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**Article**

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Global Business & Finance Review (GBFR)

**Provided in Cooperation with:**

People & Global Business Association (P&GBA), Seoul

*Suggested Citation:* Kim, Jounghyeon (2016) : Determinants and predictive powers of bankruptcy models for firms in Korea and the U.S., Global Business & Finance Review (GBFR), ISSN 2384-1648, People & Global Business Association (P&GBA), Seoul, Vol. 21, Iss. 2, pp. 65-85,  
<https://doi.org/10.17549/gbfr.2016.21.2.65>

This Version is available at:

<https://hdl.handle.net/10419/224353>

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## Determinants and Predictive Powers of Bankruptcy Models for Firms in Korea and the U.S.

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### ABSTRACT

Using a cross-section data set of manufacturing firms in Korea and the U.S., this paper explores the most significant factors that determine firm default during the periods of 1991-2001 and 1991-2003, respectively. Based on the findings, a probit default model is constructed to perform better than two default prediction models such as Altman's z-score model and the new Altman z-score model. To improve the predictive power, z-score is incorporated into the model as one of the explanatory variables with other significant default factors, which can provide additional information in predicting bankruptcy. It is found that z-score, leverage, and short-term debt ratios are the most important determinants of default for firms in both Korea and the U.S. However, soft budget constraint (SBC), defined as the ability of a firm with a low z-score to obtain short-term bank loans, and ownership concentration (ownership by the largest shareholders) are identified as strong indicators of the likelihood of bankruptcy only for Korean firms. Moreover, based on these and other significant default factors of age of a firm, export ratio, and inventory ratio, the probit default model for both Korean firms and US firms is found to perform better than the two Altman models. This suggests that the additional information gained from the z-score and the non-financial default factors in the default regression model can help improve the predictive power of a default prediction model.

*Keywords: Z-Score; Default Factor; Soft Budget Constraint; Ownership Concentration; Model Power*

## I. Introduction

Bankruptcy generally results from financial distress, i.e., insolvency, when the market value of a firm's assets is insufficient to pay its total debt. Prolonged unprofitability exacerbates a firm's insolvency, which eventually causes bankruptcy (Pompe and Bilderbeek, 2005). Many studies have focused on finding the determinants of a firm's

bankruptcy. For example, financial ratio analysis has been widely used to predict a firm's bankruptcy based on univariate (Beaver, 1966) and multivariate (Altman, 1968; Altman et al., 1977) approaches. They find that the ratios in the categories of profitability, liquidity, and leverage are important indicators of predicting bankruptcy.<sup>1)</sup>

1) Beaver (1966) identifies the following financial ratios as most significant in predicting bankruptcy: X1 = cash flow / total debt, X2 = net income / total assets, X3 = total debt / total assets, X4 = working capital / total assets, X5 = current assets / current liabilities, and X6 = no-credit interval (defensive assets - current liability to fund expenditures for operations). Altman (1968) develops the z-score model, based on 66 US manufacturing firms from 1946 through 1965 and 5 financial variables. The model is

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In another aspect, Daily and Dalton (1994) find that governance structures, such as the composition of the board leadership structure and the board of the directors, are related to a firm's bankruptcy.<sup>2)</sup> Based on bankrupt firms in Canada, Thornhill and Amit (2003) find that environment, management, age, and size of a firm are important determinants of bankruptcy and that younger firms are more exposed to bankruptcy because they have less resources and financial management skills. However, Pompe and Bilderbeek (2005) find that it is more difficult to predict bankruptcy of young firms than old firms, i.e., established firms. They argue that young firms are small, less experienced, and financially weak, so when faced with financial distress, bankruptcy is more likely to occur unexpectedly compared to older and larger firms.

In addition, many bankruptcy models have been developed to better predict the likelihood of a firm's bankruptcy. Altman (1968) estimates the Altman z-score model based on the financial ratios proven to possess explanatory power in the univariate. Later, Altman et al. (1977) constructs the ZETA model that better predicts bankruptcy than Altman's z-score model. Johnson and Melicher (1994) expands a firm's financial state to three states - bankrupt, financially weak, and non-bankrupt - and find that the additional information provided by the multinomial model helps reduce misclassification error compared to the binomial model (two-state model of bankrupt and non-bankrupt firms).<sup>3)</sup> More recently, using parametric

and non-parametric approaches, Moody's (Sobehart and Stein, 2000; Kocagil and Reyngold, 2003) develops its own default prediction model and shows that it performs better than Altman's z-score model and other risk default models such as the hazard model or the univariate ROA (return on assets) model.<sup>4)</sup>

Denis and Mihov (2003) use Altman's z-score as one of the characteristics in identifying the debt source. They find that the credit quality of a firm is related to the choice of the type of debt. That is, a firm in good financial shape borrows from public sources, whereas a firm in financial distress borrows from non-bank private sources. A firm of average soundness borrows from banks.<sup>5)</sup> Using the revised Altman z-score model (Altman, 2000), Allayannis et al. (2003) analyzes the relationship of z-score (financial performance) to different types of debt, such as local currency debt and hedged and unhedged foreign currency debt. They find that both foreign currency debt and local currency debt hurt financial performance in the Asian financial crisis.<sup>6)</sup> Based on firm-level panel data, Alexeev and Kim (2008) identify soft budget constraint (SBC) firms in Korea that increase their bank loans while having a low z-score. Recently, Kim (2016) finds that the z-score bankruptcy threshold is higher in countries with better quality of institutions. That is, the z-score bankruptcy threshold has been found to be higher in the U.S., which has a higher institutional quality than Korea.

Similar to previous studies, this paper also uses the z-score model in regression analysis and estimates a probit default model. In addition to other potential

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defined as  $Z=1.2X1+1.4X2+3.3X3+0.6X4+0.999X5$  from "Return on Investment Manual: Tools and Applications for Managing Financial Results" by Robert Rachlin (1997) where  $X1 = \frac{\text{Working Capital}}{\text{Total Assets}}$ ,  $X2 = \frac{\text{Retained Earnings}}{\text{Total Assets}}$ ,  $X3 = \frac{\text{EBIT}}{\text{Total Assets}}$ ,  $X4 = \frac{\text{Market Value of Equity}}{\text{Book Value of Total Debt}}$ , and  $X5 = \frac{\text{Sales}}{\text{Total Assets}}$ . Altman et al. (1977) define  $X1 = \text{EBIT}/\text{total assets}$ ,  $X2 = \text{standard error of estimate of EBIT}/\text{total assets}$ ,  $X3 = \text{EBIT}/\text{total interest payments}$ ,  $X4 = \text{retained earnings}/\text{total assets}$ ,  $X5 = \text{current assets}/\text{current liabilities}$ ,  $X6 = \text{common equity}/\text{total capital}$ , and  $X7 = \text{total assets}$ .

2) Through logistic regression by controlling for financial variables and firm size, they find that the interaction between a dual leadership structure (CEO/board chairperson) and a few independent directors has a significant effect on bankruptcy.  
 3) Using the financial variables of Beaver (1966) and Altman et al. (1977), they show that the multinomial model performs

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better in terms of the total number of misclassification errors than the binomial model.

4) Sobehart and Stein (2000) incorporate the financial statement and ratio data into the pure structure model (Merton model) and show a gain in accuracy.  
 5) Based on 1,560 new debt issues of 1,480 US public firms in 1995 and 1996, they observe that firms under financial distress (high chance of default), i.e., z-score less than 1.81 (bankruptcy threshold), take a higher proportion of borrowing from non-bank private sources (20.8%) than from banks (12.1%) or public sources (13.4%).  
 6) The revised z-score model excludes the sales/total assets ratio from Altman's z-score model in order to reduce the potential industry effect. The model can be used for evaluating the financial state of non-manufacturing US and non-US firms.

default factors, the z-score is incorporated into the model to improve the predictive power. To construct the probit default model, the paper examines the determinants of bankruptcy for manufacturing firms in Korea and the US, two countries with different institutional environments. This paper contributes to the existing literature by shedding light on how propensity to corporate default differs in the two countries. In addition, the probit default model is estimated by taking into account the z-score, which reflects the overall financial situation of a firm, as well as its non-financial aspects, such as concentration of ownership and SBC, which may help improve the ability to predict the likelihood of bankruptcy.

It is found that z-score, leverage, and short-term debt are the most important determinants of default for firms in both Korea and the U.S.<sup>7)</sup> For Korean firms, soft budget constraint (SBC) and ownership concentration are also identified as strong indicators of likelihood of bankruptcy, whereas they do not appear to be significant default factors for US firms.<sup>8)</sup> This might be due to fact that the present study uses a relatively weak proxy for the SBC for US firms and the less likelihood of expropriation by an entrepreneur in the U.S., thanks to its more diversified ownership structure (Judge et al., 2008).

Next, based on the significant default factors identified by probit default regressions, this study also constructs a default model for Korean firms and US firms and then compares their models' predictive power via Moody's power curve and accuracy ratio with the existing bankruptcy models such as Altman (1968)'s z-score model, which is a widely used benchmark model in literature and the new Altman z-score model, which is estimated by Kim (2016). It is found that the default model outperforms other models with the greatest model

power, i.e., the highest accuracy for predicting bankruptcy. That is, the model performs better than a benchmark model of Altman's z-score model, which is solely based on financial variables. This suggests that using additional information obtained from the z-score and the non-financial default factors in the default regression model can improve the predictive power of a model.

This paper is organized as follows. In Section II, methodology for the empirical analysis is briefly discussed. In Section III, variables, data, and sample selection for Korean and US firms are presented, default factors are identified, and default models are constructed. In Section IV, default model powers are explored via Moody's power curve and accuracy ratio, and compared with those of the two Altman models. Finally, Section V presents the conclusion.

## II. Methodology

The Altman z-score model presents the overall index score for a firm's financial state and predicts the likelihood of its bankruptcy, which is indicated by its z-score falling below the z-score threshold for bankruptcy.<sup>9)</sup> This implies that the overall financial state of a firm is an important indicator of bankruptcy. Hence, the z-score is included as one of the predictors in the default probit regression model along with other potential default factors. They may help to improve the model power by providing additional information in predicting bankruptcy.

To generate z-scores for Korean firms, a new Altman z-score model, which is developed by Kim (2016) based on the Altman (1968) method (discriminant function analysis), is used instead of

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7) For Korean firms, leverage, short- and long-term debts, short-term bank loans, and soft budget constraint (SBC) emerge as factors that increase the likelihood of default, whereas z-score, a firm's age, export ratio, and ownership concentration appear to reduce the likelihood of default. Details about SBC are discussed in Section II.

8) The result for ownership concentration is consistent with the finding of Alexeev and Kim (2012).

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9) He initially finds a midpoint threshold (2.675) to test how well the model classifies firms, and suggests two bound thresholds (1.81 and 2.99). A firm with a z-score above 2.99 and below 1.81 is taken into account as unlikely and likely to go into bankruptcy, respectively. The likelihood of bankruptcy for a firm is uncertain between the two bounds, which is called the "gray area" or "ignorance zone".

Altman's z-score model. This is because the original Altman z-score model appears to be less effective for predicting bankruptcy of Korean firms compared to US firms.<sup>10</sup> When Altman's z-score model is used to estimate the z-scores of Korean firms and to predict their likelihood of bankruptcy, the rate of correct classification (53.5%) is lower than that of US firms (83.3%) by about 30% points.<sup>11</sup> Moreover, the financial profiles of Korean firms may be different from those of the US firms that were used in estimating the original Altman z-score model.

Another default factor that is included in the model is soft budget constraint (SBC). First introduced by Kornai (1979), SBC has been discussed in many studies.<sup>12</sup> Dewatripont and Maskin (1995) state that the existence of sunk cost leads to SBC, i.e., an unprofitable project can be persistently financed due to the sunk cost. Berglöf and Roland (1997) argue that SBC is attributed to the sunk cost on existing loans and that, as a result, a credit crunch occurs on new loans. Huang and Xu (1998 and 1999) contend that SBC results from the interaction between banks and large firms, so that bad loans for bad projects keep accumulating and lead to firms' default. Alexeev and Kim (2008) find that SBC plays a role in preventing financially distressed firms from being removed from the market, especially before the financial crisis of 1998, that SBC significantly affects the default of Korean firms during the crisis, and that the phenomenon of SBC substantially drops after the crisis.

Above studies imply that SBC distorts information about a firm's financial state and that a firm under SBC is at a high risk of bankruptcy. For this reason,

SBC is also incorporated into default probit regression models as one of potential default factors. Alexeev and Kim (2008) define SBC as a condition under which a firm can borrow from banks even if it has a low Altman z-score. Similarly, this paper defines SBC as pertaining only to short-term bank loans, and a firm is classified as an SBC firm if it experiences SBC for at least one year in the sample period.<sup>13</sup> Also included are a firm's age, which is known to have a negative relationship to the likelihood of bankruptcy (Altman, 1993; Thornhill and Amit, 2003), ownership variable, which is identified as an important determinant of the likelihood of bankruptcy (Alexeev and Kim, 2012), and other potential default factors such as short- and long-term debts.

Finally, based on the significant default factors found from regression analysis, a final default model is estimated, which improves the model performance. After that, how well the model performs is evaluated using Moody's two power metrics - the power curve and the accuracy ratio, and comparison is made with other default models such as the original Altman (1968)'s z-score model and the Kim (2016)'s new Altman z-score model.

### III. Empirical Analysis

#### A. Variables, Data, and Sample Selection for Korean Firms

Variables used in probit regression include z-score [ZS], soft budget constraint [SBC], leverage [LEVR], several other financial debt ratios, and 6 non-financial control variables: the age of firm [FAGE], investment ratio to total assets (t-1) [INVS], export ratio to revenue (sales) [EXPO], and ownerships by majority

10) For similar reasons, Altman et al. (1977) constructed the ZETA model.

11) The samples of 86 Korean firms (43 default firms and 43 non-default firms) and 60 US firms (30 default firms and 30 non-default firms) used by Kim (2016) are classified by a midpoint threshold (2.675).

12) Kornai (1979) defines soft budget constraint (SBC) under a socialized regime, describing it as allowing firms to grow regardless of their current and future financial state, while sustaining financial distress via bailouts for a longer period of time despite their unprofitability. SBC is also characterized as appearing not only in a transition economy, but also in a market-based economy (Kornai et al., 2003).

13) Alexeev and Kim (2008)'s definition of SBC encompasses total bank loans, adjusted bank loans, and short-term bank loans. In order to determine SBC firms, they initially set the cutoff value of a low z-score (i.e., 10th-percentile) at 0.3, whereas it is found the cutoff value to be -0.73 for the entire sample (4,325 Obs.). The difference in the cutoff value is due to the new Altman z-score model.

shareholders, banks, and foreigners [OWNS, OWNB, and OWNF, respectively]. Five different debt ratios are introduced in order to search for the factors that are closely related to default. First, two different short- and long-term debt ratios are defined: the ratio of debt to total debt [S(L)DTD] and the ratio of debt to total assets [S(L)DTA]. Similarly, three different short- and long-term foreign loan ratios and bank loan ratios are defined: the ratios of foreign loans and bank loans to total debt [S(L)FLTD and S(L)BLTD], to total assets [S(L)FLTA and S(L)BLTA], and to short- and long-term debt [SF(B)LSD and LF(B)LLD, respectively]. The unbalanced panel data at the firm level for the empirical analysis are collected from Korea Investors Service-Financial Analysis System (KIS-FAS) and Maekyung Annual Corporation Reports (MKACR) on firms listed in the Korea Stock Exchange (KSE). The initial data set for Korean firms contain 5,557 observations (Obs.) covering 669 firms from 1991 to 2001.<sup>14)</sup>

Firms are divided into two groups: default firms and non-default firms.<sup>15)</sup> Some irrelevant firms are removed, such as firms that belong to non-manufacturing industries, as well as those identified as Chaebol firms in some years and non-Chaebol firms in others.<sup>16)</sup> The final panel data set contains 108 default firms (703 Obs.) and 381 non-default firms (3,522 Obs.). From this panel data, a cross-section sample (489 firms) is taken for use in estimating a default model. The sample for regression analysis is selected by matching defaulting firms to non-defaulting firms in terms of asset size. The data are thereby converted into cross-section data (489 Obs.), which consist of 108 default firms and 381 non-default firms.<sup>17)</sup> Based on the sample,

each firm's z-score and a SBC dummy variable in relations to the low z-score are generated by the new Altman z-score model of Kim (2016) and used in regression analysis with other variables.<sup>18)</sup>

My initial conjecture is that ZS, SBC, and LEVR are the most likely potential default factors. A higher z-score would presumably reduce the likelihood of bankruptcy because it means that a firm is in a better financial shape. Likewise, higher SBC and leverage increase the likelihood of bankruptcy because they indicate financial distress (low z-score) and financial burden, respectively.<sup>19)</sup> These three variables are referred to as "basic" factors, and they are commonly included in default probit regression.

In addition to the three basic factors, other potential default factors are examined that are likely to be important in determining bankruptcy, and then based on them, a default model is found that best captures the likelihood of bankruptcy during the sample period. One of the distinct features of the model is that it uses not only bankruptcy information i.e., z-score that the Altman z-score model generates, but also new information gained from other variables, including non-financial variables in relation to bankruptcy, such as ownership structure, a firm's age, investment ratio, and export ratio. These new variables may provide additional information for

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to default firms as follows: First, 108 observations from 108 default firms (703 Obs.) are chosen for one year before the default year and then, given the observations, 108 observations from 381 non-default firms (3,522 Obs.) are paired with them based on asset size in the given year. Second, as in the first step, the remaining 273 non-default firms (2,391 Obs.) are matched as closely as possible to 108 default firms, weighted according to the distribution in each sample year. By repeatedly doing so, all 381 observations (non-default firms) are matched and finally selected.

14) See also Alexeev and Kim (2012) and Kim (2016) about these data.

15) "Default" means that a firm has filed for bankruptcy, is bankrupt, or has anything similar in its corporate history.

16) Eleven firms are identified as Chaebol firms in some years and as non-Chaebol firms in other years of the sample period. However, they are included in generating z-scores from the entire sample (4,325 Obs.) in order to identify SBC firms. The sample data are gathered only from manufacturing firms because Altman's z-score model was developed based on the manufacturing sector.

17) Sample selection is performed by matching non-default firms

18) Based on the cross-section sample of 108 default firms and 381 non-default firms, 86 firms (consisting of 43 firms in each group) are selected, and a new Altman z-score model is estimated via multiple discriminant analysis (MDA). The new estimated model is  $Z = -0.768 + 2.257X_1 + 4.669X_2 + 4.883X_3 + 0.467X_4 + 1.507X_5$ . It is statistically significant based on Wilks' lambda criterion, and the overall predictive power is 87.2%. Refer to Kim (2016) for more details on this model.

19) Increase in borrowing may help a firm to improve its financial state unless it is in extreme financial distress or exposed to excessive leverage.

**Table 1:** Descriptive statistics for Korean firms in the sample

Variables	Total Firms					Default Firms					Non-Default Firms					t-statistics
	Obs.	Mean	S.D.	Min.	Max.	Obs.	Mean	S.D.	Min.	Max.	Obs.	Mean	S.D.	Min.	Max.	
ZS	489	0.444	1.443	-5.678	6.280	108	-0.825	1.332	-5.561	1.322	381	0.804	1.259	-5.678	6.280	-11.722***
SBC	489	0.129	0.335	0.000	1.000	108	0.398	0.492	0.000	1.000	381	0.052	0.223	0.000	1.000	10.450***
FAGE	489	29.27	11.69	6.000	97.00	108	28.16	9.189	10.00	54.00	381	29.58	12.30	6.000	97.00	-1.118
INVS	489	0.076	0.098	0.000	1.171	108	0.063	0.086	0.000	0.530	381	0.079	0.102	0.000	1.171	-1.529
EXPO	489	0.306	0.282	0.000	1.000	108	0.273	0.263	0.000	0.979	381	0.316	0.286	0.000	1.000	-1.414
OWNS	489	28.11	16.30	0.000	100.0	108	21.33	15.22	0.000	67.30	381	30.03	16.10	0.000	100.0	-5.017***
OWNB	489	6.679	10.02	0.000	89.70	108	8.169	14.73	0.000	89.70	381	6.256	8.191	0.000	56.50	1.754*
OWNF	489	5.580	11.62	0.000	91.60	108	4.204	13.54	0.000	91.60	381	5.971	11.00	0.000	86.00	-1.396
LEVR	489	0.654	0.269	0.125	2.046	108	0.898	0.346	0.338	2.046	381	0.585	0.194	0.125	1.942	12.179***
SDTD	489	0.645	0.172	0.055	0.990	108	0.628	0.197	0.055	0.990	381	0.650	0.163	0.224	0.976	-1.175
LDTD	489	0.355	0.172	0.010	0.945	108	0.372	0.197	0.00	0.945	381	0.350	0.163	0.024	0.776	1.175
SDTA	489	0.412	0.196	0.069	1.786	108	0.549	0.281	0.076	1.786	381	0.374	0.142	0.069	0.828	8.835***
LDTA	489	0.242	0.195	0.007	1.652	108	0.349	0.308	0.007	1.652	381	0.211	0.134	0.007	1.403	6.791***
SFLTD	489	0.043	0.082	0.000	0.672	108	0.032	0.056	0.000	0.327	381	0.046	0.088	0.000	0.672	-1.509
LFLTD	489	0.042	0.066	0.000	0.584	108	0.023	0.033	0.000	0.173	381	0.047	0.072	0.000	0.584	-3.315***
SBLTD	489	0.270	0.173	0.000	0.864	108	0.304	0.177	0.000	0.740	381	0.260	0.170	0.000	0.864	2.340**
LBLTD	489	0.121	0.125	0.000	0.663	108	0.129	0.154	0.000	0.663	381	0.119	0.115	0.000	0.657	0.734
SFLTA	489	0.028	0.058	0.000	0.612	108	0.027	0.046	0.000	0.252	381	0.028	0.061	0.000	0.612	-0.239
LFLTA	489	0.025	0.040	0.000	0.414	108	0.020	0.028	0.000	0.143	381	0.027	0.043	0.000	0.414	-1.608
SBLTA	489	0.183	0.143	0.000	0.927	108	0.263	0.183	0.000	0.927	381	0.160	0.120	0.000	0.696	6.961***
LBLTA	489	0.088	0.142	0.000	1.357	108	0.139	0.237	0.000	1.357	381	0.073	0.096	0.000	1.274	4.316***
SFLSD	489	0.068	0.113	0.000	0.805	108	0.058	0.097	0.000	0.418	381	0.070	0.117	0.000	0.805	-0.948
LFLSD	489	0.230	1.238	0.000	25.41	108	0.131	0.311	0.000	1.916	381	0.258	1.392	0.000	25.41	-0.937
SBLSD	489	0.412	0.219	0.000	0.916	108	0.462	0.208	0.000	0.855	381	0.398	0.221	0.000	0.916	2.693***
LBLSD	489	0.327	0.253	0.000	0.991	108	0.316	0.270	0.000	0.991	381	0.330	0.248	0.000	0.971	-0.512

Notes: \*, \*\*, and \*\*\* denote that sample means are statistically different at the level of 10%, 5%, and 1%, respectively. ZS: Z-score, SBC: soft budget constraint, FAGE: age of a firm, INVS: the ratio of investment to total asset (t-1), EXPO: the ratio of export to revenue (sales), OWNS, OWNB, and OWNF: ownerships by majority shareholders, banks, and foreigners, respectively, LEVR: leverage, S(L)DTD: the ratio of short (long)-term debt to total debt, S(L)DTA: the ratio of short (long)-term debt to total assets, S(L)FLTD: the ratios of short (long)-term foreign loans to total debt, S(L)BLTD: the ratios of short (long)-term bank loans to total debt, S(L)FLTA: the ratios of short (long)-term foreign loans to total assets, S(L)BLTA: the ratios of short (long)-term bank loans to total assets, SF(B)LSD: the ratios of short-term foreign (bank) loans to short-term debt, LF(B)LLD: the ratios of long-term foreign (bank) loans to long-term debt.

predicting bankruptcy and help improve the predictive power of the model.

Prior to running regressions, the different characteristics of the firms in each group are examined from the variables to be used in the regression analysis. Table 1 summarizes their descriptive statistics and contrasts default and non-default firms for Korean firms. The last column shows the statistical differences between default and non-default firms in terms of ZS, SBC, OWNS, OWNB, LEVR, short- and long-term debt ratios

[S(L)DTA], short- and long-term bank loan ratios [S(L)BLTA], the ratios of short-term bank loan to short-term debt and total debt [SBLSD and SBLTD, respectively], and long-term foreign loan ratio [LFLTD]. As conjectured earlier, default firms possess much lower ZS and OWNS, whereas they are higher in SBC and LEVR. In the default group, the z-score is negative and far below the cutoff of -0.73 for a low z-score, which implies that default firms are quite financially distressed and burdened than non-default firms.

## B. Default Factors and Default Model

Regression is performed using the variables explained in the earlier section to scrutinize the default factors and the default model. First, a “basic” default model is established by performing probit regression only on ZS, SBC dummy variable, and LEVR, which I believe are the most likely significant determinants of default. This is to observe whether the model correctly captures the sign and significance of the estimated coefficients. Second, by incorporating into the model the different types of financial debt ratios defined earlier, it is determined which debt ratios are significant factors of default to form a “partial” default model. Third, by adding 6 non-financial control variables to the partial default model, it is observed how the inclusion changes the significant factors and which control variables have significant effects on default. This is the “full” default model. Finally, a default model is estimated by running regression only on significant factors found in the full default model. In all regressions, it is checked for multi-collinearity in explanatory variables with three commonly used indicators: variance inflation factor (VIF), condition number, and determinant of the correlation matrix.<sup>20)</sup>

The basic default model estimates the significant coefficients for ZS, SBC, and LEVR, and correctly captures the negative effect of ZS and the positive effect of SBC and LEVR on default.<sup>21)</sup> Moreover, it is found from the partial default model that the ratios of various types of debt to total assets are significant default factors, whereas the ratios of debt to total, short- and long-term debt are not significant.<sup>22)</sup> Accordingly, full default regression is performed

on basic factors, financial ratios of debt to total assets, and control variables. The full default regression model describes the relationship between default and all potential default factors as follows:

$$D = \beta_0 + \beta_1 ZS_i + \beta_2 SBC + \beta_3 LEVR_i + \beta'_4 FV_i + \beta'_5 NFN_i + \epsilon_i$$

where D, FV, and NFN represent default dummy variable, financial variables, and non-financial variables (control variables), respectively.

Table 2 presents the regression results from the model. Equation 1 (Eq. 1) in the first column is included only to examine whether the financial ratios of short- and long-term bank loan or foreign loans to total debt are statistically significant in the full default regression. It shows that the debt ratios S(L)FLTD and S(L)BLTD are still not as significant as in the partial default regression.<sup>23)</sup> Thus, it can be concluded that no types of debt to total debt are significant default factors in any of the regression models.

Equations 2 through 2-2 represent full default regressions.<sup>24)</sup> They show that ZS, SBC, and LEVR

20) There is no consensus on detecting multi-collinearity. A rule proposed by Allison (1998) is followed that it is present if the variance inflation factor (VIF) is greater than 2. Moreover, a rule of thumb states that there is a concern of multi-collinearity if the condition number (the ratio of the largest eigenvalue to the smallest eigenvalue) is greater than 15 and the determinant of the correlation matrix is close to zero. Thus, if the condition number is one, there is no collinearity. These indicators are computed using the “collin” command in STATA.

21) The regression result from the basic default model is available upon request.

22) The partial default model is separately run on various ratios of debt to total debt and to total assets. In the regressions with the financial ratios to total debt, only LFLLD and LBLLD appear to be marginally significant at the level of 10%. Therefore, they are not taken into account as strong indicators of default at significance levels of 1% and 5%. In the regressions with the financial ratios to total assets, S(L)DTA and SBLTA appear to be statistically significant at levels of 1% and 5%, respectively, which implies that the ratios of debt to total assets are more likely to be important factors of default than are the ratios of debt to total debt. The regression results from the partial default models are available upon request.

23) This result may be spurious because the condition number is greater than 15. Thus, in order to completely remove the possibility of multi-collinearity, insignificant variables are excluded, such as ownership by banks, ownership by foreigners, and investment ratio, as well as one significant variable, FAGE, from control variables, and then the regression is run again. This reduces the condition number to 14.39, and the regression still generates insignificant debt ratios, leaving other variables significant.

24) Condition numbers in Equations 2 and 2-1 are slightly above 15, which implies some, but still acceptable, multi-collinearity. Regression is performed without putting S(L)DTA, S(L)BLTA, and S(L)FLTA together, due to the high correlation between SDTA and SBLTA (0.743) and between LDTA and LBLTA (0.794). When they are combined in regression, the condition number is 18.72, which may have led to spurious regression results.



**Table 2.** Full default regression models for Korean firms: probit regression

Variables	Dependent Variable: D							
	Eq. 1	Eq. 2	Eq. 2-1	Eq. 2-2	Eq. 3-1	Eq. 3-2	Eq. 4-1	Eq. 4-2
ZS	-0.265** (0.131)	-0.273** (0.132)	-0.276** (0.131)	-0.469*** (0.122)				
SBC	0.478* (0.257)	0.524** (0.255)	0.501** (0.252)	0.342 (0.252)	0.874*** (0.214)	1.008*** (0.218)	0.871*** (0.214)	1.080*** (0.211)
LEVR	1.921*** (0.511)	1.721*** (0.553)						
LEVR(t-1)					0.697 (0.457)	1.998*** (0.495)		
SFLTD	-1.120 (1.034)							
SBLTD	0.309 (0.550)							
SDTA			1.911*** (0.496)		2.157*** (0.625)		2.661*** (0.473)	
SFLTA				-1.554 (1.288)		-2.244 (1.467)		-2.666** (1.293)
SBLTA				1.476** (0.633)		1.419** (0.673)		2.684*** (0.566)
LFLTD	-2.567 (1.961)							
LBLTD	-0.975 (0.913)							
LDTA			1.581** (0.695)		2.002** (0.898)		2.413*** (0.772)	
LFLTA				-3.804 (2.468)		-3.773 (2.454)		-4.192* (2.364)
LBLTA				0.525 (0.695)		0.550 (0.716)		1.825*** (0.691)
FAGE	-0.026*** (0.007)	-0.026*** (0.007)	-0.026*** (0.007)	-0.027*** (0.008)	-0.024*** (0.007)	-0.024*** (0.007)	-0.023*** (0.007)	-0.022*** (0.007)
OWNS	-0.019*** (0.005)	-0.019*** (0.005)	-0.019*** (0.005)	-0.019*** (0.005)	-0.021*** (0.005)	-0.022*** (0.005)	-0.020*** (0.005)	-0.021*** (0.005)
OWNB	0.004 (0.008)	0.003 (0.008)	0.003 (0.008)	0.011 (0.007)	-0.003 (0.008)	0.001 (0.007)	-0.001 (0.008)	0.007 (0.006)
OWNF	0.000 (0.007)	0.002 (0.007)	0.002 (0.007)	-0.001 (0.007)	0.001 (0.007)	-0.002 (0.007)	0.001 (0.007)	-0.004 (0.007)
INVS	0.847 (0.827)	0.196 (0.782)	0.220 (0.789)	0.962 (0.825)	-0.027 (0.834)	0.641 (0.874)	-0.092 (0.839)	0.570 (0.882)
EXPO	-0.582** (0.293)	-0.693** (0.282)	-0.681** (0.281)	-0.548* (0.290)	-0.694** (0.278)	-0.548* (0.278)	-0.724*** (0.271)	-0.608** (0.271)
Constant	-0.703 (0.479)	-0.649 (0.486)	-0.709 (0.449)	0.270 (0.349)	-1.435*** (0.362)	-1.125*** (0.359)	-1.296*** (0.381)	-0.203 (0.284)
Observations	489	489	489	489	489	489	489	489
Pseudo R <sup>2</sup>	0.345	0.330	0.331	0.317	0.323	0.306	0.319	0.267
<i>Collinearity Indicators</i>								
Avg. VIF	1.53	1.48	1.46	1.36	1.45	1.30	1.13	1.20
Condition No.	18.52 <sup>+</sup>	15.19 <sup>+</sup>	15.76 <sup>+</sup>	12.51	14.50	14.65	13.13	11.84
Det. (corr. mtx.)	0.07	0.21	0.19	0.17	0.22	0.22	0.57	0.38
Cutoff Value	Correct Classification Rate for Default and Non-Default Firms							
0.5	84.66%	85.28%	84.87%	84.66%	85.89%	84.05%	85.48%	84.25%
0.22	78.73%	79.35%	79.55%	79.14%	77.91%	77.51%	78.53%	77.71%

Notes: \*, \*\*, and \*\*\* represent the significance at the level of 10%, 5%, and 1%, respectively, and robust standard errors are in parentheses. The cutoff value of 0.5 is the expectation by chance, and 0.22 (108/489) is the random chance of default in the sample. <sup>+</sup>represents the concern of collinearity.  
D: default dummy, ZS: Z-score, SBC: soft budget constraint, FAGE: age of a firm, INVS: the ratio of investment to total asset (t-1), EXPO: the ratio of export to revenue (sales), OWNS, OWNB, and OWNF: ownerships by majority shareholders, banks, and foreigners, respectively, LEVR: leverage, S(L)DTA: the ratio of short (long)-term debt to total assets, S(L)FLTD: the ratios of short (long)-term foreign loans to total debt, S(L)BLTD: the ratios of short (long)-term bank loans to total debt, S(L)FLTA: the ratios of short (long)-term foreign loans to total assets, S(L)BLTA: the ratios of short (long)-term bank loans to total assets.

**Table 3.** Final default regression models: probit regression

Variables	Dependent Variable: D	
	<i>Model A: D<sup>A</sup></i>	<i>Model B: D<sup>B</sup></i>
ZS	-0.259**[0.128]	-0.260**[0.128]
SBC	0.532**[0.254]	0.514**[0.250]
LEVR	1.755***[0.529]	
SDTA		1.928***[0.488]
LDTA		1.641**[0.660]
FAGE	-0.025***[0.007]	-0.025***[0.007]
OWNS	-0.019***[0.005]	-0.019***[0.005]
EXPO	-0.693**[0.279]	-0.682**[0.279]
Constant	-0.638[0.483]	-0.690[0.449]
Observations	489	489
Pseudo R <sup>2</sup>	0.330	0.331
<i>Collinearity Indicators</i>		
<i>Avg. VIF</i>	1.62	1.56
<i>Condition No.</i>	13.55	14.36
<i>Det. (corr. mtx.)</i>	0.25	0.24
<i>Cutoff Value</i>	Correct Classification Rate for Default and Non-Default Firms	
0.5	85.48%	85.28%
0.22	79.55%	79.55%

Notes: Robust standard errors are in brackets. The cutoff value of 0.5 is the expectation by chance, and 0.22 (108/489) is the random chance of default in the sample.

D: default dummy, ZS: Z-score, SBC: soft budget constraint, FAGE: age of a firm, LEVR: leverage, OWNS: ownerships by majority shareholders, S(L)DTA: the ratio of short (long)-term debt to total assets, EXPO: the ratio of export to revenue (sales).

are still strong determinants of default, and that short- and long-term debt ratios [S(L)DTA] and short-term bank loan ratio [SBLTA] are also significant. These results are consistent with the findings from partial default models, which means that inclusion of control variables do not change the results. Among control variables, a firm's age [FAGE], ownership by the largest shareholders [OWNS], and export ratio [EXPO] appear to be significant and help lessen the likelihood of default. The regression results imply that the default of Korean firms during the sample period is most likely to have been in relation to debt (leverage, including short- and long-term debts and short-term bank loans) and borrowing under financial distress (SBC), and that firms in better financial state (ZS), more operating experience (FAGE), higher ownership concentration (OWNS), and export ratio (EXPO) are less likely to go into bankruptcy.<sup>25)</sup>

Equations 3-1 through 4-2 represent additional regressions for checking the robustness of the results from the full default regression models. In Equations 3-1 and 3-2, ZS is removed and LEVR in lag is added.<sup>26)</sup> In Equations 4-1 and 4-2, ZS and LEVR, which are the most important determinants of default, are excluded. The regression results show that there is no substantial difference from those in previous regressions. That is, variables significant in Equations 2-1 and 2-2 appear to be still significant with identical signs, implying that the previous findings are robust.<sup>27)</sup>

25) Krugman (1998) ascribes the financial crisis to financial institutions' excessive borrowing in the short-term and financing loans to highly leveraged firms. Huang and Xu (1998 and 1999) argue that bad loans continued to increase with the interaction between banks and large firms, and the large increase of bad loans caused bankruptcy and the financial crisis in Korea.

26) Due to the high correlations between LEVR and SDTA and between LEVR and LDTA, its lag value is used.

Among the full default regression models, Equations 2 and 2-1 are selected as best representatives because they incorporate all of the relevant default factors and correctly capture their effects on default.<sup>28)</sup> The models exclude insignificant factors and regression is run only on the significant factors. The estimated final default models are presented in Table 3. As expected, the coefficients are all statistically significant and a concern of collinearity does not arise. The models are almost indistinguishable in terms of fitness and the classification rate. Model A provides a slightly higher correct classification rate than Model B, with the cutoff at 0.5.<sup>29)</sup> Model A is chosen as the final default model that best captures the likelihood of bankruptcy of Korean firms.<sup>30)</sup>

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27) The omission of two important variables seems to change the results in the last regression equation (Eq. 4-2). SFLTA, LFLTA, and LBLTA, which were insignificant, turn out to be significant factors, and the estimated coefficients have a higher impact on default. Thus, these are not considered as important determinants of default.

28) Equation 2-2 is not chosen not only because its predictive power is slightly lower than those of the other two equations, but also because SBC does not appear to be significant even though SBC is the most significant factor in other regression models.

29) Model A is more “comprehensive” than Model B in reflecting the relationship between debt ratios, since LEVR includes SDTA and LDTA.

30) Model B is also used for the purpose of comparison of model power with Model A in Section IV. In order to determine whether the significant factors found from default regressions actually help improve the power of the Altman z-score model, the new Altman z-score model is re-estimated with SBC, leverage, age, ownership structure, and export ratio. The results indicate that the discriminating power of the sample (84.9%) does not change. However, age, leverage, and export ratio do not show discriminating powers in univariate analysis. Moreover, even though SBC is expected to show a negative relationship with z-score because SBC increases the likelihood of default in probit regression, the sign of its coefficient is positive. Thus, the discriminant function is estimated again by dropping these variables and only including ownership structure, and the new discriminant function increases the predictive power to 87.2%. The final default model is also re-estimated by dropping ownership structure in order to observe its degree of importance, and the fitness and the predictive power of the final default model declines. These findings present evidence that ownership structure is an important determinant in predicting the likelihood of default and most likely helps improve the power of the default model.

### C. Variables, Data, and Sample Selection for US Firms

As in the previous section, the same approach is applied to determine the most important default factors and a default model for US firms. The initial panel data are collected from the COMPUSTAT industrial annual database of North America from 1990 through 2003.<sup>31)</sup>

After removing inappropriate data from the initial data set, which comprises of 2,523 inactive firms (35,322 Obs.) and 2,990 active firms (41,860 Obs.), the sample for regression analysis is extracted from the final panel data set consisting of 84 default firms (364 Obs.) and 1,222 non-default firms (9,838 Obs.).<sup>32)</sup> Initially, 84 observations in the year before default are selected from default firms, and 336 non-default firms are closely matched to 84 default firms in terms of asset size in a given year. Recall that the sample for Korean firms composes of 108 default firms and 381 non-default firms. Thus, instead of using all of the non-default US firms available in the final data set, the ratio between default and non-default firms (1:4) in the sample, similar to the ratio between the Korean counterparts (1:3.5) is maintained.

Unlike the process for analyzing Korean firms, z-scores are generated using the original Altman z-score model rather than the new Altman z-score model for US firms.<sup>33)</sup> Based on the results, an SBC dummy variable is also generated. The SBC for US firms is defined using the same method deployed for Korean firms. That is, a firm is defined as an SBC firm if it increases short-term debt (debt in current liability) while having a low z-score in any year in the sample period.<sup>34)</sup>

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31) See Alexeev and Kim (2012) and Kim (2016) for more details regarding the data.

32) Inactive firms under Chapter 7 (liquidation) of the U.S. bankruptcy code or Chapter 11 (reorganization) are classified as default firms.

33) The original Altman z-score model is used because it is a benchmark model for predicting the likelihood of bankruptcy of US firms and that it has a high correct classification rate for US firms.

34) A low z-score is defined as less than the low z-score cutoff value (0.495), which is the 10th percentile of all z-scores

**Table 4.** Descriptive statistics for the U.S. firms in the sample

Variables	Total Firms					Default Firms					Non-Default Firms					<i>t</i> -statistics
	Obs.	Mean	S.D.	Min.	Max.	Obs.	Mean	S.D.	Min.	Max.	Obs.	Mean	S.D.	Min.	Max.	
ZS	413	5.432	10.03	18.80	91.85	80	0.396	4.865	18.80	14.34	333	6.832	10.45	18.22	91.85	-6.029***
SBC	413	0.111	0.315	0.000	1.000	80	0.388	0.490	0.000	1.000	333	0.045	0.208	0.000	1.000	9.661***
OWNS	413	22.68	22.28	0.000	99.99	80	25.42	26.44	0.000	99.99	333	22.02	21.15	0.000	99.99	1.228
INVTA	413	0.221	0.145	0.000	0.668	80	0.286	0.141	0.000	0.668	333	0.206	0.141	0.000	0.655	4.560***
CAEXTA	413	0.061	0.070	0.005	0.746	80	0.056	0.067	0.005	0.365	333	0.063	0.071	0.000	0.746	-0.839
CACL	413	3.363	3.657	0.146	32.29	80	1.602	1.477	0.287	8.192	333	3.786	3.892	0.146	32.29	-4.930***
LEVR	413	0.473	0.322	0.037	2.341	80	0.802	0.376	0.047	1.947	333	0.395	0.251	0.037	2.341	11.720***
SDTD	413	0.718	0.247	0.123	1.000	80	0.730	0.271	0.123	1.000	333	0.714	0.242	0.140	1.000	0.508
LDTD	413	0.282	0.247	0.000	0.877	80	0.270	0.271	0.000	0.877	333	0.286	0.242	0.000	0.860	-0.508
SDTA	413	0.317	0.251	0.029	1.933	80	0.573	0.370	0.036	1.933	333	0.255	0.161	0.029	1.194	11.760***
LDTA	413	0.157	0.204	0.000	1.388	80	0.229	0.288	0.000	1.388	333	0.139	0.174	0.000	1.164	3.569***
SDCLTD	413	0.162	0.196	0.000	0.948	80	0.303	0.251	0.000	0.948	333	0.129	0.163	0.000	0.914	7.613***
SDCLTA	413	0.098	0.179	0.000	1.581	80	0.263	0.298	0.000	1.581	333	0.058	0.102	0.000	0.884	10.310***
SDCLCL	413	0.220	0.224	0.000	0.948	80	0.380	0.258	0.000	0.948	333	0.182	0.196	0.000	0.915	7.598***

Notes: \*\*\* denotes that sample means are statistically different at the 1% significance level.

ZS: Z-score, SBC: soft budget constraint, FAGE: age of firm, OWNS: ownerships by majority shareholders, INVTA: the ratio of inventory to total assets, CAEXTA: the ratio of capital expenditures to total assets (t-1), CACL: the ratio of current assets to current liabilities, LEVR: leverage, S(L)DTD: the ratio of short (long)-term debt to total debt, S(L)DTA: the ratio of short (long)-term debt to total assets, SDCLTD, SDCLTA, and SDCLCL: the ratios of debt in current liabilities to total debt, to total assets, and to current liabilities, respectively.

Because ownership data for US firms in the initial sample are not available in the COMPUSTAT database, data on ownership by firm “insiders” are extracted from another database, Compact D of the Securities and Exchange Commission (SEC). Out of 420 firms, 7 firms are unidentified in the database, so 413 firms (80 default firms and 333 non-default firms) are finally used in the regression analysis. In addition, some other unavailable variables are replaced by proxy variables. For example, debt in current liability ratios [SDCLTD, SDCLTA, and SDCLCL], which are defined as debt in current liability to total debt, to total assets, and to current liability, respectively, are used as proxy variables for the short-term bank loan and foreign loan ratios [SF(B)LTD, SF(B)LTA, and SF(B)LSD, respectively] previously used for Korean firms.

(10,232 Obs.) that include 93 default firms (394 Obs.) rather than 84 firms (364 Obs.). The number of firms and observations include 9 default firms (30 Obs.), which are excluded from the final panel data set as potential outliers that possess assets less than 10 million dollars or greater than 1 billion dollars in a year prior to default.

Furthermore, three additional control variables are chosen to reflect firms’ activity and liquidity: inventory ratio [INVTA], capital expenditures ratio [CAEXTA], and current ratio [CACL]. Inventory is one of the most important assets in an operating firm. INVTA is defined as inventory to total assets. Capital expenditures are investments in physical assets, such as equipment or machinery, to provide benefits to a firm. CAEXTA, which is defined as capital expenditures to total assets, is used as a proxy for the investment ratio. CACL, which is defined as current assets to current liability, is one of the measures of the extent to which a firm can pay short-term debt with short-term assets. This implies that if a firm has a current ratio of less than 1, it is likely to default.<sup>35)</sup>

Table 4 summarizes the descriptive statistics for these variables and presents *t*-statistics in the last column. The table contrasts the statistical differences

35) In the sample (413 Obs.), about 39% of default firms have a ratio less than 1, whereas only about 5% of the non-default firms do.

**Table 5.** Full default regression models for US firms: probit regression

Variables	Dependent Variable: D							
	<i>Basic model</i>	Eq. 1	Eq. 1-1	Eq. 2	Eq. 2-1	Eq. 3	Eq. 3-1	Eq. 3-2
ZS	-0.093*** (0.028)	-0.121** (0.049)	-0.130** (0.051)	-0.117** (0.050)	-0.098** (0.046)	-0.104** (0.048)	-0.106** (0.047)	-0.103** (0.047)
SBC	0.273 (0.278)	0.469 (0.355)	0.491 (0.356)	0.841** (0.345)	0.607* (0.332)	0.416 (0.352)	0.352 (0.364)	0.375 (0.359)
LEVR	1.282*** (0.312)				1.054** (0.523)			
SDTA		1.529*** (0.586)				1.814** (0.716)	1.403** (0.712)	1.560** (0.677)
SDCLTA			1.913*** (0.683)					
SDCLTD							1.188** (0.560)	
SDCLCL								1.007** (0.441)
LDTA				0.308 (0.433)		0.723 (0.556)	1.077** (0.522)	0.908* (0.511)
OWNS		0.002 (0.004)	0.002 (0.004)	0.002 (0.004)	0.002 (0.004)	0.002 (0.004)	0.001 (0.004)	0.001 (0.004)
CACL		0.022 (0.085)	-0.014 (0.080)	-0.095 (0.094)	-0.022 (0.086)	0.035 (0.084)	0.052 (0.075)	0.060 (0.070)
INVTA		2.359*** (0.677)	2.457*** (0.665)	3.012*** (0.669)	2.646*** (0.663)	2.310*** (0.682)	2.158*** (0.666)	2.107*** (0.659)
CAEXTA		1.294 (1.237)	1.361 (1.222)	1.162 (1.314)	1.405 (1.362)	1.428 (1.320)	1.561 (1.323)	1.433 (1.362)
Constant	-1.338*** (0.226)	-1.938*** (0.387)	-1.530*** (0.299)	-1.404*** (0.324)	-2.026*** (0.501)	-2.236*** (0.520)	-2.372*** (0.477)	-2.440*** (0.466)
Observations	413	413	413	413	413	413	413	413
Pseudo R <sup>2</sup>	0.285	0.327	0.329	0.306	0.326	0.335	0.347	0.349
<i>Collinearity Indicators</i>								
<i>Avg. VIF</i>	1.53	1.57	1.45	1.32	1.55	1.57	1.64	1.57
<i>Condition No.</i>	5.00	7.87	6.93	7.29	8.69	8.93	9.37	9.45
<i>Det.(corr. mtx.)</i>	0.50	0.20	0.27	0.39	0.21	0.17	0.10	0.12
<i>Cutoff Value</i>	Correct Classification Rate for Default and Non-Default Firms							
0.5	84.52%	86.20%	85.71%	84.26%	85.47%	85.71%	85.96%	86.20%
0.19	78.81%	79.66%	79.90%	80.15%	81.60%	82.32%	80.15%	80.39%

Notes: \*, \*\*, and \*\*\* represent the significance at the level of 10%, 5%, and 1%, respectively, and robust standard errors are in parentheses. The cutoff value of 0.5 is the expectation by chance, and 0.19 (80/413) is the random chance of default in the sample. D: default dummy, ZS: Z-score, SBC: soft budget constraint, LEVR: leverage, FAGE: age of a firm, OWNS: ownerships by majority shareholders, INVTA: the ratio of inventory to total assets, CAEXTA: the ratio of capital expenditures to total assets (t-1), CACL: the ratio of current assets to current liabilities, S(L)DTA: the ratio of short (long)-term debt to total assets, SDCLTA, SDCLTD, and SDCLCL: the ratios of debt in current liabilities to total assets, to total debt, and to current liabilities, respectively.

between default and non-default firms. All variables, except for OWNS, CAEXTA, and the short- and long-term debts to total debt ratios [S(L)DTD], are statistically different at the significance level of 1%. As with Korean firms, ZS is negative and lower in the default group, whereas LEVR and short- and

long-term debt ratios are higher. Among control variables, CACL is lower in the default group, whereas INVTA is higher. In particular, LEVR and all short-term debt ratios except for SDTD are more than twice as high as in the default group, whereas ZS and CACL are substantially lower, which implies

that the financially distressed firms are exposed to a higher risk of default than non-default firms and that these variables are likely to be significant factors for default.

#### D. Default Factors and Default Model

Regressions for US firms are performed similar to Korean firms using a full default model, which is based on the basic default model and the partial default model. The regression result from the basic model in the first column of Table 5 shows that ZS and LEVR are significant determinants of default, whereas SBC is not.

As in the basic model, ZS and LEVR appear to be significant, whereas SBC still does not, even in partial default regressions, based on three basic factors (ZS, SBC, and LEVR).<sup>36)</sup> In addition, various types of debt ratios, both to total assets and to total debt, are statistically significant. Thus, full default regressions are separately run by adding four control variables defined earlier. However, the regression results only with short- and long-term debt ratios to total assets are presented here to be comparable to those of Korean firms.

Tables 5 present regression results in which ZS, LEVR, and short-term debt ratios are statistically significant at the level of 5% or 1% in all regressions, which implies that they are most likely to be important default factors.<sup>37)</sup> However, SBC and ownership do not appear to be significant factors for default, except for SBC in Equations 2 and 2-1.<sup>38)</sup> This is probably

because in the U.S. with its high quality of institutions, SBC may not be sufficient evidence of future default. Moreover, ownership does not matter much for bankruptcy, presumably because it is diversified and expropriation by “insiders” is less likely to occur (Judge et al., 2008).

Among control variables, only INVTA emerges as a significant default factor at the significance level of 1%, which implies that inventory piling up increases the likelihood of default.<sup>39)</sup> In spite of the statistical difference in current ratio between default and non-default firms observed in Table 4, it does not appear to be a significant factor of default. This is probably because default firms have the ability to pay back their short-term debts with short-term assets, as shown in the cases of default firms with current ratios greater than one.

Equations 3-1 and 3-2 in Table 5 represent additional regressions performed to check whether two different short-term debt ratios [SDCLTD and SDCLCL] that appear to be significant in the regression with the short- and long-term debt ratio to total debt are still important determinants of default in the regression with the financial ratios of short- and long-term debt to total assets [SDTA and LDTA]. They are added to Equation 3 separately. The regression results show that the addition did not change their significance. Therefore, based on the full default regression models, it can be concluded that ZS, LEVR, INVTA, and the ratios of short-term debt to total debt and total assets are the most significant default factors for US firms in the sample period.

36) Regression results from the partial default models are available upon request.

37) The regression results with ratios of short- and long-term debts to total debt are very similar. ZS, LEVR and short-term debt ratios such as SDTD, SDCLTD, and SDCLCL appear to be statistically significant. The regression results are available upon request. As with Korean firms, there are high correlations between LEVR and SDTA (0.775) and between LEVR and LDTA (0.633). Due to the likelihood of the multi-collinearity between them, LEVR is dropped from all regression equations, except for Equation 2-1. Long-term debt ratios appear to be significant in some equations and not in others. Thus, long-term debts are not considered as important factors of default.

38) SBC is unlikely to be a default factor for US firms because it does not appear to be statistically significant in most of the regression equations. In addition, only 38% of default firms and 4% of non-default firms in the sample are SBC firms, compared to 50% and 20%, respectively, for Korean firms. This implies that SBC is presumably a “weak” phenomenon in US firms.

39) The same regressions are run after replacing the inventory ratio with inventory turnover. It also appears to be statistically significant at the level of 1% with other factors unchanged and with the opposite sign of the marginal effect of the inventory ratio on default. This implies that a high inventory turnover decreases the likelihood of default.

**Table 6.** Final default regression models: probit regression

Variables	Dependent Variable: D			
	Panel A		Panel B	
	Model A: D <sup>A</sup>	Model B: D <sup>B</sup>	Model A: D <sup>A</sup>	Model B: D <sup>B</sup>
ZS	-0.094**[0.046]	-0.132***[0.045]	-0.104**[0.048]	-0.138***[0.046]
SBC	0.618*[0.327]		0.551*[0.323]	
LEVR	1.112**[0.470]		1.040**[0.450]	
SDTA		1.739***[0.447]		1.685***[0.445]
INVT A	2.505***[0.633]	1.978***[0.617]	2.349***[0.609]	1.873***[0.599]
Constant	-1.965***[0.380]	-1.644***[0.272]	-1.815***[0.368]	-1.553***[0.269]
Observations	413	413	420	420
Pseudo R <sup>2</sup>	0.322	0.318	0.314	0.313
<i>Collinearity Indicators</i>				
<i>Avg. VIF</i>	1.50	1.20	1.51	1.20
<i>Condition No.</i>	5.88	4.96	5.88	4.98
<i>Det. (corr. mtx.)</i>	0.43	0.74	0.43	0.75
<i>Cutoff Value</i>	Correct Classification Rate for Default and Non-Default Firms			
0.5	85.23%	85.47%	84.76%	85.24%
0.19 (0.2)	80.39%	80.63%	80.48%	80.71%

Notes: Robust standard errors are in brackets. The cutoff value of 0.5 is the expectation by chance, and 0.19 (80/413) is the random chance of default in the sample. The cutoff value (0.2) for Panel B is in parenthesis.  
 D: default dummy, ZS: Z-score, SBC: soft budget constraint, LEVR: leverage, SDTA: the ratio of short-term debt to total assets, INVT A: the ratio of inventory to total assets.

Among the full default regression models, Equations 2-1 and 3 are chosen as the best representatives of US firms because they incorporate all of the relevant default factors and correctly capture their effects on default, and they are comparable to those of Korean firms, which are estimated based on the financial ratios of various types of debt to total assets. From the models, only the significant factors are extracted and then, based on them, a regression is performed.

Panel A in Table 6 presents the final default models estimated separately. All estimates are statistically significant, and the concern of multi-collinearity does not arise. In addition, the fitness and the predictive power of the two models are very close to each other. The final default models in Panel B are also estimated based on the 420 observations in the initial sample before incorporating the ownership variable.<sup>40)</sup> This is because the “k-fold test” for the robustness

of model power requires that each “k-fold” subsample in Section IV should consist of default firms and non-default firms of equal size. The regression results are quite similar to the models in Panel A. Thus, models in Panel B are taken into account as the best representatives of the final default model for US firms. Between them, Model B provides a slightly higher correct classification rate than Model A, and Model B is chosen as the one that best captures the likelihood of bankruptcy of US firms.<sup>41)</sup>

of default in full regression. Thus, in addition to the 413 firms, 7 others selected in the initial sample before merging ownership in subsection C of Section III are also used in the regression of the final default model.

41) Model A is also used for the comparison with Model B in Section IV.

40) Ownership structure is not identified as a significant determinant

## IV. Comparison of Model Power

A model that correctly classifies default and non-default firms with a higher accuracy rate is regarded as having a higher level of predictive power. Among many bankruptcy prediction models, Altman's z-score model is one of the most widely used benchmark models for predicting the likelihood of a firm's bankruptcy. Another popularly used model in relation to predicting bankruptcy is the hazard function model. Yang and Temple (2009) examine a firm's exit rate via a non-parametric estimation with a hazard function, and find that a firm's size is an important determinant. Moody's constructs default prediction models using both parametric and non-parametric approaches for public and private firms to estimate the probability of a firm's bankruptcy, and shows that its models perform better than Altman's z-score model, the hazard function model, and other existing credit risk models (Sobehart and Stein, 2000; Kocagil and Reyngold, 2003).

Similarly, using two Moody's power metrics - power curve and accuracy ratio - to compare the model powers of the final default model estimated in Section III with those of the original Altman model and the new Altman model, this paper determines the model that provides the best performance. Table 7 summarizes the set of variables, methodologies, and composition of data for these models. As shown in the table, the first two models are estimated using different variables and methods, but with the same data, whereas the last two models are estimated using the same Altman variables and methods, but with different data. In order to make the model powers

comparable, the same data set is applied to all three models in generating outputs (scores).

The first model is the "Probit Default Korea" model, which was estimated as a final default model from the probit regression in subsection B of Section III. The second model is the "New Altman Korea" model, which was re-estimated using the discriminant analysis by Kim (2016). The third model is the "Altman" model, which is the original Altman z-score model. Next, based on the model scores generated by these models, a power curve is constructed, the accuracy ratio is computed in order to compare model powers, and the most powerful model is determined.

### A. Power Curve

A power curve is a measure that evaluates model power via the relationship between the cumulative percentage of sample firms excluded from the data set and the cumulative percentage of default firms excluded from the data set. Given a percentage of firms excluded from the same data set, if a model excludes a higher percentage of default firms than other models, the model is regarded as more powerful than others. Accordingly, a "perfect" model is the one that gives all default firms worst scores than non-default firms. In contrast, a "random" model is the one that eliminates default firms at the same rate as non-default firms. That is, a random model is the 45-degree line on the graph that shows the relationship between the percentage of default firms excluded ( $y$  axis) and the percentage of sample firms excluded ( $x$  axis).

The power curve is constructed as follows. First,

**Table 7.** Model composition for variables, methodology, and data for Korean firms

Model	Model Variable		Methodology		Data	
	Altman	DF	MDA	Probit	for model	for score
1. Probit Default Korea		○		○	Korea (489)	Korea (489)
2. New Altman Korea	○		○		Korea (86)	Korea (489)
3. Altman	○		○		US (66)	Korea (489)

Notes: Altman, DF, MDA, and Probit represent factors from Altman's model, factors from probit regression, multiple discriminant function analysis, and probit regression, respectively. The number of observations is in parentheses.



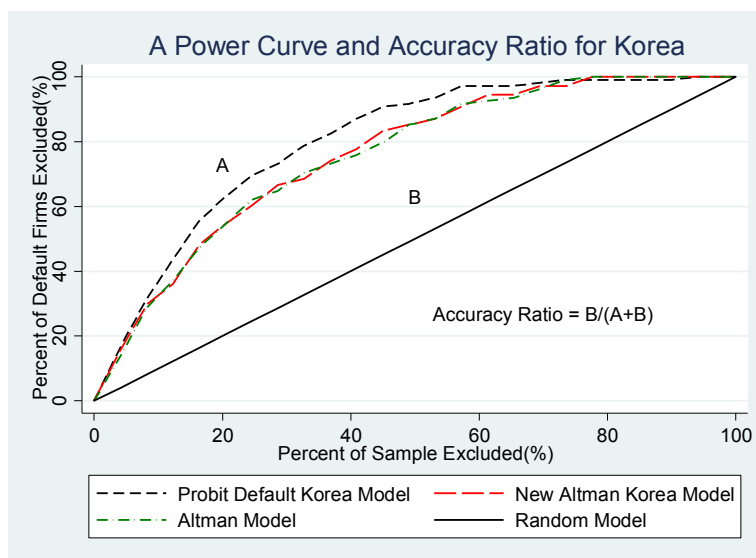


Figure 1. Power curves based on 489 observations of Korean firms

scores from an estimated model are sorted from worst to best. Second, a certain percentage of the sorted scores are repeatedly excluded from the worst until all scores are removed.<sup>42)</sup> At the same time, the percentages of sample firms and default firms excluded are cumulatively computed. Third, the power curve is drawn using the result of computation.

Following these procedures, the scores are computed from the three models - the final default model (Probit Default Korea model), the new Altman z-score model (New Altman Korea model), and the original Altman z-score model (Altman model) - with a single data set (108 default and 381 non-default firms), and a power curve for each model is constructed, as shown in Figure 1.

In the graph, the power curve of the Probit Default Korea model is furthest away from the 45-degree line, which indicates that the model performs better than the other two. With less than 20% of the sample excluded, there is almost no difference between the new Altman Korea model and the Altman model. In most parts above 20%, the curve suggests that the former has a little higher model power than the

latter. This is consistent with the argument made in Section II that the original Altman z-score model is less powerful than the new Altman z-score model in classifying Korean firms.<sup>43)</sup> Therefore, it can be concluded that the Probit Default Korea model is most powerful, followed by the new Altman Korea model and the Altman model.

Next, scores are computed from the three models with the same data set (420 Obs.) used in the estimation of the final default model for US firms. The first model is the Probit Default US model, which was estimated as the final default model from the default probit regression in Table 6. The second model is the New Altman Korea model, which was estimated using the discriminant function analysis for Korean firms by Kim (2016).<sup>44)</sup> The third model is the Altman model, which is the original Altman z-score model. The second and third models are the same ones used for comparing model powers for Korean firms. Table 8 summarizes

42) Each time, lowest 20 scores (firms) from 489 (about 4%) in the sample are excluded, except for the final removal (9 firms).

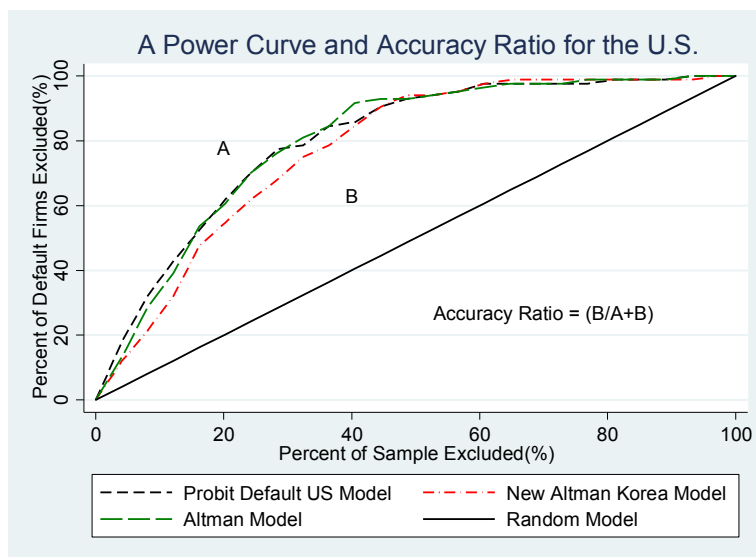
43) Model power is generally expected to decline when a model is applied to a different sample or an “out-of sample”. Thus, the higher power of the new Altman z-score model may be ascribed to using “in-sample” data (489 firms).

44) As the Altman’s z-score model is previously applied to Korean firms in the comparison of model, the new Altman z-score model is applied to US firms.

**Table 8.** Model composition for variables, methodology, and data for US firms

Model	Model Variable		Methodology		Data	
	Altman	DF	MDA	Probit	for model	for score
1. Probit Default US		○		○	US (420)	US (420)
2. New Altman Korea	○		○		Korea (86)	US (420)
3. Altman	○		○		US (66)	US (420)

Notes: Altman, DF, MDA, and Probit represent factors from Altman’s model, factors from probit regression, multiple discriminant function analysis, and probit regression, respectively. The number of observations is in parentheses.



**Figure 2.** Power curves based on 420 observations of US firms

the composition of variables, methodology, and data for these models.

Based on the scores generated by the three models with a single data set (84 default and 336 non-default firms), power curves are drawn, as shown in Figure 2. The new Altman Korea model is located closest to the 45-degree line, which implies that it has the lowest level of model power. This is not surprising since the application of the new Altman Korea model to another sample set (US firms) likely reduces its predictive power.

The difference in model power between the Altman model and the Probit Default US model is not apparent due to the similarity in their power curves, which implies that the final default model, which is found to be the best representative for US firms, is as powerful as the original Altman z-score model.<sup>45)</sup>

### B. Accuracy Ratio

As shown in Figures 1 and 2, the power curve provides visual and qualitative assessments of model performance. However, it is difficult to compare overall model powers, especially when power curves have similar shapes. Therefore, the curve is converted into a numerical metric (accuracy ratio) to measure comparative performance. In other words, the accuracy ratio converts the power curve into a single numerical measure that represents the overall

45) The power curves overlap for the most part. However, with less than 20% of the sample excluded, the power curve of the Probit Default US model is located a little bit further away from the 45-degree line than that of the Altman model. With around 40% of the sample excluded, the power curve of the latter is located slightly further away from the 45-degree line than that of the former.

**Table 9.** Comparison of accuracy ratios for Korean firms

Sample	No. of Obs.	Model		
		<i>Probit Default Korea</i>	<i>New Altman Korea</i>	<i>Altman</i>
“In-sample”	489 [108:381]	60.08% (60.24%)	51.82%	51.14%
Subsample 1	163 [36:127]	60.87% (59.91%)	54.43%	53.95%
Subsample 2	163 [36:127]	59.91% (59.91%)	51.32%	50.61%
Subsample 3	163 [36:127]	52.99% (53.95%)	50.61%	51.09%
“3-fold overall” AR	489 [108:381]	57.88% (58.03%)	51.82%	51.14%

Note: The ratios of default and non-default firms are in brackets. The percentage in parentheses is the accuracy ratio of another “Probit Default” model (Model B) in Table 3. There is no significant difference in model power between Model A and Model B.

predictive accuracy.

The accuracy ratio is defined as a ratio of the area (B) below the power curve and the area above the random model (A + B). Hence, the higher the accuracy ratio, the more powerful the model.<sup>46)</sup> The area under the power curve is approximated using the Riemann sum method because the power curve is drawn by discrete coordinates, i.e., it is not a continuous function. First, the right Riemann sum and the left Riemann sum are separately computed at each coordinate point, and then averaged.<sup>47)</sup>

The accuracy ratios from the power curves for Korean firms are summarized in Table 9. As shown in the first row, the model power ranks are consistent with the order graphically found in Figure 1. The Probit Default Korea model is identified as the most powerful with 60.08% model power, followed by the New Altman Korea model (51.82%) and the Altman model (51.14%). This finding supports the claim that using z-score as one of the predictors and incorporating additional default information from other significant default factors (non-financial variables) into the default prediction model can help improve the model performance.

Next, in order to evaluate the robustness of the model performance, accuracy ratios are computed on *k* subsamples and a *k*-fold “out-of sample”, following the procedures of Moody’s “*k*-fold test”.

First, 108 default and 381 non-default Korean firms are equally divided into 3 subsamples, each subsample consisting of 36 default firms and 127 non-default firms.<sup>48)</sup> This produces 3 different subsamples with an identical default rate (about 0.22). Second, by estimating the new default model with two of the three subsamples and computing the scores for the remaining subsample, an accuracy ratio on the latter is obtained. These procedures are performed three times for all combinations. Lastly, the scores for each remaining subsample are combined, and an accuracy ratio on the 3-fold “out-of-sample” is computed, which is the “3-fold overall” accuracy ratio.

Table 9 summarizes the accuracy ratio on each subsample and the 3-fold out-of-sample computed from the three models.<sup>49)</sup> Overall, the accuracy ratios on the subsamples are relatively stable and close to those on the initial in-sample in each model, which implies that no subsample affects the model power. Moreover, the model power ranks for the 3-fold out-of-sample do not digress from those for the initial in-sample. The Probit Default Korea model with an accuracy ratio of 57.88% is still the most powerful,

46) The accuracy ratio of the perfect model would be 100%, whereas the accuracy ratio of the random model would be 0%.

47) Since the power curve is monotonically increasing, the right Riemann sum is overestimated, whereas the left Riemann sum is underestimated. This is the reason for taking the average of the two Riemann sums.

48) In selecting subsamples, the first observation in each group from the sample is assigned to subsample 1, the second observation to subsample 2, the third observation to subsample 3, the fourth observation to subsample 1 again, the fifth observation to subsample 2, the sixth observation to subsample 3, and so on.

49) Instead of re-estimating the new Altman z-score model and the original Altman z-score model from two subsamples, the initial models are used in scoring each subsample because the data set for the original Altman z-score model is unavailable. As a result, the accuracy ratios of these models on both the initial in-sample and the 3-fold out-of-sample are identical.

**Table 10.** Comparison of accuracy ratios for US firms

Sample	No. of Obs.	Model		
		<i>Probit Default US</i>	<i>New Altman Korea</i>	<i>Altman</i>
“In-sample”	420 [84:336]	60.01% (60.29%)	55.28%	60.20%
Subsample 1	140 [28:112]	58.98% (57.76%)	57.45%	63.27%
Subsample 2	140 [28:112]	62.96% (62.96%)	55.92%	59.29%
Subsample 3	140 [28:112]	60.20% (60.20%)	53.47%	57.45%
“3-fold overall”	420 [84:336]	60.01% (60.58%)	55.28%	60.20%

Notes: The ratios of default and non-default firms are in brackets. The percentage in parentheses is the accuracy ratio via another “Probit Default” model (Model A) in Table 6. There is no significant difference in model power between Model A and Model B.

followed by the New Altman Korea model (51.82%) and the Altman US model (51.14%), suggesting that model performance is quite robust across the data set.

In sum, among the three default models, the Probit Default Korea model provides the highest model power, followed by the New Altman Korea model and the Altman model. This suggests that the non-financial factors such as SBC, age of a firm, ownership structure, and export ratio that are found to be significant in the default model can help improve the model power.

Next, based on the power curves for US firms, an accuracy ratio for each model that measures comprehensive model power with a single numerical unit is computed and presented in Table 10. The results in the first row indicate that the model power ranks are consistent with the results obtained from power curves. That is, for the initial “in-sample” consisting of 420 observations, the New Altman Korea model is the least powerful with 55.28% model power, and the power of the Probit Default US model is almost equivalent to that of the Altman’s z-score model. It is found that the former provides slightly worse performance than the latter. However, the accuracy ratio (60.29%) of another Probit Default US model (Model A) in Table 6 in subsection D of Section III shows slightly better performance than that (60.20%) of the Altman model, which implies that the additional information from the significant factors such as SBC and inventory ratio found in the full default regression may also help improve the model power for US firms.

Finally, the robustness of model performance is evaluated using Moody’s “*k*-fold test”. The initial sample is divided into three equal subsamples with an identical default ratio (20%) and the accuracy ratio of each subsample is computed by applying to each the new estimated models from the other two subsamples.

Table 10 summarizes the accuracy ratios of each model when applied to the subsamples and the 3-fold “out-of-sample”. It shows that the accuracy ratio of each subsample does not vary significantly compared to the accuracy ratio of the initial “in-sample”, which implies that none of the subsamples influence the model performance. Moreover, the accuracy ratio for the combined 3-fold out-of-sample is very similar to that for the in-sample, and the model power ranks do not change among the three models.<sup>50)</sup> This suggests that the model performance is quite robust across the data set.

## V. Conclusion

Many studies in the existing literature examine the significant determinants and the predictive models of bankruptcy. Similarly, this paper also explores the most important default factors by estimating probit

50) When applied to both the 3-fold out-of-sample and the initial in-sample, the accuracy ratios of the two Altman models appear to be identical for the same reason as noted for Korean firms in footnote 49.

default models for manufacturing firms in Korea and the U.S. in the sample periods of 1991-2001 and 1991-2003, respectively. In addition to other potential default factors, this study incorporates the z-score as one of the factors into the probit model. This is because the z-score, which reflects the overall financial situation of a firm as well as its non-financial aspects, such as ownership and soft budget constraint (SBC), may help improve the ability to predict the likelihood of bankruptcy. A probit default model is constructed based on significant factors and its predictive power is compared with those of other bankruptcy models, such as the new Altman z-score model and the Altman's z-score model.

For Korean firms, probit regression indicates that z-score, SBC, leverage, including short- and long-term debts, and short-term bank loans are the most significant default factors. Debts, especially bank loans have emerged as important factors in Korea as the financial market liberalized domestically and internationally in the 1990s. Unobserved bad or short-term loans from banks put highly leveraged firms, particularly SBC firms, in financial trouble and at a high risk of bankruptcy. In addition, age of a firm, export ratio, and concentration of ownership are also identified as significant determinants of default.

For US firms, z-score, leverage, short-term debt, and inventory are found to be the most significant default factors. Although SBC is identified as a significant factor in some cases, SBC and ownership concentration do not appear to be significant overall. This may be due to the fact that a relatively poor proxy for SBC is used for US firms and that US lenders, given a better quality of institutions, have more information concerning the ability of financially troubled firms to pay back their loans. Moreover, because US institutions have more diversified ownership structures, they may be less prone to tunneling by insiders.

These results for Korean and US firms help shed light on how propensity to corporate default differs in the two countries. Based on the significant default factors found from probit regression analyses, a

default model is constructed to outperform existing default prediction models such as the new Altman z-score model and the Altman's z-score model. To this end, in addition to other significant default factors, z-score is incorporated into the model as one of the explanatory variables, which may provide additional information for predicting bankruptcy. The power of the probit default model is compared with those of the two Altman z-score models using Moody's two power metrics: the power curve and the accuracy ratio. It is found that the probit default model possesses the highest level of predictive power for both Korean firms and US firms. These findings suggest that the additional bankruptcy information gained from the significant financial and non-financial default factors can help improve the power of a default prediction model.

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