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Efficacy of industry factors for corporate default prediction

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Abstract The paper aims to assess whether a sensitivity variable, industry beta, has a significant impact on the firm's likelihood of default, as an independent predictor variable. The study uses logistic regression and multiple discriminant analysis for matched pair sample of defaulting and non-defaulting listed Indian firms. The industry beta is estimated by regressing the monthly stock return of each individual firm on the monthly return of the respective industry index. The sensitivity variable for industry factors, industry beta, is found to be statistically significant in predicting defaults. Higher sensitivity to industry factors leads to an increased probability of default.

Introduction

Every time there is a crisis, the need to avert it, or at least to predict financial distress of a firm or an industry that could have generated the initial spark, captures the attention of all stakeholders. The inability of a firm to honour its financial obligations may largely be driven by events such as bankruptcy, bond default, an overdrawn bank account, or non-payment of a preferred stock dividend (Beaver, 1966). Of these, bankruptcy and default are the most commonly researched signals of financial distress. Given the consequences that financial distress may have for the firm in particular and the economy in general, it is imperative that the event of default be predicted in time.

Altman (1984), and Opler and Titman (1994) document the various direct and indirect costs related to financial distress, and its impact on firm's performance. While the direct costs such as auditor's fees, legal fees, management fees and other payments are incurred if the firm is forced to file for bankruptcy, the indirect costs such as lost profits and higher costs of capital are incurred even if bankruptcy is avoided. Lending and investment decisions call for accurate and timely assessment of default risk. Efficient management of exposures is particularly important for creditors, which primarily include banks and financial institutions. Determination of appropriate risk premium and pricing of corporate debt securities also necessitate an accurate estimation of default risk. Regulatory requirements such as the Basel Capital Accord require banks to develop their own internal credit risk models for objective measurement of credit risk and thereby assess the capital requirements.

The existing research primarily concentrates on the use of firm-specific factors for default prediction, the most prominent of them being accounting based models, which involve the use of information from financial statements.

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Several studies have been undertaken from time to time to provide evidence on the performance of the aforesaid models that are based on firm-specific or idiosyncratic factors. However, a limited number of studies consider the impact of industry factors on the risk of default. Even the few studies that incorporate the impact of industry factors use an industry dummy variable. An industry dummy variable, as a determinant of financial distress, essentially shows that a firm belonging to a particular industry is more likely to default on its debt obligations as compared to a reference or control group of firms belonging to some other industry.

Evidence suggests that the industry to which a firm belongs might be a significant determinant of financial distress. However, this might lead to a biased assessment of the creditworthiness of all the firms belonging to the same industry. Moreover, it has been found that financial distress of a particular firm in an industry is likely to adversely affect the availability of credit to other firms in the same industry (Tew, 2009). This is likely to result in a contagion effect thereby putting viable firms in the same industry at a disadvantage.

Departing from the existing literature, this paper is built on the conjecture that a firm need not necessarily face distress simply on account of belonging to a particular industry. Consequently, firms in the same industry may not be equally affected by distress, and the firm's sensitivity to the uncertainties in the relevant industry could have a bearing on its susceptibility to distress. This study is the first attempt to use a sensitivity variable (hereinafter referred to as "industry beta") to examine the industry effect on financial distress. Using a sample of listed Indian firms, the paper assesses whether industry beta has a significant impact on the firm's likelihood of default as an independent predictor variable.

The remainder of the paper is arranged in the following manner: the next section includes an extensive review of literature on accounting-based models and studies that incorporate the effect of industry factors on default risk. The third section describes the sources of data, the construction of the sample, the statistical technique and the variable used in the study. The fourth section consists of findings of the study and the discussion thereon. The last section provides the conclusion and implications.

Review of literature

Since the traditional accounting-based model has been the most predominant in default prediction, we briefly reflect upon the literature pertaining to the same before presenting a detailed review of the literature that examines the effect of industry factors on corporate defaults.

The initial studies on the prediction of financial distress mainly relied on the data from financial statements namely, financial ratios. In this context, the pioneering works have been those of Altman and Beaver. Beaver (1966) tested the usefulness of accounting data in the form of financial ratios in predicting financial distress. The study used univariate analysis as a statistical technique to assess the predictive ability of individual ratios. Altman (1968) attempted to combine a set of financial ratios using multivariate discriminant analysis into a risk measurement score popularly known as the Z-score. The Z-score was used to discriminate between distressed and non-distressed firms. Altman et al. (1977) developed a model for bankruptcy prediction known as the Zeta model using seven variables with some of the variables drawn from Altman (1968) and introducing certain new variables. While the use of multiple discriminant analysis was gaining ground as a well accepted statistical technique, Ohlson (1980) made one of the first attempts to use conditional logit analysis for bankruptcy prediction.

Begley et al. (1996) re-assessed the accuracy of the original models of Altman and Ohlson using data from the 1980s. They compared the original versions of these models with their respective re-estimated versions and found that in general, Ohlson's model outperformed Altman's model. Comparing the two, Pongsatat et al. (2004) reported that despite the fact that each of the two models had predictive ability, the difference in their respective predictive abilities for either large asset firms or small asset firms was not significant.

Beaver et al. (2005) reinforced the utility of accounting information in predicting corporate distress. They showed that there has been only a slight decline in the predictive ability of financial ratios over a period of 40 years from 1962 to 2002. Bandyopadhyay (2006) assessed the default risk of Indian corporate bonds using three different modified versions of the original Z-score model. He also estimated the default probabilities by combining both financial and non-financial variables like firm age, ISO certification and group affiliation. He concluded that such a combination leads to more accurate default prediction.

Wang and Campbell (2010) confirmed the usefulness of the Z-score model in predicting bankruptcy of Chinese firms. Lifschutz and Jacobi (2010) assessed the reliability of two different versions of the Altman model for bankruptcy prediction for a sample of publicly traded firms in Israel. They argued in favour of the Altman model due to its simplicity and low cost of application. Bhunia and Sarkar (2011) used financial ratios and multiple discriminant analysis for distress prediction of Indian firms. However, their study was restricted to a small sample of private sector pharmaceutical companies. They concluded that ratios relating to profitability and liquidity were significant in predicting distress.

While most traditional models used information from the accrual based financial statements namely, profit and loss statement and balance sheet, other models emphasised that cash flow based information could provide incremental value in predicting financial distress. Casey and Bartczak (1985) found that operating cash flow data did not produce higher accuracy in prediction of bankruptcy over accrual-based ratios. Gilbert et al. (1990) combined variables from Altman (1968), and Casey and Bartczak (1985) and showed that cash flow based variables improved the predictive power of the models. On the other hand, Ward (1994) argued that the usefulness of cash flow information varied from industry to industry. He showed that cash flow information was more useful in predicting financially distressed firms in mining, and oil and gas industries as compared to a control group of firms in other industries. Maux and Morin (2011) showed that the bankruptcy of Lehman Brothers was predictable from its cash flow statements for the period 2005 to 2007. They provided evidence on how consistent inability to generate cash flows and undue reliance on external financing could lead to financial distress.

Literature examining the effect of industry factors on financial distress can be found as early as the work of Lang and Stulz (1992), which investigated the effect of bankruptcy announcements on the equity value of the competitors of the bankrupt firms. It was found that bankruptcy announcements decreased the value of a value-weighted portfolio of competitors. This negative effect was significantly larger for highly leveraged industries and industries where the unconditional stock returns of the non-bankrupt and bankrupt firms were highly correlated. The effect was significantly positive for highly concentrated industries with low leverage, suggesting that in such industries competitors benefitted from the difficulties of the bankrupt firm. Lennox (1999) incorporated the industry effect in the form of industry dummies. Profitability, leverage, cashflow, company size, industry sector and economic cycle were found to be the most important determinants of bankruptcy. Tests for heteroskedasticity revealed that cashflow and leverage had significant non-linear effects, which improved the explanatory power of the model. In contrast to previous studies, the paper argued that well-specified logit and probit models could identify failing companies more accurately than discriminant analysis.

Chava and Jarrow (2004) investigated the forecasting accuracy of bankruptcy hazard rate models using both yearly and monthly observation intervals. Using an expanded bankruptcy database, the study validated the superior forecasting performance of Shumway's (2001) model as opposed to Altman (1968). It also established the importance of including industry effects in hazard rate estimation, with industry groupings significantly affecting both the intercept and slope coefficients in the forecasting equations. Bankruptcy prediction was found to be markedly improved using monthly observation intervals. Consistent with the notion of market efficiency with respect to publicly available information, the paper showed that accounting variables added little predictive power when market variables were already included in the bankruptcy model. Bandyopadhyay (2006) incorporated the effect of industry factors as 11 dummy variables. The study found industry affiliation as being important and significant in explaining defaults.

Acharya et al. (2007) demonstrated that creditors of defaulted firms recover significantly lower amounts in present-value terms when the industry of defaulted firms is in distress. The study found that creditors recovered less if the industry was in distress and non-defaulted firms in the industry were illiquid, particularly if the industry was characterised by assets that were not easily redeployable by other industries, and if such specific assets collateralised the debt. The interaction effect of industry-level distress and asset-specificity was strongest for senior unsecured creditors, and was economically significant and robust to contract-specific, firm-specific, macroeconomic, and bond-market supply effects. The paper also documented that defaulted firms in distressed industries were more likely to emerge as restructured firms than to be acquired or liquidated, and spent longer time in bankruptcy.

Tew (2009) examined the contagion and systematic effects of financial distress. The study focussed on how those firms may be affected, whose only link to the financially distressed firm was a common lender. It further dealt with those traders that previous research had determined to be informed short sellers to determine their reaction to bankruptcy announcements. It was found that when a major borrower of the lender faced financial distress in the form of bankruptcy, the lender reacted to the financial distress by significantly reducing credit to other borrowers relative to a set of control banks, and relative to itself over time. The reduction of credit had a greater effect on those borrowers, such as small and medium-sized enterprises, who were unable to obtain credit from other sources. It was also illustrated that the day after the bankruptcy announcement, short sellers significantly increased their level of shorting activity on intra-industry firms, supporting the contagion hypothesis that financial distress risk spreads through the industry.

Bhimani et al. (2010) modelled default with novel loan data that included 30 accounting ratios and non-accounting information on size, age, industry and geographic regions. Interest costs to gross income, and number of days in payables and receivables were found to have a positive and significant influence on the probability of default. Financial and asset coverage, the investment ratio, return on equity and investment, solidity, variation in gross income and working capital to total assets were negatively related to default. Interest costs to gross income, solidity and working capital to total assets exhibited larger marginal influence on the probability of default as compared to return on investment, financial coverage, days in payables, days in receivables, and return on equity. While size influenced default positively, age influenced default negatively. The findings also indicated that industry and geography influence default.

Data

Sampling and statistical technique

The data related to the sectoral index values and stock prices is collected from the CMIE Prowess database. For this study "default" carries the same meaning as defined by the credit rating agencies. Default implies any instance of a missed payment by an issuer on a rated financial instrument, which is recognised by assigning a "D" rating to the firm. Hence, the defaulting firms' sample comprises firms that have been assigned a D rating. The defaulting firms' sample is collected from four credit rating agencies – CRISIL, CARE, ICRA and Fitch (India) for the period 2000-01 to 2011-12.

Since the model has market-based variables, the sample for the study comprises listed firms. The number of listed firms that have defaulted during the study period is 135. Table 1 and Table 2 report the distribution of defaulting firms' sample across the study period and industries respectively. As shown in Table 1, the years 2009-10, 2010-11, and 2011-12 witnessed the most number of defaults. The maximum defaults are concentrated in the textiles industry followed by the metals and pharmaceuticals industries, as presented in Table 2.

The sample of non-defaulting firms has been formed using matched pair sampling technique. Matched pair sampling technique has found widespread usage not only in the initial studies of default prediction (Beaver, 1966; Beaver, 1968; Altman; 1968; Zavgren, 1985), but even several recent studies make use of the sampling technique (Begley et al., 1996; Bandyopadhyay, 2006; Adiana et al., 2008; Lifshutz and Jacobi, 2010; and Rashid and Abbas, 2011). Thus, consistent with prior studies, the sample of non-defaulting firms has been formed using matched pair sampling technique. Pairing of defaulting and non-defaulting firms has then been done on the basis of the closest asset size and industry. This finally

Table 1 Distribution of defaulting firms across the study period.

Year	No. of firms	% of Total
2000-01	5	3.7%
2001-02	6	4.4%
2002-03	3	2.2%
2003-04	2	1.5%
2004-05	0	0%
2005-06	0	0%
2006-07	1	0.7%
2007-08	0	0%
2008-09	5	3.7%
2009-10	31	23.0%
2010-11	37	27.4%
2011-12	45	33.3%
Total	135	100%

Table 2 Distribution of defaulting firms across industries.

Industry	NIC code (2-digit level)	No. of firms	% of Total
Mining & quarrying	07, 08	3	2.2%
Food products	10	7	5.2%
Tobacco products	12	1	0.7%
Textiles & apparel	13, 14	20	14.8%
Leather products	15	1	0.7%
Wood & wood products	16	1	0.7%
Paper & paper products	17	6	4.4%
Chemicals & chemical products	20	8	5.9%
Pharmaceuticals	21	12	8.9%
Rubber & plastic products	22	4	3.0%
Non-metallic mineral products	23	9	6.7%
Basic metals & fabricated metal products	24, 25	13	9.6%
Computer & electronic products	26	2	1.5%
Electrical equipment	27	6	4.4%
Machinery & equipment	28	1	0.7%
Transport equipment	30	5	3.7%
Other manufacturing	32	4	3.0%
Electricity	35	1	0.7%
Construction & civil engineering	41, 42	10	7.4%
Wholesale & retail trade	46, 47	5	3.7%
Accommodation	55	2	1.5%
Motion picture & video production	59	1	0.7%
Telecommunications	61	1	0.7%
Computer programming	62	6	4.4%
Real estate activities	68	5	3.7%
Architecture & engineering activities	71	1	0.7%
Total		135	100%

yielded a sample consisting of 135 defaulting and 135 non-defaulting firms.

To ensure that there is no statistically significant difference between the asset sizes of the two groups of firms, independent sample t-test is done. The defaulting firms sample and the non-defaulting firms sample are found to have mean asset sizes of Rs. 10379.73 million and Rs. 11616.46 million respectively. The difference between the mean asset sizes of the two groups of firms (Rs. -1236.73 million) is found to be non-significant with a p-value of 0.712.

The sample for the study has been divided into estimation sample and hold-out sample. A year-wise splitting has not been done, as the number of observations is not distributed uniformly across all the years (as reported in Table 1), and this would have shrunk the estimation sample size. The sample of firms from 2000-01 to 2010-11 constitutes the estimation sample and the sample of firms in 2011-12 constitutes the hold-out sample. Accordingly, the estimation sample has 180 firms i.e. 90 defaulting and 90 non-defaulting, and the hold-out sample has 90 firms i.e. 45 defaulting and 45 non-defaulting.

Statistical techniques including multiple discriminant analysis, logistic regression, neural networks (Wu et al., 2008; Muller et al., 2009; Jardin, 2010), genetic programming (Etemadi et al., 2009), support vector machine (Kim and Sohn, 2010; Min et al., 2011), data envelopment analysis (Premchandra et al., 2011), and self-organising maps (Jardin and Severin, 2011) have been prevalent in the literature on financial distress prediction. Kumar and Ravi (2007) present a comprehensive review of the work that makes use of such statistical techniques for bankruptcy prediction in banks and firms. The merits and demerits of each of these techniques have also been elaborated in the study.

Among the various alternative statistical techniques, logistic regression and multiple discriminant analysis have been the most dominant. While some studies show that logistic regression is more efficient than multiple discriminant analysis (Ohlson, 1980; Zavgren, 1985; Lennox 1999), other studies find both the techniques to be equally good (Gu, 2002; Aziz and Dar, 2006). Bhunia and Sarkar (2011) argue that multiple discriminant analysis could be a reliable technique for the purpose of classification, irrespective of its limitations and the availability of various advanced techniques.

Given certain set of characteristics for the predictor variables, the present study aims to classify firms as defaulters and non-defaulters and estimate their likelihood of default. Therefore, both logistic regression and multiple discriminant analysis are considered suitable for this purpose.

Known as a non-linear predictive modelling technique, logistic regression is used to estimate the probability of occurrence of an event or outcome. The event of interest for the present study is the event of default. Binary logistic regression has been used because the outcome or dependent variable can assume only two values i.e. default or no default. The probability that the event occurs is given by:

$$P(Y) = \frac{1}{(1 + e^{-z})} \quad (1)$$

Table 3 Descriptive statistics and t-test.

Variable	Defaulting firms		Non-defaulting firms		Mean difference (t-value)
	Mean	Std. dev	Mean	Std. dev	
Industry beta	0.808	1.224	0.107	0.238	0.701*** (6.527)

Note: *** denotes statistical significance at 0.01 level.

Where,

$P(Y)$ = probability of that the event Y occurs
z = linear combination of independent variables represented as:

$$\beta_0 + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + \ldots\ldots\ldots + \beta_n X_n + \varepsilon$$

Maximum likelihood method, which involves an iterative process that maximises the likelihood of predicting the observed values of the dependent variable using the observed values of the independent variables, is used to estimate the regression coefficients.

Observations are classified into one of the several a priori groups based on the characteristics of the observations using multiple discriminant analysis. For this study, the firms are classified into two groups namely, defaulting and non-defaulting firms. The classification is done with the help of a discriminant function, which is a linear combination of certain independent variables. The group membership of the observation is determined using this function that produces a discriminant score. The discriminant score is represented as:

$$Z = a + b_1 X_1 + b_2 X_2 + b_3 X_3 + \ldots\ldots\ldots + bnX_n \quad (2)$$

Where,

Z = discriminant score
a = constant
b_i = discriminant weight for independent variable X_i
X_i = independent variable

The weights for the respective predictor variables in the function reflect the relative importance of the variable in discriminating between the groups. The observations are classified into a group based on a predefined cut-off value for the discriminant score.

The independent variable

The independent variable for this study is a sensitivity variable named the industry beta, which captures the impact of industry factors on a firm's vulnerability to default. To estimate the industry beta the monthly stock return of each individual firm has been regressed on the monthly return of the respective sectoral or industry index.

$$R_i = \alpha + \beta_1 \mathrm{SectIndex} + \varepsilon_i \quad (3)$$

Where,

R_i = monthly stock return for firm i
SectIndex = monthly return on the respective sectoral index (CMIE sectoral index)
β_1 = industry beta
ε_i = error term for firm i

Findings and discussion

The descriptive statistics and t-test for the industry beta are presented in Table 3. On an average, the defaulting firms have significantly higher industry beta as compared to the non-defaulting firms, which indicates that defaulting firms are more sensitive to industry factors as compared to non-defaulting firms. The dispersion of the variable (as measured by the standard deviation) is also higher for the defaulting firms.

The results of logistic regression for the model, as revealed in Table 4, reflect that the Chi-square is significant at 0.01 level and thus the overall model is significantly better in predicting defaults. As shown by the Nagelkerke R^2, as much as 58.7% variation in the dependent variable can be explained by the independent variable.

The industry beta is found to be statistically significant in predicting defaults. The industry beta has a positive relationship with the probability of default implying that higher sensitivity to industry factors leads to an increased probability of default.

Table 5 reports the classification matrix for the model using logistic regression. The overall classification accuracy of the estimation sample is 81.7%. The default probabilities of firms in the hold-out sample are estimated using the parameters' estimates for the variables as reported in Table 4. This is represented as following:

$$P(Y) = \frac{1}{(1 + e^{-z})} \quad (4)$$

Where,

$P(Y)$ = probability of default
$z = -1.849 + 3.797$ Industry beta

Table 4 Result of logistic regression and multiple discriminant analysis.

Variables	Logistic regression coefficient	Multiple discriminant analysis coefficient
Constant	-1.849***	-0.593
Industry beta	3.797***	0.979
-2 Log likelihood	145.126	
Chi-square	104.407***	
Nagelkerke R^2	0.587	
Canonical correlation		0.411
R^2		0.168
Wilks' lambda		0.831
Chi-square		32.879***

Note: *** denotes statistical significance at 0.01 level.

Table 5 Classification matrix for logistic regression.

Estimation sample	Predicted group		
Observed group	Defaults	Non-defaults	Total
Defaults	72[a] (80%)	18 (20%)	90 (100%)
Non-defaults	15 (16.7%)	75[b] (83.3%)	90 (100%)
Overall accuracy	80%	83.3%	81.7%[c]
Hold-out sample	Predicted group		
Observed group	Defaults	Non-defaults	Total
Defaults	14[a] (31.1%)	31 (68.9%)	45 (100%)
Non-defaults	0 (0%)	45[b] (100%)	45 (100%)
Overall accuracy	31.1%	100%	65.6%[c]

Notes: [a]indicates the number or percentage of defaults correctly classified as defaults, [b] indicates the number or percentage of non-defaults correctly classified as non-defaults and [c] indicates the overall accuracy estimated as the average of [a] and [b].

Since the groups are of equal size, the cut-off probability for classification is 0.5. Therefore, firms with default probability above 0.5 are classified as defaulting, and those with default probability below 0.5 as non-defaulting. Using this procedure, the overall classification accuracy of the holdout sample is 65.6%.

Table 4 reports the results of the multiple discriminant analysis for the model. The function has a statistically significant chi-square value which indicates good discriminating ability of the function. Wilks' lambda of the discriminant function is a measure of how effectively the function separates observations into groups. The proportion of variance in the discriminant score not explained by the difference between the groups is assessed by the Wilks' lambda. Hence, lower values of this statistic indicate greater discriminatory ability of the function. Canonical correlation shows the association between the discriminant function and the discriminant score. The square of the canonical correlation results in the R^2, which is the percent variance in the discriminant score, explained by the independent variables. As reported in Table 4, the function has a Wilks' lambda of 0.831 and R^2 of 0.168.

The coefficients, as in Table 4, are used to arrive at the discriminant score or the Z-score to classify the observations into the respective groups. With these coefficients for the variables the discriminant function can be represented as:

$$Z = -0.593 + 0.979\,\text{Industry beta} \tag{5}$$

In order to determine the cut-off discriminant score to classify the observations into the respective groups, group centroids are used. The group centroid is the mean or average of the discriminant scores for all the observations within a particular group. The cut-off discriminant score is the midpoint of the two group centroids when the groups are of equal sizes. The defaulting firms' group centroid and the non-defaulting firms' group centroid is found to be 0.449 and -0.449 respectively. Thus, the cut-off point is $[(0.449 + (-0.449)] / 2 = 0$. All firms with a discriminant score greater than 0 are then classified as defaulting and those with a score less than 0 are classified as non-defaulting.

The classification matrix is reported in Table 6. The estimation sample has an overall classification accuracy of 80%, slightly lower than that obtained using logistic regression. The Z-scores for firms in the hold-out sample are estimated using the discriminant function and classified into the respective groups as described above. The overall classification accuracy of the hold-out sample of 63.3% is also slightly lower than that obtained using logistic regression.

Conclusion and implications

Studies on financial distress prediction have predominantly focussed on firm-specific factors. Use of accounting information is more common. The impact of industry factors on the risk of default has received limited attention. Even the few studies that investigate the impact of industry factors use an industry dummy variable, which provides little information on how the firm's sensitivity to the uncertainties in the relevant industry might affect its susceptibility to distress.

This study is the first attempt to use a sensitivity variable for industry factors (industry beta) and to assess its impact on a firm's default probability. The industry beta is estimated by regressing the monthly stock return of each individual firm on the monthly return of the respective sectoral or industry index. The study uses logistic regression and multiple discriminant analysis for matched pair sample of defaulting and non-defaulting listed Indian firms. The sensitivity variable for industry factors (industry beta) is found to be statistically significant in predicting defaults. Higher sensitivity to industry factors leads to an increased probability of default.

Table 6 Classification matrix for multiple discriminant analysis.

Estimation sample	Predicted group		
Observed group	Defaults	Non-defaults	Total
Defaults	68[a] (75.6%)	22 (24.4%)	90 (100%)
Non-defaults	14 (15.6%)	76[b] (84.4%)	90 (100%)
Overall accuracy	75.6%	84.4%	80%[c]
Hold-out sample	Predicted group		
Observed group	Defaults	Non-defaults	Total
Defaults	12[a] (26.7%)	33 (73.3%)	45 (100%)
Non-defaults	0 (0%)	45[b] (100%)	45 (100%)
Overall accuracy	26.7%	100%	63.3%[c]

Notes: [a]indicates the number or percentage of defaults correctly classified as defaults, [b] indicates the number or percentage of non-defaults correctly classified as non-defaults and [c] indicates the overall accuracy estimated as the average of [a] and [b].

The findings of the study have important implications for lending as well as investment decisions. The study highlights the significance of sensitivity of a firm to uncertainties in the relevant industry and its impact on default risk. This establishes the fact that each firm is uniquely affected by the changes in the industry environment in which it operates. Hence, lenders and investors need to constantly monitor the sensitivity of a firm to these changes and understand its implications for default risk.

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