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CREDIT RISK FACTORS DURING THE ASIAN AND GLOBAL FINANCIAL CRISES

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ABSTRACT

This study measures the effects of specific credit risk factors of companies that defaulted during the Asian currency and global credit crises. Using Taiwanese listed companies' data, the predictability of specific credit risk factors were discrepancies during these 2 crises. First, I captured variables from Altman's (1968) Z-score model, a pioneer and notable model based on Accounting Data, from the Merton distance to default (DD) model, and from the naïve probability model-an alternative of the Merton DD model. The significance of the Z-score model variables are examined by applying the logit model. Furthermore, the forecasting ability of the logit model, Merton DD model, naïve probability, and the Taiwan corporate credit rating index are compared. The findings of this study indicate that the financial ratio of sales to total assets was the most crucial factor during the Asian financial crisis. Moreover, the ratio of retained earnings to total assets and the Merton DD were critical factors during the Global financial crisis. The predictability of the traditional logit model using the Z-score model variables performed well.

JEL: G00, G33, G39

KEYWORDS: Credit Risk, Financial Crises, Logit Model, Merton Model, Z-Score Model

INTRODUCTION

The credit crises experienced by enterprises and financial institutions are usually exacerbated during the sudden onset of a financial tsunami. In other words, financial crises often cause widespread credit crises among enterprises. Thus, these two issues, credit crises and financial crises, are highly correlated and should be assessed simultaneously. This study examines whether there are different credit risk factors that affected defaulted companies during the 1997 Asian financial crisis and the 2007 Global financial crisis. In addition, this study examines the effectiveness of specific credit risk prediction models. These two financial crises are assessed for the following reasons. First, the causes of these crises differ. In contrast with the Asian currency attack in 1997, the global crisis was the result of credit and liquidity difficulties. Thus, an analysis of these two events could provide a suitable basis for comparison. Second, Taiwan was not the storm centre of these two crises; however, Taiwan was substantially affected by these events. Finally, because the Asian and Global financial crises were the most recent financial tsunami to affect Taiwan, these crises are valuable empirical events for researching credit risks for Taiwanese listed companies. This study could assist enterprises and financial institutions in resisting any future financial crises.

In *The New York Times* on June 27, 2010, Paul Krugman predicted that the world economy might soon experience a third recession. Unlike the previous two crises, the third recession is anticipated to cause an extended period of high currency volatility, economic instability, and high unemployment. It is likely that numerous unhealthy enterprises would experience substantial credit problems during such a financial crisis, which would negative consequences for creditors and financial institutions. In consideration of the potential consequences of a third recession, this study provides a proactive assessment of specific credit risk factors under various financial crises to provide pre-warning signals that might assist enterprises during a recession. First, this study measures the prediction accuracy of credit risk factors associated with the Asian and global financial crises for Taiwanese listed companies. The traditional financial ratio-based Z-score variables (Altman, 1968) are applied to capture the accounting data and market value information. The reason why I use Z-score variables is because the Z-score model is the basis of many commercially prevalent models, such as Moody's KMV RiskCalc, Standard and Poor's credit model, and the BondScore model. In addition to the credit risk factors based on the accounting data and market values model, I serve the distance to default of the Merton DD model as the stock price variable. However, Bharath and Shumway (2008) indicated that "the usefulness of the MKMV probability is due to the functional form suggested by the Merton model. The iterative procedure used to solve the Merton model for default probability does not appear to be useful" (p. 1367-1368). Therefore, I apply the naïve probability model proposed by Bharath and Shumway (2008) as an alternative model. Under the logit model, the information from these credit risk variables can be transformed into a default probability. Further, the significance of the credit risk variables can be detected. Second, this study further examines the forecasting ability of certain credit risk prediction models. Third, this study introduces the Taiwan corporate credit rating index (TCRI), and compares the effectiveness of TCRI with these credit risk models.

I find that the estimated coefficients for *SR/TA* are negative and statistically significantly different from zero and they are -10.328, -8.686, and -10.842 respectively for 1Q, 2Q, and 3Q in Model 2 during the Asian financial crisis. During the global financial crisis, *RE/TA* had a statistically significant and negative effect on default probability and the coefficients of *RE/TA* are -5.961, -4.195, and -6.474 respectively for 1Q ($p < .01$), 2Q ($p < .05$%), and 3Q ($p < .01$) in Model 2. Furthermore, the coefficient of DD_{Merton} variable is only statistically significantly different from zero during the global financial crisis. The remainder of this study is organised as follows. Literature review is introduced in the following section. Section 3 details the research data, variable definitions, and descriptive statistics. Section 4 shows the empirical results, including the logit model results and the predictive power of the logit, Merton DD, and naïve probability models, as well as the TCRI. Finally, Section 5 presents the conclusion for this study.

LITERATURE REVIEW

Credit risk is has been widely discussed in academic research and practical analysis for decades (Sobehart et al. 2000, Crosbie and Bohn, 2003, Delianedis and Geske, 2003, Duffie and Singleton, 2003, Huang and Huang, 2003, Leland, 2004, Parnes, 2006). Particularly, after the Basel II agreement introduced the internal rating-based approach to banks and financial institutions, banks could build internal rating models. The practitioners commenced assessing the measurement techniques of credit risk and subsequently developed numerous credit risk models. Cauette et al. (2008) separated traditional credit risk models into the following two categories: (a) models based on accounting data and market values; and (b) models based on stock prices. To predict business failures using financial ratios, Beaver (1966) built a univariate model based on the accounting data and market values model and predicted business failure by analysing specific financial ratios five years prior to a business default. Altman (1968) and Deakin (1972) also developed a multivariate model to predict business failure by employing multivariate discriminant analysis. To identify business that might vulnerable to financial failure, analysts can employ the Altman Z-score, which is calculated by applying the following five financial ratios: (a) liquidity ratio; (b) profitability ratio; (c) leverage ratio; (d) solvency capability; and (e) asset turnover ratio. Altman et al. (1977) introduced the ZETA model, which is a revision of Altman's Z-score, to predict retail business failure in response to changes in the macroeconomic conditions and accounting principles.

Despite their widespread application, multivariate models possess numerous limitations. First, the prediction accuracy decreases when nonlinear variables are analysed by applying a linear discriminant analysis method. Second, the accounting data and market values model capture the accounting book value, which occasionally fails to reflect the actual financial activities of the obligor. Third, financial experts have expressed concern over a lack of theoretical foundation supporting the validity of multivariate analysis. That's why, it is popularly accepted by the academic research when Merton (1974) interpreted company equity value as a call option on company assets, and estimated the business failure rate by applying Black-Scholes' option valuation model. In addition to the accounting variables, it seems necessary to gather other information and relevant variables to improve the accuracy of models (Ohlson, 1980). Merton (1974) included assets value to measure credit risk by applying an option pricing model. Merton's model, a pioneer model using assets value, established a more comprehensive theoretical foundation than previous research that had analysed financial ratios only. Hereafter, there are several practical techniques implementing Merton's model. For example, the expected default frequency (EDF) model of Moody's KMV (MKMV) is quite well-known in practice. To solve Merton's equations, certain studies have employed equity value and its volatilities (Ronn and Verma, 1986), and Vassalou and Xing (2004) constructed a complex iterative procedure.

DATA AND METHODOLOGY

This study examines the credit risk factors and investigates the predictive power of certain credit risk models in Taiwan during the Asian and global financial crises. Using data Taiwanese listed companies, the default companies form the experimental group, and the non-default companies are the control group. The financial ratios, stock price data, and default information employed in this study are derived from the *Taiwan Economic Journal* (*TEJ*) database. In this study, all default companies refer to companies that are categorised as "companies with insolvent problems" in the *TEJ*. During the collection of the samples, the companies with insolvent problems were chosen during the Asian financial crisis (1997–2000), and the global financial crisis (2007–2009) (Chang and Kuo, 2010). The sample excludes the finance industry as well as the building and construction industry because their industry characteristics exhibit unique capital structures in comparison with other industries. For example, the debt ratio of a typical financial institution is greater than 90%, and the asset turnover rate of a construction company different substantially from other manufacturing companies. Under these sampling criteria, there were 44 defaulted companies during the Asian financial crisis, among which 10 operated in the iron and steel industry. In addition, 43 companies failed during the global financial crisis, among which 31 operated in the electronics industry.

Next, the sample size of the non-default sample, which has similar capital to the corresponding default company during the same period, is selected twice as big as the default one. To analyse the default forecasting models, I collected data from the financial statements announced three quarters prior to defaulting. However, because three companies had missing data during Asian financial crisis period and two companies had missing data during the global financial crisis in the first quarter prior to defaulting (1Q), the sample of non-default companies was reduced to six during the Asian financial crisis, and to four during the global financial crisis. The basic inputs for the logit model in this study include the following default information and five financial ratios: (a) working capital *WC*; (b) retained earnings *RE*; (c) earnings before interest and tax *EBIT*; and (d) sales revenues *SR*. Each of these are divided by the total assets *TA*, and the market value of equity *ME* divided by the total liability *TL*, and the default indicator y_i. To capture the credit risk factor based on the stock price model, two variables were set into the logit model—the distance to default estimated from the Merton DD model and the naïve probability. The inputs to the Merton DD model and the naïve probability are *ME*, market value of each firm's equity F, face value of debt r, risk-free rate r_{it-1}, stock return of Company i over the previous year, and time T. *ME* is calculated from the *TEJ* database as the product of the share price of Company i at the end of the day and the number of outstanding shares. F is the debt in current liabilities plus half of the long term debt (Vassalou and Xing, 2004, Bharath and Shumway, 2008).

For r, this study employed the 1-year deposit rate set by the Bank of Taiwan. σ_E, the annualised standard deviation of returns, is estimated from the prior year log stock return data for each month. Data from financial statements typically contain several extreme values. To ensure that the statistical results are not affected by outliers, it is necessary to follow the Winsorisation method in Bharath and Shumway (2008). First, the prediction variables are sorted. Subsequently, all observations lower than the 1st percentile of each variable are set equal to 1st percentile, and all values higher than the 99th percentile of each variable are winsorized in the same manner. Tables 3 and 4 provide several descriptive statistics and t test results for all of the winsorized variables from the Asian and the global financial crises, respectively. First, I conducted a basic statistical analysis. Subsequently, I calculated a sample mean t test for the logit model variables to determine whether a significant difference exists for each variable between the default and non-default companies. The descriptive statistics show that the means of all logit model variables for the non-default companies are significantly greater than those for the default companies.

This shows that prior to defaulting, the default companies experienced problems associated with a lack of available funds, and their short-term solvency was relatively poor and deteriorating. Moreover, from the third quarter prior to defaulting (3Q) to 1Q, I observed that as the defaulting point approaches, the decreasing velocity of all of the variable means for the default companies is faster; however, the means are relatively stable for the non-default companies during both the Asian and global financial crises. Based on this result, it can be speculated that because of excessive borrowing, the default companies experienced short-term liquidity shortages, and mismanagement resulted in a loss that ultimately led to the financial crises. According to Table 1, during the Asian financial crisis period, the results of the sample mean *t* test are statistically significantly different from zero ($p < .01$) for all variables except *EBIT/TA* and $DD_{Naïve}$ in 1Q–3Q. The *EBIT/TA* t test is non-significant in the second quarter prior to defaulting (2Q), and the $DD_{Naïve}$ t test is only significantly at $p < .05$. The estimated results indicate that these predictor variables differ substantially between the default and non-default companies, implying that the liquidity, profitability, operating efficiency, solvency, and asset turnover rate of the non-default companies compared with the default companies are good in substance during the Asian financial crisis. In addition, the forecasting ability of $DD_{Naïve}$ seems poorer than that of $DD_{Mertton}$.

Table 1: Descriptive Statistics and T-tests (during the Asian Financial Crisis)

Panel A: The First Quarter Prior to Defaulting

	Default				Non-Default				t-test	
Variable	Mean	Stdev	Min	Max	Mean	Std. dev.	Min	Max	t-test	p-value
WC/TA	-0.093	0.244	-0.570	0.596	0.151	0.162	-0.294	0.596	-5.800	0.000
RE/TA	-0.184	0.280	-0.995	0.069	0.040	0.068	-0.127	0.191	-5.057	0.000
EBIT/TA	-0.089	0.189	-0.783	0.030	0.013	0.016	-0.034	0.043	-3.431	0.001
ME/TL	1.558	2.053	0.200	10.015	3.638	2.822	0.240	11.609	-4.652	0.000
SR/TA	0.117	0.067	0.022	0.303	0.200	0.115	0.022	0.581	-5.029	0.000
DD_{Merton}	-0.586	4.156	-6.459	12.018	2.266	2.420	-4.569	8.657	-4.064	0.000
$DD_{Naïve}$	0.013	2.683	-4.603	6.838	1.512	1.670	-2.169	6.521	-3.274	0.002

Panel B: The Second Quarter Prior to Defaulting

	Default				Non-Default				t-test	
Variable	Mean	Stdev	Min	Max	Mean	Std. dev.	Min	Max	t-test	p-value
WC/TA	0.006	0.210	-0.385	0.572	0.148	0.162	-0.279	0.572	-3.941	0.000
RE/TA	-0.050	0.107	-0.327	0.123	0.046	0.072	-0.188	0.194	-5.352	0.000
EBIT/TA	0.004	0.034	-0.072	0.081	0.012	0.019	-0.070	0.056	-1.486	0.071
ME/TL	1.783	2.152	0.307	11.432	4.112	3.155	0.363	13.228	-4.986	0.000
SR/TA	0.120	0.085	0.021	0.410	0.190	0.110	0.013	0.647	-4.041	0.000
DD_{Merton}	0.112	3.680	-5.004	12.076	2.897	2.407	-2.828	8.319	-4.557	0.000
$DD_{Naïve}$	0.373	2.159	-3.736	5.174	1.811	1.907	-1.907	7.658	-3.746	0.000

Panel C: The Third Quarter Prior to Defaulting

	Default				Non-Default				t-test	
Variable	Mean	Stdev	Min	Max	Mean	Std. dev.	Min	Max	t-test	p-value
WC/TA	0.040	0.217	-0.315	0.582	0.155	0.166	-0.264	0.582	-3.086	0.003
RE/TA	-0.043	0.106	-0.301	0.137	0.051	0.078	-0.185	0.226	-5.226	0.000
EBIT/TA	-0.014	0.051	-0.175	0.061	0.015	0.021	-0.063	0.063	-3.592	0.001
ME/TL	2.051	2.447	0.342	11.153	4.595	4.846	0.458	25.827	-4.007	0.000
SR/TA	0.119	0.077	0.014	0.378	0.207	0.123	0.016	0.735	-5.027	0.000
DD_{Merton}	0.766	3.669	-4.388	11.259	3.028	2.540	-2.900	8.177	-3.638	0.001
$DD_{Naïve}$	0.920	2.130	-3.064	6.051	1.733	1.923	-2.729	7.164	-2.117	0.038

This table reports the descriptive statistics and t tests for all variables used in the logit model for the Asian financial crisis. WC is working capital, RE is retained earnings, EBIT is earnings before interest and tax, ME is the market value of equity, SR is sales revenues, TA is total assets, and TL is total liability. DD_{Merton} *is the Merton distance to default and is calculated based on Equation (11).* $DD_{Naïve}$ *is the naïve distance to default and is calculated based on Equation (16).*

Table 2 shows the results of sample mean *t* test for the logit variables during the global financial crisis. The results of the sample mean *t* test for the ratios (*WC/TA*, *RE/TA,* and *EBIT/TA*) and variables ($DD_{Mertton}$ and $DD_{Naïve}$) all differ significantly from zero ($p < .01$) for 1Q–3Q during the global financial crisis. The difference in the estimated results for *SR/TA* is statistically significant from zero in 2Q ($p < .01$) and 3Q ($p < .05$). However, the *ME/TL* ratio is only significantly different from zero in 2Q ($p < .05$). The estimation results imply that certain financial conditions of the non-default and default companies are all affected by the overall economic environment; consequently, the differences in solvency and asset turnover rate are less obvious between the default and non-default companies during the global financial crisis. Moreover, the stock price information was a highly critical credit risk factor during the global financial crisis.

Table 2: Descriptive Statistics and T-tests (During the Global Financial Crisis

Panel A: The First Quarter Prior to Defaulting										
	Default				**Non-Default**				**t-test**	
Variable	**Mean**	**Stdev**	**Min**	**Max**	**Mean**	**Std. dev.**	**Min**	**Max**	**t-test**	**p-value**
WC/TA	-0.090	0.303	-0.852	0.395	0.238	0.190	-0.241	0.640	-6.346	0.000
RE/TA	-0.570	0.508	-1.841	0.001	0.035	0.176	-0.889	0.344	-7.399	0.000
EBIT/TA	-0.165	0.286	-1.105	0.039	0.002	0.075	-0.606	0.070	-3.681	0.001
ME/TL	2.364	8.613	0.117	55.388	5.262	8.802	0.302	55.388	-1.746	0.085
SR/TA	0.175	0.134	0.029	0.672	0.211	0.136	0.029	0.672	-1.404	0.164
DD_{Merton}	-1.647	2.333	-6.449	6.542	1.877	2.648	-3.619	8.267	-7.544	0.000
$DD_{Naïve}$	-1.056	2.164	-6.127	3.973	0.850	1.774	-3.057	5.488	-4.881	0.000
Panel B: The Second Quarter Prior to Defaulting										
	Default				**Non-Default**				**t-test**	
Variable	**Mean**	**Stdev**	**Min**	**Max**	**Mean**	**Std. dev.**	**Min**	**Max**	**t-test**	**p-value**
WC/TA	0.023	0.220	-0.382	0.464	0.251	0.198	-0.200	0.714	-5.733	0.000
RE/TA	-0.326	0.365	-1.255	0.069	0.056	0.144	-0.764	0.337	-6.616	0.000
EBIT/TA	-0.105	0.178	-0.663	0.009	0.013	0.036	-0.194	0.074	-4.293	0.000
ME/TL	2.561	8.387	0.142	55.113	5.794	9.114	0.283	55.113	-2.004	0.048
SR/TA	0.159	0.098	0.029	0.373	0.229	0.150	0.033	0.737	-3.148	0.002
DD_{Merton}	-0.968	2.288	-5.201	6.576	2.228	2.657	-2.861	8.575	-7.080	0.000
$DD_{Naïve}$	-0.708	2.217	-5.283	3.185	1.049	1.925	-2.931	8.612	-4.429	0.000
Panel C: The Third Quarter Prior to Defaulting										
	Default				Non-Default				t-test	
Variable	Mean	Stdev	Min	Max	Mean	Std. dev.	Min	Max	t-test	p-value
WC/TA	0.083	0.239	-0.397	0.728	0.260	0.193	-0.163	0.728	-4.208	0.000
RE/TA	-0.231	0.262	-0.870	0.110	0.063	0.134	-0.702	0.326	-6.902	0.000
EBIT/TA	-0.028	0.032	-0.118	0.017	0.016	0.028	-0.076	0.087	-7.556	0.000
ME/TL	3.315	10.226	0.208	66.030	6.681	9.903	0.313	66.030	-1.781	0.079
SR/TA	0.174	0.104	0.026	0.445	0.230	0.151	0.031	0.758	-2.468	0.015
DD_{Merton}	-0.310	2.533	-4.500	6.925	2.769	2.886	-4.862	10.070	-6.193	0.000
$DD_{Naïve}$	-0.346	2.306	-4.930	3.803	1.326	2.329	-3.095	9.666	-3.862	0.000

This table reports the descriptive statistics and t tests for all variables used in the logit model for the global financial crisis. WC is working capital, RE is retained earnings, EBIT is earnings before interest and tax, ME is the market value of equity, SR is sales revenues, TA is total assets, and TL is total liability. DD_{Merton} is the Merton distance to default and is calculated based on Equation (11). $DD_{Naïve}$ is the naïve distance to default and is calculated based on Equation (16).

In this study, the logit model is the first model to be employed to code the information of the five financial ratios of Altman's (1968) Z-score model and the information of stock price into a score, and to apply logistic regression to link the score to the default probability. Let β denote the coefficients attached to the five financial ratios; subsequently, I can obtain the scores for Company i by applying

$$z_i = \beta_0 + \beta_1 x_{i1} + \beta_2 x_{i2} + \beta_3 x_{i3} + \beta_4 x_{i4} + \beta_5 x_{i5} + \beta_6 x_{i6} + \beta_7 x_{i7}, \quad (1)$$

where z_i is the score for Company i. The definitions of $x_{i1}\sim x_{i5}$ are identical to those shown in Equation (1), x_{i6} is the distance to default of the Merton DD model, and x_{i7} is the distance to default of the naïve probability model. $\beta_1\sim\beta_7$ are the weights of $x_{i1}\sim x_{i7}$, and β_0 is the constant. Furthermore, y_i denotes the default indicator, and $y_i = 1$ if Company i defaulted (0 otherwise). To obtain the appropriate β coefficients, a logistic distribution function should be applied to connect the scores with the default probability by setting the default probabilities equal to function *F* of the scores

$$P(y_i) = F(z_i) = \frac{exp(z_i)}{1+exp(z_i)} = \frac{1}{1+exp(-z_i)} \;, \quad (2)$$

where $P(y_i)$ is the probability of the default rate of Company i, and function F ranges from 0 to1.
By employing the maximum likelihood method, I can estimate the β coefficients. The likelihood of a set

of N companies can be expressed as:

$$L = \prod_{i=1}^{N} \left(F(z_i)\right)^{y_i} \left(1 - F(z_i)\right)^{1-y_i} \tag{3}$$

Our second method to calculate the probability of default is the probability of Merton distance to default. According to Merton (1974), a firm's liabilities comprise only one zero-coupon bond with the notional value F maturing in time T; thus, the default probability is the probability that the value of the assets V is below the value of the liabilities at time T. With no dividends, the firm's equity value E can be determined by applying the Black-Scholes European call option formula. The bond value is the asset value minus the equity value; thus, the value of the bond at time 0 is $F = V - E$. Accordingly, the default probability is the probability that the value of the assets is below the value of the liabilities at time T:

$$\begin{aligned} Prob(Default) &= Pr\left[ln\,V^0 + \left(\mu - \frac{\sigma_V^2}{2}\right)(T-t) + \sigma_V\sqrt{T-t}Z \leq ln\,F\right] \\ &= \mathcal{N}\left[-\left(\frac{ln\frac{V}{F} + \left(\mu - \frac{\sigma_V^2}{2}\right)(T-t)}{\sigma_V\sqrt{T-t}}\right)\right], \\ &= \mathcal{N}(-DD_{Merton}) \end{aligned} \tag{4}$$

where DD_{Merton} is the Merton distance to default, V^0 is the asset value at time 0, μ is the expected return on the firm's assets, $(T-t)$ is time-to-maturity, σ_V^2 is the variance of the asset value, and $\mathcal{N}(.)$ denotes the cumulative standard normal distribution. However, when I estimated the default probability, specific problems became apparent. First, the market value of the assets could not be observed, and second, the asset volatility could not be derived. Based on research by Vassalou and Xing (2004) and Bharath and Shumway (2008), I resolved this problem by implementing an iterative approach. In Merton DD model, the underlying value of a firm and its volatility are difficult to observe. Bharath and Shumway (2008) showed that a sufficient statistic for default probability can be calculated without solving the underlying value of the firm and its volatility. Thus here we calculate the naïve probability of Merton (1974) as our third method for robustness check of Merton. We use the functional form to estimate the asset value, which is already implied in the Merton DD model (Merton, 1974). First, the market value of the firm's debt is approximated by the face value of its debt, $naïve\ D = F$, and the volatility of the firm's debt is approximated as $naïve\ \sigma_D = 0.05 + 0.25 * \sigma_E$. (5) Finally, the naïve probability is then obtained by applying

$$\pi_{naïve} = \mathcal{N}\left(-\left(\frac{ln[(E+F)/F] + \left(r_{it-1} - 0.5 naïve\ \sigma_V^2\right)(T-t)}{naïve\ \sigma_V\sqrt{T-t}}\right)\right) = \mathcal{N}(-DD_{naïve}). \tag{6}$$

where $DD_{naïve}$ is the naïve distance to default.

Compared with the iterative procedure, it is relatively easy to calculate the naïve probability. Bharth and Shumway (2008) showed that the naïve predictor performs slightly better than the Merton DD model, and a reduced-form model that uses identical inputs. Löffler and Posch (2011) indicated that the cumulative accuracy profile (CAP) and receiver operating characteristics (ROC) can be employed to evaluate the discriminatory power of these credit risk models; however, the Brier score can be used to assess the discrimination and calibration. By evaluating the discriminatory power, I could examine the quality of the rank ordering produced by the credit risk models; however, by verifying the calibration, I could observe how well the estimated probability of a default matches the true probability of the default.

RESULTS AND DISCUSSION

Logit Model Results

I implemented the Z-score variables with the stock price information variables (i.e., DD_{Merton} and $DD_{Naïve}$) through the logit regression method. Tables 3 and 4 show the results for the Asian and global financial crises, respectively. Model 1 is the logit model only with Z-score variables, Model 2 combines the Z-score variables and DD_{Merton} in the logit model, and Model 3 adds $DD_{Naïve}$ into Model 2. First, I focused on the statistics for overall fit. The null hypothesis (i.e., the five financial ratios do not contribute to the predictive ability of the model) of the likelihood ratio (LR) test can be rejected with high confidence. Although the p values in Table 3 only show three decimal points, the actually value is less than 10^{-8}. The LR test implies that the logit model is highly significant. Therefore, the logit model reliably predicted the default events. From the figure of $Pseudo\text{-}R^2$, I can summarise that the goodness of fit of the logit model during global financial crisis is superior to the model in the Asian financial crisis. Table 3 shows the regression coefficients. During the Asian financial crisis, the estimated coefficients for *SR/TA* have the expected negative sign, and are statistically significantly different from zero for 2Q–3Q ($p < .01$) and 1Q ($p < .05$). The coefficients for 4 of the 5 financial ratios (i.e., besides *WC/TA*) are statistically significant for 2Q. The predictability of Ratio *EBIT/TA* improved as the crisis point approached. Both DD_{Merton} and $DD_{Naïve}$ were non-significant predictors during the Asian financial crisis.

However, data in Table 4 show that during the global financial crisis, *RE/TA* had a statistically significant and negative effect on default probability for 1Q ($p < .01$), 2Q ($p < .05\%$), and 3Q ($p < .01$). The coefficients for *WC/TA* and *EBIT/TA* exhibit a statistically significant difference in 1Q ($p < .01$) and 3Q ($p < .05$). According to the logit model analysis, I can observe various credit risk factors based on the accounting data during these two financial crises. The logit model results support those of the sample mean t test; that is, the differences in the solvency and asset turnover rate are less obvious between the default and non-default companies during the global financial crisis. The other critical finding is that DD_{Merton} is a significant default predictor, even when $DD_{Naïve}$ is included in Model 3. This implies that the stock price information model was a critical credit risk factor during the global financial crisis. However, the coefficient for $DD_{Naïve}$ is statistically non-significant.

Table 3: Logit Model Results (during the Asian Financial Crisis)

	1Q			2Q			3Q		
Variable	**Model 1**	**Model 2**	**Model 3**	**Model 1**	**Model 2**	**Model 3**	**Model 1**	**Model 2**	**Model 3**
CONST	1.090	0.964	0.984	1.047	0.923	0.997	1.368	1.348	1.377
	(0.150)	(0.215)	(0.220)	(0.063)	(0.104)	(0.086)	(0.018)*	(0.020)*	(0.021)*
WC/TA	-0.357	-0.240	-0.239	0.383	0.741	0.867	1.903	2.376	2.398
	(0.867)	(0.9106)	(0.911)	(0.812)	(0.649)	(0.597)	(0.239)	(0.158)	(0.156)
RE/TA	-6.830	-6.096	-6.006	-13.212	-12.799	-12.821	-7.777	-6.740	-6.573
	(0.150)	(0.203)	(0.218)	(0.003)**	(0.005)**	(0.005)**	(0.056)	(0.108)	(0.123)
EBIT/TA	-29.335	-29.485	-29.594	29.497	34.068	35.312	-7.412	-8.942	-9.377
	(0.051)	(0.049)*	(0.049)*	(0.037)*	(0.024)*	(0.019)*	(0.427)	(0.332)	(0.320)
ME/TL	-0.261	-0.168	-0.173	-0.265	-0.111	-0.108	-0.199	-0.099	-0.098
	(0.160)	(0.467)	(0.465)	(0.043)*	(0.495)	(0.512)	(0.067)	(0.377)	(0.385)
SR/TA	-10.209	-10.328	-10.300	-8.041	-8.686	-8.765	-10.203	-10.842	-10.902
	(0.026)*	(0.024)*	(0.025)*	(0.010)**	(0.006)**	(0.006)**	(0.002)**	(0.002)**	(0.001)**
DD_{Merton}		0.087	0.076		0.177	0.143		0.140	0.134
		(0.533)	(0.658)		(0.181)	(0.298)		(0.249)	(0.279)
$DD_{Naïve}$			0.020			0.131			0.031
			(0.916)			(0.388)			(0.832)
LR test	74.046	74.439	74.450	48.664	50.535	51.287	47.781	48.612	48.658
	(0.000)**	(0.000)**	(0.000)**	(0.000)**	(0.000)**	(0.000)**	(0.000)**	(0.000)**	(0.000)**
Pseudo-R²	0.473	0.475	0.476	0.290	0.301	0.305	0.284	0.293	0.293

This table reports the estimation results of the logit model for the Asian financial crisis. CONST is the constant term, WC/TA is the company's financial ratio of working capital to total assets, RE/TA is the company's financial ratio of retained earnings to total assets, EBIT/TA is the company's financial ratio of earnings before interest and taxes to total assets, ME/TL is the company's financial ratio of market value equity to book value of total debt, and S/TA is the company's financial ratio of sales to total assets. DD_{Merton} *is the Merton distance to default and is calculated based on Equation (11).* $DD_{Naïve}$ *is the naïve distance to default and is calculated based on Equation (16). 1Q, 2Q, and 3Q mean the first, second, and third quarter prior to defaulting, respectively. The parenthesised values are p-values (* p < .05, ** p < .01).*

Table 4: Logit Model Results (During the Global Financial Crisis)

	1Q			2Q			3Q		
Variable	Model 1	Model 2	Model 3	Model 1	Model 2	Model 3	Model 1	Model 2	Model 3
CONST	-1.118	-2.360	-2.231	-0.633	-0.783	-0.701	-0.765	-0.558	-0.509
	(0.073)	(0.009)**	(0.014)*	(0.257)	(0.247)	(0.304)	(0.150)	(0.339)	(0.391)
WC/TA	-5.836	-3.307	-4.673	-3.007	-0.979	-0.982	-0.982	1.626	1.643
	(0.005)**	(0.140)	(0.078)	(0.088)	(0.6108)	(0.614)	(0.537)	(0.382)	(0.377)
RE/TA	-6.965	-5.961	-5.008	-4.696	-4.195	-3.745	-6.392	-6.474	-6.303
	(0.001)**	(0.003)**	(0.005)**	(0.041)*	(0.041)*	(0.079)	(0.002)**	(0.001)**	(0.002)**
EBIT/TA	0.454	-0.332	-2.957	-20.535	-16.124	-17.201	-29.878	-25.294	-25.366
	(0.907)	(0.928)	(0.497)	(0.052)	(0.089)	(0.084)	(0.012)*	(0.039)*	(0.040)*
ME/TL	0.000	0.101	0.104	-0.028	0.050	0.047	-0.021	0.024	0.024
	(0.998)	(0.031)*	(0.046)*	(0.486)	(0.230)	(0.246)	(0.547)	(0.540)	(0.543)
SR/TA	0.526	1.374	1.231	-1.082	-2.945	-3.104	-0.249	-2.423	-2.530
	(0.855)	(0.683)	(0.723)	(0.677)	(0.344)	(0.327)	(0.908)	(0.325)	(0.309)
DD_{Merton}		0.714	0.562		0.586	0.546		0.519	0.506
		(0.003)**	(0.013)*		(0.001)**	(0.003)**		(0.001)**	(0.002)**
$DD_{Naïve}$			0.540			0.148			0.069
			(0.053)			(0.445)			(0.660)
LR test	86.224	100.953	105.385	76.778	91.440	92.038	68.169	80.532	80.726
	(0.000)**	(0.000)**	(0.000)**	(0.000)**	(0.000)**	(0.000)**	(0.000)**	(0.000)**	(0.000)**
Pseudo-R^2	0.551	0.645	0.673	0.468	0.557	0.561	0.415	0.493	0.494

This table reports the estimation results of the logit model for the global financial crisis. CONST is the constant term, WC/TA is the company's financial ratio of working capital to total assets, RE/TA is the company's financial ratio of retained earnings to total assets, EBIT/TA is the company's financial ratio of earnings before interest and taxes to total assets, ME/TL is the company's financial ratio of market value equity to book value of total debt, and S/TA is the company's financial ratio of sales to total assets. DD_{Merton} is the Merton distance to default and is calculated based on Equation (11). $DD_{Naïve}$ is the naïve distance to default and is calculated based on Equation (16). 1Q, 2Q, and 3Q mean the first, second, and third quarter prior to defaulting, respectively. The parenthesised values are p-values (p < .05, ** p < .01).*

Predictive Power Among the Logit, Merton DD, and Naïve Models

To determine which model is superior in forecasting accuracy among the logit, Merton DD, and naïve models, I employed the CAP and ROC to test the discrimination, and employed the Brier score to test both the discrimination and calibration. Furthermore, the accuracy ratios, AUC, and Brier score are computed using the probabilities of default estimated by each model, and the default indicator variable for three quarters prior to default. Table 5 shows the estimated results, including two logit model results. The logit model in Model 1 only includes the traditional financial ratio-based Z-score variables. Model 4 combines the Z-score variables and DD_{Merton} in one logit model.

The results clearly show that the forecasting accuracy of all models improves as the crisis point approaches for both the Asian and global financial crisis. The average of the three quarters accuracy ratio is 73.27% in the logit model with only the Z-score variables during the Asian financial crisis; however, it reached 86.41% during the global financial crisis. The accuracy ratios, AUC, and Brier score all indicate that the logit model has better predictive power, followed by the Merton DD model, and finally the naïve model. Moreover, for the listed companies in Taiwan, the predictive power of the default probability for each model is better during the global financial crisis than during the Asian financial crisis. These estimated results show that the forecasting power of these models for predicting credit risk remains constant; thus, it is reasonable to assert that they maintain their applicability over time. Regarding the logit model in Model 1 (i.e., the Z-score variables only) and Model 4 (i.e., the Z-score variables and DD_{Merton}), the prediction ability of Model 4 is worse than Model 1 in 1Q and 2Q during the Asian financial crisis; however, compared with Model 1, Model 4 achieved considerable predictive power during the global financial crisis. This result supports the logit regression results shown in Section 4.1 and proves that the stock price information of the Merton DD model was a critical default predictor during the Global financial crisis.

Table 5: Validation of Credit Risk Models

	The Asian Financial Crisis Period			the Global Financial Crisis Period		
Model 1: Logit model (only with Z-score Variables)						
	1Q	2Q	3Q	1Q	2Q	3Q
CAP	0.822	0.697	0.679	0.901	0.853	0.838
ROC	0.911	0.849	0.840	0.951	0.926	0.919
Brier	0.107	0.148	0.151	0.077	0.099	0.113
Model 2: Merton DD Model						
	1Q	2Q	3Q	1Q	2Q	3Q
CAP	0.503	0.512	0.447	0.692	0.649	0.581
ROC	0.751	0.756	0.724	0.846	0.825	0.790
Brier	0.203	0.201	0.203	0.187	0.194	0.202
Model 3: Naïve Model						
	1Q	2Q	3Q	1Q	2Q	3Q
CAP	0.353	0.347	0.226	0.493	0.399	0.358
ROC	0.676	0.674	0.613	0.747	0.700	0.679
Brier	0.236	0.248	0.264	0.243	0.258	0.275
Model 4: Logit Model						
	1Q	2Q	3Q	1Q	2Q	3Q
CAP	0.820	0.694	0.687	0.933	0.898	0.876
ROC	0.910	0.847	0.843	0.967	0.949	0.938
Brier	0.106	0.143	0.145	0.066	0.086	0.098

This table reports the quality of credit risk models by evaluating the discriminatory power and calibration. CAP represents the accuracy ratio of the cumulative accuracy profile curve. ROC represents the area under the receiver operating characteristic curve. Brier is the Brier score. The logit model in Model 1 only includes the traditional financial ratio-based Z-score variables. Model 4 combines the Z-score variables and DD_{Merton} *into one logit model*

TCRI

TCRI is a credit rating index introduced by the *TEJ*. Having started to build this index since August 1991, the *TEJ* has formally provided the TCRI database for listed and public companies since August 1996. The TCRI is based on a "semi-expert judgment" process to obtain the rating of each company. First, the TCRI financial data are analysed using financial statement analyses and statistical models to calculate its "comprehensive scores." Subsequently, a "basic rating" is assigned according to the comprehensive scores. Second, the *TEJ* calculates two threshold limits by considering its risk-tolerance level and revenue scale. Finally, the *TEJ* employs certain non-quantitative factors, such as accounting quality, information before next financial reports released, industry future prospects, and the risk preferences level of the management team to determine the TCRI (See the TEJ website, http://www.tej.com.tw/twsite/.). The accuracy ratios and AUC shown in Table 6 are very close to 100% in 1Q during the Asian and global financial crises. This implies that the TCRI can discriminate 100% and 99% of the failed companies during Asian and global financial crises, respectively. Comparing with Models 1 and 4 of Table 5 shows that the accuracy ratios, AUC, and Brier score all demonstrate that the capability of discrimination and calibration of the TCRI is worse than that of the logit model in 3Q. The logit model with only the Z-score variables can predict the default crisis earlier than the TCRI. This also implies that the Z-score introduced by Altam almost 40 years ago is more effective than the other models.

Table 6: Validation of TCRI

	The Asian Financial Crisis Period			The Global Financial Crisis Period		
	1Q	2Q	3Q	1Q	2Q	3Q
CAP	1.000	0.805	0.616	0.993	0.921	0.825
ROC	1.000	0.902	0.808	0.997	0.961	0.913
Brier	48.902	39.621	34.568	47.130	41.116	37.519

This table reports the quality of TCRI by evaluating discriminatory power and calibration. CAP represents the accuracy ratio of the cumulative accuracy profile curve. ROC represents the area under the receiver operating characteristic curve. Brier is the Brier score.

CONCLUDING COMMENTS

This study examined the differences among credit risk factors in Taiwan during the Asian and global financial crises. Using Taiwanese listed companies' data, First, I captured variables from Altman's (1968) Z-score model, a pioneer and notable model based on Accounting Data, from the Merton distance to default (DD) model, and from the naïve probability model-an alternative of the Merton DD model. The significance of the Z-score model variables are examined by applying the logit model. Furthermore, the forecasting ability of the logit model, Merton DD model, naïve probability, and the Taiwan corporate credit rating index are compared. The results show that *SR/TA* was the most critical financial ratio during the Asian financial crisis; conversely, *RE/TA* was the most crucial financial ratio during the global financial crisis. Observing the contribution of the stock price information, the Merton distance to default was a critical predictor of credit risk during the global financial crisis; however, the performance of the naïve distance to default was poor. Regarding the model forecasting ability, the logit model using Altman's Z-score variables offers superior predictive power, and forecasts the default crisis for Taiwanese listed companies earlier than the TCRI. By incorporating DD_{Merton} variable into the logit model, the predictive ability of the traditional logit model can be improved quite substantially for the global financial crisis. Bharath and Shumway (2008) conclude that (a) DD_{Merton} is not a sufficient statistic for forecasting default, and (b) the iterative procedure for solving the Merton DD model is not useful. However, according to this study, the introduction of $DD_{Naïve}$ does not get the result of Bharath and Shumway (2008). The most serious limitation of my paper is that default samples of Taiwanese listed companies' data samples is too small to enhance the accuracy of the predictive power of the model. Constructing a new prediction model of default rate is my directions for future research.

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