Mapping Corporate Drift towards Default: A Study of Distance to Default of Indian Corporates

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Abstract

Mapping corporate drift towards default is becoming a crucial part of any financial institution's credit risk measurement. Even the banks with an internal rating system need to check the discriminatory power of the internal rating. This article focus on the use of option based models in credit risk management. Using the Black and Scholes and Merton model (BSM), we present a framework to optimally use stock market and balance sheet information of the company to predict its distance to default over a horizon of one year. We then apply this methodology on 53 large Indian Corporates over the year 1998 to 2004 and find that option model can accurately predict the default status of the firm even before the ratings are published by CRISIL. Next, in a logistic regression, we investigate the ability of the market value of assets and liquidity measures to predict default. Our empirical analysis shows that distance to default is the single most important predictor variable which can act as a single control for asset value, asset volatility and balance sheet liquidity and hence can outperform any other ratio based models.

JEL classification: G21, G33

Keywords: Distance to Default, Option theory, Bankruptcy

I. Introduction

In theory, corporate bankruptcy is hinted either by the fall in the asset value or by liquidity shortages (fall in the ability to raise capital to finance project). The market value of assets is a very powerful default predictor since it is an indicator of a firm's either economic prosperity or distress (Black and Cox, 1976; Leland, 1994; Davydenko, 2005). Moreover, some firms default at low asset values despite abundant liquidity. The market value of assets at default is on average 65 per cent of the face value of debt (Brockman and Turtle, 2003). It varies widely in the cross section, and depends on balance sheet liquidity, asset volatility and tangibility.

Correct estimation of default probabilities are becoming an increasingly important element of bank's measurement and management of credit exposures as wrong estimates of EDF could lead to inappropriate capital allocation and as a consequence, destroy shareholder value due to default.

There are certain problems with the external rating. It assumes uniform PDs across parties in the same rating class**.** Default may be continuous process, which is not addressed by credit migration approach**.** The asset value models using Black & Scholes' option theory crack on the above two observations. It is a model for assessing the credit risk of a corporation's debt. It was proposed in Black and Scholes' (1973) seminal paper on option pricing and a more detailed paper by Merton (1974). Merton anticipated the model in 1970 and actively supported the work of Black and Scholes, so the model is sometimes called the Merton model. A popular implementation of the model is the commercial KMV model of Moodys (2001 and 2002). The option model can be used in correct and quick estimation of the default probability for the corporates listed in the stock exchange.

The main aim of the analysis is to get a quick estimate of PD from the stock market information to get an early warning signal for predicting bankruptcy status of a firm. In order to accomplish that, we estimate both the risk neutral and real (or projected) expected default frequency (EDF). We have used two Black Scholes equations, Ito's lemma and Newton Raphson algorithm to solve and finally arrived at market value of firm's asset (MVA) and asset volatility of companies over few years. We have found that the market value of equity (MVE), equity volatility, risk free rate (we have taken 364 days T bills rate which has 0 beta as risk free rate), equity beta, default point are very helpful in predicting default.

From our study of 53 Indian Corporates who are listed in the stock exchange and also whose long term bonds are rated by CRISIL, we find that option model can accurately predict the default status of the firm even much before the ratings are published by CRISIL. Even the model can predict whether a poor rated (even D rated) firm's bankruptcy status can be improved in future. The model is capable of finding market value of debt which is: market value of firm's asset (MVA) minus market value of equity (MVE). The main focus is default rather than rating migration. In each case we try to predict: what is the chance that a company's MVA will hit the default boundary line defined by a default point which is a linear combination of book value of short term and long term debt.

Finally, we investigate the ability of the market value of assets and liquidity measures to predict default. For this, we run logistic regressions to study the factors triggering corporate bond using an unbalanced panel of 53 Indian corporates over the period of 1998 to 2004. Our logistic analysis shows that default may occur due to either a low asset value or due to liquidity shortage or both. More interestingly, we have found that the distance to default, which is the ratio of distance of market value of asset from default point to the multiple of market value of asset and asset volatility, is the single most important predictor variable which can act as a control for asset value, asset volatility and balance sheet liquidity and hence can easily outperform any other ratio based models. Moreover, the inclusion of distance to default (DD) along with some firm specific (non-financial) parameters dramatically increases the model's ability to predict default. The remainder of the paper is organized as follows. The next section discusses the data set. Section III discusses the methodology for estimation of market value of asset and asset volatility from the stock market and balance sheet information. Finally we derive firms distance to default (DD) and default probabilities (both risk neutral and real EDFs). In section IV, we discuss the main empirical results. Section V concludes. The details of the summary statistics and construction of variables are provided in the Appendix.

II. Data

The information on the firm's borrowings (short term as well as long term), market capitalization, balance sheet ratios and background information are obtained from their audited financial data supplied by CMIE Prowess (corporate database similar to COMPUSTAT of USA). The stock price information (closing price of stocks traded daily) and market index (S&PCNX500) are obtained from the National Stock Exchange (NSE) website[1]. The equity betas are estimated following the time series analysis of daily stock price data over a period of five years. The 364 days T-bills rates which proxy for the risk free rate obtained from the Economy Survey: Government of India (various issues).

The information on rating and defaulted bonds is obtained from CRISIL (a leading credit rating agency in India). The CRISIL's long term bond rating covers mainly 542 corporates consistently over the period of 1992 to 2005. The data on defaulted bonds are, however, available only since January 1995. Since the objective of the paper is to predict corporate bond defaults, we consider these 542 corporates as the population. However, we face a major hurdle in developing an analytical model for corporate distance to default using the company's stock market information is the non availability of stock price data of defaulted companies. This is because they are not being quoted in the market. This has restricted us to study an unbalanced panel of only 53 corporates over the period of 1998 to 2004. Even out of these 53 corporates, frequencies of time periods are different. We therefore, further have blown our unbalanced panel into cross section of 131 observations.

III. Methodology

The methodology we have followed is what was obtained by KMV (2001 & 2002) and Default Greeks under an objective probability measure (Farmen, Westgaard and Wijst, 2004) based on the Black & Scholes Merton model. Academic belief is that default is driven by a) market value of firm's assets, b) level of firm's outside obligations (or liabilities) and c) variability in future market value of assets. As the market value of firm's assets approaches book value of liabilities, the default risk of firm increases. The default point is the threshold value of firm's assets (somewhere between total liabilities & current liabilities) at which the firm defaults. Therefore, the relevant net worth of the firm is the difference between the market value of assets and the default point. Default occurs when the relevant net worth of the firm approaches to zero.

Numerical Steps

Merton (1974) proposed a model where a company's equity is an option on the assets of the company. If $V_T < D$, theoretically, a rational firm will default on its debt obligations at time T. The value of equity is then zero. If $V_T > D$, the company makes the debt repayment at time T and the value of the equity at this time is $V_T - D$; since equity holders are the residual claimants of the firm. Note that V and D stand for market value of asset and the book value of debt. Merton's model, therefore, gives the value of the firm's equity at time T as:

$$E_T = \max(V_T - D, 0)$$

This shows equity is a call option on the value of the assets with a strike price=repayment required on debt.

The Black-Scholes formula gives the value of equity today as:

$$E_0 = V_0 N(d_1) - De^{-rT} N(d_2) \tag{1}$$

where

$$d_1 = \frac{\ln \frac{V_0}{D} + (r + \sigma_V^2 / 2)T}{\sigma_V \sqrt{T}} \tag{1a}$$

$$d_2 = d_1 - \sigma_V \sqrt{T} \tag{1b}$$

The market value of debt today is: V_0-E_0

The risk neutral Probability of default on the debt is: *N (-d2)*

We can observe E_0 if the company is publicly traded

We can also estimate equity volatility

From Ito's Lemma:

$$\sigma_E E_0 = \frac{\partial E}{\partial V}\sigma_V V_0$$

$$\sigma_E E_0 = N(d_1)\sigma_V V_0 \qquad (2)$$

We use Newton Raphson algorithm as suggested in Hull (2002) to solve the system of two non-linear equations (1) and (2) of the form $F(x,y)=0$ & $G(x,y)=0$ to obtain the two unknowns: market value of asset (*V*) and asset volatility (σ_V). In order to accomplish that we write the optimization problem in excel routine solver and minimize $F(x,y)^2+G(x,y)^2$ with respect to V & σ_V and subject to the constraints $V_0 > 0$ & $\sigma_V > 0$. Here we assume the maturity period (T) is equal to 1 year since we are interested in estimating yearly EDFs.

Steps in Estimating Risk Neutral EDFs

After solving the two Black-Scholes equations, we obtain the firm's market value of asset within a year and the volatility of asset return. In the next step, we plug in these two values V & σ_V along with the risk free rate (*r*) to obtain the "distance to default" (DD) which is d_2.

where $d_2 \equiv \dfrac{\ln\dfrac{V}{D} + (r - \dfrac{\sigma_V^2}{2})T}{\sigma_V\sqrt{T}}$

According to the Black Scholes and Merton (BSM) formulation, the risk neutral probability of default at any time t is given by:

$$P_{Default} = \Pr[V_t \le D] \qquad (2a)$$

If we transform the probability of default into a normalized threshold, with mean 0 and variance 1, we get

$$P_{Default} = \Pr\left[\frac{\ln\frac{V}{D} - (r - \sigma_V^2/2)t}{\sigma_V\sqrt{t}} \geq Z_t \right] \qquad (2b)$$

Having found the value of the firm (V) and its volatility (σ_V), the risk neutral probability of default can be calculated as:

$$P_{Default} = N\left(Z_t \leq -\frac{\ln\frac{V}{D} + (r - \sigma_V^2/2)t}{\sigma_V\sqrt{t}} \right) \equiv N(-d_2) \qquad (2c)$$

where r is the risk free rate & $N(\cdot)$ is the cumulative standard normal distribution.

We have also mapped the DD with the CRISIL's rating and found that DD of 2.33 is equivalent to long term bond rating of CCC. We have defined default point (which is D in the above equation) as sum of short term debt and half of long term debt. Where, short term debt is sum of commercial paper, short term bank borrowing (repayable within 1 year) and current portion of long term debt (repayable within a year). On the other hand, long term debt is the difference between total debt and short term debt. Long term debt mainly comprises of long term bank borrowing, long term debentures, loan from DFIs etc. We have used 364 T bills rate as risk free rate (r).

Finding the Drift of Assets and Real Default Probability (or EDFs)

The credit risk model should use the real default probabilities instead of the risk neutral default probability. In general risk neutral default probabilities are easier to estimate than real default probabilities. Risk neutral probability should serve as a upper bound to real default probabilities. In fact, the risk adjusted and risk neutral distribution of the firm have the same variance, and the risk adjusted distribution must generally have a mean greater than the risk free rate, then the risk neutral distribution implies a higher probability of default. In practice, one has to find the drift of the asset (or expected return of the firm) to estimate the real default probability. In order to accomplish that, we calculate average market return of the portfolio of stocks. For this, we estimate mean return from historical data on S&PCNX500 return and then annualize it to get the average return of the portfolio which has beta=1.We have also calculated equity beta from daily historical stock price data of each company (begin from June7 1999 to 31st December 2004). This beta is not always equal to beta supplied by Prowess. We also have calculated equity volatility from daily stock data (closing price) and annualized after multiplying it by SQRT (T). T=number of working days in a year which we assume as 250.

Having found the asset value V and the volatility of the asset value σ_v, the next step to obtain the real default probability is finding the drift of the asset μ_v. This asset drift can be estimated by solving the following two equations (3 & 4):

$$dE_t = \mu_E E_t dt + \sigma_E E_t dZ_t \tag{3}$$

The above expression shows the equity process following stochastic differential equations. Here E_t represents the value of equity and σ_E represents the equity volatility. At any time, the following definition relations obtain: $V_t = E_t + D_t$ and $dV_t = dE_t + dD_t$, that is, the value of the firm's asset must be equal to the value of debt and equity and the change in the value of the assets must be equal to the change in the values of equity and debt.

By Ito's lemma, we can also represent the process for the equity as:

$$dE_t = \left(\frac{\partial E}{\partial t} + \mu_v V_t \frac{\partial E}{\partial V} + \frac{1}{2}\sigma_V^2 V_t^2 \frac{\partial^2 E}{\partial V^2} \right) dt + \sigma_V V_t \frac{\partial E}{\partial V} dZ_t \tag{4}$$

By comparing the diffusion terms in the equity process in (3) and (4), we get the following relationship:

$$\sigma_E E_t = \sigma_V V_t \frac{\partial E}{\partial V} = \sigma_V V_t N(d_1) \tag{5}$$

Here, $N(d_1)$ is the hedge ratio or the equity "delta" (Δ^E) in the standard option terminology.

In the next step, we obtain the "equity gamma" by using the following expression:

$$\text{Equity Gamma } \Gamma^E = \frac{\partial^2 E}{\partial V^2} = \frac{n(d_1)}{V\sigma_V \sqrt{T}} \tag{6}$$

Equity Theta $\Theta^{E} = \frac{\partial E}{\partial t} = -\frac{Vn(d_1)\sigma_V}{2\sqrt{T}} - rDe^{-rT}N(d_2)$ (7)

It can be shown that:

$$\frac{\partial N(d_1)}{\partial V} = n(d_1) = \frac{1}{\sqrt{2\pi}} e^{-d_1^2/2}$$

$\because N(x) = \frac{1}{\sqrt{2\pi}} \int_{-\infty}^{x} e^{-\frac{1}{2}z^2} dz$ denotes the distribution function of the standard normal distribution.

The above measures are similar to the well-known standard sensitivity measures (option Greeks) for a European call option.

Having found expressions for $\Lambda^E, \Gamma^E, \& \Theta^E$, we can now compare the drift terms of equations (3) and (4) and solve for drift of the asset μ_V:

$$\mu_E E = \frac{\partial E}{\partial t} + \mu_V V \frac{\partial E}{\partial V} + \frac{1}{2}\sigma_V^2 V^2 \frac{\partial^2 E}{\partial V^2} \quad (8)$$

$$\mu_E E = \Theta^E + \mu_V V \Delta^E + \frac{1}{2}\sigma_V^2 V \Gamma^E \quad (9)$$

$$\Rightarrow \mu_V = \frac{\mu_E E - \Theta^E - \frac{1}{2}\sigma_V^2 V^2 \Gamma^E}{V\Delta^E} \quad (10)$$

The equity drift (expected growth rate) or μ_E can be estimated from the stock market. In order to estimate μ_E, we have used capital asset pricing model (CAPM). According to CAPM, we have:

$$\mu_E - r = \beta\pi \quad (11)$$

Here β is the beta of the equity with the market portfolio (in our analysis S&PCNX500).

$\beta = \frac{\text{cov}(R_E, R_M)}{\text{var}(R_M)} = \rho \frac{\sigma_E}{\sigma_M}$; where R_E and R_M denote the return on the firm's equity and the market return respectively. σ_E, σ_M and ρ is the volatility of the firm's equity, the volatility of the market portfolio and the correlation between the equity return and the market return respectively. These market returns are obtained from their daily closing prices by using the formula: $ln(S_t/S_{tt-1})$. The standard deviations of daily returns are the daily volatilities. In order to estimate the beta of the stocks, we have regressed daily market return (R_M) on stock return (R_E). π is the market risk premium for a unit of beta risk or the "market price of risk". It is given by:

$$\mu_M - r = \pi \qquad (12)$$

where μ_M denote the expected return on the market portfolio which is the mean return of S&PCNX500.

Once we obtain β and π, using the 365 T-bills rate as the risk free rate (r), using equations (11) and (12), we obtain the equity drift μ_E. In the next step, we plug in μ_E along with the equity theta, delta and gamma in equation (10) to obtain the asset drift μ_V.

Having found V, σ_V and μ_V, we can now calculate the real default probability:

$$N(-d_2) = N\left(-\frac{\ln\frac{V}{D} + (\mu_V - \sigma_V^2/2)T}{\sigma_V\sqrt{T}} \right) \qquad (13)$$

IV. Empirical Results

Based on the above methodology, we have made an attempt to forecast the bankruptcy status of 53 Indian corporates within one year. Figure 1 illustrates the movement of market value of asset and default point (book value of short term debt plus half of long term debt) of BPL Ltd. whose bond defaulted in the year 2003. BPL Ltd. is an electronics company. As one can see the default risk of the firm increases as the value of the assets approaches the default point, until the firm defaults when the market value of the assets is insufficient to repay the liabilities. The figure clearly shows the firm's relevant net worth (difference between MVA and DP) is falling and approaches zero in the year 2003. In the same figure, we have superimposed the yearly risk neutral and real EDFs of the firm and compared with the CRISIL's yearly long term bond ratings. In the year 2003, CRISIL downgraded the company's bond rating from A to D which is in line with our estimates (in 2003, DD of the company was 1.64, much lower than the 2.33 which corresponds to CCC).

[FIGURE 1 HERE]

Like the firm's asset value, the market measure of net worth must be considered in the context of the firm's business risk. A firm's ability to take higher levels of leverage may vary across industries. Like firms in the food and beverage industries can afford lower market net worth than high technology business because of their business, and consequently their asset values are more stable and less uncertain. Moreover, the asset volatility may vary across firms in different industries. Therefore, the difference in the default probabilities of companies may be driven by the difference in the risks of their business, not just their respective asset values or leverages. Accordingly, one has to control for this industry effect to capture the business risk. Consequently, we study default risk of other firms also.

In figure 2, we see the evolution of asset values and default points for Arvind Mills Ltd. which is a textile firm. We clearly see that there is a sharp fall in asset value since 1999 and it went much below the default point in 2000 and 2001 and 2002 end which means negative net worth. The EDFs shown in the figure 2 are the one year expected default rates which measure the probability that the firm will default in the ensuing year. As one can see, distance to default fell and EDFs shoot up to danger level in the year 2000. The erosion of distance to default had already given an early warning signal since 1999 as evident from the graph. In reality, the company had grossly overestimated demand, set up huge capacities and taken on massive amounts of debt.[2] In October 2000, CRISIL downgraded its long term debt instrument to default grade (D). However, things dramatically changed since October 2003 after the company followed a debt restructuring programme and the company bounced back to the investment grade (BBB). Our estimate also shows fall in default probability from year 2003 onwards (with rising distance to default of 2.6).

[FIGURE 2 HERE]

Similarly, we also study the default paths of RPG Transmission Ltd. The company already had shown deterioration in asset value as projected in Figure 3 much before CRISIL downgraded its rating to D in 2001. However, EDFs in each year actually is the projection of the next year. For example, in case of RPG Transmission Ltd., bond rating for the year 1999 was BB where risk neutral and real EDFs for the year 1999-2000 is 7.54% and 6.53% respectively. The corresponding distance to default was 1.44 (much lower). Therefore, our projection shows that the company should default by December of next year (i.e., 2000) since EDFs are approaching to approximately 8% by the year 2000. However, CRISIL downgraded the company's bond rating to D in the year 2000.

[FIGURE 3 HERE]

In figure 4, we track the movement of asset value and book value of default point for Vardhman Spinning and General Mills Ltd which is again a textile firm. Though CRISIL confirms the stable rating of AA for the firm, our model shows some alarm about the deteriorating condition of the firm. Like in 2002, company's asset value was very close to its default point (DD was 1.52). However, the company is improving after that. Our projection for the year 2004-05 is that the distance to default would be 2.5 in December 2005 which is not as good as AA rating.

[FIGURE 4 HERE]

In the graphical analysis of default of companies, one can also see that risk neutral EDFs acts as an upper bound of the real default probabilities. This is because since the risk adjusted and risk neutral distribution of the firm have the same variance, and the risk adjusted distribution must generally have a mean greater than the risk free rate, then the risk neutral distribution implies a higher default probability. However the risk neutral default probabilities have similar sensitivities as real default probabilities.

In Table I, we study default status of 53 Indian corporates from different industries and report their yearly projections. One can see that both risk neutral and actual EDFs are inversely related to the market value of firm's asset but positively related to asset volatility. One can compare the CRISIL long term bond rating of these companies with our estimates of distance to default (DDs), risk neutral and real default probabilities. We found that if DD falls below 2.33, the firm's chance of default is very high.

[TABLE I HERE]

One may be interested to know the significance of DDs on actual default outcomes. The basic empirical question is whether default is triggered by low asset values or by liquidity shortages? The question finally boils down into whether the market value of firm's assets and volatility of assets obtained from the stock market information is the powerful default predictor. Default may be triggered by both low asset values and by liquidity shortages, and the importance of liquidity varies depending on costs of outside financing. Accordingly, we run a logit model to test the significance of distance to default which combines firm's MVA, asset volatility as well as firm's leverage condition (captured by the default point).

In the logit analysis, we have taken an unbalanced panel data of the same 53 corporates over the period 1998 to 2004. In this panel, total number of observations we found is 131 and they have been treated as cross-sections. The sample firms are generally large firms and their asset sizes are comparable. The purpose of the logistic analysis is to study the ability of the market value of assets, liquidity measures and distance to default to predict default. The Table II reports results of logistic regression estimates of the default decision of three models. The dependent variable is a dummy which takes the value one if the company's bond defaults in a particular year (as reported by CRISIL's rating) and zero otherwise.

[TABLE II HERE]

The results reported in column 1 of Table II are the re-estimation of Altman's 1968 original Z score model in Indian scenario. In the second model (see column 2), we test the significance of market value of firm's assets on bond default prediction. We control the age effect by taking natural log of the year since the company incorporated. We have used another dummy DUMTOP50=1 for the firms belonging to top 50 business group as against zero for smaller group or private standalone firms. This dummy proxy for corporate governance as well as it captures group reputation (Bandyopadhyay and Das, 2005). These two dummies are taken as control variables to reduce firm wise heterogeneity. The results of MVA model shows as soon as we include market value of firm's assets as proportion to default point (MVA_DPT), the result significantly improves as far as pseudo R^2 (0.54 as compared to Altman's 0.43)[3] and predictive powers (94% as compared to Altman's 89.27%).[4] This is despite the fact that Z-score already includes the ratio of the market value of equity to book value of total liabilities (MVE_BVL). We also have found that many of the five accounting ratios used by Altman (1968) are correlated to each other which may bias the results (See the correlation table III given in the appendix). However, in the MVA and DD model there is no multicollinearity problem. The coefficient of MVA_DP is negatively significant implying that higher the market value of firm's assets, lower is the chance of default. Model 3 results give evidence that distance to default (DD) is itself a very powerful variable to predict bond default (with predictive power of 91.57%) as expected. One can clearly see that DD is negatively significant on the probability of default. This means that as distance to default increases, the chance of default comes down.[5] One can also see the table IV displayed in the appendix that the average distance to default when the company is solvent is significantly higher than when the company is in distressed condition (5.78 in comparison to 1.09). However, there is lot of variations even across the solvent firms. One interesting fact is that we have also checked the correlation of DD with solvency and liquidity ratios and the correlation coefficients are highly significant. Thus, our results suggest that distance to default (DD) variable can capture both movement of asset values and liquidity of the firms. By comparing the DD across various firms in different industries, one can accurately predict corporate default. As far as control variables are concerned, our results show that the age parameter (LNAGE) is negatively significant which means that older firms are safer in comparison to the younger firms. Intuitively, matured firms may have established reputation with credit institutes or rating agencies that alleviates the asymmetric information problems. We have also found that the likelihood of default is less if the firm belongs to top 50 business group suggesting group reputation matters for solvency. This is expected as the other studies have also shown that top business groups have stability in cash flows and show better productivity as well as risk sharing through mutual debt guarantees than unaffiliated firms (Gangopadhyay, Lensink and Molen, 2001).

V. Conclusions

This paper investigates whether the market value of firm assets that can be obtained from its stock market information can predict bankruptcy. The option based default probability estimation may be an innovative approach for measuring and managing credit risk. In this paper, we optimally use the stock market information of the company and compare with the balance sheet information to predict its distance to default over a year or over six months. While comparing the estimated distance to default of solvent and defaulted Indian listed firms, our asset value model based on the BSM model can facilitate the Indian banks as well as investors to get an early warning signal about the company's bankruptcy status.

The results of our analysis of 53 Indian corporates clearly reveal that the BSM model has the capacity to discriminate between the defaulted and solvent firms. In a logistic regression, we also investigate the ability of the market value of assets and liquidity measures to predict default. We found empirical evidence that distance to default is the single most important predictor variable which can act as a single control for asset value, asset volatility and balance sheet liquidity and hence can outperform any other ratio based models. Therefore, banks can no longer ignore the equity market information in their credit risk capital estimation and risk adjusted performance. The BSM approach to bankruptcy prediction would assist banks and financial institutions to bring market capitalization and stock volatility into the lending equation and therefore can enhance their corporate credit appraisals and pricing decisions.

Notes

1 See historical stock price data and S&PCNX500 market price volume data at: http://www.nseindia.com/

2 See Business Standard, Special 2003, "Restructuring's Fall Out: New Investment".

3 Pseudo R^2 is a likelihood ratio index similar to the R^2 in a conventional regression model. Pseudo $R^2 = 1 - \frac{L_{\max}}{L_0}$; where L_{max} is the highest value of the likelihood function and L_0 is the initial value.

4 The predictive power of the model is obtained by estimation of logistic receiver operating characteristic curve (LROC). LROC measures the proportion of defaulted outcomes correctly specified (otherwise type 1 error) vs. percentage of good outcomes correctly specified (otherwise type 2 error).

5 The correlation between DD and WK_TA is 0.45, correlation between DD and PBIT_TA is 0.58 and correlation between DD and QR is 0.44. All the coefficients are significant at 1% or better level.

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Figure 1:

Figure 2:

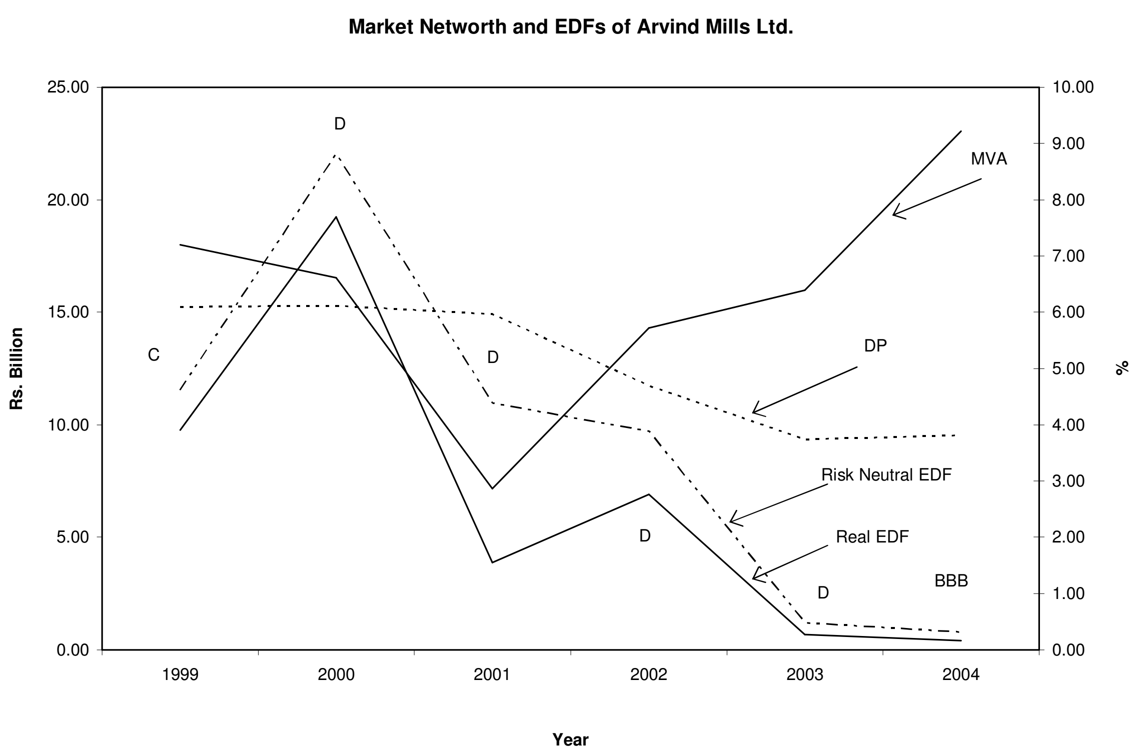

Figure 3:

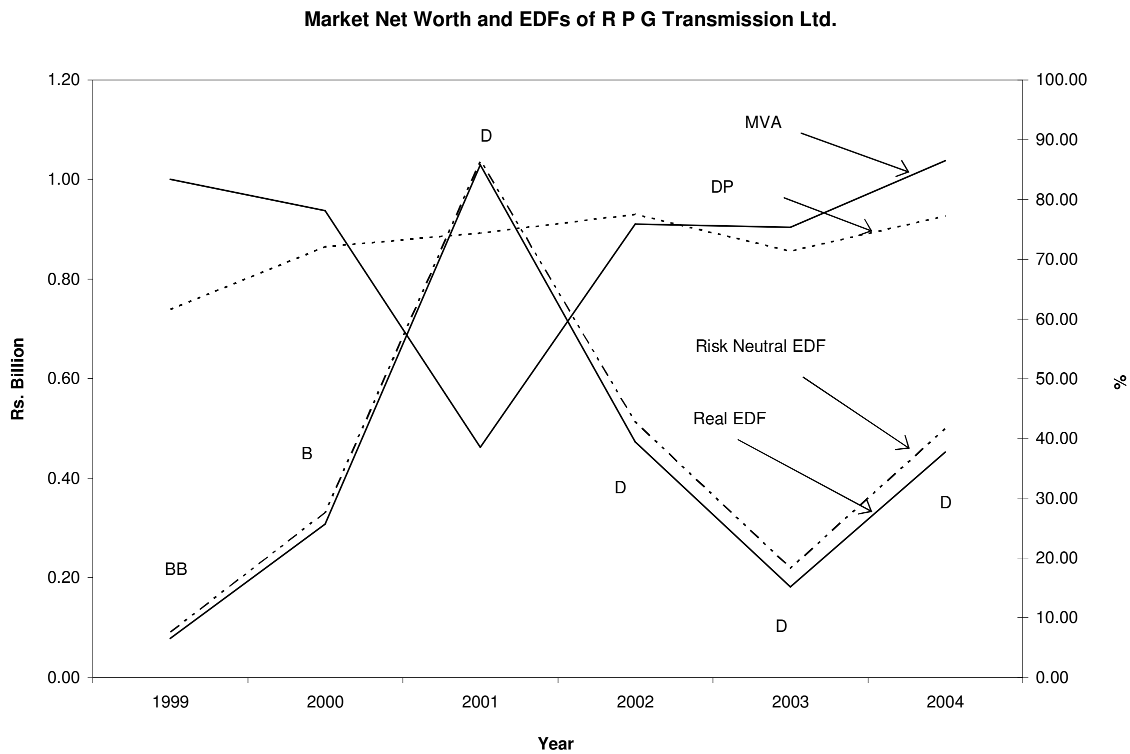

Figure 4:

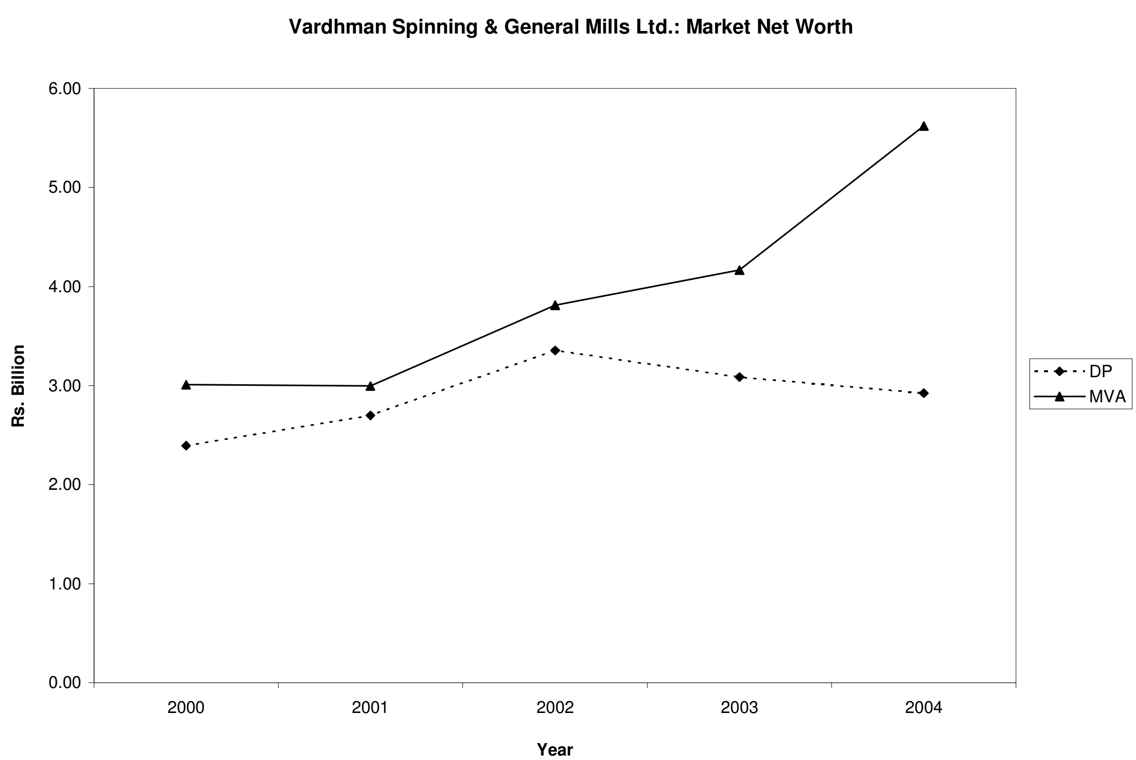

Table I: Risk Neutral and Real EDFs of 53 Indian Corporate (Yearly Projections)
(Units are in Rs. Billion others in either ratio or in %)

Company Name	Year	Asset-vol	MVA	DD	Risk Neutral EDF%	CRISIL Bond Rating	Asset-drift	Real-EDF%
A B B Ltd.	2003	0.35	17.05	16.36	0.00	P1+	0.10	0.00
A B B Ltd.	2004	0.31	31.82	26.90	0.00	P1+	0.09	0.00
Amforge Industries Ltd.	1999	1.12	0.51	-0.66	74.39	D	0.13	73.55
Amforge Industries Ltd.	2000	0.39	0.66	-0.22	58.59	D	0.11	57.20
Arvind Mills Ltd.	2003	0.22	15.97	2.59	0.48	D	0.10	0.27
Arvind Mills Ltd.	2004	0.32	23.04	2.73	0.32	BBB	0.11	0.17
Asian Paints (India) Ltd.	2003	0.44	26.03	7.91	0.00	AAA	0.08	0.00
Asian Paints (India) Ltd.	2004	0.22	30.35	18.36	0.00	AAA	0.06	0.00
Bell Ceramics Ltd.	2003	0.14	0.61	1.48	6.94	D	0.08	5.16
Bell Ceramics Ltd.	2004	0.45	0.79	0.89	18.78	D	0.10	15.74
Bharat Gears Ltd.	2003	0.22	0.48	0.57	28.44	C	0.08	25.89
Bharat Gears Ltd.	2004	0.25	0.67	1.36	8.77	C	0.07	6.98
B P L Ltd.	2003	0.07	9.63	1.64	5.06	D	0.07	3.41
B P L Ltd.	2004	0.11	6.76	1.40	8.09	D	0.07	5.61
Cable Corpn. of Indian Ltd.	1998	0.28	1.13	1.94	2.63	AA	---	---
Cable Corpn. of Indian Ltd.	2001	0.13	0.78	0.07	47.1	D	---	---
Coromandel Fertilisers Ltd.	2003	0.23	3.07	3.09	0.10	AA	0.08	0.08
Coromandel Fertilisers Ltd.	2004	0.31	5.21	3.22	0.06	AA	0.07	0.05
D C M Shriram Inds. Ltd.	2003	0.04	1.77	1.97	2.43	D	0.06	1.72
D C M Shriram Inds. Ltd.	2004	0.13	2.28	1.78	3.73	D	0.06	2.70
Dabur India Ltd.	2003	0.38	16.11	8.33	0.00	AA	0.11	0.00
Dabur India Ltd.	2004	0.43	22.41	9.89	0.00	AA	0.11	0.00
Dhampur Sugar Mills Ltd.	2003	0.12	2.97	1.12	13.20	D	0.08	9.86
Dhampur Sugar Mills Ltd.	2004	0.25	3.95	1.44	7.52	D	0.10	4.90
Dr. Reddy's Laboratories Ltd.	2003	0.62	80.95	9.18	0.00	P1+	0.12	0.00
Dr. Reddy's Laboratories Ltd.	2004	0.81	69.01	5.82	0.00	P1+	0.11	0.00

Essar Shipping Ltd.	1999	0.16	8.33	1.03	15.14	C	0.11	13.38
Essar Shipping Ltd.	2000	0.10	8.57	1.37	8.49	D	0.10	6.89
Escorts Ltd.	2003	0.20	9.14	2.55	0.54	A	0.10	0.32
Escorts Ltd.	2004	0.24	10.71	2.34	0.97	C	0.09	0.58
F D C Ltd.	2003	0.51	4.54	10.96	0.00	AA	0.11	0.00
F D C Ltd.	2004	0.75	9.49	5.22	0.00	AA	0.10	0.00
Flex Industries Ltd.	2003	0.19	4.06	1.81	3.52	D	0.09	2.35
Flex Industries Ltd.	2004	0.25	4.68	2.03	2.12	D	0.10	1.24
Garware Polyester Ltd.	1999	0.11	2.49	0.73	23.32	D	0.11	21.96
Garware Polyester Ltd.	2000	0.12	2.43	0.17	43.42	D	0.10	41.97
Gujarat Ambuja Cements Ltd.	2003	0.23	42.25	6.05	0.00	AA	0.11	0.00
Gujarat Ambuja Cements Ltd.	2004	0.31	64.31	6.30	0.00	AA	0.11	0.00
Hero Honda Motors Ltd.	2003	0.39	56.58	11.25	0.00	AAA	0.09	0.00
Hero Honda Motors Ltd.	2004	0.38	67.56	11.52	0.00	AAA	0.08	0.00
Hindalco Industries Ltd.	2003	0.24	87.34	7.65	0.00	AAA	0.09	0.00
Hindalco Industries Ltd.	2004	0.32	125.11	6.72	0.00	AAA	0.09	0.00
Hindustan Lever Ltd.	2003	0.28	409.52	13.19	0.00	AAA	0.10	0.00
Hindustan Lever Ltd.	2004	0.31	398.59	10.51	0.00	AAA	0.09	0.00
Hindustan Organic Chemicals Ltd.	2003	0.21	3.33	1.94	2.59	D	0.08	2.02
Hindustan Organic Chemicals Ltd.	2004	0.25	4.15	1.57	5.85	D	0.07	4.72
Indian Aluminium Co. Ltd.	2002	0.20	9.62	6.61	0.00	AAA	0.09	0.00
Indian Aluminium Co. Ltd.	2003	0.27	12.43	4.79	0.00	AAA	0.09	0.00
Indian Seamless Metal Tubes Ltd.	1998	0.16	1.14	1.25	10.56	A	0.09	9.43
Indian Seamless Metal Tubes Ltd.	2000	0.03	1.96	1.58	5.70	D	0.10	5.08
Jain Irrigation Systems Ltd.	2003	0.43	5.24	1.97	2.47	D	0.09	2.10
Jain Irrigation Systems Ltd.	2004	0.39	6.44	2.88	0.20	D	0.08	0.15
Jindal Iron & Steel Co. Ltd.	2003	0.31	11.03	2.12	1.71	D	0.12	1.05
Jindal Iron & Steel Co. Ltd.	2004	0.40	15.12	2.65	0.40	D	0.14	0.20
Jindal Vijayanagar Steel Ltd.	2003	0.31	41.94	0.87	19.12	D	0.07	18.02

Jindal Vijayanagar Steel Ltd.	2004	0.20	38.81	2.08	1.88	D	0.06	1.54
K D L Biotech Ltd.	2003	0.22	0.86	1.69	4.58	D	0.10	2.98
K D L Biotech Ltd.	2004	0.29	0.84	1.70	4.43	D	0.11	2.73
Larsen & Toubro Ltd.	2004	0.30	99.62	7.72	0.00	AA	0.13	0.00
Lloyds Steel Inds. Ltd.	2003	0.07	14.93	0.59	27.92	D	0.07	23.90
Lloyds Steel Inds. Ltd.	2004	0.09	14.67	0.77	22.04	D	0.06	17.68
Lupin Ltd.	2003	0.45	18.72	2.82	0.24	BB	0.13	0.15
Lupin Ltd.	2004	0.49	30.23	4.49	0.00	BB	0.14	0.00
Mukand Ltd.	2004	0.25	9.10	0.68	24.75	D	0.08	20.81
Neyveli Lignite Corpn. Ltd.	2003	0.44	73.04	5.11	0.00	AAA	0.15	0.00
Neyveli Lignite Corpn. Ltd.	2004	0.56	99.16	4.49	0.00	AAA	0.15	0.00
Orient Paper & Inds. Ltd.	2001	0.31	1.28	0.40	34.29	C	0.89	35.52
Orient Paper & Inds. Ltd.	2004	0.16	3.55	1.40	8.02	D	0.05	7.91
Orient Press Ltd.	2003	0.32	0.45	-0.55	70.73	D	0.08	68.59
Orient Press Ltd.	2004	0.16	0.57	0.32	37.37	D	0.06	33.48
Ponni Sugars (Orissa) Ltd.	2002	3.33	0.04	-2.10	98.22	D	0.16	98.08
Ponni Sugars (Orissa) Ltd.	2003	0.83	0.10	-0.98	83.61	D	0.11	82.18
R P G Transmission Ltd.	2003	0.12	0.90	0.91	18.24	D	0.07	15.12
R P G Transmission Ltd.	2004	0.39	1.04	0.21	41.56	D	0.08	37.71
Rajasthan Petro Synthetics Ltd.	1998	0.24	0.42	-0.18	57.06	D	0.08	56.70
Rajasthan Petro Synthetics Ltd.	1999	1.50	0.13	-1.59	94.44	D	0.11	94.40
Rama Newsprint & Papers Ltd.	2003	0.30	3.37	1.52	6.38	D	0.09	5.30
Rama Newsprint & Papers Ltd.	2004	0.38	3.97	2.29	1.09	D	0.09	0.78
Ranbaxy Laboratories Ltd.	2003	0.25	150.34	24.35	0.00	AAA	0.12	0.00
Ranbaxy Laboratories Ltd.	2004	0.26	192.66	19.48	0.00	AAA	0.11	0.00
Reliance Industries Ltd.	2003	0.21	433.18	6.73	0.00	AAA	0.12	0.00
Reliance Industries Ltd.	2004	0.29	730.02	5.78	0.00	AAA	0.12	0.00
Sabero Organics Gujarat Ltd.	2003	0.35	0.52	1.22	11.05	D	0.09	9.38
Sabero Organics Gujarat Ltd.	2004	0.43	0.68	1.44	7.53	D	0.09	6.06

Shamken Multifab Ltd.	2001	0.42	1.16	0.90	18.30	D	0.10	17.45
Shamken Multifab Ltd.	2002	0.22	1.16	1.12	13.13	D	0.07	11.94
Soma Textiles & Industries Limited	2003	0.30	0.54	0.40	34.59	----	0.08	31.99
Soma Textiles & Industries Limited	2004	0.22	0.72	1.91	2.82	BB	0.08	1.96
Tata Chemicals Ltd.	2003	0.26	23.10	4.23	0.00	AA	0.11	0.00
Tata Chemicals Ltd.	2004	0.34	34.74	3.91	0.00	AA	0.11	0.00
Tata Iron & Steel Co. Ltd.	2003	0.24	69.05	4.81	0.00	AA	0.10	0.00
Tata Iron & Steel Co. Ltd.	2004	0.54	123.71	3.36	0.04	AAA	0.11	0.02
Tata Motors Ltd.	2004	0.42	164.19	7.55	0.00	AA	0.14	0.00
V S T Industries Ltd.	2003	0.43	2.35	7.49	0.00	AA	0.08	0.00
V S T Industries Ltd.	2004	0.30	3.26	13.34	0.00	AA	0.07	0.00
Vardhman Spinning & General Mills Ltd.	2003	0.15	4.16	2.34	0.97	AA	0.06	0.91
Vardhman Spinning & General Mills Ltd.	2004	0.27	5.62	2.48	0.66	AA	0.05	0.61
Videocon International Ltd.	2003	0.11	17.40	1.68	4.64	BB	0.08	3.31
Videocon International Ltd.	2004	0.12	18.21	1.73	4.20	BB	0.07	2.79
Videsh Sanchar Nigam Ltd.	2003	0.36	34.01	6.34	0.00	AAA	0.12	0.00
Videsh Sanchar Nigam Ltd.	2004	0.48	51.82	6.79	0.00	AAA	0.13	0.00
Wipro Ltd.	2003	0.47	283.30	12.94	0.00	AA in 2001	0.20	0.00
Wipro Ltd.	2004	1.18	400.16	4.56	0.00	---	0.21	0.00

Notes:
MVA: Market Value of Asset; DP: Default Point=Short term debt+0.5*long term debt; Asset Vol.: Asset volatility; DD: Distance to Default (d_1) = *(MVA-DP)/ (MVA*Asset Vol.)*
Bond ratings of Indian corporates are obtained from the CRISIL's monthly rating scan (December rating of respective years).
P-1: this rating indicates that the degree of safety regarding timely payment on the instrument is very strong.
AAA: Highest safety on the long-term bond issued; AA: High safety; A: Adequate safety; BBB: Moderate safety; BB: Inadequate safety; C: Substantially risky instrument; D: obligation is in default or expected to default (as defined in CRISIL rating scan)

Table II: Logit Model: Bond Default Prediction Models and the importance of market value of assets (MVA) and distance to default (DD)

Variables	Altman's Z-score (1968) Model	MVA model	DD model
Distance to Default (DD)	---	---	-1.04*** (-4.10)
MVA_DP	---	-1.09*** (-2.67)	---
WK_TA	-6.56*** (-2.79)	---	---
RETPROF_TA	-11.11 (-0.99)	---	---
PBIT_TA	9.64 (0.78)	---	---
MVE_BVL	-2.45*** (-2.64)	---	---
SALES_TA	-0.66 (-0.66)	-2.33* (-1.87)	---
QR	---	-2.12* (-1.68)	---
DUMTOP50	---	-2.82*** (-3.62)	-1.60*** (-2.69)
LNAGE	---	-0.93** (-1.96)	-1.01** (-2.41)
Intercept	1.06 (1.36)	9.39*** (4.63)	2.64* (1.71)
Number of Observations	131	130	131
Chi^2 statistics (d.f)	77.96 (5)	96.23 (5)	85.97 (3)
Prob>Chi^2	0.00	0.00	0.00
Pseudo R^2	0.43	0.54	0.48
Predictive Power	89.27%	94%	91.57%

Notes:

The dependent variable of the logistic regressions DEF is a bond default dummy. MVA_DP is the market value of asset (MVA) normalized by the default point (DP). Default point is the book value of short term debt plus half of long term debt. DD is the distance to default=$\frac{MVA - DP}{MVA \times \sigma_A}$; where σ_A is the asset volatility. QR is the quick ratio which is the sum of cash and receivables divided by current liabilities. DUMTOP50 is a dummy representing top 50 business groups. LNAGE is the natural logarithm of number of years since incorporation. WK_TA is the working capital over total assets. RETPROF_TA is the retained profit over total assets. PBIT_TA is the profit before interest and tazxover total assets. MVE_BVL is the market value of equity as proportion to book value of liabilities. SALES_TA is the ratio of total sales to total assets. Figures in the parentheses are the z-values. ***, **, and * denotes significance at 1% or better, 1%-5% and 5%-10% level respectively.

Appendix A:

Table III: Correlation Matrix

	DD	WK_TA	RETPROF_TA	PBIT_TA	MVE_BVL	SALES_TA	QR	DUMTOP50	LNAGE	MVA_DP
DD	1.00									
WK_TA	0.45***	1.00								
RETPROF_TA	0.27***	0.21**	1.00							
PBIT_TA	0.58***	0.54***	0.71***	1.00						
MVE_BVL	0.52***	0.46***	0.07	0.35***	1.00					
SALES_TA	0.52***	0.40***	0.12	0.57***	0.26***	1.00				
QR	0.44***	0.74***	0.47***	0.54***	0.67***	0.29***	1.00			
DUMTOP50	-0.1	-0.04	-0.05	-0.04	-0.04	-0.24***	-0.12	1.00		
LNAGE	0.32	0.16*	0.06	0.21**	0.21**	0.33***	0.15*	0.06	1.00	
MVA_DP	0.55***	0.20**	0.05	0.11	0.21**	0.16*	0.19	-0.11	0.12	1.00

Notes:
***, **, and * denotes significance at 1% or better, 1%-5% and 5%-10% level respectively.

Table: IV Descriptive Statistics for Logit Model: Comparison between Defaulted Bonds and Solvent Bonds

	Mean	Std. Dev.	Mean DEF=0	Std. Dev.	Mean DEF=1	Std. Dev.	t-statistics for difference
DD	3.67	4.74	5.78	5.5	1.09	1.07	6.44***
WK_TA	0.065	0.18	0.15	0.14	-0.04	0.16	7.1***
RETPROF_TA	0.018	0.23	0.07	0.28	-0.05	0.16	3.02***
PBIT_TA	0.09	0.12	0.14	0.105	0.02	0.11	6.36***
MVE_BVL	1.73	4.52	3.01	5.8	0.18	0.16	3.74***
SALES_TA	0.80	0.49	0.98	0.55	0.59	0.30	4.84***
QR	0.53	0.50	0.72	0.58	0.29	0.24	5.27***
DUMTOP50	0.59	0.49	0.68	0.47	0.49	0.50	2.22**
LNAGE	3.41	0.64	3.67	0.50	3.1	0.65	5.59***
MVA_DP	57.94	372.65	104.35	499.4	1.29	0.55	1.58*
No. of observations	131		72		59		

Notes:
***, **, and * denotes significance at 1% or better, 1%-5% and 5%-10% level respectively.