Evolution of Credit Risk Management Models for Business Loans: A Systematic Literature Review

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Abstract

A robust Credit Risk Management (CRM) framework is a pre-requisite for success of banks. The recent focus on recognition and management of Non Performing Assets has necessitated the use of sophisticated credit risk analysis models for banks. CRM models adequately capture and quantify the credit risk inherent in a loan proposal. This paper studies the evolution of such CRM models using a systematic literature review approach. It intends to present effective and time tested CRM models for the use by banks for managing their credit risk. The study is primarily divided into three important time horizons. In the pre 1800 era, subjective methods were used, as banking mostly remained in close circles. From late 1800s till 1950s, CRM models used univariate models to assess credit risk. These models used standalone figures such as past and projected figures of Sales, Profit and Cash Flow to assess credit risk. From late 1950s to early 2000s, CRM models based on multivariate models were developed and used. These models used key financial and industry ratios, regression, logit and probit models etc. to quantify the credit risk and estimate probability of default. Altman's Z score, Emerging Market Scoring Model, Wilcox's risk of ruin were some of the prominent multivariate models developed and used during this period. From the year 2000 onwards the focus shifted to Artificial Intelligence, Machine Learning and Neural Network based models. These models acquired the capacity to process voluminous data to arrive at predictions about default. Parallel to these financial models, the regulatory evolution part of this paper traces the evolution of regulations from late 1970s in the form of BASEL accords and Reserve Bank of India's Master Circulars and Guidance Notes issued from time to time. Using systematic literature review, this paper delves into the evolution of the models and practices adopted by lenders for containment of credit risk. The literature referred and cited in this paper are mostly the seminal work of many pioneers of bankruptcy prediction such as Edward Altman and Wilcox etc. The major findings of this paper are that a combination of multivariate and AI based models should be used by the banks in current times for identifying the risk inherent in a loan proposal and

assessing the probability of default. This could save the banks from making adverse selection of borrowers and improve quality of credit.

Keywords: Credit Risk Management, Univariate and Multivariate Models, Bankruptcy Predictors, Probability of Default, Loss given Default, and Artificial Intelligence

Introduction and Definition of Credit Risk Management:

Banking is believed to have originated in 2000 BC in India, Assyria and Sumeria. The prototype banks of that time used to lend grain based loans to farmers and traders. Medici Bank is operating since 1397 in Italy (Goldthwaite, 1995). Giovani Medici established it. Banca Monte dei Paschi di Siena at Siena is the oldest Italian bank, functioning since 1472 (Boland, 2009).

Banks have always struggled with credit risk and therefore credit risk management is as old as credit itself in the banking system. The modern techniques for management of credit risks date back to the 20th century. The credit risk management techniques are believed to be developed in the industrialized countries post World War II (Ricardo, 2016). With the financial markets getting more and more sophisticated during late 50s and mid 80s, there was enhanced focus on objective CRM techniques. The term Credit Risk Management (CRM) gained enormous significance with the emergence of industrial revolution when entrepreneurs started investing in large industries with the help of bank's money. The works of various authors with regard to the definition of CRM is discussed below.

Risk Management Association defines CRM as “Credit risk management can be summed up as how a bank measures, manages, and monitors its exposures to achieve a desired return on its capital” (RMA, 2021). Two important terms that emerge from this definition are Measurement of exposure and desired return on capital. “Credit risk management is the practice of mitigating losses by understanding the adequacy of a bank's capital and loan loss reserves at any given time – a process that has long been a challenge for financial institutions” (SAS, 2021). This definition places emphasis on the probability of loss due to a borrower not fulfilling his/her debt obligation. Also, how capital adequacy and loan loss reserves can serve as a cushion against any non performing assets. “CRM techniques assess the impact on lenders should a loan go under default” (TGT, 2019). CRM techniques assess the impact on lenders should a loan go under default. 'Probability of default' assumes significance in this definition. “Credit risk management ensures that the bank understands, measures, and monitors the various risks that arise and that the organization adheres strictly to the policies and procedures established to address these risks” (CFI, 2021). This definition places emphasis on policies and procedures in place to monitor and manage credit risks. “Credit risk is most simply defined as the potential that a bank borrower or counter party will fail to meet its obligations in accordance with agreed terms. The goal of credit risk management is to maximize a bank's risk-adjusted rate of return by maintaining credit risk exposure within acceptable parameters” (BIS, 2021). This definition focuses on credit risk models based on credit appraisal, credit scoring, stress testing, and bankruptcy prediction.

The Reserve Bank of India (2002) defines credit risk models as models which “seek to determine, directly or indirectly, the answer to the following question: Given our past experience and our assumptions about the future, what is the present value of a given loan or fixed income security? A credit risk model would also seek to determine the (quantifiable) risk that the promised cash flows will not be forthcoming. The techniques for measuring credit risk that have evolved over the last twenty years are prompted by these questions and dynamic changes in the loan market”. The RBI Guidance Note on Credit Risk Management (2010) suggests that while measuring credit risk, “models may be classified along three different dimensions: the techniques employed in the domain of applications in the credit process, and the products to which they are applied”. With regard to the techniques employed for credit risk appraisal, econometric techniques like linear and multiple discriminant analysis, multiple regressions, logit analysis and probability of default, etc. are widely used.

This current literature review study aims to explore the evolution of CRM under the streams of (a) CRM models focused on credit appraisal, credit scoring, stress testing and bankruptcy prediction, (b) Regulatory developments surrounding CRM, and (c) Future of CRM in ensuring bank's financial stability through systematic literature review.

Objectives, Research Methodology and Structure of the Paper:

This paper studies the evolution of CRM models through a systematic review of literature. The primary objective of this paper is to present time tested CRM models to the banks for their use. It also focuses on identifying effectiveness of such CRM models in the current times and business context. The paper is structured on the basis of systematic development of CRM models. The study is primarily divided in to three important time horizons. In the era pre 1800, subjective methods were used, as banking mostly remained in close circles. From late 1800s till early 2000s, CRM models used multivariate models to assess credit risk. These models used key financial and industry ratios of the borrower to quantify the credit risk and estimate probability of default. Altman's Z score, Emerging Market Scoring Model, Wilcox's risk of ruin were some of the prominent multivariate models used during this period. From year 2000 onwards the focus shifted to Artificial Intelligence, Machine Learning and Neural Network based models. These models acquired the capacity to process enormous volume of data to arrive at predictions about default.

Also, there has been evolution of regulations simultaneously from late 1970s in the form of BASEL accords. The Reserve Bank of India has also issued master circulars and guidance notes from time to time to guide the banks in respect to their CRM practices. The regulatory evolution part of this paper deals with the same. Using systematic literature review, this paper has delved into systematic evolution of the models and practices adopted by lenders for containment of credit risk. It is a literature review based research paper.

Evolution of Credit Risk Management Models:

This section covers the evolution of credit risk management models broadly classified as subjective models, univariate models, multivariate and regression models, option/ contingent claims models, and Artificial Intelligence Systems (Structural Framework).

Subjective Models:

Early models in the pre-1800 era remained primarily subjective. The lenders used to give grain based loans. The borrowers were closely known to the lenders. The subjective models used to focus on character, enterprising spirit, paying capacity and reputation of the borrower. In the 1800s the lenders used to lend mainly to the travelers. They used to evaluate the proposals based on ownership and management structures of the borrower (Altman, 2019). The models of credit appraisal in the late 1800s were based on objective methods and variables. The focus shifted to quantification of credit risk. Henry Varnum Poor (1860) published the “History of Railroads and Canals in the United States” and gave a framework of securities analysis and reporting. The formal credit risk assessment in the securities market developed thereafter (CFI Team, 2022).

Univariate Measures (Accounting or Market Variables Measures):

In early 1900s Du Pont introduced Du Pont system of Corporate Regrowth, ROE growth, other univariate accounting measures and industry peer group comparisons with rating designations (Altman, 2017). Moody (1909) published the first debt ratings in his manual of Railroad Securities. Thereby, he introduced rating system to the US Bond market. These ratings later had a prominent impact in 1936 when the banks were prohibited to invest in speculative bonds of corporate that had low credit rating (Moody's, 2009). Standard & Poor (1916) began credit rating in the year 1916 by assigning rates private placements, bank loans, bank guarantees and ability of insurance companies to pay claims (SEC, 2002).

Multivariate (Regression) Models:

The focus in credit risk assessment models took a paradigm shift from univariate measures to multivariate measures from 1960s onwards. Discriminant, Logit and Probit Models (Linear, Quadratic) that took shape from 1960s are popularly known as regression models. Linear discriminant analysis and quadratic discriminant analysis gained significance during the 1960s. The seminal study of Altman (1968) on bankruptcy prediction was conducted by Edward Altman in the backdrop of great depression.

Altman studied 65 manufacturing public (U.S.) firms and relevant ratios of such firms. The study provided the seminal bankruptcy predictor model for use of the lenders for determining bankruptcy of borrowers. He constructed a discriminant logit model. This multiple discriminant score (Z score) used various ratios to determine the Z score. It was further upgraded by Altman. The Zeta model was developed by Edward Altman in 1977 as an extension to the Z score family. Here, the weight values assigned were;

"ζ=1.2A+1.4B+3.3C+0.6D+E[1]".

Bankruptcy is predicted keeping Zeta score in view. The ranges of Z indicate; Z > 2.99 -"Safe", 1.81 < Z < 2.99 - "Grey" and Z < 1.81 -"Distress" Zones (Altman 1977).

FICO popularly known as the Fair Isaacs Company started the construction of FICO score in the late 1950s and early 1960s. It constructed the score by assigning weightages such as: "payment history (35%), amounts owed/credit utilization (30%), length of credit history (15%), credit mix (10%), and new credit (10%)".

Emerging Markets Scoring Model (1995) incorporates particular credit characteristics of emerging market companies. In the paper "An emerging market credit scoring system for corporate bonds" Altman studied Mexican companies before the Mexican crisis using, "EM

score = 6.56(X1) +3.26(X2) +6.72(X3) +1.05(X4) + 3.25"[2]

(Altman, 2005). Where EM score <1.75indicates Default, 1.75<EM score<4.5 indicates Distress and 4.5<EM score<6.5 is rated as grey zone. Another important development was Bank Specialized Systems Basel 2 impetus (1990s). These models, however, are discussed under the regulatory development part of this paper. Edmister (1972) in the paper, "Financial Ratios as Discriminant Predictors of Small Business Failure" has outlined several other comparisons for a comprehensive prediction about small businesses. Edmister advocated that a single financial statement based ratios are not sufficient to predict the future of the businesses. "Methods of analysis found useful are (i) classification of a borrower's ratio into quartiles relative to other borrowers in the sample, (ii) observation of an up- or down-trend for a three-year period, (iii) combinatorial analysis of a ratio's trend at recent level, (iv) calculation of the three-year average ratios, and (v) division of a ratio by its respective Risk Management Association's industry average ratio" Edmister (1972). Altman & Sabato (2007) in their paper, "Modelling Credit Risk for SMEs: Evidence from the US Market" have extended the bankruptcy prediction for SMEs. They used a logit regression technique on a dataset "of over 2,000 U.S. firms (with sales less than $65 million) over the period 1994–2002". They developed a "one-year default prediction model" (Sabtao, 2008).

Ranjan & Dhal (2003) highlighted the use of a regression model for credit risk management. This paper focuses on influence of terms "of credit, bank size induced risk preferences and macro-economic shocks" on non performance of loans. This paper builds upon a seminal study titled "credit policy, systems and culture" (Reddy 2004). The paper also borrows from (Mohan 2003) "which conceptualized "Lazy Banking" while reflecting on banks' investment portfolio and lending policy critically". Using a panel regression model the authors denote the level of NPA as a function of macroeconomic environment (E), terms of credit (ToC), bank size(Bj), collateral security(S) and (P) is loan to priority sector. They developed the model "NPA j, t = F (Et, ToC, Bj, S, P)" Ranjan & Dhal (2003). This empirical study found that "credit variables have significant effect on the banks' non-performing loans in the presence of bank size and macroeconomic shocks" and also found that "positive deviation of an individual bank's credit-deposit ratio (CDR), from that of industry's average could have favorable effect on reducing NPAs".

Patel (2005) has prescribed various methods for credit appraisal and management. It has laid down guidelines to determine the financial sustainability of the borrower with emphasis on the following processes.

- Credit appraisal: screening by loan officer, business plan and cash flow interview of credit committee, documentation and disbursement, loan supervision and monitoring, repayment of loan, loan delinquency, portfolio quality and risk management and reporting
- Classification of loan portfolio into standard loans, non standard loans, problem loans, uncollectible loans, dangerous loans and bad loans

- Non- accrual of interest, loan restructuring, provisioning and write off
- Bankruptcy prediction remains the most critical success factor of any CRM model. It is further compared with the Z score value of 2.675. If the Z score falls below 2.675, it can be predicted that the company is heading towards bankruptcy. Z score finds its application in the modern banking world also (Institute of Actuaries of India, 2016). The conference presentation presents an analysis of Jindal Steel's probability of default using Altman's Z score. Sang-Bing Tsai et al. (2016) identified five assessment dimensions and five criteria in each assessment dimension of the corporate borrower namely; operational capability (operational experience, industry experience, internal controls, successor system, media management), repayment ability (operation growth, fund position, business revenue, operating revenue, financial planning), financing capacity (seasoned equity offering, bond financing, capital turnover, capital expenditure), competitiveness (Product market share, product leading position, price advantage, product diversification, product upgrading ability) and response ability (industry cycle, operational crisis, ineffective capital turnover, operational strategy, operational transformation) to construct a direct relational matrix. The study finds that operational capability and competitiveness are highly related to high performance of the corporate loans. As the banks have to strike a delicate balance between profitability and credit risk, the study aids the banks in assessing the default risk at the stage of initial appraisal by estimating the operational capability and competitiveness dimensions.
- Credit Risk Monitor (2017) developed Revised FRISK Scores by a huge database of 9600 unique businesses which includes 580 US public company bankruptcies. Using stock market data (market cap, dividend, and stock volatility), financial ratios and credit ratings, the FRISK scores are determined. The FRISK scores proved better indicators than Altman's Z score (Monitor, 2018). Allen Berger (2002) analyzed the economic effects of small business credit scoring (SBCS) system developed by Federal Reserve and found that "it is associated with expanded quantities, higher average prices, and greater risk levels for small business credits under $100,000. These findings are consistent with a net increase in lending to relatively risky "marginal borrowers" that would otherwise not receive credit, but pay relatively high prices when they are funded". Robert B. Avery (2003) studied "the ability of statistical scoring systems to accurately identify an individual's credit risk. The evidence from a national sample of credit-bureau records suggests that concerns about omitted-variable bias may be justified, as local economic factors show significant correlations with credit scores" (Altman, 2008). Boris et al. (2015) elaborated JP Morgan credit metrics, which has four essential ingredients; "value at risk due to credit, portfolio value at risk due to credit, correlations and exposure", that provides a strong framework for this study as the researcher would explore the usage of the credit metrics in commercial banks in India. Using the metrics, VaR calculations depend on standard deviation and correlations depend upon cross correlation with bond prices. The exposures reflect on the risk arising due to sensitivity to market fluctuations.
- Kanungo et al. (2008) assessed a credit appraisal system Quattro Pro® developed at SBI. This system helps perform analysis of ratios, cash flow, financial statements, future projections and risk. Using an experimental Solomon's four group design, they found the Quattro Pro® system to be effective.

Option/Contingent Claims Models (1970s → Present):

These models were based on option pricing approach. Risk of ruin alternatively known as Gambler's Ruin Approach was developed by W.Wilcox in 1970s (Wilcox, 1973). Wilcox used the following model;

Wilcox's Risk of Ruin[3]: $W = X_1 + .7X_2 + .5X_3 - X_4 - X_5$

The model uses coefficients of 1, 0.7 and 0.5 for the liquidation value of cash and cash equivalents, other liquid assets and other assets respectively and for all the liabilities it uses a coefficient of 1. When $W < 0$, the net liquid value of the assets is greater than liabilities and when $W > 0$, the liquid value of assets don't cover the liabilities. The model is criticized for its arbitrary use of coefficients for different assets as the net realizable value may differ in practical scenarios. However, it offers a pragmatic assessment of the net realizable values of other liquid assets and other assets based on prior experience.

Extensions of Merton (1974) proposed a “structural credit risk model by modeling the company's equity as a call option on its assets using Black-Scholes-Merton option pricing model”. Merton used the model;

Probability of Default (PD) = 1 – N (DD)

“Where, N is the Cumulative Standard Normal Distribution and DD is the Distance to Default”.

KMV Credit Monitor (1993) by KMV Corporation is a rating model which is built upon Merton's option pricing approach. It uses asset liability structure and an equity value based approach.

Artificial Intelligence Systems (Structural Framework): (1990s → Present):

AI has played an immense role in analyzing complex data for credit risk quantification and management. Since the early 90s various publications have placed enormous reliance on the utility and promise of AI for CRM process of banks. The UK based fin-tech firm Wiserfunding Ltd. entered Indian market in 2016 with tie ups with banks and NBFCs for credit risk assessment solutions for the SME borrowers. Wiserfunding uses Artificial Intelligence in the SME Z score framework to accurately predict the SME credit quality. It determines credit quality for companies having less than 300 employees and £150 mn in revenues. The uniqueness of their models is the usage of past financial history, robust data available privately and publicly on the SME through automated AI, over 40 financial ratios based on industry and geography, corporate governance and quality variables and macroeconomic variables (Wiserfunding Ltd., 2016).

Frydman (1985) presented a new classification procedure based on Recursive Partitioning Algorithm (RPA). “RPA is a computerized and nonparametric technique based on pattern recognition having attributes of both univariate and multivariate procedures”. RPA outperformed the discriminant analysis with additional information for analysis. This marks the advent of the use of computer algorithm and discovery. Jensen (1992) used “a standard back propagation neural network running on a DOS personal computer with 125 credit applicants whose loan outcomes are known. Applicant characteristics are described as input neurons receiving values representing the individuals' demographic and credit information. Three categories of payment history, delinquent, charged off, and paid off, are used as the networks output neurons to depict the loan outcomes. After training on part of the data, correct classifications were made on 76–80% of the holdout sample using neural networks for credit scoring”.

West (2000) studied “credit scoring accuracy of five neural network models: multilayer perception, mixture-of-experts, radial basis function, learning vector quantization, and fuzzy adaptive resonance”. He found that multilayer perception is not the most appropriate model but a mix of experts and radial basis function gives most accurate results in the credit appraisal process. Logistic regression remains the most accurate among traditional models. An earlier work by Tam and Kiang (1992) introduced a neural-net approach to perform discriminant analysis in business research. “Using bank default data, the neural-net approach is compared with linear classifier, logistic regression, kNN, and ID3. Empirical results show that neural nets are a promising method of evaluating bank conditions in terms of predictive accuracy, adaptability, and robustness”. In a comparison between linear discriminant analysis models and neural networks on a dataset of “1,000 healthy, vulnerable and unsound Italian firms, a balanced degree of accuracy and other beneficial characteristics between LDA and NN was indicated”(Altman et al 1994). The authors also advocated for combination of the methods for predictive reinforcement.

Later, a study by Lee et al (2002) integrated the back propagation neural networks with the traditional discriminant analysis approach and found that “the hybrid approach converged much faster with higher credit scoring accuracies”. Huang et al (2004) used a new machine learning method support vector machines and benchmarked it against back-propagation neural networks and observed slight improvement (around 80%) for both in accuracy. Angelini et al (2008) developed two neural network systems. "One with a standard feed forward network, while the other with special purpose architecture. The application is tested on real-world data, related to Italian small businesses. It was observed that neural networks can be very successful in learning and estimating the in default tendency of a borrower". Chauhan et al (2009) proposed to use differential evolution (DE) algorithm to train a wavelet neural network (WNN) naming it as differential evolution trained wavelet neural network (DEWNN). "The efficacy of DEWNN is tested on bankruptcy prediction datasets viz. US banks, Turkish banks and Spanish banks. Results show that soft computing hybrids viz., DEWNN and TAWNN outperformed the original WNN in terms of accuracy and sensitivity across all problems. Furthermore, DEWNN outscored TAWNN in terms of accuracy and sensitivity across all problems except Turkish banks' dataset". The two neural networks are similar, but they differ for the activation function adopted. Khemakhem and Younes (2017) tried to use Probability of Default to measure credit risk in a Tunisian commercial bank. By comparing Logit models, NN, SVM, Radial Bias Functions (RBF), it was found that RBF Kermel SVM is the most accurate and performing method to measure and monitor credit risk. Bussman et al (2021) proposed "a model applying correlation networks to Shapley values of 15,000 SMEs so that Artificial Intelligence predictions are grouped according to the similarity in the underlying explanations".

Blended Ratio/Market Value Models: Bond Score (Credit Sights, 2000) and RiskCalc (Moody's, 2000) models "generate forward-looking probability of default (PD) or expected default frequency (EDF) calculations, loss given default (LGD), and expected loss (EL) credit measures". Shumway (2001) proposed a discreet time Hazard model for prediction of bankruptcy as most ratios used in discriminant analysis are statistically insignificant. Along with ratios, "market size, past stock returns and idiosyncratic returns variability could strongly produce accurate forecasts".

To estimate default intensity, Kamakura's Reduced Form, Term Structure Model (2002), a proprietary model used bond prices, equity prices, and accounting data. "The default intensity process is modeled as a function of stochastic default-free interest rates, liquidity factors, and lognormal risk factors, such as a stochastic process for the market index".

Z-Metrics, also known as RiskMetrics developed by Altman et al (2010) analyzed over 50 financial statement variables in relation to "solvency, leverage, size, profitability, interest coverage, liquidity, asset quality, investment, dividend payout, and financing results and the trends thereof".

Re-introduction of Qualitative Factors and Real-Time Data (FinTech), Stand-alone Metrics, e.g., Invoices, Payment History and Multiple Factors - Data Mining (Big Data Payments), Governance, Time spent on individual firm reports has a potential to provide a lot of insights into the financial health of the borrower.

Regulatory Framework of Credit Risk Management:

Risk management approaches were largely influenced by BASEL accord of risk management, the internationally acclaimed CRM practice followed by the commercial banks. Basel Committee on Bank Supervision (BCBS) and Bank for International Settlements (BIS) has put forth Basel I, Basel II and Basel III norms so far.

"Basel I was enforced by law in G10 countries in 1992, but more than 100 countries implemented the regulations with minor customizations. The regulations aimed to improve the stability of the financial system by setting minimum reserve requirements for international banks. It also provided a framework for managing credit risk through the risk-weighting of different assets. According to Basel I, assets were classified into four categories based on risk weights:

0% for risk-free assets (cash, treasury bonds)

20% for loans to other banks or securities with the highest credit rating

50% for residential mortgages

100% for corporate debt

Banks with a significant international presence were required to hold 8% of their risk-weighted assets as cash reserves."

Basel II introduced additional three key requirements; minimum capital requirements, supervisory mechanisms and transparency, and market discipline.

Basel III additionally introduced various capital, leverage and liquidity ratio requirements.

Tier I Capital Ratio: The ratio between Equity Capital and Risk Weighted Assets should be more than or equal to 4.5%

Leverage Ratio: The ratio between Tier I Capital and Average Total Assets should be more than or equal to 3%

Liquidity Coverage Ratio: The ratio between Liquid Assets and Total Outflows over next 30 days should be more than or equal to 100%

Indian Regulatory Developments:

The foundation of the regulatory framework of credit risk management in India is the Master Circular on Loans and Advances - Statutory and other Restrictions 2009.

This master circular provides a regulatory framework to scheduled commercial banks. "Banks/FIs are free to finance technically feasible, financially viable and bankable projects undertaken by both public sector and private sector undertakings subject to the following conditions:

(i) The amount sanctioned should be within the overall ceiling of the prudential exposure norms prescribed by RBI for infrastructure financing.

(ii) Banks/ FIs should have the requisite expertise for appraising technical feasibility, financial viability and bankability of projects, with particular reference to the risk analysis and sensitivity analysis." It guides on the dos and don'ts in the process of lending of business loans. It specifies that the owners need to bring their amounts of equities upfront.

The master circular doesn't prescribe any specific method of credit appraisal. The credit appraisal practices are mostly developed by the lenders for their own use. Hence, exploring this under regulated area is important.

Credit approvals and sanctions are mostly confidential arrangements and internal affairs of the bank. However, if any inconsistency, contradiction, conflict of interest in policy or malpractice is found, RBI points out those irregularities in its credit risk assessment reports. Activist, Girish Mittal obtained these reports through RTI. RBI opposed disclosure of these reports in the public domain as these reports have been obtained in fiduciary capacity. However, Supreme Court declined this argument of RBI and allowed public disclosures of the same. As per news report of Bloomberg Quint, RBI's Credit Risk Assessment Report of 2015 points to serious irregularities in the credit risk management frameworks of four major commercial banks, SBI, ICICI Bank, Axis Bank, and HDFC Bank.

The second type of modelling approach tries to "capture distribution of the firm's asset-value over a period of time. This model is based on the expected default frequency (EDF) model. It calculates the asset value of a firm from the market value of its equity using an option pricing based approach that recognizes equity as a call option on the underlying asset of the firm. It tries to estimate the asset value path of the firm over a time horizon. The default risk is the probability of the estimated asset value falling below a pre-specified default point". This model is based conceptually on Merton's (1974) contingent claim framework and has been working very well for estimating default risk in a liquid market.

Conclusion and Future Direction:

The credit risk management models have evolved over time. The credit risk models before 1800s were based on subjective assessment of borrower's creditworthiness, based on personal relationship and trust. As banking remained in close circles of banks and borrowers, the subjective methods relied on inter personal behaviour, traits and enterprising attitude of borrowers. However, the focus shifted to objective methods in the late 1800s. The objective methods began with univariate measures such as key financial ratios. As corporations started growing in size and complexity of operations, the financial statements and broad ratios calculated from the financial statements proved to be important indicators of creditworthiness. The focus shifted from univariate measures to multivariate measures from 1960s onwards. Discriminant, Logit and

Probit Models (Linear, Quadratic) and regression models gained significance using complex set of data and cause and effect relationships. In the 2000s the Artificial intelligence based methods gained wide acceptance as sophisticated credit risk models, credit scoring agencies and ability to process terabytes of borrower data was developed by the banks either in-house or through outsourcing of credit appraisal functions.

The future of risk is definitely going to be much more uncertain, uncharted and unexpected. Phillip H et al (2015) in the Mc Kinsey working papers on risk have identified six structural trends that will transform the risk management at banks namely: (a) continued expansion of the breadth and depth of regulation such as principled compliance, automated compliance etc., (b) changing customer expectations, (C) technology and analytics as a risk muscle such as big data, machine learning, crowd sourcing etc. (d) emergence of additional non-financial risk types such as contagion risk, model risks, cyber-attacks etc., (e) biases recognition and elimination and (f) strong cost savings.

Future studies have the scope of expanding the variables by time dimensional maturity composition of loans. With the increase in NPA levels in the recent decade, advent of Basel III and RBI induced recognition norms, additional variables of forced default, willful default; extraneous factors leading to adverse selection of borrowers and macroeconomic shocks inducing bankruptcy can be included in the models for improved results.

References

- Allen Berger, W. F. (2002). Credit Scoring and the Availability, Price, and Risk of Small Business Credit, *Journal of Money Credit and Banking*, 1-39.
- Altman, E. (2005). An Emerging Market Credit Scoring System for Corporate Bonds. *Emerging Markets Review-6*, 311-323, Retrieved from http://people.stern.nyu.edu/ealtman/emerging_markets_review.pdf
- Altman, E. (2019). A 50-Year Retrospective on Credit Risk Models, the Altman Z-Score Family ofModels and Their Applications to Financial Markets and Managerial Strategies, *Q Group*.
- Altman, E. I. (1968). Financial Ratios, Discriminant Analysis and the Prediction of Corporate Bankruptcy, *Journal of Finance*.
- Boland, V. (2009, June 12). "Modern dilemma for world's oldest bank". (12 June 2009), Retrieved 23 February 2010, *Financial Times*.
- Bussmann, N., Giudici, P., Marinelli D. et al. (2021), Explainable Machine Learning in Credit Risk Management. Comput Econ 57, 203–216, https://doi.org/10.1007/s10614-020-10042
- CFI Team. (2022, December 28), *S&P – Standard and Poor's*, Retrieved from corporatefinanceinstitute.com: https://corporatefinanceinstitute.com/resources/fixed-income/sp-standard-poors/
- CFI. (2021), *Credit Risk*, Retrieved from www.corporatefinanceinstitute.com: https://corporatefinanceinstitute.com/resources/knowledge/finance/credit-risk/
- Corporate Finance Institute (2020), *What are the Basel Accords?*, Available at: https://corporatefinanceinstitute.com/resources/knowledge/finance/basel-accords/ , accessed 30 August 2020.
- Corporate Finance Institute. (2021), *History of Standard and Poor's*. Retrieved from https://corporatefinanceinstitute.com/: https://corporatefinanceinstitute.com/resources/knowledge/finance/sp-standard-poors/
- E. Angelini, G. Tollo and A. Roli (2008), "A Neural Network Approach for Credit Risk Evaluation," The Quarterly Review of Economics and Finance, Vol. 48, No. 4, pp. 733-755.
- E. I. Altman, G. Marco and F. Varetto (1994), "Corporate Distress Diagnosis: Comparisons Using Linear Discriminant Analysis and Neural Networks (the Italian Experience)," Journal of Banking and Finance, Vol. 18, No. 3, pp. 505-529.

- Edward I. Altman, N. H.-S. (2008), Credit Scoring via Altman Z-Score, *Encyclopedia of Quantitative Risk Analysis and Assessment*.
- Frydman. (1985), Introducing Recursive Partitioning for Financial Classification: The Case of Financial Distress, *The Journal of Finance*. Retrieved 1985, from https://www.jstor.org/stable/2328060
- Goldthwaite. (1995), *Banks, Places and Entrepreneurs, Renaissance, Florence.*
- Institute of Actuaries of India. (2016), *Credit Risk-Merton KMV and Altman's Z Score Model*, Institute of Actuaries of India.
- Jensen. (1992). Using Neural Networks for Credit Scoring. *Managerial Finance- Vol 8*, 15-26, Retrieved from https://www.emerald.com/ insight/content/doi/10.1108/eb013696/full/html?skiptracking=true
- K. Y. Tam and M. Kiang (1992), "Managerial Applications of Neural Networks: The Case of Bank Failure Predictions," Management Science, Vol. 38, No. 7, pp. 926-947
- Khemakhem, Sihem & Boujelbene, Younes. (2017). Artificial Intelligence for Credit Risk Assessment: Artificial Neural Network and Support Vector Machines, ACRN Oxford Journal of Finance and Risk Perspectives, pp. 1-17.
- Kollar Boris et al. (2015), Quantification of credit risks with the use of CreditMetrics (2015), Procedia Economics and Finance, 26, pp. 311 – 316
- Moody's. (2009). *Moody's Investor Service*. Retrieved from Moody's.com: https://www.moodys.com/sites/products/productattachments/moody's%20rating%20system.pdf
- N. Chauhan, V. Ravi and K. Chandra (2009), "Differential Evolution Trained Wavelet Neural Networks: Application to Bankruptcy Prediction in Banks," Expert System with Applications, Vol. 36, No. 4, pp. 7659-7665.
- Nair V(2020), A 'What-Not-To-Do' Guide From RBI's Risk Assessment Reports, Bloomberg Quint News Website, Available at: https://www.bloombergquint.com/business/a-what-not-to-do-guide-from-rbis-risk-assessment-reports, Accessed 25 August 2020
- Patel A(2005), Manual on Loan Policy & Procedure for Non-Bank Financial Organizations, Farm Privatization Support Project Tazikistan, March 2005
- Rajiv R and Sarat C (2003), Non-performing loans and terms of credit of Public Sector Banks in India: An empirical assessment, RBI occasional paper series
- Reserve Bank of India (2009), *RBI Master Circular on Loans and Advances - Statutory and other Restrictions*, RBI/2009-10/69 DBOD No. Dir. BC 13/13.03.00/2009-10, available at: https://www.rbi.org.in/scripts/BS_ ViewMasCirculardetails.aspx?id=5113#a, accessed 20 June 2020.
- Ricardo. (2016, October 04), A brief history of risk management in banks, *Prometia*.
- RMA (2021), *Credit Risk Management*. Retrieved from rmahq.org: https://www.rmahq.org/credit-risk/
- Robert B. Avery, R. W. (2003), Credit Scoring: Statistical Issues and Evidence from Credit-Bureau Files, *Real Estate Economics*, 523-547.
- Sabtao, A. a. (2008), Modelling Credit Risk for SMEs: Evidence from the U.S. Market, *Abacus: The University of Sydney*, Retrieved from https://onlinelibrary.wiley. com/doi/abs/10.1111/j.1467-6281.2007.00234.x
- Sang-Bing Tsai et al (2016), An empirical research on bank's credit assessment of corporate customers, SpringerPlus 2016, 5:2088 DOI 10.1186/s40064-016-3774-0
- SAS. (2021), *Credit Risk Management*, Retrieved from www.sas.com: https://www.sas.com/en_in/insights/risk-management/credit-risk-management.html

- SEC. (2002). *Role and Function of Credit Rating Agencies in the U.S. Securities Markets*, Retrieved from sec.gov.in: https://www.sec.gov/news/extra/credrate/standardpoors.htm
- T. S. Lee, C. C. Chiu, C. J. Lu and I. F. Chen (2002), "Credit Scoring Using the Hybrid Neural Discriminant Technique", Expert System with Applications, Vol. 23, No. 3, pp. 245-254.
- TGT. (2019). *Credit risk management principles, tools and techniques*. Retrieved from www.theglobaltreasurer.com: https://www.theglobaltreasurer.com/2019/02/07/credit-risk-management-principles-tools-and-techniques/
- The Reserve Bank of India (2002), Guidance Note on Credit Risk Management, The Reserve Bank of India Notification
- V. Pacelli and M. Azzollini (2011), "An Artificial Neural Network Approach for Credit Risk Management," Journal of Intelligent Learning Systems and Applications, Vol. 3 No. 2, pp. 103-112, doi: 10.4236/jilsa.2011.32012.
- West, D. (2000), Neural network credit scoring models, *Computers and Operations Research- Vol 27*, 1131-1152. Retrieved from https://www.sciencedirect.com/science/article/abs/pii/S0305054899001495
- Z. Huang, H. Chen, C. J. Hsu, W. H. Chen and S. Wu (2004), "Credit Rating Analysis with Support Vector Machines and Neural Networks: A Market Comparative Study," Decision Support System, Vol. 37, No. 4, pp. 543-558.

Endnotes:

[1]**Where:** ζ=score, *A*= Working Capital / Total Assets, *B*= Retained Earnings / Total Assets, *C*= Earnings before Interest and Tax / Total Assets, *D*= Market Value of Equity / Total Liabilities, *E*= Sales / Total Assets.

[2]Where, X1 = Working Capital/Total Assets, X2= Retained Earnings/Total Assets, X3 = Operating Income/Total Assets and X4 = Book value of Equity/Total Liabilities

[3]Where, X_1 =Cash and cash equivalents, X_2= Other liquid assets, X_3 = Other assets, X_4 = Short term liabilities , and X_5 = Long term liabilities

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