non-failed” and the “failed firms” can be most accurately distinguished in binary logit model, so the accuracy rate of binary logit model at 0.05 cut-off point in 2007 and 2008 are listed in Table 2. The accuracy rates of the original sample firms are listed in the diagonal of the table and expressed by italic words. The accuracy rates of non-failed firms are 90.98% and 91.44% in multinomial logit model and binary logit model, respectively in 2007. The accuracy rates of non-failed firms are 95.91% and 96.09% in multinomial logit model and binary logit model, respectively in 2008. Since the accuracy rates is greater in binary logit models than in multinomial logit model, binary logit model performs better than multinomial logit model in predicting the financial health of companies both in 2007 and 2008.

Table 2. Accuracy rate of multinomial logit model and binary logit model in 2007 and 2008

Multinomial		True Condition			Binary	True Condition	
2006		Non-failed	Slightly-distressed	Bankruptcy and Reorganization		Non-failed	Failed
	Non-failed	*90.98%*	7.14%	12.50%			
Test	Slightly- distressed	6.79%	*7.14%*	0.00%	Non-failed	*91.44%*	9.09%
	Bankruptcy and reorganization	2.23%	85.71%	*87.50%*	Failed	8.56%	*90.91%*
2007		Non-failed	Slightly-distressed	Bankruptcy and Reorganization		Non-failed	Failed
	Non-failed	*95.91%*	62.50%	20.00%			
Test	Slightly- distressed	3.18%	*33.33%*	40.00%	Non-failed	*96.09%*	55.17%
	Bankruptcy and Reorganization	0.91%	4.17%	*40.00%*	Failed	3.91%	*44.83%*

Notes: The accuracy rates are listed in the diagonal of the table and expressed by italic words.

In terms of misclassification, the possible mistakes of the binary logit model are only two types: misclassifying non-failed firms as failed firms, and vice versa. However, the possible mistakes of the multinomial logit model are much more: misclassifying non-failed as bankrupt or as slightly-distressed; misclassifying slightly-distressed or bankrupt firms as non-failed; and misclassifying bankrupt firms as slightly-distressed, or vice versa. Binary logit model eliminates the possibility of the last two mistakes of misclassifying bankrupt firms as slightly-distressed, and vice versa. However, even without considering these two mistakes, the binary logit model is still more accurate than the multinomial logit model. In 2007, the misclassification of non-failed firms into "slightly-distressed" firms (6.79%) and into "reorganization and bankruptcy" firms (2.23%) are totally 9.02% in multinomial logit model. The misclassification rate of "slightly-distressed" and "reorganization and bankruptcy" firms into non-failed firms is totally 19.64% (7.14%+12.50%=19.64%) in multinomial logit model. In binary logit model, the misclassification rate of failed firms into non-failed ones and non-failed firms into failed ones are only 9.09% and 8.56%, respectively.

In 2008, the misclassification of non-failed firms into "slightly-distressed" firms (3.18%) and "reorganization and bankruptcy" firms (0.91%) are totally 4.09% in multinomial logit model, the misclassification rate of "slightly-distressed" and "reorganization and bankruptcy" firms into non-failed firms is totally 82.50% (62.50%+20%=82.50%). In binary logit model, the misclassification rate of failed firms into non-failed ones and non-failed firms into failed ones are only 55.17% and 3.91%, respectively. Generally speaking, the misclassification error rate of the binary logit model is also smaller than that of the multinomial logit model in predicting corporate failures in 2008. Comparing the forecast accuracy in 2007 with that in 2008, the forecast is much more accurate in 2007 than in 2008. This suggests the short-run forecast is more accurate than the long-term forecast. To further compare forecast ability between binary and multinomial logit models at various cut-off points, the error comparison of each cut-off point are listed in Table 3 and Table 4.

Table 3. Error comparison at various cut-off points between binary and multinomial logitmodels for the test sample in 2007, namely, (*Error*^{Binary}-*Error*^{Multinomial})

Cut-off	**Type I plus Type II Error**		**EMC**		**Type I Error**	
Point	Difference	t-value	Difference	t-value	Difference	t-value
0.0100	0.0209	9.0712 ***	-0.1546	-34.1663 ***	-0.0312	-34.5097 ***
0.0200	0.0017	1.2997	-0.0575	-22.3968 ***	-0.0118	-12.7919 ***
0.0300	-0.0147	-13.5369 ***	-0.0587	-31.2063 ***	-0.0169	-15.5883 ***
0.0400	-0.0162	-14.1563 ***	-0.0499	-32.8143 ***	-0.0146	-11.1022 ***
0.0500	-0.0108	-9.0942 ***	-0.0399	-32.8288 ***	-0.0084	-6.1135 ***
0.0600	-0.0081	-6.8035 ***	-0.0351	-35.6351 ***	-0.0056	-4.0338 ***
0.0700	-0.0071	-5.8651 ***	-0.0319	-38.1936 ***	-0.0054	-3.9584 ***
0.0800	-0.0068	-5.8643 ***	-0.0291	-42.0479 ***	-0.0062	-4.7401 ***
0.0900	-0.0076	-6.4670 ***	-0.0270	-43.4525 ***	-0.0080	-6.1444 ***
0.1000	-0.0072	-6.1902 ***	-0.0246	-44.1382 ***	-0.0082	-6.4029 ***
0.1100	-0.0102	-8.5670 ***	-0.0239	-46.2504 ***	-0.0116	-8.9917 ***
0.1200	-0.0157	-12.5414 ***	-0.0243	-48.7952 ***	-0.0174	-12.8647 ***
0.1300	-0.0202	-15.6430 ***	-0.0241	-51.2031 ***	-0.0219	-15.8854 ***
0.1400	-0.0264	-19.3331 ***	-0.0245	-53.9408 ***	-0.0281	-19.4292 ***
0.1500	-0.0314	-21.9158 ***	-0.0245	-56.4990 ***	-0.0331	-21.8436 ***
0.1600	-0.0368	-24.4316 ***	-0.0245	-58.6098 ***	-0.0386	-24.3371 ***
0.1700	-0.0419	-26.1006 ***	-0.0243	-59.0351 ***	-0.0438	-26.1032 ***
0.1800	-0.0467	-27.4975 ***	-0.0241	-60.0369 ***	-0.0487	-27.4896 ***
0.1900	-0.0501	-27.9628 ***	-0.0236	-59.8692 ***	-0.0521	-28.0378 ***
0.2000	-0.0532	-28.2550 ***	-0.0232	-60.1727 ***	-0.0551	-28.3271 ***
0.2100	-0.0559	-27.8395 ***	-0.0228	-59.9150 ***	-0.0576	-27.8726 ***
0.2200	-0.0576	-26.9853 ***	-0.0223	-59.6278 ***	-0.0592	-26.9644 ***
0.2300	-0.0584	-25.7026 ***	-0.0217	-58.8539 ***	-0.0597	-25.6470 ***
0.2400	-0.0579	-24.1308 ***	-0.0210	-58.0643 ***	-0.0590	-24.0358 ***
0.2500	-0.0561	-22.5275 ***	-0.0201	-57.1200 ***	-0.0570	-22.4026 ***
0.2600	-0.0519	-20.0069 ***	-0.0190	-55.7799 ***	-0.0526	-19.8430 ***
0.2700	-0.0474	-17.6140 ***	-0.0181	-54.9593 ***	-0.0478	-17.3875 ***
0.2800	-0.0432	-15.5411 ***	-0.0172	-53.7589 ***	-0.0434	-15.3064 ***
0.2900	-0.0387	-13.4798 ***	-0.0164	-52.6677 ***	-0.0386	-13.1960 ***
0.3000	-0.0333	-11.1964 ***	-0.0155	-51.2647 ***	-0.0330	-10.8934 ***
0.3100	-0.0277	-9.0396 ***	-0.0146	-50.1151 ***	-0.0273	-8.7194 ***
0.3200	-0.0213	-6.7581 ***	-0.0139	-48.8066 ***	-0.0206	-6.4104 ***
0.3300	-0.0132	-4.0748 ***	-0.0130	-46.7130 ***	-0.0123	-3.7259 ***
0.3400	-0.0045	-1.3749	-0.0121	-45.4159 ***	-0.0034	-1.0163 ***
0.3500	0.0034	0.9944	-0.0114	-44.0808 ***	0.0047	1.3756 ***
0.3600	0.0116	3.4120 ***	-0.0107	-43.3076 ***	0.0132	3.8043 ***
0.3700	0.0205	6.0137 ***	-0.0099	-42.1006 ***	0.0223	6.4004 ***
0.3800	0.0291	8.5165 ***	-0.0093	-40.9201 ***	0.0310	8.9039 ***
0.3900	0.0379	11.1738 ***	-0.0087	-40.1384 ***	0.0400	11.5775 ***
0.4000	0.0457	13.5730 ***	-0.0082	-39.7785 ***	0.0479	13.9733 ***
0.4100	0.0530	15.9481 ***	-0.0078	-39.6724 ***	0.0555	16.3729 ***
0.4200	0.0592	18.0212 ***	-0.0076	-40.2485 ***	0.0619	18.4925 ***
0.4300	0.0639	19.6323 ***	-0.0074	-41.0098 ***	0.0667	20.1418 ***
0.4400	0.0678	21.1043 ***	-0.0073	-42.0614 ***	0.0708	21.6590 ***
0.4500	0.0724	22.7879 ***	-0.0072	-43.0497 ***	0.0756	23.3899 ***
0.4600	0.0753	24.0059 ***	-0.0071	-44.4138 ***	0.0786	24.6525 ***
0.4700	0.0788	25.4285 ***	-0.0070	-45.0814 ***	0.0821	26.1184 ***
0.4800	0.0810	26.2849 ***	-0.0070	-46.4352 ***	0.0844	27.0195 ***
0.4900	0.0824	26.5590 ***	-0.0070	-47.8547 ***	0.0860	27.3357 ***
0.5000	0.0843	27.3249 ***	-0.0070	-49.3293 ***	0.0879	28.1427 ***
Mean		-0.0049	-0.0226		-0.0026	

*Significant at the 10% level; **Significant at the 5% level; ***Significant at the 1% level.

Table 4. Error comparison at various cut-off points between binary and multinomial logit models for the test sample in 2008, namely, ($Error^{Binary}$ - $Error^{Multinomial}$)

Cut-off Point	Type I plus Type II Error: Difference	Type I plus Type II Error: t-value	EMC: Difference	EMC: t-value	Type I Error: Difference	Type I Error: t-value
0.0100	0.0297	10.8061 ***	-0.0143	-1.9942 **	-0.0129	-6.1345 ***
0.0200	-0.0017	-0.8389	-0.0402	-8.8914 ***	-0.0332	-13.3814 ***
0.0300	-0.0184	-8.7591 ***	-0.0326	-10.8517 ***	-0.0341	-14.1946 ***
0.0400	-0.0034	-1.6292	-0.0041	-1.8803 *	-0.0104	-4.5846 ***
0.0500	0.0126	5.9887 ***	0.0108	6.2841 ***	0.0091	4.1042 ***
0.0600	0.0159	7.3784 ***	0.0113	7.7557 ***	0.0141	6.3092 ***
0.0700	0.0139	6.0319 ***	0.0083	6.3158 ***	0.0130	5.5048 ***
0.0800	0.0079	3.1807 ***	0.0040	3.2923 ***	0.0078	3.0229 ***
0.0900	0.0029	1.0758	0.0012	1.0527	0.0030	1.0838
0.1000	-0.0026	-0.9522	-0.0011	-1.0992	-0.0024	-0.8500
0.1100	-0.0050	-1.8486 *	-0.0019	-2.0874 **	-0.0048	-1.7079
0.1200	-0.0067	-2.5057 **	-0.0022	-2.7517 ***	-0.0065	-2.3787
0.1300	-0.0054	-2.1116 **	-0.0016	-2.2319 **	-0.0054	-2.0528
0.1400	-0.0013	-0.5184	-0.0002	-0.3353	-0.0015	-0.5788
0.1500	0.0032	1.3538	0.0011	1.9867 **	0.0028	1.1519
0.1600	0.0050	2.2001 **	0.0015	3.2706 ***	0.0044	1.8934
0.1700	0.0052	2.4466 *	0.0016	3.8658 ***	0.0046	2.0833
0.1800	0.0054	2.6675 ***	0.0016	4.3943 ***	0.0048	2.2654
0.1900	0.0058	3.0104 ***	0.0016	5.2904 ***	0.0051	2.5296
0.2000	0.0068	3.6470 ***	0.0018	6.3511 ***	0.0061	3.1209 ***
0.2100	0.0058	3.2425 ***	0.0015	6.2367 ***	0.0051	2.7159 ***
0.2200	0.0062	3.5359 ***	0.0015	6.6281 ***	0.0055	3.0237 ***
0.2300	0.0062	3.6375 ***	0.0014	6.8980 ***	0.0056	3.1279 ***
0.2400	0.0060	3.6299 ***	0.0012	6.7000 ***	0.0055	3.1675 ***
0.2500	0.0062	3.8394 ***	0.0012	6.7432 ***	0.0058	3.4161 ***
0.2600	0.0055	3.4664 ***	0.0009	5.8902 ***	0.0052	3.1203 ***
0.2700	0.0048	3.0989 ***	0.0007	5.0271 ***	0.0046	2.8243 ***
0.2800	0.0042	2.8242 ***	0.0006	4.2565 ***	0.0041	2.6127 ***
0.2900	0.0040	2.6827 ***	0.0004	3.2954 ***	0.0040	2.5579 **
0.3000	0.0033	2.2700 **	0.0003	2.1231 ***	0.0034	2.2244 **
0.3100	0.0033	2.2657 **	0.0002	1.7237 ***	0.0034	2.2518 **
0.3200	0.0032	2.1584 **	0.0001	0.9314 ***	0.0034	2.2004 **
0.3300	0.0036	2.4685 **	0.0001	0.7454 ***	0.0039	2.5340 **
0.3400	0.0031	2.1662 **	0.0000	0.1075 ***	0.0034	2.2574 **
0.3500	0.0022	1.4975	-0.0001	-1.1565 ***	0.0025	1.6461 *
0.3600	0.0015	1.0154	-0.0002	-2.1373 ***	0.0018	1.2094
0.3700	0.0019	1.3126	-0.0002	-1.7618 ***	0.0022	1.4830
0.3800	0.0020	1.3729	-0.0002	-2.2757 ***	0.0024	1.5699
0.3900	0.0017	1.1958	-0.0002	-2.7889 ***	0.0021	1.4120
0.4000	0.0007	0.4757	-0.0003	-3.8543 ***	0.0011	0.7331
0.4100	0.0002	0.1505	-0.0004	-4.6022 ***	0.0007	0.4367
0.4200	-0.0007	-0.4837	-0.0004	-5.5130 ***	-0.0002	-0.1609
0.4300	-0.0013	-0.9138	-0.0005	-6.0035 ***	-0.0009	-0.5764
0.4400	-0.0016	-1.1363	-0.0005	-6.5480 ***	-0.0011	-0.7687
0.4500	-0.0014	-1.0128	-0.0005	-6.6657 ***	-0.0009	-0.6364
0.4600	-0.0018	-1.3120	-0.0005	-7.0543 ***	-0.0013	-0.9196
0.4700	-0.0019	-1.3252	-0.0006	-7.2961 ***	-0.0013	-0.9213
0.4800	-0.0014	-0.9990	-0.0005	-6.9108 ***	-0.0009	-0.6166

0.4900	-0.0013	-0.9108	-0.0005	-7.1111 ***	-0.0008	-0.5237
0.5000	-0.0011	-0.7864	-0.0005	-7.0129 ***	-0.0006	-0.4057
Mean	0.0027		-0.0010		0.0006	

*Significant at the 10% level; **Significant at the 5% level; ***Significant at the 1% level.

4.3 Comparison of Errors at Various Cut-off Points Ranging from 0.01 to 0.50 between Binary and Multinomial Logit Model

In this section, bootstrapping is iterated 1,000 times to estimate the empirical distributions of misclassification error rates and EMCs to determine the critical values for hypotheses testing. Table 3 and Table 4 illustrate error comparison of these 1,000 resamples at various cut-off points ranging from 0.01 to 0.5 between binary and multinomial logit models for the test sample in 2007 and 2008, respectively. Three errors indicators are Type I plus Type II errors, EMCs and Type I errors. In Table 3, the Type I plus Type II errors, EMCs and Type I errors are larger in multinomial logit models than binary logit models on average. Only eighteen, zero, sixteen of the 50 error difference ($Error^{Binary}$-$Error^{Multinomial}$) in Type I plus Type II errors, EMCs and Type I errors are positive in 2007. In general, the EMCs of binary logit model are statistically smaller than those of multinomial logit model at all of 50 cut-off points ranging from 0.01 to 0.50 in 2007. Binary logit model performs superior to multi-nominal logit model in 2007.

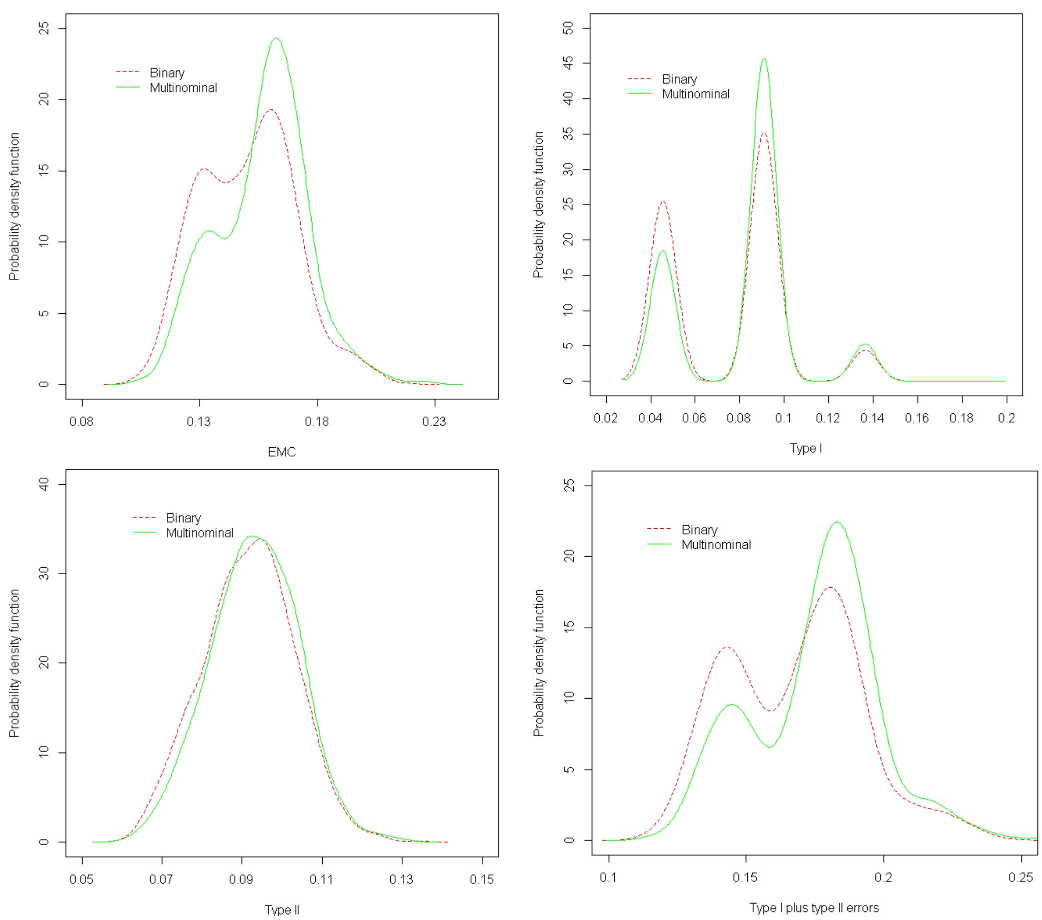

Figure 1. Probability density function of misclassification errors and EMC at cut-off points 0.05 in 2007

In Table 4, the average error difference ($Error^{Binary}$-$Error^{Multinomial}$) of Type I plus Type II errors, EMCs and Type I errors are 0.0027, -0.0010 and 0.0006. 33, 25, and 32 of 50 error difference ($Error^{Binary}$-$Error^{Multinomial}$) of Type I plus Type II errors, EMCs and Type I errors are almost positive at all of 50 cut-off points ranging from 0.01 to 0.50 in 2008. Combining the results in EMCs and misclassification errors, the difference between these two models is not clearly substantial in 2008. This work can not conclude which model performs better than the other in 2008.

4.4 Comparison of PDF between Binary Logit Model and Multinomial Logit Model

This work iterates bootstrapping simulations 1000 times to obtain 1,000 resamples. Figs. 1 and 2 depict the PDF of the misclassification error rate graph for the 1,000 resamples at 0.05 cut-off points (λ=0.05) for the test sample in 2007 and 2008, respectively, because in binary logit model 0.05 is the most optimal cut-off point at which the classification between "non-failed" and the "failed firms" can be most accurately distinguished. The PDF results indicate the proportion of the 1,000 re-samples at each misclassification error rate or EMC. More EMCs of the 1000 re-samples in 2007 are computed by the multinomial logit model to be over 0.1516 than those computed by the binary logit model. More type I plus type II errors of the 1000 re-samples are computed by the multinomial logit model to be over 0.1708 than those computed by the binary logit model. On the other hand, it is difficult to compare the forecast accuracy through the PDF of binary logit model and multinomial logit models in 2008. Generally speaking, the misclassification error rates computed by the multinomial logit model are more than those computed by the binary logit model, signifying that the multinomial logit model is consistently less precise and yields more estimated error.

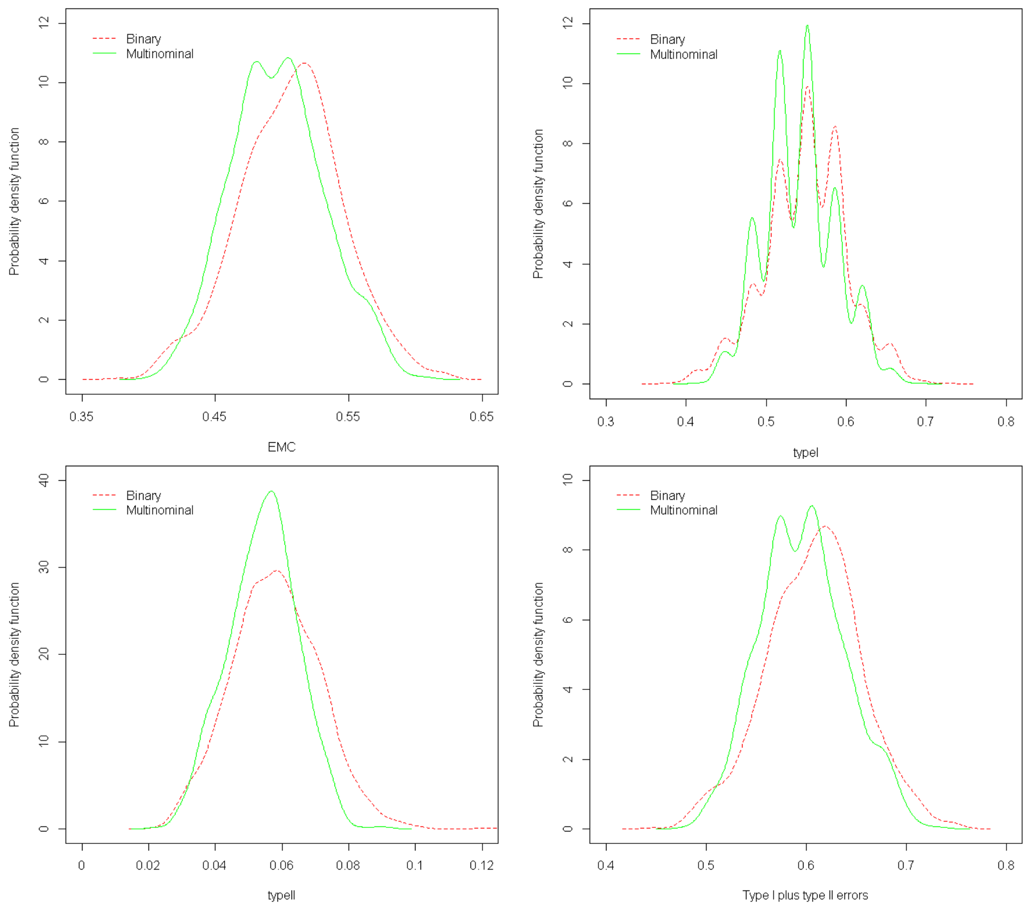

Figure 2. Probability density function of misclassification errors and EMC at cut-off points 0.05 in 2008

5. Conclusions

This study classifies two financial difficulties according to the magnitudes that personnel outside the corporations are able to detect: "slightly-distressed" and "reorganization and bankruptcy" events. The multinomial logit model is therefore employed to capture the differential extents of whether financial ratios, market variables or corporate governance indicators are related to different financial states. In addition, this paper further estimates the probabilities that a firm will enter each of the three financial statuses and compares the forecast accuracy between the multinomial logit model and the binary logit model.

As for the sample firms in 2007, the misclassification error rates of binary logit model is smaller than multinomial logit model in predicting corporate failures. Of the 1,000 resamples iterated through 1000 times of bootstrapping simulations, the average Type I plus Type II errors, EMCs and Type I errors of binary logit model are statistically smaller than those of multinomial logit model at all of 50 cut-off points ranging from 0.01 to 0.50 in 2007. Binary logit model performs superior to multinominal logit model in 2007. Additionally, this works depict the PDF graph of the misclassification error rates and EMCs for the 1,000 resamples at 0.05 cut-off points in 2007 and 2008, respectively. More errors of the 1000 re-samples are computed by the multinomial logit model than those computed by the binary logit model in 2007. More EMC and errors are generated by the multinomial logit model than those generated by the binary logit model in 2007. This work finds that the binary logit model performs superior to the multinomial logit model.

This work finds that the binary logit model performs superior to the multinomial logit model. The results of this study indicate that the forecast performance of the multinomial logit model, which classifies corporate failure events as slightly-distressed firms and bankruptcy-and-reorganization firms, is not more accurate than that of the binary logit model which categorizes both slightly-distressed firms and bankruptcy-and-reorganization firms as corporate failure. The results imply that the slightly-distressed firms and bankruptcy-and-reorganization firms are similar in characteristics. The misclassification loss does not decrease if we employ multiple classifications of corporate failures. The occurrence of slightly-distressed events is already on the verge of bankruptcy, so investors and debtors should be alert to withdraw their investments or terminate their loans to prevent loss.

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