Modelling credit risk for SMEs: Evidence from the Indian market

Dr. Anirban Ghatak, Asst. Professor,
Christ University Institute of Management, Bangalore

ABSTRACT

SME sector is subject to high credit risk and several credit risk models are being developed taking into account only quantitative factors and no model is being developed with relevance to Indian market. This calls for a need to study the industry practices and develop credit risk model for SME sector. This calculated PD helps the bank in decision making regarding credit risk and also helps in identifying the capital requirement that a bank is supposed to keep against the credit risk portfolio which is usually 8% as per Basel II in which 4.5% to be kept in Tier 1 capital. The result shows that the model is almost 30 percent higher than the performance of the generic corporate model.

Key Words: Credit Risk, Profitability of default, portfolio, Basel II

Introduction:

SMEs have been playing a critical role in both the developed and the developing economies. SMEs contribute about 40 per cent of India's domestic production, almost 50 per cent of total exports and 45 per cent of industrial employment; they are also the largest direct and indirect employer (41 million). SMEs produce a diverse range of products (about 8000 odd items), including consumer items, capital and intermediate goods. SMEs in India, constitutes more than 80 percent of the total number of industrial enterprises and form the backbone of industrial development.

The aim of this paper is to analyze a complete set of financial ratios linked to Indian SMEs and find out which are the most predictive variables affecting an entities’ credit worthiness. One motivation is to show the significant importance for banks of modeling credit risk for SMEs separately from large corporate.

In the above background, the present study aims to develop a credit risk model for SMEs in India.

Reviews of Literature:

Ulrich (2001), in the paper titled “Models of Joint Defaults in Credit Risk Management” reviewed the models of joint defaults of the current major industry-sponsored credit risk frameworks. Recognizing the need for further improvements of these models, we address the following issues. First, we identify the most important modelling drawbacks that could be fixed on a short-term basis. Second, we analyze which of the proposed models is the conceptually most promising basis for next-generation models. Concluding that the KMV methodology is the most suitable to go forward, we set out a research agenda aiming at further improvements and at extending the KMV model to nonquoted firms.

Altman and Gabriele (2001), in the paper titled “Modeling Credit Risk for SMEs: Evidence from the US Market” developed a distress prediction model specifically for the SME sector and to analyze its effectiveness compared to a generic corporate model. The behavior of financial measures for SMEs is analyzed and the most significant variables in predicting the entities’ credit worthiness are selected in order to construct a default prediction model.

Fernandes, (2005), in the paper titled “Corporate Credit Risk Modeling: Quantitative Rating System and Probability of Default Estimation” analyzed the corporate credit risk modeling for privately-held firms. Although firms with unlisted equity or debt represent a significant fraction of the corporate sector worldwide, research in this area has been hampered by the unavailability of public data. This study is an empirical application of credit scoring and rating techniques applied to the corporate historical database of one of the major Portuguese banks. Several alternative scoring methodologies are presented, thoroughly validated and statistically compared. In addition, two distinct strategies for grouping the individual scores into rating classes are developed. Finally, the regulatory capital requirements under the New Basel Capital Accord are calculated for a simulated portfolio, and compared to the capital requirements under the current capital accord.

Jones, David and John, (2007), in their paper titled “Industry Practices in Credit Risk Modeling and Internal Capital Allocations: Implications for a Models-Based Regulatory Capital Standard: Summary of Presentation”, provided examples by which information from internal credit risk models might be usefully incorporated into regulatory or supervisory capital policies. In view of the modeling concerns described, incorporating internal credit risk measurement and capital allocation systems into the supervisory and/or regulatory framework will occur neither quickly nor without significant difficulties. Moreover, the process of "patching" regulatory capital "leaks" as they occur appears to be less and less effective in dealing with the challenges posed by ongoing financial innovation and regulatory capital arbitrage. Finally, despite difficulties with an internal models approach to bank capital, no alternative long-term solutions have yet emerged.

Dalessandro (2011), in the paper titled “All Your Hedges in One Matrix”, presents a credit migration model that aims to consistently capture the point-in-time dynamics of
the credit worthiness of debt issuers and their obligations, and a calibration routine that permits the model to effectively fit historical ratings data. The credit model accounts not only for default risk dynamics but also for the entire transition among states of the rating migration matrix. This modeling feature is fundamental for an efficient risk management of credit derivatives and credit risk portfolios conditionally on a state of the economy or specific macro factors. We fit our model to the historical average rating migration matrices published by Moody’s Investors Service, focusing on the banking sector over the period 1920-2005. The results show that the model can identify the through-the-cycle transition across rating scales and that the point-in-time migration probabilities are only generated by stressed economic conditions and can only be justified by the influence of macro factors on the through-the-cycle unconditional probability values. The great level of modeling details and the accuracy of the produced results is an improvement over those of other available models.

Research Methodology:

Statement of the problem

Although many studies have been conducted on the capital structure, still there is a gap of satisfactory, comprehensive and positive explanation for firms’ capital structure observed behaviour. Most of the research on capital structure has focused on public, nonfinancial corporations with access to U.S. or other international capital markets. The study on the determinants of capital structure of SME’s in the developing countries like India has been overlooked and therefore a study on testing the hypotheses based on Pecking Order Theory by examining the most important factors that influence the capital structure decisions of SMEs in India is an important research area that needs to be explored.

Objectives of the study

The present study has been undertaken with the following objectives:

i. To identify the various government policy for promotion of SMEs in India.
ii. To understand the credit risk associated with the SME sector
iii. To identify the qualitative and quantitative factors that affects the credit risk in SME industries.
iv. To develop a credit risk model in order to reduce the bank capital requirement.

Variables of the study

Dependent variable

The dependent variable in the study is the Default/Non Default (Binary)

Independent variable

<table>
<thead>
<tr>
<th>Variables entered in the model</th>
<th>Accounting ratio category</th>
</tr>
</thead>
<tbody>
<tr>
<td>Working Capital/Total Assets</td>
<td>Liquidity</td>
</tr>
<tr>
<td>Retained Earnings/Total Assets</td>
<td>Coverage</td>
</tr>
<tr>
<td>EBIT/Total Assets</td>
<td>Profitability</td>
</tr>
<tr>
<td>Debt/Equity</td>
<td>Leverage</td>
</tr>
<tr>
<td>Sales/Total Assets</td>
<td>Turnover</td>
</tr>
</tbody>
</table>

Hypotheses

Hypothesis 1: The WC/TA add nothing to the prediction of PD.
Hypothesis 2: The RE/TA add nothing to the prediction of PD.
Hypothesis 3: The EBIT/TA add nothing to the prediction of PD.
Hypothesis 4: The D/E add nothing to the prediction of PD.
Hypothesis 5: The S/TA add nothing to the prediction of PD.

Sampling procedure

For data analysis the SME’S data were chosen from the CMIE Prowess database. Totally 4000 SMEs for a period of 10 years (2001 – 2010) are chosen for the current study.

Data Analysis:

Insert Table 1: Finding Probability of Default (PD) Using Logit Regression

Logit Regression

Applying the LOGIT function to the data in the table with logical values for constant and statistics both set to 1, we obtain the result as mentioned in table 1. With the statistics on overall fit the LR test i.e LR Test/p-value is 160.1 & 0.000 (table 1.1) which implies that the logit regression is highly significant. The hypothesis ‘the RE/TA, EBITD/TA & D/E add nothing to the prediction’ can be rejected with high confidence. As the p-value is less than 0.05 the model recommends rejection null hypothesis and there by clearly suggests to accept alternative hypothesis that the five ratios adds to the prediction of default. The hypothesis ‘the WC/TA & S/TA add nothing to the prediction can be accepted as the p-value is more than 0.05.

How well the model predicts default can be identified with the help of Pseudo-$R^2$ but when interpreting it one should note that it does not measure whether the model correctly predicted default probabilities- this is infeasible because we do not know the true default probabilities. Instead, the Pseudo $R^2$ (to a certain degree) measures whether we correctly predicted the defaults. These two aspects are related but not identical. Take a borrower that defaulted although it had a low default probability: If the model was correct about this low default probability, it has fulfilled its goal, but the outcome happened to be out of line, thus reducing Pseudo $R^2$. In a typical loan portfolio, most default probabilities are in range of 0.05-5%. Even if we get each single default probability right, there will be many cases in
which the observed data (=default) is not in line with the prediction (low default) and we therefore cannot hope to get Pseudo-$R^2$ close to 1. A situation in which the Pseudo-$R^2$ would be close to 1 would look as follows: Borrowers fall into one of the two groups; the first group is characterized by very low default probabilities (0.1% and less), the second group by very high ones (99.9% or more). This is clearly unrealistic for typical credit portfolios.

Turning to the regression coefficients, we can summarize that three out of the five ratios have coefficients $b$ that are that are significant on the 1% level or better i.e., $p$-value is below 0.01. If we reject the hypothesis that one of these coefficients is zero, we can expect to err with a probability of 1%. Each of the three variables has a negative coefficient, meaning that increasing values of the variables reduce default probability. Thus retained earnings, EBIT, debt-to-equity are inversely related to probability of default. The constant is also highly significant.

Coefficients on working capital over total assets and sales over total assets, by contrast, exhibit significance of 28% and 48.5%, respectively. By conventional standards of statistical significance (5% is most common) it could be concluded that these two variables are not or only marginally significant, and probably consider not using them for prediction.

Before removing two or more variables simultaneously based on their $t$-ratios, one should check the possibility that the variables might jointly explain default even though they are insignificant individually. To test this possibility statistically, we can run a second regression in which we exclude variables that were insignificant in the first run, and then conduct a likelihood ratio (LR) test.

In model 2, WC/TA and S/TA variables will be removed i.e., we impose the restriction that the coefficients on these two variables are zero. The likelihood ratio test for the hypothesis $b_{WC/TA}=b_{S/TA}=0$ is based on a comparison of the likelihood $L$ of the two methods. It is constructed as $LR=2\ln L$ (model 1) - $\ln L$ (model 2) and referred to a chi-squared distribution with two degrees of freedom as we impose two restrictions. In table 1.2 LR test leads to a value of 1.90 with a $p$-value of 38.69%. This means that if we add two variables WC/TA and S/TA to model 2, there is a probability of 38.69% that we do not add explanatory power. The LR test thus confirms the results of the individual tests: individually and jointly, the two variables would be considered only marginally significant. After this we calculate the probability of default (PD) using $PD=1/(1+\exp(-K2+SUMPRODUCT(LS2:PS2,E2:1)))$ which covers $b$ i.e., coefficient of constant and variables.

**Findings:**
- WC/TA & S/TA are marginally significant or insignificant individually as well as jointly, in predicting PD
- RE/TA, EBIT/TA &D/E are significant in predicting PD and are negatively correlated to PD.
- PD and CAPREQ are directly correlated. Higher the PD higher is the capital requirement.

**Advantages:**
- Model helps in identifying the probability of default (PD)
- Model also identifies LGD
- In the model PD and LGD along with Maturity adjustment helps in identifying the capital required which a bank is supposed to keep against credit risk portfolio
- The model helps to identify whether we correctly predicted default probabilities by referring to Pseudo $R^2$.
- Model helps in identifying variables which are highly significant in predicting the PD and there by ensures the accuracy of the model.
- Model helps in checking individual as well as joint impact of variables on PD.

**Conclusion:**
After reviewing various research papers the researcher have considered 5 financial ratios namely: WC/TA - Liquidity Ratio, RE/T - Coverage Ratio, EBIT/TA - Profitability Ratio, D/E- Leverage Ratio, S/TA - Turnover ratio. These ratios are considered as per Altman Z score model and also considered LOGIT Regression to build the credit risk modelling because of its advantage over MDA. Using the above mentioned independent variables and one dependent variable i.e. Default/non default Logit regression function is run to obtain the probability of default. This calculated PD helps the bank in decision making regarding credit risk and also helps in identifying the capital requirement that a bank is supposed to keep against the credit risk portfolio which is usually 8% as per Basel II in which 4.5% to be kept in Tier 1 capital.

The performance, in terms of prediction accuracy, of specific SME model is almost 30 percent higher than the performance of the generic corporate model. Thus, the banks will likely enjoy significant benefits in terms of SME business profitability by modelling credit risk for SMEs separately from large corporate.

**References:**


Gunter Loffler, Peter. N. Posch. (2010). In P. .. Gunter Loffler, 'Credit risk modeling using Excel and VBA' (pp. 04-36).


