HOW GOOD IS MERTON MODEL AT ASSESSING CREDIT RISK?

EVIDENCE FROM INDIA

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This paper models the default probabilities and credit spreads for select Indian firms in the Black-Scholes-Merton framework. Counter to previous research, we show that the objective (or 'real') probability estimates are higher than the risk-neutral estimates over the sample period. However, the probability measure is found to be robust to the 'default trigger point'. The model output also compares favorably with the default rate reported by CRISIL's Average 1-year rating transitions as well as the Altman Z-score measure. However it does not generate spreads as high as those observed in the corporate bond market. Perhaps not surprisingly, this is consistent with the received literature on credit spreads.

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Introduction:

Credit risk modelling is deemed to be the cornerstone of the Basel II Accord. This is rightly so because bank's economic capital requirement is directly a function of the risk inherent in the credit portfolio. One of the guiding principles of the new Accord is that the size of the required capital should be contingent on counterparty credit risk instead of being constant per credit type as under the Basel I Accord. This fact has induced banks and other financial institutions to invest sizeable resources in assessing their credit risk exposures.

Credit risk modelling entails a theoretical framework that describes the causality between the attributes of the borrowing entity (a corporation) and its potential bankruptcy. The approach which has particularly gained prominence in credit risk literature is the Contingent Claims Approach. It was proposed by Robert Merton (1974) in his seminal paper on the valuation of corporate debt. Largely as a logical extension of the Black-Scholes (1973) option pricing framework, he conceived a model for assessing the credit risk of a firm by characterizing the firm's equity as a call option on its assets. Alternatively, the debtholders of the firm could be viewed as holding a short put position on the firm's assets. Merton's approach is referred to as the 'structural approach' because it relies entirely upon the capital structure of the firm (viz, debt and equity) for modelling credit risk. It builds a setup within which credit events are triggered by movements of the firm's value relative to some pre-defined threshold or barrier. Consequently, a major issue within this framework is the modelling of the evolution of the firm's value and capital structure.

The model assumes that a company has equity and certain amount of zero-coupon debt that will become due at a future time T [1]. The equity receives no dividend. Although Merton model is an ingenious application of the classical option pricing theory, its performance in predicting defaults (or credit rating changes) depends on how realistic its assumptions are. The model is a somewhat stylized structural model that requires a number of simplifying assumptions. Following limitations would undermine the model efficiency;

(a)The assumption that the firm can default only at time T and not before[2] . If the firm's value falls down to minimal levels before the maturity of the debt but it is able to recover and meet the debt's payment at maturity, the default would be avoided in Merton's approach.

(b) Firm's asset values follow log-normal distribution

(c) Default probability for private firms (not listed on the stock exchange) can be estimated only by performing some comparability analysis based on accounting data[3].

(d) The model does not distinguish among different types of debt according to their seniority, collaterals, covenants or convertibility

(e) It is "static" in that the model assumes that once management puts a debt structure in place, it leaves it unchanged even if the firms assets have increased. As a result, the model cannot capture the behavior of those firms that seek to maintain a constant or target leverage ratio across time.

(f) The model implies a 'shrink' in the default probability and credit spreads as the debt approaches maturity. Indeed, the implication of the model is that, with perfect information, the credit spread at the very short end should be near zero. In general, however, observable short-term credit spreads are non-zero. The model predicts default with increasing precision as the maturity of the debt comes near. As a result, in this approach default does not come as a surprise, which makes the models generate very low short-term credit spreads. However, with asymmetric information, yield spreads are strictly positive at zero maturity because investors are uncertain about the nearness of the assets to the trigger level at which the firm would declare default.

(g) Another potential shortcoming of the option based approach is that the stock market may not efficiently incorporate all publicly-available information about default probability into equity prices. In particular, prior studies suggest that the market does not accurately reflect all of the information in the financial statements (Sloan, 1996). Furthermore, equity market volatility need not always bear credit risk implications (noise trading).

(h) The assumption of a constant and flat term structure of interest rates is other major criticism the model has received.

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[1] Credit risk models routinely assume one-year time horizon for debt maturity and subsequent estimation of default probability. One year is perceived as being of sufficient length for a bank to raise additional capital on account of increase in portfolio credit risk (if any). Furthermore, implicit in the regulatory approach to capital requirements is an assumption that if large losses (short of insolvency) are experienced during the analysis period, a bank will take actions such that its probability of remaining solvent during the following period will remain high. Such actions include raising new equity to replace that which has been lost or rebalancing to a safer portfolio such that the remaining equity is adequate to preserve solvency with the specified probability. For bank loan portfolios, substantial rebalancing is usually difficult to accomplish quickly, especially during the periods of general economic distress that are typically associated with large losses. Thus, unless a bank is able to raise new equity by the end of the analysis period, it will begin the next period with a larger-than-desired probability of insolvency. The one-year convention may have arisen largely because, until recently, default rates and rating transition matrices were most easily available at a one-year horizon, and such data are key inputs to conventional portfolio credit risk models. However, Carey (2000) contends that this time horizon is too short.

All things considered, these limitations should not prompt us to belittle the substance of Merton model; the model is being extensively used by Moodyskmv[4], S&P and other credit rating agencies worldwide for assessing the default probability of borrowing firms. The main advantage in employing option-pricing models in bankruptcy prediction is that they provide guidance about the theoretical determinants of bankruptcy risk and they supply the necessary structure to extract bankruptcy-related information from market prices.

The received literature on empirical assessment of contingent claims approach has mainly been located in the context of developed economies. In this paper, we intend to fill this lacuna by employing the balance sheet and market data of select Indian corporates for modelling credit risk. Varma and Raghunathan (2000) did assess the credit risk from Indian perspective; however we depart from them with respect to the problem being studied and the methodology employed for analysis. Subsequent sections delve further into this issue.

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[2] Bankruptcy can only occur at time T because BSM assumes that the firm holds only zero-coupon debt maturing at time T. Subsequent studies have incorporated more realistic assumptions, such as allowing for debt covenants (e.g., Black and Cox, 1976) and multiple classes of debt (e.g., Geske, 1977).

[3] Credit rating agencies have developed models that estimate empirical EDF scores for private firms

[4] KMV is a trademark of KMV Corporation. Stephen Kealhofer, John McQuown and Oldrich Vasicek founded KMV Corporation in 1989. On February 11, 2002, Moody's announced that it was acquiring KMV for more than $200 million in cash.

In the present study, we propose to test the relevance and validity of contingent claims approach as applied to Indian corporates. A-priori, the default probability and credit spreads are expected to widen as a firm gradually gets into bankruptcy mode. Furthermore, assuming that credit rating agencies are privy to inside information on companies getting rated, one may assume that it is impossible for a firm to experience a change in its default probability without also experiencing a rating change. We also propose to make some tentative comments in this direction. In case the results hold for the subset of companies shortlisted for the study, the model can very well be applied across a wide spectrum of companies representing various other sectors. This is particularly important in light of the Reserve Bank of India's stated objective to gradually move Indian banks towards adoption of Internal Ratings Based Approach. We also compare the performance of the Merton model to that of other popular alternatives like agency ratings and Z-Scores.

The layout of the paper is as follows; Section 2 sets out the model specification, Section 3 provides a brief survey of the empirical literature on estimation and analysis of default probability and credit spreads, data details are presented in Section 4, Section 5 reports the results and Section 6 concludes.

2) The Model:

The Merton model generates the probability of default for each firm in the sample at any given point in time. To calculate the probability, the model subtracts the face value of the firm's existing debt from an estimate of the future market value of the firm and then divides this difference by an estimate of the volatility of the firm (scaled to reflect the horizon of the forecast). The resulting score, which is referred to as the distance to default, is then substituted into a cumulative density function to calculate the probability that the value of the firm will be less than the face value of debt at the forecasting horizon. The market value of the firm is simply the sum of the market value of the firm's debt and the value of its equity. If both these quantities were readily observable, calculating default probabilities would be trivial. While equity values are readily available, reliable data on the market value of debt is generally unavailable. The Merton model makes two particularly important assumptions. The first is that the total value of a firm is assumed to follow geometric Brownian motion,

$$dV = \mu V dt + \sigma V dZ \qquad \text{……..(1)}$$

where V is the total value of the firm, μ is the expected continuously compounded return on V (i.e., the asset drift) , σ is the volatility of firm value and dZ is a standard Weiner process. The incremental changes in ln V follow a generalized Wiener process with drift

$\mu - \sigma^2 / 2$

$$\mathrm{d}\ \ln V_T \approx \phi\left[(\mu - \frac{\sigma^2}{2})\,T, \sigma\sqrt{T}\right] \qquad \text{……..(2)}$$

Since the logarithm of V_T is normal, V_T is log normally distributed.

The value of the firm's assets at time *T* is given by,

$$V_T = V_0 \exp\left[(\mu - \frac{\sigma^2}{2})\, T + \sigma \sqrt{T} Z_T \right] \qquad \text{……..(3)}$$

The basic feature of Merton's model is that the firm's value drifts upwards over time (at the risk-free rate in the risk-neutral world of option pricing) and so its leverage falls. The second critical assumption of the Merton model is that the firm has issued just one discount bond maturing at time *T*. The company defaults if the value of its assets is less than the promised debt repayment at time *T*. The equity of the company is a European call option on the assets of the company with maturity *T* and a strike price equal to the face value of the debt. The model can be used to estimate the risk-neutral probability that the company will default as well as the credit spread on the debt[5.] As inputs, Merton's model requires the current value of the company's assets, the volatility of the company's assets, the outstanding debt, and the debt maturity. In order to make the model analytically tractable, one has to estimate the current value and volatility of the company's assets from the market value of the company's equity and the equity's instantaneous volatility. A debt maturity date is chosen and debt payments are mapped into a single payment on the debt maturity date in some way. The rest of the implicit assumptions are the absence of transaction costs, bankruptcy costs, taxes or problems with indivisibilities of assets, continuous time trading; unrestricted borrowing and

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[5]A number of authors such as Black and Cox (1976), Geske (1977), Longstaff and Schwartz (1995), Leland and Toft (1996), and Collin-Dufresne and Goldstein (2001) have developed interesting extensions of Merton's model, but none has emerged as clearly superior. See Eom *et al* (2003) which compares the performance of alternative models using bond spreads. Gemmill (2002) shows that Merton's model works well in the particular case where zero-coupon bonds are used for funding.

lending at a constant interest rate r, no restrictions on the short selling of the assets and few more.

Define E as the value of the firm's equity and V as the value of its assets as of today (t=0). Let E_T and V_T be their values at time T when the debt with face value of F matures. More formally, the value of equity at time T in the Merton framework is given by:

$$E_T = \max(0, V_T - F) \qquad \text{……..(4)}$$

In accordance with the option pricing theory, the value of equity can be found from the following partial differential equation,

$$\frac{\partial E}{\partial t} + rV\frac{\partial E}{\partial V} + 1/2\sigma^2 V^2 \frac{\partial^2 E}{\partial V^2} - rE = 0 \qquad \text{……..(5)}$$

subject to the following boundary condition,

$$E_T = \max\,(V_T - F, 0) \qquad \text{....…...(6)}$$

Symbolically, the Merton model stipulates that the equity value of a firm satisfies the following equation within risk neutral framework,

$$E = VN(d_1) - Fe^{-rT}N(d_2) \qquad \text{...……..(7)}$$

where r is the instantaneous risk-free rate and $N(\cdot)$ is the cumulative standard normal distribution function, d1 is given by

$$d_1 = \frac{\ln(\frac{V}{F}) + (r + \frac{\sigma^2}{2})T}{\sigma\sqrt{T}} \qquad \text{………(8)}$$

$$d_2 = d_1 - \sigma\sqrt{T} \qquad \text{...…….(9)}$$

Equation (7) will hold irrespective of equity holders exercising their call option on or before the maturity date $T;$ the reason being the proposition from the option pricing theory that early exercise of call option is suboptimal. Consequently, the price of a call option is the same no matter whether it is European or American.

At time zero, Default probability

$$= \Pr(V_T \leq F) \qquad \text{........(10)}$$

$$= \Pr(\ln V_0 + (r - 1/2\sigma^2)T + \sigma\sqrt{T}Z_T \leq \ln F) \qquad \text{..........(11)}$$

$$= \Pr\left(-\frac{\ln(V_0/F) + (r - 1/2\sigma^2)T}{\sigma\sqrt{T}} \geq Z_T\right) \qquad \text{........(12)}$$

Under the risk-neutral probability measure, the default probability is given by,

$$N(-d_2) = N\left(-(\frac{\ln(\frac{V}{F}) + (r - \frac{\sigma^2}{2})T}{\sigma\sqrt{T}})\right) \qquad \text{........(13)}$$

The “probabilities” in the Merton formula do not represent the actual probability of being above or below the strike price at expiration. Since the underlying asset is risky, it does not actually drift at the risk free rate. If we replace the risk free interest rate, r, in equation (13) with the expected return on the asset value or the ’drift’ of the asset value, μ , we get the default probability of the firm under an objective probability measure:

$$N(-\hat{d}_2) = N\left(-(\frac{\ln(\frac{V}{F}) + (\mu - \frac{\sigma^2}{2})T}{\sigma\sqrt{T}})\right) \qquad \text{.........(14)}$$

As shown in Deliandes and Geske (2003), risk neutral default probabilities serve as an upper bound to objective default probabilities. Although the objective and risk neutral distributions of the firm’s value have the same diffusion terms (i.e. variance), however, the objective distribution must generally have a mean greater than the risk free rate (the drift is generally higher than the risk free rate of return), it follows that the risk neutral distribution implies a higher default probability. However, it is well known that expected returns on equities are estimated with significant error. Because risk neutral probabilities of default can be calculated without estimating the firm's expected return, they may be more accurately estimated than objective default probabilities.

Equation (7) includes two unknowns in the form of V and volatility of V, i.e., σ. In order to identify two unknowns with two equations, the model invokes the Weiner process to model equity value, i.e., E,

$$dE = \mu_E E dt + \sigma_E E dz \qquad \text{.......(15)}$$

where μ_E is the expected continuously compounded return on E , σ_E is the volatility of equity value and dZ is a standard Weiner process. By Ito's lemma, we can also represent the process for equity as[6]:

$$dE = \left(\frac{\partial E}{\partial V} \mu V + \frac{\partial E}{\partial t} + 1/2 \frac{\partial^2 E}{\partial V^2} \sigma^2 V^2 \right) dt + \frac{\partial E}{\partial V} \sigma V dZ \qquad \text{.........(16)}$$

where,

$$EquityDelta \Delta^E = \frac{\partial E}{\partial V} = N(d_1) > 0 \qquad \text{..........(17)}$$

$$EquityGamma \Gamma^E = \frac{\partial^2 E}{\partial V^2} = \frac{n(d_1)}{V \sigma \sqrt{T}} > 0 \qquad \text{..........(18)}$$

$$EquityTheta \theta^E = \frac{\partial E}{\partial t} = -\frac{Vn(d_1)\sigma}{2\sqrt{T}} - rDe^{-rT} N(d_2) \lesseqgtr 0 \qquad \text{..........(19)}$$

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[6]Farmen, Westgaard et al (2003) show how a risk neutral default probability can be transformed into an objective probability.

Since the diffusion terms in the equity process in (15) and (16) are equal,

we can write,

$$\sigma_E E = \sigma V \frac{\partial E}{\partial V} = \sigma V N(d_1) \qquad \text{.........(20)}$$

Equations (7) & (20) complete the system of two simultaneous nonlinear equations with two unknowns which can very well be solved in Microsoft Excel using Solver routine[7]. Similarly, we can compare the drift terms of equations (10) and (12) and solve for the asset drift μ,

$$\mu_E E = \frac{\partial E}{\partial t} + \mu V \frac{\partial E}{\partial V} + \frac{1}{2}\sigma^2 V^2 \frac{\partial^2 E}{\partial V^2} \qquad \text{..........(21)}$$

$$\mu_E E = \theta^E + \mu V \Delta^E + \frac{1}{2}\sigma^2 V^2 \Gamma^E \qquad \text{...........(22)}$$

$$\Rightarrow \mu = \frac{\mu_E E - \theta^E - \frac{1}{2}\sigma^2 V^2 \Gamma^E}{V \Delta^E} \qquad \text{...........(23)}$$

The approach followed here assumes that the drift of equity or expected return of equity μ_E can be estimated from the stock market price data. In order to estimate μ_E, we may employ a pricing model such as the CAPM. Having found V, σ and μ, we can now calculate the objective probability of default using (14)[8].

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[7]To solve two nonlinear equations of the form F(x,y)=0 and G(x,y)=0, we can use the Solver routine in Microsoft Excel to find the values of x and y that minimize $[F(x,y)]^2+[G(x,y)]^2$ (Hull, 2003). Also refer Benos and Papanastasopoulos (2005) for similar application of the same algorithm.

[8]Crouhy, Galai, Mark (2000) show that risk neutral default probabilities serve as an upper bound to objective default probabilities if and only if asset drift μ is greater than the risk free rate r.

At this stage, we need to point out that there are certain aspects which differentiate the Merton model which we test from that being actually employed by Moody's KMV. One important difference is that Moody's KMV uses a proprietary model that they call the VK model. Apparently the VK model is a generalization of the Merton model that currently incorporates five classes of liabilities; short-term, long-term, convertible, preferred equity, and common equity. Another difference is that we use the cumulative normal distribution to convert distances to default into default probabilities. Moody's KMV uses its large historical database to estimate the empirical distribution of distances to default and it calculates default probabilities based on that distribution. Finally, KMV may also make proprietary adjustments to the accounting information that they use to calculate the face value of debt. We cannot perfectly replicate the methods of Moody's KMV because several of the modelling choices made by Moody's KMV are proprietary information, and subscribing to their database is prohibitively expensive for us[9].

The market value of a firm comprises of the market value of equity and market value of debt. It can be represented as,

$$V = E + D \qquad \text{.........(24)}$$

Hence, $D = V - E$ (as a European Call)

$$= V - [\, VN(d_1) - Fe^{-rT}N(d_2) \,]$$

$$= VN(-d_1) + Fe^{-rT}N(d_2) \qquad \text{........(25)}$$

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[9]Sobehart,Keenan and Stein (2000) report that the Merton model performs almost as well as the Moody's model in the case of extremely poor quality firms. However, the Moody's KMV model clearly performs better beyond 10% of the population and is much better at discriminating defaults in the middle ranges of credit.

or alternatively,

$$D = Fe^{-rT} – \text{European Put}$$

$$= Fe^{-rT} – [-VN(-d_1) + Fe^{-rT}N(-d_2)]$$

$$= VN(-d_1) + Fe^{-rT}N(d_2) \qquad \text{.........(26)}$$

Thus, the market value of debt can be represented as a portfolio comprising of money lent at a risk free rate and a short put option. It is common in dealing with bonds to discuss them in terms of yields rather than prices. The yield to maturity, y, of a corporate zero-coupon bond in continuous-time finance is a solution to,

$$D = Fe^{-yT} \qquad \text{.........(27)}$$

The yield for the bond today (t=0) maturing at time T , y(T), is simply,

$$y(T) = -\frac{\ln(D/F)}{T} \qquad \text{.........(28)}$$

Define F´ as the present value (discounted at riskfree rate) at time zero of the promised debt F maturing at time T.

$$F' = Fe^{-rT} \qquad \text{.........(29)}$$

and let L = F´/ V be a measure of leverage, termed as Quasi-Debt ratio.

The yield to maturity on the debt becomes,

$$D = Fe^{-yT} = F'e^{(r-y)T} \qquad \text{.........(30)}$$

Substituting this into equation (26) and using the Quasi-Debt ratio gives the credit spread as,

$$y - r = -\frac{\ln[N(d_2) + N(-d_1)/L]}{T} \qquad \text{.........(31)}$$

The expression for credit spread shows that the credit spread is an increasing function of the Quasi-Debt ratio and of the volatility of the firm's asset values. As is the case with option pricing, the asset drift μ has no impact on the credit spread. Empirical studies of credit spreads using structural models are quite rare. They are complicated by the following features: (i) companies have more than one issue of debt; (ii) the debt is coupon-paying; (iii) there are call features and sinking funds; and (iv) the firm value must be known in order to find its volatility, yet at the same time the volatility affects the value of the debt and hence the firm value (v) the presence of liquidity premium, transaction costs and taxes. In particular the need to exclude companies which do not have very simple capital structures has led to small samples of bonds being available for testing the models. One basic feature of Merton model is that the firm's value drifts upwards over time (at the risk-free rate in the risk-neutral world of option pricing) and so its leverage falls. Hence, the resulting profile for the term-structure of credit spreads generated by the model is downward-sloping , because of the implicit fall in leverage of the firm over time.

3) Literature Review:

Over the past several years, number of researchers have examined the contribution of the Merton model. The first authors to examine the model carefully were practitioners employed by either KMV or Moody's. Crosbie and Bohn (2003) summarize KMV's default probability model. Several papers addressing the accuracy of the KMV-Merton model are available on the internet[10]. Stein (2002) argues that KMV-Merton models can easily be improved upon. Other papers, including Bohn, Arora and Korablev (2005), argued that KMV-Merton models capture all of the information in traditional agency ratings and well known accounting variables. Both Hillegeist, Keating, Cram and Lundstedt (2004) and Du and Suo (2004) examine the model's predictive power. Duffie and Wang (2004) show that KMV-Merton probabilities have significant predictive power in a model of default probabilties over time, which can generate a term structure of default probabilities. Farmen, Westgaard et al (2003) investigate the default probabilities and their comparative statics (default Greeks) in the Merton framework using the objective or 'real' probability measure.

Bohn (2000) surveys some of the main theoretical models of risky debt valuation that built on Merton (1974) and Black and Cox (1976). Empirical evidence has suggested that the actual credit spreads are higher than model spreads. Jones, Mason, and Rosenfeld (1983) and Frank and Torous (1989) find that contingent-claim models yield theoretical credit spreads much lower than actual credit spreads. In the same year, Sarig and Warga (1989) estimate the term structure of credit spreads and show it to be

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[10] The website www.defaultrisk.com has an enormous collection of research papers on credit risk modelling.

consistent with contingent claim model predictions. A more recent study by Wei and Guo (1997) tests the models of Merton (1974) and Longstaff and Schwartz (1995) and finds the Merton model to be empirically superior. However, Gemmill(2002) employs zero coupon corporate bonds data and concludes that model and market spreads are on average of similar magnitude. Similar to previous research, market spreads are high (relative to model spreads) for bonds which have low risk and for bonds which are near to maturity. Longstaff and Schwartz (1995) argue that an additional element in the spread is the expectation that equity holders and other junior claimants receive in the bankruptcy settlement more than what is consistent with absolute Priority rule. In addition, Anderson and Sundaresan (1996) suggest that debt holders are forced to accept concessions to receive less than the originally agreed amount, prior to formal bankruptcy proceedings. Mella-Barral and Perraudin (1997) incorporate this strategic debt service into an option pricing-based model and show that the spread widening impact can be significant. The upshot of the study is that the simple structural models (eg. Merton,Geske) forecast spreads which are smaller than market spreads, particularly for companies which have low leverage and low volatility, but the more complicated structural models which produce larger spreads (eg. Longstaff/Schwartz and Leland/Toft) also produce large errors. Another finding is that whether a model allows for stochastic interest rates or not does not make much difference.

In the Indian context, credit risk modelling has been attempted based on corporate bond ratings. Varma and Raghunathan (2000) analyze credit rating migrations in Indian corporate bond market to bring about greater understanding of its credit risk. Their dataset comprises of the ratings of debentures of manufacturing companies by the

Credit Rating and Information Services of India Limited (CRISIL). CRISIL is India's largest and oldest credit rating agency. The ratings were collected from CRISIL's *Rating Scan* for 24 quarters from January 1993 to October 1998. Darbha, Roy, Pavaskar (2003) employ Nelson-Siegel formulation to incorporate the impact of shifts in the sovereign term structure and equity index movements into the credit spread estimates. Their model compares favorably with similar estimates of corporate term structures for developed countries. Bose and Coondoo (2003) produce estimates of yields to maturity for corporate bonds based on the available bond price data. Their results suggest that on the whole the pricing mechanism of the Indian corporate bond market, in spite of its underdeveloped state, was consistent with the theory of bond pricing. Tracking daily data, for a period of 38 months between April 1997 to March 2001, they find that the secondary market for (exchange traded) corporate bonds is characterized by shrinking depth and width in recent years. This is borne out by the decreasing frequency of trades per month and the rising concentration of trading in an increasingly lesser number of securities as revealed by the 5, 10 and 15 bond concentration ratios in each month. Ramakrishnan (2005) has assessed the applicability of two well-known financial distress models, namely, Multiple Discriminant Analysis and Logistic Regression analysis by using a sample of 298 Indian firms.

Contingent-claim valuation of equity has also been used extensively in the literature on bank deposit insurance where the equity-call model is 'reversed' to generate estimates of the market value of assets from observed stock prices. This approach, along with the observation in Merton (1977) that deposit insurance can be modeled as a put option, allows the calculation of fair deposit insurance premia. Duan (1994) proposes another method of estimating asset value and asset volatility, based on Maximum Likelihood estimation using equity prices. Shah and Thomas (2000) utilize option pricing theory in order to obtain empirical estimates for the extent of leverage present, the stock of assets required to recapitalize the Indian banking system and the subsidy implicit in the deposit insurance scheme.

4) Sample Period and Dataset:

Modelling credit risk of Indian corporates gets seriously handicapped on account of the lack of reliable data. The difficulty is particularly pronounced in case of credit spreads because the corporate bond market is only an insignificant part of the Indian Debt Market. A large part of the issuance in the non-Government debt market is currently on private placement basis. On an average, private placements account for little over one third of the debt issuance. Unofficial estimates indicate that about 90 per cent of the private corporate sector debt has been raised through private placement in the recent past. Credit spread data is particularly missing for non-investment grade bonds.

Notwithstanding these difficulties, we proceed with our analysis based on the data for select companies representing diverse sectors. The companies are tracked from March 1998 to March 2004. We employ the CMIE Prowess database for equity values, balance sheet information and credit ratings for outstanding issues, whereas, Credence Analytics provides the average credit spreads for “AAA” to “A” rated corporate bonds at monthly frequency. Credit spread data is not available separately for each bond traded in the market. This fact pre-empts the possibility of comparing company-wise actual credit spread with the model spread. The companies selected for the purpose of analysis comprise four top rated corporates, one merged banking institution and seven companies which filed for bankruptcy with the Board for Industrial and Financial Reconstruction (BIFR), either in 2003 or 2004. Table 1 presents the details for these firms. Since the accounting year runs from 1st April to 31st March for Indian firms, we compute the default probability and credit spreads for the aforementioned corporates as on 31st March every year during the sample period.

Consistent with prior literature and KMV methodology, for book value of debt we use the "debt due in one year" plus half the "long-term debt"[11]. The "debt due in one year" comprises of current liabilities and provisions, commercial papers outstanding, deferred tax payments, short-term bank borrowings and also current portion of long-term debt reported in Prowess database. "Long-term debt" is set equal to total long-term debt less the current portion of long-term debt. We calculate the equity return volatility σ_E as the annualized standard deviation of daily returns during the given year. The market value of equity *MVE* is the average market capitalization reported by CMIE for the year. The yield on a government security with one year remaining to maturity constitutes the discrete risk-free rate of return. This rate is converted into continuously compounded rate for further analysis. Equity returns volatility is 'de-levered' to generate a seed value for asset volatility. From equation (20), de-levered equity returns volatility implies $\sigma_E E = \sigma V$ where $N(d_1) = 1$, implying zero debt. Market value of the firm V is proxied by the sum of market value of equity and book value of debt. Based on these initial estimates, we perform iterations with the Solver routine to generate final values for V and σ which serve as inputs for computing risk neutral default probability and theoretical credit spreads.

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[11]KMV has observed from a sample of several hundred companies that firms default when the asset value reaches a level somewhere between the value of total liabilities and the value of short-term debt. The default point is in reality also a random variable. In particular, firms will often adjust their liabilities as they near default. It is common to observe the liabilities of commercial and industrial firms increase as they near default while the liabilities of financial institutions often decrease as they approach default. How does the model deal with off-balance-sheet liabilities? Fortunately, the model is surprisingly robust to the precise level of the liabilities (Crosbie and Bohn, 2003).

The procedure continues in this manner until it converges. Subsequently, CAPM model is employed for calculating equity drift which goes into the final estimation of objective default probability.

5) Results:

In Appendix (A), tables 2 to 14 present the default probability estimates (Risk-neutral and Objective) for the sample firms. The results clearly bring out the fact that the firms filed with BIFR definitely had default probability much higher than the four top-rated corporates. Furthermore, the estimates are found to be extremely sensitive to the equity volatility experienced during the period of study (refer charts in Appendix (B)). For example, the annualized equity returns volatility for Mardia Chemicals Ltd. increased from 69.5% (1997-98) to 180% (1998-99). Consequently the risk-neutral probability jumped nine-fold from 8.54% (1997-98) to 76.62% (1998-99). Likewise, for RPG Cables Ltd. the risk-neutral probability increased from 2.016% (2002-03) to 22.384% (2003-04) as a result of the increase in equity volatility from 49.6% (2002-03) to 90.8% (2003-04).This evidence fully documents the dependence of Merton model estimates on the equity price fluctuations which in itself underscore the equity shareholders' trading on varied information sets.

Table 19 reports the Coefficient-of-Variation (COV) estimated for the risk - neutral default probability measures of the sample firms. The COV measures for the four top-rated firms included in the sample are much higher than that for the defaulted firms. However, a certain degree of caution is necessary while interpreting this result. Higher COV for top-rated firms need not imply any significant 'credit erosion' and subsequent rating downgrade, the reason being these firms have extremely low base-level default probabilities and hence the possibility of moving from AAA to speculative grades is negligible (if not nil). For example, the COV is 250.76% for HLL and 196.74% for Bajaj

Auto. However, the risk-neutral probability has never exceeded 0.01% for these firms over the sample period.

In the conventional analysis, risk-neutral probability estimate is always supposed to exceed the objective probability estimate, the reason being that the riskfree rate is less than the rate of asset drift (refer equations (13) and (14)). However, in direct opposition to this view, the evidence from the present study is markedly different. Of greater significance empirically is the fact that the real world (i.e., objective) default probability estimates are higher than the risk-neutral probability estimates for the sample firms across the period of study; the source of this result can be traced to the riskfree rate which has been persistently higher than the rate of asset drift over the sample period. This result has serious implications from the viewpoint of maintaining adequate level of economic capital. Risk-neutral probabilities cannot be used for risk management purposes; this requires objective default probabilities. A correct estimation of a counterpart's objective probability of default is crucial in any credit risk management system. To illustrate, banks use default probability to compute expected and unexpected loss, economic capital and risk adjusted profitability. Pricing guidelines are based on these measures. An incorrect estimation of default probability may result in mispricing of credit risk. Underprediction of this measure will subsequently lead to inadequate capital allocation.

The probability estimates compare quite well with CRISIL's Average 1 year rating transition matrix (see Table 15). The default rate is 0% for AAA ratings in the transition matrix. Compare it with the default probability predicted for the three AAA rated firms (HLL, Reliance Industries & Bajaj Auto). Except for the values predicted for

Reliance Industries over the year 1997-98 and 1999-2000, the estimates are virtually zero. Similar arguments can be made in the context of defaulted firms. Although the matrix doesn't report the stability rates for D category, it does report a default rate of 28.57% for C rating class. This also compares well with the probabilities modeled for various defaulted firms in the sample. A cursory glance at the probability estimates of the three AAA rated firms and the single AA rated firm (Telco) further validates the performance of the Merton model at tracking credit ratings. The results could also be interpreted in a different way. They signify the ability of rating agencies to correctly assess the credit risk of firms which had been assigned the lowest probabilities of default by the Merton model. However, the performance of these agencies seems to occasionally falter in the case of failed firms. For example, ITI limited was persistently rated AAA by various rating agencies although the Merton model had rightly predicted it to be a 'problem firm' (refer Table 9).

In the literature, very little attention has been paid to the more pedestrian issue of the sensitivity of default probability estimates to the change in 'default trigger point'. Tables 16, 17 and 18 summarize the results of the sensitivity analysis undertaking in this direction. It also reports the percentage change in risk-neutral probability if entire debt (Total short-term debt plus Total long-term debt) is incorporated in the analysis. The results are reported for the one AA rated firm (Telco) and two defaulted firms (ITI Ltd. and Surat Textile Mills Ltd.). The evidence brings to light the fact that the probability measure for top-rated firms (low base-level probability) is relatively more sensitive to the changes in default trigger point. However, the incremental difference in probability measure on account of this change is not sizeable enough to push such firms in the subsequent lower rating grade. In case of defaulted firms (high base-level probability), the impact is quite nominal. Pursuing this issue further, with reference to equation (20), equity volatility (σ_E) and market capitalization (E) are independent of the value assigned for default trigger point. Any increase in this level increases the leverage, thus reducing the volatility (σ) of firm value and increasing the firm value (V). As derived by Farmen, Westgaard et al (2003), the sensitivity of the default probability with respect to a change in the value of the firm (V) is negative and with respect to change in the volatility of the firm (σ) is positive. However, differentiating equation (13) with respect to default trigger point (F) brings out the fact that any change in F has a direct positive effect on the probability measure. Consequently, the overall impact on probability is negligible (but positive). The robustness of the probability measure especially augurs well for testing the model on firms which carry sizeable off- balance sheet exposures.

We now return to tables 3 to 14 which also report the Altman Z-scores for the sample firms[12]**.** As is evident from these tables, the Z-scores seem to track the probability predictions quite well. For example, the AAA rated firm HLL has been consistently assigned the Z score above 5 which is in line with its default probability estimate of 0%. Similarly, almost all the defaulted firms have obtained the scores well below 1.81 over the period of study. Barring few exceptions, such as, Bajaj Auto (2000-01) and Reliance Industries Ltd. (2002-03), the predictions made by the Merton model and Altman Z-Score model are analogous. However, notwithstanding the precision of Altman Z-Score model at predicting future bankruptcy, Z-Scores are not directly interpreted as default probabilities and they work as ordinal measures of financial health. Therefore, they cannot be directly used for valuation, quantitative risk assessment, and capital allocation purposes. However, Merton model is far more functional on account of its ability to assign different default probability estimates across firms in the same rating class.[13]

In Tables 3 to 6, we also depict the ability of the Merton model to predict credit spreads. Pooling quarterly data since March 2002 provides adequate number of observations to draw certain conclusions; however, the data are not sufficiently dispersed across issuers or maturity horizons. Consequently, we restrict our estimates only to the four top-rated firms, the reason being absence of active secondary market for Non-Investment Grade rated bonds. A sizable chunk of such speculative category bonds change hands through private placements. The credit spread estimates are compared with the actual market data on credit spreads as presented in Table 20. This table summarizes the standard deviation, maximum, minimum and mean values for the actual credit spreads on an aggregate basis.

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[12]Altman Z-Score is a classificatory model for corporate customers;

Zscore > 2.99	-	Firm is in a good shape
2.99 > Zscore >1.81	-	Warning signal
1.81 > Zscore	-	Firm could be heading towards bankruptcy

Therefore, the greater a firm's distress potential, the lower its discriminant score.

[13]An interesting result to note here is that the performance of the default probability measure improves with firm size (Prediction Accuracy Ratio increases from 0.74 to 0.88), while that of the Z-score deteriorates slightly with size (Prediction Accuracy Ratio deteriorates from 0.60 to 0.58). This is because the probability measure relies on an informative equity price for its effectiveness. While equity markets are usually efficient and equity prices are a good indicator of the intrinsic worth of the firm, there is noise around them in reality. For larger firms, due to an increased market interest and larger number of analysts following them, the equities are more transparent, making them more reliable. On the other hand, larger firms have more sophisticated financial statements since they usually operate in multiple segments across the world. This makes their financial ratios more difficult to interpret. Since the Z-score primarily depends on the financial ratios, its effectiveness reduces with size (Bohn, Arora & Korablev, 2005).

Absence of company-wise spread data seriously impedes the explanation of spread estimates. However, notwithstanding this difficulty, the results clearly highlight the fact that the Merton model *underpredicts credit spreads* for AAA and AA rating grades vis-à-vis the actual market spreads. The mean value of actual credit spreads is 0.889% and 1.222% respectively for these rating grades over the period from March 2002 to March 2004. Comparing this market evidence with the estimates reported in tables underscores the propensity of Merton model to underpredict credit spreads. The results are clearly in confirmation with the received literature on credit spreads (see for example Jones, Mason, and Rosenfeld (1984), Gemmill(2002), Teixeira (2005), Eom,Helwege,Huang(2003)). Ogden (1987) conducted a similar study using prices from new offerings and reported that the Merton model underpredicts spreads by 104 basis points (bps) on average. Our results lends credence to this observation with reference to Indian corporate bond spreads. The model's underprediction problem is quite severe for low leverage and low volatility firms, so unless these firms have many years left for the debt to mature, there is little chance in the model to generate a high spread (Eom,Helwege,Huang(2003))[14]. The firms' volatility and Quasi-Debt ratios reported in the tables 3 to 6 confirm this proposition [15].

Ericsson and Renault (2001) find that there is liquidity premium in the observed credit spread which increases its size relative to the model spread. Bose and Coondoo (2003) report that during the sub-period April 1998- February 1999, the share of AAA and AA rated bonds together in total traded volumes went down to 22% This share went down further to 15% during the last sub-period of their study ,i.e., April 2000 to March 2001. This evidence points out the volatile traded volumes experienced in the

Investment –Grade rated segment of the Indian corporate bond market. Dwindling volumes quite often manifest themselves in the form of higher liquidity premium. Elton et al (2001) attribute about one third of the observed US spread to state and local taxes, which apply to corporate bonds but not to treasuries. It would therefore not be surprising if model spreads appeared to be smaller than market spreads in the US. Quite analogous to this, the interest income receivable from Indian corporate bonds and debentures is subject to Tax Deduction at Source (TDS), whereas, the maturity or redemption of a zero coupon bond is treated as transfer giving rise to capital gain which is subject to tax. Incidentally, Huang and Huang (2003) conclude that, for investment grade bonds (those with a credit rating not lower than Baa) of all maturities, credit risk accounts for only a small fraction—typically around 20%, and, for Baa-rated 10-year bonds, in the 30% range—of the observed yield spreads, and it accounts for a lower fraction of the observed spreads for bonds of shorter maturities. For junk bonds, however, credit risk accounts for a much larger fraction of the observed spreads.

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[14]Note that the Merton model estimates credit spreads assuming one year of residual maturity across entire debt outstanding

[15]Absence of sizeable dataset on zero-coupon bonds has forced researchers in the past to employ coupon-bearing bonds for estimating the structural models (which implicitly assume zero-coupon debt). This has seriously undermined the efficacy of the existing research on predicting credit spreads. The present study is no exception to this limitation. Moreover, due to lack of bond issue-wise data, bonds with different maturity profiles have been bunched together assuming one year residual maturity.

6) Concluding Remarks:

This paper derives a risk-neutral (and objective) indicator of credit risk, the distance-to-default, that can be used to assess financial distress. This indicator, that is based on Robert Merton's structural model of credit risk, measures the distance between the asset value of a firm and its liabilities at any given point in time. Therefore, the lower the absolute value of the distance-to-default, the higher the risk of default. We construct this measure for select Indian firms and find that it is able to correctly differentiate top-rated firms from those in default mode. We then demonstrate that the Merton model estimates depend significantly on the equity price volatility, which in itself need not always carry credit risk implications. Another aspect on which we shed some light is whether the default measure is sensitive to the 'default trigger point' chosen for analysis, i.e. the sum of short-term and long-term debt employed in the modelling framework. Our tests, however, confirm the robustness of this indicator. This especially augurs well for testing the model on firms which carry sizeable off- balance sheet exposures.

Given that the riskfree rate is less than the rate of asset drift, in conventional analysis the risk-neutral probability estimate is always supposed to exceed the objective probability measure. However, the evidence from the present study is markedly different. We find that the real world (i.e., objective) probability estimates are higher than the risk-neutral measures across the period of study; the reason being the rate of asset drift persistently falling short of the riskfree rate over the sample period. We have attempted to map our estimates to the Altman Z-scores as well as the default rate reported by CRISIL's Average 1-year rating transition matrix. The results are found to compare quite well with both these benchmarks. In the concluding part, we employ the Merton model to estimate credit spreads for the four top-rated firms included in the sample. The findings which we confirm empirically are twofold. First, the model spreads are small relative to the spreads observed in the secondary market for these bonds. Second, the model's underprediction problem is quite severe for low leverage and low volatility firms, so unless these firms have many years left for the debt to mature, there is little chance in the model to generate higher spreads. The observations broadly support the argument that liquidity premium and transaction costs account for the unexplained component of market spreads.

APPENDIX (A) :

Table 1: Sample Firms

Sr.No.	Company	Particulars	Industry
1	Bajaj Auto Limited	“AAA rated	Two and Three wheelers
2	Hindustan Lever Limited	“AAA” rated	Consumer goods
3	TELCO	“AA” rated*	Cars and Heavy vehicles
4	Reliance Industries Limited	“AAA” rated	Petrochemicals
5	Core Healthcare Limited	Filed with BIFR	Pharmaceuticals
6	Global Trust Bank	Merged (2004)	Banking
7	ITI Limited	Filed with BIFR	Electronics
8	Mardia Chemicals Limited	Filed with BIFR	Dyes and Pigments
9	Modi Rubber Limited	Filed with BIFR	Tyres and Tubes
10	Punjab Alkalies & Chemicals Limited	Filed with BIFR	Caustic Soda
11	RPG Cables Limited	Filed with BIFR	Wires and Cables
12	Surat Textile Mills Limited	Filed with BIFR	Synthetic Yarn

*Securitized debt rated “AAA” since 2001.

Table 2: Notations

R_f	Riskfree rate
σe	Equity returns volatility
σa	Asset returns volatility
MVA	Total market value of the firm
Debt	Short-term debt + 50% of Long term debt
μ_a	Asset drift rate
DD	Distance-to-Default
P_{RN}	Risk-neutral probability of default
P_O	Objective probability of default
Q-D	Quasi-debt ratio
Spread	Credit spread (Merton model)
Rating	Credit rating (CRISIL , ICRA, CARE or Fitch)
Z score	Altman’s Z score estimate

Table 3: Bajaj Auto Ltd.

Years	1997-98	1998-99	1999-00	2000-01	2001-02	2002-03	2003-04
R_f	0.089	0.095	0.096	0.093	0.069	0.057	0.045
σe	0.513	0.395	0.480	0.351	0.361	0.291	0.336
σa	0.433	0.322	0.358	0.240	0.220	0.191	0.242
MVA	8227.75	8467.59	7336.69	5140.42	5363.00	7331.34	10812.55
Debt	1395.83	1724.79	2049.71	1776.26	2244.89	2676.02	3122.55
μ_a	0.024	0.025	0.037	0.076	0.058	0.028	0.024
DD	4.084	5.082	3.650	4.685	4.167	5.494	5.190
P_{RN}	0.002%	0.000%	0.013%	0.000%	0.002%	0.000%	0.000%
P_O	0.004%	0.000%	0.024%	0.000%	0.002%	0.000%	0.000%
Q-D	0.155	0.185	0.254	0.315	0.391	0.345	0.276
Spread	0.0002%	0.0000%	0.0011%	0.0000%	0.0001%	0.0000%	0.0000%
Rating	AAA	AAA	AAA	AAA	AAA	AAA	AAA
Z score	5.33	4.56	3.72	2.73	2.84	2.89	3.54

Table 4: Hindustan Lever Ltd.

Years	1997-98	1998-99	1999-00	2000-01	2001-02	2002-03	2003-04
R_f	0.089	0.095	0.096	0.093	0.069	0.057	0.045
σe	0.305	0.309	0.415	0.427	0.306	0.252	0.316
σa	0.284	0.291	0.395	0.403	0.286	0.231	0.277
MVA	28651.59	39709.11	56373.91	52436.81	50942.12	43613.02	43913.75
Debt	2188.04	2592.84	3001.185	3286.27	3693.83	3854.445	5709.41
μ_a	0.010	0.031	0.043	0.064	0.025	0.003	0.013
DD	9.242	9.567	7.475	6.911	9.281	10.617	7.387
P_{RN}	0.000%	0.000%	0.000%	0.000%	0.000%	0.000%	0.000%
P_O	0.000%	0.000%	0.000%	0.000%	0.000%	0.000%	0.000%
Q-D	0.070	0.059	0.048	0.057	0.068	0.083	0.124
Spread	0.000%	0.000%	0.000%	0.000%	0.000%	0.000%	0.000%
Rating	AAA	AAA	AAA	AAA	AAA	AAA	AAA
Z score	10.32	11.71	13.83	12.01	10.55	8.91	6.52

Table 5: TELCO

Years	1997-98	1998-99	1999-00	2000-01	2001-02	2002-03	2003-04
R_f	0.089	0.095	0.096	0.093	0.069	0.057	0.045
σe	0.357	0.591	0.663	0.564	0.522	0.341	0.415
σa	0.246	0.283	0.392	0.210	0.177	0.167	0.269
MVA	12528.19	9579.64	9419.25	7058.74	6864.24	9531.53	16599.53
Debt	4284.26	5535.07	4292.64	4899.22	4888.64	5142.66	6105.64
μ_a	0.027	0.034	0.031	0.061	0.051	0.019	0.006
DD	4.608	2.132	2.052	2.075	2.223	3.947	3.746
P_{RN}	0.000%	1.652%	2.008%	1.898%	1.310%	0.004%	0.009%
P_O	0.001%	2.758%	2.964%	2.712%	1.682%	0.010%	0.016%
Q-D	0.313	0.526	0.414	0.633	0.665	0.510	0.352
Spread	0.0000%	0.1534%	0.2557%	0.1360%	0.0763%	0.0001%	0.0005%
Rating	AA	AA	AA	AA	AA	AA	AA
Z score	2.32	1.23	1.95	1.16	1.36	2.02	3.03

Table 6: Reliance Industries Ltd.

Years	1997-98	1998-99	1999-00	2000-01	2001-02	2002-03	2003-04
R_f	0.089	0.095	0.096	0.093	0.069	0.057	0.045
σe	0.776	0.456	0.538	0.390	0.434	0.298	0.305
σa	0.529	0.262	0.372	0.310	0.274	0.176	0.207
MVA	22919.72	22305.17	29708.50	46065.91	52768.92	55947.04	88390.95
Debt	8189.09	10470.795	10137.63	10365.85	20885.955	24303.2	29764.72
μ_a	0.011	0.030	0.019	0.033	0.016	0.011	0.012
DD	1.851	3.123	2.965	4.951	3.497	4.978	5.376
P_{RN}	3.207%	0.089%	0.152%	0.000%	0.024%	0.000%	0.000%
P_O	4.428%	0.200%	0.292%	0.000%	0.048%	0.000%	0.000%
Q-D	0.327	0.427	0.310	0.205	0.369	0.410	0.322
Spread	0.5585%	0.0060%	0.0146%	0.0000%	0.0015%	0.0000%	0.0000%
Rating	AAA	AAA	AAA	AAA	AAA	AAA	AAA
Z score	1.94	1.67	2.23	3.13	2.3	2.16	2.43

Table 7: Core Healthcare Ltd.

Years	1997-98	1998-99	1999-00	2000-01	2001-02	2002-03	2003-04
R_f	0.089	0.095	0.096	0.093	0.069	0.057	0.045
σe	0.730	1.053	0.834	0.789	0.936	0.749	0.973
σa	0.101	0.129	0.093	0.035	0.020	0.015	0.020
MVA	561.97	633.62	796.95	1086.80	1154.25	1246.72	1362.57
Debt	539.6	652.59	800.925	1150.495	1220.34	1297.775	1409.13
μ_a	0.083	0.082	0.086	0.090	0.068	0.055	0.043
DD	1.228	0.443	0.929	0.997	0.631	1.088	0.549
P_{RN}	10.982%	32.904%	17.652%	15.927%	26.412%	13.830%	29.140%
P_O	12.093%	36.710%	20.498%	17.713%	27.971%	16.522%	31.315%
Rating	BB	D	D	D	D	D	D
Z score	0.05	0.01	-0.12	-1.25	-1.1	-1.12	-1.79

Table 8: Global Trust Bank

Years	1997-98	1998-99	1999-00	2000-01	2001-02	2002-03
R_f	0.089	0.095	0.096	0.093	0.069	0.057
σe	0.526	0.570	0.715	0.916	0.659	0.374
σa	0.345	0.258	0.338	0.506	0.276	0.120
MVA	684.11	978.88	1109.76	1625.37	664.93	712.12
Debt	256.59	593.24	661.42	865.775	421.55	511.68
μ_a	0.021	0.047	0.051	0.032	0.028	0.034
DD	2.923	2.178	1.643	1.176	1.760	3.162
P_{RN}	0.173%	1.470%	5.018%	11.979%	3.921%	0.078%
P_O	0.319%	2.314%	6.528%	14.565%	5.347%	0.148%
Rating	P1+	P1	P1	P1+	P1	P3
Z score	1.72	0.97	0.95	0.98	0.79	0.51

Table 9: ITI Ltd

Years	1997-98	1998-99	1999-00	2000-01	2001-02	2002-03	2003-04
R_f	0.089	0.095	0.096	0.093	0.069	0.057	0.045
σe	0.903	1.108	0.836	0.736	0.774	0.703	0.688
σa	0.089	0.120	0.154	0.088	0.038	0.055	0.045
MVA	1473.66	1653.92	2022.15	1997.14	2568.34	2900.82	2775.86
Debt	1500.83	1736.36	1892.75	1965.55	2642.175	2862.99	2733.425
μ_a	0.082	0.082	0.074	0.079	0.064	0.048	0.041
DD	0.752	0.326	0.976	1.195	1.039	1.260	1.297
P_{RN}	22.606%	37.240%	16.448%	11.606%	14.947%	10.391%	9.730%
P_O	24.877%	41.380%	20.160%	14.876%	18.056%	13.881%	11.141%
Rating	AAA	AAA	AAA	AAA	AAA	AAA	AAA
Z score	1.07	1.32	1.48	1.41	1.21	0.25	-0.75

Table 10: Mardia Chemicals Ltd.

Years	1997-98	1998-99	1999-00	2000-01	2001-02	2002-03
R_f	0.089	0.095	0.096	0.093	0.069	0.057
σe	0.696	1.796	1.272	2.286	1.787	1.442
σa	0.128	0.463	0.081	0.393	0.059	0.031
MVA	501.70	479.64	788.00	610.52	1213.90	1260.67
Debt	456.24	663.15	864.47	1093.79	1362.51	1346.81
μ_a	0.082	0.090	0.092	0.080	0.067	0.055
DD	1.370	-0.726	-0.002	-1.443	-0.823	-0.307
P_{RN}	8.538%	76.623%	50.067%	92.548%	79.463%	62.043%
P_O	9.399%	76.906%	51.753%	93.012%	80.122%	64.040%
Rating	NA	NA	NA	NA	NA	NA
Z score	0.22	-1.61	-1.5	-0.39	-1.94	-1.46

Table 11: Modi Rubber Ltd.

Years	1997-98	1998-99	1999-00	2000-01	2001-02	2002-03
R_f	0.089	0.095	0.096	0.093	0.069	0.057
σe	0.608	0.784	0.721	0.766	0.833	0.745
σa	0.151	0.162	0.258	0.253	0.269	0.144
MVA	455.26	370.84	445.09	418.92	392.26	383.14
Debt	378.48	335.04	324.15	320.03	300.64	336.10
μ_a	0.081	0.092	0.091	0.090	0.059	0.048
DD	1.734	1.132	1.469	1.303	1.108	1.231
P_{RN}	4.142%	12.883%	7.095%	9.624%	13.393%	10.922%
P_O	4.598%	13.300%	7.323%	9.825%	14.194%	12.159%
Rating	NA	NA	NA	NA	NA	NA
Z score	2.43	2.14	2.6	1.92	1.18	-0.6

Table 12: Punjab Alkalies & Chemicals Ltd.

Years	1997-98	1998-99	1999-00	2000-01	2001-02
R_f	0.089	0.095	0.096	0.093	0.069
σe	0.567	1.116	1.522	1.623	1.057
σa	0.211	0.253	0.421	0.414	0.108
MVA	117.54	107.58	97.96	89.83	111.84
Debt	81.28	103.94	111.79	109.85	113.77
μ_a	0.074	0.081	0.101	0.077	0.064
DD	2.060	0.385	-0.296	-0.468	0.423
P_{RN}	1.970%	34.995%	61.650%	68.018%	33.618%
P_O	2.333%	36.961%	61.149%	69.419%	35.055%
Rating	Suspended	Suspended	Suspended	Suspended	Suspended
Z score	0.76	0.26	0.51	1.14	0.8

Table 13: RPG Cables Ltd.

Years	1997-98	1998-99	1999-00	2000-01	2001-02	2002-03	2003-04
R_f	0.089	0.095	0.096	0.093	0.069	0.057	0.045
σe	0.733	0.955	0.823	0.612	0.562	0.496	0.908
σa	0.114	0.169	0.257	0.134	0.060	0.050	0.113
MVA	288.64	233.27	301.11	274.51	279.34	243.75	250.06
Debt	272.32	225.135	240.08	237.98	268.65	232.71	238.42
μ_a	0.081	0.088	0.070	0.075	0.064	0.050	0.038
DD	1.234	0.689	1.125	1.687	1.769	2.051	0.759
P_{RN}	10.858%	24.544%	13.032%	4.584%	3.843%	2.016%	22.384%
P_O	12.166%	25.853%	15.266%	5.977%	4.549%	2.796%	24.228%
Rating	NA	NA	NA	NA	NA	NA	NA
Z score	1.47	1.45	1.62	1.3	1.02	0.81	-1.64

Table 14: Surat Textile Mills Ltd.

Years	1997-98	1998-99	1999-00	2000-01	2001-02	2002-03	2003-04
R_f	0.089	0.095	0.096	0.093	0.069	0.057	0.045
σe	2.458	5.621	3.822	3.005	2.647	1.823	1.422
σa	1.678	5.594	3.555	2.419	1.810	0.790	0.560
MVA	33.24	14.09	14.13	18.47	21.38	54.38	67.10
Debt	73.04	65.4	74.27	71.33	67.81	70.1	61.43
μ_a	0.124	0.042	0.148	0.147	0.066	0.050	0.040
DD	-1.255	-3.054	-2.217	-1.730	-1.505	-0.644	-0.042
P_{RN}	89.532%	99.887%	98.669%	95.815%	93.379%	74.021%	51.690%
P_O	89.151%	99.891%	98.618%	95.612%	93.401%	74.293%	51.987%
Rating	NA	NA	NA	NA	NA	NA	NA
Z score	0.68	0.77	0.89	1.11	0.99	1.27	1.43

Table 15: CRISIL Average 1-Year Rating Transition Matrix over 1992-2004 (%)

From\To	AAA	AA	A	BBB	BB	B	C	D
AAA	96.64	3.36	0.00	0.00	0.00	0.00	0.00	**0.00**
AA	2.36	89.26	7.24	0.57	0.33	0.16	0.08	**0.00**
A	0.00	3.61	82.40	7.50	4.40	0.22	0.87	**1.01**
BBB	0.00	0.33	5.45	73.27	14.19	1.65	1.65	**3.47**
BB	0.00	0.61	0.00	1.83	75.30	0.91	5.49	**15.85**
B	0.00	0.00	0.00	6.06	0.00	57.58	6.06	**30.30**
C	0.00	0.00	0.00	1.19	0.00	0.00	70.24	**28.57**

(Source: "Insight" CRISIL Default Study, 2004-05)

Table 16: TELCO (Risk-Neutral probability at Total debt level)

	1997-98	1998-99	1999-00	2000-01	2001-02	2002-03	2003-04
STD + 0.5LTD	0.00020%	1.65%	2.00%	1.89%	1.31%	0.003%	0.008%
STD + LTD	0.00059%	1.95%	2.52%	2.12%	1.47%	0.005%	0.012%
% change	190.03%	18.03%	25.81%	11.97%	12.76%	42.86%	40.01%

Table 17: ITI Ltd. (Risk-Neutral probability at Total debt level)

	1997-98	1998-99	1999-00	2000-01	2001-02	2002-03	2003-04
STD + 0.5LTD	22.606%	37.240%	16.448%	11.606%	14.947%	10.391%	9.730%
STD + LTD	22.730%	37.463%	16.723%	11.733%	14.970%	10.439%	9.836%
% change	0.55%	0.60%	1.67%	1.10%	0.15%	0.46%	1.09%

Table 18: Surat Textiles Ltd. (Risk-Neutral probability at Total debt level)

	1997-98	1998-99	1999-00	2000-01	2001-02	2002-03	2003-04
STD + 0.5LTD	89.53%	99.88%	98.66%	95.81%	93.37%	74.02%	51.69%
STD + LTD	91.27%	99.91%	98.96%	96.66%	94.57%	76.36%	55.03%
% change	1.95%	0.03%	0.30%	0.89%	1.28%	3.16%	6.47%

Table 19: Coefficient of Variations (COV) of the Risk-Neutral default probabilities

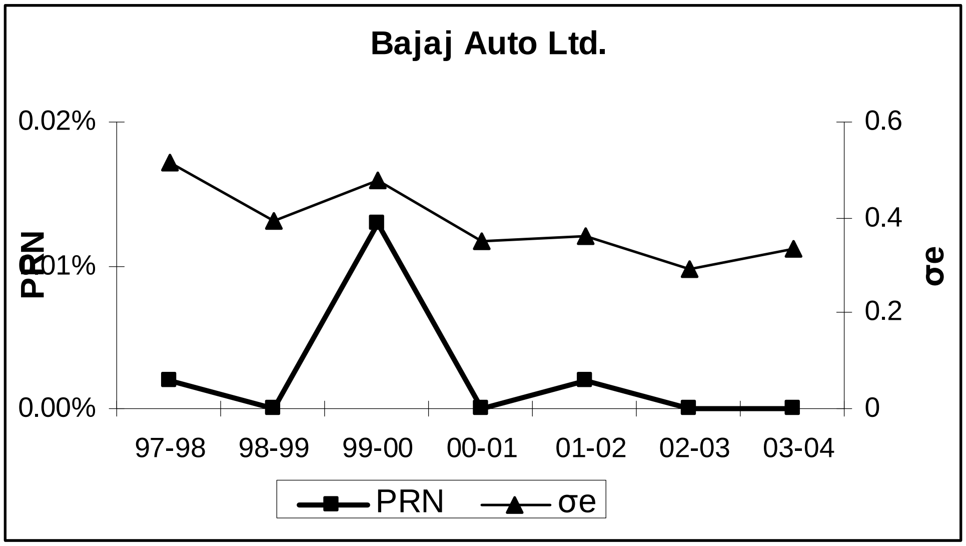
Firm	**COV (%)**
Bajaj Auto Limited	196.73
Hindustan Lever Limited	250.76
TELCO	95.74
Reliance Industries Limited	241.33
Core Healthcare Limited	40.16
Global Trust Bank	119.01
ITI Limited	55.43
Mardia Chemicals Limited	48.47
Modi Rubber Limited	36.67
Punjab Alkalies & Chemicals Limited	65.65
RPG Cables Limited	77.66
Surat Textile Mills Limited	20.31

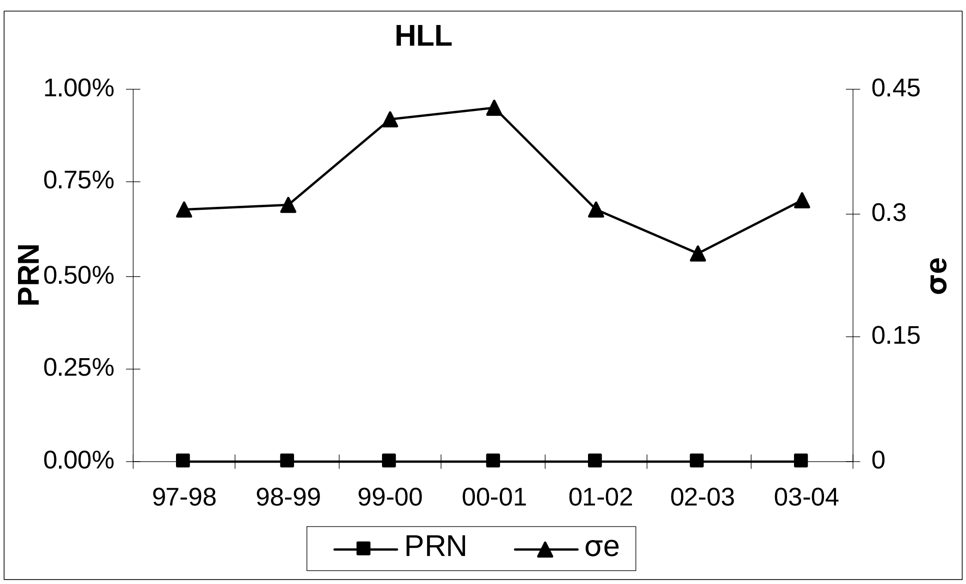
Table 20: Credit Spreads (%)

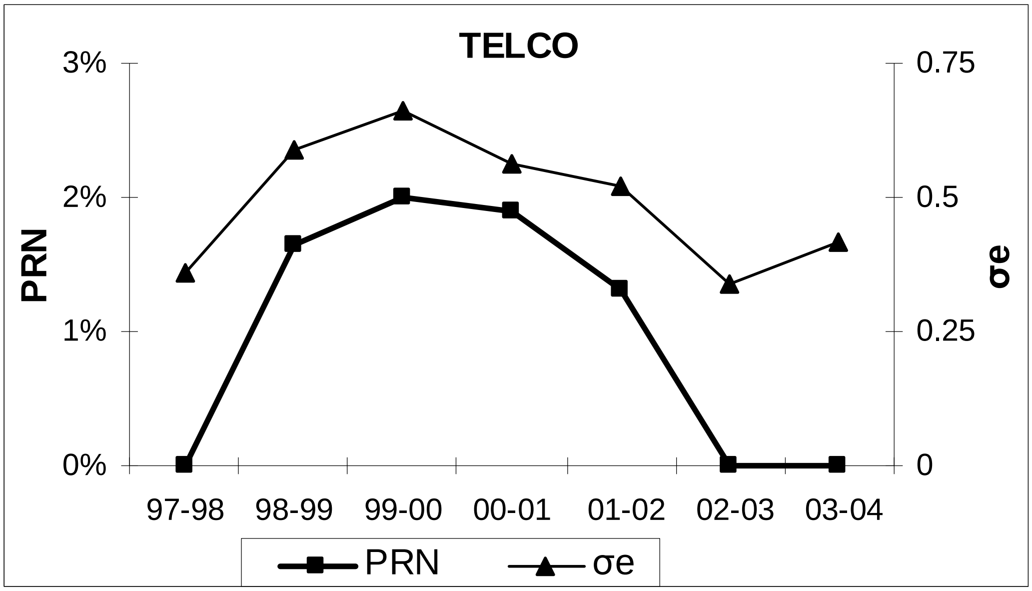
	AAA	AA+	AA	AA-	A+	A
31/03/2002	2.04	2.95	3.56	4.07	4.67	5.37
01/07/2002	1.75	2.15	2.94	3.44	4.17	4.91
30/09/2002	0.73	0.94	1.32	1.72	2.32	2.8
31/12/2002	0.28	0.52	0.86	1.27	1.92	2.43
31/03/2003	0.78	1.15	1.46	1.96	2.82	3.25
01/07/2003	0.41	0.61	0.98	1.45	2.13	2.75
30/09/2003	0.77	0.95	1.36	1.85	2.62	3.22
31/12/2003	0.37	0.61	0.95	1.34	1.97	2.55
31/03/2004	0.87	1.12	1.49	2.03	2.88	3.79
Average	**0.889**	**1.222**	**1.658**	**2.126**	**2.833**	**3.452**
Stdev	**0.611**	**0.811**	**0.944**	**0.974**	**0.971**	**1.048**
Maximum	**2.040**	**2.950**	**3.560**	**4.070**	**4.670**	**5.370**
Minimum	**0.280**	**0.520**	**0.860**	**1.270**	**1.920**	**2.430**

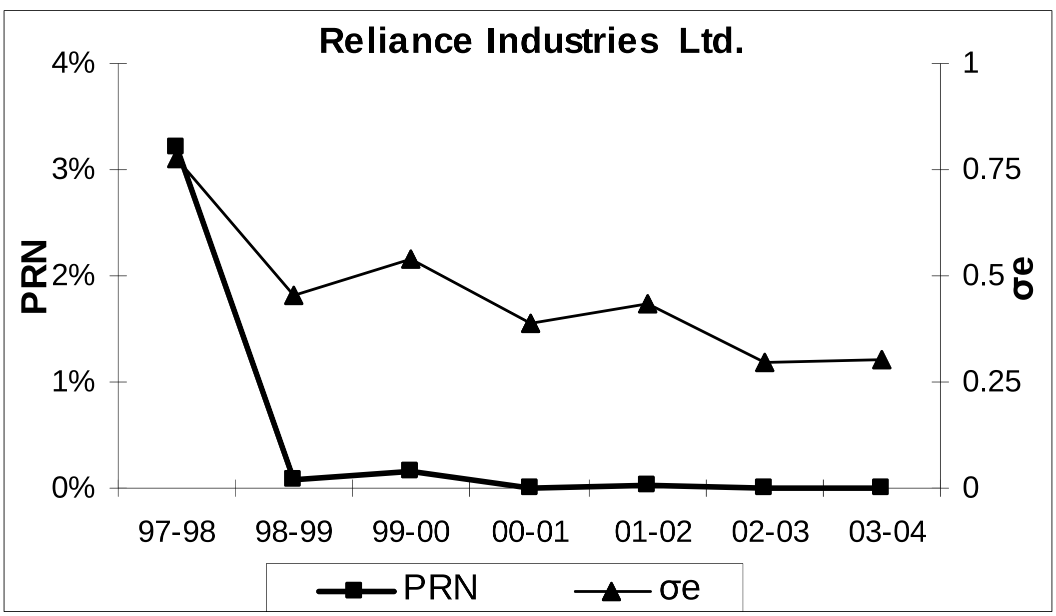
APPENDIX (B):

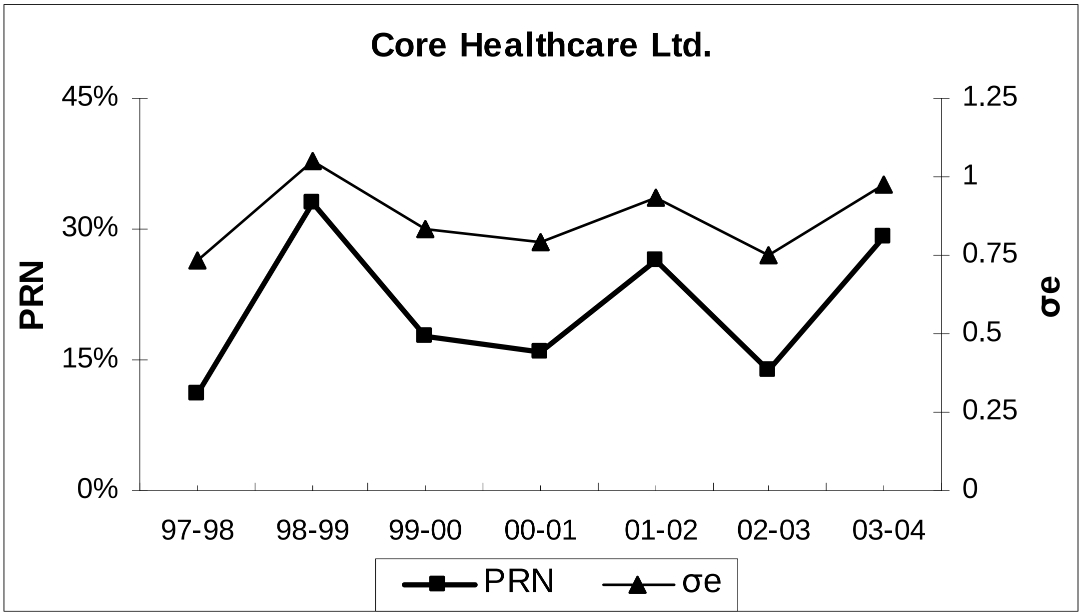
Note: PRN refers to Risk-Neutral probability of default, whereas, σe refers to volatility of equity returns.

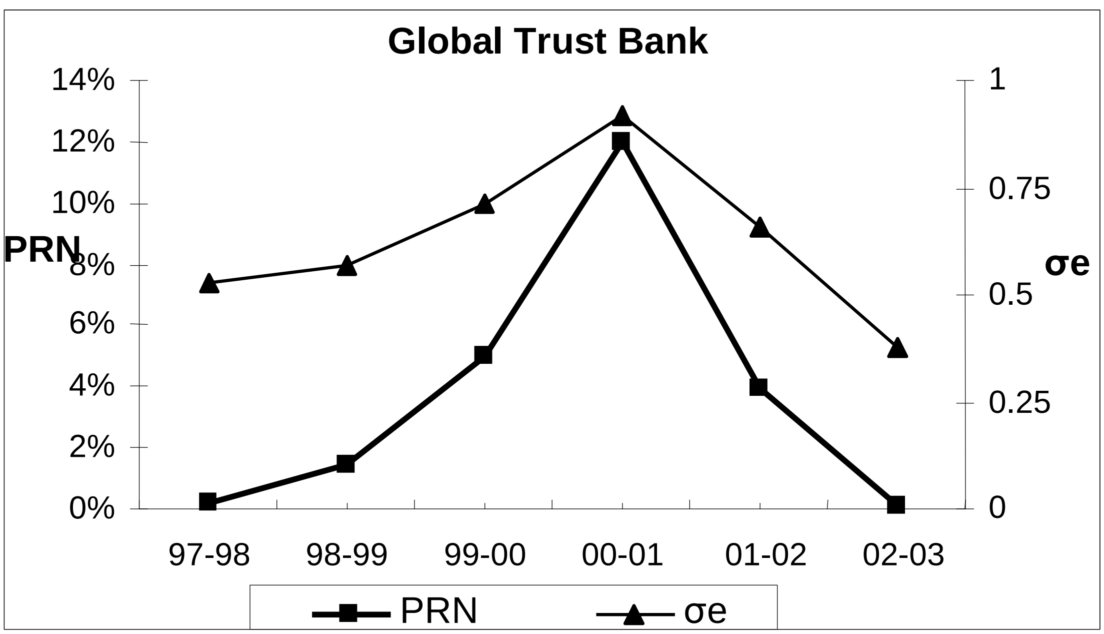


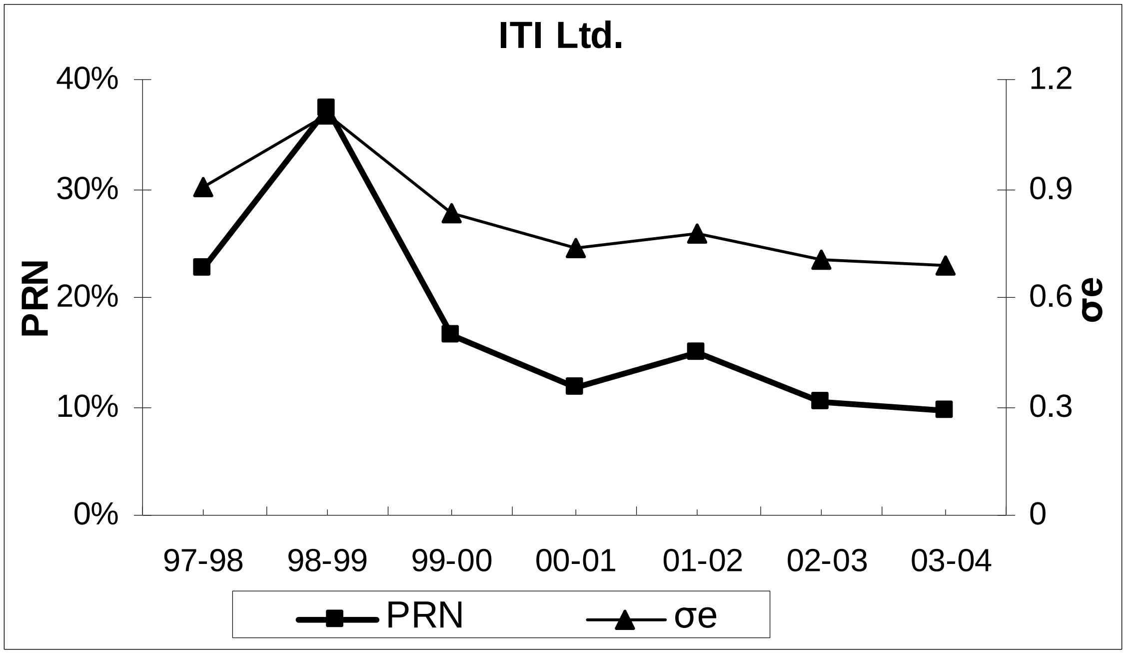


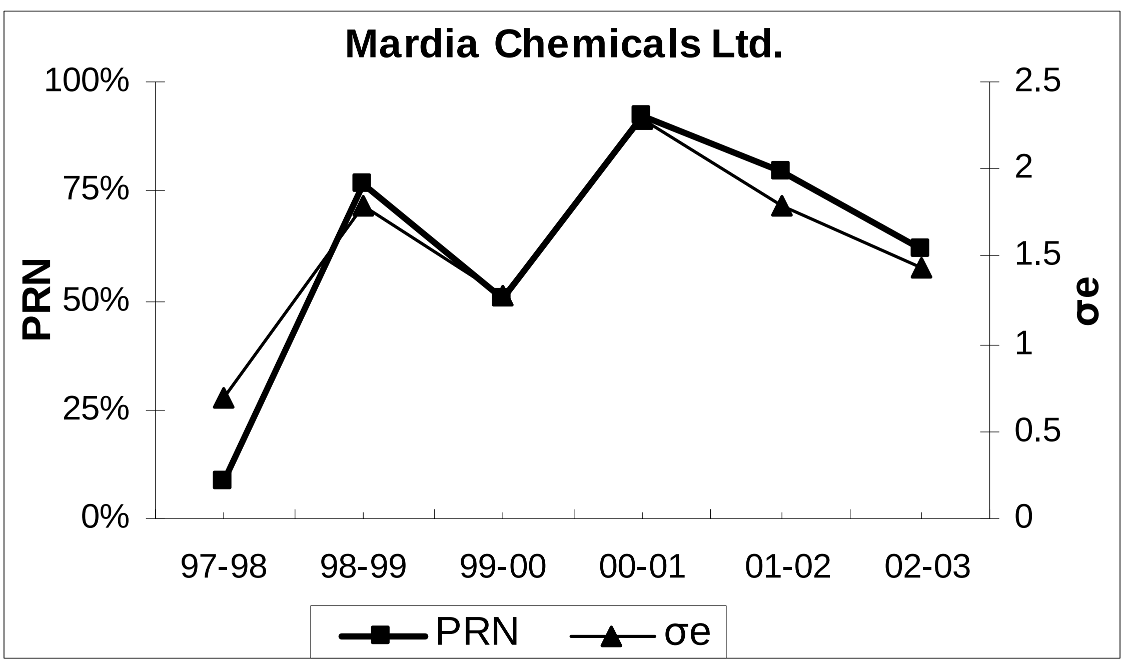

TELCO
3%
2%
1%
0%
PRN
0.75
0.5
0.25
0
σe
97-98
98-99
99-00
00-01
01-02
02-03
03-04
PRN
σe

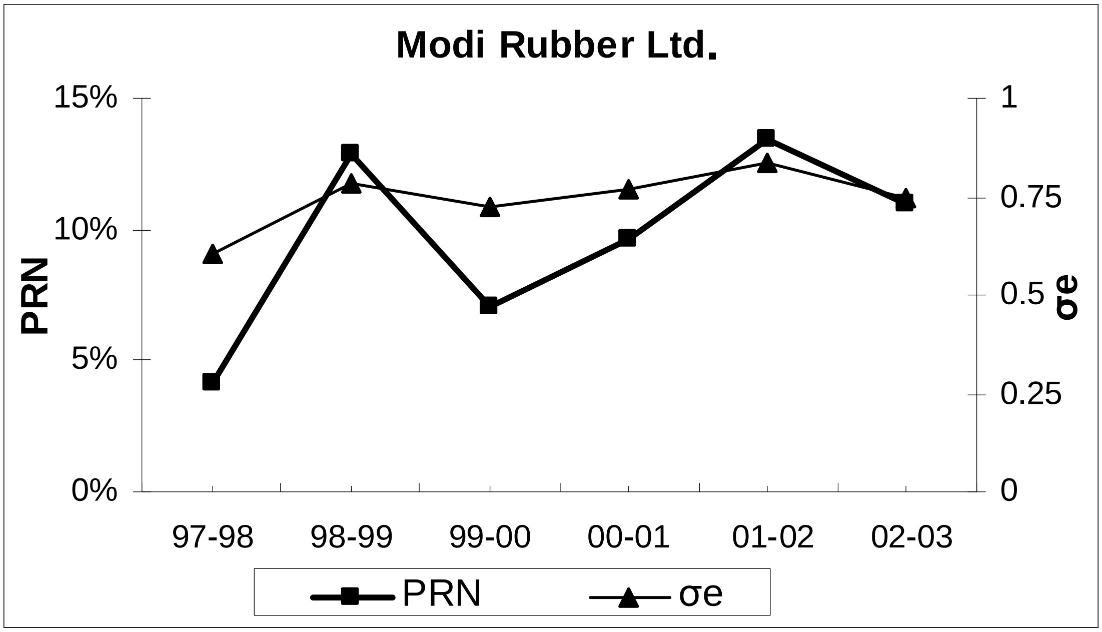

Reliance Industries Ltd.
4%
3%
2%
1%
0%
PRN
1
0.75
0.5
0.25
0
σe
97-98
98-99
99-00
00-01
01-02
02-03
03-04
PRN
σe

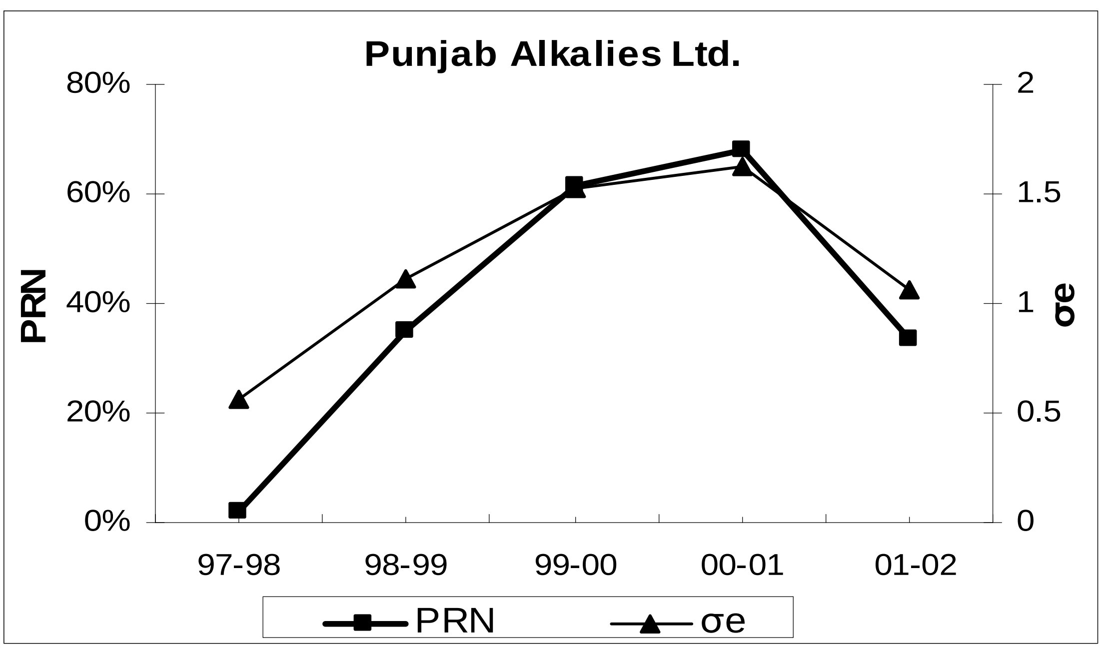

Core Healthcare Ltd.
PRN
σe
45%
30%
15%
0%
1.25
1
0.75
0.5
0.25
0
97-98
98-99
99-00
00-01
01-02
02-03
03-04
PRN
σe

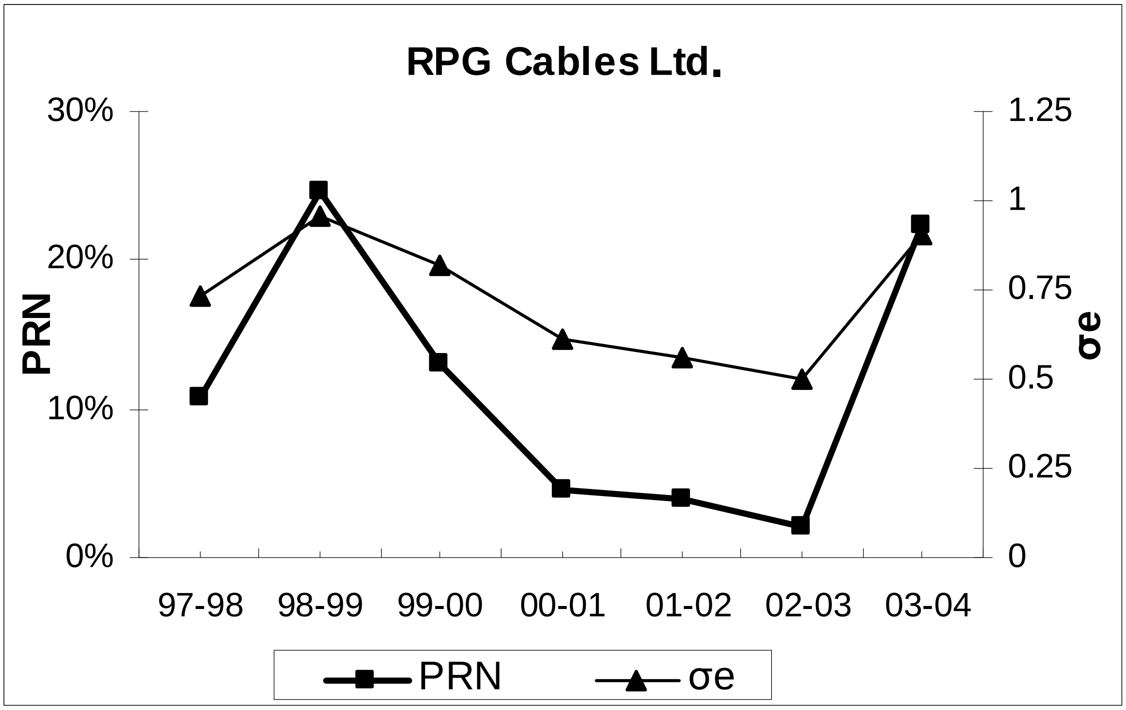

Global Trust Bank
PRN
σe
14%
12%
10%
8%
6%
4%
2%
0%
1
0.75
0.5
0.25
0
97-98
98-99
99-00
00-01
01-02
02-03
PRN
σe

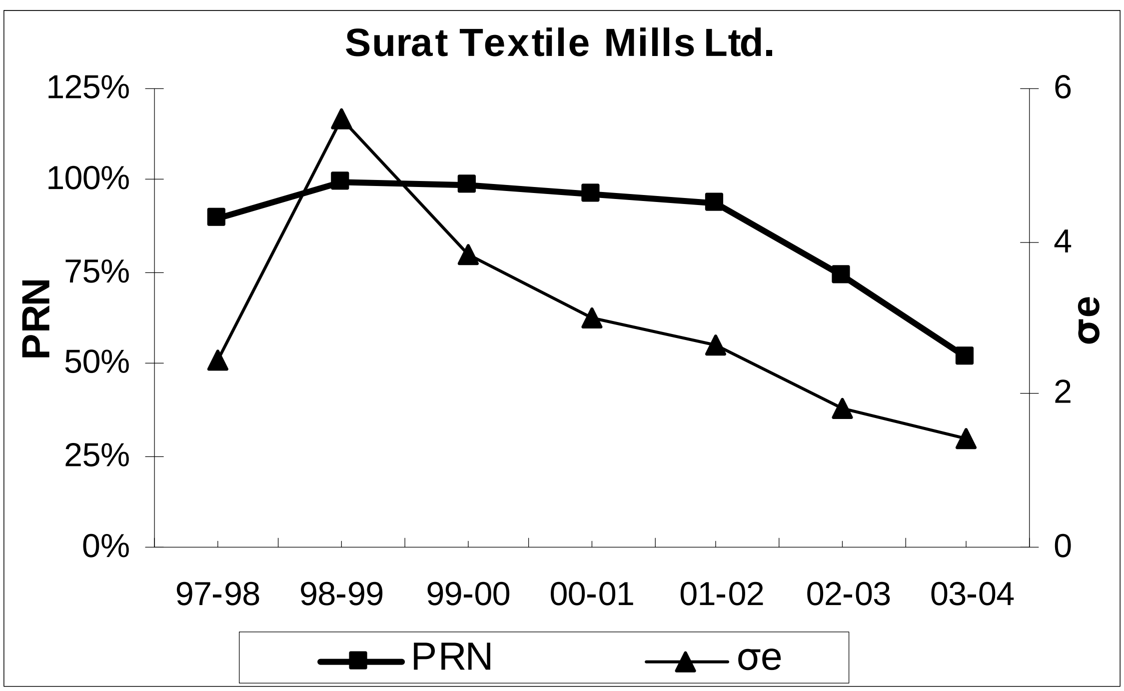

ITI Ltd.
40%
30%
20%
10%
0%
PRN
1.2
0.9
0.6
0.3
0
σe
97-98
98-99
99-00
00-01
01-02
02-03
03-04
PRN
σe


Mardia Chemicals Ltd.
100%
75%
50%
25%
0%
PRN
2.5
2
1.5
1
0.5
0
σe
97-98
98-99
99-00
00-01
01-02
02-03
PRN
σe


Modi Rubber Ltd.
15%
10%
5%
0%
PRN
1
0.75
0.5
0.25
0
σe
97-98
98-99
99-00
00-01
01-02
02-03
PRN
σe


Punjab Alkalies Ltd.
80%
60%
40%
20%
0%
PRN
2
1.5
1
0.5
0
σe
97-98
98-99
99-00
00-01
01-02
PRN
σe


RPG Cables Ltd.
PRN
σe
30%
20%
10%
0%
1.25
1
0.75
0.5
0.25
0
97-98
98-99
99-00
00-01
01-02
02-03
03-04
PRN
σe


Surat Textile Mills Ltd.
PRN
σe
125%
100%
75%
50%
25%
0%
6
4
2
0
97-98
98-99
99-00
00-01
01-02
02-03
03-04
PRN
σe

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