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Default risk modelling using macroeconomic variables

Khushbu Agrawal Yogesh Maheshwari

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Khushbu Agrawal
International Management Institute Kolkata, Kolkata, India, and
Yogesh Maheshwari
Indian Institute of Management Indore, Indore, India

Abstract

Purpose – This paper aims to find out significant macroeconomic variables, incorporated as sensitivity variables (macroeconomic sensitivities), affecting financial distress for a sample of listed Indian firms.

Design/methodology/approach – The study uses a matched pair sample of defaulting and non-defaulting listed Indian firms. It uses two alternative statistical techniques, viz., logistic regression and multiple discriminant analysis. The macroeconomic sensitivities are estimated by regressing the monthly stock return of the individual firm on the monthly changes in each macroeconomic variable.

Findings – Sensitivity to changes in the stock market (stock market sensitivity) and sensitivity to changes in inflation [Consumer Price Index (CPI) sensitivity] have a significant impact on the default probability of a firm. Stock market sensitivity has a significant positive relationship with the probability of default, and CPI sensitivity has a significant negative relationship with the probability of default.

Originality/value – The study links the developments in the external environment to the firm's susceptibility to default. Furthermore, it highlights the significance of sensitivity of a firm to uncertainties in the macroeconomic environment and its impact on default risk. This establishes the fact that each firm is uniquely affected by the changes in the overall macroeconomic environment. The findings could be valuable to lenders such as banks and financial institutions, investors and policymakers.

Keywords Financial distress, Macroeconomic factors

Paper type Research paper

1. Introduction

The banking system is the lifeline of any economy. In the past few years, India has witnessed an increasing trend in non-performing assets and restructured accounts of banks. This is certainly not desirable for any economy. While recession and slowdown had its impact on demand, the Indian economy has also been characterized by high rates of inflation and the tightening of interest rates. The overall macroeconomic environment had an adverse impact on the debt servicing capacity of firms, leading to financial distress. Financial distress refers to the inability of a firm to pay its financial obligations in time. Defaults may encompass events such as bankruptcy, bond default, an overdrawn bank account or non-payment of a preferred stock dividend (Beaver, 1966). However, in the Indian context, events such as non-payment of a preferred stock dividend are not considered as default. Among the various events that signal a state of financial distress, bankruptcy and default have been the most widely researched. The

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event of default indicates deterioration in the financial health of a firm, which needs to be identified in time.

Financial distress leads to a less than economically feasible production and also deterioration in value. It is associated with various direct and indirect costs (Altman, 1984; Opler and Titman, 1994). Accurate and timely assessment of default risk has important implications for lending and investment decisions. It serves as a warning signal to the creditors, particularly banks and financial institutions and investors for managing their exposures to a particular class of firms, which might be more vulnerable to experiencing distress than others. Modelling of default risk also helps in determining the appropriate risk premium and thereby pricing of corporate debt securities. Accurate assessment of default risk is also mandated by regulatory requirements.

While substantial research exists on the prediction of financial distress, most of these studies focus on firm-specific factors. Among these, accounting-based models that make use of information from financial statements are the most widely used ones. Not many attempts have been made to develop models that could include macroeconomic variables. Moreover, there is a lack of consensus on the significance of specific macroeconomic variables in predicting distress. For instance, Figlewski *et al.* (2012) find that growth of industrial production is an important determinant of corporate defaults. On the contrary, Giesecke *et al.* (2011) show that growth rates of industrial production are not important in forecasting defaults. To the best of our knowledge, the impact of macroeconomic variables on default risk has not been investigated in the Indian context. Given the inconclusive evidence and increased instances of default in the post-recession period in India, we are motivated to develop an empirical model that incorporates the effect of macroeconomic factors at the firm level.

The main purpose of this paper is to find out the significant macroeconomic variables affecting financial distress for a sample of listed Indian firms. The existing literature on default prediction includes models that incorporate firm-specific and macroeconomic variables. However, the aim of the present study is to find out the impact of macroeconomic factors on the default risk of firms, given that there is no other firm-specific information. Hence, departing from the existing literature, the study uses only macroeconomic variables. The study incorporates the impact of the macroeconomic variables on the default risk of firms in the form of sensitivity of a firm to changes in the respective macroeconomic variables (macroeconomic sensitivities). The default risk modelling is done from the lenders' point of view. Further, the modelling is done for the default happening due to distress caused by macroeconomic factors and not due to the willingness to make default.

The rest of the paper is structured as follows. Section 2 consists of a detailed review of literature on accounting-based models and studies that use macroeconomic variables for distress prediction. Section 3 describes the sampling technique, sources of data, variable description and methodology. Section 4 consists of discussion on the results and findings of the study. Section 5 presents concluding remarks following from the key findings of the study.

2. Literature review

While inclusion of macroeconomic variables may impact default prediction, it would be worthwhile to briefly review the literature relating to the traditional accounting-based model before presenting a detailed reflection on the literature that examines the contribution of macroeconomic variables in predicting corporate defaults.

One of the earliest works on prediction of financial distress using the accounting-based model was perhaps Beaver (1966). The study used financial ratios for the prediction of failure. This was followed by another attempt to use ratios by Altman (1968), which assessed the analytical quality of ratio analysis. A set of financial ratios was combined in a discriminant analysis approach to the problem of corporate bankruptcy prediction, as traditional ratio analysis was found to be inadequate and the need to assess its potential rigorously was recognized. As an extension, incorporating comprehensive inputs with respect to discriminant analysis and utilizing a sample of bankrupt firms, Altman *et al.* (1977) explored the development of a bankruptcy classification model. Ohlson (1980) found four basic factors that measured size, financial structure, performance and current liquidity of a firm to be statistically significant in affecting the probability of failure.

Casey and Bartczak (1985) examined if operating cash flow data could increase the accuracy of accrual-based multiple discriminant and logit models in distinguishing between bankrupt and non-bankrupt firms and found it was not so. Gilbert *et al.* (1990) demonstrated that a bankruptcy model developed by using a bankrupt/random estimation sample was not able to distinguish firms that fail from other firms that were financially distressed, and cash flow variables added to the explanatory power of the models developed. Ward (1994) found cash flow information to be more useful to creditors in predicting financially distressed mining, oil and gas firms as compared to predicting financial distress in other industries. Begley *et al.* (1996) questioned the applicability of Altman's (1968) and Ohlson's (1980) bankruptcy prediction models as indicators of financial distress and showed that they did not perform as well as they did in their early stages, even when the coefficients were re-estimated. Pongsatat *et al.* (2004) also compared the two and reported that although each of the two models had predictive ability, no significant difference existed in their respective predictive abilities for either large asset or small asset firms.

Beaver *et al.* (2005) used a hazard model for examining secular changes in the ability of financial statement data to predict bankruptcy. Three trends in financial reporting were identified, namely, the Financial Accounting Standards Board standards, the perceived increase in discretionary financial reporting behaviour and the increase in unrecognized assets and obligations that had a bearing on the predictive ability with respect to bankruptcy. Bandyopadhyay (2006) developed a *z*-score model using multiple discriminant analysis for predicting corporate bond default in India. A high classification power on the estimated sample was depicted by the model. The model also exhibited a high predictive power in terms of its ability to detect bad firms in the holdout sample.

Using publicly listed companies in China, Wang and Campbell (2010) provided *ex ante* evidence on the failure prediction power of various *z*-score models. Lifschutz and Jacobi (2010) showed that the Ingbar version of the Altman Model having a critical value of 1 was a preferable model for predicting financial failure. Using multiple discriminant analysis, Bhunia and Sarkar (2011) found 7 out of 16 financial ratios to be significant in discriminating power. The classification results of the study showed high predictive accuracy rates. Maux and Morin (2011) analysed the statements of cash flows for establishing if the failure of Lehman Brothers was predictable in the financial crisis of

2008. The study demonstrated that several signs of financial distress, such as chronic inability to generate cash from operating activities, substantial and systematic investments in working capital and financial instruments, systematic use of external financing for offsetting operating deficits and steady decline in the cash situation over three consecutive years, were detectable in the financial statements of Lehman Brothers for 2005, 2006 and 2007.

Macroeconomic conditions have a significant impact on the operations of a firm. Economic slowdown has an adverse impact on demand, which in turn affects the firm's ability to generate cash flows and meet payment obligations in time. Hence, recessionary conditions in the economy lead to financial distress and may even cause massive bankruptcies. Literature examining the effectiveness of macroeconomic variables in predicting financial distress can be seen as early as the work of Tirapat and Nittayagasetwat (1999), who developed a macro-related micro-crisis investigation model using a logit regression. The model was able to bridge a firm's sensitivity to macroeconomic conditions and its financial characteristics to explore financial distress. The findings indicated that macroeconomic conditions were critical indicators of potential financial distress for a firm. It was also shown that the higher a firm's sensitivity to inflation, the higher was the firm's exposure to financial distress. Hackbarth *et al.* (2006) built a framework for analysing the impact of macroeconomic conditions on credit risk and dynamic capital structure choice. The model could replicate observed debt levels and the counter cyclicality of leverage ratios. It was demonstrated that the model could reproduce the observed term structure of credit spreads and generate strictly positive credit spreads for debt contracts with very short maturities. The study also characterized the impact of macroeconomic conditions on the pace and size of capital structure changes and debt capacity.

Carling *et al.* (2007) estimated a duration model to explain the survival time to default for borrowers in the business loan portfolio. The model took both firm-specific characteristics, such as accounting ratios, payment behaviour and loan-related information, and the prevailing macroeconomic conditions into account. The output gap, yield curve and consumers' expectations of future economic development were found to have significant explanatory power for the default risk of firms. The model was also compared with a frequently used model of firm default risk that conditioned only on firm-specific information. The comparison showed that while the latter model made a reasonably accurate ranking of firms according to default risk, the former model, by taking macro conditions into account, was also able to account for the absolute level of risk.

Exploring the links between credit risk and macroeconomic developments, Bonfim (2009) observed that in periods of economic growth, tendency towards excessive risk-taking might exist. The study showed that default probabilities were influenced by several firm-specific characteristics. The results were found to improve substantially when time-effect controls or macroeconomic variables were also taken into account. Though the firms' financial situation had a central role in explaining default probabilities, macroeconomic conditions were also very important when assessing default probabilities over time. Tsai *et al.* (2009) investigated the usefulness of auditors' opinions, market factors, macroeconomic factors and industry factors in predicting financial distress. It was found that the macroeconomic factors significantly explained financial distress. Models with auditors' opinions, market factors, macroeconomic factors and industry factors performed better in financial distress prediction than the model with only financial ratios.

Liu (2009) examined the interactions between business failures and macroeconomic aggregates, and specifically the accounts of policy-induced changes in the economy for the observed fluctuations of business failures, using the vector error-correction model. Macroeconomic aggregates such as interest rate, credit, profits, inflation and business births were found to exert differential impacts on business failures both in the short and the long run. The study revealed that structural changes in the financial and real sectors made an impact on the way in which the economy affected business failures. In particular, business failures increasingly reacted to monetary policy changes. Furthermore, the shocks to business failures could generate large fluctuations in macroeconomic aggregates.

Observing that the corporate bond market repeatedly suffered clustered default events much worse than those experienced during the Great Depression, Giesecke *et al.* (2011) used a regime-switching model to examine the extent to which default rates could be forecasted by financial and macroeconomic variables. It was found that stock returns, stock return volatility and changes in gross domestic product were strong predictors of default rates. Surprisingly, however, credit spreads were not and they did not even adjust in response to realized default rates. Figlewski *et al.* (2012) examined the impact of general economic conditions on defaults and major credit rating changes by fitting reduced-form Cox intensity models with a broad range of macroeconomic and firm-specific ratings-related variables. Both types of factors were found to strongly influence the risk of a credit event. However, while the effects of ratings-related factors were consistent with expectations and very robust under different specifications, significance levels and macro variable coefficients depended heavily on which other variables were included.

There are certain limitations and gaps associated with the literature that investigates the impact of macroeconomic variables on the default risk of firms. These are described as follows. While the models developed in some studies are primarily theoretical and lack empirical testing, others do not incorporate the effect of macroeconomic factors at the firm level. Additionally, there is a lack of consensus on the significance of specific macroeconomic variables in predicting distress. The present study is an attempt to fill the aforesaid gaps by linking the developments in the macroeconomic environment to the firm's risk of default in India. Increased instances of default in the post-recession period further warrant an examination of the macroeconomic factors and motivate us to undertake the study.

3. Data and methodology

3.1 Sample selection and description

The present study considers the event of "default" to be the same as that used by the credit rating agencies, which indicates an instance of any missed payment by an issuer on a rated financial instrument. Such an event is recognized by assigning a "D" rating to the firm by the rating agencies. Thus, firms that have been assigned a "D" rating constitute the sample of defaulting firms. The study uses these data from four credit rating agencies, namely, CARE, CRISIL, ICRA and Fitch (India) for the period 2000-2001 to 2011-2012. The data on macroeconomic variables are collected from the Reserve Bank of India's database on Indian economy and that related to the stock prices are drawn from the CMIE Prowess database.

Owing to the presence of market-based variables in the model, the sample for the study comprises listed firms. The study period witnessed defaults by 135 listed firms. The year-wise distribution of the defaults is described in Table I. As is evident, the post sub-prime crisis period has seen the highest number of defaults.

Most of the prior studies, including Beaver (1966), Beaver (1968), Altman (1968), Zavgren (1985), Begley *et al.* (1996), Bandyopadhyay (2006), Adiana *et al.* (2008), Lifschutz and Jacobi (2010) and Rashid and Abbas (2011), have used matched pair sampling technique for constituting their samples. In line with these works, the present study also uses matched pair sampling for constituting its samples of non-defaulting firms. The firms have then been matched on the basis of the closest asset size as at the end of the sample period, i.e. 2011-2012, and industry. Accordingly, the study has 135 defaulting and 135 non-defaulting firms.

With a view to make certain that the difference in the asset sizes of the two groups of firms is not statistically significant, independent sample *t*-test has been done. The descriptive statistics of the asset sizes and the result of the *t*-test are listed in Table II. There is no significant difference between the mean asset sizes of the two groups of firms, as revealed by the result of the *t*-test.

Year	No. of defaulting firms
2000-2001	5
2001-2002	6
2002-2003	3
2003-2004	2
2004-2005	0
2005-2006	0
2006-2007	1
2007-2008	0
2008-2009	5
2009-2010	31
2010-2011	37
2011-2012	45
Total	135

Table I.
Year-wise distribution of defaulting firms

Sample	Mean	SD
Panel A: Descriptive statistics – asset size (Rs. million)		
Defaulting firms	10379.73	22392.84
Non-defaulting firms	11616.46	31845.90
Mean difference	*t*-value	Significance (*p*-value)
Panel B: Independent sample t-test		
−1236.73	−0.369	0.712

Table II.
Descriptive statistics and *t*-test for asset size

An estimation sample and a holdout sample have been formed for the study. With the number of observations not uniformly distributed across all years, a year-wise splitting of the sample would have resulted into very few observations in the estimation sample. Hence, instead of a year-wise splitting, the sample of firms from 2000-2001 to 2010-2011 has been taken as the estimation sample and the sample of firms in 2011-2012 as the holdout sample. The estimation sample thus consists of 180 firms (90 defaulting and 90 non-defaulting firms) and the holdout sample consists of 90 firms (45 defaulting and 45 non-defaulting firms).

3.2 Statistical technique

The extant literature on financial distress prediction uses different alternative statistical techniques, such as 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-organizing maps (Jardin and Severin, 2011). The use of such statistical techniques in bankruptcy prediction for banks and firms has been comprehensively reviewed by Kumar and Ravi (2007). They also elaborate on the advantages and disadvantages of each of these techniques.

Of these, logistic regression and multiple discriminant analysis have been the most widely used ones. Although some studies find logistic regression to be more efficient than multiple discriminant analysis (Ohlson, 1980; Zavgren, 1985; Lennox, 1999), others show that both the techniques work equally well (Gu, 2002; Aziz and Dar, 2006). Notwithstanding some of its limitations and the availability of several advanced techniques, Bhunia and Sarkar (2011) advocate the use of multiple discriminant analysis for the purpose of classification.

Both logistic regression and multiple discriminant analysis have proved to be efficient, despite the availability of several alternative techniques. Hence, the present study uses both of these techniques. The purpose of the present study is to find out which macroeconomic variables are significant in affecting the probability of default for a sample of listed Indian firms. Given the macroeconomic variables, the probability of default can be estimated using logistic regression. Multiple discriminant analysis is used to generate a discriminant score to classify firms as defaulting and non-defaulting. Although multiple discriminant analysis does not produce probabilities, it is used as an alternative classification technique to see whether the classification results are closely aligned with those of logistic regression.

Logistic regression, as is known, is a non-linear predictive modelling technique for estimating the probability of occurrence of an event or outcome. For the present study, the event of interest is the event of default. The outcome or dependent variable can assume only two values, i.e. default or no default. Hence, binary logistic regression has been used. The probability of the event occurring is found as:

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

where,

P (Y) = probability of the event Y occurring.
MI = linear combination of independent variables represented as:

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

In logistic regression, the regression coefficients are estimated using the maximum likelihood method, which uses an iterative process to maximize the likelihood of predicting the observed values of the dependent variable using the observed values of the independent variables.

Multiple discriminant analysis, which is used for classifying observations into one of the several a priori groups based on the observations' characteristics, is used in the present study to classify the firms into two groups, namely, defaulting and non-defaulting firms. A linear combination of certain independent variables known as discriminant function is used for classification. This function produces a score that is used to determine the group membership of the observation. The discriminant score is represented as:

$$Z = a + b_1 X_1 + b_2 X_2 + b_3 X_3 + \ldots\ldots\ldots + bnX_n \tag{2}$$

where,

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

3.3 Variable description

The present study uses industrial growth, interest rates, stock market index, inflation and money supply as the macroeconomic variables. The rationale for choosing these specific macroeconomic variables is drawn from their usage in the literature. Variables such as industrial growth could be important determinants of likelihood of default. An increase in industrial growth is associated with lower probability of default (Figlewski *et al.*, 2012). Increases in interest rates put a strain on the debt servicing capacity of the firm, thereby affecting the probability of default (Bonfim, 2009; Figlewski *et al.*, 2012). Variables such as stock market indices also have a bearing on defaults. Increases in stock market indices indicate a broad-based improvement in the financial condition of firms and hence are likely to have a negative relationship with the likelihood of default (Bonfim, 2009; Tsai *et al.*, 2009; Figlewski *et al.*, 2012). Higher rates of inflation indicate higher consumer demand and are associated with lower likelihood of default. Money supply also affects the probability of default by way of changes in the liquidity conditions in the economy (Tsai *et al.*, 2009).

Tirapat and Nittayagasetwat (1999) argue that higher the firm's sensitivity to economic shocks, the more vulnerable it is to experiencing financial distress. Hence, the present study incorporates the impact of macroeconomic variables on the default risk of firms in the form of sensitivity of each firm to changes in the respective macroeconomic variables. The macroeconomic sensitivities are obtained using a multifactor model and are measured by the respective slope coefficients (β) of an ordinary least squares regression of the monthly stock return of the individual firm on the monthly changes in each of the macroeconomic variable.

$$R_i = \alpha + \beta_1 \Delta IIP + \beta_2 \Delta CPI + \beta_3 \Delta IntRate + \beta_4 \Delta MS + \beta_5 \Delta SMkt + \varepsilon_i \tag{3}$$

where,

R_i	= monthly stock return for firm i.
ΔIIP	= monthly changes in Index of Industrial Production (General Index).
ΔCPI	= monthly changes in Consumer Price Index (CPI; Industrial workers: General Index).
ΔIntRate	= monthly changes in interest rate (364-day T-bill).
ΔMS	= monthly changes in money supply (M1).
ΔSMkt	= monthly return on the stock market (Sensex).
β_1	= IIP sensitivity.
β_2	= CPI sensitivity.
β_3	= IntR sensitivity.
β_4	= MS sensitivity.
β_5	= SMkt sensitivity.
ε_i	= error term for firm i.

4. Results and discussion

Before proceeding further, we check whether multicollinearity affects the model. This is examined by looking at the variance inflation factor (VIF) and tolerance as reported in Table III. VIF is the ratio of a variable's actual variance to the perfect variance of zero collinearity. Perfect collinearity is said to exist when one predictor variable is a perfect linear combination of the others. Hence, each independent variable has been regressed against all other independent variables. The resulting values of R^2 and VIFs are reported in Table III. If the largest VIF is less than 10 and the average VIF for all the variables is not substantially greater than 1, then multicollinearity is not a serious problem. Tolerance is another statistic to look at. Tolerance is the reciprocal of VIF. Tolerance values above 0.2 are not a cause for concern. As reported in Table III, VIFs range from 1.014 to 1.398 and the largest VIF is well below 10. The average VIF is close to 1. Tolerance values are also well above 0.2. Hence, it can be concluded that the model is not affected by multicollinearity.

The descriptive statistics and univariate t-test for the macroeconomic sensitivities are reported in Table IV. On an average, defaulting firms are found to have a significantly higher stock market sensitivity (SMkt sensitivity) as compared to non-defaulting firms. Dispersion, as measured by the standard deviation, in each of the macroeconomic sensitivities for the defaulting firms is found to be greater than that of the non-defaulting firms. This difference in standard deviations of the macroeconomic sensitivities might be attributed to the higher uncertainty regarding the defaulting

Variable	R^2	VIF = 1/(1 - R^2)	Tolerance = 1/VIF
SMkt sensitivity against other independent variables	0.014	1.014	0.986
IIP sensitivity against other independent variables	0.085	1.093	0.915
CPI sensitivity against other independent variables	0.285	1.398	0.715
MS sensitivity against other independent variables	0.185	1.227	0.815
IntR sensitivity against other independent variables	0.269	1.367	0.731
Average VIF		1.220	

Table III.
Multicollinearity test

firms' response to changes in the macroeconomic variables as compared to the non-defaulting firms.

4.1 Result of logistic regression

As seen in Table V, the results of logistic regression for the model show that the chi-square is significant at 0.01 level. This shows that the overall model is significantly better in predicting defaults. Almost 85.5 per cent variation in the dependent variable can be explained by the independent variables, as is reflected by the Nagelkerke R^2.

Among the macroeconomic variables, SMkt sensitivity and CPI sensitivity are found to be statistically significant at 0.01 level. SMkt sensitivity has a significant positive relationship with the probability of default, indicating that higher the sensitivity of a firm to changes in the stock market, higher its probability of default. The results are inconsistent with Tsai *et al.* (2009), who find a significant negative relationship between changes in stock market index and the probability of default arguing that because an increase in stock market index is an indicator of economic boom, it reduces the probability of default. However, a plausible explanation for the contradictory finding in the present study is as follows. The Indian stock markets have been characterized by high volatility, particularly in the post-recession period. Thus, firms that were more vulnerable to adverse movements in the stock market might have been subject to higher likelihood of default.

CPI sensitivity has a significant negative relationship with the probability of default. This is consistent with Tsai *et al.* (2009), who find a significant negative relationship between changes in CPI and the likelihood of financial distress. They argue that higher inflation

Variable	Defaulting firms Mean	Defaulting firms SD	Non-defaulting firms Mean	Non-defaulting firms SD	Mean difference (*t*-value)
SMkt sensitivity	0.952	0.639	0.038	0.137	0.914*** (16.251)
IIP sensitivity	0.030	0.660	0.045	0.178	−0.015 (−0.256)
CPI sensitivity	−0.473	1.529	0.015	0.768	−0.489 (−1.237)
MS sensitivity	−0.179	1.503	−0.151	1.069	−0.028 (−0.179)
IntR sensitivity	−0.063	0.537	−0.077	0.381	0.013 (0.242)

Note: ***Denotes statistical significance at 0.01 level

Table IV. Descriptive statistics and univariate *t*-test

Variables	Beta coefficient (Wald statistic)
Constant	−3.265*** (36.210)
SMkt sensitivity	11.770*** (19.717)
IIP sensitivity	0.485 (0.338)
CPI sensitivity	−0.771*** (11.730)
MS sensitivity	0.385 (1.525)
IntR sensitivity	−1.862 (1.341)
−2 Log likelihood	65.113
Chi-square	184.420***
Nagelkerke R^2	0.855

Note: ***Denotes statistical significance at 0.01 level

Table V. Result of logistic regression indicates higher consumer demand and stronger economy, thereby leading to lower probability of default. As the present study incorporates the effect of inflation in the form of sensitivity, the results can be interpreted as follows. Changes in inflation lower the probability of default. Consequently, higher the sensitivity of a firm to this variable, lower would be the probability of default. The results are, however, inconsistent with Tirapat and Nittayagasetwat (1999), who find a significant positive relationship between CPI sensitivity or sensitivity to inflation and the probability of distress.

The classification matrix for the model using logistic regression is reported in Table VI. The estimation sample has an overall classification accuracy of 94.4 per cent. The parameters' estimates for the variables, as reported in Table V, are used to estimate the default probabilities of firms in the holdout sample as follows:

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

where,
P(Y) = probability of default

$$z = -3.265 + 11.770\,\text{SMkt sensitivity} + 0.485\,\text{IIP sensitivity} - 0.771\,\text{CPI sensitivity} + 0.385\,\text{MS sensitivity} - 1.862\,\text{IntR sensitivity}$$

As the groups are of equal sizes, the cut-off probability is 0.5. Consequently, firms with default probability greater than 0.5 are classified as defaulting and those with default probability less than 0.5 as non-defaulting. Using this procedure, the holdout sample has an overall classification accuracy of 82.2 per cent.

4.2 Result of multiple discriminant analysis

Test of equality of group means is first used to assess an independent variable's potential before it is entered into the model. This is done with Wilks' lambda and F-statistic. The variable is better at discriminating between the groups if the value of F-statistic is significant and the value of Wilks' lambda is small. The null hypothesis

Observed group	Predicted group Defaults	Non-defaults	Total
Estimation sample			
Defaults (%)	82[a] (91.1)	8 (8.9)	90 (100)
Non-defaults (%)	2 (2.2)	88[b] (97.8)	90 (100)
Overall accuracy (%)	91.1	97.8	94.4[c]
Hold-out sample			
Defaults (%)	30[a](66.7)	15 (33.3)	45 (100)
Non-defaults (%)	1 (2.2)	44[b](97.8)	45 (100)
Overall accuracy (%)	66.7	97.8	82.2[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; [c] indicates the overall accuracy estimated as the average of a and b

Table VI.
Logistic regression classification matrix

of equal group means is tested by the *F*-statistic. Table VII reflects the test of equality of group means for macroeconomic sensitivities. As shown by the *F*-statistic, there is a significant difference between the group means for SMkt sensitivity. The variable also has the lowest Wilks' lambda among all the variables. This indicates that the variable has the highest potential to contribute significantly to the model.

The results of the multiple discriminant analysis are as shown in Table VIII. The chi-square value of the function is statistically significant. This indicates good discriminating ability of the function. Wilks' lambda of the discriminant function, which measures the effectiveness of the function in separating observations into groups, shows the proportion of variance in the discriminant score unexplained by the difference between the groups. Therefore, lower values of this statistic show greater discriminatory ability of the function. Canonical correlation is a measure of the association between the discriminant function and the discriminant score. The square of the canonical correlation gives the R^2. This is the per cent variance in the discriminant score explained by the independent variables. In the present study, the function can be seen to have a Wilks' lambda of 0.374 and R^2 of 0.626.

Unlike logistic regression, multiple discriminant analysis does not produce probabilities but rather produces discriminant scores for classifying the observations into the respective groups. The results are thus interpreted accordingly. Table VIII shows the unstandardized coefficients that are used to arrive at the discriminant score or the *z*-score for classifying the observations into the respective groups. Thus, using these coefficients for the variables, the discriminant function can be represented as:

Variable	Wilks' lambda	*F*-statistic
SMkt sensitivity	0.399	267.986***
IIP sensitivity	0.999	0.122
CPI sensitivity	0.993	1.246
MS sensitivity	0.999	0.090
IntR sensitivity	1.000	0.029

Table VII. Test of equality of group means

Variables	Unstandardized coefficients
Constant	−1.388
SMkt sensitivity	2.229
IIP sensitivity	−0.134
CPI sensitivity	−0.095
MS sensitivity	0.045
IntR sensitivity	−0.360
Canonical correlation	0.791
R^2	0.626
Wilks' lambda	0.374
Chi-square	172.734***

Note: ***Denotes statistical significance at 0.01 level

Table VIII. Result of multiple discriminant analysis

$$Z = -1.388 + 2.229\,\text{SMkt sensitivity} - 0.134\,\text{IIP sensitivity} - 0.095\,\text{CPI sensitivity} + 0.045\,\text{MS sensitivity} - 0.360\,\text{IntR sensitivity} \quad (5)$$

The cut-off discriminant score for classifying the observations into the respective groups is determined using the group centroids. The group centroid is the average of the discriminant scores for all the observations within a particular group. If the groups are of equal sizes, the cut-off discriminant score is the mid-point of the two group centroids. The defaulting firms' group centroid is at 1.287, and the non-defaulting firms' group centroid is at −1.287, as shown in Table IX. Thus, the cut-off point is $[(1.287 + (-1.287)]/2 = 0$. Consequently, firms with a positive discriminant score are classified as defaulting, and those with a negative score are classified as non-defaulting.

The classification matrix in Table X shows that the estimation sample has an overall classification accuracy of 89.4 per cent. Although slightly lower, the results are closely aligned to those obtained using logistic regression. The discriminant function is used to estimate the *z*-scores for firms in the holdout sample and classify them into the respective groups as described above. The holdout sample has an overall classification accuracy of 77.8 per cent, which is also slightly lower but closely aligned to that obtained using logistic regression.

5. Conclusion

The extant research work on prediction of financial distress has largely been based on the firm-specific factors, including the use of accounting information. There have been limited attempts to include macroeconomic variables in the models. Moreover, there is a lack of consensus on the significance of specific macroeconomic variables in predicting distress. Given the increased instances of default in the post-recession period in India,

Table IX.
Functions at group centroids

Group	Group centroid
Defaulting firms	1.287
Non-defaulting firms	−1.287

Table X.
Multiple discriminant analysis classification matrix

Observed group	Predicted group Defaults	Non-defaults	Total
Estimation sample			
Defaults (%)	71[a] (78.9)	19 (21.1)	90 (100)
Non-defaults (%)	0 (0)	90[b] (100)	90 (100)
Overall accuracy (%)	78.9	100	89.4[c]
Hold-out sample			
Defaults (%)	25[a] (55.6)	20 (44.4)	45 (100)
Non-defaults (%)	0 (0)	45[b] (100)	45 (100)
Overall accuracy (%)	55.6	100	77.8[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; [c] indicates the overall accuracy estimated as the average of a and b we are motivated to develop an empirical model that incorporates the effect of macroeconomic factors at the firm level. The model so developed helps in linking the developments in the macroeconomic environment to the firm's risk of default. The study contributes to the literature by establishing that it is plausible to predict the likelihood of default with a given set of macroeconomic variables even when there is no other firm-specific information available.

The study incorporates the impact of the macroeconomic variables on the default risk of firms in the form of sensitivity of a firm to changes in the respective macroeconomic variables (macroeconomic sensitivities). These macroeconomic sensitivities are estimated using a linear regression of the monthly stock return of the individual firm on the monthly changes in each of the macroeconomic variable. The study uses a matched pair sample of defaulting and non-defaulting listed Indian firms. Two alternative statistical techniques, i.e. logistic regression and multiple discriminant analysis, have been used. The findings of the study show that sensitivity to changes in the stock market and sensitivity to changes in inflation have a significant impact on the default probability of a firm. Stock market sensitivity has a positive relationship with the probability of default, and CPI sensitivity is negatively related to the probability of default.

The findings of the study have important implications for lenders such as banks and financial institutions, investors and policymakers. Banks and financial institutions need to be wary of undue volatility in the stock markets, as it might indicate that there is higher likelihood for sensitive firms to default. However, increase in inflation, although significant, may not be a cause for concern taking into account its negative relationship with the probability of default. Given the sensitivity of a firm to changes in macroeconomic factors, naïve investors need to appreciate the fact that each firm is uniquely affected by the changes in the overall macroeconomic environment. Hence it is important to monitor and consider the impact of macroeconomic factors at the firm level and understand the relevant effect on default risk. Policymakers need to take into cognizance the impact of policy changes on macroeconomic variables and their subsequent effects on the debt servicing capacity of firms.

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Corresponding author
Khushbu Agrawal can be contacted at: khushbu1981@gmail.com