Chapter 2

Review of Literature

2.1 Introduction

Interest in credit risk as a topic for research has grown as the subject has increasingly assumed global significance. In this chapter the available literature on the subject has been reviewed to understand the dimensions of research done so far and to identify any research gaps. Study and research on credit risk follows two broad streams. First, there is extensive literature on credit risk itself. This has been one of the more active areas of recent financial research, as credit risk has found multiple applications in finance. These include traditional activities like portfolio management; newer markets like credit derivatives trading which have seen rapid growth in volumes; & also future events such as the anticipated adoption of the revised Basel Capital Accord. Besides, the regulatory response to the sub-prime crisis has focused heavily on credit risk. Within this stream of study on credit risk, research has analyzed the meaning, role, and influence of credit ratings.

The second strand of literature is on the credit risk models. Though credit ratings find wide application as barometers of default risk, several credit risk models have also been proposed by both academicians and practitioners as alternative measure of credit risk.

The first section of literature review on credit ratings has been subdivided into sections as follows:

(i) Information content of credit rating.
(ii) Rating determinants and stability.
(iii) Impact of cyclicality on credit ratings.
(iv) Research on rating transitions.
(v) Internal ratings by banks.

In the second section of literature review on credit risk models, there are sub-sections based on the different models:

(i) Accounting models.

(ii) Structural models.

(iii) Portfolio reduced form models and Markov chain models.

(iv) Factor models.

(v) Other credit risk models

The objective of dividing the literature review into sections and sub-sections is to get a better understanding on the subject of research study.

2.2 Literature review on credit rating

Given the relevance of credit ratings in measuring credit risk or the risk of default, the research on credit ratings is vast. In this section, research on some of the broad issues relating to credit ratings has been mentioned.

2.2.1 Information content of credit ratings

CRAs play a key role in financial markets by helping in reducing the informational asymmetry about the creditworthiness of companies (corporate risk) between lenders and investors on one side, and issuers on the other side. For most of their history, credit ratings alone have been relied on to measure and rank the relative creditworthiness of debt issuers. It is felt that the credit ratings convey information about the company’s future earnings to the capital markets. Moreover, information on credit ratings for a company impact financing and investing decisions. Hickman (1958) in his seminal study found that default rates increased monotonically with lower credit ratings. He further stated that rating agencies are impacted by the cyclicality of the economy.
Ramakrishnan and Thakor (1984) attributed the existence of rating agencies to the economics of information argument. They identified credit rating agencies as intermediaries of information. Their model suggested that information intermediaries are formed with the objective of lowering production costs.

Millon and Thakor (1985) took a different view on the existence of information gathering credit rating agencies. They argued that information gathering agencies are welfare enhancing even if the role of monitoring is neglected. They were of the view that the benefits from rating agencies accrued from two sources: (i) the diversification benefits to risky payoffs which result in the overall risk being reduced for risk-averse individual agents; & (ii) benefits of sharing information. The authors differed from Ramakrishnan and Thakor (1984) in two regards: (i) there was no information sharing in Ramakrishnan and Thakor (1984); & (ii) Millon and Thakor (1985) were of the opinion that internal monitoring is neglected by the rating agencies.

Lizzeri (1999) studied optimal disclosure policies of an intermediary who learns perfectly the information about the quality of the seller and communicates it to the buyer. The author showed a unique equilibrium in which all types of sellers pay to be rated. However, the intermediary does not disclose any information except that the seller has obtained a rating. Since the benefit of a rating is higher for better types of sellers, the coverage of the market is determined by the lowest rated type. To increase the willingness of this type to pay, the intermediary pools all better types. This implies that the buyer is ready to pay the same price regardless of whether the quality is known for sure or is uncertain. In other words, the buyer does not value the precision of information disclosed by the intermediary.

In addition to the rating level, credit rating actions – rating upgrades and downgrades – signal changes in rating agencies’ opinions of relative credit risk, and therefore, in realized default risk. Altman and Kao (1992) and Altman and Saunders (1998) first documented the now well-known phenomenon of ratings momentum; credit rating
downgrades tend to be followed by further downgrades, and conditional on a downgrade, default risk is many times higher.

Boot and Milbourn (2002) stated that credit rating agencies not only act as information providers but also act as watchdogs over the credit quality of borrowers. They further said that there is a positive fraction of investors who believe in the ratings and base their investment decisions on these ratings. Although the behavior of the rating agency itself is not analyzed, the rating function is explicitly modeled and is a single variable monotonic function of the unconditional credit quality of the firm. They assumed that ratings are absolute and since the rating function is deterministic, it remains invariant over time.

Hull, et al. (2004) analyzed data on credit default swap spreads collected by a credit derivatives broker. The first objective of the research was to examine the relationship between credit default swap spreads and bond yields. They found that reviews for downgrade contain significant information, but downgrades and negative outlooks do not. The second objective of their study was to examine the relationship between credit default swap spreads and announcements by rating agencies. They concluded that either credit spread changes or credit spread levels provide helpful information in estimating the probability of negative credit rating changes.

Doron, et al. (2009) believed that negative cross-sectional relation between dispersion in analysts' earnings forecast and future stock returns can be explained by financial distress, as proxied by credit rating downgrades. The research focused on a sample of firms rated by S&P. The findings showed that the profitability of dispersion-based trading strategies concentrates in a small number of the worst-rated firms and is significant only during periods of deteriorating credit conditions.

Jorion and Zhang (2010) conducted research on the information transfer effects of bond rating downgrades. These transfer effects of bond rating downgrades were measured by equity abnormal returns for industry portfolios. The authors were of the opinion that industry rivals can be subjected to two opposing effects, the contagion effect and the
competition effect. For investment grade (speculative grade) firms, industry abnormal equity returns are negative (positive), which implies a predominant contagion (competition) effect. The findings revealed a pattern of positive and negative correlations across negative credit events, to be used to improve understanding of portfolio credit risk models.

2.2.2 Rating determinants and stability

Several studies have been conducted on assessing the rating standards; to what extent can there be improvements in the quality of ratings and consistency in the ratings awarded. Rating agencies maintain that their ratings should generally be stable through credit cycles. However, prompted by the large number of rating downgrades during the period 2001–2002 and the enhanced role proposed for ratings in bank regulation under Basel II, market participants have expressed concern about the stability of ratings over the credit cycle.

Blume, Lim, and Mac Kinlay (1998), hereafter BLM, reported a secular tightening of rating agency standards, and concluded that it became more difficult for firms to obtain high ratings in the mid-1980s and early 1990s. BLM’s panel regression of the determinants of ratings included annual dummies and a measure of firm size (market capitalization). They documented that credit ratings have, on average, become worse through time, conditional on a set of variables that proxy for the financial and business risks of the rated firm. Their findings showed that the standards of ratings agencies have become more stringent over time. Altman and Rijken (2004) took cognizance that panel regression estimates of rating determinants implicitly assume that ratings adjust instantaneously to new information. The authors compared actual rating transitions to those implied by various point-in-time rating models. Using a fixed set of explanatory variables, they estimated a default prediction and rating prediction model. The coefficients on the rating prediction model more closely resembled those of the long-term default prediction model than those of the short-term default prediction model. They
concluded that agencies’ focus on long-term investment horizons only partly explains the relative stability of agency ratings.

Prakash (2005) applied a combination of structural models of default and econometric model of ratings to study the determinants of rating standards. He hypothesized that the standards of a rating agency are conditional upon the distribution of default risk in the economy at the time. He conducted an empirical analysis of the classification errors using receiver operating characteristic analysis. The results suggested that error rates decrease at the extreme ends of the rating spectrum over time while they increase in the middle rating categories. An important issue that was explored in his work was whether ratings are an accurate reflection of the cardinal measure of probability of default.

Hamilton, et al. (2006) quantified the rating transitions and default rates when conditioned on rating history and outlook Watch list status. They also analyzed how much the predictive power of Moody’s credit ratings is increased by recognizing the information contained in rating outlooks and reviews. They examined to what extent rating outlook assignments affect investors’ view on credit risk as reflected in market prices of credit default swaps (CDS).

Cheng and Neamtiu (2009) observed that credit rating agencies faced increased regulatory pressure and investor criticism for their ratings’ lack of timeliness. They concluded that credit rating agencies improve their rating timeliness in the period following increased regulatory scrutiny and investor criticism brought about by several high-profile bankruptcy scandals. They also concluded that the rating agencies improve rating accuracy and reduce rating volatility in the post-regulatory period, suggesting that credit rating agencies enhance rating timeliness by improving their credit analysis, and not by sacrificing rating accuracy and/or volatility.

Stolper (2009) observed a repeated principal-agent problem in which a regulator approves credit rating agencies. They were of the opinion that though credit rating agencies may collude to assign inflated ratings; yet there exists an approval scheme which induces
credit rating agencies to assign correct ratings. The conclusion from the research was that if credit rating agencies do not collude to offer inflated ratings, the regulator can filter out the common shock by evaluating the relative performance of credit rating agencies. If the credit rating agencies’ discount factor is sufficiently high, the threat to deny approval in future periods can deter credit rating agencies from offering inflated ratings.

2.2.3 Impact of cyclicality on credit ratings

One of the key tasks of the credit rating agencies is to measure the credit risk and to examine to what extent they are prone to fluctuations in cyclical trends. One important challenge in measuring credit risk is the identification of systematic risk exposures over the business cycle. In particular, often it is desirable to have measures of credit risk that are unaffected by cyclical fluctuations (e.g. long-horizon investment strategies and capital allocation). Credit ratings can play a key role in this case. One of the main goals of rating agencies is to assign ratings that are insensitive to undue cyclical influences.

Unlike bank lending standards, bank supervisors and credit risk models, credit ratings are not supposed to vary in a pro-cyclical manner. Instead, credit ratings are intended to distinguish the relatively risky firms (or specific bonds) from the relatively safe. To do so, credit ratings need not reflect an absolute measure of default risk, but are rather intended to be ordinal rankings of risk at a particular point in time. In fact, rating agencies insist that their ratings should be interpreted as ordinal rankings of default risk that are valid at all points in time rather than absolute measures of default probability that are constant through time.

Thus there can be two aspects of ‘through-the-cycle-rating’ concept of rating agencies. The first aspect of this rating methodology is the disregard of short-term fluctuations in default risk. The second aspect is the enhancement of rating stability by a prudent migration policy. Only substantial changes in the permanent component of default risk result in rating migrations, and if triggered, ratings are partially adjusted to the actual
level in the permanent component of default risk. The research investigations carried out in this area of credit ratings are summarized below.

Treacy and Carey (1998) described the through-the-cycle rating methodology as a rating assessment in a worst case scenario, in the bottom of a presumed credit quality cycle and believed that banks do not employ this approach when they assign internal credit ratings to their borrowers.

Carey and Hrycay (2001) described the through-the-cycle methodology as a rating assignment based on a stress scenario. They opined that when firms are consequently rated in the bottom of the credit quality cycle, agency ratings are insensitive to the credit quality cycle and focus on the long term horizon. Contrary to agency ratings, bank ratings are usually based on the actual default probability over a specific horizon. They labeled such ratings as current-condition or point-in-time ratings.

Cantor and Mann (2003) stated that the objective of rating agencies is to provide an accurate relative (i.e. ordinal) ranking of credit risk at each point in time, without reference to an explicit time horizon. They were of the opinion that the through-the-cycle methodology aims at avoiding excessive rating reversals, while holding the timeliness of agency ratings at an acceptable level. An alternative interpretation of through-the-cycle methodology is to extract the permanent component from changes in the observed credit quality, on the basis of a forecasting analysis. They concluded that even though an issuer might experience a change in its financial performance as a result of an adjustment in the macroeconomic environment, its rating may nonetheless remain unchanged if it is likely that its previous financial condition will be restored during the next phase of the cycle.

Loffler (2004) explored the through-the-cycle effects on rating stability and default prediction performance in a quantitative manner by modeling the separation of permanent and temporary components of default risk. He used a structural model of default in a time series setting and derived predictions about rating characteristics if ratings are meant to look through the cycle as opposed to being based on the borrower’s current condition.
The findings revealed that several empirical irregularities of agency ratings could be the consequence of such a rating method. The stability of through-the-cycle ratings is relatively high, while their default prediction power is low. Ratings are not perfectly correlated with actual default risk, and they are correlated with past rating changes provided contemporaneous information is controlled for.

Altman and Rijken (2004) quantified the impact of the long term default horizon and the prudent migration policy on rating stability from the perspective of an investor; without rating stability. This was done by benchmarking agency ratings with a financial ratio-based (credit scoring) agency rating prediction model and (credit scoring) default prediction models for various time horizons. By varying the time horizon in the estimation of default prediction models, they concluded that in contrast to one-year default prediction models, agency ratings place less weight on short term indicators of credit quality and are focused on the long term.

Amato and Furfine (2004) assessed the influence of the state of the business cycle on credit ratings. Their analysis was based on a model of ratings that included factors as a measure of business and financial risks of firms and indicators of macroeconomic conditions. They applied an ordered probit model to predict a firm’s credit rating, and found no evidence that credit ratings were unduly influenced by the business cycle. They found that ratings do not generally exhibit excess sensitivity to the business cycle.

### 2.2.4 Internal ratings by banks

There has been increasing emphasis on the internal rating-based models (IRBs) used by banks to assess and measure the creditworthiness of their customers. These models are regarded as a credit management tool that can improve the precision and consistency of the loan origination process. The Basel Committee on Banking Supervision (2001,2006) is encouraging banks to adopt the internal rating-based models gradually on the assumption that external ratings may not be adequate. During the last few years, most approaches in credit risk modeling involve the estimation of three parameters: (i) the
probability of default (PD) on individual loans; (ii) the estimate of the loss given default (LGD); & (iii) the correlation across defaults and losses. Some of the studies on the internal ratings by banks are stated below.

Treacy and Carrey (2000) suggested that in designing a credit rating system, a bank should consider numerous factors, including cost, efficiency of information gathering, consistency of ratings produced, staff incentives, nature of a bank’s business, and uses to be made of the internal ratings. They observed that the proportion of grades used to distinguish among relatively low risk credits versus the proportion used to distinguish among riskier pass credits tend to differ with the business mix of a bank. They concluded that a rating system with more rating categories is better than a system with just a few categories.

Resti and Omacini (2001) were of the opinion that internal ratings represent an important input to the new generation of “credit portfolio models” and to the new capital requirements proposed by the Basel Committee. They explained the main theoretical and practical aspects of the relevance gained by internal ratings in the banks' operating practices and in the reform proposals on bank capital regulations. Their methodology included setting up a binomial model using discriminant analysis to capture the main drivers of a borrower's default, and then to develop a multinomial model to factor the judgments issued by human experts. Their conclusions were that the inconsistencies between the default model and the rating model could be due to some psychological factors that bias the behavior of credit analysts.

Rosch (2005) found that the Basel Capital Accord allowed the determination of banks’ regulatory capital requirements due to probabilities of default (PDs) which are estimated and forecasted based on internal ratings. Broadly, two rating philosophies are distinguished in their research, through-the-cycle versus point-in-time ratings. They employed a likelihood ratio back testing of both types with respect to the probability of default forecasts and correlation derived from a non-linear random effects panel model
using data from Standard & Poor’s. They believed that point-in-time ratings exhibit much lower correlations and thus, default probability forecasts should be more precise.

Stefanescu, et al. (2009) developed a model that described the typical internal credit rating process used by banks. The model captured patterns of obligor heterogeneity and ratings migration dependence through unobserved systematic macroeconomic shocks. A Bayesian hierarchical framework was described for model calibration from historical rating transition data. A rating transition data set from Standard and Poor's during 1981-2007 was analyzed. The results had implications for the Basel II policy debate on the magnitude of default probabilities assigned to low risk assets.

2.2.5 Rating transition

A popular tool used by bond market participants to gauge the prospects that a firm will be downgraded or upgraded is rating transition matrices. Credit risk modeling has been emphasized in the recent research works driven by advancements in portfolio management and growing markets for derivatives. Moreover, with the Basle II, the Basel Committee on Banking Supervision (2006) has recommended that banks can use their own internal rating-based models (IRBs) in addition to external ratings. This has led to several studies on rating transitions.

Rating agencies often report transition matrices computed from their own rated firms on a regular basis. The matrices represent a historical measurement of firm’s movements across rating classes over a specific time horizon. The absorbing state in the matrices is an actual default event or transition to non-rated.

Developments in credit ratings commonly reveal an improvement or deterioration in the credit-worthiness of a firm. Although rating agencies primarily meant to utilize credit ratings to signify the current credit quality, several theories used the rating transition phenomenon to forecast default events, or to price risky bonds.
Belkin, *et al.* (1998) and Nickell, *et al.* (2000) showed that transition matrices of bond ratings depend on the business cycle. Belkin, *et al.* (1998) applied a univariate model whereby all ratings respond to business cycle shifts in the same manner whereas Nickell, *et al.* (2000) proposed an ordered, discrete choice model which allowed a transition matrix to be conditioned on the industry, the country domicile, and the business cycle. However, these studies did not consider the rating category specific variables that have an effect on the individual category (e.g. AAA, BB) rating transitions.

Kim (1999) estimated conditional Credit Rating Transition Probability (CRTP) matrices quarter-by-quarter by applying an ordered probit model. The author forecasted the CRTP matrix was done by conditioning on the speculative issuers’ default rate.

Kavvathas (2000) and Lando and Skodeberg (2002) estimated the generation of the continuous time credit rating transition matrices from historical credit rating data. To improve the explanatory and predicting power of their hazard rate models, they included both economy-wide and firm-specific factors as independent variables. They documented that both the previous and current ratings have influence on the rating transition, which suggests that credit rating changes do not follow Markovian processes, as is usually assumed in reduced form credit risk models.

Bangia, *et al.* (2002) in their study proposed that underlying macroeconomic volatility is a key part of a useful conceptual framework for stress testing credit portfolios, and that credit migration matrices provide the specific linkages between underlying macroeconomic conditions and asset quality. By separating the economy into two states or regimes: expansion and contraction, and conditioning the migration matrix on these states, they showed that the loss distribution of credit portfolios can differ greatly, as can the concomitant level of economic capital to be assigned.

Jafry and Schuermann (2004) compared the implications of the two estimation methods; the cohort/multinomial and continuous-time/duration methods to evaluate the importance of relaxing time homogeneity assumption common to both. They developed a new
metrics for comparing transition matrices and showed that the migration matrices have been increasing in ‘size’ since the mid-1990s. They demonstrated that different estimation techniques can imply large differences in portfolio risk capital requirements, larger even than differences implied by moving between a recessionary and expansionary environment. They concluded that ignoring the efficiency gained through duration estimates (relative to cohort methods) is more valuable than the error introduced by imposing a (possibly false) assumption of time homogeneity.

Parnes (2007) examined an alternative approach for simulating credit ratings migration by associating firm's survivability and transitivity to a valuable economic parameter; the market-density. The article contrasted several known methodologies over the S&P long term credit ratings from 1985 to 2004, and authenticated that the density-dependent model is the most realistic scheme. The study concluded that the proposed model statistically and economically dominates the homogeneous Markov chain process, the stochastic business cycles notion, as well as the momentum technique in describing credit rating transitions. Its main advantages rely upon simplicity of deployment, and its improved ability to track observed default patterns.

Koopman, et al. (2008) introduced a new reduced-form model for credit rating transitions. The model was a parametric intensity-based duration model with multiple states, and driven by exogenous covariates and latent dynamic factors. The model had a generalized semi-Markov structure designed to accommodate many of the stylized facts of credit rating migrations. They introduced a multi-state latent factor intensity (MLFI) model for credit rating transitions. The model included a common dynamic component that can be interpreted as the credit cycle. Asymmetric effects of this cycle across rating grades and additional semi-Markov dynamics were found to be statistically significant.

Yoonseong, et al. (2008) proposed a random effect transition model based on multinomial regression to estimate transition probabilities of credit ratings. The authors applied a random effects model, which accommodated not only the environmental characteristics of the exposures of a rating, but also the uncertainty not explained by such
factors. The rating category specific factors such as retained earnings and market equity were included in the proposed model. The credit rating data used for the empirical analysis was obtained from Korea Investors Service (KIS), which offered fixed income securities ratings such as commercial papers, bonds and structured finances.

Eduardo, et al. (2010) used the internal ratings provided by banks to estimate credit quality transition matrices. Using a unique data set on credit ratings of commercial loans in Colombia, they showed that 70% of the time we cannot reject the null hypothesis of time homogeneity of transition matrices estimated this way. They found that obtaining matrices for different sub-samples is not necessary, given the similarities of the survival functions. Results showed that the covariates included in the estimations are jointly significant; therefore they help explain transition intensities/probabilities. This result confirmed the non-Markovian behavior of rating transitions, implying that one can obtain more accurate credit quality transition matrices, for this sample, when conditioned on economic variables.

2.2.6 Models used by credit rating agencies in India for default analysis

2.2.6.1 Transition matrices

A popular tool used by the CRAs in India is to gauge the prospects that a firm will be downgraded or upgraded using rating transition matrices. The matrices represent a historical measurement of firm’s movements across rating classes over a specific time horizon. One clear pattern that emerges is that the probabilities decline gradually when moving away from the diagonal, and thus ratings are sticky. High variability in the matrices over time makes it difficult to draw consistent inferences. On a related note, rating changes tend to exhibit positive serial correlation. Additionally, not only transition matrix vary significantly over time, but they also co vary with economic conditions.
2.2.6.2 Cohort approach

Average default frequencies are simple averages of actual defaults over a time horizon. They reflect neither newly available information arriving in the market, nor distinctions among the firms of the same ratings. The cohort approach obtains default probabilities from transition matrices. The last column in the transition matrices denotes the default frequency of each letter rating class. The duration approach, on the other hand, counts all rating changes over a year and divides them by the time spent in the initial ratings to obtain migration intensity.

2.3 Literature review on credit risk models

Important research studies having relevance to the present work have been reviewed under broad categories viz. (i) studies on accounting models; & (ii) studies on structural models for better clarity and understanding. “The ‘structural approach’ defines both the event that triggers default and the payoffs to the bondholders at default in terms of the assets and liabilities of the firm. The reduced form or statistical approach moves way from the economic notion of bankruptcy and treats default as an event governed by exogenously specified jump process.

Structural models are in general based around a stochastic model of variation in asset-liability ratio. Both classes have their own advantages and disadvantages. Although reduced-form models have a lot of room for calibrating to historical data, they lack the financial ingredient for the model parameters. On the other hand structural models have a nice explanation in financial terms and are rather intuitive, but they lack measuring in particular the short-term credit risk and are much harder to apply when there is more than one name involved. Hence, a framework that would combine the two general classes of models with the merits of both models would be the ideal framework to model credit risk.
2.3.1 Studies on accounting models

Accounting-based models test the usefulness of information contained in the financial statements of a company to provide an adequate assessment of the financial distress risk. The first set of accounting models to assess firms’ risk of bankruptcy was developed by Beaver (1966, 1968) and Altman (1968). Beaver (1966), one of the precursors of modern distress risk assessment, applied a univariate statistical analysis for the prediction of corporate failure.

Altman (1968), developed the Z-Score model to identify accounting variables and financial ratios that separate defaulting and surviving firms. He is among the first to use a discriminate model to predict default probabilities for up to two years prior to actual filings for bankruptcy, by using financial ratios of the underlying firm. Altman’s Z-Score is a measure of a company's health and utilizes several key ratios for its formulation. The model incorporates five weighted financial ratios into the calculation of the Z-Score. An extension to this approach has used linear or nonlinear regression models to directly estimate the probabilities of default. These models allow several ratios and assorted financial data to be considered simultaneously. Logit and probit models are often used. Typically, the greatest variations in the probabilities of default come from ratios capturing firm’s profitability, level of indebtedness, and liquidity. These models can be estimated on cross-sectional or panel data.

2.3.1.1 Altman Z-Score model

The Z-Score is a measure of a company's health and utilizes several key ratios for its formulation. The model incorporates five weighted financial ratios into the calculations of the Z-Score. The model is continuously being updated to incorporate new information. The Altman Z-Score uses the Linear Discriminant Analysis (LDA) to identify five key ratios that can predict bankruptcy for public and private companies. They are:
(i) \( X_1 = \frac{\text{Working Capital}}{\text{Total Assets}} \)
(ii) \( X_2 = \frac{\text{Retained Earnings}}{\text{Total Assets}} \)
(iii) \( X_3 = \frac{\text{Earnings before Interest and Taxes (EBIT)}}{\text{Total Assets}} \)
(iv) \( X_4 = \frac{\text{Market Value of Equity}}{\text{Total Assets}} \)
(v) \( X_5 = \frac{\text{Net Sales}}{\text{Total Assets}} \)

The Z-Score model is easy to calculate and interpret. Therefore it is one of the most widely used credit scoring models. It is observed that higher is the calculated Z-Score of a firm, the healthier it is. Once the respective ratios for a company (publicly or privately held) are calculated, the respective formulas are used to calculate the Z-Score.

If two or more explanatory variable are linearly dependent upon each other, one encounters the multi-co linearity problem in regression estimation. On the right hand side of the Z-Score model, theoretically as well as empirically, one would expect a positive correlation between net sales, EBIT and retained earnings. This makes the model suffer from multi-co linearity. This means that there is unnecessary bias towards a firm which will be classified into non-default zone if net sales are higher. One can expect that if the net sales are higher, then so will be EBIT and retained earnings. In other words, the variables EBIT and retained earnings are not adding any significant information to the model over and above what net sales has done. In fact, this is the classic case of double counting. One possible method of overcoming the multi-co linearity problem is to omit all but one variable that are linearly dependent upon each other. However, that would mean a different model with different explanatory variables.

2.3.1.2 Extensions of Altman Z-Score model

Altman, Haldeman and Narayanan (1977) constructed a second-generation model with several enhancements to the original Z-score approach. The new model called ZETA was effective in classifying bankrupt companies up to five years prior to failure on a sample of corporations consisting of manufacturers and retailers. The ZETA model tests included non-linear (e.g. quadratic) as well as linear discriminate models. The authors presented a
review on international studies conducted in 22 countries in which half of them were on developing countries. The major conclusion of all these studies is that the multivariate techniques such as multiple discriminant analysis (MDA), logistic regression, and probit models built on the basis of accounting ratios are effective tools for predicting default companies.

Subsequently, Altman, Hartzell and Peck (1995) modified the Z-Score model in the context of corporations in emerging markets, especially of Mexican firms that had issued Eurobonds denominated in US dollars. In this enhanced Z-Score model, Altman dropped Sales/Total Assets ratio and used book value of equity ratio for the fourth and final variable to make it more suitable for the private firms.

2.3.1.3 Other accounting models

Ohlson’s O-Score model (1980) is often referred to as residual income model as it expresses firm value as a function of the book value of net assets and the present value of expected residual earnings on those net assets. Ohlson selected nine ratios or terms which he thought should be useful in predicting bankruptcy.

\[
\text{O-Score} = -1.32 - 0.407(\text{SIZE}) + 6.03*(\text{TL}/\text{TA}) - 1.43*(\text{WC}/\text{TA}) - 1.83*(\text{EBDITA}/\text{TL}) + 0.285*(\text{INTWO}) - 1.72*(\text{OENEG}) - 0.52*(\text{Nit-Nit-1})/|\text{Nit1} + |\text{Nit-1}|
\]

Where the variables are as follows:

(i) SIZE is inflation adjusted total assets  
(ii) WC is Working Capital  
(iii) TA is Total Assets  
(iv) TL is Total Liabilities  
(v) CA is Current Assets  
(vi) CL is Current Liabilities  
(vii) NI is Net Income  
(viii) EBDITA is Earnings before Interest and Tax
(ix) INTWO is Indicator equal to ‘1’ if net income was negative for the last two years or ‘0’ if otherwise

(x) OENEG is Indicator equal to ‘1’ if book value of equity is negative or ‘0’ if otherwise.

The log transformation is:

$$\frac{E^{\text{score}}}{1+E^{\text{score}}}$$

The final score is between 0 and 1.

$$P (O \text{ score}) > 0.50 \Rightarrow \text{Failed}$$

Otherwise $$\Rightarrow \text{Non-failed}$$

One eminent and commonly used Z-Score model has been developed by Taffler (1983). He used the same technique as in Altman’s study (1968) to develop the UK-based Z-score model. Taffler (1984) provided a critical review of the outstanding features of the Z-score models documented in the UK.

Zmijewski (1984) developed a model also known as Probit Analysis where first the constant and each parameter of the model is multiplied by 1.8138 and then multiplied by the financial measure. The independent variables are the ratio of net income to total assets (NI/TA), the ratio of total liabilities to total assets (TL/TA), and the ratio of current assets to current liabilities (CA/CL). Two alternative set of parameters are provided, either of which can be used for estimation weighted measures based on varying proportions of bankrupt and non-bankrupt firms.

Lennox (1999) showed that profitability, leverage, and cash flow have important effects on the probability of bankruptcy on a sample of 90 bankrupt firms. Logit and probit models are found to perform better than multiple discriminate analysis (MDA) approaches in his study. His bankruptcy model showed a decline in accuracy for more distant bankruptcy horizons.
Shumway (2001) criticized the static nature of one-period logit or probit models. He recommended using a duration model and a combination of accounting-based and market-driven variables to improve forecasting performance.

Altman (2002) highlighted that credit scoring models are the backbone of the most advanced credit value at risk models. Bhatia (1988) and Sahoo, et al. (1996) examined the predictive power of accounting ratios on a sample of sick and non-sick companies by applying the multiple discriminant analysis technique. In their study, the selected accounting ratios were effective in predicting sickness with high level of accuracy.

Bandyopadhyay (2006) compared three models: (i) the original Z-Score model; (ii) the Z-Score model for emerging markets; & (iii) logistic regressions, to predict the probability of default. His conclusions from the empirical analysis were that inclusion of financial and non-financial parameters would be useful in more accurately describing default risk.

Jaydev (2006) analysed the power of financial risk factors in predicting default of companies. His study differs from earlier work in that the financial risk factors are selected by surveying the internal credit rating models of the Indian banks and the default companies are selected by following the banking definition of default as per the default database of five largest Indian banks. On comparing the internal credit risk model of banks, Altman’s original model and the emerging markets model, he concluded that the internal risk models of banks are less efficient compared to the other two models and the inclusion of certain financial ratios will improve the risk model.

Agarwal and Taffler (2007) highlighted the high predictive ability of Taffler’s Z-Score model in assessing the distress risk over a 25-year period. Agarwal and Taffler (2008a) compared the performance of Taffler Z-Score to that of two market based models which were developed by Hillegeist, et al. (2004) and Bharath and Shumway (2008). They found that both methods carry distinctive information about corporate failure.

Laitinen (2010) assessed the importance of interaction effects in predicting payment defaults. Two different types of logistic regression models were estimated: (i) model
based on main effects (reduced model); (ii) model based on main and interaction effects (full model). The conclusion from the study was that size and growth are important contingency factors in interaction effects when explaining likelihood of default.

Baninoe, R. (2010) evaluated the predictive ability of two types of bankruptcy models; a reduced form logistic model and an option pricing method based on UK data. He opined that the distressed stocks (i.e. high bankruptcy probability derived from the reduced form model), generated high returns. The results showed that both the econometric reduced form model and the option pricing method of Black Scholes (BS) are successful in predicting corporate bankruptcy in the UK market.

Kumar and Kumar (2012) working on Texmo industry, Coimbatore conducted empirical analysis on three types of bankruptcy models: (i) the Altman Z-Score; (ii) Ohlson’s model; & (iii) Zmijewski’s model to predict the probability that a firm will go bankrupt in two years. They concluded that the best model among the existing financial distress models is Ohlson’s model since it uses binary logistic regression which indicated better prediction performance as compared to discriminate analysis.

2.3.2 Studies on structural models

Although accounting-based models are still widely used in empirical research, they have serious limitations, especially when utilized explicitly for measuring distress risk. These obstacles are overcome in market-based models which attempt to estimate the distress risk by means of a combination of the firm’s liability structure with market prices of its assets. The fundamental assumption of market-based models is that market values contain all information relevant to the providers of capital for computing the probability of default. The first market-based model was introduced in 1974 by Merton.

Merton (1974) applied the option pricing methodology developed by Black and Scholes (1973) to the valuation of a leveraged firm and related the risk of default to the capital structure of the company. According to this model, the firm’s equity can be seen as a European call option on the firm’s assets with a strike price equal to the book value of the
firm’s liabilities. Merton model (Hull, 2008) is based on the assumption that all liabilities are due on the same date, namely at the maturity of the option. If the market value of the firm’s assets is greater than the book value of liabilities at maturity, then the shareholders exercise their option on the assets. In this case, the shareholders pay off the debt-holders and the firm continues to exist. If the value of the firm’s assets is lower than the book value of liabilities, the option will expire implying that the equity value is zero and the firm defaults. In this case the value is transferred to the debt holders. Therefore, in the Merton framework, the value to the shareholders at the date of maturity of debt is defined by the following boundary condition

\[ V_E = \max (V_A - X, 0) \]

where \( V_E \) is the market value of the firm’s equity and \( V_A \) is the market value of the firm’s assets and \( X \) is the book value of liabilities.

KMV, a subsidiary of Moody’s rating agency, modified this model and mapped the output directly to real default probabilities. The model set the exogenous default barrier at total short debt plus 50% of long-term debt. The approach of Merton (1974) assumes that the stockholders hold a put option over the market value of assets of a firm and if the market value of equity is below the outstanding debt amount, then that firm defaults on payment of debt. The default probability is derived out of the value of the put option. KMV (2003) modified this approach slightly and developed a proprietary model for estimating probability of default (PD) which is termed as expected default frequency (EDF). Several variations and extensions have been made to this basic model.

Black and Cox (1976) researched further on this and specified that default event can happen not only at the debt’s maturity, but can also be prior to that date, as long as the firm’s asset value falls to the ‘pre-specified barrier’ (that is, default trigger value). Thus, the model not only allows valuation of debt with an infinite maturity, but more importantly, allows for the default to arrive during the entire life-time of the reference debt or entity.

Longstaff and Schwartz (1995) in their research on market-based models, treated the short-term risk-free interest rate as a stochastic process which converges to long-term
risk-free interest rate and is negatively correlated to asset value process, so that the effect of monetary policy to macro economy is considered.

Duan (1994) proposed another method of estimating $V_t$ and $\sigma_V$, based on the maximum likelihood estimation using equity prices and the one-to-one relationship between equity and asset levels. Duan, *et al.* (2003) followed the maximum likelihood approach introduced by Duan (1994) but unlike previous works, they took into account the survivorship issue, by incorporating into the likelihood function, the fact that a firm survived. They argued that it is imperative for analysts to recognize the fact that a firm in operation has by definition survived so far.

Brockman and Turtle (2003) proposed that a firm is declared bankrupt as soon as the value of its assets reaches the barrier i.e. at any time before, or at, the debt’s maturity.

Duan, *et al.* (2004) demonstrated that using the maximum likelihood estimation (MLE) method to estimate the parameters of the Merton model yield results resembling those generated by the iterative estimation method.

Hull, *et al.* (2004a) proposed a method to estimate the structural model’s parameters from implied volatilities of options on the company’s equity, avoiding to estimate $\sigma_E$ and to transform the firm’s debt structure into a zero-coupon bond. Using as inputs two equity implied volatilities and an estimate of the firm’s debt maturity $T$, their model provided an estimate of $\sigma_V$ and the leverage ratio, to determine the probability of default.

Bruche (2005) described in his study how structural models could be estimated using a simulated maximum likelihood procedure. The model included the use of data on any of the firm’s traded claims (bonds, equity, CDS, etc.) as well as balance sheet information to improve the efficiency of the estimation. The research showed that even small amounts of noise can have serious consequences for estimation results when they are ignored.

Hui, *et al.* (2006) developed a stationary-leverage-ratio model to incorporate a time-depending target leverage ratio. They advocated that a firm’s leverage ratio varies across
time, because of the movement of initial short-term to long-term target ratio. Their model assumed that default occurred when a firm’s leverage ratio increases above a pre-specific default trigger value and the dynamic of interest rate follows the set of Longstaff and Schwartz (1995). By doing so, the model captured the characters of the term structure of PD, which was mentioned in Hui, et al. (2003).

Bandyopadhyay (2007) presented Black-Scholes-Merton (BSM)-based market approach to quantify the default risk of publicly-listed individual companies. In the first part of the research, a framework to optimally use stock market and balance sheet information of the company to predict its probability of failure as well as ordinal risk ranking over a horizon of one year was used. In the second part of the research, the ability of the market value of assets, asset volatility and firm's leverage structure measures to predict future default was investigated along with accounting variables and other firm specific characteristics. The results indicated that a mix of asset volatility, market value of asset and firm's leverage structure along with other financial and non financial factors can give a more accurate prediction of corporate default than the ratio-based reduced form model.

Katiuscia (2007) proposed and empirically tested a two-step model to forecast the downgrade probability of sterling-denominated euro bonds. In the first step, the conditional expectation of credit rating was estimated, employing an ordered probit model. In the second step, the likelihood of downgrade was modeled using credit rating, as obtained from the conditional mean in the first step, alongside with traditional operating measures in a binary-probit framework. By parameterizing a system of two equations, the authors accommodated the disentangled effect of credit quality and company financial information on the downgrade risk. They found evidence of a nonlinear response to shifts in both credit rating and leverage.

Agarwal and Taffler (2008) stated that the contingent claims approach and traditional accounting based approach to corporate bankruptcy capture different aspects of bankruptcy risks. However, their findings were that the Z-Score approach leads to
significantly greater bank profitability in conditions of differential decision error costs and competitive pricing regime.

Dionne, et al. (2008) based their research on Canadian publicly traded companies. They assessed how combining the market variables along with the inputs given in the financial statements of companies enhances prediction of a company’s probability of default. The hybrid model they applied used two versions of the structural model: (i) the Merton model (Merton, 1973, 1974); & (ii) the default barrier model (Brockman & Turtle, 2003) and this hybrid model outperformed other models. Specifically, estimated structural probabilities of default (PDs) contributed significantly to predicting default probabilities when they were included alongside accounting and macroeconomic variables in the hybrid model.

2.3.3 Portfolio reduced-form models and Markov chain models

The reduced-form approach to modeling credit risky portfolios has a number of advantages over the older Merton or copula approach to the simulation of a credit risky portfolio. Reduced-form refers to the process of estimating default probabilities with a broad array of explanatory variables, including macro-economic factors, instead of using the Merton structural model approach. In the Merton approach, the probability of default is derived from the capital structure of the company which has only one random variable, the value of the assets of the firm. In the reduced-form approach, analysts either imply default probabilities from the observable values of traded securities or estimate them from a historical data base of defaults and the relevant explanatory variables.

Reduced form portfolio modeling consists of the following steps:

(i) The analyst selects some or all of the explanatory variables to model as random variables.

(ii) Probability distributions of these random inputs are selected, as is the correlation between random variables.
(iii) Default probabilities for each counterparty are simulated forward on a multi-period basis.

(iv) Credit spreads for each counterparty are derived from the simulated default probabilities and other random variables, typically macro economic variables, that drive the supply and demand for credit.

(v) Each transaction in the portfolio is valued at each time step in the multi-period simulation, and related cash flows and financial accruals are generated.

(vi) The value of the portfolio is the sum of the values of individual transactions.

(vii) The value of tranches of the portfolio (whether the tranching is by maturity like a mortgage-backed security or by seniority from a credit loss perspective like a collateralized debt obligation) is then derived from the cash flows to each tranche, as described by the indenture of the tranched transaction.

These models were originally introduced by Jarrow and Turnbull (1992) and widely mentioned by later studies. Their idea behind these models is highly associated with the concept of ‘risk neutral’, which means a common technique to determine the probability of a future cash flow and then to discount this cash flow at the risk-free interest rate. They decomposed the credit risk premium (credit spread) to two components, \( PD \times LGD \), and the core problem of credit risk modeling became to model the distributions of PD and LGD. The simplest model of reduced-form consideration was proposed by Jarrow and Turnbull (1995) where the default process was modeled as a Poisson process \( N(t) \) with constant intensity \( \lambda \), default time \( \tau \) that is exponentially distributed as a consequence.

The Markov chain model considers default event as an absorbing state and default time as the first time when a continuous Markov Chain hits this absorbing state. This kind of model was first mentioned by Jarrow and Turnbull (1997). In their model, they assumed fixed probabilities for credit quality changes, which were estimated from historical credit
transition matrices, and a fixed RR in the event of default. These time-homogenous discrete-time Markov chain models are widely used.

Gagliardini and Gourieroux (2005) applied ordered probit model to estimated migration correlations. They pointed out that the traditional cross-sectional estimated migration correlations are inefficient.

Monteiro, et al. (2006) suggested using finite non-homogenous continuous-time semi-Markov process to model time-dependent matrices. They showed that the nonparametric estimators of the hazard rate functions can be used for consistently estimating these time-dependent transition matrices. Feng, et al. (2008) introduced unobservable factors and stated that credit risk showed a preference for the use of unobservable factors. In addition, the ordered probit model can also be applied in sovereign credit migration estimation. The authors did a comparison between homogeneous and heterogeneous estimators.

Frydman and Schuermann (2008) and Kadam and Lenk (2008) applied Markov mixture model to their analysis. In their work, the original Markov chain model was extended to a mixture of two Markov chains, where the mixing is on the speed of movement among credit ratings. The main difference of these two works is that the estimation of the former one was based on maximum likelihood method while the latter used Bayesian estimation.

2.3.4 Factor models

Mathematical profile, measure the extent a portfolio of stocks is influenced by a range of economic factors such as changes in interest rates, inflation, and/or oil prices. There are several types of factor models, including a few proprietary ones, but they are all constructed using factor analysis techniques and can be divided into three basic categories: (i) statistical; (ii) macroeconomic; & (iii) fundamental. Statistical factor models attempt to explain returns from an investment in terms of risk factors such as cash flow risk, currency risk, and purchasing power risk. Macroeconomic factor models attempt to do the same in terms of factors that affect the economy as a whole. And
fundamental factor models focus on economic factors that affect a particular industry or market.

Factor models consider two vectors of explanatory variables for latent variable. The first one is a set of macro-economic variables, such as GDP growth, interest rate, money supply growth, inflation rate, stock index and firm’s industry as well. This vector intends to explain systematic risk, which leads the correlations of default events. The second vector is a set of firm-specific variables which account for individual risk. This vector may include contemporaneous and lagged variables regarding several dimensions of the firm’s property, such as age, size, asset growth, profitability, leverage and liquidity. Partly because of IRB approach in Basel II, factor models are most widespread in current literature.

Gordy (2000) pointed out that structural models can map to reduced-form models to some degree under factor models framework. Regardless of the different distributions and functional forms these two kinds of models assume; both of them actually use the similar correlation structures that the correlation between defaults is totally driven by some specific common risk factors, which can be called as ‘systematic factors’.

2.3.5 Related research on credit risk models

Lopez and Saidenberg (2000) highlighted the importance of model validation standards that must be satisfied for models in banks to be used for regulatory capital purposes. They were of the opinion that a serious impediment to such model validation is the small number of forecasts available due to the long planning horizons typical of credit risk models. Using a panel data approach, they proposed evaluation methods for credit risk models based on cross-sectional simulation. They believed that specifically, models are evaluated not only on their forecasts over time, but also on their forecasts at a given point in time for simulated credit portfolios.

Crouhy, et al. (2000) reviewed the industry sponsored Credit Value-at-Risk (VAR) methodologies. The first methodology- the credit migration approach, proposed by JP
Morgan with Credit Metrics, is based on the probability of moving from one credit quality to another, including default, within a given time horizon. The second methodology is the option pricing or structural approach, as initiated by KMV and which is based on the asset value model originally proposed by Merton and the actuarial approach as proposed by Credit Suisse Financial Products (CSFP) with Credit Risk+ and which only focuses on default. They concluded that KMV and Credit Portfolio View, base their approach on the same empirical observation that default and migration probabilities vary over time. KMV adopts a microeconomic approach which relates the probability of default to the market value of its assets; while Credit Portfolio View propose a methodology which links macroeconomics factors to default and migration probabilities.

Samuel, et al. (2008) explored the extent to which the default probability based on structural models provides additional information that accounting ratios do not contemplate. They designed a hybrid model by including the default probability from structural models as explanatory variable, in addition to accounting ratios, in order to evaluate the differences in the accuracy of default predictions using an accounting-based model and a hybrid model. Their results showed that the market information obtained from the structural models included additional information not reflected in the accounting information. It could also be concluded that including default probability from structural models as an explanatory variable allowed the out-sample predictive capacity of accounting-based models to be improved.

Dubrana (2011) proposed a model that described credit risk in a portfolio including the modeling of both credit default risk and credit migration risk. The credit default risk model is described as an extended version of the Credit Risk+ model. The attractive feature of both models was that only a few inputs are required to perform well and no assumptions are made on the default event so that the model can be easily extended to some risk categories such as operational risk.
Hurd and Zhou (2011) considered a structural credit risk framework where the log-leverage ratio of the firm was a Lévy process in the form of a time-changed Brownian motion (TCBM) where the time-change process has identically distributed independent increments. In models of this type, ‘vanilla’ credit derivative pricing formulae are in closed form in terms of an explicit one-dimensional Fourier transform. Their primary aim was to investigate whether two very simple specifications of the time change process, namely the variance gamma (VG) model and the exponential jump model (EXP), can lead to good fits to CDS data for a representative firm with an interesting credit history, Ford Motor Co. The main conclusion was that the two TCBM models significantly outperformed the classic Black-Cox model. The statistical methodology proposed can be effectively implemented for many other variations of TCBMs and applied to a wide range of firms.

Antonio, et al. (2012) examined what best explained corporate credit risk, accounting-based versus market-based models. They used a sample of 2,186 credit default swap (CDS) spreads quoted in the European market during the period 2002-2009. Their findings suggested that there is little difference in the explanatory power of the two approaches. They suggested that both accounting and market data complement one other and a comprehensive model that includes both types of variables appeared to be the best option for explaining credit risk. They also showed that the explanatory power of accounting- and market-based variables for measuring credit risk are particularly strong during periods of high uncertainty.

Creal, et al. (2012) presented a methodology for rating the creditworthiness of public companies in the U.S. from the prices of traded assets. Their approach used asset pricing data to impute a term structure of risk neutral survival functions or default probabilities. For firms whose assets are not traded, they showed how they can be indirectly rated through the use of matching estimators. They also showed how the resulting ratings could be used to construct loss distributions for portfolios of bonds.
Tasche (2012) believed that the estimation of probabilities of default (PDs) for low default portfolios by means of upper confidence bounds is a well established procedure in many financial institutions. He demonstrated that in the case of independent default events, the upper confidence bounds can be represented as quantiles of a Bayesian posterior distribution based on \textit{a priori} that is slightly more conservative than the uninformed prior.

Calabrese (2012) in his research proposed a regression model for a fractional variable with nontrivial probability masses at the extremes. In particular, the dependent variable is assumed to be a mixed random variable, obtained as the mixture of a Bernoulli and beta random variables.

Lu (2012) adopted a continuous-time non-homogeneous mover-stayer model for the measurement of the credit risk associated with bank loans. This model is an extension of a Markov chain model. Furthermore, the time varying risk premium was extracted to convert the mover-stayer model to a risk-neutral mover-stayer model. The conclusion was that first, the mover-stayer model is better suited than the Markov chain model in estimating the credit risk of loans, according to likelihood ratio statistics. Second, they found that borrowers of investment grades are less likely to remain at their original rating. On the other hand, rating classes had a strong tendency to be downgraded, inferring the likelihood that downgrade momentum is an element of rating behavior. Third, they estimated time-varying risk premium to transfer transition matrices to risk-neutral transition matrices. Fourth, estimated default probabilities match business cycle indicators particularly well. Finally, estimation procedures are easy to follow and implement. Consequently, the findings in this study have important implications for the management of risk assumed by financial institutions.

2.4 Research gaps

The above literature review reveals the following deficiencies:
(i) The main benefit of accounting models is their precision in estimating probabilities of default. They are easy to use as the financial institutions are equipped with strong database management systems. On the other hand, they are not flexible because they require information from audited financial statements. It thus proves difficult to update probabilities of default over the course of a year. Some institutions may produce financial statements on a quarterly basis, but these are rarely audited. Thus, they provide information only on the firm’s past and are therefore backward-looking. Moreover, financial statements are generated in accordance with the conservative accounting principles. As a result, book values of assets are understated relative to their market values (especially in the case of fixed assets and intangibles). Moreover, the application of overstated leverage measures produces distortions in the overall discriminant score of a firm. Finally, accounting information is unable to explain assets volatility, which is an important factor of credit risk. Thus, accounting models admit of further improvements in their structure.

(ii) The main criticism of Merton’s structural model is that it does not account for the possibility that the firm may default before the debt matures. The default probability estimated from the structural model is not a sufficient statistics of the actual probability of default. Also, only stockholders are involved in exercising the option. Despite the flexibility and forward-looking nature of the structural model, asset prices may not be sufficient to estimate the borrower’s credit worthiness. Such information is, for instance, unable to predict defaults due to severe liquidity problems.

Thus, there is a need for a model which is able to blend the merits of both the accounting and market-based models. The fundamental assumption of market-based models is that market values contain all information relevant to the providers of capital for computing the probability of default. It is believed that the stock prices reflect all the information pertaining to the financials of the company. Market-based models have good predictive power in being flexible, providing continuous probability of default, and being forward looking. However, to make the probability of default more exhaustive, it is important to
understand the financial statements, namely the Balance Sheet and Income Statement of
the company, and determine the predictive power of key accounting variables.

There is another advantage of using such models that are a ‘marriage’ between structural
and reduced form models. For firms that are non-listed, obtaining default probabilities
based on KMV is impossible, however, the model proposed in the research looks at key
ratios. It is with this aim that the continuous valuations of companies by applying the
structural KMV model are combined with the statistical Logit model in determining
default risk, and in identifying the key ratios which add to the predictive power of the
model. The research study thus focuses on the issue that the default measures calculated
from structural models and by the statistical models have some common predictive
variables.

2.5 References


