4. Data and Methodology

4.1 Sample selection and description

The sample of defaulting firms is collected from four credit rating agencies – CRISIL, ICRA, CARE and Fitch (India) for the period 2000-01 to 2011-12. This particular study period was chosen so as to cover the longest period possible. Since data on firms defaulting prior to 2000-01 was not available and the most recent year ended was 2011-12, the above mentioned period was chosen for the study. The data related to the financial statements and stock price is collected from the CMIE Prowess database and the data on macroeconomic variables from the RBI’s Database on Indian Economy. For the purpose of the present study the event of ‘default’ has the same meaning as defined by the credit rating agencies. As described in section 1.1, the event of ‘default’ is uniformly defined by the four rating agencies as an instance of any missed payment by an issuer on a rated financial instrument. The default event is recognised by assigning a ‘D’ rating to the firm. Thus, the sample of defaulting firms comprises of firms which have been assigned a ‘D’ rating.

There are 135 distinct listed firms which have defaulted during the study period. Table 4.1 contains the year-wise and agency-wise distribution of the defaults. The maximum number of defaults has occurred in the post recession period 2009-10 to 2011-12. The industry-wise distribution of the sample of defaulting firms is reported in Table 4.2. The maximum defaults are concentrated in the textiles industry followed by the metals and pharmaceuticals industries.
### Table 4.1 Year-wise & rating agency-wise distribution of defaulting firms

<table>
<thead>
<tr>
<th>Year</th>
<th>CRISIL</th>
<th>ICRA</th>
<th>CARE</th>
<th>Fitch (India)</th>
<th>Total</th>
</tr>
</thead>
<tbody>
<tr>
<td>2000-01</td>
<td>5</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>5</td>
</tr>
<tr>
<td>2001-02</td>
<td>5</td>
<td>0</td>
<td>0</td>
<td>1</td>
<td>6</td>
</tr>
<tr>
<td>2002-03</td>
<td>2</td>
<td>0</td>
<td>0</td>
<td>1</td>
<td>3</td>
</tr>
<tr>
<td>2003-04</td>
<td>1</td>
<td>1</td>
<td>0</td>
<td>0</td>
<td>2</td>
</tr>
<tr>
<td>2004-05</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>2005-06</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>2006-07</td>
<td>0</td>
<td>1</td>
<td>0</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>2007-08</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>2008-09</td>
<td>4</td>
<td>0</td>
<td>1</td>
<td>0</td>
<td>5</td>
</tr>
<tr>
<td>2009-10</td>
<td>9</td>
<td>16</td>
<td>1</td>
<td>5</td>
<td>31</td>
</tr>
<tr>
<td>2010-11</td>
<td>7</td>
<td>13</td>
<td>11</td>
<td>6</td>
<td>37</td>
</tr>
<tr>
<td>2011-12</td>
<td>12</td>
<td>15</td>
<td>11</td>
<td>7</td>
<td>45</td>
</tr>
<tr>
<td><strong>Total</strong></td>
<td><strong>45</strong></td>
<td><strong>46</strong></td>
<td><strong>24</strong></td>
<td><strong>20</strong></td>
<td><strong>135</strong></td>
</tr>
</tbody>
</table>

### Table 4.2 Industry-wise distribution of defaulting firms

<table>
<thead>
<tr>
<th>Industry</th>
<th>NIC Code (2-digit level)</th>
<th>No. of firms</th>
<th>% of Total</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mining &amp; Quarrying</td>
<td>07, 08</td>
<td>3</td>
<td>2.2%</td>
</tr>
<tr>
<td>Food Products</td>
<td>10</td>
<td>7</td>
<td>5.2%</td>
</tr>
<tr>
<td>Tobacco Products</td>
<td>12</td>
<td>1</td>
<td>0.7%</td>
</tr>
<tr>
<td>Textiles &amp; Apparel</td>
<td>13, 14</td>
<td>20</td>
<td>14.8%</td>
</tr>
<tr>
<td>Leather Products</td>
<td>15</td>
<td>1</td>
<td>0.7%</td>
</tr>
<tr>
<td>Wood &amp; Wood Products</td>
<td>16</td>
<td>1</td>
<td>0.7%</td>
</tr>
<tr>
<td>Paper &amp; Paper Products</td>
<td>17</td>
<td>6</td>
<td>4.4%</td>
</tr>
<tr>
<td>Chemicals &amp; Chemical Products</td>
<td>20</td>
<td>8</td>
<td>5.9%</td>
</tr>
<tr>
<td>Pharmaceuticals</td>
<td>21</td>
<td>12</td>
<td>8.9%</td>
</tr>
<tr>
<td>Rubber &amp; Plastic Products</td>
<td>22</td>
<td>4</td>
<td>3.0%</td>
</tr>
<tr>
<td>Non-Metallic Mineral Products</td>
<td>23</td>
<td>9</td>
<td>6.7%</td>
</tr>
<tr>
<td>Basic Metals &amp; Fabricated Metal Products</td>
<td>24, 25</td>
<td>13</td>
<td>9.6%</td>
</tr>
<tr>
<td>Computer &amp; Electronic Products</td>
<td>26</td>
<td>2</td>
<td>1.5%</td>
</tr>
<tr>
<td>Electrical Equipment</td>
<td>27</td>
<td>6</td>
<td>4.4%</td>
</tr>
<tr>
<td>Machinery &amp; Equipment</td>
<td>28</td>
<td>1</td>
<td>0.7%</td>
</tr>
<tr>
<td>Transport Equipment</td>
<td>30</td>
<td>5</td>
<td>3.7%</td>
</tr>
<tr>
<td>Other Manufacturing</td>
<td>32</td>
<td>4</td>
<td>3.0%</td>
</tr>
<tr>
<td>Electricity</td>
<td>35</td>
<td>1</td>
<td>0.7%</td>
</tr>
<tr>
<td>Construction &amp; Civil Engineering</td>
<td>41, 42</td>
<td>10</td>
<td>7.4%</td>
</tr>
<tr>
<td>Wholesale &amp; Retail Trade</td>
<td>46, 47</td>
<td>5</td>
<td>3.7%</td>
</tr>
<tr>
<td>Accommodation</td>
<td>55</td>
<td>2</td>
<td>1.5%</td>
</tr>
<tr>
<td>Motion Picture &amp; Video Production</td>
<td>59</td>
<td>1</td>
<td>0.7%</td>
</tr>
<tr>
<td>Telecommunications</td>
<td>61</td>
<td>1</td>
<td>0.7%</td>
</tr>
<tr>
<td>Computer Programming</td>
<td>62</td>
<td>6</td>
<td>4.4%</td>
</tr>
<tr>
<td>Real Estate Activities</td>
<td>68</td>
<td>5</td>
<td>3.7%</td>
</tr>
<tr>
<td>Architecture &amp; Engineering Activities</td>
<td>71</td>
<td>1</td>
<td>0.7%</td>
</tr>
<tr>
<td><strong>Total</strong></td>
<td></td>
<td><strong>135</strong></td>
<td><strong>100%</strong></td>
</tr>
</tbody>
</table>
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; Altman, 2000; Charitou and Trigeorgis, 2002; Bandyopadhyay, 2006; Hao, 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. Each defaulting firm has been paired with a non-defaulting firm matched on the basis of the closest asset size, industry and year of default. Specifically, a non-defaulting firm has been selected based on the following criteria.

- The firm should belong to the same industry as the defaulting firm (2-digit NIC code)
- The asset size of the firm should be closest to that of the respective defaulting firm
- Financial statement data, one year prior to the year of default of the corresponding defaulting firm, should be available
- The firm should be listed on one of the national stock exchanges (BSE or NSE)

Based on the above selection method the sample for the study consists of 135 defaulting firms and 135 non-defaulting firms resulting into a full sample of 270 firms. In order to ensure that there is no statistically significant difference between the asset sizes of the two groups of firms, independent sample t-test and paired sample t-test has been done. The descriptive statistics of the asset sizes and the results of the t-
test (independent sample and paired sample) are reported in Table 4.3. As shown by the independent samples t-test, the value of p is 0.712, which is greater than 0.05. Thus, it can be concluded that there is no significant difference between the mean asset sizes of the two groups. Similarly, the result of the paired samples t-test also shows non-significant difference between the mean asset sizes of the two groups of firms.

Table 4.3 Descriptive statistics and t-test for asset size

| Panel A. Descriptive Statistics – Asset size (Rs. Million) |
|-----------------|------------|------------|
| Sample          | Mean       | Std. Deviation |
| Defaulting Firms| 10379.73   | 22392.84   |
| Non-Defaulting Firms | 11616.46 | 31845.90   |

<table>
<thead>
<tr>
<th>Panel B. Independent sample t-test</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mean Difference</td>
</tr>
<tr>
<td>-1236.73</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Panel C. Paired sample t-test</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mean Difference (between pairs)</td>
</tr>
<tr>
<td>-1236.73</td>
</tr>
</tbody>
</table>

The sample has been divided into estimation sample and hold-out sample. The estimation sample is used to estimate the parameters of the predictor variables. Whereas the hold-out sample is used for testing how the model performs when applied to a different sample of firms not used for estimation. As it is important to test how a model performs for a recent sample of firms it is appropriate to use the most recent period as the hold-out sample.

The sample of firms from 2000-01 to 2010-11 is taken as the estimation sample and the sample of firms in 2011-12 as the hold-out sample. As the number of observations
are not distributed uniformly across all years (as reported in Table 4.1), a year-wise splitting of the sample would have resulted into very few observations in the estimation sample. Hence, year-wise splitting has not been done. Consequently, there are 180 firms in the estimation sample (90 defaulting and 90 non-defaulting firms) and 90 firms (45 defaulting and 45 non-defaulting firms) in the hold-out sample.

4.2 Statistical technique

The various alternative statistical techniques used in the literature on financial distress prediction include Multiple Discriminant Analysis or MDA, 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). Kumar and Ravi (2007) provide a comprehensive review of the work done using such statistical techniques for bankruptcy prediction in banks and firms. They also elaborate on the merits and demerits of each of these techniques.

Among the various alternative statistical techniques, Logistic Regression and Multiple Discriminant Analysis or MDA have been the most dominant ones. While some studies find logistic regression to be more efficient than MDA (Ohlson, 1980; Zavgren, 1985; Lennox 1999), other studies show that both the techniques work equally well (Gu, 2002; Aziz and Dar, 2006). Bhunia and Sarkar (2011) argue in favour of MDA as being a reliable and potent statistical technique for the purpose of classification despite some of its limitations and the presence of several advanced techniques. The present study aims to classify firms as defaulters and non-defaulters
and estimate the likelihood of default for a firm, given certain set of characteristics for the predictor variables. Thus both Logistic Regression and Multiple Discriminant Analysis are appropriate techniques for this purpose.

Logistic regression is a non-linear predictive modelling technique that helps in estimating the probability of occurrence of an event or outcome. For the present study the event of interest is the event of default. Since the outcome or dependent variable can assume only two values i.e. default or no default, binary logistic regression has been used. The probability of the event occurring is given by -

\[ P(Y) = \frac{1}{(1 + e^{-Z})} \]

Where,

\[ P(Y) = \text{probability of the event } Y \text{ occurring} \]

\[ Z = \text{linear combination of independent variables represented as:} \]

\[ \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + \ldots + \beta_n X_n \]

The regression coefficients are estimated using the maximum likelihood method (MLE). This method involves an iterative process that maximizes the likelihood of predicting the observed values of the dependent variable using the observed values of the independent variables. The estimated coefficients which indicate the impact of a one unit change in the independent variable on the dependent variable are interpreted in terms of the odds ratio. The odds ratio is nothing but the probability of the event occurring to the probability of its not occurring.

\[ \text{Odds} = \frac{P(\text{event})}{P(\text{no event})} \]
Since probabilities must range from 0 to 1, odds help in maintaining the upper and lower bounds of the probabilities.

Multiple Discriminant Analysis is a statistical technique that helps in classifying observations into one of the several a priori groups based on the observations’ characteristics. For the present study, the firms have been classified into two groups namely, defaulting and non-defaulting firms. The classification is done using a discriminant function which is a linear combination of certain independent variables. The discriminant function results in a score that is used to determine the group membership of the observation. The discriminant score is represented as:

\[ Z = a + b_1X_1 + b_2X_2 + b_3X_3 + \ldots + b_nX_n \]

Where,

\[ Z = \text{discriminant score} \]
\[ a = \text{constant} \]
\[ b_i = \text{discriminant weight for independent variable } X_i \]
\[ X_i = \text{independent variable} \]

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 optimal cut-off score depends on whether the groups are of equal sizes or unequal sizes. For groups of equal sizes, the optimal cut-off score is the mid-point between the two group centroids. The group centroid is the average or mean of the discriminant scores for all the observations within a particular group.
\[ Z_{CE} = \frac{Z_A + Z_B}{2} \]

Where,

\( Z_{CE} \) = optimal cut-off score for groups of equal sizes

\( Z_A \) = centroid for group A

\( Z_B \) = centroid for group B

For groups of unequal sizes, the optimal cut-off score is the weighted average of the group centroids.

\[ Z_{CU} = \frac{N_A Z_A + N_B Z_B}{N_A + N_B} \]

Where,

\( Z_{CE} \) = optimal cut-off score for groups of unequal sizes

\( Z_A \) = centroid for group A

\( Z_B \) = centroid for group B

\( N_A \) = number of observations in group A

\( N_B \) = number of observations in group B

4.3 Variable description

4.3.1 Accounting based model

In the accounting based model for default prediction a combination of ratios representing profitability, leverage, solvency, liquidity and efficiency have been used. The variables have been selected considering their prevalence in some of the past studies. A detailed note on the definition and constitution of these variables is given in Appendix A and Appendix B respectively.
Profitability

Profitability has been emphasized as an important determinant of the ability of a firm to repay its debt obligations. Firms with higher profits are less likely to default on their debt obligations and hence a negative relationship is expected between profitability and default probability. As has been done frequently by many prior studies, profitability has been measured by Net Income to Total Assets (Beaver, 1966; Ohlson, 1980; Zmijeswski, 1984; Casey and Bartczak, 1985; Jantadej, 2006; Kim and Sohn, 2010; Bhunia and Sarkar, 2011; Rashid and Abbas, 2011; Premchandra et al., 2011) and Earnings before Interest and Tax (EBIT) to Total Assets (Altman, 1968; Altman et al., 1977; Beaver et al., 2005; Wu et al., 2008; Bhunia and Sarkar, 2011; Rashid and Abbas, 2011; Premchandra et al., 2011; Jardin and Severin, 2011).

Leverage

Leverage indicates the extent of debt in the capital structure of the firm. Higher amount of debt as compared to owner’s equity in the capital structure restricts a firm’s financial flexibility and imposes higher fixed costs in the form of principal and interest payments. Thus, higher leverage leads to increased risk of defaulting. Hence a positive association is expected between leverage and default probability. Following prior studies, leverage has been measured by Liabilities to Total Assets (Beaver, 1966; Ohlson, 1980; Zmijeswski, 1984; Beaver et al., 2005; Wu et al., 2008; Kim and Sohn, 2010; Rashid and Abbas, 2011) and Liabilities to Owner’s Equity (Casey and Bartczak, 1985; Ward, 1994; Jardin and Severin, 2011).
Solvency

Beaver (1966) defines solvency of a firm as a situation wherein the pool of its liquid assets is sufficient to repay its debt obligations as they mature. Adequate solvency leads to lower probability of default and hence a negative relationship is expected between solvency and default probability. Consistent with prior studies, solvency has been measured by Cash flow from operations to Liabilities (Beaver, 1966; Casey and Bartczak, 1985; Ward, 1994; Jantadej, 2006; Rashid and Abbas, 2011; Bhunia and Sarkar, 2011) and EBIT to Interest payments, which represents the debt servicing capacity of the firm (Altman et al., 1977; Premchandra et al., 2011).

Liquidity

Liquidity is a measure of the extent of current or short-term assets available with the firm. Current assets enable the firm to meet its short-term payment obligations. Thus, higher liquidity leads to lower likelihood of default and hence a negative relationship between the two. Following past studies liquidity has been measured by Working Capital to Total Assets (Beaver, 1966; Altman, 1968; Ohlson, 1980; Bandyopadhyay, 2006; Muller et al., 2009; Bhunia and Sarkar, 2011; Rashid and Abbas, 2011; Premchandra et al., 2011) and Current Assets to Current Liabilities (Beaver, 1966; Altman et al., 1977; Zmijewski, 1984; Casey and Bartczak, 1985; Ward, 1994; Jantadej, 2006; Rashid and Abbas, 2011; Bhunia and Sarkar, 2011).

Activity

Activity ratios indicate the efficiency with which the firm’s assets are able to generate sales. The higher this efficiency, the faster illiquid assets get converted into liquid assets and lower the probability of default. Following prior studies, efficiency has
been measured by Sales to Total Assets (Altman, 1968; Bandyopadhyay, 2006; Wu, Liang and Yang, 2008; Kim and Sohn, 2010; Bhunia and Sarkar, 2011; Rashid and Abbas, 2011) and Sales to Current Assets (Zulkarnain et al., 2001; Ugurlu and Aksoy, 2006; Etemadi et al., 2009).

4.3.2 Option based model

The option-based model, also known as the contingent claims analysis (CCA) approach is derived from the works of Black and Scholes (1973) and Merton (1974). Under this approach the equity of a firm is viewed as a call option on the value of firm’s assets with the strike price equal to the face value of the debt. If at the maturity of the debt, the value of the firm is above the face value of the debt the equity holders choose to exercise their option by repaying the debt. But if the value of the firm is below the face value of the debt the equity holders opt to leave their option unexercised thereby defaulting on the repayment of the debt.

The model assumes that the firm value follows Geometric Brownian motion,

\[ dV = \mu V dt + \sigma \sqrt{V} dW \]

(1)

Where,

\( V \) is the total value of the firm, \( \mu \) is the expected continuously compounded return on \( V \), \( \sigma \) is the volatility of firm value and \( dW \) is a standard Wiener process. The second assumption of the model is that the firm has issued only one single zero-coupon bond maturing in \( T \) periods (one year). Some of the other assumptions of the model are - refinancing and renegotiation of firm’s debt obligations is not allowed, liquidation of the firm is costless and default boundary is constant. The model recognizes that neither the underlying value of the firm nor its volatility is directly observable. Under
the model's assumptions both can be inferred from the value of equity, the volatility of equity, and other observable variables by using an iterative procedure to solve a system of nonlinear equations.

According to the Merton model, the equity value of a firm satisfies

\[ E = VN(d_1) - e^{-rT} FN(d_2) \]  

(2)

Where,

- \( E \) = Market value of the firm's equity
- \( V \) = Market value of the firm's assets
- \( F \) = Face value of the firm's debt
- \( r \) = instantaneous risk-free rate
- \( T \) = Time to maturity of the firm's debt
- \( N(\cdot) \) = cumulative standard normal distribution function

\[ d_1 = \frac{\ln \left( \frac{V}{F} \right) + \left( r + 0.5 \sigma_v^2 \right) T}{\sigma_v \sqrt{T}} \]

\[ d_2 = d_1 - \sigma_v \sqrt{T} \]

The volatility of the firm's value, \( \sigma_v \), is related to the volatility of firm's equity, \( \sigma_E \), by the following expression:

\[ \sigma_E = \frac{V}{E} N(d_1) \sigma_v \]

(3)

Solving the non-linear system of Equations (2) and (3) gives the firm's value, \( V \), and its volatility, \( \sigma_v \). These two variables along with the face value of the debt, \( F \), are inputs for estimating the distance-to-default, \( DD \), which is defined as:

\[ DD = \ln \left( \frac{V}{F} \right) + \left( r - 0.5 \sigma_v^2 \right) T \]

(4)

\[ \sigma_v \sqrt{T} \]
The distance-to-default indicates the number of standard deviations that the firm value is from the default point. Smaller the value of DD the closer the firm is to the default point and larger the probability of default.

In an alternative approach, Bystrom (2006) suggests a simplified spreadsheet version of the Merton model that uses only observable parameters i.e. the market value and volatility of the firm’s equity and the book value of the firm’s debt in order to estimate the distance to default. This simplified version is based on three assumptions with respect to equations (3) and (4):

- Since in most practical situations the drift term, \((r - 0.5\sigma_v^2)T\), is found to be small and empirically it is very difficult to estimate the drift rate of stocks or other assets, this is assumed to be zero.

- Only in extreme cases where \(V\) is close to \(F\) (the option is almost at the money) and the underlying asset volatility is very high is \(N(d_1)\) significantly different from one. Hence, \(N(d_1)\) is assumed to be close to 1.

- Since it is the book value of debt that needs to be paid back, not the market value of debt, the book (face) value of debt is used to calculate the leverage ratio, \(F/V\).

Based on the first assumption and the original Merton model’s assumption of time to maturity of debt as 1 year, the expression for distance to default is reduced to the following.

\[
DD = \frac{\ln(V/F)}{\sigma_v} \tag{5}
\]

Further replacing \(\sigma_V\) with \(\sigma_EE/V\) using (3) and the second assumption of \(N(d_1)\) being close to one, we get:
\[ DD = \frac{\ln(V/F)}{\sigma_{E/V}} \]  

(6)

As the leverage ratio is defined as \( L = F/V \), the simplified expression for distance-to-default can be written as:

\[ DD_{\text{Modified Merton}} = \frac{\ln(1/L)}{\sigma_E (1-L)} = \frac{\ln(L)}{(L-1) \sigma_E} \]  

(7)

Thus, the simplified version of distance-to-default is estimated as:

\[ DD_{\text{Modified Merton}} = \frac{\ln(L)}{(L-1) \sigma_E} \]  

(8)

Where, \( L \) is the leverage ratio calculated using the market value of equity \( V_E \) and book value of debt \( D \) as \( D/(V_E + D) \). And \( \sigma_E \) is the volatility of the firm’s equity.

Bystrom (2006) argues that apart from being simple and intuitive, his measure of distance-to-default highlights the drivers of default namely, equity volatility and a firm’s leverage ratio. Whereas the Merton model assumes constant debt, which lacks empirical support, the modified version is more dynamic in terms of advocating a constant leverage ratio, which is more realistic. Given the fact that the measure can be calculated for any firm irrespective of its capital structure or asset volatility, Bystrom (2006) further argues that his measure could be useful for estimating the default probabilities of firms in emerging markets as well as those operating in volatile markets.

Bystrom (2006) empirically shows that the distance-to-default measures obtained by his model are very similar to those calculated using the original Merton model. The measure of distance-to-default developed by Bystrom (2006) has the advantage of
simplicity along with generating values similar to the traditional Merton model. Hence, for the option based model in the present study, the modified distance-to-default developed by Bystrom (2006) has been used.

4.3.3 Macroeconomic and Industry Variables

Tirapat and Nittayagasetwat (1999) argue that higher a firm’s sensitivity to economic shocks the more vulnerable it is to experiencing financial distress. For the present study, the impact of the macroeconomic variables on the default risk of firms has been incorporated in the form of sensitivity (β) of each firm to changes in the respective macroeconomic variables. The sensitivities (β) to each of the variables have been estimated using an OLS regression of the monthly stock return of the individual firm on the monthly changes in each of the variable.

\[ R_i = \alpha + \beta_1 \Delta IIP + \beta_2 \Delta CPI + \beta_3 \Delta IntRate + \beta_4 \Delta MS + \beta_5 \Delta SMkt \]  

(1)

Where,

- \( R_i \) = Monthly stock return for firm i
- \( \Delta IIP \) = Monthly changes in Index of Industrial Production (General Index)
- \( \Delta CPI \) = Monthly changes in Consumer Price Index (Industrial workers: General Index)
- \( \Delta IntRate \) = Monthly changes in Interest rate (364-day T-bill)
- \( \Delta MS \) = Monthly changes in Money Supply (M1)
- \( \Delta SMkt \) = Monthly return on the Stock Market (Sensex)

- \( \beta_1 \) = IIP Beta
- \( \beta_2 \) = CPI Beta
- \( \beta_3 \) = IntR Beta
\[ \beta_4 \] = MS Beta
\[ \beta_5 \] = SMkt Beta

Similarly, the impact of industry factors on a firm’s vulnerability to default has been captured by the sector or industry beta (\( \beta \)) for each individual firm. For estimating the sectoral beta the monthly stock return of each individual firm has been regressed on the monthly return of the respective sectoral or industry index.

\[ R_i = \alpha + \beta_1 \text{SectIndex} \] \hspace{1cm} (2)

Where,

\[ R_i \] = Monthly stock return for firm \( i \)

\[ \text{SectIndex} \] = Monthly return on the respective Sectoral Index (CMIE Sectoral Index)

\[ \beta_1 \] = Industry Beta