Chapter 6

Findings and Recommendations

6.1 Introduction

This chapter presents the important findings of the study. Credit risk has emerged as an important area of finance driven by the increasing complexities of the financial markets, the number of financial instruments developed and its wide applications in portfolio management, and risk management techniques. At the centre of credit risk is the risk of default by the issuer company, which is the failure to honor a financial commitment.

The most important indicator of credit risk has been the credit ratings provided by the external credit rating agencies. The role of the credit rating agencies has increased over the years with their increasing applications to serve the regulators, issuers and investors. In the emerging markets like India, Credit Rating Agencies (CRAs) have been the predominant source for assessing the credit quality of borrowers. Since upgrades and downgrades of ratings can impact the price of traded debt and equity, market participants are interested in developing good forecasting models. Given the relevance of credit ratings in measuring credit risk or the risk of default, it is imperative that the rating process and methodology accurately measure the credit worthiness of the issuer company and the ratings be proactive.

6.2 Objectives and Methodology

The present study has been carried out with the following objectives:

(i) To analyze the methodologies and practices adopted by the Credit Rating Agencies (CRAs) in India regarding Corporate Debt Ratings.

(ii) The research study attempts to combine financial variables and the market-based default drivers in a hybrid form to predict corporate default. The proposed model will determine the predicted probability of default on debt instruments and provide a measure of assessing credit quality.
Extensive review of literature has been carried out in the light of above objectives of the study. Within these two broad objectives, the framework of research has been to examine the rating process and methodologies of credit rating agencies in India to highlight the gaps in the rating process and practices as given in Chapter 4, and emphasize the need for research in this field. There are some issues in credit ratings that detract from their information content which have been highlighted in Chapter 1 of the thesis. These gaps in the methodologies and practices of the rating agencies have entailed the need to develop a unified credit risk model to measure default risk that attempts to combine accounting information and stock price data. In the literature, there are two approaches to model credit risk. The market based models (Merton, KMV) are structural models; while those based on Logistic regressions or the Altman scores are reduced form models. This research study is based on the application of the structural KMV model and the statistical reduced-form model into one integrated framework. A unified default prediction model, as proposed attempts to overcome the limitations of the two models.

One model is market-based (structural) which is not self-reported and the second model (reduced-form) is self reported where the ratios are already reported by the firm. The structural form KMV model provides continuous probability estimates; those are the ‘Y’ variables to observe how close the Balance Sheet information is explained by the market variables. Since the Probability of Default (PD) calculated from KMV model is continuous, the combined valuations from the market along with accounting information enables us to observe the consistency between market variables and other financial statement information. Eventually ratings are based on financial statements.

The KMV model can be applied to determine the theoretical PD based on market factors. However, this study assesses if accounting variables and other firm specific characteristics can provide additional significant information in assessing the real world credit quality of a firm in a hybrid model.

In this study for the market-based model, the works of KMV model have been extended in developing a suitable algorithm for determining probability of default of Indian listed
companies. The continuous observations of default probability obtained from KMV have been used and balance sheet ratios (as the reduced form) to obtain a simple default probability model that Financial Institutions can use.

The PD is calculated from the KMV model, with an underlying assumptions that the market is at least weakly efficient. Therefore all available historical information is already incorporated in the market price and hence the PD. Therefore it is worthwhile to see which accounting ratios predict these PDs best. These ratios once identified will provide an easy to use default prediction model.

To combine the continuous valuations by the market with the accounting information given in the financial statements to determine the key financial ratios for each sector, multiple regression is run, (using SPSS version 20.0) with the PD as the dependent variable and the set of accounting ratios as the explanatory variables. The accounting ratios identified are indicators of profitability, liquidity and solvency position of the company. The Altman ratios are also included as predictors. The key ratios for all the sectors are identified. Then in a set of logistic regressions, efforts have been made to establish linkage between the implicit default probability and financial ratios of these firms and assess their predictive power.

For the second model, net worth has been identified as a measure of default risk. With net worth/ total assets as the dependent variable and the set of accounting ratios as the independent variable, the binary logistic regression is run (using SPSS version 20.0). A similar structure of Logit model is applied with ratings (coded as 0 for investment grade and 1 for speculative grade) as the dependent variable and the accounting ratios as the independent variables.

Null Hypothesis (H₀) is taken as the model with only the constant (the intercept) and no predictors (financial ratios), with all the coefficients in the equation taking the value 0 and the Alternate Hypothesis (H₁) is taken as the model with predictors currently under consideration. It is observed that the proposed logit model is accurate and differs

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significantly from the null of zero, i.e. gives significantly better than a chance or random prediction level of the null hypothesis. When predictors are added to the model, the model performance is significantly better.

6.3 Key findings

The important findings of the study have been summarized below:

- It is observed that the market-based KMV model is able to explain the default risk on account of the financial parameters. Since the analysis is done sector-wise, the significant ratios for each of the sectors are identified. These ratios can be used by financial institutions and other lenders in assessing the default risk of companies. It is also observed that the original Altman ratios also bear significance for some of the sectors (significant at p-value<.05). There is a moderate relation between the PD and the predictors as evident by the adjusted R square. The ratios that are common for all the three models are as follows:

**Table 6.1: Accounting ratios common across the three models**

<table>
<thead>
<tr>
<th>Sector</th>
<th>Key ratios between KMV and Ratings model</th>
<th>Key ratios common between KMV and Logit model</th>
</tr>
</thead>
<tbody>
<tr>
<td>Auto</td>
<td>Cash profits</td>
<td>PAT/CE, NWC/TA</td>
</tr>
<tr>
<td>Non metals</td>
<td>PAT/Sales, Debtors</td>
<td>PBIT/TA, D/E</td>
</tr>
<tr>
<td>Metals</td>
<td>D/E</td>
<td>D/E</td>
</tr>
<tr>
<td>Textiles</td>
<td>NWC/TA</td>
<td>Interest coverage, D/E</td>
</tr>
<tr>
<td>Machinery</td>
<td>D/E, Debtors</td>
<td>D/E</td>
</tr>
<tr>
<td>Manufacturing</td>
<td>RE/TA</td>
<td>RE/TA</td>
</tr>
<tr>
<td>Chemicals</td>
<td>Debtors</td>
<td>PBIT/TA</td>
</tr>
</tbody>
</table>
**Auto sector:** The reason for cash profit being significant for the auto sector is that this sector requires considerable cash as high inventory is blocked in the sector. The other reason for the cash requirement to be high is that for the auto sector, the investment in capital expenditure is all the year round, thus cash profits are significant for the sector to fund the capital expenditure. (PAT/CE) is a sign of growth opportunities for the auto sector companies and thus higher returns from investments will reduce the probability of default for the companies in this sector. Similarly, a high proportion of net working capital to total assets would require cash outflows thereby putting a strain on cash resources and thus increasing the possibility of default. A negative working capital does not imply that the sector is in need of funds, but rather indicates better lines of credit from the suppliers and thus more efficient management of working capital. A better cash cycle will reduce the default risk for the companies.

**Non-metals sector:** A higher operating profit (PBIT/TA) as a proportion of total assets is a sign of positive financial health of a company. Sales/TA is a significant ratio generated by regressions from KMV model. This ratio indicates asset turnover ratio, which reflects an effective utilization of the assets. It signifies how rapidly the assets can be turned around to generate sales. A high sales turnover ratio indicates efficiency in operations and thus reduces the default risk. This sector focuses on efficient utilization of capital. This sector comprises cement companies primarily. The pace of capacity addition has slowed down in the cement industry since the peak addition seen in FY10. This can be mainly attributed to the fact that bulk of the cement capacity addition programme had been initiated in the period FY06-FY09 and completed by FY10. Fresh capacity launches has slowed down subsequently. (ICRA research, 2012). Though capacity addition has slowed down, capacity utilisation for most companies was efficient (as reflected in the ratio). Moreover, demand for cement is a derived demand, where demand is from the construction industry. Thus receivables remain high for this sector. A higher collection period from debtors will lead to longer cash cycle and thus probability of default may increase. Being capital intensive, with long gestation period, leveraging is important and thus D/E is a significant ratio for the sector.
Metals sector: The metals sector comprises companies which are part of aluminium, steel and sugar sectors. The sectors are highly capital intensive. The capacity expansion specifically for steel companies is in multiples, as the companies are doing backward integration and diversifying into power. Thus, the companies have a high financial leverage and D/E or the gearing ratio is the most significant ratio for this sector.

Textiles sector: The significant ratios for this sector are primarily the solvency ratios. The textiles industry was faced with rising interest rates during the year 2011. The spinning companies were able to pass on the soaring cotton prices to their customers on the back of strong demand for cotton yarn in domestic as well as international markets and steep fall in cotton prices. However, the ban on exports of cotton yarn in the last quarter of 2011 burdened the companies with huge inventory, in addition to closure of dying units in one of the plants. Unsold stock squeezed the liquidity of spinners, which in turn affected cotton purchases by mills and had a further cascading effect on cotton prices. Thus huge inventories coupled with high cost cotton squeezed the liquidity of the companies. (ICRA Research, 2011). The highly leveraged capital structure along with rising interest rates exposes the industry to higher risk of defaults. Thus the solvency ratios (D/E and interest coverage) are significant ratios for this sector. Piling up of inventory also led to a rise in working capital as evident by the ratio NWC/TA which is significant for the model.

Machinery sector: The gearing ratio is a significant variable as for this sector. As the sector is capital intensive in nature, financial leveraging is on the higher side. Long business cycles and massive capital investment are the hallmarks of this sector. Moreover, a large number of companies fall as public sector undertakings (PSUs), thus, receivables are high as the collection period tends to be longer.

Manufacturing sector (FMCG, paper and media): The bulk of the companies are FMCG. These companies are by and large cash rich. This is evident by the RE/TA ratio which is a significant predictor for the model. The FMCG sector has low leveraging as they rely on the internal accruals for their expansion, to fund regular capital expenditure. Thus, retained earnings are an important variable for this sector.
Chemicals sector: Leading Indian players continue to exhibit strong profitability indicators (excluding one-time instances like exclusivity-related aberrations or impact of foreign exchange fluctuations) and credit metrics. These strengths are also reflected in their strong credit profile. The balance sheets of major pharmaceutical companies are strong providing adequate room for fund raising. The competitive pressure in the domestic formulations market has been rising steadily. While on one hand, this has been prompted by significant increase in investments by domestic players in marketing efforts through expansion in field force, on the other, MNC have also renewed their focus on India. Some of the smaller players have also contributed to the competitive intensity by offering huge discounts and incentives to the distribution network and doctors. Structural demand drivers including 1) rising household income levels, 2) increasing prevalence of lifestyle related diseases, 3) improving healthcare infrastructure/delivery systems and 4) rising penetration in smaller towns and rural areas continue to support long-term growth led to high profitability margins and better lines of credit from supplier companies.

The proposed model is an efficient predictor and also parsimonious. This is evident by logistic regressions run on the KMV findings to obtain the predicted probability of default. The default rates assigned by the credit rating agencies across the spectrum of ratings are compared with the predicted probability of default. It is observed that the correlation of what the model predicts as default probability and what rating agencies rate these firms is moderate. (Table 6.2) This implies that the proposed model is an efficient predictor. The reason for the correlation not to be very high is that both the models are conceptually different, and ratings in themselves include qualitative and macro variables when assigned which are not reflected in our market-based model.
Table 6.2: Correlation between implied PD as per KMV with default rates by Rating Agencies

<table>
<thead>
<tr>
<th>Sectors</th>
<th>Correlation between PD as per KMV with CRISIL default rates</th>
</tr>
</thead>
<tbody>
<tr>
<td>Auto</td>
<td>78%</td>
</tr>
<tr>
<td>Non metals</td>
<td>82%</td>
</tr>
<tr>
<td>Metals</td>
<td>72%</td>
</tr>
<tr>
<td>Textiles</td>
<td>70%</td>
</tr>
<tr>
<td>Machinery</td>
<td>67%</td>
</tr>
<tr>
<td>Manufacturing</td>
<td>83%</td>
</tr>
<tr>
<td>Chemicals</td>
<td>77%</td>
</tr>
</tbody>
</table>

- For the reduced-form statistical models; two different types of logistic regression are estimated 1) model based on net worth 2) model based on ratings. By taking the dependent variable as 1) net worth and 2) ratings and the set of accounting ratios as the predictors, binary logistic regression has been applied. The findings and result largely support the hypothesis that adding the accounting ratios as predictors significantly increases the predictive ability of the models, thus rejecting the null hypothesis.

- The predicted probabilities of default for all the three models were compared with the actual default (as defined). ROC curves were plotted for the same. As is observed from Table 6.3 below, the predictive ability of the logit model where net worth is identified as the measure of default risk is the highest. Thus, the logit model is the most robust model.

Table 6.3: ROC curves for the three models

<table>
<thead>
<tr>
<th>Sectors</th>
<th>KMV</th>
<th>LOGIT-NW</th>
<th>RATINGS</th>
</tr>
</thead>
<tbody>
<tr>
<td>Auto</td>
<td>76.9%</td>
<td>83.4%</td>
<td>76.1%</td>
</tr>
<tr>
<td>Non metals</td>
<td>75%</td>
<td>99.1%</td>
<td>90.7%</td>
</tr>
</tbody>
</table>
It is observed from table 6.2 that the correlation between the predicted probability of default between the KMV model and the ratings ranges from 40% to 50% on an average. For the correlation between the predicted probability for logit model with net worth and logit model with ratings is ranging between 40% to 80% while for KMV and Logit for net worth is between 40% to 50%. It can be inferred that though there is some correlation, it is not very high for most of the sectors which implies that each model in itself is not a sufficient statistic, but the market based variables and the accounting information together can provide a high predictive ability to the credit risk model for measuring probability of default.

**Table 6.4: Correlation of predicted PD between the three models**

<table>
<thead>
<tr>
<th>Sectors</th>
<th>KMV-Ratings</th>
<th>LogitNW-Ratings</th>
<th>KMV-Logit</th>
</tr>
</thead>
<tbody>
<tr>
<td>Auto</td>
<td>76%</td>
<td>70%</td>
<td>50%</td>
</tr>
<tr>
<td>Non metals</td>
<td>40%</td>
<td>50%</td>
<td>45%</td>
</tr>
<tr>
<td>Metals</td>
<td>62%</td>
<td>81%</td>
<td>50%</td>
</tr>
<tr>
<td>Textiles</td>
<td>63%</td>
<td>66%</td>
<td>62%</td>
</tr>
<tr>
<td>Machinery</td>
<td>42%</td>
<td>40%</td>
<td>85%</td>
</tr>
<tr>
<td>Manufacturing</td>
<td>50%</td>
<td>71%</td>
<td>40%</td>
</tr>
<tr>
<td>Chemicals</td>
<td>42%</td>
<td>64%</td>
<td>40%</td>
</tr>
</tbody>
</table>
6.4 Recommendations

- By applying the KMV model and the Logit model into an integrated framework, a hybrid form of relatively simple, widely understood, and easy-to-interpret parsimonious model based on publicly available information has been developed that factors in market-based information along with the self reported financial data available with the firms.

- This model 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.

- The theoretical justification for combining accounting and market data is that the accounting data becomes out of date and added to this, firms in default tend to be late reporting. In such circumstances, combining accounting data with information in market prices may help overcome the timeliness problem. Market price not only reflects a wide variety of information related to the expected future cash flows but it also reveals a subset of information about the likelihood of liquidation and cash flow impact.

- Accurate and timely information from the equity market provides a continuous credit monitoring process that is difficult and expensive to duplicate using traditional credit analysis. Annual reviews and other traditional credit processes cannot maintain the same degree of vigilance that expected default frequency (EDF) values calculated on an ongoing basis can provide.

- 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. Thus, it is proposed to use the combining valuations by the market with the information given in the financial statements of companies to measure default. The study recommends that inclusion of market data makes the default risk quantifiable and recommend a hybrid type of model that combines both market specific and financial factors in predicting default risk of firms.

- The benefits of implementing and using quantitative risk models cannot be fully realized without an understanding of how accurately any given model represents the dynamics of credit risk. This makes reliable validation techniques crucial for both commercial and regulatory purposes. In this research study; a set of measures and a testing approach has been applied and found useful for benchmarking default models and validating their performance.

- Unlike the discriminant model where the research on accounting models is more, the logistic model has the flexibility to incorporate both the financial as well as non-financial factors in predicting default. While the financial ratios capture the firm specific information, the non-financial factors help to evaluate the link of the firm with macroeconomic factors and the capability of the firm to churn out cash flow in the required numbers.

- The accounting ratios common to the KMV and logit model can be directly used to determine the credit worthiness of an issuer company. The significant ratios for both the models together can also be applied to measure the default risk of companies. Since the ratios are identified for different sectors, the probability of default can be determined on the ratios. and to offer a simple model that can measure default risk and complement the functions of the credit rating agencies in India.

- A combination of structural model and statistical model have been used to study to what extent the parameters applied can overcome the methodological shortcomings of credit ratings. Comparing the KMV model to the reduced-form alternative gives a new perspective about how realistic the model’s assumptions are.
The three models are compared by conducting an empirical analysis of the classification errors using receiver operating characteristics curve (ROC curve). The results suggest that the accuracy ratio is highest for the logit model with net worth as the key determinant of default risk. It is also observed that the accuracy ratio (area under ROC curve) is also higher than 75% for all the three models for all the sectors. These findings strengthen result testing and help in identifying the best model in terms of its predictive ability.

6.5 Major limitations

(i) The limitations of the statistical (reduced-form) models are the exclusion of 'qualitative' variables and macro-economic variables that might play a significant role in driving the analyst's decision. Moreover, corporate disclosures can also be a predictor of default.

(ii) The performance limits of the statistical model (which tries to summarize a number of ratings into a small set of rules and criteria) can also reflect a lack of consistency in the work of human experts. In other words, when two raters assign different judgments to similar firms, no sophisticated model can translate their behavior into an efficient algorithm.

(iii) In spite of the advantages of KMV credit measure, there are certain shortcomings related to estimating asset values or volatilities when either (i) the market is not efficient, or (ii) when the firm is not listed.

(iv) The quantitative models cannot assess the management quality of a firm, the promoters track record and other qualitative parameters which can impact the credit quality of a firm.

(v) Despite the flexibility and forward-looking nature of the structural model, asset prices may not suffice to estimate the borrower’s credit worthiness.

(vi) The present study is focused on public limited companies spanning 7 sectors. The scope of research can be expanded to include the financial services sector too.
6.6 Concluding Remarks

It is concluded from the above analysis that accounting ratios do impact the dependent variable, the probability of default. The liquidity, profitability and leverage impact the default risk for a company, but the degree to which each would impact varies across sectors. However, this research does not intend to establish the superiority of one set of accounting ratios over the other but emphasizes on the importance of a careful selection of accounting ratios in designing the credit risk models. The differences and inconsistencies that will come out of the empirical testing can be used by the rating agencies to improve the default prediction and ultimately assess the role of credit quality in determining the likelihood of downgrade/default. The objective is not to maximize model accuracy, but rather to examine the performance of a relatively simple, widely understood, and easy-to-interpret model that would have broad applicability.

This research study has been undertaken with the objective of combining financial variables along with market-based default drivers to predict corporate default. By applying the KMV model and the logit model into an integrated framework, a hybrid form of relatively simple, widely understood, and easy-to-interpret parsimonious model based on publicly available information has been developed that factors in market-based information along with the self reported financial data available with the firms. The structural model is model-driven with quantitative estimates that use current stock price information, Ratings, by contrast, are judgmental assessments of long-term credit quality. For rating agencies, accurate default prediction is not the only objective; they trade off timeliness and accuracy against stability. Both are not complete in themselves. Rating drift reduces the default prediction power of ratings and thus offers scope for improvement through alternative measures of default risk. However, it appears that the long-term qualitative assessment inherent in ratings is something that cannot easily be replaced by a statistical analysis of the process that governs short-term default risk. Likewise, market-based measures seem to provide information not conveyed by the
traditional rating. Both are complementary in nature. The default probability estimated from the structural model is not a sufficient statistic of the actual probability of default.

6.7 Contribution of the researcher

- Several empirical problems in prior literature have been examined and an attempt is made to address them. This study has used a combination of structural models of default and econometric model of ratings to study the determinants of default risk and, by doing so, overcome the earlier methodological shortcomings.
- The KMV model based PD provides a forward looking structural default probability provide leading information about changes in the credit quality of a debt issuer, and thus help to understand impending rating changes and default.
- Continuous monitoring is one of the effective early warning protection against deteriorating credit quality. EDF values are also often used to help the focus of the efforts of traditional credit processes. They provide a cost-effective method to screen credits quickly and to focus credit analysis where it can add the most value. Further, because EDF values are real probabilities, they are the key data items in many institutions’ provisioning, valuation and performance measurement calculations.
- For firms that are non-listed, obtaining default probabilities based on KMV is impossible, however the proposed model that looks at key ratios can be used.
- As financial ratios are used as explanatory variables for all the three models, the common ratios for the models or a set of ratios which are significant for all the models can be used when the default risk is to be measured for any company.
- Logit model provides an early warning signal for predicting corporate default. It presents a method for directly estimating predicted PD using financial variables.
- The structural model framework is a useful tool in the analysis of counterparty risk for banks when establishing credit lines with companies and a useful tool in the risk analysis of portfolios of securities.
- When the PD is calculated across different sectors, it can be seen which sectors have companies which have a higher PD and which are the ones with low PD. Thus, lenders can decide on a range of PD while fixing exposures going forward. This
model can be forward looking; reduce exposures for sectors with high PD and otherwise.

- The riskier the sector, the cap on the amount of exposure maybe fixed at say 80% or 70% of what is asked.

### 6.8 Directions for future research

- In this research study Net worth/Total Assets is proposed as a measure of default risk. However, the research can be extended by taking other measures of default risk such as credit default swaps, bond yields.

- Although financial ratios have been identified as predictors (explanatory variables) for the purpose of the research, the logistic model has the flexibility to incorporate both the financial as well as non-financial factors in predicting default. While the financial ratios capture the firm specific information, the non-financial factors help to evaluate the link of the firm with macroeconomic factors and the capability of the firm to churn out cash flow in the required numbers. The research scope can be expanded to take macroeconomic variables. Thus, the differences and research gaps that are observed by this model can help in default prediction through other credit risk models. Corporate disclosures can also be examined in their impact on predicting default risk.

- Future research on this topic can be related to the field of Earnings Management. The direct correlation between Earnings management and PD can be ascertained if PDs calculated from market-based variables lead to weak earnings management. The impact of corporate disclosures and governance at the time of default status, or impending default on earnings management can also be explored. Moreover, one other area to explore in earnings management can be prior to an anticipated rating downgrade. Is it probable that firms will inflate their reported earnings before an anticipated rating downgrade?

- This research study has identified logit model as the relevant statistical (reduced-form) model for default prediction. The scope can be extended to examining other statistical models as probit models, among others.