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Predicting financial distress: revisiting the option based model

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1. Introduction

The theoretical definition of 'financial distress' implies the inability of a firm to pay its financial obligations as they mature. The operational definition encompasses the occurrence of events such as bankruptcy, bond default, an overdrawn bank account, or non-payment of a preferred stock dividend (Beaver, 1966). Among the various events that signal a state of financial distress, bankruptcy and default have been the most widely researched. The event of default indicates deterioration in the financial health of a firm, which needs to be identified in time.

The various direct and indirect costs associated with financial distress and its impact on firm's performance has been well documented in the literature (Altman, 1984; Opler and Titman, 1994). Accurate and timely assessment of default risk has important implications for lending and investment decisions. It serves as a warning signal to the creditors, particularly banks and financial institutions and investors for managing their exposures to a particular class of firms that might be more vulnerable to experiencing distress than others. Modeling of default risk also helps in determining the appropriate risk premium and thereby pricing of corporate debt securities. Accurate assessment of default risk is also mandated by regulatory requirements such as the Basel Capital Accord which require banks to develop their own internal credit risk models for objective measurement of credit risk and thereby assessing the capital requirements.

Prediction of financial distress has drawn considerable attention of researchers since a long time. The initial studies primarily relied on information from the financial statements for predicting distress. However, traditional accounting based default prediction models have been subject to criticism on several grounds. They rely on the financial statements, which are backward looking as they measure past performance of the firm and may not be very informative about the future status of the firm. The asset valuations are sometimes misleading due to the adoption of certain accounting principles such as conservatism. Moreover, they fail to incorporate a measure of asset volatility (Hillegeist *et al.*, 2004; Vassalou and Xing, 2004; Bystrom, 2006). Given the criticism for the traditional accounting based approach, it was realized that a market-based measure could be more efficient in anticipating the risk of distress than the static financial statements. Consequently, the works of Black and Scholes (1973) and Merton (1974) motivated the application of option pricing theory in modeling of default risk and came to be popularly known as the Merton model.

Under the option approach the equity of a firm is considered as a call option on the value of firm's assets with the strike price equal to the face value of the debt. If at the maturity of the debt, the value of the firm is above the face value of the debt the equity holders choose to exercise their option by repaying the debt. But if the value of the firm is below the face value of the debt the equity holders opt to leave their option unexercised thereby defaulting on the repayment of the debt.

Several recent studies employ the option based Merton model in different contexts (Eichler *et al.*, 2011; Allen and Powell, 2012; Auvray and Brossard, 2012; Keehwan *et al.*, 2013; Kim, 2013; Friewald *et al.,* 2014; Erlenmaier and Gersbach, 2014; Jessen and Lando, 2015). While considerable research exists on the option based Merton model, the evidence is mixed. Some studies strongly favour the approach whereas others argue against it. Few studies have been done in the Indian context. And even those that exist are insufficient due to certain reasons. For instance, they pertain to a relatively older study period which is prior to the global financial crisis (Bandyopadhyay, 2007 and Mishra *et al.*, 2008) and use small sample sizes (Mishra *et al.*, 2008 and Sinha *et al.*, 2013). This paper contributes to the literature in terms of the methodology employed to investigate the utility of the Merton model in India. This includes the use of a simplified version of the Merton model, a reasonably larger sample size and a more recent study period covering the post global financial crisis period. The main purpose of this paper is to assess the significance of the Merton distance-to-default (alternatively referred to as DD) in predicting defaults for a sample of listed Indian firms.

The rest of the paper is structured as follows. The next section consists of a detailed review of literature on option based modeling of default risk. The third section describes the sampling technique, sources of data, variable description and methodology. The fourth section consists of the results and findings of the study. The fifth section contains the discussion on the findings of the study and the last section presents the concluding remarks.

2. Literature review

The need for a market-based assessment of default risk led to the development of a model that used option pricing theory based on the works of Black and Scholes (1973) and Merton (1974) and came to be known as the Merton model. Ever since the existence of the model, researchers have made several attempts to establish as well as question its utility and develop alternatives and modifications to the original model. Attempts have also been made to further examine the inputs of the model as key drivers of default. Following is the review of studies organized into different themes reflecting the development of the Merton model in the literature.

While attempting to investigate the usefulness of the Merton model, studies provided mixed empirical evidence. Refuting the earlier findings on shortcomings of the option-based model, Kealhofer (2003) provided a compelling case that the conceptual approach pioneered by Fischer Black, Robert Merton, and Myron Scholes provided a powerful practical basis for measuring credit risk given the revolution that had come about in credit-risk measurement. Analysts were then able and willing to adequately quantify absolute levels of default risk. Crosbie and Bohn (2003) adjudged default probability to be the most critical input to the management of credit portfolios. The study focused on the determination of default probability using information from a firm's financial statements and the market price of its equity. It used a three-step process to calculate the expected default frequency, which included estimation of market value and volatility of firm's assets, calculating the distance-to-default, and transforming it to expected default frequency using an empirical default distribution. Taking a divergent view, Stein (2005) provided some evidence that unmodified, option-based models are not complete in the sense that additional information provided better discrimination between defaulters and non-defaulters even when conditioned on option-based variables. Using Moody's extensive database of corporate defaults, it was shown heuristically that partitioning a standard Merton model by a second variable provided more information about default. The econometric tests of significance refuted the assertion that additional information did not help explain default. Results also suggested that even a simple regression-based multi-factor model appears to outperform its single-factor counterpart in rigorous out-of-sample and out-of-time validation. Du and Suo (2007) found that the distant-to-default alone did not adequately capture the firm's credit quality information from the equity market.

Some studies focused on comparing the effectiveness of the option model with the traditional accounting based approach to default prediction. Hillegeist *et al.* (2004) assessed the effectiveness of two popular accounting-based measures, Altman's (1968) Z-Score and Ohlson's (1980) O-Score, in summarizing publicly available information about the probability of bankruptcy. The relative information content of these scores was compared to a market-based measure of the probability of bankruptcy based on the Black–Scholes–Merton option-pricing model. The study showed that the option-based model provided significantly more information than either of the two accounting-based measures. Tudela and Young (2005) exhibited the use of option-based model to develop measures of the probability of failure of individual quoted UK companies. Probability estimates were constructed for a control group of surviving companies and a group of failed companies and their properties as leading indicators of failure assessed. These were used in probit regressions to evaluate the information content of the Merton-based estimates relative to information available in company accounts. The paper substantiated the usefulness of information in the option-based model estimates. Gharghori *et al.* (2006) found that the option-based models outperform their accounting ratio counterparts. Agarwal and Taffler (2008) compared the Merton model with the traditional accounting-based model. The study found that the two approaches capture different aspects of bankruptcy risk, and while there is little difference in their predictive ability, the z-score approach led to significantly greater bank profitability in conditions of differential decision error costs and competitive pricing regime. Campbell *et al.* (2008) explored the determinants of corporate failure and the pricing of financially distressed stocks having a high failure probability as estimated from a dynamic logit model using accounting and market variables.

Some other studies involved using the option model to estimate the default risk and later examining its relationship with other variables such as equity returns and default correlations. Vassalou and Xing (2004) used the option-based model to compute default measures for individual firms and assess the effect of default risk on equity returns. The size and book-to-market effects were found to be default effects. Both existed only in segments of the market with high default risk. Campbell *et al.* (2008) found that financially distressed stocks delivered anomalously low returns with much higher standard deviations and market betas. These patterns were more pronounced for stocks with possible informational or arbitrage-related frictions. The results were inconsistent with the conjecture that the value and size effects were compensation for the risk of financial distress. Friewald *et al.* (2014) explored the link between a firm's stock returns and credit risk using insights from structural models following Merton model. Risk premium on equity and credit instruments are related because all claims on assets must earn the same compensation per unit of risk. Consistent with theory, they found that firms' stock returns increased with credit risk premium estimated from CDS spreads. Credit risk premium contains information not captured by physical or risk-neutral default probabilities alone. This shed new light on the 'distress puzzle', the lack of a positive relation between equity returns and default probabilities. Erlenmaier and Gersbach (2014) studied the relationship between default probabilities and default correlations of two firms in the Merton model. They found that default correlations increased under a homogeneous increase of default probabilities. The same held true even when the increase of default probability was more pronounced for the firm with lower likelihood of default. Default correlations would only decline if the increase of the default probability is significantly larger for the firm with higher default risk.

A few studies also focused on using the option model to find out the key drivers of default. Patel and Vlamis (2006) estimated the distance-to-default and the risk neutral default probabilities using the option-based model. The empirical results classified failed and non-failed companies into Type I error, where the model failed to predict default when it did occur, and Type II error where the model predicted default when there was none. While there was no Type I error, the Type II error was observed in 12 out of 112 companies, supporting the theoretical underpinnings that the two driving forces of default were high leverage and high asset volatility. Bystrom (2006) showed equity volatility and firm leverage ratio to be the drivers of default. Triandafil *et al.* (2009) applied Black and Scholes structural approach on credit risk. A key element in the study was represented by the assets volatility, which was correlated with the country risk premium in order to highlight a potential macroeconomic impact on corporate failure.

A considerable number of studies concentrated on developing simpler and better alternatives to the original Merton model by way of making certain modifications. Bystrom (2006) introduced a simple approximation to the option-based model and showed that the errors induced by the simplification were relatively small when compared with those caused by other deficiencies of option-based model. The distance-to-default measures for a sample of U.S. firms were found to be very similar to those of the original option-based model. The distance-to-default measure was found to be insensitive to the leverage ratio at high levels of debt. The work claimed its measure to be significant regardless of a firm's capital structure or asset volatility, which could be useful for assessing the default probabilities of firms in volatile environments.

Gharghori *et al.* (2006) evaluated the performance of three alternate default-risk models, seeking to find that measure which performs best, using a comprehensive sample drawn from the Australian equities market. The first two models were based on Merton's (1974) insight that equity can be viewed as a call option on a firm's assets, modeled as a standard call option in the first case and as a path-dependent barrier option in the other. The third model was created using accounting ratios similar to Altman's (1968) Z-Score. Based on the variations of each model and the prediction-oriented tests, it was found that the option-based models outperformed their accounting ratio counterparts. The option-based models were very successful at ranking firms by default probability. Reisz and Perlich (2007) modeled common equity as a down-and-out barrier option on the firm's assets. Asset values and volatilities as well as firm-specific bankruptcy barriers were simultaneously backed out from the prices of traded equity. Implied barriers were significantly positive and monotonic in the firm's leverage and asset volatility. The study contended that its default probabilities displayed better calibration and discriminatory power than the ones inferred in a standard option-based model.

Incorporating the dynamics of firm-specific and macroeconomic covariates in their study, Duffie *et al.* (2007) provided maximum likelihood estimators of term structures of conditional probabilities of corporate default. This term structure was found to depend on a firm's distance-to-default, its trailing stock return, the trailing S&P 500 returns, and US interest rates. The out-of-sample predictive performance of the model was an improvement over that of other available models. Du and Suo (2007) investigated the empirical performance of default probability prediction based on the option-based model. It was shown that a simplified model outperformed the option-based model for both in-sample fitting and out-of-sample predictability for credit ratings, and that both could be greatly improved by including the firm's equity value as an additional variable.

Bharath and Shumway (2008) examined the accuracy and contribution of the option-based model by comparing it to an alternative using the functional form suggested by the model but not solving the model for an implied probability of default. The alternative predictor was found to perform better in hazard models and in out-of-sample forecasts than both the option-based model and a reduced-form model that used the same inputs. The study concluded that while the option-based model did not produce a sufficient statistic for the probability of default, its functional form was useful for forecasting defaults.

Keehwan *et al.* (2013) tested the Merton-type model of credit risk in the Korean corporate bond market. They considered two alternative firm value processes: diffusion process for the Merton (1974) model and jump-diffusion process for their extended model in a general equilibrium setting. They found that the diffusion model generally under-predicted spreads, referred to as "the credit spread under-prediction puzzle" in the literature, while the jump-diffusion model somewhat raises the predicted spreads. Kim (2013) derived closed-form solutions for the probability of default and the expected loss of commercial real estate mortgages in a Merton framework. The model was a single risk factor model, although there was a sector risk factor that influenced both the net operating income and the property value. The economic capital was also obtained analytically for the corporate-wide commercial real estate portfolio, with granularity adjustments for name concentration and sector concentration.

Jessen and Lando (2015) argued that distance-to-default had empirically proven to be a strong predictor of default. They used simulations to demonstrate that the empirical success of DD may well be a result of its strong robustness to model misspecifications. They considered a number of deviations from the Merton model which involved different asset value dynamics and different default triggering mechanisms and showed that, in general, DD is successful in ranking firms' default probabilities, even if the underlying model assumptions are altered. A possibility of large jumps in asset value or stochastic volatility challenged the robustness of DD. They proposed a volatility adjustment of the distance-to-default measure that significantly improved the ranking of firms with stochastic volatility, but this measure was less robust to model misspecifications than DD.

Application of the Merton model and its variations are not restricted to corporate defaults alone but have also been applied in the financial sector such as banks and financial institutions. Koutsomanoli-Filippaki and Mamatzakis (2009) provided empirical evidence on the dynamic interactions between risk and efficiency. A panel VaR analysis on the option-based bank default risk evidenced that the effect of a one standard deviation shock of the distance-to-default on inefficiency was negative and substantial. There was some evidence of a reverse causation. The sensitivity analysis extended an investigation into the relationship between efficiency and default risk for banks with different types of ownership structures and across financial systems with different levels of development. Post financial crisis, Huang *et al.* (2010) used KMV model to calculate the distance-to-default and also compare the default rate of top three banks of China, namely, Industrial and Commercial Bank of China (ICBC), Bank of China (BOC) and China Construction Bank (CCB). It was found that the risk of three banks had tended to increase and CCB had the highest risk of default based on the key financial indicators including the non-performing loan ratio, the loan-to-deposit ratio, and the proportion of non-interest income accounted for revenue.

Eichler *et al.* (2011) employed a compound option-based structural credit risk model for estimating banking crisis risk for the United States based on market data on bank stocks on a daily frequency. They attempted to provide separate information on short-term, long-term and total crisis risk instead of a single-maturity risk measure as inferred by Merton-type models or barrier models. Banks that defaulted during the crisis were found to have a considerably higher crisis risk (especially higher long-term risk) than banks that survived the crisis. In another study on similar lines, Allen and Powell (2012) used the KMV/Merton structural methodology to examine default probabilities of Australian banks. They also modified the model to incorporate conditional probability of default, which measured extreme credit risk. During the global financial crisis, Australian banks experienced significant deterioration in the market values of assets. The study concluded that based on extreme asset value fluctuations, default probabilities of Australian banks fared only slightly better than their global counterparts. Auvray and Brossard (2012) developed a model of bank distress based on Merton KMV distance-to-default. Using a sample of European banks, they found that the significance of DD was dependent on the efficacy of shareholders' monitoring. The predictive power of DD was satisfactory only when banks' shareholding was characterized by the presence of blockholders.

In the Indian context, Bandyopadhyay (2007) presented a methodology to use the Black-Scholes-Merton structural model to predict financial distress for a sample of Indian firms over the years 1998 to 2005. The methodology involved extracting the market value of assets and asset volatility of companies from their stock market and balance sheet information. He found that the option model was capable of providing ordinal ranking of companies on the basis of their default risk. Mishra *et al.* (2008) used the traditional Black-Scholes-Merton framework to estimate the default probabilities for selected Indian firms covering a period from 1998 to 2004. However, their sample size was small comprising of only 12 firms. They found that the Merton model estimates depend significantly on the equity price volatility. Sinha *et al.* (2013) used the Merton model for estimating the market value and volatility of banks' assets in India for a small sample of 13 public and 8 private sector banks. They found the market value of banks' assets obtained from Black-Scholes-Merton to be below its enterprise value. The volatility of banks' assets was found to be significantly different for public and private sector banks.

Thus, limited number of studies have been done in the Indian context. Even the ones that exist are insufficient due to certain reasons such as the use of traditional and complex Merton model, relatively older study period and smaller sample sizes. The present study attempts to fill this gap by investigating the utility of the Merton model in India using a simplified version of the Merton model that can be easily operationalized by practitioners, a reasonably larger sample size of 135 defaulting firms and is done in a more recent period covering the post global financial crisis period.

3. Data and methodology

3.1 Sample selection and description

The rating agencies in India assign a 'D' rating to firms that have had an instance of a default wherein they have missed payment on their rated financial instrument. This study adopts the definition of default in line with that used by the rating agencies. Four rating agencies, namely, ICRA, CRISIL, CARE and Fitch (India) have been used as the source for the sample of defaulting firms. The data covers the period from 2000-01 to 2011-12. The data related to the stock prices and financial statements is collected from the CMIE Prowess database.

The sample for the study consists of listed firms due to the presence of market-based variables in the model. 135 listed firms have defaulted during the period under consideration. Matched pair sampling technique has been used to form the sample of non-defaulting firms, as has been prevalent in several prior studies (Beaver, 1966; Beaver, 1968; Altman; 1968; Zavgren, 1985; Begley *et al.*, 1996; Bandyopadhyay, 2006; Adiana *et al.*, 2008; Lifshutz and Jacobi, 2010; and Rashid and Abbas, 2011). Each defaulting firm is paired with a non-defaulting firm matched on the basis of the closest asset size, industry and year. Hence, the sample for the study has 135 defaulting firms and 135 non-defaulting firms resulting into a full sample of 270 firms.

The sample is partitioned into estimation sample and hold-out sample. This is a widely accepted method used to test the efficiency of the model. The estimation sample is used to estimate the parameters of the predictor variables. Whereas the hold-out sample is used for testing how the model performs when applied to a different sample of firms not used for estimation. Using any other financial or economic indicator in order to align the debt servicing capability at the market value might not be able to reflect the performance of the model used in the study.

Since the number of observations is not distributed uniformly across all years, splitting the sample year-wise would have resulted into very few observations in the estimation sample. A year-wise splitting has thus been avoided. The sample of firms from 2000-01 to 2010-11 is taken as the estimation sample and the sample of firms in 2011-12 as the hold-out sample. Considering the distribution of the firms across the study period, the hold-out sample has been taken as one year. Any period more than a year would be suboptimal as it would render less number of firms in the estimation sample as compared to the hold-out sample. As a result, 180 firms constitute the estimation sample (90 defaulting and 90 non-defaulting firms) and 90 firms (45 defaulting and 45 non-defaulting firms) constitute the hold-out sample.

3.2 Statistical technique

Logistic regression, multiple discriminant analysis, neural networks (Wu *et al.*, 2008; Muller *et al.*, 2009; Jardin, 2010), genetic programming (Etemadi *et al.*, 2009), support vector machine (Kim and Sohn, 2010; Min *et al.*, 2011), data envelopment analysis (Premchandra *et al.*, 2011), and self-organizing maps (Jardin and Severin, 2011) have been the commonly used statistical techniques for financial distress prediction. A comprehensive review of the use of such statistical techniques for bankruptcy prediction in banks and firms has been done by Kumar and Ravi (2007).

Logistic regression and multiple discriminant analysis have been the most dominant ones among the various alternative statistical techniques. Some studies find logistic regression to be more efficient than multiple discriminant analysis (Ohlson, 1980; Zavgren, 1985; Lennox 1999), whereas other studies show that both the techniques work equally well (Gu, 2002; Aziz and Dar, 2006). Bhunia and Sarkar (2011) argue in favour of multiple discriminant analysis as being a potent statistical technique for the purpose of classification regardless of some of its limitations.

This study considers both logistic regression as well as multiple discriminant analysis appropriate for classification, given that it intends to classify firms as defaulters and non-defaulters and estimate their probability of default, with certain set of characteristics for the predictor variables.

Logistic regression is a non-linear predictive modeling technique that aids in estimating the probability of occurrence of an event or outcome. For the purpose of this study the event of interest is default. As the outcome or dependent variable can assume only two values i.e. default or no default, binary logistic regression has been employed. The probability of the occurrence of the event is ascertained as:

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

Where,

$P(Y)$ = probability of the event Y occurring

Z = linear combination of independent variables represented as:

$\beta_0 + \beta_1X_1 + \beta_2X_2 + \beta_3X_3 + \ldots\ldots\ldots + \beta_nX_n$

The regression coefficients in logistic regression are estimated using the maximum likelihood method. This method consists of an iterative process that maximizes the likelihood of predicting the observed values of the dependent variable using the observed values of the independent variables.

As is known, multiple discriminant analysis aids in classifying observations into one of the several a priori groups given the observations' characteristics. For the present study, the firms have been classified into two groups, defaulting and non-defaulting firms. A discriminant function, which is a linear combination of certain independent variables, is used for classifying the firms into two groups i.e. defaulting and non-defaulting firms. The outcome of the discriminant function is a score that is used to determine the group membership of the observation. The discriminant score is represented as:

$$Z = a + b_1X_1 + b_2X_2 + b_3X_3 + \ldots\ldots\ldots\ldots + bnX_n$$

Where,

Z = discriminant score

a = constant

b_i = discriminant weight for independent variable X_i

X_i = independent variable

3.3 Variable description

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

Distance-to-default denotes the number of standard deviations that the firm value is from the point of default. Lower values of this variable show that the firm is closer to the default point and there is larger probability of default. For estimating the distance-to-default the traditional Merton model uses the following process.

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

$$dV = \mu V dt + \sigma_V V dW$$

Where,

V = total value of the firm
μ = expected continuously compounded return on V
σ_V = volatility of firm value
dW = standard Wiener process

The second assumption of the model is that the firm has issued only one single zero-coupon bond maturing in *T* periods (one year). Some of the other assumptions of the model are as follows. Refinancing and renegotiation of the firm's debt obligations is not allowed, liquidation of the firm is costless and default boundary is constant. The model recognizes that neither the underlying value of the firm nor its volatility is directly observable. Under the model's assumptions both can be inferred from the value of equity, the volatility of equity, and other observable variables by using an iterative procedure to solve a system of nonlinear equations.

The equity value of a firm satisfies the following.

$$E = VN(d_1) - e^{-rT} FN(d_2)$$

Where,

E = market value of the firm's equity
V = market value of the firm's assets
F = face value of the firm's debt
r = instantaneous risk-free rate
T = time to maturity of the firm's debt
$N(\cdot)$ = cumulative standard normal distribution function
$d_1 = \dfrac{\ln(V/F) + (r + 0.5\sigma_V^2)\, T}{\sigma_V \sqrt{T}}$
$d_2 = d_1 - \sigma_V \sqrt{T}$

The volatility of the firm's value, σ_V, is related to the volatility of the firm's equity, σ_E, by the following expression.

$$\sigma_E = (V/E)\, N(d_1)\, \sigma_V$$

Solving the above two non-linear system of equations gives the firm's value, V, and its volatility, σ_V. These two variables along with the face value of the debt, F, are inputs for estimating the distance-to-default or DD, which is defined as:

$$DD_{Merton} = \frac{\ln(V/F) + (r - 0.5\sigma_V^2)T}{\sigma_V \sqrt{T}}$$

Bystrom (2006) proposes a simplified spreadsheet version of the Merton model that makes use of only observable parameters i.e. the book value of the firm's debt and the market value and volatility of the firm's equity in order to estimate the distance-to-default. This simplified version is based on three assumptions with respect to equations (3) and (4): First, since in most practical situations the drift term, $(r - 0.5\sigma_V^2)T$, is found to be small and empirically it is very difficult to estimate the drift rate of stocks or other assets, this is assumed to be zero. Second, only in extreme cases where V is close to F (the option is almost at the money) and the underlying asset volatility is very high is $N(d_1)$ significantly different from one. Hence, $N(d_1)$ is assumed to be close to 1. Third, since it is the book value of debt that needs to be paid back and not the market value of debt, the book (face) value of debt is used to calculate the leverage ratio, F/V.

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

$$DD = \frac{\ln(V/F)}{\sigma_V}$$

Further, replacing σ_V with $\sigma_E E/V$ using $\sigma_E = (V/E)\, N(d_1)\, \sigma_V$ (as stated earlier) and the second assumption of $N(d_1)$ being close to one, we get:

$$DD = \frac{\ln(V/F)}{\sigma_E E/V}$$

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

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

Where,

L = leverage ratio estimated using the market value of equity E and book value of debt F and calculated as F/(E +F)

σ_E = volatility of the firm's equity

As argued by Bystrom (2006), apart from being intuitive and simple, his measure of distance-to-default highlights the drivers of default namely, a firm's leverage ratio and equity volatility. While the Merton model's assumption of constant debt lacks empirical support, the modified version is more dynamic in terms of favouring a constant leverage ratio, which is more realistic. Considering that the measure can be estimated for any firm regardless of its capital structure or asset volatility, Bystrom (2006) argues that his measure could be effective in estimating the default probabilities of firms in emerging markets as well as those operating in volatile markets. The distance-to-default measures obtained by his model are empirically shown to be very similar to those calculated using the original Merton model. The measure has the advantage of simplicity along with obtaining values that are similar to the traditional Merton model. Thus, for the present study, the modified version of the distance-to-default as developed by Bystrom (2006) has been used.

4. Results

4.1 Results of logistic regression

The results of logistic regression for the option based model are reported in Table I. The model Chi-square is significant at 0.01 level which shows that the overall model is significantly better in predicting defaults. The Nagelkerke R^2 shows that 17.3% variation in the dependent variable can be explained by the independent variable. The option based distance-to-default is statistically significant in predicting defaults.

Insert Table I here

Table II reports the classification matrix for the model using logistic regression. The estimation sample has an overall classification accuracy of 63.3%. The parameters estimates for the variables, as reported in Table I, are used to estimate the default probabilities of firms in the hold-out sample as following.

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

Where,

P(Y) = probability of default

Z = 1.809 - 0.863 Distance-to-default

The cut-off probability is 0.5 for groups of equal sizes. Hence, firms having a default probability greater than 0.5 are classified as defaulting and those having a default probability less than 0.5 as non-defaulting. Using this procedure, the hold-out sample has an overall classification accuracy of 54.4%. The results between the estimation sample and hold-out sample, in terms of the number of defaults and non-defaults ratio, are varying as reported in Table II. The hold-out sample has a lower ratio of defaults to non-defaults correctly classified as compared to the estimation sample. This is probably because the cut-off probability of 0.5, above which the firms are classified as defaulting, is too high, leading to misclassification of some defaults as non-defaults.

Insert Table II here

4.2 Results of multiple discriminant analysis

Table I reports the results of the multiple discriminant analysis for the model. Statistically significant Chi-square value of the function shows its good discriminating ability. How well the function separates observations into groups is measured by the Wilks' lambda of the discriminant function. It indicates the proportion of variance in the discriminant score not explained by the difference between the groups. Thus, a lower value of this statistic is an indicator of greater discriminatory ability of the function. The association between the discriminant function and the discriminant score is indicated by the Canonical correlation. Squaring the canonical correlation gives the R^2 i.e. the percent variance in the discriminant score explained by the independent variables. Here, the function has a Wilks' lambda of 0.890 and R^2 of 0.110, as shown in Table I.

The discriminant score or the Z-score for classifying the observations into the respective groups is computed using the unstandardized coefficients, as reported in Table I. Thus, using these coefficients for the variables the discriminant function can be represented as:

$$Z = -1.889 + 0.853 \text{ Distance-to-default}$$

Table III reports the classification matrix. Consistent with the results of logistic regression as reported in section 4.1, the estimation sample has an overall classification accuracy of 63.3%. The discriminant function is used to estimate the Z-scores for firms in the hold-out sample and classify them into the respective groups as described above. The hold-out sample has an overall classification accuracy of 61.1%, which is higher than that obtained using logistic regression. There is greater misclassification of defaults as compared to non-defaults in the hold-out sample. This is probably because the cut-off discriminant score, below which the firms are classified as defaulting, is too low, leading to misclassification of some defaults as non-defaults.

Insert Table III here

4.3 Cumulative accuracy profile

Moody's Cumulative Accuracy Profile (CAP) has been used as an alternative tool to assess the quality of default prediction of the model. As described by Sobehart *et al.* (2000), the CAP curve represents the cumulative probability over the entire population. To plot the cumulative accuracy profiles, companies are first ordered from riskiest to safest. For a given fraction x% of the total number of companies, a CAP curve is constructed by calculating the corresponding number of defaulting companies as a percentage of the total number of defaulting companies. A good model clusters the defaulters at the riskiest scores and so the percentage of all defaulters identified (on the y axis) increases quickly as one moves up the sorted sample (along the x axis). A totally uninformative random model would capture a proportional fraction, i.e., x% of the defaulters with about *x%* of the observations, resulting into a straight line or Random CAP. Figure 1 shows the Cumulative Accuracy Profile for the option based model (solid line). The CAP for the model is well above the random model (dotted line) indicating that the model carries useful information in predicting defaults.

Insert Figure 1 here

4.4 Impact of inclusion of another variable

As shown by the analysis so far, in absence of any other information, the distance-to-default proves to be significant as a sole predictor of default. However, it would be worthwhile to examine if the addition of any other variable affects its significance. For this purpose, the Altman's Z-score has been added to the regression. As shown in Table I, the distance-to-default retains its significance even after the addition of Altman's Z-score. However, the Altman's Z-score is insignificant with Wald statistic close to zero.

5. Discussion

The option based distance-to-default is found to be statistically significant in predicting defaults. This is consistent with Jessen and Lando (2015), who find the distance-to-default to be, by and large, successful in estimating the firms' default probabilities. Distance-to-default has a significantly negative relationship with the probability of default, which is consistent with previous studies (Papanastasopoulos, 2007; Campbell *et al.*, 2008; Xu and Zang, 2009). This implies that smaller the value of this variable higher the probability of default.

The robustness of distance-to-default is established as it is found to be significant even after the addition of Altman's Z-score. However, unlike some other studies (Hillegeist *et al.*, 2004 and Agarwal and Taffler, 2008) the Altman's Z-score is insignificant with Wald statistic close to zero. This may be probably because the Altman's Z-score has very little information content for predicting the probability of default.

This study contributes to the literature by establishing the significance of a simplified version of the Merton model that can be easily operationalized by practitioners. As shown in this study, accounting information (in the form of Altman's Z-score) is found to meagerly contribute in default prediction. This finding probably questions the reliability and quality of such information in attempting to estimate the debt servicing capacity of the firm. Consequently, future researchers may incorporate some other variables in the analysis such as the quality of accounting information and financial reporting, quality of management, etc. Further, other alternative market based measures of default prediction may also be explored.

6. Conclusion

Financial default prediction has come a long way since the traditional models that relied on information from the financial statements. The option based model has continued to be extensively used by researchers. However, the extant studies provide mixed empirical evidence on the usefulness of the model in predicting defaults. Limited number of studies have been done in the Indian context. Even those that exist are insufficient due to certain reasons such as the use of traditional and complex Merton model, relatively older study period and smaller sample sizes. This study contributes to the literature by investigating the utility of the Merton model in India using a simplified version of the Merton model that can be easily operationalized by practitioners, a reasonably larger sample size and is done in a more recent period covering the post global financial crisis period.

This paper aims to assess the significance of the Merton distance-to-default in predicting defaults. The study uses logistic regression and multiple discriminant analysis for a matched pair sample of defaulting and non-defaulting listed Indian firms. Consistent with some previous studies, the option based distance-to-default is found to be statistically significant in predicting defaults and has a significantly negative relationship with the probability of default. The distance-to-default retains its significance even after the addition of Altman's Z-score. This further establishes its robustness as a significant predictor of default. A plausible limitation of the study is that the sample consists of only listed firms due to the presence of market-based variables in the model.

Although the traditional Merton model provides the theoretical base for assessing default risk it is difficult to implement due to certain complex and unpractical assumptions. The study bridges the gap between theory and practice by providing empirical evidence on the utility of a modified, simple, practical and easily adaptable measure of default risk derived from directly observable variables.

The findings of the study have important implications for lending and investment decisions. The study re-establishes the utility of option based distance-to-default as a significant predictor of defaults and having an ability to capture important information relating to the creditworthiness of a firm. This might serve as a predictive tool to lenders, particularly banks and financial institutions and investors for managing their exposures efficiently and determining the appropriate risk premium, which might be of use in their loan pricing. The findings of the study also have important implications for managers and other stakeholders. The potential direct as well as indirect costs of financial distress can be avoided by timely and accurate assessment of default risk.

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Figure 1. Cumulative accuracy profile for the model

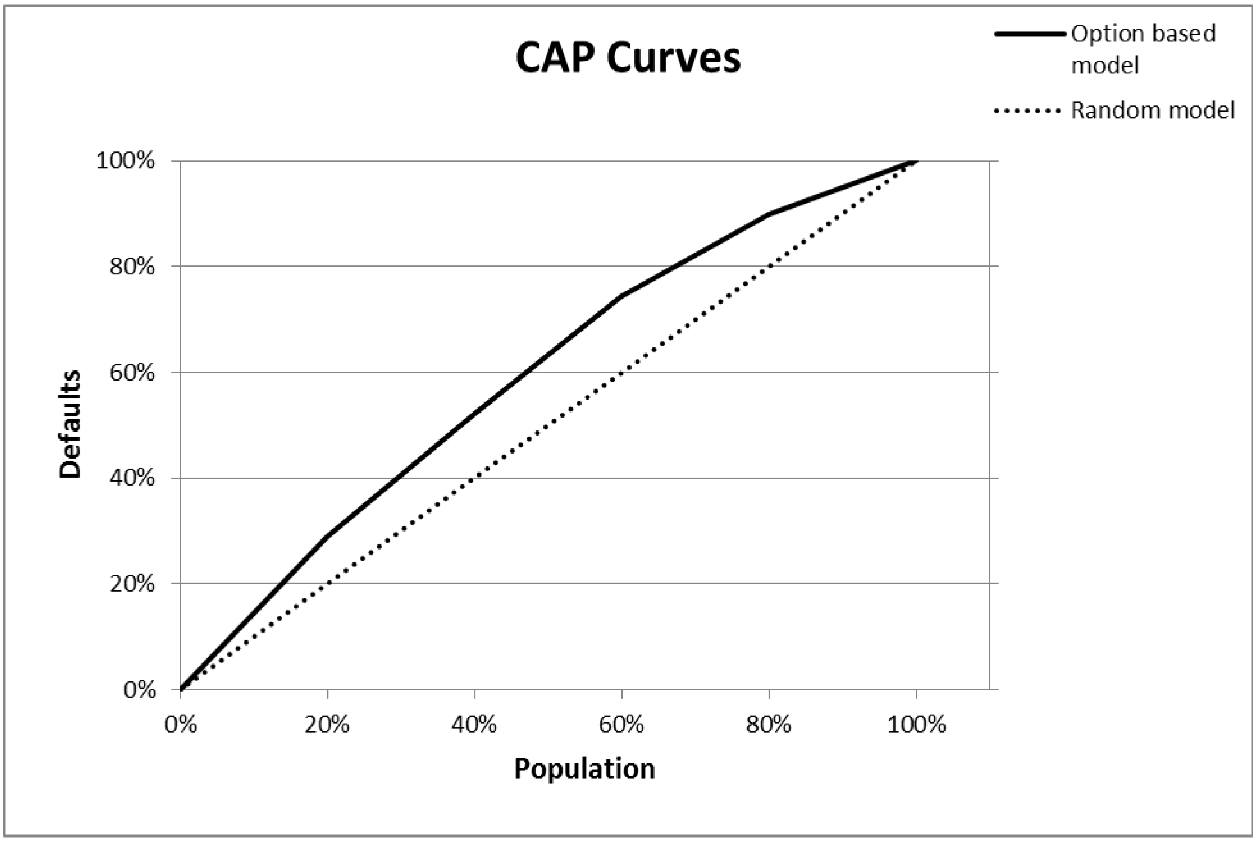

Table I. Result of logistic regression and multiple discriminant analysis

Variables	*Logistic regression*	*Logistic regression (with Altman's Z-score included)*	*Multiple discriminant analysis*
	Beta coefficient (Wald statistic)	**Beta coefficient (Wald statistic)**	**Unstandardized coefficients**
Constant	1.809*** (14.538)	1.811*** (14.409)	-1.889
Distance-to-default	-0.863*** (14.671)	-0.865*** (13.821)	0.853
Altman's Z-score		0.001 (0.001)	
-2 Log likelihood	224.560	224.560	
Chi-square	24.973***	24.974***	
Nagelkerke R^2	0.173	0.173	
Canonical correlation			0.332
R^2			0.110
Wilks' lambda			0.890
Chi-square			20.779***

Note: *** denotes statistical significance at 0.01 level

Table II. Logistic regression classification matrix

Estimation sample	Predicted group		
Observed group	Defaults	Non-defaults	Total
Defaults	69[a] (76.7%)	21 (23.3%)	90 (100%)
Non-defaults	45 (50%)	45[b] (50%)	90 (100%)
Overall accuracy	76.7%	50%	63.3%[c]
Hold-out sample	Predicted group		
Observed group	Defaults	Non-defaults	Total
Defaults	15[a] (33.3%)	30 (66.7%)	45 (100%)

Non-defaults	11 (24.5%)	34[b] (75.5%)	45 (100%)
Overall accuracy	33.3%	75.5%	54.4%[c]

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

Table III. MDA classification matrix

Estimation sample	Predicted group		
Observed group	Defaults	Non-defaults	Total
Defaults	74[a] (82.2%)	16 (17.8%)	90 (100%)
Non-defaults	50 (55.6%)	40[b] (44.4%)	90 (100%)
Overall accuracy	82.2%	44.4%	63.3%[c]
Hold-out sample	Predicted group		
Observed group	Defaults	Non-defaults	Total
Defaults	22[a] (48.9%)	23 (51.1%)	45 (100%)
Non-defaults	12 (26.7%)	33[b] (73.3%)	45 (100%)
Overall accuracy	48.9%	73.3%	61.1%[c]

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

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