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Full Length Research Paper

Design and development of credit rating model for public sector banks in India: Special reference to small and medium enterprises

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This research focuses on the design and development of the credit rating model for public sector banks in India. The need to enhance the existing model and to realize the impact of BASEL II Norms was the reason for the development of the models. Also, the absence of appropriate weights in the current system triggers the need for the development of the same model. Different models were constructed using weighted average method and discriminant analysis. Under the weighted average model, various risks and their sub-parameters were identified. The parameters were classified under four heads namely: industry, business, financial and management risk. The weights developed in this study were based on a conceptual understanding and the importance attached by people that are proficient in this area. A questionnaire was developed and a judgmental survey was conducted among 15 banks with 30 credit rating managers extending the loans of small and medium enterprises (SME). A total of 35 cases were taken for the validation of the model. The new model was able to classify 32 records correctly out of the 35 cases. Further, discriminant analysis was used to classify objects/records into two or more groups based on the knowledge of some variables related to them. Under the discriminant model, the sample size taken was 100 clients of the corporate banking branch. Census was used as the sampling technique, in which 69 records were taken for the development of the model and 31 for validation. However, discriminant functions were constructed, and it was observed that the discriminant and classification scores aided in the classification of the clients. The discriminant model was able to classify 27 records correctly out of 31 cases. Thus, it was concluded that the weighted average model can be used for predicting the credit worthiness of the clients because it has higher predictive power.

Key words: Small and medium enterprise (SME), discriminant, commercial banks, credit risk, credit risk model.

INTRODUCTION

Current scenario

The Indian banking system is financially stable and resilient to the shocks that may arise due to higher non-performing assets (NPAs) and the global economic crisis.

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A progressively growing balance sheet, higher pace of credit expansion, expanding profitability and productivity akin to banks in developed markets, lower incidence of nonperforming assets and focus on financial inclusion have contributed to making the Indian banking vibrant and strong. Indian banks have begun to revise their growth approach and re-evaluate the prospects on hand to keep the economy rolling.

The way forward for the Indian banks is to innovate to take advantage of the new business opportunities and at the same time ensure continuous assessment of risks. The most significant achievement of the financial sector reforms has been the marked improvement in the financial health of commercial banks in terms of capital adequacy, profitability and asset quality, as well as greater attention to risk management. Further, deregulation has opened up new opportunities for banks to increase revenues by diversifying into investment banking, insurance, credit cards, depository services, mortgage financing, securitisation, etc.

The last decade has seen many positive developments in the Indian banking sector. The policy makers, which comprise the reserve bank of India (RBI), Ministry of Finance and related government and financial sector regulatory entities, have made several notable efforts to improve regulation in the sector. The sector now compares favourably with banking sectors in the region on metrics like growth, profitability and non-performing assets (NPAs), while improved regulations, innovation, growth and value creation in the sector remain limited to a small part of it.

Indian banks have compared favourably on growth, asset quality and profitability with other regional banks over the last few years. Policy makers have made some notable changes in policy and regulation to help strengthen the sector. These changes include strengthening prudential norms, enhancing the payments system and integrating regulations between commercial and co-operative banks.

A rigorous evaluation of the health of commercial banks, recently undertaken by the committee on financial sector assessment (CFSA), also shows that the commercial banks are robust and versatile. The single-factor stress tests undertaken by the CFSA divulge that the banking system can endure considerable shocks arising from large possible changes in credit quality, interest rate and liquidity conditions. These stress tests for credit, market and liquidity risk show that Indian banks are by and large resilient.

However, the cost of intermediation remains high and bank penetration is limited to only a few customer segments and geographies. While bank lending has been a significant driver of GDP growth and employment, periodic instances of the “failure” of some weak banks have often threatened the stability of the system. Structural weaknesses such as a fragmented industry structure, restrictions on capital availability and deployment, lack of institutional support infrastructure, restrictive labour laws, weak corporate governance and ineffective regulations beyond scheduled commercial banks (SCBs), unless addressed, could seriously weaken the health of the sector. Further, the inability of bank managements (with some notable exceptions) to improve capital allocation, increase the productivity of their service platforms and improve the performance ethic in their organisations could seriously affect future performance.

Opportunities and challenges for banks

Indian banks have the following opportunities and challenges. First, the market sees discontinuous growth driven by new products and services to include opportunities in credit cards, consumer finance and wealth management on the retail side and fee-based income and investment banking on the wholesale banking side. These require new skills in sales and marketing, credit and operations. Secondly, banks will no longer enjoy windfall treasury gains that the decade-long secular decline in interest rates provided. This will expose the weaker banks. Thirdly, increased interest in India will only intensify the competition from foreign banks. Fourthly, given the demographic shifts resulting from changes in age profile and household income, consumers will increasingly demand enhanced institutional capabilities and service levels from banks. The extent to which Indian policy makers and complementary agenda to tackle emerging discontinuities will lay the foundations for a high-performing sector in 2010.

The main challenges facing the banking industry bank managements develop and execute such a clear and are shown in Figure 1. (http://www.gov.im/lib/docs/cso/candoeconomy2014reportappendi.pdf).

Swot analysis of the banking sector

Table 1 shows the swot analysis of the banking sector. Source: http://www.gov.im/lib/docs/cso/candoeconomy2014reportappendi.pdf.

Impact of Basel-II norms

Banking is a commodity business; as such, for banks to earn an adequate return of equity and compete for capital along with other industries, they need to be highly leveraged. The primary function of the bank's capital is to absorb any loss a bank suffers.

Norms set in the Swiss town of Basel determine the ground rules for the way banks around the world account for loans they give out. These rules were formulated by the Bank for International Settlements in 1988.

Credit risk is not the only type of risk that banks face, but also, they are faced nowadays with operational risks which are huge. The various risks that come under operational risk are competition risk, technology risk, casualty risk, crime risk, etc. The original Basel rules did

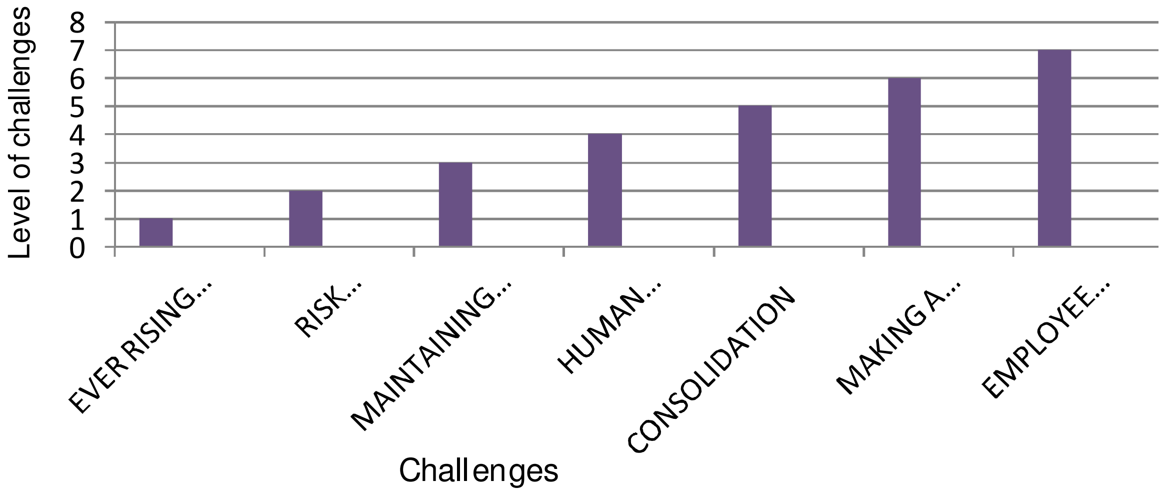

Figure 1. Challenges faced by Indian banks.

Table 1. Swot analysis of the banking sector.

Strengths	**Weaknesses**
(1) Valuable contributor to GDP over a period of 15 years and of pivotal importance to India's economy.	(1) Weak retail and mass affluent customer proposition
(2) High standard regulatory environment.	(2) Lack of competitive differential with other offshore centres
(3) Flexible work permit system.	(3) Rigid legislation that inhibits business development.
Opportunities	**Threats**
(1) Active and aggressive targeting of corporate and private clients and institutions that attract such clients.	(1) Anti-offshore regulations in foreign target markets restricting the development of products and new markets.
(2) Coordinating business relationships across the finance sector to increase revenue, thus investing in the ecosystem.	(2) Downsizing and reduction in banking operations in favour of rival jurisdictions.
	(3) Outsourcing to cheaper jurisdictions.
	(4) Subsequent impact on the finance sector ecosystem.

not take into account the operational risks. As per the Basel-II norms, banks will have to set aside 15% of their net income to protect themselves against operational risks.

Definition of key terms

Small and medium enterprise (SME)

Small and medium enterprises (SMEs), also known as small and medium businesses (SMBs) and which have other variations thereof, are companies whose headcount or turnover falls below certain limits.

SMEs always represented the model of socio-economic policies of the Government of India which emphasized the judicious use of foreign exchange for import of capital goods and inputs, labour intensive mode of production, employment generation, non concentration of diffusion of economic power in the hands of few (as in the case of big houses), discouraging monopolistic practices of production and marketing and finally, contributing effectively to foreign exchange earning of the nation with low import-intensive operations.

SMEs that have strong technological base, international business outlook, competitive spirit and willingness to restructure on their own shall withstand the present challenges and come out with shining colours to make their own contribution to the Indian economy.

Non performing assets

A loan or lease that is not meeting its stated principal and interest payments is known as non performing asset. Banks usually classify nonperforming assets as any commercial loans which are more than 90 days overdue and any consumer loans which are more than 180 days overdue. More generally, non performing assets are assets which do not produce income.

Credit risk

Probability of loss from a credit transaction is the plain-vanilla definition of credit risk. Credit risk is defined as "the risk of loss following a change in the factors that drive the credit quality of an asset". According to Basel committee, "Credit risk is most simply defined as the potential that causes a borrower or counter party not to meet its obligations in accordance with the agreed terms".

The reserve bank of India has defined credit risk as "the possibility of losses associated with diminution in the credit quality of borrowers or counterparties". Credit risk management function has become a centre of gravity, especially in a financial services industry like banking. It involves identifying and analyzing risk in credit transaction.

Credit rating

The Basel committee has defined credit rating as a 'summary indicator' of the risk inherent in individual credit, embodying an assessment of the risk of loss due to the default of a counter party by considering relevant quantitative and qualitative information.

Credit rating, through the use of symbols, can be defined as an expression of the opinion about credit quality of the issuer of securities with reference to a particular instrument. Rating is a measure of credit risk and is only one element in investment decision making. However, credit rating does not indicate market risk or predict prices or yields of credit instruments.

Credit risk model

A credit risk model is a quantitative study of credit risk, covering both good borrowers and bad borrowers. It is a mathematical model containing the loan applicant's characteristics that is either used to calculate a score representing the applicant's probability of default or to categorize borrowers into different default risk classes. A model is considered effective if a suitable validation process is also built with adequate power and calibration.

Outcomes of the risk assessment model

The following are the outcomes of the risk assessment model.

Defining the pricing bands: The grade on the rating scale is expected to define the pricing and related terms and conditions for the accepted credit exposures. As such, the higher the risk, the higher the price that could be charged.

Limits on exposure: The amount sanctioned would depend on the credit-score found on the RAM. These limits could be linked to specific parameters, like a certain percentage of the total debt required by the borrower.

Tenure of loans: The rating scale could also be used for deciding the tenure of the proposed assistance. Thus, a longer term could be offered to safe customers.

REVIEW OF LITERATURE

Small and medium enterprises (SMEs) constitute a significant part of the developing economies, and this was emphasized in the research works of Zolton and Audretsch (1993), OECD SMEs Outlook (2002) and Allen et al. (2004). Majority of these enterprises fund their capital through family or other networks; as a result, a sizeable group will borrow from traditional suppliers of credit.

In India, it is often stated that 60% of SMEs do not borrow from traditional sources. A question arises with regard to the measures that should be taken to assess the loan applications of those who borrow from traditional sources. Most of the Small and Medium Enterprises operate in a very small scale with very limited equity of the owner and more on a high cost debt fund from other sources such as external borrowing from non banking firms.

In India, the concept of small scale industry has primarily been in vogue for a long time, while the medium enterprise definition has a more recent origin. An SSI is defined on the basis of limit of historical value of investment in plant and machinery, which at present is up to Rs. 1 crore. However, with respect to some specified items, this investment limit has been hiked to Rs. 5 crore. For the recently announced small and medium enterprises fund, the Government of India has approved the limit of investment in plant and machinery to be from above Rs. 1 crore and up to Rs. 10 crore for defining a unit as a medium enterprise. Amongst the developing countries, India has been the first to display special consideration to SSIs and basic focus was on making economical use of capital and to absorb the abundant labour supply in the country. Despite its commendable contribution to the economy, MSME sector does not get the required support from the concerned government departments, banking sector, financial institutions and corporate sector, which is a obstacle in becoming more competitive in the national and international markets and which needs to be taken up for immediate and proper redressal.

MSME sector faces a number of problems, such as: absence of adequate and timely banking finance, limited knowledge and non-availability of suitable technology, low production capacity, ineffective marketing and identification of new markets, constraints on modernization and expansions, non availability of highly skilled labour at affordable cost, follow up with various agencies in solving regular activities and lack of interaction with government agencies on various matters.

Over the years, the SSI sector in India has continued to remain an important sector of the economy with its noteworthy contribution to the gross domestic product, industrial production, employment generation and exports. As per the third all India Census of SSIs (2001 to 2002), there were 10.52 million SSI units in the country, of which 1.37 were registered and 9.15 were unregistered units. For the year ended (March 2004), the said number increased to 11.52 million, providing employment to 27.40 million persons and contributing an output of over Rs. 3,480 billion in 2004.

SMEs encompass family business, small consultancies, startup companies and companies employing 100 or more employees. Hence, it is a diverse group of companies. The assessment of their likelihood of default is not immediately straightforward. The two approaches to assessment of default within companies are the accounting based approach and the Merton based approach (Merton, 1974). The Merton based approach [4] aims to compare empirically the two approaches as applied to SMEs. There is a considerable literature on accounting based approaches to assessment of companies (Beaver, 1966; Altman, 1968; Altman and Narayanan, 1997). All these research works are based on accounting concepts and generally accepted accounting principles, which are more conventional in nature. Drawback accounting based approach is predominantly historical in nature and is based on the static data provided by the clients.

Added to the historical nature, most of these accounting statements are prepared for different purpose rather than for the credit seeking purpose. For example, under mandatory disclosure, Norm companies have to publish their audited financial statement for stakeholders' purpose.

Beaver (1966) research was based on financial ratio, and in this approach, financial ratios were used as predictors of failure. However, the main focus of the study was on leverage and liquidity ratios.

Charitou et al. (2004), Keasey and Watson (1986), Lennox (1999), Ohlson (1980) and Peel et al. (1986), and recently more researchers, have acknowledged the importance of SMEs.

Keasey and Watson (1986) show that the main purpose of this paper is to review and assess the progress in developing small firm failure prediction models. It highlights a number of issues that are of particular importance in evaluating small firm failure prediction models and indicates where future research might be usefully directed. The authors conclude that while it is not yet clear whether or not they are worthwhile tools in many decision contexts, the present general models may provide material benefits as relatively cheap. Thus, it is simple to use preliminary screening devices for routine credit/lending decisions. This is because the classifications' accuracy of even relatively simple quantitative models has been shown to outperform human decision makers consistently. If, however, predictive model is required as an input into more strategic decision making, then the utility of the existing empirical models is, to a great extent, less certain.

Peel and Wilson (1986), since the seminal work of Altman (1968), and a large number of researchers have developed statistical models, derived from accounting data, with the aim of predicting corporate failure as evidenced by the event of "bankruptcy". Such models are now apparently widely and successfully used by credit/investment analysts as an aid to assessing corporate viability (Altman, 1983). However, an area which has received little attention in the management literature, but is of much importance to the analyst, is whether or not it is possible to discriminate between those financially distressed firms which fail, and those where a timely merger appears to serve as a viable alternative to corporate bankruptcy. As such, Peel and Wilson (1986) made an attempt to find some evidence on discriminating between failing and distressed acquired firms in the UK corporate sector.

Forecasted company failure in the UK using discriminant analysis and financial ratio data in the modeling of default using accounting based approach. Within this paper, the range of variables considered was extended and the standard credit scoring approaches were applied in modeling (Lin et al., 2007).

In the Merton based approach, the implementation was followed according to the method in the work of Bharath and Shumway (2004). Hence, the value of the firm is determined in terms of share price. This poses a limitation on the types of SMEs that can be considered. One could have spent time on investigating alternative valuation of the firm, but in this current research, this was not explored.

Larry and Timothy (1986), in their paper on “A note on rank transformation discriminant analysis: An alternative procedure for classifying bank holding company commercial paper ratings”, made an attempt to improvise using multiple discriminant analysis. Recent studies in the financial literature have developed models to predict the rating assigned to a firm's debt by the rating agencies. However, multiple discriminant analysis (MDA) has served as the primary statistical tool.

On the other hand, the results of MDA can be biased. This study presents a less biased procedure which closely follows that suggested by the rating agencies. The improved results of the model support such a procedure.

Chandy and Duett (1990) extended the previous work in the area of commercial paper on rating models. Using the data obtained in 1985 and 1986 they rated the commercial paper as “standard, poor and moody”. MDA, LOGIT and CART were the three statistical tests used. The models had a prediction rate of about 85%. It was found that in some rating categories, the quality component (judgment by analysts) played a greater role than in other categories. Variables such as sales, earning power, return on assets, and amount of equity were identified as most important in explaining the ratings of the commercial paper.

Bonds ratings by Pinches and Mingo (1973), Kaplan and Urwitz (1979), Belkaoui (1983), Kim (1993), Manzoni (2004) and Huang et al. (2004) showed that much attention was not given to the examination of individual firms’ ratings, known as counterparty ratings. Although, some studies examine the ratings assigned to non-financial firms by local credit agencies (Laitinen, 1999; Doumpos and Pasiouras, 2005), evidence on the counterparty ratings assigned to banks by one of the large agencies is quite limited.

Manickavasagam and Srinivas (2009) in their research paper on risk management frame work for ITES organizations provided risk management frame work based on the operational aspects of the organization. Risk management is the process of identification, measuring or assessing the process deviations from the predetermined targets. Also, it involves developing a frame work for evaluation and quantification of deviations through mathematical modeling. Further, from a management perspective, risk management was employed to formulate the strategies used to manage it. The strategies include: transferring the risk to another party, avoiding the risk, reducing the negative effect of the risk and accepting some or all of the consequences of a particular risk. Traditional risk management focuses on risks stemming from physical or legal causes, while financial risk management, on the other hand, focuses on risks that can be managed using traded financial instruments. Preparing the risk assessment frame is the most important step in the risk management process and may also be the most difficult risk since it is prone to subjectivity and understanding of the analyst. Once uncertainties have been identified, evaluated and assessed, the steps to properly handle the risk management in ITES organizations become more systematic and programmable.

Patricia and David (2009) in their paper, seek to show that research in the risk management area has been 'framed', leading to predictable outcomes. Presentation (framing) blinkers the way a problem is perceived and reviewed. Positive labels are more likely to evoke positive associations; negative labels are more likely to evoke negative associations leading to evaluations dependent on how the situation has been labeled. A much prior literature has focused on the negative area of small business failure. An established framework is used to analyze and illustrate that framing has occurred within that literature with respect to assessment of small business failure. Many researchers have accepted that small business is likely to fail with the result that their research is aimed at supporting this contention. Such acceptance has impacts on policy decisions and decisions of venture capitalists, bankers and potential entrepreneurs.

Manickavasagam and Srinivas (2009), in their paper said that a risk assessment model (RAM) is necessary to avoid the limitations associated with a simplistic and broad classification of applicants into a "good" or "bad" category. The absence of appropriate weights in the current evaluation system triggers the need for the development of the comprehensive model based on the proven statistical application. The literature survey undertaken brought to surface 28 parameters that need to be taken into account while evaluating a prospect. These parameters were classified under four heads namely: credit, operations, liquidity and market risks. Weights developed in this study were based on a conceptual understanding and the importance attached by people that are proficient in this area. A questionnaire was developed and a judgmental survey was conducted for this purpose amongst various credit officers extending commercial vehicle and construction equipment financing. The sample size was 117 small and medium corporate clients. The existing model was able to classify 28 records correctly. So the predictive power of the original/existing model was about 80%. However, the proposed/new model is able to classify 30 records correctly. So the predictive power of the proposed/new model is 85.71%.

In a relatively recent study, ordered logistic regression was employed to examine the individual financial strength ratings assigned by Moody in a sample of 130 banks in 1997. These ratings differed in their study from those of others in several aspects. Fotios Pasiouras, Chrysovalantis Gaganis and Michael Doumpos A multicriteria was developed by a discrimination approach for the credit rating of Asian banks. In this paper, they developed a multicriteria decision aid model, to investigate whether or not it is possible to replicate the credit ratings of Fitch on Asian banks using publicly available data. The model is developed with the multi-group hierarchical discrimination (MHDIS) approach, following a tenfold cross validation procedure. Five financial variables are selected from a list of nineteen variables through factor analysis. An additional set of five non-financial variables covering ownership, corporate governance, auditing, strength of bank's franchise and its banking environment are also being used.

Manickavasagam and Srinivas (2010) risk assessment model was used for assessing NBFCs' (asset financing) customers. In this paper, the focus is on the risk model for NBFCs, though non-banking financial companies (NBFCs) form an integral part of the Indian financial system. The history of the NBFC Industry in India is a story of under-regulation, followed by over-regulation. Policy makers have swung from one extreme position to another in their attempt to set controls and then restrain them so that they do not curb the growth of the industry. This report covers the industry. Most of these NBFCs are operating with high risk of lending and more often they lend credit to small and medium size enterprises, which are categorized as high risk class of assets. To assess such high risk assets we need to have a comprehensive model. Thus, this paper aims to build risk assessment model for NBFCs' based on both qualitative and quantitative aspects of the client.

Of course, one can ultimately argue that the qualitative and quantitative aspect should jointly be used for the determination of lending decisions, in order to explore whether or not the models signal early the default made by a comparison of the predictive accuracy over a 3 year period before distress. The Merton type models are explored from the 2001 to 2004 year horizon, while the distance to default (DD) and the expected default frequency (EDF) are calculated. Accounting based (Credit scoring) models are based on a previous paper by Lin et al. (2007). Overall, the predicted correct percentages, as well as Types I and II error from various models are described. Merton models and accounting based models are compared for their ability to predict accurately different groups of SMEs. A power curve is used for measuring the predictive accuracy of models with different financial distress across groups of SMEs. Receiver operation characteristics (ROC) plots show the discrimination ability of different models. The test statistic of the areas under ROC (AUROC) is used to measure the performance of models.

Despite the fact that quite a number of studies have modeled commercial paper ratings (Peavy and Edgar, 1983, 1984; Chandy and Duett, 1990) and bonds ratings (Pinches and Mingo, 1973; Kaplan and Urwitz, 1979; Belkaoui, 1983; Kim, 1993; Manzoni, 2004; Huang et al., 2004), much attention has not been given to the examination of individual firm's ratings, known as counterparty ratings. Although, some studies examine the ratings assigned to non-financial firms by local credit agencies (Laitinen, 1999; Doumpos and Pasiouras, 2005), evidence on the counterparty ratings assigned to banks by one of the large agencies is quite limited. In a relatively recent study, employed ordered logistic regression was used to examine the individual financial strength ratings assigned by Moody's in a sample of 130 banks in 1997. Thus, we differentiate our study from that of several studies, where Fotios Pasiouras, Chrysovalantis Gaganis and Michael Doumpos A multicriteria was used to develop a discrimination approach for the credit rating of Asian banks. In this paper, they developed a multicriteria decision aid model, to investigate whether it is possible to replicate the credit ratings of Fitch on Asian banks using publicly available data. The model is developed with the multi-group hierarchical discrimination (MHDIS) approach, following a tenfold cross validation procedure. Five financial variables are selected from a list of nineteen through factor analysis. An additional set of five non-financial variables covering ownership, corporate governance, auditing, strength of bank's franchise and its banking environment was also used.

"Credit risk rating at large U.S. banks", explains how a bank's decisions about its internal rating system can have a material effect on its ability to manage credit risk. The central role of human judgment in the rating process and the variety of possible uses for ratings mean that internal incentives can influence rating decisions. Thus, careful design of controls and internal review procedures is a crucial consideration in aligning its form with function. Banks with a substantial large corporate market presence are likely to benefit from a rating system that achieves fine distinctions among relatively low-risk credits. In addition, independent credit staff are often solely responsible for rating large loans. Such an arrangement can greatly reduce potential incentive conflicts.

Manickavasagam and Srinivas (2009), in their paper "Property valuation for investment decision [with special reference to commercial mortgage backed securities (CMBS)]", showed that the discriminant model application was used to determine factors discriminating the valuation of the property. The ultimate aim of any investor is to maximize his returns and minimize his risk. In order to achieve this aim, diversification of investment is made by investors in various types of securities which may lie at a continuum between highly risky and risk free investment. Commercial mortgage backed securities (CMBS) is one of such types of instrument where people who are willing to take benefit of the real estate boom, but are not backed by real estate knowledge, can invest in these pooled and repacked loans on commercial property mortgages. The need for the study is to help the investors in better investment decision, while investing in CMBS. The level of risk involved to get an 'x' rate of yield could be determined by analyzing the various characteristics in a CMBS pool affecting the yield, thereby finding out the level of relationship between each independent variable (LTV, DSCR, loan term, amortization term, etc.) and the dependent variable (yield). This study gives an investment pattern for the investors which can be applied for property evaluation and investment decisions.

Ben et al. (2008), in their paper "The influence of the financial and accounting information adjustments on the decisions of rating agencies", show that credit rating agencies (CRA) are qualified as "auxiliaries of the financial information" by all the investors. Ratings are the results of a methodology used by CRA. Within the framework of a demystification of the agencies' method of work, the objective of this paper is to identify the importance of the accounting and financial information adjustments in the decisions of rating agencies. This allows the explanation proportion of this type of information that contributes in the development of the assigned rating to be estimated. We suggest a statistical and econometrical study that aims at determining the ratings from the accounting and financial variables adjusted by the credit rating agencies to better understand the relation between the adjustments of the ratings and the level of the ascribed score.

Young-Chan Lee, in the application of support vector machines to corporate credit rating prediction and corporate credit rating analysis, has drawn a lot of research interests in previous studies, while recent studies have shown that machine learning techniques achieved better performance than the traditional statistical ones. This paper applies support vector machines (SVMs) to the corporate credit rating problem in an attempt to suggest a new model with better explanatory power and stability. To serve this purpose, the researcher uses a grid-search technique via 5-fold cross-validation to find out the optimal parameter values of RBF kernel function of SVM. In addition, to evaluate the prediction accuracy of SVM, the researcher compares its performance with those of multiple discriminant analysis (MDA), case-based reasoning (CBR) and three-layer fully connected back-propagation neural networks (BPNs). The experiment results show that SVM outperforms the other methods.

In banking and financial markets, credit rating agencies (CRAs) have very credible and constructive role in providing the unbiased information and also helps in reducing the informative asymmetry between lenders and investors on one side, and issuers on the other side, about the credit worthiness of companies. Hence, the CRAs' role has expanded with financial globalization and has received an additional boost from Basel II which incorporates the ratings of CRAs into the rules for setting weights for credit risk. Ratings tend to be sticky, ragging markets, and overreact when they do change. This overreaction may have aggravated financial crises in the recent past, contributing to financial instability. The recent bankruptcies and in increasing of nonperforming assets of many nationalized banks have prompted scrutiny of the agencies and also banker assessment models. Criticism has been especially directed towards the high degree of concentration on qualitative and financial aspects of the company. This means that the focus is more on the financial and accounting parameters rather than the comprehensive fundamental analysis comprising economy, industry and company analysis (EIC Framework) frame work.

Credit rating agencies (subsequently denoted as CRAs) specialize in analyzing and evaluating the creditworthiness of corporate securities and issuers of debt securities. In the new financial architecture, CRAs are expected to become more important in the management of both corporate and credit risk. Their role is limited to the large scale companies and multi corporations. However, the focus of credit rating agencies was never on Small and Medium Enterprises where credit worthiness related information asymmetry was too large. On the other hand, banks were also handicapped by not having robust comprehensive models. This research attempt has been made to bridge the gap and to provide solutions to the banks. At the same time, all the banks, sooner or later, will have to adopt the rational model for assessing the credit worthiness of their clients and it will become mandatory for all banks to follow the basel committee on banking supervision (BCBS) of capital standards for banks culminating in Basel II.

The logic underlying the existence of CRAs is to solve the problem of the informative asymmetry between lenders and borrowers regarding the creditworthiness of the latter. Issuers with lower credit ratings pay higher interest rates embodying larger risk premiums than higher rated issuers. Moreover, ratings determine the eligibility of debt and other financial instruments for the portfolios of certain institutional investors due to national regulations that restrict investment in speculative-grade bonds. The rating agencies fall into two categories: (i) recognized and (ii) non-recognized. The former are recognized by supervisors in each country for regulatory purposes. In the United States, only five CRAs of which the best among them are moody, standard and poor (S and P) are recognized by the security and exchange commission (SEC). The majority of CRAs, such as: the Economist Intelligence Unit (EIU), Institutional Investor (II) and Euro Money, are "non-recognized". There is a wide disparity among CRAs, in that they may differ in size and scope (geographical and sectoral) of coverage. There are also wide differences in their methodologies, and a definition of the default risk, which renders a comparison between them, becomes difficult.

In preparing for the formal implementation of the new Basel capital accord (Basel II) at the end of 2006, our banking sector has been studying relevant provisions and response strategies. In the hope to promote and keep our banking supervision and risk management at the international level, the bureau of monetary affairs under the financial supervisory commission (formerly the Bureau of Monetary Affairs under the Ministry of Finance) in particular has set up a new basel capital accord joint research taskforce with bankers association to study relevant regulatory and implemental issues. The banking sector is paying particular attention to the internal-ratings based (IRB) approaches for credit risk provided in Basel II. In particular, model validation has been the focus among practitioners, which plays an important role in IRB qualification by supervisors. As an introductory effort, this paper tackles the subject of credit rating model validation. In reference to current theories and practices on the subject, we examine the considerations for model validation and introduce currently adopted approaches.

However, readers should keep in mind that this paper only discusses quantitative approaches. New theories and approaches for qualitative validation will be discussed at a later date as this field of study develops. If a bank realizes the whole picture about model validation, it will facilitate the work of IRB model construction and strategic planning for its business operation. More so, if the rating system is accepted by the regulatory authority, it will certainly boost the bank's stature and market competitiveness. The following is an introduction to the minimum operational requirements for the validation of IRB model outputs suggested in the draft of Basel II, complemented with the actual case study.

The existing models are based on just financial information of the companies and very less weight age has been given to the economic issues concerning the business. Most of the models have short term assessment features and they do not look into the dynamic change process of the economy. Another concerned issue is that ranks are just valid for a certain period of time or for the particular issue. If any changes occur in the economic cycle or in government policies with respect to business or trade, the existing models do not have a mechanism to reveal the impact of such implications on the quantitative aspects of the economic decision, such as monetary policy, fiscal policy and changes in trade policies that are not integrated in any of the models which are in use. Over and above each financial institution and bank is the use of its own method in assessing credit worthiness of the customers. Credit rating agencies are also not providing comprehensive information regarding credit worthiness of the companies; hence, this research is aimed at providing solution to all concerned agencies.

RESEARCH METHODOLOGY

Need for this study

The public sector bank for which the proposed model is developed is currently using a risk score card by Crisil called the risk assessment model. For loans above Rs.10 million, only this model is used, while for loans below Rs 10 million, the bank uses its own ratings and the internal scoring model. This study is mainly done to build a model for public sector bank with various exhaustive list parameters amid different degrees of importance. This model will facilitate the bank to check the credit worthiness of the clients. Also, the bank intends to reduce the non-performing assets in SME loans.

The bank is also interested in knowing the other methods of risk assessment. All Indian banks have to adopt to the Basel II norms, which have prompted Indian overseas bank to understand how the other banks are adopting to these changes which will be implemented in the near future.

Scope of the study

The scope of this study has been restricted only to 29 variables and extraneous factors have not been considered.

1. The study is confined to identify the credit worthiness of the clients based on weighted average model and discriminant model.
2. For the weighted average model, only 15 banks have been considered and for the discriminant analysis, the bank has provided data for 100 clients.

Objective of the study

The main objective of this study is to develop a credit rating model for IOB by studying the credit rating systems of other banks and comparing it with that of the existing model of Indian overseas bank.

Limitations of the study

1. The purview of the project is limited to the Small And Medium Enterprises' (SME) division.
2. Only 15 banks have been considered for the weighted average model.

Research design

Nature of the study

The study is a descriptive design. Descriptive research is used to obtain information concerning the current status of the phenomena to describe "what exists" with respect to variables or conditions in a situation. The methods involved range from the survey which describes the status quo, and the correlation study which investigates the relationship between variables, to the developmental studies which seek to determine changes over time. Here, it involves identifying the various risks and the sub-parameters of those risks by assigning weights to all of them.

Sampling design: Weighted average model

Source of data: The type of data used in assigning appropriate weights and aiding the development of the model is the primary data. However, the various risks and their parameters were identified using secondary data.

Population: The population includes all the banks (Public, private and development banks) in Chennai who are engaged in small medium enterprise (SME) financing.

Sample size and technique: The sample size is 15 banks and the number of officers with whom judgmental survey was conducted is 30. All major players in SME financing were taken into consideration and 35 clients were taken to test the model. The sampling technique used is convenience sampling. Nonetheless, banks which offered data were selected and their data were used.

Data collection instrument: The instrument used for the survey is a questionnaire. Here, various risks and their parameters were to be rated by credit managers of different banks.

Data collection method: Personal interview method is used for collection of primary data. Here, personal interviews were conducted with the credit managers of different banks.

Data analysis tool: The weighted average method is used for data analysis, while the weighted average score helps in categorizing the various clients into different risk levels.

Discriminant model

Source of data: The data used are secondary data taken from the bank's records.

Population: The population represents all the clients of the corporate banking division.

Sample size and technique: The sample size is 100 clients of the corporate banking division. The sample consists of clients of different banks, 95% of which have good, ongoing accounts and 5% have non-performing accounts. A total of 69 clients were taken for developing the model and 31 for testing it. The sampling technique used was judgment sampling, although only those records suggested by the chief manager were taken for the development and validation of the model.

Data collection method: Data were collected from the bank's records and the secondary method was adopted.

Data analysis tool

The discriminant method was used for data analysis, and the discriminant score was used to categorize the applicants into various risk categories.

DATA ANALYSIS

Steps in development of the weighted average model

Identification of the parameters that affect SME financing

The first step in the development of the model is the identification of the various risks and parameters used in this study. For this purpose, the various manuals, websites, books and papers pertaining to the credit appraisal for small and medium enterprise were carefully studied. Also, credit appraisals done at other leading organizations were taken into consideration.

Both quantitative and qualitative aspects need to be taken into consideration while computing the risk levels. There might be certain qualitative parameters which also affect the credit worthiness of the company.

Classification of risk

Industry risk: Industry risk refers to the impact that the state's industrial policy can have on the performance of a specific industry. An industry analysis shows how diverse and different forces act on an industry, thereby creating impact on its survival and profitability. It is these risks that the companies face by virtue of the industry they operate with. For example, many REITs run the risk that despite due diligence, they will acquire properties with significant environmental issues. The parameters of industry risk are as follows:

(1) Industry cyclicality: It explains as to what stage of the life cycle the industry operates. The growth to stabilization stage can be considered as low/moderate risk stages, while the introduction and decline stages belong to the high risk categories.
(2) Demand-supply gap in the industry: Such gaps represent the relationship between the demand for a

product and the supply thereof. Thus, the higher the level of supply as compared to demand, the higher the level of the competition would be. On the other hand, the organizations in the industry having higher demand and lower supply, would find the going much easier.
(3) Government policies: The priorities of the government do affect the industry. While governments actively protect and encourage certain industries, other industries might be facing discouragement or no protection at all.
(4) Entry barriers into the industry: The possibility that new firms may enter into the industry also affects competition. Industries possess characteristics that protect the high profit levels of firms in the market and inhibit additional rivals from entering the market. It is a situation which determines the level of comfort a particular business organization can enjoy. The ease of entry leads to more competition. Also, if the ease of entry in an industry is very high, then the risk levels are low and vice versa.
(5) Growth prospects of the industry: The growth prospects for the industry refer to the outlook of the industry in both short and long term. Industry with excellent growth prospects in both short and long term are considered to be less risky, while industries with uncertainty in its growth prospects are considered to be highly risky.
(6) Technological competence: This refers to the deployment of technology in any industry. If the usage of technology is superior, then it is low/moderate risk, while technologies which are prone to fast obsolescence are highly risky.

Business risk: Business risk is defined as the probability of not attaining the expected financial results. There are several factors which contribute to business risk. Some of them are:

i. Business movement in tune with economy.
ii. Vulnerability of the business.
iii. Concentration of current assets.

The sub-parameters of business risk are as follows:

1. Client's history: This refers to the client's tenure in the business. If the client has a successful track record of more than ten years, then he will be rated high and is considered to be less risky when compared to financing a new venture which is highly risky.
2. Relationship with suppliers: It pays to invest time in building good relationships with key suppliers. If you can save money or improve the quality of the goods or services you buy from your suppliers, your business stands to gain. If the client has a long term contract with the supplier then he is less risky when compared to the one who is unimportant to the suppliers.
3. Relationship with the customers: Customer relationships are at the heart of every business, that is, how the people who keep your company afloat are treated. If the client has a long term contract with the customers, then he will be rated high and is less risky when compared to the one who is unimportant to the customers.
4. Competition: This refers to the extent of market share the client holds in the business. A client who is the local market leader is rated high and is less risky when compared to the one who is an insignificant player in the market.
5. Technology: This refers to the level of speed of innovation and time to the market. A client with very high speed of innovation and shorten time to market will be rated high and is less risky when compared to the one with no support for innovation.
6. Expertise: This refers to the level of understanding of the business process. A client who has a good business history and good professional background has high expertise and is rated high.
7. Demand for the product: This refers to the periodicity for the product. If the demand for the product the client manufactures is regular, then he is rated high and is less risky.
8. Distribution network: Distribution is the process of moving a product from its manufacturing source to its customers. This refers to the strength of the distribution network. A client who has a very good distribution network will be rated high and is less risky.

Financial risk: Financial risk is normally any risk associated with any form of financing. It is the risk that a firm will be unable to meet its financial obligations. This risk is primarily a function of the relative amount of debt that the firm uses to finance its assets. A higher proportion of debt increases the likelihood that at some point, the firm will be unable to make the required interest and principal payments. Thus, the balance sheet is a critical tool for an effective credit evaluation. Nonetheless, the sub parameters under financial risk are:

1. Liquidity: The importance of adequate liquidity is in the sense of the ability of a firm to meet current/short term obligations when they become due for payment. It is the pre requisite for the very survival of the firm. Quantity and quality of liquid assets are important and are assessed with reference to the following:

i. To understand the liquidity of the issuer, the focus of the analysis is on the maturity matching between the sources of funds and the deployment of funds.
ii. It is measured based on the current ratio. The current

ratio measures the firm's ability to meet its short term liabilities and generally, the higher the ratio, the better it is. A client with the current ratio greater than two is rated high and is less risky.
2. Leverage: The long term lenders would judge the soundness of the firm on the basis of the long-term financial strength measured in terms of its ability to pay the interest regularly as well as repay the installment of the principal on due dates or in one lump sum at the time of maturity. It represents the level of financial stake of the promoters in the business in the form of own funds, such as capital, reserve and surpluses. The highly leveraged business organization will have high debt equity ratio indicating lower financial stakes. A client with debt equity ratio lesser than 0.50 is rated high and is less risky.
3. Sales growth: It represents the percentage increase in the sales turnover as compared to that of the previous year. The higher the growth in the sales accompanied by the operating profit or net profit, the positive its indication.
4. Profitability: These are profits before depreciation, interest and tax (PBDIT). The profitability taken in this case is the relationship between operating profit and the sales. A client with PBDIT >25% is rated high and is less risky.
5. Debt service coverage ratio (DSCR): This ratio tells the repayment ability of not only the interest portion but also that of installments. As such, the higher the ratio, the better the client's rating.
6. Activity ratio: These ratios measure the speed with which various accounts/ assets are converted into sales or cash. This ratio measures the average collection period and the inventory turnover rate. A client with very low average collection period and high inventory turnover rate will be rated high.

Management risk: Management risk refers to the defects, inadequacies and lack of skill and experience in the people in key positions. The parameters used are as follows:

1. Integrity: A lender always runs the risk of dealing with a person whose integrity is doubtful or turns to be doubtful in the subsequent stage which creates a problem for the lender in the recovery of funds also. A client with highly tested and proven integrity is rated high and is less risky.
2. Family standing: A client with the good respected family standing is rated high and is less risky.
3. Financial standing: When the client has good liquidity and considerable amount of free assets, then he is rated high and is less risky when compared to the client with low liquidity.
4. Management commitment: A client with sole business and unwavering commitment is rated high and is considered to be in low/moderate risk.
5. Succession: A company with good succession plan devised by the owner is rated high and is considered to be low in risk.
6. Employee quality: Employees are the dynamic resource of any organization. A company with highly qualified and motivated employees is rated high and is considered to be low in risk.
7. Repayment record: A company with good history of repayment is rated high and is considered to be low in risk.
8. Compliance record: A client that complied with all conditions is rated high and is considered to be low in risk.

Study the weights in other banks

Once the parameters are identified, a questionnaire is prepared with all the risks and their parameters (Appendix). This is circulated among credit managers of 15 banks (Public, private and development banks) in order to find out the weights for them. However, two credit managers from each bank gave the ratings.

Assign weights to the various risk parameters

The data collected from all the banks is classified and tabulated. The average is computed for all the four risks and their sub-parameters. Since the rating is done on a ten point scale, the weights are ten percent of the individual risk scores.

The weights assigned to various parameters developed in this study are based on a conceptual understanding of the relative impact of these parameters. The weights may change if the external economic environment undergoes substantial changes. It is not possible here to claim full objectivity in assignment of different weights, which requires empirical testing of success and failure experiences of a lending organization over a substantially long period of time. The various weights assigned to different parameters are illustrated in Table 2.

Development of the risk assessment model

A comprehensive model is constructed after attaching the weights. Each client will be rated on each of the parameters based on the scorecard provided. Each score of the client will be multiplied by the corresponding weights and a weighted score will be calculated for each parameter. The weighted scores of all the parameters will be summed to arrive at the final score of each client. Based on the final score, the client is given a rating by referring to the rating scale of the model. This final score

Table 2. Various parameters and their weights.

S/N	Industry risk	[280 points]
1	Industry cycle	4.85
2	Demand -supply gap	4.71
3	Government policies	4.71
4	Entry barriers	5.13
5	Growth	4.38
6	Technology status	4.22
	Business risk	**[260 points]**
7	Client history	3.46
8	Relationship with suppliers	3
9	Relationship with customers	2.9
10	Competition	4
11	Technology	2.77
12	Expertise	2.9
13	Demand for the product	2.9
14	Strength of distribution networks	4.07
	Financial risk	**[290 points]**
15	Liquidity	5.51
16	Leverage	5.31
17	Sales growth	4.35
18	Profitability	4.54
19	Interest coverage	4.75
20	Activity ratio	4.54
	Management risk	**[170 points]**
21	Integrity	1.77
22	Family standing	2.11
23	Financial standing	1.55
24	Management commitment	2
25	Succession	2.29
26	Employee quality	1.62
27	Organization structure	1.93

decides the risk involved in operating with each client.

To aid the assessment process and to systematize the entire process, a score card has been developed in consultation with people well versed in this field. The score for each parameter in each risk category should be given based on the score card. This will then standardize the whole process.

In this model, risk rating is measured on a scale of 3 which takes into account different scoring bands beginning from 100 to 50. The first two items are in the score level of 51 categories, while the borrowers are in the five risk categories. The remaining one places the borrower in the non-performing category, based on the parameters prescribed by the bank.

Rating scale

The rating scale indicates the level of risk a particular borrowing transaction carries with it. It begins from the minimum risk category and ends with the loss asset category. A rating model helps to make distinction between various stages of loan transaction and to draw appropriate conclusions. RBI has prescribed that the overall score for risk should be placed on a numerical scale rating between 1 and 6 or 1 and 8 on the basis of the credit profile of the bank concerned. RBI usually prescribes a six point rating scale (Appendix 3), but in this model's development, the reasons for adopting a three point scale are explained in Table 3.

Reserve bank of India (RBI) has prescribed a six point rating scale, but we have condensed the rating to a three point scale. The reasons for the following are:

1. The sample size which is taken as only 30.
2. Out of the 5 NPAs, 4 have a score between 27 and 60 and only one has less than that.
3. Out of the 35 clients used for testing the model, three of them fall between the 50 and 60 ranges.
4. The six point rating scale has been condensed to a three point rating scale.

Validation of the model

For checking the consistency of performance of the model, the thirty-five existing clients were considered and rated. The comparison of the rating of the customer and the current status of the performance determines the consistency of the model.

Case 1 – EID parry (India) Ltd., Madras (Figure 2)

EID parry has the following scores:

1. It scores 107.17 on a total of 280 for industry risk.
2. It scores 107.22 on a total of 260 for business risk.
3. It scores 121.5 on a total of 290 for financial risk.
4. It scores 66.19 on a total of 170 for management risk.
5. It has an overall score of 402.08 on a total of 1000.
6. The client is put in risk category 3 which implies it belongs to NPA category.

Result: The case may not be granted credit.

Case 2 - Aban Loyd Chiles offshore Ltd., Madras (Figure 3)

Aban Loyd Chiles has the following scores:

1. It scores 210.95 on a total of 280 for industry risk.

Table 3. Rating scale.

S/N	Risk score (%)	Client risk rating	Explanation	Nature of case
1	100 to 81	1	Very low or no risk	Good
2	80 to 61	2	Tolerable risk	Moderate
3	Below 60	3	High risk	NPA

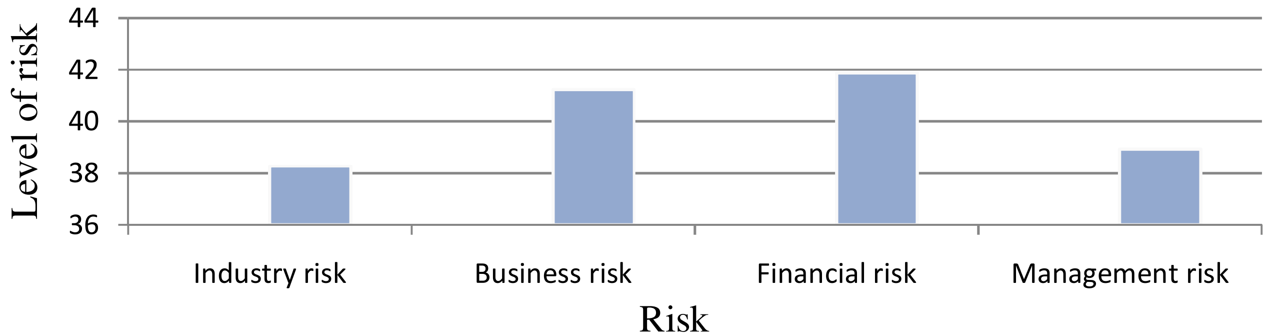

Figure 2. Validation result of EID parry.

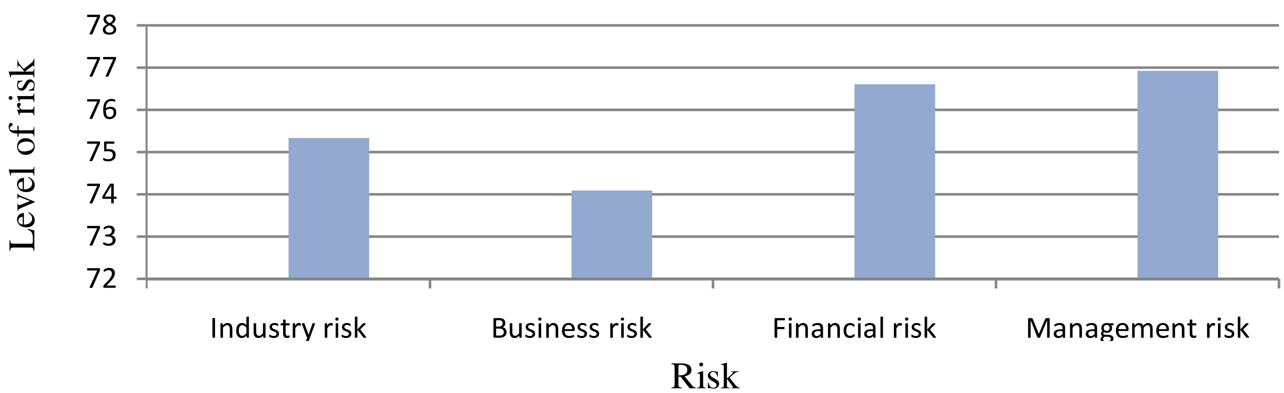

Figure 3. Validation result of Aban Lloyd.

2. It scores 192.635 on a total of 260 for business risk.
3. It scores 222.15 on a total of 290 for financial risk.
4. It scores 130.765 on a total of 170 for management risk.
5. It has an overall score of 756.5 on a total of 1000.
6. The client is put in risk category 2 which implies tolerable risk.

Result: The case may be granted credit.

Case wise statistics: A total of 35 cases were taken for the validation of the model (Table 4).

Interpretations

1. The existing model was able to classify 28 records correctly out of 35. So, the classification accuracy is 80%.
2. The new model was able to classify 32 records correctly out of 35. So, the classification accuracy is 91.42%.

Discriminant analysis

Discriminant analysis is a technique used for classifying a set of observations into predefined classes. The purpose is to determine the class of an observation based on a

Table 4. Case wise statistics.

Case number	Existing model's score	New model's score	Actual performance
1	2 (Tolerable risk)	2 (Tolerable risk)	Good
2	1(Comfortable risk)	1 (Comfortable risk)	Good
3	1 (Comfortable risk)	3 (High risk)	NPA
4	1(Comfortable risk)	1 (Comfortable risk)	Good
5	1 (Comfortable risk)	3 (High risk)	NPA
6	2 (Tolerable risk)	2 (Tolerable risk)	Good
7	3 (High risk)	1 (Comfortable risk)	Good
8	1 (Comfortable risk)	1 (Comfortable risk)	Good
9	2 (Tolerable risk)	2 (Tolerable risk)	Good
10	2 (Tolerable risk)	1 (Comfortable risk)	Good
11	2 (Tolerable risk)	2 (Tolerable risk)	Good
12	2 (Tolerable risk)	2 (Tolerable risk)	Good
13	1 (Comfortable risk)	1 (Comfortable risk)	Good
14	3 (High risk)	1 (Comfortable risk)	Good
15	2 (Tolerable risk)	2 (Tolerable risk)	Good
16	2 (Tolerable risk)	2 (Tolerable risk)	Good
17	3 (High risk)	3 (High risk)	NPA
18	3 (High risk)	3 (High risk)	Good
19	2 (Tolerable risk)	3 (High risk)	NPA
20	2 (Comfortable risk)	3 (High risk)	Good
21	1 (Comfortable risk)	1 (Comfortable risk)	Good
22	2 (Tolerable risk)	2 (Tolerable risk)	Good
23	2 (Tolerable risk)	2 (Tolerable risk)	Good
24	1 (Comfortable risk)	1 (Comfortable risk)	Good
25	1 (Comfortable risk)	2 (Tolerable risk)	good
26	2 (Tolerable risk)	3 (High risk)	NPA
27	1 (Comfortable risk)	2 (Tolerable risk)	good
28	2 (Tolerable risk)	2 (Tolerable risk)	good
29	2 (Tolerable risk)	2 (Tolerable risk)	good
30	1 (Comfortable risk)	1 (Comfortable risk)	good
31	1 (Comfortable risk)	1 (Comfortable risk)	good
32	1 (Comfortable risk)	1 (Comfortable risk)	good
33	1 (Comfortable risk)	1 (Tolerable risk)	NPA
34	2 (Tolerable risk)	2 (Tolerable risk)	good
35	3 (High risk)	3 (High risk)	NPA

set of variables known as predictors or input variables. The model is built based on a set of observations for which the classes are known. Discriminant analysis is used to classify objects/records into two or more groups based on the knowledge of some variables related to them.

Discriminant function

$Y=a+ k_1x_1 +k_2x_2 +\ldots\ldots\ldots. +k_nx_n$

where Y is a dependent variable, a is a constant, x_1, $x_2 \ldots x_n$ are independent variables, and k_1 and k_2 are coefficients of the independent variables. In this case, for the development of the model, the dependent and independent variables are as follows:

1. The dependent variable (Y) is the client risk rating (CRR).
2. The independent variables (x_1, $x_2 \ldots\ldots x_{20}$) are as follows:

X1 = Industry cyclicality, X2 = demand-supply gap in the industry, X3 = government policies towards the industry, X4 = entry barriers in the industry, X5 = growth prospects

Table 5. Discriminant model.

Discriminant models	Function	
	1	2
Industry cycle	0.841	-0.360
Demand supply	0.369	0.034
Govt. policies	0.548	0.226
Entry barriers	-0.205	0.407
Growth prospects	-0.002	0.092
Technological competence	-0.055	-0.074
Client history	-0.069	0.688
Relationship with suppliers	0.845	-0.646
Relationship with customers	-0.087	-0.431
Competition	-0.021	0.375
Technology	0.616	-0.778
Expertise	-10.068	-0.049
Demand for the product	0.535	0.068
Strength of distribution network	0.017	0.632
Liquidity	0.177	-0.405
Leverage	0.062	0.008
Sales growth	0.280	-0.247
Profitability	0.490	-0.293
Interest coverage	-0.217	-0.333
Activity ratios	-0.112	0.132
Integrity	0.469	0.320
Family standing	-0.218	0.305
Financial standing	-0.026	0.457
Management commitment	-0.160	0.050
Succession	0.298	0.155
Employee quality	-0.597	0.153
Organisation structure	-0.015	-0.433
Repayment records	-0.226	0.430
Compliance records	0.502	0.122
(Constant)	-170.438	-10.663

for the industry, X6 = technological competence, X7 = client's history, X8 = relationship with suppliers, X9 = relationship with customers, X10 = competition, X11 = technology, X12 = expertise, X13 = demand for the product, X14 = strength of the distribution network, X15 = liquidity, X16 = leverage, X17 = sales growth, X18 = profitability, X19 = interest coverage, X20 = activity ratio, X21 = integrity, X22 = family standing, X23 = financial standing, X23 = management commitment, X24 = succession, X25 = employee quality, X26 = repayment records, X27 = compliance records and X27 = organization structure.

Building the discriminant model

To build the discriminant model, the value of the dependent and the independent variables for the 69 records are entered in the SPSS software. The discriminant scores are computed by solving all the 69 equations. Thus, the weights/coefficients for all the parameters are computed and are illustrated in Table 5.

Discriminant functions

The discriminant functions are generated from a sample of individuals (or cases), for which group membership is known. The functions can then be applied to new cases with measurements on the same set of variables, but with unknown group membership. The coefficients for the first discriminant function are derived so as to maximize the differences between the group means.

The coefficients for the second discriminant function are derived to maximize the difference between the group means, subject to the constraint that the values on the second discriminant function are not correlated with the values on the first discriminant function and so on. In other words, the second discriminant function is orthogonal to the first and the third discriminant function is orthogonal to the second, and so on.

The maximum number of unique functions that can be derived is equal to the number of groups minus one or is equal to the number of discriminating variables, which are less. The first function will be the most powerful differentiating dimension, but later functions may also represent additional significant dimensions of the differentiation.

Function 1

Y = 0.841 (industry cycle) + 0.369 (demand – supply gap) + 0.548 (government policies) - 0.205 (entry barriers) - 0.002 (growth prospects) - 0.055 (technological competence) - 0.069 (client history) + 0.845 (relationship with suppliers) - 0.087 (relationship with customers) - 0.021 (competition) + 0.616 (technology) - 1.068 (expertise) + 0.535 (demand) + 0.017 (strength of distribution network) + 0.177 (liquidity) + 0.062 (leverage) + 0.280 (sales growth) + 0.490 (profitability) - 0.217 (interest coverage) - 0.112 (activity ratios) + 0.469 (integrity) - 0.218 (family standing) - 0.026 (financial standing) - 0.160 (management commitment) + 0.298 (succession) - 0.597 (employee quality) - 0.015 (organisational structure) - 0.226 (repayment records) + 0.502 (compliance records).

Function 2

Y = - 0.360 (industry cycle) + 0.034 (demand – supplygap)

Table 6. Functions at group centroids.

Risk category	Function	
	1	2
Low risk	1.285	-0.085
Moderate risk	-0.755	0.168
High risk	-1.696	-4.816

+ 0.226 (government policies) + 0.407 (entry barriers) + 0.092 (growth prospects) - 0.074 (technological competence) + 0.688 (client history) - 0.646 (relationship with suppliers) - 0.431 (relationship with customers) + 0.375 (competition) - 0.778 (technology) - 0.049 (expertise) + 0.068 (demand) + 0.632 (strength of distribution network) - 0.405 (liquidity) + 0.008 (leverage) - 0.247 (sales growth) - 0.293 (profitability) - 0.333 (interest coverage) + 0.132 (activity ratios) + 0.320 (integrity) + 0.305 (family standing) + 0.457 (financial standing) + 0.050 (management commitment) + 0.155 (succession) + 0.153 (employee quality) - 0.433 (organizational structure) + 0.430 (repayment records) + 0.122 (compliance records).

Discriminant score

The discriminant score, also called the DA score, is the value resulting from applying a discriminant function formula to the data for a given case. The Z score is the discriminant score for the standardized data. Discriminant score derived from the two functions can be used to predict/determine the grouping of the unclassified cases.

Functions at group centroids

Functions at group centroids are the mean discriminant scores for each of the dependent variable categories for each of the discriminant functions. The centroids give the group mean on the ldf. If the two groups are of equal size, the best cutting point is half way between the values of the functions at group centroids (that is, the average). Under “functions at group centroids”, we gave the group means of each of the discriminant functions (Table 6).

Classification function coefficient

Classification function coefficients are shown in Table 7.

Interpretation

1. Each column contains estimates of the coefficients for a classification function for one group.
2. The functions are used to assign or classify cases into groups.
3. To obtain a classification score for each case in each group, multiply each coefficient by the value of the corresponding variable, sum the products, and add the constant to get the score.
4. A case is predicted as being a member of the group in which the value of its classification function is largest.

Validation of the model

For checking the consistency of the model’s performance, thirty-one existing clients were considered and rated. The comparison of the rating of the customer and the current status of the performance determines the consistency of the model.

Case 1- Mysore Petrochemicals Ltd., Madras

1. The discriminant score for function 1 is 0.128.
2. This lies in the moderate risk category.
3. The classification score for the moderate risk category is the highest.

Result: The client belongs to the moderate risk category and he may be given credit.

Case 2- Ultramarine and Pigments Ltd., Ranipet

1. The discriminant score for function 1 is 2.248.
2. This lies in the high risk category.
3. The classification score for the high risk category is the highest.

Result: The client belongs to the very high risk category and he may be refused credit.

Case wise statistics

Table 8 shows the case wise statistics.

Table 7. Classification function coefficients.

Discriminant functions	Risk category		
	Low risk	Moderate risk	High risk
Industry cycle	23.538	21.732	22.734
Demand supply	11.864	11.121	10.603
Government policies	33.845	32.784	31.140
Entry barriers	-9.390	-8.868	-10.702
Growth prospects	17.944	17.970	17.516
Technological competence	4.042	4.135	4.553
Client history	11.724	12.039	8.676
Suppliers	28.610	26.724	29.150
Customers	9.322	9.390	11.617
Competition	9.418	9.556	7.709
Technology	27.592	26.139	29.438
Expertise	-18.847	-16.682	-15.434
Demand	18.607	17.532	16.692
Strength	12.561	12.686	9.519
Liquidity	17.356	16.894	18.748
Leverage	1.635	1.510	1.413
Sales growth	21.294	20.661	21.628
Profitability	23.601	22.526	23.525
Interest coverage	13.378	13.736	15.602
Activity ratios	11.785	12.047	11.495
Integrity	29.515	28.640	26.602
Family standing	9.118	9.640	8.323
Financial standing	2.466	2.634	.379
Management commitment	-7.875	-7.535	-7.636
Succession	15.536	14.968	13.917
Employee quality	-14.956	-13.699	-13.900
Organisation structure	-12.413	-12.492	-10.323
Repayment records	-.471	.100	-1.828
compliance records	-.403	-1.396	-2.476
(Constant)	-930.169	-894.010	-885.790

Interpretations

1. The existing model was able to classify 25 records correctly out of 31. So, the percentage of classification accuracy is 80.6%.
2. The new model was able to classify 27 records correctly out of 31. So, the percentage of classification accuracy is 87.1% (Table 8).

FINDINGS AND SUGGESTIONS

The amount of risk assessed and which is now experienced in respect of these clients were found to be similar in the case of the weighed average model. Clients with high scores and low risk have been prompt payers on the other hand, while those with low scores and high risks were found to be defaulters. One company which was operating in tolerable or medium risk was found to have a high risk NPA. The following are the key findings of each of the model:

Weighted average model

1. Financial risk is considered to be the most significant of all risks.
2. Business risk is rated second in vitality, followed by management risk and lastly industry risk.
3. The existing model was able to classify 28 records correctly out of 35. So, the classification accuracy is 80%.
4. The new model was able to classify 32 records

Table 8. Case wise statistics.

Case no.	Existing model's score	New model's score	Actual performance
1	3 (High risk)	3 (High risk)	NPA
2	3 (High risk)	3 (High risk)	NPA
3	2 (Tolerable risk)	3(High risk)	NPA
4**	2 (Tolerable risk)	3 (High risk)	Good
5	3 (High risk)	3 (High risk)	NPA
6	2 (Tolerable risk)	2 (Tolerable risk)	Good
7	1 (Comfortable risk)	1(Comfortable risk)	Good
8**	2 (Tolerable risk)	3(High risk)	Good
9	1 (Comfortable risk)	1(Comfortable risk)	Good
10**	2 (Tolerable risk)	2(tolerable risk)	NPA
11	1 (Comfortable risk)	1 (Comfortable risk)	Good
12	2 (Tolerable risk)	2 (Tolerable risk)	Good
13	3 (High risk)	2 (Tolerable risk)	Good
14	2 (Tolerable risk)	2 (Tolerable risk)	Good
15	2 (Tolerable risk)	2 (Tolerable risk)	Good
16**	1 (Comfortable risk)	3 (High risk)	Good
17	2 (Tolerable risk)	2 (Tolerable risk)	Good
18	1 (Comfortable risk)	1 (Comfortable risk)	Good
19	1 (Comfortable risk)	1 (Comfortable risk)	Good
20	1 (Comfortable risk)	1 (Comfortable risk)	Good
21	3 (High risk)	2 (Tolerable risk)	Good
22	2 (Tolerable risk)	2 (Tolerable risk)	Good
23	2 (Tolerable risk)	2 (Tolerable risk)	Good
24	2 (Tolerable risk)	2 (Tolerable risk)	Good
25	2 (Tolerable risk)	2 (Tolerable risk)	Good
26	1 (Comfortable risk)	1 (Comfortable risk)	Good
27	3 (High risk)	2 (Tolerable risk)	Good
28	3 (High risk)	2 (Tolerable risk)	Good
29	2 (Tolerable risk)	2 (Tolerable risk)	Good
30	1 (Comfortable risk)	1 (Comfortable risk)	Good
31	1 (Comfortable risk)	1 (Comfortable risk)	Good

correctly out of 35. So, the classification accuracy is 91.42%.

Discriminant model

1. The existing model was able to classify 25 records correctly out of 31. So, the percentage of classification accuracy is 80.6%.
2. The new model was able to classify 27 records correctly out of 31. So, the percentage of classification accuracy is 87.1%.
3. All the NPAs have been correctly identified by the new model.

Suggestions

Weighted average model can be used by Indian overseas bank to check the client's credit worthiness.

Conclusion

Based on the previous findings, we can conclude that:

1. Weighted average model can be used for predicting

the credit worthiness of the clients, because it has higher predictive power.

2. The new discriminant model can be used to identify NPAs. This will help the bank to reduce their non-performing assets.

3. Qualitative factors play a major role in evaluating the credit worthiness of the clients.

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