EFFECTIVENESS OF CREDIT RATING: A STUDY OF BOND RATING AND ITS IMPACT ON STOCK PERFORMANCE

A thesis submitted during September 2021 to the University of Hyderabad in partial fulfillment of the award of a Ph.D. degree in School of Management Studies

By

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CERTIFICATE

This is to certify that the thesis entitled **"Effectiveness of Credit Rating: A Study of Bond Rating and its Impact on Stock Performance"**, submitted by **Manisha Kumari**, bearing Registration No. 17MBPH08 in partial fulfillment of the requirement for the award of Doctor of Philosophy in Management is a bonafide work carried out by her under my supervision and guidance.

This thesis has not been submitted previously in part or in full to this or any other University or Institution for award of any degree or diploma.

Further, the student has the following Publication(s) before submission of the thesis/monograph for adjudication and has produced evidence for the same in the form of acceptance letter or the reprint in the relevant area of her research: (Note: at least one publication in referred journal is required).

1. Kumari, M. & Jessica, V. M. (in press). Reliability and Credibility of Credit Rating: An Evidence from Indian CRAs. *International Journal of Economic Policy in Emerging Economies*. ISSN online: 1752- 0460, Print: 1752- 0452. https://doi.org/10.1504/IJEPEE.2020.10032356

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3. Academic Writing for Doctoral Students	4	Pass
4. Financial Management and Strategic Finance	3	Pass
5. Financial Services and SAPM	3	Pass

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(Prof. V. Mary Jessica) **(Prof. V. Mary Jessica)**

DECLARATION

I, **Manisha Kumari** hereby declare that the thesis entitled **"Effectiveness of Credit Rating: A Study of Bond Rating and its Impact on Stock Performance"**, submitted by me under the guidance and research supervision of **Prof. V. Mary Jessica,** is a bonafide research work, which is also free from plagiarism. I also declare that it has not been submitted previously in part or in full to this University or any other University or Institution for the award of any degree or diploma. I hereby agree that my thesis can be deposited in Shodganga /INFLIBNET.

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ABSTRACT

The present research aimed to study the effectiveness of credit rating in India. CRAs have played major role in enhancing capital market but in recent past have been criticized for low quality rating. Credit Rating is a grade assigned by credit rating agencies on creditworthiness of debt issuers. These grades reflect the quality and risk of rated instruments. This study focused on quality of bond rating grades and their impact on stock performance. In India, the mandatory bond rating, compulsory capital financing through bonds and at the same time, the presence of weak corporate bond market motivated me to carry out the research in Indian corporate bond market. The study proceeded with two research questions - whether the rating grades are reliable and do the bond ratings have the ability to influence stock prices?

The research involved only secondary data. Investors consider rating grades as a source of information about risk associated with bond. They rely on credit rating agencies' opinion for investment decisions. The CRAs were blamed for the GFC 2008 and were questioned for the latest crisis and collapse of high profile cases. The upgrade/downgrade of rating should be systematic and happen gradually to the normal course over time. However, in the recent past, most of the cases were sudden downgrades in ratings. This study is an attempt to examine the quality of rating through rating prediction model.

All the previous studies done until now have now considered the ordinal nature of credit rating. The ordinal nature of rating is found suitable with ordered probit regression. As the distance between two rating grades was unknown, ordered probit regression was taken up. The increased number of defaults and criticism of ratings quality so far, have made the rating prediction essential for present day. Accounting standards in different countries were different,

as also policies framed for companies by respective governments. Hence, all the variables would not be equally significant for all the countries. In the present study, cash ratio, quick ratio, working capital ratio and capital to total assets were found insignificant whereas other variables like size of bond issue, book value of total assets, interest coverage ratio, equity ratio, debt ratio, equity to debt ratio, gearing ratio, debt-to-profit ratio, negative debt, operating profit, net profit margin, current ratio, current assets to total assets, retained earnings to total assets, assets turnover ratio, return on assets before interest and tax, operating cash flow to total debt, total rent expenses to total assets, net property, plant, and equipment to total assets and operating cash flow to total assets were found significant. The variables used in the previous prediction model of rating are extended in present study by incorporating an additional variable i.e. size of bond issued. Concurrently, Z-score is also calculated for all the rated bonds.

The other hypothesis is to answer the objective based on EMH. The information disclosure by CRAs with initial CR and changed CR was a controversial topic. The literature had ambiguity in the results that they claimed. The previous studies are, extensively done on strong form market. Hence, it is criticised mostly because in a strong form market, all the information is already revealed to market participants. India has an emerging bond and semi efficient market. Therefore, it was interesting to examine the impact of rating announcement (Initial, Upgrade, Downgrade, Reaffirmed, Withdraw, and Suspended, Speculative and Investment-Grade) on the stocks' abnormal return. Event study method has been employed for this analysis.

Credit rating grades and financial variables have been extracted from ProwessIQ CMIE database. Whereas, stock price data is collected from NSE, BSE and ProwessIQ CMIE database. Credit ratings issued by ICRA, CRISIL, CARE, BRICKS and India Rating have been considered for analysis. The period of the study considered was from March 2010 to March 2020 for rating

prediction and for event study, observations of data included for the study was from January 2009 to March 2020.

The ratings grade coded from 1 to 16 in group 1 are as follows: AAA=1, AA+ = 2, AA=3, AA- = 4, A+ = 5, ..., B=14, C=15 and D=16, in group II CR grades coded from 1 to 8 and 1 to 3 in group III. The result showed that the CR grades of the instruments are deteriorating from AAA to D if the firms have high debt of different kinds, high debt to equity ratio, paying higher rent and having high gearing ratio. The creditworthiness decreases with increase in the size of bond issued, low interest coverage ratio, low equity ratio and low profit margin (i.e. low value of operating profit, lower net profit margin and low operating profit to total debt), of firm, and so rating grades also decreases. The CR grades improved from D to AAA or got better CR grades with higher value of assets turnover ratio, high value of retained earnings to total assets and having lower value of current assets to total assets ratio, lower debt to profit ratio with exception to low operating cash flow to total assets ratio. The actual rating grades falling under investment-grade were found to be higher than predicted rating whereas the actual ratings awarded speculative grades reported comparatively equal to the predicted rating.

The three zones of z-values are calculated and compared with the actual rating. The ratings calculated with z-value have a significant difference from the actual rating. The actual rating grades awarded are found to be higher than the grades calculated through z-score. Z-score is used widely in the UK and US for predicting the bankruptcy of firms. In this study z-scores are compared with the actual rating. Actual ratings are categorized into three levels. The result suggests that many ratings found in distress level through z-score calculation were actually awarded safety levels by CRA's. Actual ratings are higher than those obtained through z-score.

The bond value (size of bond issue), added in the prediction model was found significant at 0.001 significance level. Whereas, all other variables such as equity ratio, debt ratio, debt to equity ratio, gearing ratio, operating profit, current ratio, retained earnings to total assets, assets turnover, current assets to total assets, operating cash flow to assets are found significant at 0.05, 0.01and 0.001 levels of significance. The predicted ratings were found to be conservative for even highest safety grade cases whereas, actual ratings are found to be very high in highest safety grades. Hence, the result suggests that CRAs are lenient in assessment and generous in assigning the high-grade rating.

The impact of initial rating announcements for investment-grade ratings is found significant after six days of the event. The market has not shown any response around events. The CAAR is found positive immediately after the announcement, whereas downgrade rating is negatively associated with the stock return. The result of initial investment-grade rating, rating upgrade, rating downgrade and investment-grade rating showed different reactions in the stock return whereas reaffirmed rating, initial speculative-grade rating, withdrawn rating and speculative-grade ratings did not show any reaction in the stock prices.

The study finds that the entities that had distress financial status also received safe rating grades. The predicted ratings were found conservative in obtaining AAA and AA rating, whereas actual ratings were found to be overgenerous in nature to provide AAA and AA rating grades. CRAs provided safe rating grades even to the default entities.

Initial speculative grade ratings, reaffirmed ratings, suspended ratings, withdrawn ratings and subsequent speculative-grade rating announcements are found to be insignificant and it may be concluded that these rating announcements do not convey any information to the market.

Whereas, the Upgraded rating announcements are associated positively with abnormal return and were found significant with the stock price. However, we can conclude that all CRAs probably not give credit ratings with informational content. The market which is probably in semi-efficient form reacts to some rating announcements.

The study adds to the growing body of evidence that CRAs have become charitable in rewarding high ratings. Corporate failures cannot be sudden, especially with strong profitability and balance sheet; it is rare and can happen only with sudden economic changes in the environment. The result showed that ratings are positively biased towards issuers. The study provides few suggestions to the regulators to improve the quality of rating and protect the interest of investors. The recommendation given to the investors is that they should not rely solely on rating for investment decisions. The study also provides few suggestions to CRAs and Issuers.

The present study contributes to literature by providing a rating prediction model for the Indian Bond market. This model can be used further to calculate the risk associated with the bond. The major contribution of the study is adding new variable to the rating prediction model. The existing model has been improved with the addition of bond value (size of the bond issue) by the issuer.

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LIST OF ABBREVIATIONS

AAR	Average Abnormal Return
ABS	Asset Backed Securities
AR	Abnormal Return
BoD	Board of Directors
BR	Bond Rating
CAAR	Cumulative Average Abnormal Return
CBM	Corporate Bond Market
CBR	Corporate Bond rating
CDO	Collateralized Debt Obligation
CEO	Chief Executive Officer
CMIE	Center for Monitoring Indian Economy
CR	Credit Rating
CRA	Credit Rating Agency
EMH	Efficient Market Hypothesis
GFC	Global Financial Crisis
ISOCO	International Organization of Securities Commissions
MBS	Mortgage Backed Securities
MDA	Multiple Discriminant Analysis
NISM	National Institute of Securities Markets
OLM	Ordered Logit Model
OLS	Ordinary Least Squares
OPM	Ordered Probit Model
RBI	Reserve Bank of India
RW	Rating Watch
SEBI	Securities and Exchange Board of India
SEC	U.S Securities and Exchange Commission

LIST OF SYMBOLS

$\sum$ ……... Sigma

θ …….Theta

Π ……. Pi

i……. Interest Rate

t …… Time Period

p ……... Probability

β …… Beta

α …… Alpha

μ ……Mu

δ …… Delta

σ……. Standard Deviation

χ^2…….. Chi-Square

R^2……..Coefficient of Determination

SE……Standard error

1. INTRODUCTION

1.1 Background

A financial system plays an important role in economic growth. A financial system provides and facilitates efficient and effective deployment of funds; hence it encourages investments and economic development. The functioning of financial system is observed on different levels like, global, national, regional, and company specific. The modern financial system includes financial markets, financial institutions, financial instruments and financial services (Chandra, 2011). The nature of a financial system established in the economy plays a major role in facilitating and deciding the level of economic growth. An underdeveloped financial system can hamper the economic growth of a firm or country. The continuous need for funds by firms plays a significant role in thriving capital markets. This is one of the fundamental principles of economics. Companies need to raise capital to cover their operating costs and execute expansion plans in the real world.

A financial market facilitates fund mobilization among competitive clients for production activities. Companies may gather the funding needs by various means such as issuing securities, applying for a bank loan, trade financing, credit lines, issuing bonds or fixed deposits, etc. With the globalization and deepening of financial markets, investors in one part of the world can lend money to borrowers in another part of the world through different financial tools and intermediaries. But on the flipside, accessing full information about the financial position of the borrowers is impossible for the lenders. For ensuring the sustainability and the continuation of confidence in financial market, investors should be aware of borrowers' capabilities to fulfil their debt obligations and the associated risks. Financial markets facilitate the exchange of assets,

services and securities known as financial instruments. The uncertainty associated with the instruments is known as risk of the instruments (Markowitz, H., 1952). These risks could be loss of principal or interest and is known as credit risk.

Credit risks are associated with default risks, i.e., the inability of borrowers to make the payment to investors. The Basel Committee defined credit risk as “the potential that a borrower or counterparty will fail to meet its obligations in accordance with agreed terms” (Apostolik et al., 2009). At present, the mitigation and management of the oldest financial risk i.e. credit risk has become the most important task. The risks and returns associated with all instruments are not identical. The returns expected by investors depend on the risks associated with the securities/projects. The increase in the risk of default perturbs the market participants (Gregory, John, 2011). The expansion of complicated financial instruments has necessitated a quantitative model for credit risk calculation. There are many options available for measuring the credit risk such as, "credit rating, rating transmission tables, credit Value-at-Risk (VAR) and tracking error due to credit risk" (Fabozzi, Mann, & Choudhry, 2003). All these methods of credit risk calculation come under financial services. Economic growth and the expansion of financial services have brought about globalization, thus leading to the development of unrivalled privatization, liberalization, and multi-nationalization of companies like never before. Shareholders, specialists (financial experts/advisors) and public financial institutions, banks and insurance firms provide financial services.

The collapse of high profile financial institutions like “Barings-1995, Long Term Capital Management-1998, Enron-2001, Worldcom-2002, Parmalat-2003 and Lehman Brothers-2008” has introduced a revolution in credit risk management (Gregory, Jon, 2010). Such events have showed that inadequate risk management may result in huge losses and send negative waves to

the global financial markets. The importance of evaluating the whole market as well as the individual financial instruments, in different categories, has been acknowledged by the investment market players. The results of such evaluation provide the right direction for portfolio management and assistance in making an investment decision. The evaluation is done on national and international levels either by financial institutions or individuals. In the market, an investor based on his or her credit assessment skills assesses the investment risks differently. For markets to operate smoothly and to increase the confidence of investors, it is necessary to ensure that financial regulators protect the investors' interests against any misconduct. This points to the need for credit rating in financial markets. Among all the available options for credit risk management, credit rating is the most commonly used method for about 150 years. Growing sophistication in financial markets and rising integration of capital markets have been observed in the wake of rapid globalisation. This has accentuated the importance of the rating and credit rating agencies (CRAs) over the years. They serve investors, issuers and regulators; and also become the principal sources of information for borrowers about the quality of credit issuers.

1.2 Credit Rating (CR) and Credit Rating Agency (CRA)

Credit Rating (CR) as a financial service has attracted the attention of investors after the financial crisis. It provides the details of a company's risk profile and helps the investors in the investment-related decision. CR originated in the United States in the 1840s after the 1837 financial crisis. CR is given by an independent agency or company known as Credit Rating Agency (CRA). Louis Tappen established the first commercial CRA in 1841 to ascertain the capabilities of the traders to fulfil their financial obligations. Another similar CRA was founded in 1849 by the John Bradstreet. He also published a book on rating in 1857. Later in 1933, both the agencies were merged and in 1967 it was absorbed by the Moody's Investor Services,

popularly known as Moody's. Moody's group was established by John Moody in 1900. The company issued its first rating on the bonds issued by the railway industry. Several other companies were established including “Low Publishing Company”, “Standard Statistics Company”, and “Fitch Publishing Company” in 1916, 1921, and 1924 respectively. In 1941, the world’s largest CRA called Standard & Poor’s was formed by merging two firms. The names of the two firms were “Poor Publishing Company”, and “Standard Statistics Company”. Later many CRAs were established in different countries. The first CRA established in India was CRISIL in 1987. This was followed by ICRA in 1991, CARE in 1993, Duff & Phelps in 1996 (later absorbed by Fitch India in 1999), SMERA 2000, and Brickworks in 2008 (NISM, 2009). All “the CRAs in India are regulated by Securities and Exchange Board of India (SEBI) under the SEBI (Credit Rating Agencies) Regulations 1999” (SEBI, 1999). The global players (international CRAs) work within the objectives and principles of investor protection guidelines issued by the “International Organization of Securities Commission” 2003 (IOSCO, 2003).

1.2.1 Overview of Indian Credit Rating Agencies

1. CRISIL: -Credit Rating Information Services of India Limited **(**CRISIL**)** was the first CRA established in India in 1988. It was also the first CRA to be listed in Indian stock exchange. The head-quarters of CRSIL are located in Mumbai with branch offices in Delhi, Kolkata, Hyderabad, Ahmedabad, Chennai, and Pune. CRISIL is promoted by different Indian banks and foreign banks. Indian banks include UCO Bank, Bank of India, Allahabad Bank, Bank of Baroda, Canara Bank, Vysya Bank, Central Bank of India, Bank of Madhura, Indian Overseas Bank. Foreign banks include Banque Indo – Suez, Standard Chartered Bank, Mitsui Bank, Bank of Tokyo, Deutsche bank, Hong Kong bank, Citi bank, Grindlays bank and Societe Generale Banque National de Paris. Standard & Poor’s (S&P) is the largest shareholder of CRISIL.

2. ICRA: - The second CRA is ICRA and it started its operations in 1991. Initially it was known as "Investment Information and Credit Rating Agency" of India Limited. The head-quarters of ICRA are located in Gurgaon and Delhi; and its registered branch offices are located in Mumbai, Kolkata, Hyderabad, Bangalore, Ahmedabad, Chennai and Pune. It is promoted by Industrial Finance Corporation (IFC) of India Ltd, Moody's Investment Corporation India Pvt. Ltd., LIC (Life Insurance Corporation), GIC, and banks like State Bank of India (SBI), Allahabad Bank, HDFC, Union Bank of India, Canara Bank, etc.

ICRA has signed an Memorandum of Understanding (MoU) with Financial Performance Inc. which is a subsidiary of Moody's group formed to provide credit analysis, risk assessment, and other consulting services to financial institutions and commercial banks. Moody's group holds the largest amount of shares in ICRA and it has been the major shareholder of ICRA in 2001. Since 2005, ICRA has been listed on both Bombay Stock Exchange (BSE) and National Stock Exchange (NSE).

3. CARE: - Credit Analysis & Research Limited or CARE started its operations in 1993. The registered office of CARE is located in Mumbai and its regional offices are in New Delhi, Hyderabad, Bangalore, Chennai, Ahmedabad, Kolkata, Jaipur, and Pune. CARE also operates in the Republic of Maldives and Male. CARE covers many segments including infrastructure, manufacturing and financial sector including banks, non- banking financial (NBFCs) services.

4. Ind-Ra: - India Ratings and Research (IND-RA) started operating in 1996. It is head-quartered in Mumbai with branch offices in Delhi, Kolkata, Bangalore, Hyderabad, Ahmedabad, Chennai, and Pune. It is recognised by RBI (Reserve Bank of India), SEBI (Security Exchange Board of India) and NHB (National Housing Board). It provides rating and grading to corporate

issuers and financial institutions that include finance and leasing companies, banks and insurance companies. It manages funds of urban local bodies and also provides project finance grading. It is a subsidiary completely owned Fitch Group also known as Fitch India Rating.

5. BWR: - Brickworks Rating (BWR) is a Bangalore based CRA founded in 2008. It is registered with National Small Industries Corporation Limited (NSIC), SEBI and RBI. The RBI has endorsed the BRW with External Credit Assessment Institutions (ECAI) in 2012. Further, RBI has permitted BWR to rate Ministry of New and Renewable Energy (MNRE) and to issue green rating to bank loans. Its branch offices are in New Delhi, Mumbai, Hyderabad, Kolkata, Chennai, Ahmedabad, and Guwahati. It was the first Indian CRA to setup a regional office in Guwahati, Assam in North East India, in the year 2014.

6. SMALL MEDIUM ENTERPRISE RATING AGENCY (SMERA): - SMERA started in 2005 as an independent body for MSME (Macro, Small & Medium Enterprises). This rating agency is a joint initiative of SIDBI (formally as Small Industries Development Bank of India), DBIS (known as Dun and Bradstreet Information Services India Private Limited), and leading public and private banks such as BOI, BOB, Canara Bank, ICICI, Indian Bank, UoB (Union Bank of India), SBI, PNB, OBC, etc. It is headquartered in Mumbai and its branch offices are in New Delhi, Hyderabad, Kolkata, Bangalore, Chennai, Ahmedabad, Coimbatore, Jaipur and Surat.

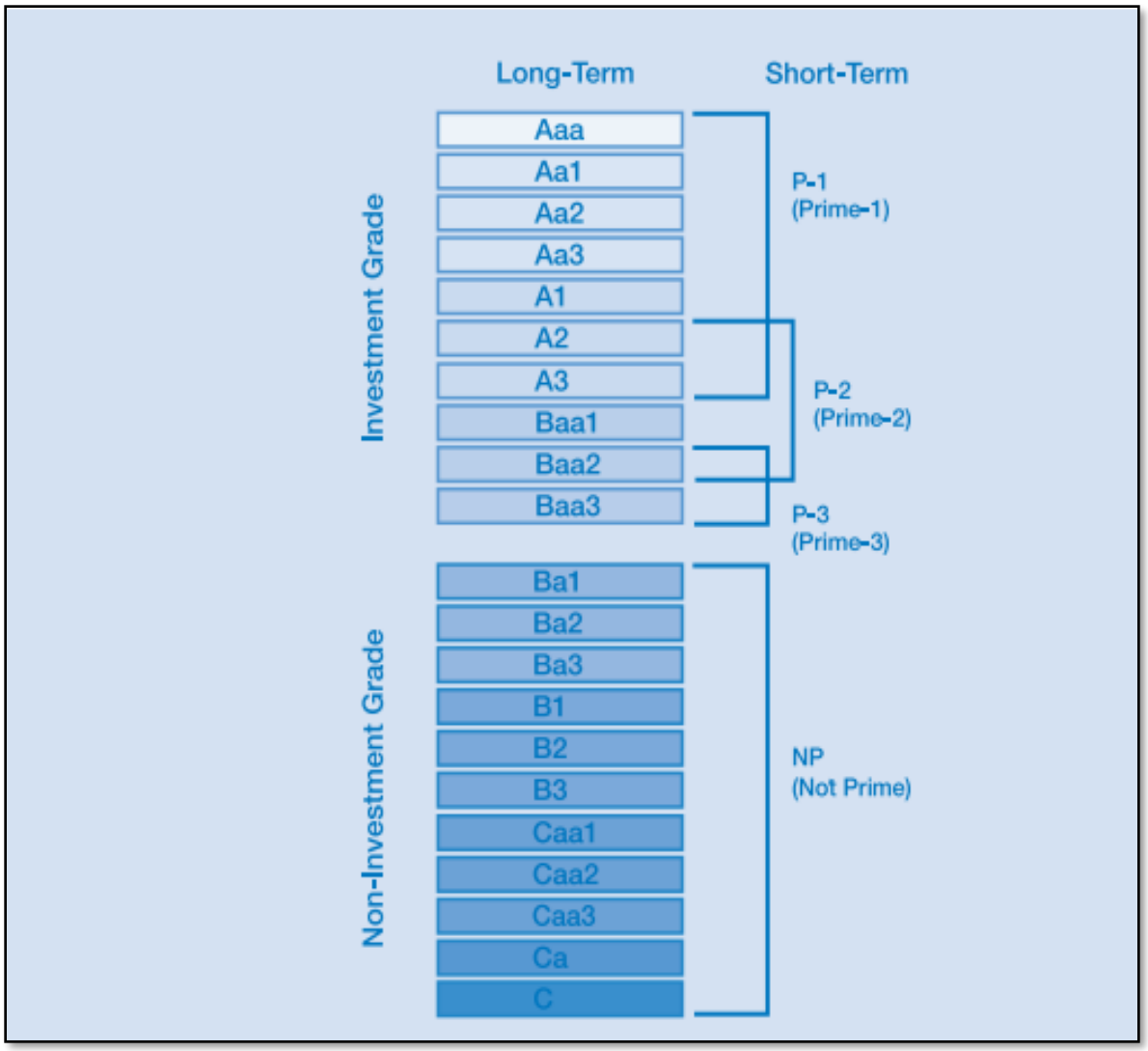
1.2.2 Overview of Credit Rating

Credit rating grades are opinions provided by CRAs on the creditworthiness of financial instruments and issuers. CRAs are independent bodies formed to provide information about the credibility of issuers. By evaluating qualitative and quantitative information about the borrowers

and estimating their abilities to repay debts, the agencies determine the prospective risks of borrowers. In other words, it is an assessment of the probability of default on debt that may result from the failure of a borrower to make payment. The CRAs rate creditworthiness of many instruments that are secured by collateral. CRAs give required information to the investors but they are also often identified as the culprits in financial crises.

The CR of an entity affects its capital cost if the rating is issued as investment-grade. In times of financial crises, CRAs have been criticized for being too late in downgrading the ratings. Moody's group was the first CRA to introduce a simple rating grade symbol for CR, and it is still used as shown in Figure 1. The simple letter used for rating grades helps investors to quickly judge and compare the default risks of investment opportunities. Many factors are associated with issuers influence the rating grades of securities. Hence, CRAs are considered as essential elements in CR. The prominent factors are financial risk and business risk.

Figure 1. 1 Rating Scale Given by Moody's



S*ource: Moody's Investor Services*

International Organization of Securities Commissions (IOSCO) defined CR as "a CRA's opinion of how likely an issuer is to repay, in a timely fashion, a particular debt or financial obligation, or its debts generally" (IOSCO, 2003). As the global standard-setter for the securities industry, IOSCO is known as an international body that brought together the world's securities regulators. IOSCO establishes, implements, and facilitates compliance with internationally recognised securities regulatory requirements. It works intensively on the global agenda of regulatory

reform with the G20 and the Financial Stability Board (FSB). It mainly works on three objectives: (i) Protecting investors, (ii) Ensuring the transparent, efficient and fair market, and (iii) Reducing the systematic risk.

Standard and Poor's (S&P) and Moody's group are both global leaders in CR industry and they defined ratings as opinions given on the financial creditworthiness of companies. The global leader of CRAs, Standard & Poor's (S&P) company has defined CR as "judgments of borrowers' creditworthiness based on relevant risk factors, expressed by letter grade rating symbol, which markets have come to depend on as reliable, user friendly tool for differentiating credit quality" (Standard & Poor's, 2009). Moody's Investor Services also stated that ″ratings assigned on Moody's global long-term and short-term rating scales are forward-looking opinions of the relative credit risks of financial obligations issued by non-financial corporates, financial institutions, structured finance vehicles, project finance vehicles, and public sector entities″ (Moody's, 2021).

SEBI defined CR as "an opinion regarding securities, expressed in the form of standard symbols or in any other standardized manner, assigned by a credit rating agency and used by the issuer of such securities, to comply with a requirement specified by these regulations" (SEBI, 1999). India's largest credit rating agency CRISIL has defined CR as "an unbiased, objective and independent opinion as to an issuer's capacity to meet financial obligations. It is the current opinion about the relative safety of timely payment of interest and principal on a particular debt instrument. Hence, rating applies to a particular debt obligation of the company and is not a rating for the company as a whole" (CRISIL, 2019). The grades issued by the Indian CRAs were standardized in 2011 by SEBI (SEBI, 2011). All the Indian CRAs are required to use the same

rating grades and definitions to rate the various instruments of companies. The symbol and definition of rating grades are summarised in Figures 1.2 to 1.6.

Figure 1. 2 Rating Symbols and Definitions for Long Term Debt Instruments

I. Rating Symbols and Definitions for Long Term Debt Instruments

Long term debt instruments: The instruments with original maturity exceeding one year

Rating symbols should have CRA's first name as prefix

AAA - Instruments with this rating are considered to have the highest degree of safety regarding timely servicing of financial obligations. Such instruments carry lowest credit risk.

AA - Instruments with this rating are considered to have high degree of safety regarding timely servicing of financial obligations. Such instruments carry very low credit risk.

A - Instruments with this rating are considered to have adequate degree of safety regarding timely servicing of financial obligations. Such instruments carry low credit risk.

BBB - Instruments with this rating are considered to have moderate degree of safety regarding timely servicing of financial obligations. Such instruments carry moderate credit risk.

BB - Instruments with this rating are considered to have moderate risk of default regarding timely servicing of financial obligations.

B - Instruments with this rating are considered to have high risk of default regarding timely servicing of financial obligations.

C - Instruments with this rating are considered to have very high risk of default regarding timely servicing of financial obligations.

D - Instruments with this rating are in default or are expected to be in default soon.

Source: SEBI Act 2011

Figure 1. 3 Rating Symbols and Definitions for Long Term Structured Finance

III. Rating Symbols and Definitions for Long Term Structured Finance *Instruments*

Long term* structured finance *instruments: The instruments with original maturity exceeding one year

Rating symbols should have CRA's first name as prefix

AAA (SO) - Instruments with this rating are considered to have the highest degree of safety regarding timely servicing of financial obligations. Such instruments carry lowest credit risk.

AA (SO) - Instruments with this rating are considered to have high degree of safety regarding timely servicing of financial obligations. Such instruments carry very low credit risk.

A (SO) - Instruments with this rating are considered to have adequate degree of safety regarding timely servicing of financial obligations. Such instruments carry low credit risk.

BBB (SO) - Instruments with this rating are considered to have moderate degree of safety regarding timely servicing of financial obligations. Such instruments carry moderate credit risk.

BB(SO) - Instruments with this rating are considered to have moderate risk of default regarding timely servicing of financial obligations.

B(SO) - Instruments with this rating are considered to have high risk of default regarding timely servicing of financial obligations.

C (SO) - Instruments with this rating are considered to have very high likelihood of default regarding timely payment of financial obligations.

D (SO) - Instruments with this rating are in default or are expected to be in default soon.

Source: SEBI Act 2011

Figure 1. 4 Rating Symbols and Definitions for Short Term Debt Instruments

II. Rating Symbols and Definitions for Short Term Debt instruments

Short term debt instruments: The instruments with original maturity of upto one year

Rating symbols should have CRA's first name as prefix

A1 – Instruments with this rating are considered to have very strong degree of safety regarding timely payment of financial obligations. Such instruments carry lowest credit risk.

A2 - Instruments with this rating are considered to have strong degree of safety regarding timely payment of financial obligations. Such instruments carry low credit risk.

A3 - Instruments with this rating are considered to have moderate degree of safety regarding timely payment of financial obligations. Such instruments carry higher credit risk as compared to instruments rated in the two higher categories.

A4- Instruments with this rating are considered to have minimal degree of safety regarding timely payment of financial obligations. Such instruments carry very high credit risk and are susceptible to default.

D - Instruments with this rating are in default or expected to be in default on maturity.

Source: SEBI Act 2011

Figure 1. 5 Rating Symbols and Definitions for Short Term Structured Finance

IV. Rating Symbols and Definitions for Short Term Structured Finance Instruments

Short term* structured finance instruments*: The instruments with original maturity of upto one year

Rating symbols should have CRA's first name as prefix

A1 (SO) – Instruments with this rating are considered to have very strong degree of safety regarding timely payment of financial obligation. Such instruments carry lowest credit risk.

A2 (SO) - Instruments with this rating are considered to have strong degree of safety regarding timely payment of financial obligation. Such instruments carry low credit risk.

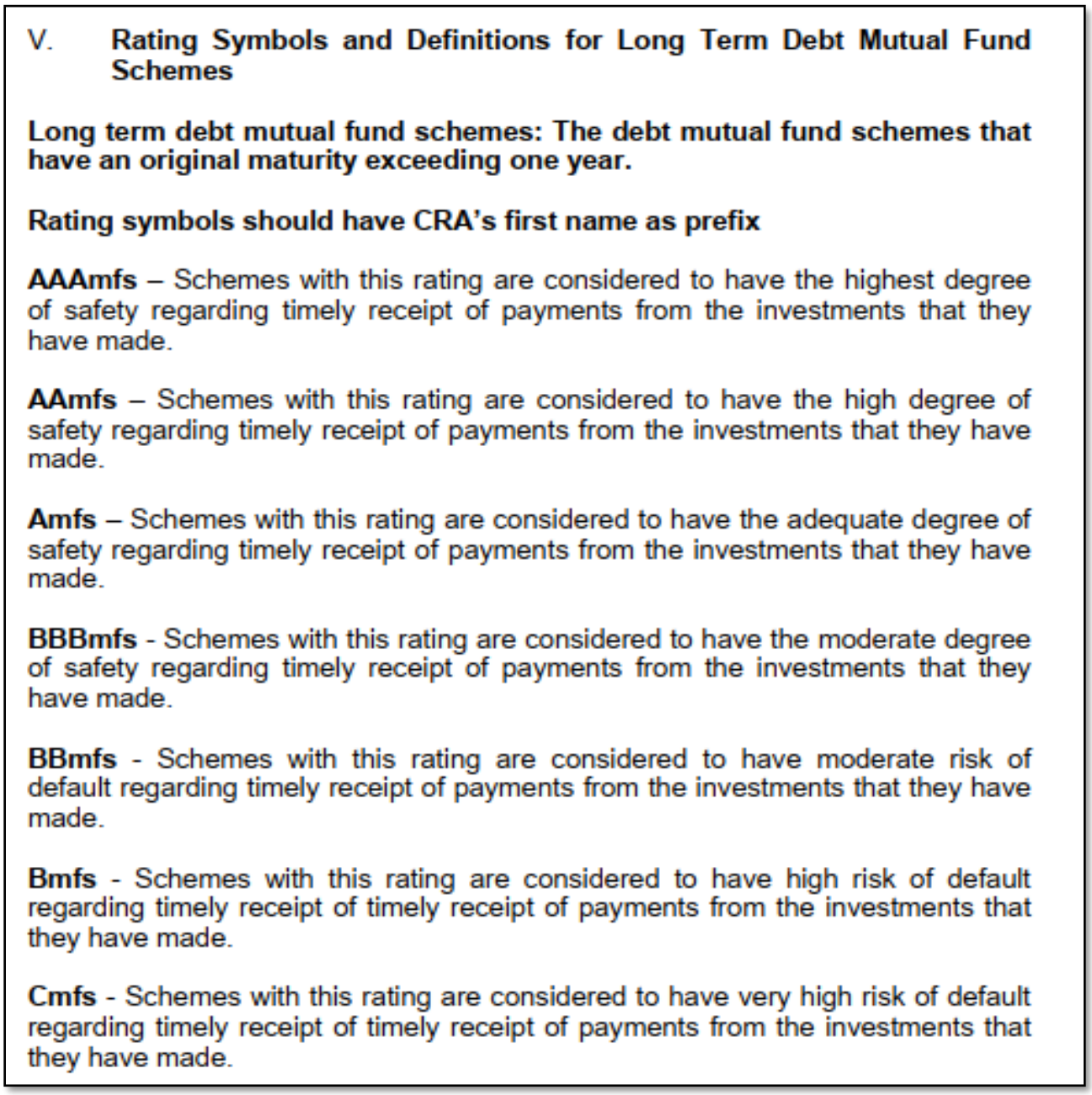
A3 (SO) - Instruments with this rating are considered to have moderate degree of safety regarding timely payment of financial obligation. Such instruments carry higher credit risk as compared to instruments rated in the two higher categories.

A4 (SO) - Instruments with this rating are considered to have minimal degree of safety regarding timely payment of financial obligation. Such instruments carry very high credit risk and are susceptible to default.

D (SO) - Instruments with this rating are in default or expected to be in default on maturity.

Source: SEBI Act 2011

Figure 1. 6 Rating Symbols and Definitions for Long Term Debt Mutual Fund Schemes



V. **Rating Symbols and Definitions for Long Term Debt Mutual Fund Schemes**

Long term debt mutual fund schemes: The debt mutual fund schemes that have an original maturity exceeding one year.

Rating symbols should have CRA's first name as prefix

AAAmfs – Schemes with this rating are considered to have the highest degree of safety regarding timely receipt of payments from the investments that they have made.

AAmfs – Schemes with this rating are considered to have the high degree of safety regarding timely receipt of payments from the investments that they have made.

Amfs – Schemes with this rating are considered to have the adequate degree of safety regarding timely receipt of payments from the investments that they have made.

BBBmfs - Schemes with this rating are considered to have the moderate degree of safety regarding timely receipt of payments from the investments that they have made.

BBmfs - Schemes with this rating are considered to have moderate risk of default regarding timely receipt of payments from the investments that they have made.

Bmfs - Schemes with this rating are considered to have high risk of default regarding timely receipt of timely receipt of payments from the investments that they have made.

Cmfs - Schemes with this rating are considered to have very high risk of default regarding timely receipt of timely receipt of payments from the investments that they have made.

Source: SEBI Act 2011

Prior to 2011, the Indian CRAs were free to use their own grading scale symbols. The varied symbols and definitions used by different CRAs created confusion among investors about the risks involved in an investment (SEBI, 2011; SEC, 2012). Therefore, in 2011 SEBI had taken initiative and passed a circular that standardized uniform rating symbols and definitions. In 2012,

Security Exchange Commission (SEC) also standardized the rating definitions (SEC, 2012). CRAs act as intermediaries between lenders and borrowers in a financial market. CRAs can also monitor financial health of banks, pension funds, and other financial institutions. These roles help investors to know the risks associated in an investment and adjust their portfolios according to the change in the risks. Academicians use CR as a measure for default probability to study the relationship between corporate bond (CB) yield spread and credit risk (Elton, Gruber, Agrawal & Mann, 2001). Credit rating can be used as a useful tool to measure the risks involved in an investment for investors. (Opp. et al., 2013; Bongaerts et al., 2012)

The primary objective of CRAs is the evaluation of fixed income securities. Generally, CRAs focus on the assessment of debt obligations of issuers. Previous researchers have studied the workings of CRAs. A CRA is viewed as a 'reputable auditor' (Wakeman, 1981); a 'signal provider' about a firm's creditworthiness (Thompson & Vaz, 1990); a 'third party certification' (Stover, 1996); or an intermediary offering informative services (Kuhner, 2001). The above briefly mentioned works have indicated that additional information is given by CRAs to reduce the information asymmetry among entities and outside investors. CRAs also play a significant role in "debt financing by solving problem of asymmetric information faced by investors in the markets" (Forsythe et al., 1999). CR can also indicate a "government's financial capability and preparedness to promptly pay back sovereign debt obligations" (Liu & Tan, 2009).

CRAs are institutions that provide information about the creditworthiness of bonds (Ryan, John, 2012). Here, creditworthiness is indicated by evaluating "the likelihood that an issuer will default on the interest or principal due on its bonds" (Ryan, J., 2012). CRAs award ratings to an instrument by using certain criteria to examine whether a government or issuer could maintain the required "cash flow for paying back debt" (Collins, 2014; Liu & Thakor, 1984). Cavallo, E.,

Powell, A., & Rigobon, R. (2013) stated that CR adds value to the bond and it does matter for the investors. The CR provided by CRAs helps in obtaining a correlation between risk and return of an instrument. Hence, they allow investors to measure the risks of any debt instrument and decide if the returns are worth the risks.

The question often asked is, does rating matter? As financial markets grow, sophisticated products are developed to deliver a variety of benefits to investors. Although these instruments provide the market with depth, the issue frequently raised by investors is, how do they assess the credibility of a debt investment? To help institutions and individuals make a more informed decision, most of these institutions have a team of analysts. Non-institutional investors, however, typically adopt market sentiment approach and invest based on the perceived value of an instrument. When it comes to the investment in different instruments (like Debt, Bond, Equity etc.), knowing the risks of the instruments are difficult for investors. Here, CR does matter as it shows the risk of default level. To provide ratings CRAs analyse the relevant factors related to issuers at macro level along with micro level factors.

1.2.3 Funding Credit Rating Activities

Initially, CRAs functioned on ‘investor pay model’. An investor needed to pay the fee for accessing a borrower's rating (White, 2010). Later in the 1970s, they adopted the ‘issuer pay model’. Hence; information obtained by investors about the risks of instruments was for free (Schroeter, U. G., 2013). In the new model that is ‘issuer pay model’, CRAs charge rating fees to the issuers. In other words, issuers have to pay CRAs to rate the instruments they are issuing. Often the CRAs have assigned high ratings to quite risky and worthless financial instruments susceptible to collapse, for which they have faced severe backlashes and harsh criticism.

The primary reason attributed for the crises is the practice of rating shopping in the ‘issuer pay model’. The certifications by CRAs had often had real and profound effect on the economy. The reputation of CRAs is the main asset that reflects the credibility of their work that attracts people to hire their services. Hence, CRAs are required to maintain good name and reputation. This has also been summarised in The Economist under the heading "The Use and Abuse of Reputation" on April 6th, 1996, (page no. 20) as below:

"Even more than for accountants and lawyers, the rating agencies must trade on their reputations. If bond investors lose faith in the integrity of rating agencies' judgments, they will no longer pay attention to their ratings; if rating agencies' opinions cease to affect the price that borrowers pay for capital, companies and governments will not pay their fees. So, market forces should make rating agencies careful of their good names" (cited by Crockett et. al., 2003; Mariano, 2008).

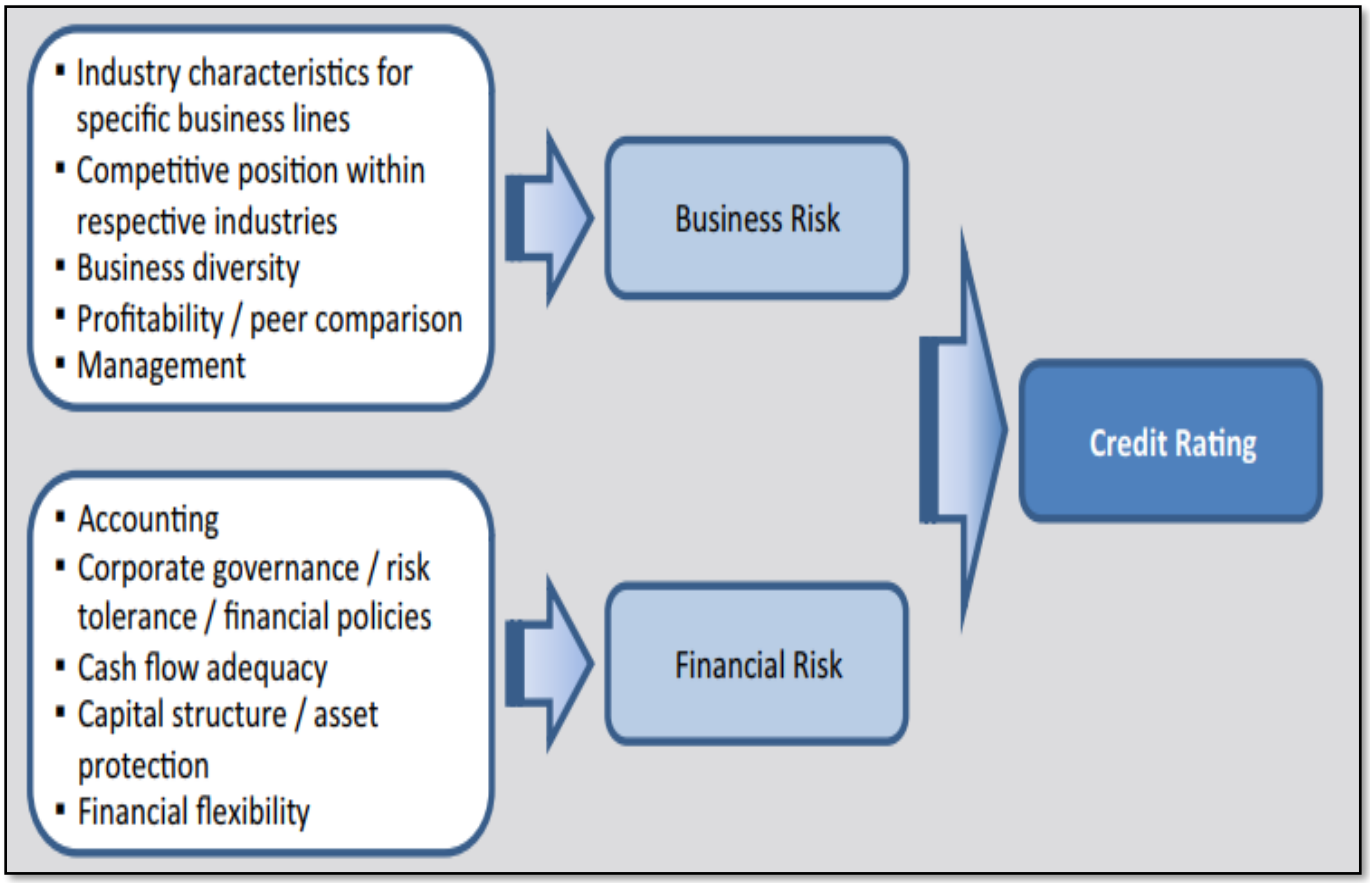
Hence, one would expect only fair and accurate information about debt obligation from the CRAs without making any mistake. For this, the CRAs should use all the public and private information carefully to assign CR grades. But this faith in CRAs has often come into question during financial crises, and the CRAs have been criticized for downgrading the rating grades too late. The CRAs need to evaluate all the factors before reporting their judgements as rating grades to the public or borrowers.

1.2.4 Factors Considered for Credit Rating by CRAs

CRAs need to analyse a borrower’s credit risk and other risks related to a company. Credit risk evaluation requires additional care. The financial crisis of 2008, popularly known as GFC 2008, and the European Union (EU) sovereign debt crisis in 2009 drew a lot of attention on credit risk.

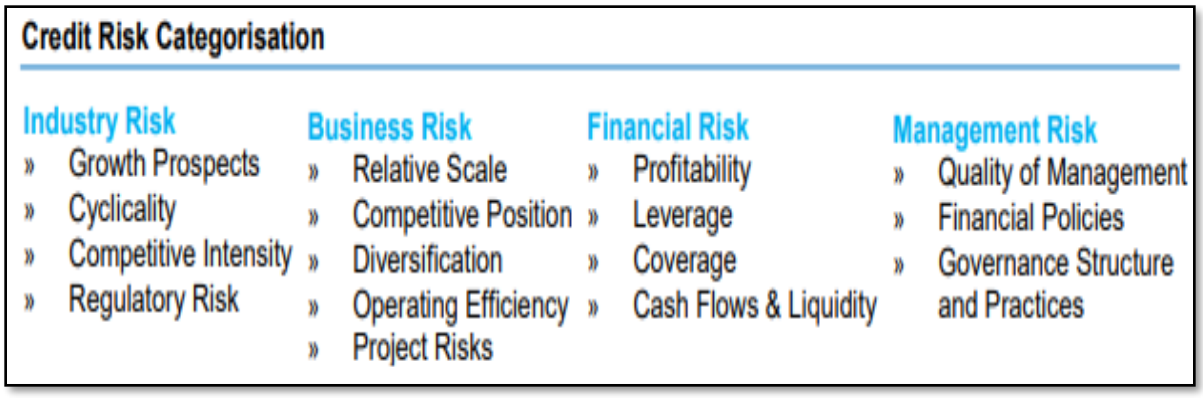
Credit Crisis originated in U.S. which disturbed the credit market and affected the global economy. Heart of the GFC 2008 aligned with "the dramatic expansion and collapse of mortgage lending" documented by using microeconomic data (Mian & Sufi, 2010; Helbling et al., 2011). CRAs methodology should examine financial risk, business risk, industry risk and political risk factors, to provide credit ratings to the borrowers' instruments. Traditionally, rating analysis consists of only two factors: (i) Business Risk, and (ii) Financial Risk (Langohr & Langohr, 2010) as shown in Figure 1.7. Whereas domestic CRAs in our country categorise risk into four types: "(a) Industry Risk, (b) Business Risk, (c) Financial Risk and (d) Management Risk" (ICRA, 2021). They are shown in Figure 1.8 and are discussed below.

Figure 1. 7 Traditional Factors Considered for Credit Rating Analysis



Source: Standard & Poor's

Figure 1. 8 Risk Factors Considered by ICRA for Corporate Debt Rating



Source: ICRA

1. **Industry Risk:** Different industries are exposed to different risks. Hence, issuers operating in a particular industry are associated with the circumstances and risks of that type of industry. Two companies can have different credit ratings if they operate in industries with varying characteristics of risk despite having identical risk profiles in all other respects (ICRA, 2021). The various factors of an industry considered are: growth prospects, cyclicality, competitive intensity and regulatory risk.

   Country Risk: This relates to the dynamic environment of the country in which a company operates. It includes the rules and regulations of the government, and the political environment of the country. A company ought to follow all the rules and regulations of the country in which it is operating. The government restrictions, tax policy, environment clearance policy, political influence or relation with the ruling party, company law, etc. play important role in success of a business enterprise which varies from country to country.

Company-Specific Risk: The comparison of the company with respect to its competitors (a special reference to the price, product, sales growth, diversification) and company management (shareholders, policy and rule to achieve the goals and objectives can come under this head). If a firm is not able to meet the competition and has very less market share, it may impact the business adversely. A firm needs to maintain its cash cows and harvest the dogs (as termed in BCG matrix) immediately as both have move in inverse direction.

2. **Business Risk:** Business risk measures the competitive position of the issuers, products diversification, market share, channels of distribution, market growth status, etc. The availability of raw material, strategic location of a firm for its advantage, relationships with labour and technology used for production etc., help in generating large profit. A firm should be able to survive in the market with good market share and growth. To maintain the business, a firm needs to diversify and minimize the systematic risk.

3. **Financial Risk:** The financial strength of the issuers is assessed through ratio analysis, capital structure evaluation, and cash flow analysis. The present and the past financial performance of the issuers are evaluated to know the credibility of the issuers. The important factors analysed under financial risk include:

    - Profitability: It shows the return on investment that the firm is able to generate from the available resources. This indicates the firm's efficiency and eventually the success or failure of business.
    - Liquidity: It measures the issuers' ability to meet short-term cash requirement from difference sources. According to ICRA, (2021) internal resources include

"cash flows from operations, unencumbered cash and cash equivalents on balance sheet and cash inflows expected from the monetisation of physical and financial assets" and external resources include "undrawn lines of credit or equity capital".

- Leverage: This shows the portion of debt firm holds against equity (firm's ordinary shares).
- Coverage: It shows the adequacy of the firm's earnings (EBIDT) to service the interest payments and principal repayment obligations. It indicates the ability of firm to pay its debt obligations. Higher ratios show greater ability of payment however lower ratios indicate the lower ability towards payment of financial obligations.
- Cash flow Analysis: This shows the inflow and outflow of cash for different activities i.e., operating activities, financing activities and investing activities. In other words, it indicates the consumption and generation of cash through different business activities.

These help in understanding the efficiency of resource utilization of a firm. For instance, if a firm is able to generate a profit and maintain a high liquidity, it is considered to be in good financial health. The funding of business activities through undesirable sources can hamper the payments of financial obligations of a firm. Also, generating cash from business activities has significant impact on financial health of a firm. In the process of assessing the creditworthiness of the issuers, financial risk plays a major role.

4. **Management Risk:** A company's success is greatly influenced by aims, plans and strategies of its management, and its ability to resolve adverse situations, the expertise and skills of the workers, the planning and control systems. Grading a debt instrument

also involves evaluating the strengths and limitations of management as well. The quality of management, relationships between employees and employers, labour and management, organisation culture and the planning and control mechanism, etc., are analysed under this. The other factors under management risk includes:

- Quality of management
- Financial policies

CRAs are required to complete the analysis of all the risks mentioned above to assign rating to the instruments of companies which is called credit risk analysis. The extensive scope of risk analysis requires credit analysts to undertake an integrated examination of the company which may put the company ahead of its downturn. Credit analysts' task is to identify a borrower's creditworthiness by putting a quantitative value on the risk of loss that a lender faces. S&P has summarised the importance of credit risk analysis for rating as:

"Credit ratings often are identified with financial analysis, and especially ratios. But it is critical to realize that rating analysis starts with assessing the company's business and competitive profile. Two companies with identical financial metrics are rated very differently, to the extent that their business challenges and prospects differ. Standard & Poor's developed the metrics to make explicit the rating outcomes that are typical for various business risk/financial risk combinations" (Standard & Poor's, 2006).

Based on the risks, CRAs give opinions on an obligor's creditworthiness represented with alphabetical symbols called rating grades. Hence, grades represent the ability of a borrower to repay its debt and also implicitly forecast the probability of default. Higher grades (i.e., AAA, AA, etc.) can fetch funds at lower interest rates, whereas lower grades (i.e. BB, B, C & D) can

fetch funds at higher interest rates to compensate the lenders who have taken high risk. There is no universal or standard formula to calculate the grades. Moreover, it needs to be remembered that the rating does not recommend selling or purchasing securities, and it never comments on the sustainability of the investors (Standard & Poor's, 2006).

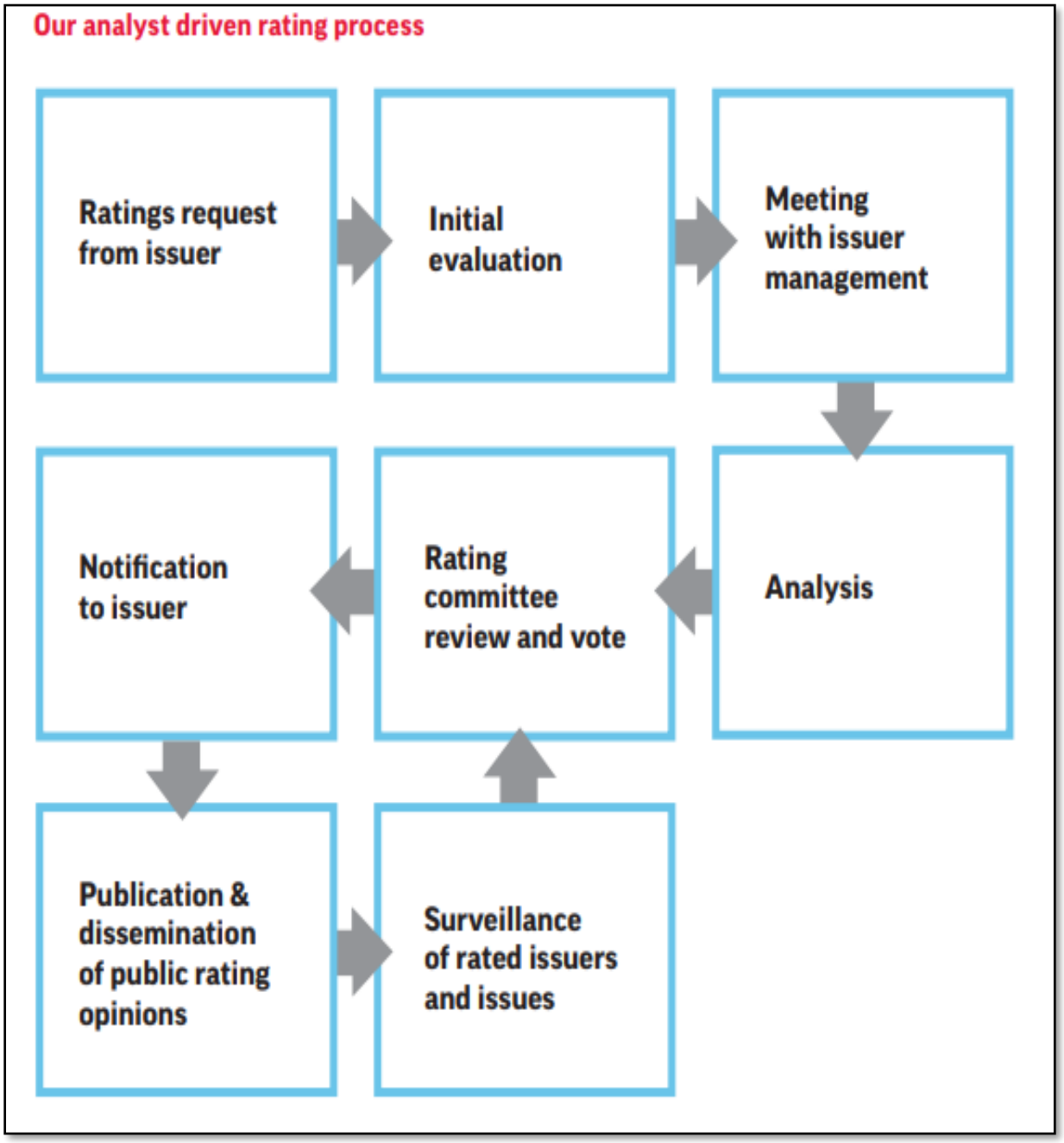
1.2.5 Credit Rating Process

Credit rating process starts on the request of issuer and ends with the award of rating grade and maturity of a rated debt. An issuer needs to initiate a formal rating request to CRAs for assigning rating grades to their securities. An issuer enters into an agreement with the CRAs that allows the rating agencies to access all the information related to the issuer, but they (CRAs) need to maintain the confidentiality of the information obtained from the issuer. Also, the regulators give the right to an issuer to accept or reject a rating. An issuer should provide complete and accurate information. After signing the agreement, CRAs assign their analysts to analyse the information of an issuer. Here, the analysts obtain all the relevant information from an issuer and have a meeting with issuer's management team and also physically visit the organisation. After analysing the information, reports are presented to the rating committee.

The rating committee comprises of board members, senior analysts, independent directors, etc. The rating committee then conducts a meeting to discuss the reports and assigned grades to the instruments through voting. Once they have decided on the rating grade, the same is communicated to issuer. Once the rating is issued, an issuer can either accept or reject the assigned rating, but the same needs to be displayed publicly with the remark that the rating is accepted or not. This can be better understood with the flow chart of rating process by different CRAs (International and Indian) presented in the following pages. Rating procedure of Standard

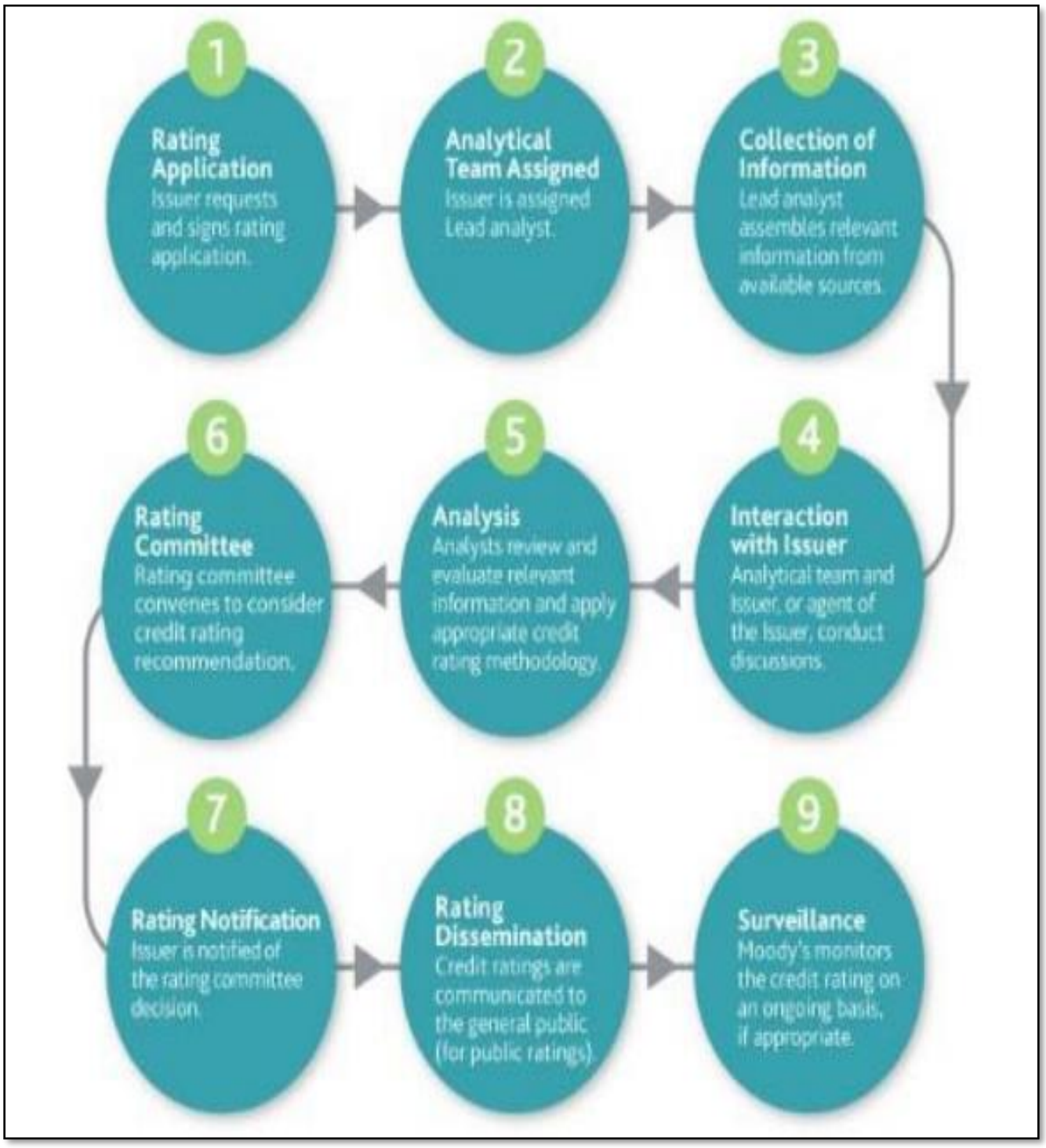
& Poor's in Figure 1.9, Moody's in Figure 1.10, CRISIL in Figure 1.11, ICRA in Figure 1.12, CARE in figure 1.13, INDIA-RA in Figure 1.14, Brickwork in Figure 1.15 and SMERA in Figure 1.16.

Figure 1. 9 Rating procedure of Standard & Poor's



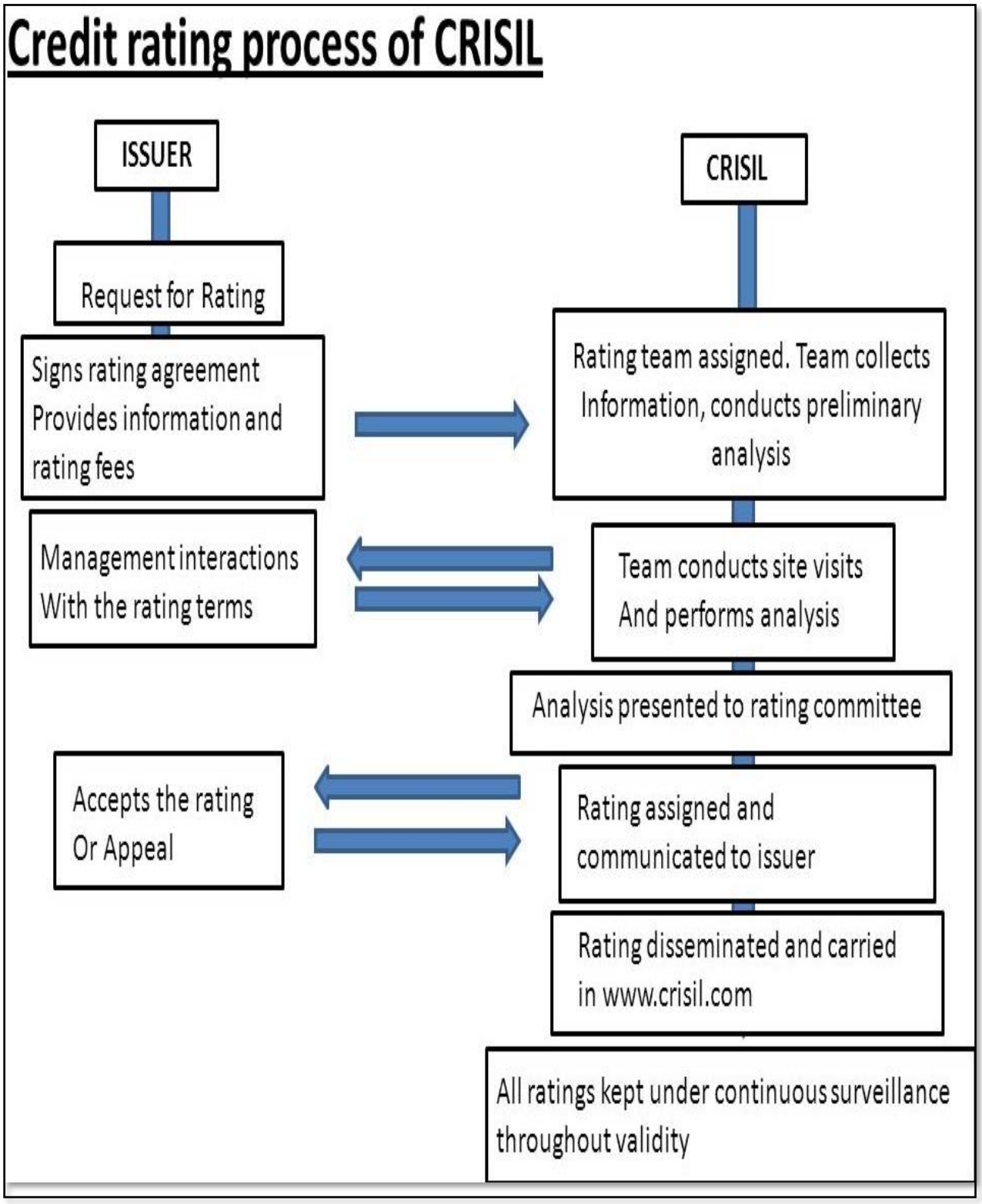
Source: Standard & Poor's

Figure 1. 10 Rating Procedure of Moody's



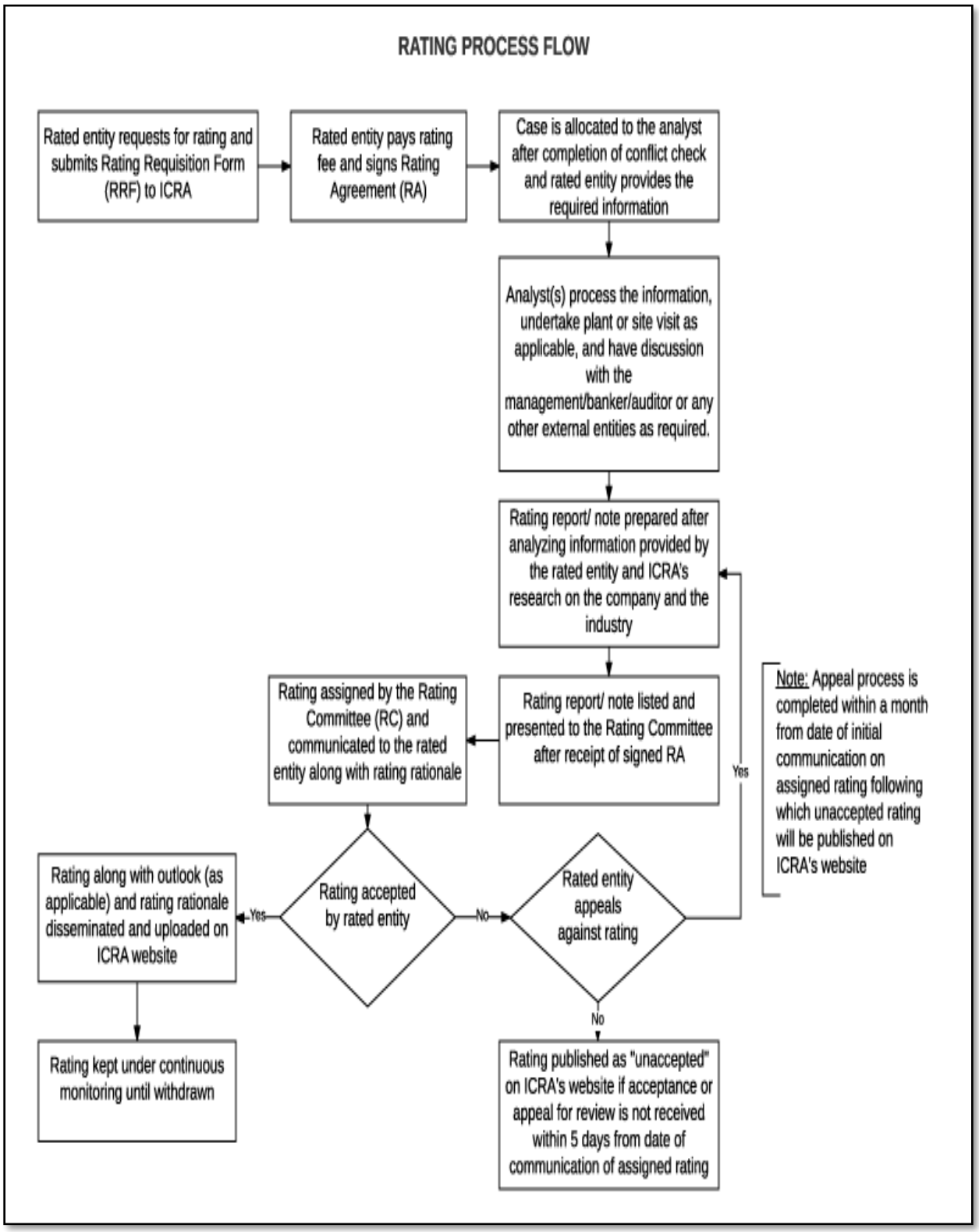
Source: Moody's Investor Services

Figure 1. 11 Rating Process of CRISIL



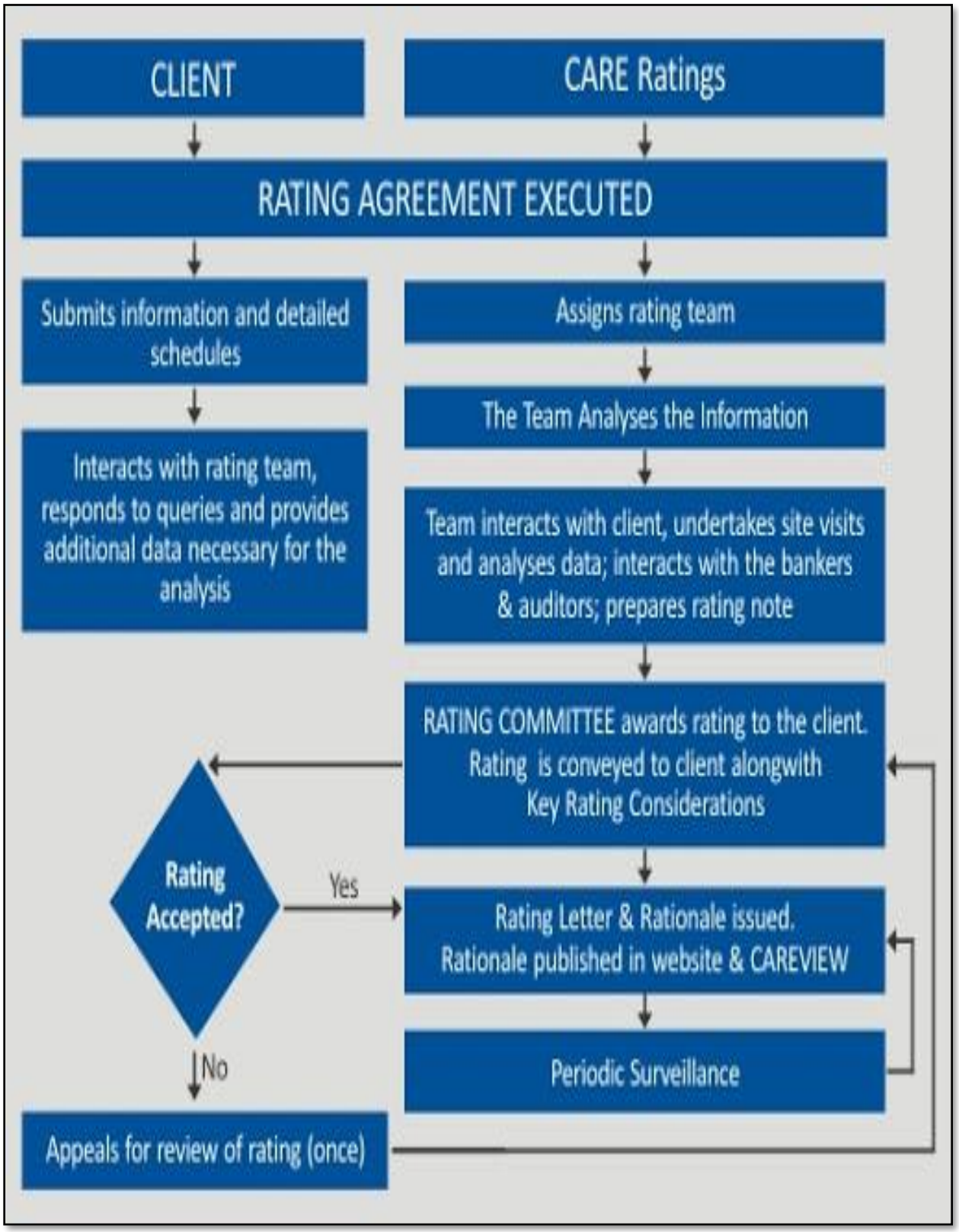
Source: CRISIL

Figure 1. 12 Rating Process of ICRA



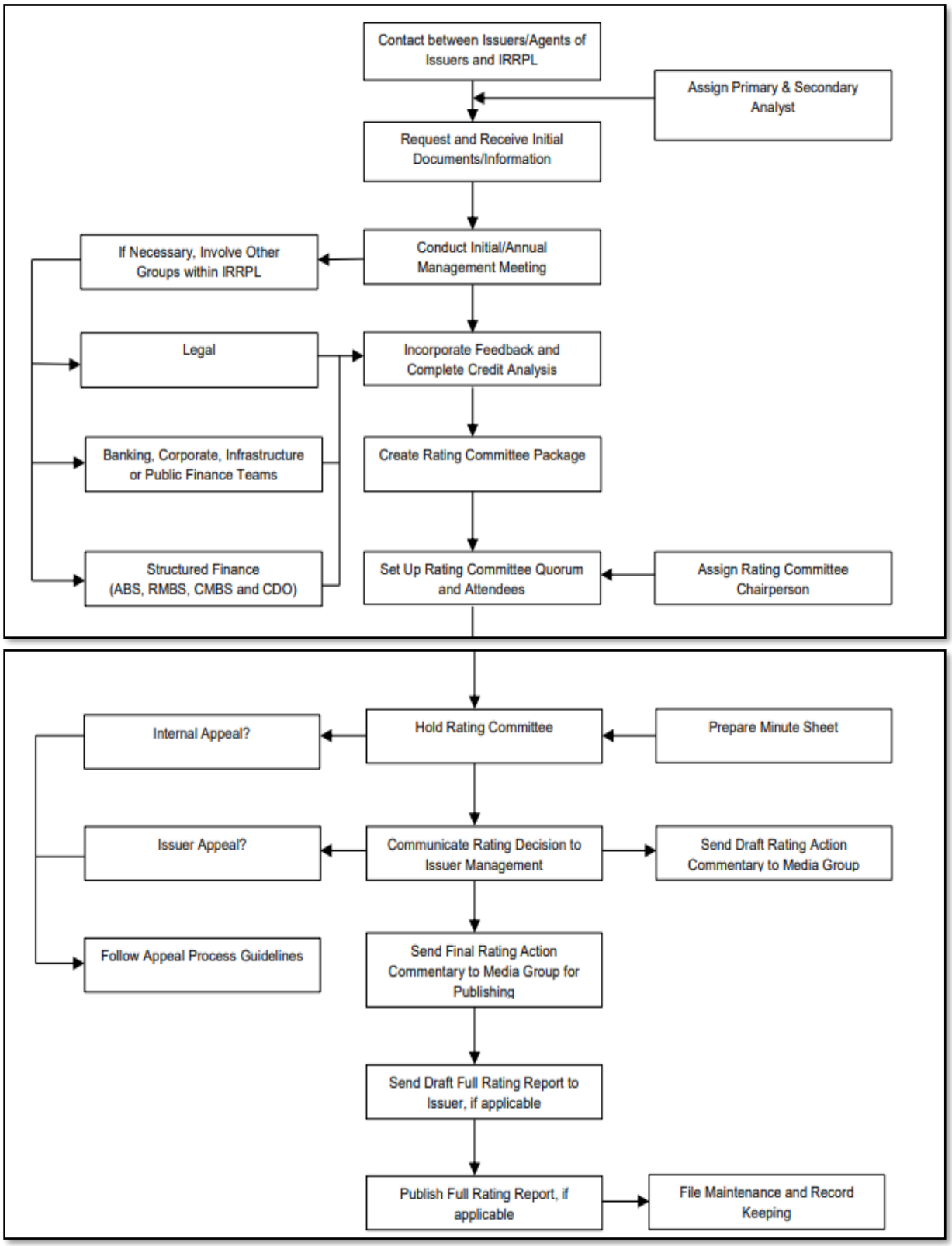
Source: ICRA

Figure 1. 13 Rating Process of CARE



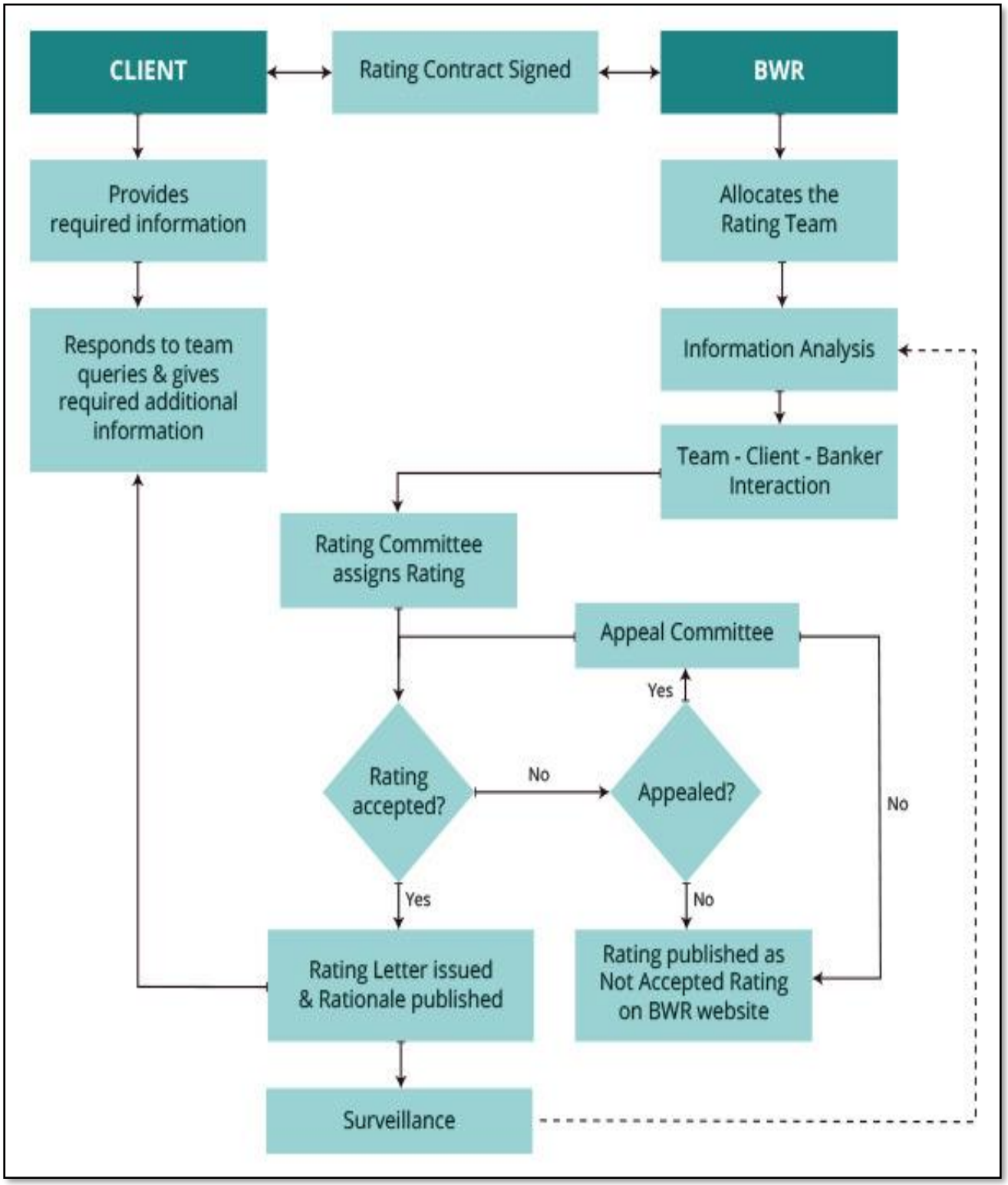
Source: CARE

Figure 1. 14 Rating Process of INDIA-RATING



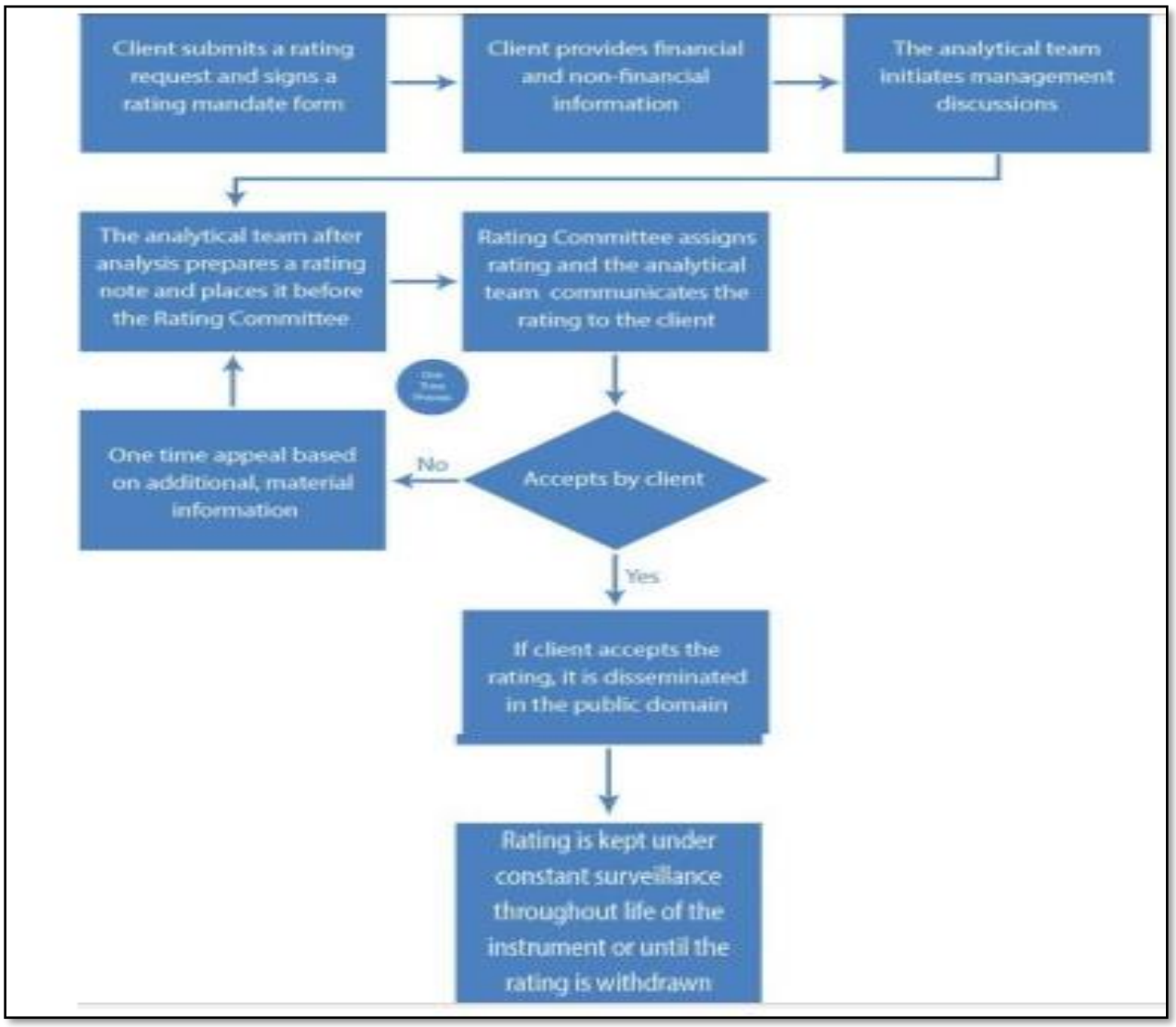
Source: INDIA-RATING

Figure 1. 15 Rating Process of Brickwork Rating



Source: Brickwork

Figure 1. 16 Rating Process of SMERA



Source: SMERA

The efficiency of CR grades through above CR procedure cannot be quantified. Edward Z. Emmer, Executive MD (Managing Director), Standard & Poor's has stated, "Credit risk analysis is an art, not a science. It is impossible to quantify all the elements that one must consider in credit analysis" (Ganguin & Bilardello, 2005). The CRAs offer a wide range of services and ratings to different instruments used by individuals, investors, institutions, and issuers. The users of rating services are discussed below.

1.2.6 Users of Credit Rating Services

- **Issuers/Debtors/Borrowers:** They use credit rating services to enhance the marketability (by increasing the reputation and trust of the investors and other counterparties) and the price of their securities (US SEC, 2008). Rating services also provide access to capital market and further help in reducing borrowing cost and make funds easily available.

- **Investors/lenders:** They use credit rating services to reduce the information cost and risk analysis cost for debt investments. The information gap and the risk associated risk with securities is reduced by CR. The risk and return correlation stated by CR helps in making investment decisions. Also, CR is used to diversify the portfolio by comparing the risks of securities (Langohr & Langohr, 2010).

- **Underwriters, Brokers, and Investment Bankers:** Similar to the investors, they also use credit rating services for the same purpose to a large extent. They use credit rating to benchmark the risks associated with various instruments issued and also to fix the initial price of the instruments. It saves time and effort as well as manpower for convincing investors about potential investments. It reduces the burden of explaining the risk level of the instruments issued to the clients.

- **Regulators:** CR uses all information (quantitative and qualitative) about an issuer to award a credit rating. Rational investors do not have easy access to the information of an issuer which is available with CRA. It also makes the process of investing in such resources more straightforward and transparent. Regulators use credit rating to monitor and access the investment risk held by a regulated entity like bank.

1.2.7 Types of Rating

Issuers finance their capital in different ways such as equity, bank loans, preference shares, bonds, short term instruments, etc. Instrument rating has been prevalent and it is widely used. However, issuer rating has also become increasingly more desirable. The CRAs have expanded their offerings through the emergence of new areas of rating. The traditional and the emerging areas of rating are listed below.

Traditional areas of rating

i. Corporate Debt Rating
ii. Equity Rating (equity shares issued by a company)
iii. Issuer Rating
iv. Preference shares rating (Preference shares issued by a company)
v. IPO Grading
vi. Commercial papers issued by different firms such as manufacturing companies, finance companies, banks, and financial institutions for raising short-term loans.
vii. Mutual Fund Rating
viii. Bank Loan Rating
ix. Fixed Deposits (short term and long term FDs).
x. Borrower rating: The ratings of borrowers who have borrowed money are called borrowers credit rating.
xi. Individuals rating: Rating provided to the individuals
xii. Structured Finance Rating: "Asset-backed Securities" (ABS), CDOs ("Collateralized Debt Obligations"), MBS ("Mortgage-backed Securities") etc. are assessed "to determine

the risk associated with them. The objective is to determine the quantum of cash flows emerging from the asset that would meet committed payments" (Muraleedharan, D., 2014).

xiii. Project Finance Rating

xiv. Real Estate Development rating

xv. Sovereign Rating

xvi. Urban Local Bodies Rating

xvii. Corporate Governance Rating

Emerging areas of rating

1. Rating of Indian States
2. Microfinance Institutions Grading
3. Social Rating

Among all the instruments, bond is a low-cost source of finance to meet a firm's capital requirement. It is a straightforward investment used to diversify the investment portfolio. CRAs were established in the 1840s to evaluate the credibility of an entity. Corporate bond rating is the oldest type of rating, and the first rating was given to railway bonds by Moody's group. A bond is rated by CRAs according to the default risk associated with a borrower.

1.2.8 Types of Rating Announcements

Rating announcements can be made any time until the maturity of rated securities. The first (Initial) rating may not survive until maturity as it changes according to the performance of a firm and its securities. The different rating announcements made by rating agencies are listed below:

1. **Initial Rating:** The rating issued to an instrument by rating agency for the first time to grade its securities is called initial rating. This can be done at the time an instrument is available for issue to the public or immediately after the issue. In case of bond, rating should be obtained by the issuer before the bond is issued and the same should be announced when the bond is issued for first time.
2. **Rating Upgrade:** Securities are issued for a specific time period called maturity period. The ratings assigned to instruments are monitored and observed and revised when necessary based on their performance till they mature. For instance, if an instrument's performance/return increases, CRAs will revise the ratings and announce higher grades of CR. The improvement in rating grade is called rating upgrade.
3. **Rating Downgrade:** If the performance/return of an instrument decreases before the maturity period, CRAs will revise the ratings and announce new rating with lower grades. The decrease in rating is called rating downgrade. The rationale is that with the increase in CR grades the safety level of an instrument also increases and vice versa.
4. **Rating Reaffirmed:** When the last rating grades are revisited and there is no change observed in the performance/return by CRAs, then the same grades are assigned. This is called rating reaffirmed. Reaffirmed rating is considered to indicate a constant growth

creditworthiness of an instrument. Usually this announcement is considered either as a positive or stable information about the risk associated with an instrument.

5. **Suspended Rating:** A rating can be cancelled either by CRAs or issuer, under SEBI (Credit Rating Agencies) regulations, 1999 and this cancelled rating is called suspended rating. It does not mean that the financial position of an issuer has deteriorated or the issuer is unable to fulfil debt obligations. This happens if the important information of an issuer like cash flow statements, liquidity positions, operating expenses etc., is not available to the CRAs or if the issuer refuse to cooperate with the assigned rating, the following remarks are released in the market through press, "Issuer did not co-operate; Based on best available information" (SEBI, 2016) for the benefit of CR users.

   Another scenario of receiving suspended rating would be if a rated entity is in the process of merging with another entity but the process is taking more time than expected. The gap between merger process and assignment of rating to the new entity should not be more than three months, as per guidelines (SEBI, 2016).

6. **Rating Watch:** Credit rating of an instrument cannot be ascertained fully or partially due to unanticipated events. Such events can be merger, demerger, acquisition, change in capital structure or spontaneous regulatory change. To track ongoing changes and obtain additional information, CRAs use the time during which a credit rating remains on 'Watch' to determine whether the current credit rating should be revised or not; and if it is to be revised, what should the revised grading be.

7. **Rating Withdrawal:** Rating withdrawal is done either on request of the issuer or when the market does not require the coverage of CRAs, that is public information is enough to know the creditworthiness of an issuer. Rating withdrawal announcement reflects the

opinions of CRAs for an instrument at the time of withdrawal. Issuer can withdraw rating by making full payment of the debt obligation. But in a press release, CRAs need to display the withdrawn rating and also state the reason (SEBI, 2016).

The reasons for withdrawing rating are: (i) if the information provided by issuers to CRAs are inadequate to assess the obligation or creditworthiness of an issuer, (ii) if an issuer get liquidated or bankrupt, or a firm has merged with another entity, in such a situation there is no need to maintain the ratings issued by CRAs, and (iii) if the debt obligation is paid in full on the maturity of debt obligation.

1.3 Fundamentals of Indian Bond Market

Bonds are known as fixed-income securities and are considered as safer investments. Debt instrument promises the investors to pay a certain given amount as interest on the original principal, and repayment of principal on maturity (Moody, J. & Utans, J., 1994). A choice of investment in a bond requires careful examination of a huge volume of information about a firm's risk. This information includes statistics concerning a firm's performance in the areas of CSR ("Corporate Social Responsibility"). Crises of ethics, environmental, or social responsibility have triggered investors' attention. One such example is the melamine-tainted milk controversy in China.

The default risk of a bond depends on the credit risk of an issuer. Credit risk shows the possibility of loss if a borrower or counterparty fails to meet the obligation under agreed terms. Credit risk would be affected due to the cause or the effect of possible future default. The management and mitigation of this risk has become essential. A default event is triggered by a

firm's capital structure when its value falls below the financial obligation. Corporate bond prices are likely to be lower than government bond prices.

Full-fledged and liquid Corporate Bond Market (CBM) plays a significant role in developing economies especially for emerging countries like India. A corporate sector's long-term capital requirement for investments and creation of assets is done through the banking system; this system also helps in economic development. It is a vital supplement for any source of finance at a time when equity market is volatile. It provides an established source of finance because of reduced activities of Development Financial Institutions (DFIs) in India (Shubha, B.N. & Das, Rina, 2017). In India, capital financing market is dominated by banks and equity financing to meet the capital requirement of companies.

The debt market in India comprises of Corporate Bonds (CB) and government bonds. Of the two, government bonds are predominant because they are more liquid and safe, and thus form a prominent component of the bond market (Raju, M.T., Bhutani U. & Sahay, 2004; Patil, 2001). After the economic reforms in 1990s, India has developed a government security market and equity market. But corporate bond market is still small and it is not active compared to the other developed countries (Acharya, Amarendra, 2011). In India, corporate bonds as long term investments are not as visible as in other countries like the United State, China, and Japan.

Government bond market in India has a significant positive impact on CBM, but this is not the same for other countries like South Korea (Raghavan & Sarwano, 2012; Acharya, Amarendra, 2011). The primary CBM is dominated by private placement, and corporate companies prefer this route for operational ease (Khan, 2012; Banerji et al., 2012). The major reasons for the slow development of CBM in India are because of its over-lapping

regulations, low equilibrium, and benchmarks (Chaudhari, Raje & Singh, 2014). To strengthen the CBM, India has made bond rating mandatory and capital financing through bonds compulsory. SEBI has issued a circular stating that 25% of the capital should be mandatorily financed through CB by large enterprises in July 2019.

1.4 Corporate Bond Rating

Corporate Bond Rating (CBR) is the primary source of information for the investors about the quality and marketability of the various bonds issued. For instance, an investor is able to know whether the promised principal and the interest payment would be made on time by accessing the information associated with a bond issued. Bond rating does not only provide information about the risk and quality of a bond, but it also affects an investor's decision of investment and the cost of borrowing for an issuer's firm. Its primary purpose is to ascertain the financial strength of a bond issuer and the capability of an issuer to repay the interest and principal amount of a bond on time (Shin & Han, 2001). Since bond rating is mandatory, it alerts the investors about the stability and quality of the bonds. Bond rating greatly influences investment appetite, interest rate, and bond pricing. Rated bonds attract investors' attention because of the prospect of high yield in case of speculative-grade ratings. Highly rated bonds are considered safer and this positive outlook attracts low-risk investors and those who want to diversify their portfolios.

The ratings provided by rating agencies are based on different factors associated with the companies like financial risk, business risk, market risk, industry risk, political risk, etc. (Gonzales et al., 2004). After analysing all the risks, CRAs assign ratings to the instruments in grades form, which indicate the probability of defaults. Ratings provided by different CRAs to a company might be the same or different, depending on the risks and performances of the

instruments issuers use rating as a corporate governance measure to show transparency and low investment risk (Nordberg, D., 2010). Banks and potential investors use the ratings as benchmarks to compare their internal ratings and analysis (Erlenmaier, 2006).

CRAs work on 'issuer pay model' which means the issuers have to pay the rating agencies for assigning ratings to their instruments (SEBI, 1999). Criticisms against credit rating agencies started when they adopted 'issuer pay' working model. CRAs are criticised for rating shopping and people have blamed CRAs for giving favourable rating in exchange of high fees and rewards. For instance, this working model has been heavily criticised for assigning high rating grades to MBS (Mortgage Backed Securities) when their actual values were in fact supposed to be given lower grades. Other criticism is with regard to the relationship between CRAs and issuers. This can be better understood with the statement given by an analyst quoted below:

"The investment could be structured by cows and we would rate it" (Quoted by US SEC, 2008)

The above statement was given by an analyst in an internal communication email to another analyst of the credit rating agency. The statement of the analyst reflects the puzzled reactions of CRAs when they rate a product of a principal revenue source firm. This statement continuously attracts the public's attention especially during financial crises. The existence of trustworthy investors and the lack of fear among CRAs to issue favourable ratings for certain incentives over their reputation have given rise to inflated ratings (Bolton et al., 2012). Hence, the quality of the ratings assigned by CRAs to a company's bond have been questioned and heavily criticized especially in GFC 2008. People have mostly questioned the merit and accuracy of the ratings provided by CRAs as there have been instances when the ratings were not updated and inaccurate.

The ratings given by the CRAs are made available to public and their complete archival records are maintained. Companies which issue bonds may have their equity trading stocks in different stock exchanges. But the stock price data of these entities, both current and historical are easily accessible to the public just like Bond Ratings (BRs) information. This makes it quite easy to test the value of ratings, as the information provided through a company's stock prices could be directly related to the ratings of the bonds of a firm. This can be done by examining the impact of rating downgrade on a firm's stock prices.

A rating is not permanent and it changes according to the performance of a rated instrument until its maturity period (SEBI, 1999). A change in rating occurs when there is either an upgrade or a downgrade on an entity's creditworthiness. The CRAs give only opinions on the risks associated with securities, and they do not recommend selling or holding or buying the securities (Gonzales et al. 2004). Several studies have examined the effect of change in bond rating on stock prices and bond prices (Katz, 1974; Rogalski, 1975; Grier & Katz, 1976; Hettenhouse & Sartoris, 1977; Weinstein, 1977; Pinches & Singleton, 1978; Ingram, Rooks & Copeland, 1983; Peavy, 1984; Wansley & Clauretie, 1985**;** Cornell et al., 1989; Hand et al., 1992; Barron, Clare & Thomas, 1997, etc.). In the recent years, there have been debates on the information content of BR actions. Some authors have argued that there is no valuable information in rating actions, but on the contrary some have pointed out that rating actions contain useful information. Bond rating has been in existence in the US since 1900s, and therefore a lot of research has been done in relation to the US. The US bond market is globally the strongest, comprising of over 80 percent of corporate bonds. Whereas India is an emerging bond market which is dominated by government bonds. Bond rating started in India only in 1991, and so there has been only little research done on bond rating in India.

CBRs are ordinal measures to reflect a firm's credit quality and also its default probability. Investors rely on the accuracy of CRs and procedures of evaluation used by CRAs (Kiesel, F., 2016). In last few years, CR has gained significant importance in the Indian market. But in the recent past, sharp downgrades have been observed in the ratings of instruments issued by few firms causing huge losses to the investors. So panic has gripped the investors in the market. This has triggered a debate on the reliability of CRAs and its real economic functions in a financial system. The CRAs are criticised for two reasons: one, for being slow to revise ratings, and two, for inflating ratings due to conflict of interest and competition among CRAs (Bolton, Freixas & Shapiro, 2012; Becker & Milbourn, 2011; Becker & Milbourn, 2008). Issuers obtain ratings from more than one agency and they choose the most favourable ratings (Faure, Grimaud, Peyrache & Quesada, 2009). In a nutshell, CRAs sell the ratings and issuers shop the ratings (White, L. J., 2010). Multiple ratings for the same bond/security from different CRAs cause split rating.

CRAs do not follow a uniform method to assign grades to a bond (SEBI, 1999) and so the same bond is rated by differently by the various agencies thus resulting in what is called "split rating" (Ederington, 1986). Researchers have argued that split rating is caused by random errors and it has been mostly received by the banks (Morgan, 2002). Research works on the issue of split rating and its impact have come up with evidences that affirm that difference in grades of a bond was due to the fact that there was no uniform methodology used by CRAs. Since the issuer has the right to obtain a rating from more than one rating agencies for the same instrument (SEBI, 1999), the use of different methodologies resulted in split ratings. It might be a positive sign for some corporations, but certainly not for all. Split rated CBs are common due to rating shopping, but their influence on further rating change has received little attention (Livingston et al., 2007; Jewell & Livingston, 1998). So a better understanding of this relationship has become essential

because changes in CR have significant impacts on bond yields, bond prices and stock prices. The wide gap between the reality of CRAs and the negative perception about their credibility is the motivation behind this study to investigate the real impact of CRAs' certification from a fresh perspective.

1.5 Theoretical Background

This thesis draws its theoretical framework from two important theories of finance: one, Market Efficiency Theory also known as Efficient Market Hypothesis (EMH) and two, Principal-Agent Theory or Agency Theory.

1.5.1 Efficient Market Hypothesis

Recent research studies have focused on the behaviour of stock prices. The majority of theories believe that stock markets are efficient and so prices cannot be predicted. On the other hand, practitioners have never believed it. Instead they attempted to maximise profit using advanced forecasting methodologies. For considering a bond yield formation, the efficient market hypothesis is probably the best place to start. The efficient market hypothesis is influenced by the interactions of rational market participants who are interested in determining share prices. The efficiency of information is determined by how stock prices represent all necessary information (Fama, 1970).

Efficient Market Hypothesis (EMH) theory assumes that market price reflects all relevant information of a firm. This theory was developed and theorized by Eugene F. Fama in 1970. EMH attempts to describe why stocks behave the way they do. The hypothesis states that the current prices of the assets summarise all the publicly available information related to the assets. Investors' stock prices forecast cannot be done in the stock market, as all the available

information is assumed to be integrated in stock prices. Fundamental analysis and technical analysis cannot help investors to get large return on stock portfolio. Randomly selected stocks give better return compared to portfolio selected after doing fundamental analysis and technical analysis. The stock prices need not be necessarily “right”, but are as accurate as possible. EMH enjoys a strong support by academician like Malkiel (1973) who stated that “A blindfolded monkey throwing darts at a newspaper's financial pages could select a portfolio that would do just as well as one carefully selected by experts". Fama (1970) stated that “support of the efficient market models is extensive, and contradictory evidence is sparse.” Hence, it can be concluded that EMH has become a modern financial theory. A market responds to new information which is reflected with the adjusted stock price (Bodie et al., 2008). Fama’s Efficient Market Hypothesis states that market can exist in the following three forms:

- *The strong form:* Price reflects public information, historical price, and insider information. Hence, the stock price reflects all the related information about a company.

- *The semi-strong form:* Stock price reveals all the publicly available information along with historical information.

- *The weak form:* Stock price reveals only historical price and trade volume.

According to efficient market hypothesis, stock price should not react with the announcement of CR in the market in strong form. However, the CRAs propose to reveal new information with CR announcements. Thus in a strong market, CRAs should not exist because there is no information asymmetry in the market. Whereas in the weak market, CR would accomplish their purposes, as they use private and public borrowers’ information which get reflected in the rating

grades (Micu et al., 2004). Hence, the impact of CR on stock price is considered only in the semi-strong market (Naseer & Tariq, 2015).

CRAs have access to private information of a company for assigning CR. The strong form market expects stock price to not change in response to CR announcements if CRAs used publicly-traded information to provide credit ratings. It is important to note that no information is privy. This is because CR change announcements are already noticed and adjusted by the market (Brooks et al., 2004). To understand the information effect, one should test the effect of CR announcements on stock price.

1.5.2 Agency Theory

Agency theory was developed by Jensen and Meckling in 1976, as a branch of study of contract theory (Eisenhardt, 1989). This theory describes the relationship between principal and agent, and it is also known as principal-agent theory. While studying CR, CRAs forge a relationship between issuers, investors, analysts, and regulators. In the context of a bond market and BR, the discussion on the relationship between investors, CRAs and issuers brings in agency theory. The theory functions in the following manner. First, a firm issues securities to borrow funds from the market. And second, the ratings on the securities reduce borrowing cost. As a result, a firm needs the help of CRAs to get ratings for its securities. Here, the CRAs act as agents and issuers are principals. However, this relationship is loaded with a lot of conflict of interest.

CRAs are responsible for assessing the issuers' information and to get it examined by specialist analysts. In this process, the analysts visit the issuers to access confidential and private information. The ratings are assigned after examining the analysts' reports though voting by the management team. The rating grades published by the issuers and by CRAs are freely available

to the public. The grades reflect the credibility of the issuers that serve as a useful pointer for investors. The CRAs act as intermediaries between investors and issuers and also reduce the agency cost between the two. However, cases of inflated ratings, biased ratings and low-quality ratings have posed questions on the veracity of the relationship and existence of CRAs. A latest study has suggested that co-opted directors are treated negatively by CRAs for providing inadequate/low CR grades (Lee et al., 2021).

1.6 Research Problem and Motivation

There are only three CRAs which can be considered as global leaders in the rating industry. They are Moody's group, S&P, and Fitch. Besides these global leaders, many other CRAs also exist in different countries. In India there are six domestic CRAs. However, the rating process of all the CRAs is time-consuming and costly as it requires strong analysis by experts (Hajek & Michalak, 2013). It is found that the cost of rating, paid by issuer, reduces a firm's return resulting in lower return to its investors. CRAs have also been criticised for their inaccurate or partial information and also for the opaqueness of the methodologies they use. The role of CRAs has triggered financial crises and scandals such as the financial crisis of 2008, Enron's bankruptcy 2001, etc. The rating slipped from an 'investment-grade' to 'default' in just five days before Enron declared bankruptcy in 2001. This raised doubts and questions regarding the quality of rating (White, J., 2010). Such an instance like that of Enron has led many firms to distrust CRAs.

In recent years, CRAs have once again come under suspicion because of their apparent failure to predict default ratings and to warn investors on time about impending firm-related financial difficulties. These instances were seen in the case of IL&FS, DHFL, R. Com, Eros, Zee, etc. CRAs have been criticized for misleading the investors by issuing untimely rating changes, and

issuing the wrong ratings. Shopping of rating and issuer pay model are cited as the reasons behind this (Chang et. al., 2020; Bolton et al., 2012; White, J., 2010; Sangiorgi et al., 2009). Other reasons could be the expanding business of CRAs and the close familial relationship between issuers' managing directors and management of CRAs (Bungum, 2017). If the CRAs work fairly and independently, the rating would be reliable. Similarly, bond rating agencies would be more active in systematically downgrading and upgrading ratings of the numerous firms' securities if the firms show signs of deterioration in financial and operating conditions. The above cases questioned the justification for existence of CRAs.

The global crisis of 2008, Enron 2001, Kingfisher, DHFL, Eros, Suzlon Energy, Amtek Auto, Zee group, RCom, and the most recent IL&FS show the ineffectiveness of the rating system. These high-profile cases are just a few examples of the unethical behaviour of CRAs. In these cases, CRAs were either bought-out by the issuers or the credibility of the issuers could not be examined on time. Sudden changes in the rating grades from an 'investment-grade' to 'junk' without any extreme incident raise questions about the working of CRAs and reason for their existence. The CRAs are considered as essential gatekeepers in maintaining the investors' trust in bond markets (CRISIL, 2019b). For information, investors rely on CR grades, and it is considered as an essential parameter for investment by investors (Jaleel, 2018). The above two natures of CR contradict each other. One shows that CR plays an important role for investors, while the other illustrates that CR misleads the investors with partial information. Regardless of these views, CRAs' opinions are important in the financial market for many participants.

Rating would be more reliable if CRAs' opinions work according to the performance of instruments. And should there be any downgrade, it should happen step by step until there is no extreme change. Also, announcement should convey information to the market because CRAs

have access to private information of a firm which are not available to the public. And, the reliability should be measured by checking the impact of BR announcements (initial, changes, and reaffirmed) on stock prices (Indian markets). From the above mentioned examples, it can be deduced that CRAs have sacrificed their long-term reputation by issuing inflated ratings for short term benefits (Bolton et al., 2012). In this process, CRAs have lost their importance as well the trust of the investors. And as a result the investors have reduced their reliance on CR. In a meeting with the officials of CRAs, Central bank's governor and deputy governors, Central bank has stated that "ratings were supposed to be forward-looking, but they were always a laggard" (Zachariah, Reena, 2019). The growing perception in India is that CRAs have become too charitable in rewarding ratings thereby raising questions about their authenticity, honesty, and utility (Dhanorkar, 2019).

The CR change announcements made by CRAs have raised another important question about whether all pricing information is incorporated into the share price or not. This question focuses on the efficiency of the market. According to the strong form of efficiency, the volatility of financial market depends on the information reflected in the stock price. In this market form, stock price reflects both public and private information of an issuer. Further, it states that in the strong form of efficient market, investors have the option to select according to their return expectations and risk apatite because all the information is available (Fama et al., 1970). Hence, it has been concluded that investors with accurate private information would not harm the market (Damodaran, 2012). Considering the above scenario, CR change has the power to affect the value of the firm in question.

The numbers of companies that have AAA status in India are extremely high compared to other nations. In the US, the share of "AAA rated companies is less than 5 per cent of bond issuances,

while A and BBB rated issuers consist of more than 60 per cent, and speculative-grade companies about 20 percent" (Bloomberg, 2018). SBI Chairman Rajnish Kumar (2019) has stated that, "It should not be so easy to get a AAA rating. In the US and Europe, companies are not given triple-A so easily as it is in India, we have to adjust to the new realities." The statement came at the time when IL&FS collapsed, and regulators were glaring at CRAs for assigning high grades to risky instruments. A total of 32,534 rated companies in India issued bonds in the domestic market in 2018. Despite this the corporate bond market in the country is very shallow, constituting only 16 per cent of GDP as against 120 per cent of GDP in the US. Reporting on this data, CRISIL has stated that, "As a result, 85-90 percent of bond issuances are by AAA and AA rated companies. Beyond this rating category, the financial flexibility to tap the capital market instruments drops drastically" (CRISIL, 2019). India and other emerging markets do not have wide and deep bond market. Also, large investors (including pension funds and insurers) because on their fiduciary status, invest in highly rated instruments. Hence, the investors' low risk bearing ability has been acting as an incentive to award high credit rating grades. An article published in *Business Line* by *The Hindu* in July 2020 stated that according to Bloomberg data, 53 per cent of the rating assigned by CRAs were based on inadequate information, and therefore ratings were unreliable (Kalyanasundaram, S., 2020).

From the above analysis, it can be concluded that CRAs could not meet the objective for which they were initially set up. Rating agencies have been repeatedly found guilty of failing to provide information about issuers' credibility on time. Ratings issued based on inadequate information, low-quality ratings, and inflated ratings are the reasons behind their failures. Dr. Ajay Shah, a professor at "*National Institute of Public Finance and Policy*" (New Delhi), has stated that "Where we have gone wrong in India is where regulators have written regulations that force

regulated entities, such as banks, mutual funds, to use the rating. A rating company should be just a research company, which has to sink or swim based on the value that it contributes to the institutional investor" (Bremner, Joshi, & Sanjai, 2018). Still India has a mandatory bond rating, mandatory capital financing, and 25 per cent of capital through CB. The enormous gap between the reality and the negative perception of people about CRAs has motivated this research. The current situation of CRAs has raised various questions-Are rating reflecting the actual financial position of the company? Can we still rely on CR? What is the utility of a rating? All these questions are related to CRAs' inability to predict the creditworthiness of the borrowers and the risk factors on time. In the light of the above discussions, this thesis attempts to fuse the queries into a single research question- Is credit rating effective? This thesis examines the credit rating prediction model using the same variables which are used by CRAs and compares them with the actual rating grades issued by CRAs. It also studies the effect of the Bond Rating announcements on stock prices.

1.7 Need for the Study

An effective CBM is essential for Indian economy for many reasons. CBM facilitates well-organized allocation of funds, provides financing to infrastructure, upgrades the well-being of corporate balance sheets, encourages "the financial inclusion for the Small and Medium Enterprises (SMEs) and the retail investors, leads to financial steadiness protection, and empowers the municipal bond market development" (Khan, 2012). For the regulators too, development of CBM is high on the agenda since it is undeveloped. Recently SEBI has issued a circular in July 2019 stating that 25% of the capital needs to be financed through corporate bonds by large companies, and rating of CB is mandatory.

There is a huge body of literature on downgrade and upgrade effect of rating changes on stock prices in the global context. But very less research work has been done in the area of developing a comprehensive model covering all the aspects. In the past, a few researchers have analysed the impact of rating outlook and rating watch but they could not establish a concrete understanding. In addition, the increasing number of defaults of large corporations that enjoy high ratings has not been examined. Given the circumstances, it has become essential to find out the effectiveness of credit rating and provide appropriate suggestions to the regulators. In the Indian context, there has hardly been any study on the impact of CR changes on stock prices by differentiating the changes categorically in terms of CRAs, grade, industry, and year. Only a few researchers have studied rating announcements such as initial rating, reaffirmed rating, and rating watch. But these studies have not examined cases of ratings withdrawn and rating suspensions. Many researchers have examined default rating with different factors, but again the existing trend of increasing number of defaults question the quality of rating provided by CRAs. Rating plays a crucial role in financial markets and influences investment decisions. Hence, with the development of a bond market and people's interest for CR, there is a need for a thorough academic research (CRISIL, 2019b; Raju et. al., 2018).

This research adds to the existing literature on CRAs and rating by analysing the effectiveness of credit rating. This research seeks to examine the accuracy of rating, and how its announcement affects stock price. A previous academic research on rating has suggested that competition in the market leads to inflated rating (Becker & Milbourn, 2008; Becker & Milbourn, 2011). Still, the study has left an unsolved question and that is whether the industry has too much competition or too less competition. Many research papers have discussed about inflated rating and shopping of favourable rating. CRAs have been criticized because they are willing to sacrifice their

reputation for issuing inflated rating. Additionally, there is a lot of pressure on analysts to present desired ratings rather than real ratings. When a desired rating is not presented to an issuer, the case is viewed as an 'impeding deal', and this result in damaging rating business. Such analysts face discrimination, inter-department transfer, punishment, and harassment in the department. And in some cases they are even laid off. This shows the primary conflict of interest between CRAs and issuers. Hence, it is necessary to make the working of CRAs transparent so that agencies would follow a standard operating procedure and give fair and accurate ratings. Also, the research on CBR with respect to their working, reliability, and role in developing CBM is either too little or untouched by academic researchers. This thesis attempts to reduce this gap.

It is observed that the rating process can be improved by increasing transparency, and improving the timelines of rating. There is an extensive body of literature in the academic arena where researchers have tried to set up a rating model based on publicly available information. According to these researches, if there is enough public information to highlight the risks, then CR announcements would be less necessary in financial markets. A study suggests that after the global financial crisis of 2008, CRAs issued lower rating grades, gave false warnings, and downgraded rating announcements that were less informative (Dimitrov, Palia, and Tang, 2015). Contrary to this, the failure of Indian CRAs to proactively assess the deteriorating condition of big corporations such as Satyam, Kingfisher, Ansal Properties, Zee, Arvind Products, Suzlon Energy, RCom, DHFL, IL&FS, and other corporations have put a question mark on the credibility of the rating process of the Indian CRAs.

The body of literature provides evidences that most of the studies have focused on the informational content of rating, the effect of change in rating and rating model, using public information. The theoretical and empirical works also show that most of the studies done in the United States, United Kingdom, and China have covered diverse aspects of CRAs which are yet to be researched in the Indian context **(**Arora, 2003; Archana, 2018). CRAs' opinions on the risks of securities/instruments as grades should be beneficial for the investors. Hence, it has become extremely crucial to add to the existing literature the effectiveness of CR and also bring to the surface the different facts of CRAs and their services in the Indian context.

However, this should not lead us to a hasty conclusion that no work has been done on Indian CRAs and their services in India. Few studies have been conducted on the topic but the focus of these researches was mainly on the performance of CRAs, investors' perception towards CRAs and some from other different perspectives. The anticipated gap in research on the CRAs and their services has encouraged this research. There are also other reasons for conducting the present study. One, the widespread perception that the opinions of rating agencies are biased continues to have influence on the investment community. Two, when these ratings are assigned incorrectly, the entire economy gets affected (for example, the 2008 crisis). Drawing on these reasons, CRAs have been criticized for being responsible for GFC 2008 by giving wrong ratings to mortgage securities (Financial Crisis Inquiry Commission, 2011). Such incidents have motivated the study to look into the working of CRAs and their effect in the financial market which have already been the subject of extensive studies. The debates on the accountability of CRAs during the recent financial crises indicate that it is still a contentious issue.

1.8 Research Questions

Considering the above circumstances, this thesis attempts to address the various questions raised in the statement of problem. The thesis asks the following questions - Is rating reliable? Do we need CRAs? Are CRAs capable of analysing the creditworthiness of an issuer? What is the utility of the rating? Can we still rely on rating? To answer these questions, we draw below the research questions:

1. Are bond ratings reliable?

2. Do bond rating announcements have the ability to influence stock prices?

1.9 Research Objectives

The primary goal of this study is to know the effectiveness of rating. To answer the above research questions, the study has developed three main objectives and few sub-objectives that are listed below:

1. To examine the differences between actual rating and predicted rating.
2. To examine the difference between actual rating and z-score.
    I. To examine the difference between safety zone of Z-score and actual safe rating grade.
    II. To examine the difference between distress zone of Z-score and actual default rating grade.
3. To examine the impact of bond rating announcements on stock prices.
    1. To examine the impact of the initial bond rating announcements on stock prices.
    2. To examine the impact of rating change announcements on stock prices.
    3. To examine the impact of bond rating awarded announcements on stock prices.

1.10 Significance of the Study

Credit rating and insolvency evaluation are crucial parts of the financial market. The primary purpose of CRAs is to assess credit risk and reduce the information barrier for investors. The current study focuses on credit rating industry, corporate bond market, investors, and regulators in India. This study is significant for the following reasons.

One, it contributes to the existing literature. This is done by providing credit rating prediction model using public information for Indian CBM, by providing accuracy of rating, by comparing the actual rating provided by CRAs and predicted rating through the model, and by analysing the impact of reaffirming rating, rating withdrawal, and suspended rating announcements on the stock price.

Two, it suggests the various ways through which CRAs can work on saving their reputation, businesses, and on maintaining investors' trust.

Three, the study will help investors in making investment decisions and also make them aware about how to understand rating and calculate risk.

The last and most important contribution is that, it provides suggestions to the regulators to improve the corporate bond market and to strengthen the rating industry.

1.11 Structure of the Thesis

This thesis has five chapters. The first chapter which is titled the introduction introduces the topic of the study and lays out the theoretical framework. This chapter outlines the problem statement of the research, the motivation to take up this research and the need to carry out the research in the Indian context. It also spells out research questions framed in relation to the

research problem. Further, the objectives and sub-objectives of the research are stated to find answers for the research questions.

The second chapter which is the “review of literature” provides the background and the basis of this thesis. It discusses the context of the problem statement, reviews existing literature on the area of research, and looks at related works that have been done on the reliability of CRAs, CR and the announcement effect of rating on stock price. Further this chapter summarizes the findings and gaps of the previous studies and draws from them to develop the hypothesis and model for the current study.

The third chapter describes the “research methodology” adopted for the study which is supported by background literature. The data and database used for the study and the duration of the study are also explained in this chapter.

The fourth chapter analyses the data and the findings of the research are furnished herein. Further the result is interpreted and discussed in relation with results of previous studies.

The fifth chapter is the “conclusion” which highlights the observations of the study. It states in detail the difficulties faced while carrying out the research and also the limitations and strengths of the study. Further, the main contribution of the thesis and future scope of this research work are summarised.

CHAPTER 2

2. LITERATURE REVIEW

This chapter reviews the existing literature on the effectiveness of CR. Here the effectiveness means the accuracy of rating. Literature reviewed also includes studies on predicted rating model and impact of CR on stock prices. To ascertain the effectiveness of CR, we shall look at both the older studies and more recently published literature. The idea here is to present an overview of the past research works on the topic and also furnish relevant articles and their key findings.

Numerous studies have been done in developed countries on the accuracy of CR and its default prediction, and the effect of rating on stock price, bond price, capital structure, and informational asymmetry in the market. CR started in the 1940s, but the demand for it had grew exponentially after the Great Depression of 1929. This was primarily because of the investors' fear of default risk. CRAs were initially setup to provide issuers' actual default information to investors and safeguard their investments. In the initial years, investors needed to pay for rating to CRAs. However, this practice changed in the 1970s when the issuers started paying to assess their instruments to be rated (Jiang, Stanford & Xie, 2012). This change started a new trend called 'rating shopping' by issuers, and led to the issue of 'inflated rating' by CRAs.

Studies have suggested that before the 1970s rating grades awarded were lower compared to the ones based on the model of payment by the issuers which started in the 1970s (Jiang, Stanford & Xie, 2012; Beaver, Shakespeare & Soliman, 2006). The CRAs faced heavy criticisms after the Global Financial Crisis (GFC) 2008 for issuing inflated and low-quality ratings (White, 2010). Before the GFC 2008, rating was treated as an essential risk measurement tool but the GFC

exposed that there was problem in that line of thinking. From the GFC 2008 till date, the CRAs have not been able to improve the quality of CR. CRAs are continuously found guilty for not downgrading ratings on time and for providing inadequate information.

In India, the cases of IL&FS, DFHL, ZEE, and R.Com illustrate the failure of CRAs because ratings changed suddenly from 'investment grade' to 'default'. This unreliability is common around the world and even the largest debt market economy which is China is not an exception. The CRAs have been questioned for the increase in debt defaults due to faulty or improper investment-grade rating. (Sheng, 2019; Chang et al., 2020).

In recent times, the workings of CRAs and CR quality have become controversial subjects of debates in the financial market. Statements from regulators, CRA officials, academic researchers, and current cases have expressed contradictory opinions. The function of CRAs is to evaluate a firm's financial and business risk; and portray the actual credit risk (SEBI, 1999). An analyst of the largest CRAs, in an email conversation, stated that "Investment could be structured by cows and we would rate it" (US SEC, 2008). This indicates the behaviour and the key problem of CRAs towards the issuers who are the principal source of their revenue. CRAs act as essential gatekeepers for investors and they provide information about credit risk default (CRISIL, 2019b). The increasing cases of debt default in the US, China, India, and other countries have raised doubts about the credibility of CRAs. The growing perception in India is that CRAs have become too charitable in awarding ratings (Dhanorkar, 2019). In light of the above observations, we need to re-evaluate and ask why CRAs exist at all.

2.1 Credit Rating Model Prediction

At present, the CRAs do not follow any standard methodology for rating securities/instruments. Grades of rating depend on the opinions of the CRAs about issuers' creditworthiness (US SEC, 2008; SEBI, 1999). The opinions on creditworthiness of entity provided by the CRAs are reflected in rating grades. Both qualitative and quantitative methods are applied to evaluate the credit quality of a firm. The credibility or credit risk which is measured through financial ratios uses market-based information and financial statements of the firm, like leverage, liquidity, solvency, and profitability (Standard & Poor's, 2013). Based on credit risk, rating grades of entities are assigned. CRs are provided either by CRAs or banks which use internal rating system (Hirk, 2019). The increasing number of defaults in the financial market has led to the evolution of credit risk measurement dramatically and also increased the demand for credit rating. CRAs act as gatekeepers of the capital market for market participants and debt issuers (Williams, Alsakka, & Gwilym, 2013). In general, the rating grades of all the CRAs for same instruments might vary. The reason could be methodology; all CRAs are independent and have their own methods to award rating grades.

To increase the reputation of the issuers, CRAs provide safe investment-grade rating even to default risk debt. In the past, the CRAs have gone beyond their standard rating model to inflate the ratings and to favour the issuers (White, 2010). The issuers also put pressure on CRAs to issue or maintain the desired ratings. Such practices by CRAs have cost them their reputation, and the resultant inaccurate ratings have forced firms into bankruptcy. The literature on CR prediction evolved sharply after the GFC 2008 as compared to the last 125 years of CR evolution. The increasing default cases, wrong ratings, unreliable CRAs working condition and inflated ratings have forced academic researchers to come up with CR prediction model. The

predicted CR could help market participants and others with early warning signs of bankruptcy or financial crisis. The credit rating prediction models are made using different approaches by researchers.

For the past few decades, credit risk is measured through traditional accounting ratios. The failure of corporate instruments and the decline in credit quality are the results of poor calculation of credit risk for several years which could have been prevented by using accounting ratios (Agarwal & Taffler, 2008). Contingent claim-model evolved as a comparable alternative model for accounting information-based model to predictive accuracy (Agarwal & Taffler, 2008; Bauer and Agarwal, 2014). The failure of accounting ratio based on predictive model of credit risk was due to the lack of theoretical grounding (Jones & Hensher, 2007). Furthermore, the accounting-based model is improved by adding market information to predict a publicly traded firm (Campbell et al., 2008). Because of the absence of definition of default and standard theory of business default, the selection of ratios for the model became vague. From the literature it can be concluded that a good predictive model should have financial analysis ratios from diverse categories. The ratios from the same categories are likely to demonstrate the extensive amount of correlation, whereas the ratios from different categories with reduced number give more accuracy (Vana, 2018).

The lack of information disclosures and captive markets stopped academic researchers until now to develop a rating prediction model. Credit rating industry expanded rapidly until the GFC 2008 but after the crisis the frauds committed by CRAs have been exposed. With regard to the fear of default among investors, Mr. Nirmal Gangwal, a distressed asset turnaround specialist and founder of Brescon Corporate Advisors Pvt., has stated that “Rating agencies need better market intelligence and surveillance rather than depending upon historical data and some structure based

on past estimates. They also need to factor in changes on the ground like change of leadership, cash flow management in recent past and market environment" (Bremner, Joshi. & Sanjai, 2018). Researchers have also criticised the model used by CRAs for assigning rating grades (White, 2009). Despite the flaws in the practice of rating, regulators, financial institutions and investors continue to ask for ratings from CRAs. The reason why regulators, institutions and investors continue to rely on this flawed rating system could because there is no other alternative available. The other reason could be due to the long term experience of CRAs in this field. It is widely believe that the academic world is a better place to develop a rating prediction model.

Credit rating prediction has become a conventional topic in CR literature. Credit rating prediction was started in 1959 by Lawrence Fisher who determined the risk premium of CB. The main objective of Fisher's study was to test and present the determinants of risk premium on CB. The difference between bond market yields and corresponding rate of interest which prevail in the risk free market is called risk premium (Fisher, J., 1959). Fisher used a statistical method called least square regression to analyse the industrial bond risk (Fisher, J., 1959). The variables regressed by Fisher were earning variability, equity/debt ratio, the period of insolvency, volume of trading, ratio of standard deviation in earnings to equity, and bond outstanding. Fisher found that the elasticity of independent variables was stable across 25 years. Further, William H. Beaver criticised the other model and added financial ratios as important variables in default prediction of a firm. The failure/default prediction of a firm through accounting ratios based on univariate model was introduced by Beaver (1966), who used six different ratio categories to test the importance of 30 accounting ratios.

In 1966, accounting ratios and linear regression were used to model CR by Horrigan (Horrigan, 1966). Horrigan and Fisher regressed the variables in the model and they achieved the accuracy

rating of 58% for Moody's group and 52 percent for S&P. This was followed by Altman in1968, Edmister used financial ratios and multivariate discriminant analysis (MDA) to predict the bankruptcy of companies in the US (Edmister, 1972). Altman developed a numerical measurement Z-score to measure the risk using five sets of financial ratios. West (1970) commented on Horrigan (1966) model and further extended Fisher's model with additional variable stating that it sounded theoretical.

Robert C. Merton developed the distance-to-default calculation model to measure different financial variables in his seminal work "On the Pricing of Corporate Debt: The Risk Structure of Interest Rates" (Merton, 1974). Merton measured a firm's asset log value from distance to default on a real-line threshold to default. The model assumed that default will occur if creditworthiness variables fall below the threshold limit. The data used for bankruptcy prediction failed to meet the MDA assumptions (the financial ratios have a high correlation with each other and they are not distributed normally). The market-based variables and accounting information were used to conduct similar studies (Baghai et al., 2014; Alp, 2013; Blume et al., 1998). The failure of OLS and MDA models encouraged the use of logistic regression and it soon gained popularity. Kaplan and Urwitz (1979) were critical of all the previous studies till then because no one had taken care of the ordinal nature of bond rating. Kaplan and Urwitz applied the multivariate probit regression model, and the prediction showed 69 percent accuracy.

In 1980 James A. Ohlson (1980) introduced logistic regression to predict CR and bankruptcy in his work "Financial ratios and the probabilistic prediction of bankruptcy", and the probit model was introduced by Mark E. Zmijewski in 1984 under work "Methodological Issues Related to the Estimation of Financial Distress Prediction Models" (Zmijewski, 1984). These models are still used now as evident in the works of Chib & Greenberg (1998); Trevino & Thomas (2000a);

Shumway, (2001); Balcaen & Ooghe, (2006); Bellovary et al., (2007); Campbell et al., (2008). These models were also used by Ederington (1985) who had benchmarked different techniques of regression. The logistic model and ordered probit model are more efficient in providing interpretation about regression coefficients for ordinal ranking of rating grades. The conversion of rating into alphanumeric characters by assigning numbers to rating grades could be the reason for using an Ordered Least Square (OLS). There is a limitation of using OLS approach and that is the distance between two ratings is considered as equal rating. In real rating grades, the distances are unknown and therefore they cannot be expressed in numerical value. Contrary to this, other researchers have successfully used the ordered probit and logistic model to predict CR (Cantor & Packer, 1996; Trevino & Thomas, 2000b; Ahn et. al,, 2019; Hirk et al., 2020).

The ordinal nature of rating is suitable with ordered probit regression. Since the distance between two rating grades is unknown, ordered probit regression has been considered. Another method used by researchers to make inference about regression coefficients is the ordinary least square method. This method is used with consideration of ordinal nature of rating but it has drawbacks. The authors (for example, Fisher) converted the grades into numerical characters, but they assumed that there is equal distance between the two rating grades. Similar drawbacks are also found in multinomial regression. But the rating grades used by CRAs have ordinal nature. The distance between the AAA grade and AA grade is unknown. Also, the distance between two rating grades is not equal such as the distance between AAA and AA is not equal to distance between AA and A. The present study has adopted ordered probit model to predict the rating.

Earlier studies have focused on the quantitative structured information called ‘hard facts’ to determine the CR for corporates (Altman 1968; West 1970; Surkan & Singleton, 1990; Caridada et al., 2019). Lately, few researchers have added qualitative information called ‘soft facts’, with

quantitative information and tried to predict CR (Bozanic & Kraft, 2014; Bonsall & Miller, 2017; Choi, Suh & Jung, 2019). 'Hard facts' are used for quantitative variables, whereas 'soft facts' are used for qualitative variables. The increase in the number of default cases and the criticism on rating has made the rating prediction essential in the present times. Previous studies which have used credit rating prediction model have focused only one CRA. For example, financial ratios are considered as explanatory variables by Blume et al. (1998) and Alp (2013). They used ordinal regression model to obtain insights on the behaviour of rating by S&P. The variables used in the present study are taken from the previous literature shown in below Table 2.1 and in the methodology of CRAs (Indian CRAs).

Table 2. 1 Variables Included in the Final Model

VARIABLES	
1. Total income	13. Current Assets
2. Total Assets	14. Current Liabilities
3. Total Liability	15. Inventories
4. Net worth	16. Operating Cash Flow
5. Profit after tax	17. Cash and cash equivalents
6. PBDITA	18. Retained profits/Accumulated losses
7. PBIT	19. Net PPE
8. PBT	20. Rent Expenses
9. Interest expense	21. Tangible net worth
10. Net sales	22. Capital work-in-progress
11. Long Term Debt	23. Borrowings
12. Short Term Debt	

There are many accounting standards for companies which differ from country to country and so the governments form their own policies to oversee them. And so for this reason all the variables are not significant for all the countries. In the present study, few variables are insignificant; and they are quick ratio, time interest, earned cash to debt ratio, working capital intensity, etc. The final model consists of 23 variables explained in Table 2.1. Previous models have considered combinations of many variables, but they did not include bond size. The latest study suggests that bond size positively impacts bond rating (Bradford et al., 2019). For this reason, the current study has included bond size in the final model for predicting rating.

2.2 Credit Rating Criticism and Shopping of Ratings

"The Investment could be structured by cows and we would rate it".

-Quoted by Securities and Exchange Commission, 2008

The CRs by CRAs are regularly available to the public for free. CRAs are essential for the capital market to perform efficiently because they remove the information gap between issuers and investors regarding creditworthiness. CRs help issuers in borrowing money from the capital market and reduce the cost of borrowing. Additionally, the well-known scale of CR allows market participants and investors to assess the credit risk of a firm, and to be informed about a business and also shape their investment decisions (Standard & Poor's, 2018). The capital cost consists of equity, debt cost, financing cost and other different sources. Hence, the importance of CR is linked to the cost of debt (Damodaran, 2012). CRAs provide ratings to the instruments at the request of issuers in exchange of fees, and the instruments remain under observation till the maturity period and rating grades can be changed. However, paid ratings create conflicts as they are assigned by CRAs on the request of issuers for certain allied services (Stolper, 2009; Chang

et al., 2020). A latest study contradicts this perspective and states that 'issuer paid model' provides a timely rating, and it is more concerned than 'investors pay model', thus vouching for the reputation of CRAs as primary information providers (Toscano, 2020).

CRAs are criticised for not cautioning almost possible default on time. The rating of Lehman Brothers was in investment-grade before it was declared bankrupt. In India, the high default period was during 1997-1999 when the economic yield was low, and interest rates were very high. Research works in the 1990s on India CRAs have suggested that the ratings provided by CRISIL were too liberal (Raghunathan & Varma, 1992). Retail investors lacked confidence as defaults were high, and there were no alerts from CRAs before the defaults (Gupta, Gupta & Jain, 2001). Another study on India suggested that the ratings given by ICRA were not reliable and accurate; and investors should not depend on CRAs (Gill, 2005). The same was proven in 2018 and 2019 with the defaults of IL&FS, DHFL and R.Com. In view of recent crises, Mr. Rajiv Kumar, India's banking secretary, has stated that "There is definitely a case for revisiting ratings standards and the whole rating framework. Some kind of accountability needs to be there. It has to be made more robust" (Bloomberg, 2018). Thus, the ratings provided by CRAs were questioned then and it continues to be so.

W. Braddock Hickman (1958) was the first to examine the quality of rating for which CR was meant in his seminal work "Corporate Bond Quality and Investor Experience". He found a positive relationship between the defaults of the entity with the low rating grades assigned by CRAs. Another study has observed that the ratings given by S&P could not predict "financial distress" for the subsequent years due to poor or weak rating quality (Ang & Patel, 1975). Ang and Patel also warned the institution and investors not to consider the ratings for long term investment. A study by behavioural researcher has suggested that affective reaction or positive

feeling towards a firm by CRAs could influence rating (Tsui & Barry, 1986). Another researcher has also concluded that the CRAs have the opportunity to carry out diligent surveillance and they should not lose their reputation (Choi, S., 1997). An example of relationship with poor rating was observed in GFC-2008 with regard to the novel financial instrument MBS (Bolton et. al, 2009). The issuers obtained ratings from different CRAs and they displayed only favourable ratings (White, J., 2010). In relation to this practice of shopping for ratings, there is a competition among CRAs to obtain business and they issue inflated or favourable ratings for certain incentives (Bolton et. al, 2012).

The above studies conclude that CR does not provide either quality rating or any new or valuable information to the market. On the contrary, Hsueh and Kidwell (1988) stated that CR plays important in providing information to the market.

2.2.1 Issuer Pay Model

"I mean come on we pay you to rate our deals, and the better the rating the more money we make?!?! What's up with that? How are you possibly supposed to be impartial????"

(Email chat between analyst and investment banker in July 2007. Quoted by Mclean, 2017)

The CRAs changed their operation model from 'investors-pay-model' to 'issuer-pay-model' in the 1970s. Prior to that, investors had to pay for rating. The freedom that the CRAs had to charge a fee for rating created conflict among issuers (SEBI, 1999; SEC, 2003). Investors claimed that payment of fees by issuers allowed CRAs to issue inflated ratings was a way to promote their business among the buyers. These practices were evidenced in the wake of high-profile bankruptcy cases such as "Enron in 2001" and "WorldCom in the 2000s". The provision of selecting CRAs by regulators for rating the instruments of issuers encouraged them to choose

favourable ratings (SEBI, 1999; SEC, 2003). An issuer's preference to shop ratings introduced inflated ratings by CRAs (White, 2010; Strobl & Xia, 2012). The reputation concerns failed to discipline the CRAs from issuing inflated ratings which in turn harmed the market participants as they rely on CR grades (Ang & Patel, 1975; Jiang et al., 2012; Cornaggia & Cornaggia, 2013; Efing & Hau, 2015; Baghai & Becker, 2020).

The switching of payment mode has made CRAs more conservative towards assigning rating because of financial constraint (Beaver, Shakespeare, & Soliman, 2006). This means that the 'issuer pay model' has forced CRAs to become more conservative. However, another study has contradicted this theory and suggested that CRAs like to issue inflated ratings to firms. This is done at the cost of their reputation by awarding an inflated value to an asset rather than the actual one (Becker & Milbourn, 2008; Bolton et al., 2012). Going by this practice, shopping of rating has become a fashion, and CRAs have sacrificed long-term reward, i.e., reputation for short-term incentives (incentive in the form of availing other allied services offered by the CRAs). This trend has been rightly pointed to by a researcher, "It is not surprising that the members of a tight, protected oligopoly might become complacent and less worried about the problems of protecting their long-term reputations" (White, 2010). A study has also suggested that ratings after "investor-pay-model" were inflated and rated with high grades (Mählmann, 2011; He, Qian, & Strahan, 2011).

Rating inflation and availing other allied services offered by the CRAs are found to be very high if CR is issued during a boom period in the market (Bar-Isaac & Shapiro, 2013). Likewise, regulatory arbitrage has a positive relationship with inflated rating and higher incentive (Acharya & Richardson, 2009; Acharya, Schnabl, & Suarez, 2013; Opp et. al, 2013). High inflated ratings are given to the instruments so than even the rational investors are persuaded to invest even if the

value of the instruments are not accurate (Skreta & Veldkamp, 2009; Bolton et al., 2012; Sangiorgi & Spatt, 2017). There is opaqueness in the relationship between CRAs and issuers which is not visible to the investors, and this opaqueness enables the issuers to cherry-pick ratings and the CRAs to generate more surpluses (Sangiorgi & Spatt, 2013). Another study has found that Moody's group was slow to give default risk signal in 'issuer pay model' (Cornaggia & Cornaggia, 2013**).** Similarly, the quality of rating by S&P was better in 'investors-pay-model and it provided timely and accurate information (Xia, 2014, Huang & Shen, 2019).

A study conducted by Bonsall IV (2014) showed that rating quality has improved and the future economic outcomes have become more predictive in issuer pay model. Contrary to this, other researchers have observed that in the issuer pay model CRAs issued inflated rating grades for the higher incentives (allied services offered by CRAs) and fees (Xia, 2011; Bongaerts, Cremers, & Goetzmann, 2012; Jiang et al. 2012; Frenkel, 2015; Kashyap & Kovrijnykh, 2016). This model allowed issuers to shop for better ratings; even when they were close to default (Drago & Gallo, 2018). And the "investor paid model" reflected the real and accurate investment information (Bhattacharya, Wei & Xia, 2019). Thus, shopping of ratings has a negative relation with rating quality. Inflated or favourable ratings led to low-quality ratings (Badoer et al., 2019; Chang et al., 2020; Kempf, E., 2020).

2.2.2 Rating from two or more CRAs

The issuers have the freedom to get ratings from two or more CRAs for the same instrument. This freedom introduced rating shopping by issuers, and this resulted in assigning inflated ratings by CRAs (SEC, 2003). If rating grade provided by one CRA was not favourable, an issuer has the freedom to get another grade from a different CRA. The shopping of CR happens because the

issuers have the liberty to choose CRAs to issue ratings and publish the ratings. But in the US such liberty is not given to the issuers, and they have to depend only on one CRA (Sangiorgi et al., 2009). The demand from issuers for favourable rating has encouraged shopping of rating. Issuers are no longer satisfied with one rating so they pay the rating agencies for the rating they want. (Becker & Milbourn, 2011; Bongaerts et al., 2012). However, previous studies did not make clear whether single rating or multiple ratings is better.

Previous literature has showed that CRAs have traded their reputation in exchange of huge incentives from the issuers (Mathis, McAndrews, & Rochet, 2009). The common research finding suggested that favourable ratings dominated their market and the revenue of CRAs was constantly growing. CRAs also issue inflated rating to increase the market share (Bolton et. al., 2012). The issuers need high rating grades to offer low interest and attract more investors with low cost of borrowing and vice versa. Hence, the issuers try to get favourable ratings by approaching different CRAs in exchange of payment combined with enormous incentives (in the form of availing other allied services offered by the CRAs).

The rating grades provided by CRAs might be different since they follow their different methodologies. The issuers choose favourable ratings if grades are different (Cantor & Packer, 1997; Bongaerts et al., 2012). It is found that the market reacts positively towards superior rating and negatively towards low rating. This forces the issuers to get the favourable ratings from CRAs (Ismail et al., 2015; Vu et al., 2015). The immediate downgrade of ratings by CRAs after closing the issue highlights the biased rating for incentives (Tennant & Tracey, 2016; Kronland, 2020). However, shopping of ratings from different CRAs and publishing only favourable ratings is not assured (Bae et al., 2017). The issuers displayed the favourable rating prominently

whereas, the other are shown in smaller font. The dual rating creates confusion among investors, whereas other studies suggest increase in the rating shopping (Ryoo, Lee & Jeon, 2020).

2.2.3 Competition among CRAs

The competition among CRAs harms the quality of ratings. CRAs provide favourable ratings for certain fees to default issuers just to expand their businesses and revenues. The quality of ratings has come under fire by investors after GFC 2008, and it continues to be so as CRAs are still criticised for inflated ratings. A study on the financial crisis of 2008 showed that CRAs have graded 60 percent of the instruments in the US as AAA grade and only one percent was rated in the non-investment category (Coval, Jurek & Stafford, 2009).

Multiple researches have suggested that increase in competition among CRAs have led to the low quality rating (Becker & Milbourn, 2011; Bolton, Freixas, & Shapiro, 2012). Other studies have indicated that the increased competition among CRAs also increases their incentives (incentive in the form of availing other allied services offered by the CRAs) and they issue more inflated ratings (Sangiorgi, Sokobin, & Spatt, 2009; Bolton, Freixas, & Shapiro, 2012). For instance, S&P and Moody's adjusted their ratings because they faced competition from Fitch (Bae et al., 2015). Other studies have also made similar conclusions and observations that ratings have become more inflated and less informative to the market (Becker & Milbourn, 2011; Bae et. al., 2019). Another study has reported that competition among CRAs only meant increased reliance on them, and ratings they provided were not reliable (Abad et al., 2019).

2.2.4 Auxiliary Business and Interpersonal Relations

The function of CRAs is not limited to providing rating, and over the years they have extended their businesses in diverse areas such as financial consultancy, market research, assessment,

consulting, and risk management services (SEC, 2003; SEBI, 1999). The additional services offered by CRAs have created additional conflict of interest. It is stated that the purchase decision of additional services provided by CRAs affects the CR grades. The establishment of profitable businesses by the vital consumers of CRAs have substantial impact on giving favourable ratings for colossal incentive. CRAs are known to issue favourable ratings to their loyal clients who reward them with high fees (Bolton et al., 2012). The interpersonal relationship between CRAs and issuers also impact rating decisions (Kisgen, 2007). Shopping of ratings usually occurs when issuers are involved personally with CRAs (Griffin, Nickerson, & Tang, 2013). A latest study suggests that CRAs with alternative businesses issue inflated ratings and market have relied on ratings (Hu, Huang, Pan & Shi, 2019).

2.3 Bond Rating and Effect on Stock Prices

> *"The United States can destroy you by dropping bombs, and Moody's can destroy you by downgrading your bonds. And believe me, it's not clear sometimes who's more powerful"*
>
> *(Quoted in* White, 2013*)*

The information content in CR announcements is always questioned and is a topic of extensive research. Researchers have suggested that there is ambiguity in the information provided to the market through CR announcements. The CRAs act as mediators between issuers and investors by reducing the information asymmetry of the capital market. The CRAs also are supposed to offer accurate risk information to investors. These roles make them fundamental players in the market (White, 2013; CRISIL, 2019b; Hu et al., 2019). In brief, CRAs are considered to improve the quality of information in the market (Rhee, 2015).

The seminal paper "Corporate Bond Quality and Investor Experience" by Hickman, W. Braddockon proved that CR is an important indicator of bond quality and help in ranking the bond outstanding and offering according to their subsequent risk of default. The empirical result of the study suggests that “promised yields at offering were higher for low than for high grades, the differences between the promised yield and the yield realized from offering to default (i.e. the loss rate over that period) was largest for the low-grade issues. On the other hand, the recovery of the low grades from default to extinguishment was greater than that of high grades, so that the returns obtained by those purchasing low grades at default were greater” (Hickman, 1958). Another study on the impact of rating on stock price suggests that there was a negative return for lower rating (Melicher & Rush, 1973). Extensive studies have been conducted on bond market and stock return in the US. The studies done in the early 1970s on bond market showed that stock prices did not react to rating changes (Katz, 1974; Hettenhouse & Sartoris, 1976; Weinstein, 1977; Wakeman, 1998). Contradicting the above studies on stock prices, Pinches and Singleton argued that CR announcements have impact on stock price (Pinches & Singleton, 1978). Research on industrial bond has also shown that change in ratings effect stock prices compared to earlier studies on utility bonds (Grier & Kartz, 1976). A study conducted by George Hettenhouse and William Sartoris (1976) showed that downgrade of BR caused price adjustment. But the same was not correct for an upgrade analysed for investment-grade public utility. They suggested that a change in CR either had little or no information about a firm's credibility.

There is a negative effect on stock if there is a downgrade in rating. On the other hand, upgrade rating has no effect on stock price. The first study on upgrade and downgrade of rating was done by Griffin and Sanvicente (1982). The CR downgrade announcements by S&P and Moody’s

group were informative and resulted in negative abnormal return (AR) of stocks within two days of the announcements. This result was ascertained by examining the daily stock return data (Holthausen & Leftwich, 1986; Hand et al., 1992; Barron et al., 1997). A case in which an unexpected deterioration of a firm's financial situation showed significant reaction the market, but it was not the same for a change in financial leverage (Goh & Ederington, 1993; Huang et al., 2018). Hence, downgrade in such a case does not lead to negative stock return; rather it depends on the cause of downgrade. The difference in results or claims might be due to the nature and size of samples, observation frequency of stock returns, difference in the bond market and news contamination. The majority of changes in BR follow the direction of credit watch and rarely in the opposite direction.

CR downgrade is treated as the most unpleasant news for bondholders and stockholders. Many of the researchers claim that downgrade of CR has a negative impact on market return (Cornell et al., 1989; Creighton et al., 2007; Dichev & Piotroski, 2001; Hand et al., 1992; May. D. A., 2010; Poornima et al., 2015; Kenjegaliev et al., 2016; Reddy et al., 2019). Dichev and Piotroski (2001) conducted a study on long term stock return in relation with BR change from 1970 to 1997. The samples of BR change collected were rated by Moody's group. They examined the buy-hold return and AR after controlling a firm's size and its book-to-market value. The result showed that there was no abnormal return for an upgrade, but there was negative AR following a downgrade. The downgrade impact lasted for a minimum one month and a maximum of one year. Norden and Weber (2004) examined stock reactions for both initial rating change announcements and rating watch announcements provided by global leaders amongst CRAs namely Moody's group, S&P and Fitch. They found that rating downgrade was predicted 60-90 days before rating change announcement in the market (Steiner & Heinke, 2001). Similarly, a previous study also claimed

that stock showed a negative abnormal return at the time of rating downgrade, but showed no significant return for an upgrade of rating. Kim and Nabar (2003) concluded that abnormal return for stock near CR change was more negative for a firm that has lower institutional ownership. They also suggested that debt-to-equity ratio has a negative association with stock return. Another study also examined the relationship between CDS, bond yield, and CR announcement; and it concluded that there was significant return for a downgrade but not for an upgrade of CR (Hull et al., 2004). A similar study was conducted in Australian market and the same result was found for a downgrade of CR (Choy et al., 2006).

Multiple studies have been carried in the past few decades with proper theoretical bases and empirical evidences to support the proposed hypotheses for the different forms of market. The results are varying and they are often contradicting the theory (Jensen, 1978). The share price could be diverted from the principal value temporarily but it does not over-react in the financial market. This was contrary to efficient market hypothesis, resulting in asset prices discrepancy (De, Bondt & Thaler, 1987). The question of whether CR change conveys new information about a firm's debt obligation depends on the nature of information revealed with rating change (Richards & Deddouche, 1999). However, CR services are needed in order to reduce information asymmetry, if they do not serve this purpose they need not exist. Studies on Malaysian market which is a strong form, semi-strong form and weak form of market produced contradicting results. Studies in semi-strong form market and weak form market ratings were found to be informative (Barnes, 1986; Laurence, 1986; Abdullah, Abdul Rashid, & Ibrahim, 2002; Soon & Abdul, Rahim, 2017). However, another study stated that "Malaysian Stock Market is still inefficient in the weak form. The weak form of inefficiency implies that investors who are

proficient in using technical analysis have a great chance of obtaining abnormal profit from the stock market in particular form" (Soon et al., 2017).

Studies have claimed that CBR changes by CRAs are negatively correlated with abnormal return of stock; however only few support that upgrade of CR has positive impact on abnormal return of stock. Although CR has an impact on both stock return as well as bond return, during a CR change the capital market tends to appear asymmetric (Choy et al., 2006; Kim & Wu, 2008; May, 2010; Freitas & Minardi, 2013; Fatnassi et al., 2014; Poornima et al., 2015; Kenjegaliev et al., 2016). The impact of upgrade and downgrade announcement of rating has been explained through flexible discrepancy theory, i.e., when manager has to announce confidential information on disclosure but prefers to reveal the good announcement straight forward whereas bad news is revealed slowly (Bae et al., 2006; Chen et al., 2001; Akhtaruddin, 2005; Kothari et al., 2009; Alsakka & Gwilym, 2012; Paiement & Chura, 2016). Thus, the upgrades are good news and they reduced asymmetry of information; whereas downgrade announcements of CR convey bad news and they increase information asymmetry (He et al., 2011).

Extensive researches have shown that CR change has different effects on stock return (Avramov et al., 2009; Bissoondoyal-Bheenick & Brooks, 2015; Nedumparambil & Bhandari, 2020). A significant abnormality was noted while analysing German stock data for CR change. The stock price was adjusted before the announcement of CR change. However, it is claimed that the market reacts more strongly to a downgrade compared to an upgrade (Kenjegaliev et al., 2016). A rating grade reflects a firm's credit risk and a high grade reflects low-risk investment and vice versa. Empirical researches have suggested that on the one hand there is a strong positive relation between the stock return of a firm and high rating grades, on the other, a firm shows a negative return if it holds lower grades (Bissoondoyal-Bheenick & Brooks, 2015; Narayan et al., 2017).

But the authors have not mentioned anything about the risk premium for the additional risk born by the investor in lower grade securities.

Mokoaleli-Mokoteli and Mongalo (2017) examined the effects of CR change on the firms listed on the Johannesburg Stock Exchange between 2000 and 2015 for abnormal return on stock. The result claimed that CR upgrades by CRAs have no significant impact on equity prices. But the market reacted negatively to a firm's CR downgrade announcements. Hence, the study on negative abnormal return due to CR downgrade concluded that CR downgrade conveys essential pricing information. The latest study suggests that market returns are statistically significant around the CR downgrade announcement. A downgrade event is treated as a negative attitude toward the issuers by CRAs and it influences the market around the time of announcement (Hull et al., 2004; Kaminsky & Schmukler, 2002; Afonso et al., 2012; Böninghausen & Zabel, 2015; Xie et al., 2019; Reddy et al., 2019; Kenourgios et al., 2020).

In strong form markets, all the information is reflected in stock prices, so rating change announcements do not convey new information to the market (Weinstein, 1977; Pinches &Singleton, 1978; Poornima et al., 2015; Mokoaleli, Mokoaleli & Mongalo, 2017). Other academicians have stated that CR changes have impact on stock prices. Upgrades of rating convey new information to the market about firms (Wansley et al., 1992). The downgrades of rating also have negative effect on stock prices (Holthausen & Leftwich, 1986; Hand et al., 1992; Dichev & Piotroski, 2001; Freitas & Minardi, 2013; Kenjegaliev et al., 2016; Haung et al., 2018; Xie et al., 2019; Reddy et al., 2019; Kenourgios et al., 2020). In the present study, the existence of different market forms in India is not tested; rather it assumes that the market is in semi-strong form based on the findings of previous studies. This study attempts to know the effects of different CR announcements on stock prices. In strong efficient market there will be no reaction

to the announcements, but in semi- strong form and weak form market there will be reactions to CR announcements.

2.4 Hypothesis Development

Credit rating has been treated as a source of information about the credit risk of a security. Rated entities are desired more than unrated entities. Further, the prime source of revenue for CRAs is from the issuers in lieu of providing rating services which often create conflict of interest. This is because they act as information intermediaries between the issuers and investors and this relation is best explained through the agent-principal theory (Stolper, 2009; Bolton et al., 2012; Chang et al., 2020). The CRAs have become charitable and have issued inflated rating desired by issuers (White, 2010; Rhee, 2015). The rating of Lehman and Brothers was in investment-grade five days before it went bankrupt. The CRAs were heavily criticized during GFC 2008 because many of the reputed firms' bonds defaulted. To expand their businesses and generate more revenues, CRAs have sacrificed long-term reputation by issuing inflated ratings (Becker & Milbourn, 2008; Bolton et al., 2012). Recent studies have also suggested that CRAs have allowed issuers to shop favourable ratings and they have issued inflated ratings for incentives. These studies were conducted mostly in the developed economies. And the studies done in the Indian market also did not present a rosy picture. The surveys of Indian market showed that CRAs were too liberal and they did not issue warnings for defaults (Raghunathan & Varma, 1992; Gupta, Gupta & Jain, 2001; Xie et al., 2020). Researchers have talked about the informational aspect of CR and its contribution of both private and public information in the different market forms.

Lynch (2009) has discussed the same issue concerning conflict of interest created by CRAs using the agent-principal theory. Researchers have identified three problems concerning agent-

principal theory (Huang et al., 2021; Doan, 2020; Yamamoto, 2019). One, credit rating agencies generate revenues by issuing inflated ratings to the issuers and they use the revenue to expand their businesses. So CRAs have an incentive to expand the market share by generating more revenues. Two, the auxiliary services offered by CRAs and the decision by issuers to buy these services or not has affected rating grades (Kisgen, 2007; Hu et al., 2019c). The offer of auxiliary services could help CRAs in getting the same customers for other services. And three, CRAs have accessed private information which is not shared publicly. Since, information is private the investors would not know it anyway. The above agency theory highlights that CRAs are meant to provide information symmetry and to protect the investors' interest as defined by regulators, i.e., NRSRO, SEC and SEBI. The criticisms for low-quality ratings have questioned the role of CRAs and their existence. Based on the literature, the rating prediction model of this study includes bond size which has been ignored by other authors so far. The variables used in the study are explained in the appendix and the variables of the final model are mentioned in Table 2.1. So in the light of the above problems, and the gaps in existing literature, the hypotheses formulated are:

H_1: There is a significant difference in actual rating and predicted rating.

H_2: There is a significant difference between the risk of Z-score and the actual rating.

H_{2a}: There is a significant difference between the safety zone of Z-score and actual safe rating grade.

H_{2b}: There is a significant difference between distress zone of Z-score and actual default rating grade.

The rating prediction model includes standard variables used by other authors and CRAs. The predicted rating and z-score are compared with the actual rating. The other hypothesis aims at answering the objective based on efficient market form. The information disclosure by CRAs with the initial CR and changed CR is a controversial topic. Previous studies have ambiguities in the results presented. The results from previous studies suggest that rating grades did not convey any new information to the market (Katz, 1974; Weinstein, 1977; Poornima et al., 2015; Rhee, 2015; Mokoaleli, Mokoaleli & Mongalo, 2017). On the contrary, certain other researchers have suggested that rating grades conveyed information to the market (Cornell et al., 1989; Dichev & Piotroski, 2001; Hand et al., 1992; Hu et al., 2020; May. D. A., 2010; Poornima et al., 2015; Reddy et al., 2019; Nedumparambil & Bhandari, 2020).

Previous researchers have extensively studied strong efficiency form of markets. Such studies have been criticised because strong markets have already supplied all the information to the market participants. The market in India is an emerging bond market and the nature of the market is a semi-strong form (Xi et al., 2020). From the review of previous works, it is observed that most of the studies were conducted in the US, UK, Europe, and China. Only a few studies were conducted in Sweden, Japan, Sri-Lanka, India, and other countries. India has a semi-strong form market, so rating should convey new information to market and the stock return should also react. Therefore, it will be interesting to examine the impact of rating announcements (Initial, Upgrade, Downgrade, Reaffirmed, Withdrawn, and Suspended, Speculative and Investment-Grade) on the stock returns of firms. In light of the above discussion, the following hypotheses are framed:

H_3 – There is a significant association between stock price and rating announcement.

H_{3a} – There is a significant positive impact of Initial investment-grade rating on stock price.

H_{3b} – There is a significant negative impact of Initial speculative-grade rating on stock price.

H_{3c} – There is a significant positive relationship between rating upgrade and stock price.

H_{3d} – There is a significant negative relationship between rating downgrade and stock price.

H_{3e} – There is a significant positive association of stock price with reaffirmed rating.

H_{3f} – There is a significant negative association of stock price with rating watch.

H_{3g} – There is a significant negative association of stock price with withdrawal rating.

H_{3h} – There is a significant negative association of stock price with suspended rating.

H_{3i} – There is a significant positive association of stock price with investment-grade rating.

H_{3j} – There is a significant negative association of stock price with speculative-grade rating.

In view of the objectives and hypotheses stated above, the present study is divided into two parts. The first part focuses on predicting credit rating based on available information in the market and calculation of z-score. The predicted rating and z-score are then compared with the actual rating provided by CRAs. The second part of the study examines the impact of the different types of CR announcement on stock prices. The types of announcements considered for examination are placed under sub-hypotheses of third hypothesis.

CHAPTER 3

3. RESEARCH METHODOLOGY

"*Research is to see what everybody else has seen and to think what nobody else has thought"*

Albert Szent-Gyorgyi, 1851

This chapter lays out the statistical tools, variables, methodologies, and sample characteristics that are used to answer the research questions framed for the study. This study titled "Effectiveness of Credit Rating: A Study of Bond Rating and its Impact on Stock Performance" will address the problems faced by investors because of their blind faith on CRAs. The present study is divided into two parts to achieve the objectives of the research. The first part focuses on rating prediction, calculation of Z-score, and compares them with actual rating. The second part examines the impact of different ratings and rating change announcements on stock prices. The methodology and data description of the research are explained separately and distinctly for both the parts.

3.1 Credit Rating Prediction

Credit rating modelling was started by Lawrence Fisher in 1959. Fisher used a statistical method to analyse industrial bond rating by using publicly available information. Even now there is no standard formula and methodology available or prescribed for CRAs to provide rating grades. Hence, CRAs assign ratings based on the different quantitative and qualitative variables. CRAs have been using both private as well as public information for analysing the creditworthiness of the borrowers. The increasing demand for CR and growing market have attracted the attention of the public. Without calculating risk in quantitative form on their own, this service provides

opinion to the investors about an issuer's creditworthiness and has become popular in the market. Now academicians are looking at the question why grade rating is so popular in the market even through it is based only on the opinions of CRAs and not based on standardized methodological calculation of risk.

Previous studies on rating prediction model were based on multivariate analysis, logistic regression, decision analysis, and Machine learning. A study that performed multivariate analysis used four approaches: "(a) linear probability, (b) logit model, (c) probit model and (d) discriminant analysis" (Altman, E. and Saunders, A., 1998). Multivariate Discriminant Analysis (MDA) and logistic model have dominated artificial intelligence since 1960s (Aziz and Dar, 2006). Recently, statistical and AI technique were used for comparing quantitative methods in rating forecast (Gangolf et al., 2016).

CRAs use ordinal rating grade to show the risk of an instrument. It means that the difference between two successive rating grades cannot be the same. For example, the difference between AAA & AA, and AA & A would not be equal. The ordinal nature of rating was a drawback for most of the previous models for rating prediction (Hwang, R.C., 2013). Drawing from previous literature and the ordinal nature of rating, ordered probit model is used in this research for rating prediction (Cantor & Packer, 1996; Trevino & Thomas, 2000b; Vana, 2018; Bonsall IV et al., 2018). Previous studies on the same subject are listed in Table 3.1.

Table 3. 1 Previous Studies on Credit Rating Prediction

Authors	Method	Country	Rating Grouping	Sample
Horrigan (1966)	OLS	US	6	352
West (1970)	OLS	US	6	313
Pinches and Mingo (1973)	MDA	US	5	180
Kaplan and Urwitz (1979)	Probit	US	6	327
Blume et al. (1988)	OPM/OLM	US	4	7324
Amato &Furfine (2004)	OPM/OLM	US	8	10,144
Bennell et al., (2006)	OPM/OLM	Canada	16	1383
Alsakka and Gwilym (2010)	OPM/OLM	90	20	4624
Hung et al. (2013)	OPM/OLM	US	5	245
Baghai et al. (2014)	OPM/OLM	US	21	29,636
Ahn et al.(2019)	OPM/OLM	US	21	26,758

Most of the methods used previously were multiple discriminant methods and linear discriminant analyses. Of late, researchers have started using logit/probit model. The logit model considers only the binary form of dependent variables, but ratings have ordinal grades. Due to the ordinal nature of rating, researchers prefer using ordered probit model as it is suitable for the study

(Vana, 2018). The same method is followed in this study. Multinomial regression can be used for such study, but multinomial assumes that there is no order in outcome variables (Borooah, 2002). So the major drawback of this multinomial regression methodology is that the information content of outcomes is lost. Due to this limitation of multinomial regression, ordered probit regression is preferred for the present study. Before explaining the model, a look at the data, nature of data, and data preparation method would be insightful.

3.1.1 Data Collection and Preparation

This section presents the data collected for the study and also the methods deployed for collecting the data. It will engage with the specific data required to address the research questions and also explain the steps followed to obtain the raw data. It also describes the research strategy and methods deployed to determine the nature of data and explain in detail the process of processing the raw data in order to suit the model chosen for this study. Further the data will be used to test the hypotheses developed to achieve the objectives of the study. Thereafter the characteristics of data used for rating prediction model are described.

3.1.1.1 Nature of Data

The present study is based on secondary data. To predict CR and to calculate Z-score, credit rating data, and the financial variables of a certain period is required. The financial variables of the issuers allow us to examine the factors that probably affect credit rating and creditworthiness. The raw data are processed before they are used for modelling. The descriptions of the data extracted are given below. The selected variables of the study are based on the information provided by CRAs on methodology and from the previous literature on the same topic.

CR grades and financial variables are extracted from ProwessIQ CMIE database. CRs issued by ICRA, CRISIL, CARE, BRICKS and India-Ra Rating are considered for the analysis. The financial variables of issuers considered for the analysis are taken before rating announcements. The time frame considered for the study is from March 2010 to March 2020. Only Indian firms are considered for the analysis. Indian banks are intentionally excluded because of the difference in the accounting systems of banks and other firms. In India, bond rating and investment-grade rating are required before a bond is issued. For this study government bonds are deliberately omitted because the government bonds are safer and liquid compared to corporate bonds. For instance, at time of bankruptcy, government entities offer significant protection due to government's obligations. For this reason only non-government bonds are used in this study.

3.1.1.2 Variables and Calculation of Ratios

In order to compare the data of different issuers, financial ratios are used instead of using direct financial data. The independent variables considered for the model are listed in table 3.2 and the formula is explained in appendix A.3.3. The financial ratios included in the model are taken from CRAs credit rating methodology information, and from previous studies such as Beaver (1966), Edmister (1972), Altman and Kao (1991), Puccia et al. (2013), Baghai et al. (2014), Vana, (2018), Caridada et al., (2020) and Cardarelli, (2020). The ratios used by CRAs for credit evaluation of issuers to assign rating are used in the present model. Taking a cue from previous works on CR on credit risk modelling, all the financial ratios are used as explanatory variables. Table 3.2 provides the details of explanatory variables used in the study. The sources of the variables and the code provided to each variable used in the Ordered Probit Model (OPM) are also given in Table 3.2.

Table 3. 2 Details of Independent Variables and Sources

Code	Variables*	Sources
X_1	Log Bond	Bradford et al.(2019)
X_2	Log TA	Puccia et al. (2013), Baghai et al. (2014), Vana, (2018), Daniel et al., (2020)
X_3	Interest Cov	Vana, (2018), Caridada et al., (2020)
X_4	Equity Ratio	Edmister (1972) Vana, (2018), Daniel et al., (2020), Cardarelli, (2020)
X_5	Debt Ratio	Beaver (1966); Baghai et al. (2014), Vana, (2018), Caridada et al., (2020), Cardarelli, (2020)
X_6	Debt-to-Equity	Puccia et al.(2013) Vana, (2018), Caridada et al., (2020)
X_8	Gearing Ratio	ICRA (2019)
X_9	Debt-to-Profit	Baghai et al. (2014), Ahn et al.(2019)
X_{10}	Neg. Debt-to-profit	Ahn et al.(2019)
X_{11}	Operating Profit Margin	Ahn et al.(2019); Cardarelli, (2020)
X_{12}	Net Profit Margin	Altman (1968); Altman and Kao (2007) Vana, (2018), Cardarelli, (2020)
X_{13}	Current Ratio	Baghai et al. (2014), Cardarelli (2020)
X_{14}	RE-to-Assets	Wu et al., (2014), David (2018)
X_{15}	CA-to-Assets	Wu et al., (2014), David (2018)
X_{16}	RoABT	David (2018), Cardarelli (2020)

X_{17}	Assets Turnover Ratio	David (2018)
X_{18}	OCF-to-Debt	Wu et al., (2014), ICRA (2019)
X_{19}	OCF-to-Assets	Wu et al., (2014), ICRA (2019)
X_{20}	Rent-to-TA	Wu et al., (2014), Ahn et al.(2019), Daniel et al., (2020), Cardarelli (2020)
X_{21}	PPE-to-TA	Ahn et al. (2019)

Size of bond issue: It is an amount a borrower needs to get from the bond market in the form of loan to finance his capital or project. If the size of a bond increases the financial obligation of the borrower increases due to uncertainty of return associated with project. Hence, lower size indicates less risk and vice versa.

The book value of total assets: It indicates the value of assets which a company owns and the usage of the items to operate, lease or use by oneself to create value for the business. Total assets include both tangible and intangible assets. The natural log value of total assets is considered in the rating model. It plays an important role in calculating the liquidity and solvency ratios.

Interest coverage ratio: It is calculated by dividing the "earnings of a firm before interest and tax" by "interest expenses". It shows the number of times interest expenses can be covered with pre-tax earnings. In other words, it can be explained as the ability of a firm to pay or cover its obligation for interest payment. Hence, a firm with higher interest coverage ratio indicates a higher solvency nature. Higher ratios allow a company to borrow more. The prompt payment of interest by a firm encourages lenders and borrowers to believe in lending money to that firm.

Equity ratio: It shows the proportion of an owner's investment in the total assets of a firm. The ratio is calculated by dividing "the total equity (shareholders' investment) by total assets". This ratio reveals the share of an owner's investment in the assets of a firm. Higher ratios are considered good for a firm.

Debt ratio: It shows the part of firms' assets which is financed by debt. It is calculated by dividing total liabilities (which includes both long term debt as well as short term debt) by total assets. Hence, it shows the solvency status of a firm. Higher debt ratios indicate a firm's good financial health and higher degree of debt financing.

Debt-to-Equity ratio: It is associated with the solvency of a firm which indicates the contribution of borrowers and shareholders in the capital. It is calculated by dividing the total debt by total equity. A high debt-to-equity ratio leads to high interest expense. For instance, a company has to pay interest at stipulated intervals and principal amount of the debt on its maturity. Hence, it increases the expense and also hurts the cash flow of a firm as it required to be paid in cash. It helps shareholders and lenders to understand the distress which will occur if a firm has adverse business circumstances and has to stop functioning.

Gearing ratio: The ratio of total debt a firm holds (including long term and short term) by Tangible Net Worth is known as gearing ratio. A gearing ratio highlights the source of a firm's operating financing. It gives a deep understanding of a firm's dependability and ability to withstand financial shocks. A low gearing ratio indicates financial stability and low chance of default.

Debt-to-profit ratio: It indicates the ability of a firm to pay its total debt and interest. A debt-to-profit ratio is a leverage matrix of a firm which indicates the income which is available for the payment of debt before interest, depreciation, tax, and amortization expense. A high debt-to-profit ratio indicates that a firm has more debt than profit which it is not able to handle. If the value is negative, it has been replaced with 0 and added as a dummy variable with the name negative debt.

Negative Debt: It is a dummy variable added for debt-to-profit ratio. If the debt-to-profit ratio is negative assigned 1 in Neg. Debt and 0 if the value of debt-to-profit ratio is positive.

Operating Profit Ratio: It is a profitability ratio that measures the total earnings of a firm from its operations before taxes and interests are paid. It is calculated by dividing a "firm's operating profit by net sales". The operating profit margin ratio of a firm indicates how profitable its activities are. A business with a large profit margin generates more money on each sale than the one with a small profit margin.

Net profit margin: The net profit of a firm can be calculated by "dividing the net income by total sales". The ratio is a measure of total margin, or the amount of money available to pay for taxes, financial expenses and to return profit to shareholders.

Current ratio: The current ratio is a measure of the liquidity of a firm. It is frequently used in banks to decide whether working capital loans should be granted to customers or not. The current ratio is a measure of how well short and long-term assets and liabilities are aligned. A healthy current ratio ensures adequate liquidity for day-to-day operations. It is calculated by dividing "the current assets by current liabilities".

Retained earnings to total assets: This is a simple ratio of retained earnings and total assets that shows cumulative profitability (which is retained earnings) as a percentage of a firm's total assets over time. The perfect ratio of retained earnings total assets is 100 percent or 1:1. However, most organisations will not be able to achieve this ratio. A firm will have a low reliance on other types of financing (i.e., debt and equity) if retained earnings to total assets ratio is high. Compared to debt and equity financing, using internally generated revenue for reinvestment has a number of advantages.

Current assets to total assets: This ratio is used to assess a company's liquidity. A company with a high ratio has a lot of cash, and vice versa. The following formula is used to compute the current assets to total assets ratio and the formula is current assets divided by total assets. It shows the amount of total cash, inventory invested for working capital as well as receivables from indent sales, and it also sheds light on the relevance of the current assets of a company. Current assets are primarily forms working capital and they also play an active role in generating liquidity. Thus it is worth noting how much of that percentage of total assets is devoted current assets.

Return on assets before interest and tax: This is another profitability ratio which determines the effective utilisation of assets by a firm to generate profit. This is calculated by dividing "EBIT (Earnings before Interest and Tax) by total assets". Higher ratios indicate that a firm is using its assets efficiently and it is generating higher income.

Assets turnover ratio: Asset turnover ratio is a form of efficiency ratio that compares the value of a firm's assets to the value of its sales revenue. It is a good indicator of how effectively a firm can employ its resources to increase its income. The total assets turnover ratio is often

determined on a yearly basis. But it can also be estimated over a shorter or longer duration if necessary. It is calculated by dividing net sales to total assets.

Operating cash flow to total debt: A cash-flow to debt ratio informs investors of the amount of cash flow generated by a company's regular operating activities in comparison to its total debts. For example, if the ratio is 0.25, the operating cash flow is one-fourth of the total debt on the books. The debts include principal payments, interest payments, and even lease payments to cover off balance sheet financing. "Operating cash flow to total debt = Operating Cash Flow / Total Debt".

Operating cash flow to total assets: It is an indicator of financial health of a firm. It measures the operating cash flow that a firm can generate from per unit of its own assets. A higher ratio is considered as good for a firm and it shows the efficient use of its assets owed. The operating cash flow to total assets ratio is expressed as a "Net cash flow from operating activities divided by total assets".

Total rent expenses to total assets: The rent paid by a firm divided by total assets is considered as an important financial ratio. High rent leads to low profitability.

Net property, plant, and equipment to total assets: It is calculated as Net Property, Plant, and Equipment (Net PP&E) divided by total assets. PP&E are the long term fixed assets of a firm which cannot be liquidated easily into cash. It plays an essential role in business operation and in maintaining the financial health of a firm. A Higher ratio represents better financial health of a firm.

3.1.1.3 Data Cleaning and Winsorising

DATA CLEANING

After collecting the data, the process of data cleaning is initiated. We begin by eliminating the non-applicable ratings issued by CRAs for the instruments of the firms. For this study only the ratings issued first in the year are considered. In case if more than one rating is issued on the same day for different bonds of a company, the average rating grades and sum of total bonds are considered. After the calculation of financial ratios, the firms with missing data are eliminated from the sample. Further, the firms which are not rated or whose ratings are not listed are also eliminated. Finally, we removed the missing variable dataset to get the final data which will be used in the analysis.

In ordered probit regression, the dataset with less or missing value are removed because it can give unstable result. The timeframe used for this study is from 2011 to 2019. Due to GFC 2008, the data of most the firms are not available, and the values of some firms are very minimal. The period immediately after GFC 2008 could have an inconsistent impact on the model, so the period from 2009 to 2010 is not considered in the study for better result. The overview of the raw data and final data set are given in Table 3.3, Table 3.4 and Table 3.5. The initial dataset collected for rating and the final data used in rating for the analysis are given in Table 3.3. The final rating samples after removing the non-applicable samples used in the study are given in the last column. Table 3.4 gives the details of initial rating with their rating grades obtained for analysis. The table shows the number of instruments of each rating grade. Table 3.5 contains the final data set of ratings with their rating grades employed in the analysis. The rating grades are converted into numerical metrics such as “AAA=1, AA+ = 2, AA= 3, ……, CCC/C=15 and

D=16". Each row presents the number of rating samples for each grade, whereas the columns represent the total sample of all the grade ratings of a particular year.

Table 3. 3 Overview of Data Observations per step

Year	Initial Observation	Removed non-applicable Rating	Final Rating
2011	2237	658	417
2012	2215	859	541
2013	2036	1002	717
2014	2134	1090	828
2015	2499	1217	953
2016	3346	1529	1,231
2017	3691	1789	1,419
2018	3771	2063	1,628
2019	4474	1950	1,417
Total	26403	12157	9,151

Table 3. 4 Initial Rating Data List Year Wise

Rating / Year	AAA	AA	A	BBB	BB	B	C	D	Total
2011	1012	638	229	235	92	15	6	10	2237
2012	603	669	368	344	144	49	11	27	2215
2013	542	519	342	358	175	52	7	41	2036

2014	505	569	390	382	189	44	13	42	2134
2015	657	648	492	382	206	57	9	48	2499
2016	777	857	669	528	291	108	14	102	3346
2017	767	939	777	611	334	134	17	112	3691
2018	577	898	868	720	395	152	14	147	3771
2019	676	1050	1076	781	455	202	48	193	4481
Total	6116	6787	5211	4341	2281	813	139	722	26410

Table 3. 5 Final Ratings Data List Year Wise

Year	**2011**	**2012**	**2013**	**2014**	**2015**	**2016**	**2017**	**2018**	**2019**	**Total**
1	31	26	32	32	38	47	56	62	50	374
2	28	14	17	23	27	34	42	49	56	290
3	32	20	24	26	31	51	84	84	71	423
4	38	22	26	34	40	51	73	99	102	485
5	24	44	44	46	63	103	107	136	106	673
6	23	40	47	63	65	81	95	115	108	637
7	21	37	44	66	95	123	138	130	121	775

8	48	64	83	82	103	128	142	181	150	981
9	42	63	83	113	113	140	164	163	134	1,015
10	58	80	107	112	121	144	145	152	141	1,060
11	21	44	66	72	71	89	87	106	100	656
12	20	32	52	46	67	65	61	87	75	505
13	10	10	21	32	33	53	65	75	43	342
14	14	27	42	44	51	70	86	98	83	515
15	1	4	5	7	11	10	11	11	11	71
16	6	14	24	30	24	42	63	80	66	349
Total	**417**	**541**	**717**	**828**	**953**	**1,231**	**1,419**	**1,628**	**1,417**	**9,151**

Winsorising

The extreme and interim values (i.e., outliers) require appropriate treatment in order to perform Ordered Probit Regression. To manage the outliers of raw data, winsorisation is used. Here, we would not lose any data, and the outliers would not affect the estimation model significantly through this process. The data winsorised at 5 percent and 95 percent percentile is used following Baghai et al. (2014), Bonsall et al., (2018), and Johannesson and Zedendahl, (2019). This method helps in saving more data in the cleaning process. The method employed in the study i.e. ordered probit regression, requires a large amount of data for consistent results.

To compare the financial data of different firms, a comparable scale is required. So to make the data comparable, financial ratios are calculated for all the samples over the period. The calculation of ratios is explained in appendix A3.2. The summary of the statistics of the financial variables (independent variables) is presented in Table 3.6.

Table 3. 6 Descriptive Statistics of Variables Used in Rating Prediction Model

Variable	**Mean**	**Min**	**Max**
Rating	8.298437	1	16
Log Bond	6.360237	-2.302585	15.74478
Log TA	8.358736	-2.302585	31.20423
Interest Cov	15.69918	-.0202889	129.2118
Equity Ratio	.3628959	.0044521	.7826286
Debt Ratio	.3394104	.0000447	.7900801
Debt-to-Equity	1.418489	0	6.592148
Gearing Ratio	27826.51	106.8074	105180
Debt-to-Profit	10.60366	0	25786.33
Neg. Debt-to-profit	.049175	0	1
Operating Profit Margin	.1631275	-.014643	.7791988
Net Profit Margin	.2615375	-1.327861	1.26317
Current Ratio	1.307084	.2294114	3.789892
RE-to-Assets	.0254049	-.1076664	.121876
CA-to-Assets	.4716229	.0483842	.8995763

RoABT	.0458624	-.1073386	.1995956
Assets Turnover Ratio	1.075344	0	25.72653
OCF-to-Debt	.490909	-.5445266	4.413844
OCF-to-Assets	.0504929	-.17397	.2385398
Rent-to-TA	.0053889	0	.0365615
PPE-to-TA	.2558589	0	.676698

3.1.2 Grouping of Ratings

Rating grades are converted into a numerical value metrics and then grouped into three parts. The first rating group is categorised considering the positive and negative outlook of the ratings (Such as "AAA=1, AA+=2, AA=2, AA- = 3, A+ = 4, AA= 5, AA- = 6, BBB+ = 7, …….., B = 14, CCC/C= 15 and D = 16"). For the second rating group, the outlook signs are ignored and then they are categorised into eight numerical metrics. And for the third group, rating is organised according to the safety level of the instruments. The top grades are considered as high safety grades, middle level rating grades are considered as moderate risk grades, and lower rating grades are considered as risky grades. Hence, all the rating grades are converted into three categories in the third group. To compare the rating grades of different class categories, actual grades are grouped into three. The groups are named "Group I", "Group II" and "Group III", and they are explained in Table 3.7.

Table 3. 7 Grouping of Credit Rating Grades

Rating Grades	Group I	Group II	Group III
AAA	1	1	1 Safer Zone
AA+	2	2	
AA	3		
AA-	4		
A+	5	3	2 Moderate safe/risk
A	6		
A-	7		
BBB+	8	4	
BBB	9		
BBB-	10		
BB+	11	5	3 Risk Zone
BB	12		
BB-	13		
B	14	6	
C	15	7	
D	16	8	

The rating grades of the majority of the issuers fall under investment-grades, especially for AAA, A and BBB issuers. Issuers rated below investment grade rating are very less. The data shows

that CRAs favour borrowers. The distribution of rating grades for all the three groups is summarized in Table 3.8, 3.9 and 3.10. Chart 3.1 shows the rating distribution of the final sample considered for analysis of the study. The final samples considered for rating prediction mostly belong to the moderate safety/risk zone of rating grade.

Table 3. 8 Rating Distribution Group I

Group I	Rating Grades	Rating Count	Percentage
1	AAA	374	4.09
2	AA+	290	3.17
3	AA	423	4.62
4	AA-	485	5.3
5	A+	673	7.35
6	A	637	6.96
7	A-	775	8.47
8	BBB+	981	10.72
9	BBB	1,015	11.09
10	BBB-	1,060	11.58
11	BB+	656	7.17
12	BB	505	5.52
13	BB-	342	3.74
14	B	515	5.63
15	C	71	0.78
16	D	349	3.81
Total		**9,151**	**100**

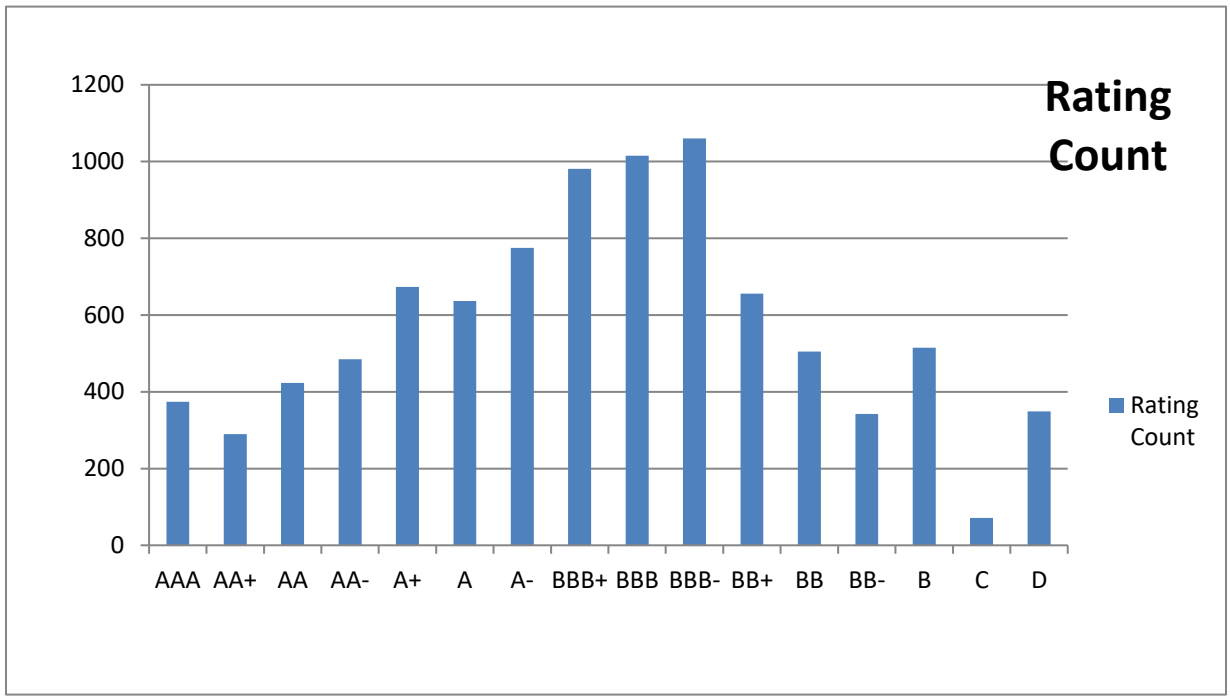
Table 3. 9 Rating Distribution Group II

Rating Grades	Rating	Rating Count	Percentage
AAA	1	374	4.09
AA	2	1,198	13.09
A	3	2,085	22.78
BBB	4	3,056	33.4
BB	5	1,503	16.42
B	6	515	5.63
C	7	71	0.78
D	8	349	3.81
Total		**9,151**	**100**

Table 3. 10 Rating Distribution Group III

Rating Grades	Rating	Rating Count	Percentage
AAA, AA	1	1,572	17.18
A, BBB, BB	2	6,644	72.6
B, C, D	3	935	10.22
Total		**9,151**	**100**

Chart 3. 1 Rating Distribution Graph of Final Sample for Rating Prediction Model



3.1.3 Ordered Probit Model (OPM)

This section provides a brief description of ordered probit model regression used in the present study. The dependent variables are frequently found in ordinal, but the letter grades used to code the variables are not necessarily meaningful and continuous. For example to rate the satisfaction level of food, we take five point scale ranging from 0 to 5. 0 point indicates highly dissatisfied and 5 represent highly satisfied. But the difference between the metrics will not be the same. For instance, the difference between dissatisfied i.e. 2 and neutral i.e. 3 will not be equal to difference between neutral i.e. 3 and satisfied i.e. 4. To estimate this type of model, an ordered probit model has been used widely.

An OPM is helpful in explaining dependent variables having ordinal categories with function of one or more independent variables. This model is useful only with the variables having ordinal

categories i.e. weakest to strongest, lowest to highest, strongly agree to strongly disagree etc. The variables do not have equal distance between the categories. Hence, OPM regression has been used for calculating the coefficient of independent variables. Such variables cannot be explained in quantity, and the distances between the two order categories are unknown. Likert scale (strongly agree-disagree), bond rating, movie rating, satisfaction level (unhappy to happy), etc are such examples. In these situations, response variables are classified in ordinal nature and they have more than two categories. This model provides a significance level for independent variables, and coefficients for the various that are obtained through the marginal effect. The marginal effect shows the relationship between independent and dependent variables.

The purpose of this examination is to find out the probability of each coefficient attributed to the rating as a function of the financial variables (market based information). Ordered grading model is identified as the indexed nature of many response variables. In this examination, rating grade has ordinal rank. The grades assigned by CRAs as credit ratings are coded in alphabetic letters: AAA, AA, A, …….., CCC, D. However, the distance between AAA and AA is not the same as the distance between AA and A. Hence, it is considered as ordinal grading. The random errors linked with explanatory variables in an ordered probit model are assumed to follow a normal distribution. In comparison to OPM, the widely used models in this field are multinomial logit model and probit model. The major drawback of these two models is that they neglect the ordinal nature of variables. The OPM can be estimated with many software packages available commercially (like SPSS and STATA) and freely (like R programming, and student version of STATA). Compared to other models, OPM is theoretically superior for data analysis in this area. OPM assumes that the numerical values of dependent variables reveal ordered categories that go with an unobservable continuous variable Y (Greene, William, 2003). Further, Y is assumed to

be linear function of explanatory variable X, and the error term is normally distributed. The model built around latent regression for this study is as follows:

$$\mathbf{Y^* = X' \beta + \varepsilon}$$

Thus, to predict the continuous unobserved variable Y, OLS model is used, whereas to find the cut off points (i.e. μ_1, $\mu_2, \ldots, \mu_{16}$), 'maximum likelihood method' of OPM is used along the distribution of Y in constructing discrete selection prediction. Hence, the model built for this study is as follows:

$$Y = a_0 + a_1 X_1 + a_2 X_2 + a_3 X_3 + a_4 X_4 + a_5 X_5 + a_6 X_6 + a_7 X_7 + a_8 X_8 + a_9 X_9 + a_{10} X_{10} + a_{11} X_{11} + a_{12} X_{12} + a_{13} X_{13} + a_{14} X_{14} + a_{14} X_{14} + a_{15} X_{15} + a_{16} X_{16} + a_{17} X_{17} + a_{18} X_{18} + a_{19} X_{19} + a_{20} X_{20} + a_{21} X_{21} + \varepsilon$$

Here, Y is the rating grade provided by CRAs and X_1, X_2, X_3, X_4, ..., X_{20}, X_{21} are the explanatory variables explained in Table 3.2. The rating grades are divided into three groups and converted into numerical grades. They are coded as "AAA=1, AA+ =2, ..., D=1 6 for group one, AAA=1, AA=2, A=3,....., D= 8" for group two, "AAA, AA= 1, A, BBB, BB = 2, B, C, D=3" for group three. The detail explanation of all the ratings and numerical codes of the three groups is provided in Appendix A3.1.

Y* is an unobserved variable (Predicted Rating). So the observable will be:

" Y = 1, if $Y^* \leq 1$

= 2, if $0 < Y^* \leq \mu 1$

= 3, if $\mu 1 < Y^* \leq \mu 2$

= 4, if $\mu 2 < Y^* \leq \mu 3$

.....

.....

= 16, if $\mu 15 \leq Y^*$"

The unknown parameters which are μ, are estimated with β. The predicted ratings depend on some measurable variables X_1, X_2, X_3, X_4, X_5, X_6, ..., X_{21} and some unobservable variables ε. The firms have their own strengths that are dependent on assured explanatory factors X and some unobservable variables ε. It is assumed that ε is distributed normally with the value 0 and variation 1 across observations. The probabilities found are positive and we get $0 < \mu 1 < \mu 2 < \cdots < \mu 16$. Figure 3.1 illustrates the inference of the construction. The log-likelihood function and its derivatives are obtained, and the usual means are used for optimization. As usual, "the Marginal effects of the regressors x on the probabilities are not equal to the coefficients". The probabilities for all the categories when the model has only one unknown threshold parameter are:

$$\text{Prob}\,(Y=1 \mid X) = \Phi\,(-X'\,\beta),$$

$$\text{Prob}\,(Y=2 \mid X) = \Phi\,(\mu_1 - X'\beta) - (-X'\beta),$$

$$\text{Prob}\,(Y=3 \mid X) = (\mu_2 - X'\,\beta) - (\mu_1 - X'\,\beta),$$

.....

.....

.....

$$\text{Prob}\,(Y=16 \mid X) = 1 - (\mu_{15} - X'\beta).$$

For the above probabilities, the "marginal effect of change" in the regressors is

$$\frac{\partial\,\text{Prob}(Y=0 \mid X)}{\partial X} = -\,\Phi\,(-X'\,\beta)\beta$$

$$\frac{\partial\,\text{Prob}(Y=1 \mid X)}{\partial X} = [\Phi\,(-X'\beta) - \Phi\,(\mu 1 - X'\beta)]\,\beta$$

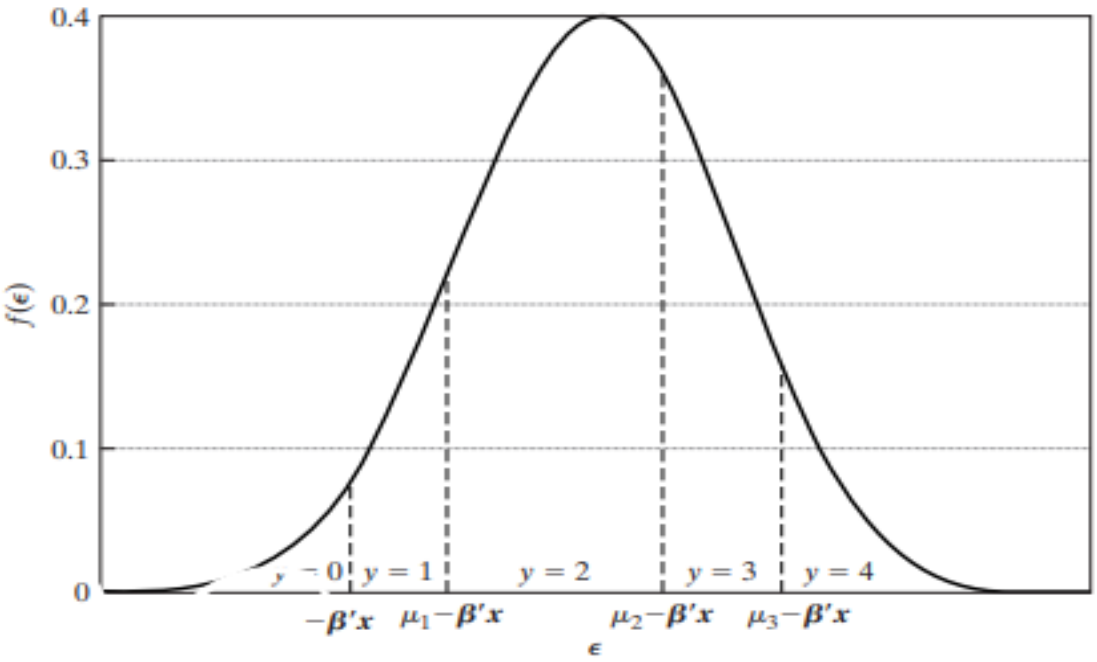
$$\frac{\partial\,\text{Prob}(Y=2 \mid X)}{\partial X} = \Phi\,(\mu 1 - X'\beta)\,\beta$$

.....

.....

$$\frac{\partial\,\text{Prob}(Y=16 \mid X)}{\partial X} = [(\mu 15 - X'\beta) - 1\,]\beta$$

Figure 3. 1 Probabilities in OPM (Ordered Probit Model)



3.1.4 Altman Z-Score

The first multivariate "bankruptcy prediction model" was developed by Professor Edward I. Altman in 1968 (Altman, 1968). This model is popularly known as Altman Z-Score model. Altman used different financial ratios and other variables in his model to calculate the credit qualities of issuers and to predict bankruptcy. Altman studied the problem of bankruptcy in manufacturing industry reported during 1946 to 1965. The financial ratios used for the study were obtained from the financial statements of firms prior to bankruptcy. Bankruptcy was predicted by using 22 financial ratios obtained from previous research works and few ratios were introduced by him. In the final model, from the 22 ratios only 5 ratios were included. MDA (Multiple Discriminant Analysis) is used by Altman to obtain his final model.

Altman Z-score presents financial distress of a firm expressed as a numerical value. It is widely used for predicting the probability of bankruptcy that a firm could face in future. The Altman Z-

score presents the probability of bankruptcy a firm could face in two years. The Z-score is calculated with the linear combination of five financial ratios. Each ratio is weighted by coefficients. These ratios increase the model's accuracy while determining the financial strength and the probability of bankruptcy of a firm. The formula of z-score is as follows:

$$\mathbf{Z= 1.2\ X_1+1.4\ X_2+\ 3.3X_3+\ 0.6X_4\ +\ 1X_5}$$

Where, X_1 = Working Capital to the Total Assets

X_2 = Retained Earnings to the Total Assets

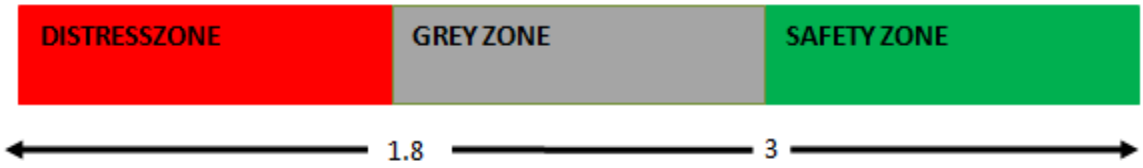
X_3 = PBIT to the Total Assets

X_4 = Market Value of Equity to the Book Value of Total Liabilities

X_5 = Sales to the Total Assets

The coefficient of the variables is at first dependent on information from free markets, yet the model has since been adjusted to suit different industry. Consequently, at times of high number of defaults such as the Asian emergency in 1998 or the eruption of the website bubble in 2001, the model probably did not have a solid prescient force. If the value of z-score is greater than three, it is considered as safe. If the value of Z-score is between 3 to 1.8, it is regarded as grey zone, and if it is less than 1.8, it is marked as distress zone. This can be better understood with reference to Figure 3.2.

Figure 3. 2 Different Zones of Altman Z-Score



3.2 Rating Announcements' Impact on Stock Price

The second part of the study focuses on the effects of rating announcements on stock prices. Rating is useful, if the rating conveys some information to the market; and the market reacts accordingly. In order to test the third hypothesis of the study, event study approach is used. An event study approach is a widely used method by economists to check the impact of a particular event on microeconomic variables. The announcements of rating are considered as events and they have impact on stock prices. Here pre-event and post-event prices are examined. The effects of rating announcements on stock prices are examined through event study (Hand et al., 1992; Goh and Ederington, 1993; Norden and Weber, 2004; Huang et al., 2018; Xie et al., 2019). This study is inspired to some extent by Xie et al. (2019), who examined the effects of rating announcements on stock prices for different industries.

3.2.1 Event Methodology

Event study is commonly used in finance and economics to know the effect of a specific event on a particular variable. In the present study the event "rating announcements" is used for examining the behaviour of returns. The occurrence of event can be on different dates in a calendar time. The primary objective of event study is to examine the response of market around the event. Event study is also crucial to test the market efficiency in the capital market.

“Systematically non-zero abnormal security returns that persist after a particular type of corporate event are inconsistent with market efficiency” (Brown & Warner, 1980; Kothari & Warner, 2007). Accordingly, “event studies focusing on long-horizons following an event can provide key evidence on market efficiency” (Fama, 1991). The behaviour of an issuer’s stock price after an event announcement is examined through event study (Beaver, 1968). From corporate perspective, event study is important to study the actual extent of abnormal performance of stock price after a particular event announcement. So event study is mainly used to examine the effect of an event on a firm’s value. The event can be any decision, disclosure of information, occurrence of activities, News, etc., related to the firm.

The relationship between BR announcement and stock price in terms of effect is measured through event study. Before the analysis of an event, we need to define estimation window and event window. An estimation window is the period used to calculate the slope and intercept of the regression line. Whereas event window is a specific time period around the event, used to examine the impact of an event. For this study, the period of estimation window is 200 days and the event window period is 61days (-30 to +30, event day considered as 0, 30 days before event as -30 and 30 days after event as +30). The negative and positive numerical digits show the number of pre-event and post-event days. For example, the event day, i.e., BR announcement day is marked as 0 day, the day before the announcement as minus one (-1) and the day after announcement as plus one (+1) and so on.

The unusual return (excess profit/loss) on security/stock in a specific period around any event is called Abnormal Return (AR). AR is different from the expected rate of return on portfolio or securities. It is calculated by deducting the predicted return from actual return investors received on assets. AR can be negative or positive depending on performance of security. The predicted

return is also called Expected Return (ER), which can be calculated using market model. The AR at time 't' for security 'i' which is associated to the event for each security is calculated as,

$$AR_{it} = R_{it} - E(R_{it})$$

Where "AR_{jt} is the Abnormal Return; R_{it} is the Actual Stock Return (ASR) and $E(R_{it})$ is the Expected Return (ER) of security 'i' at time 't'" (Neuhierl, A., Scherbina, A., and Schlusche, B., 2011). In order to get the AR, both Actual Stock Return (ASR) and ER need to be calculated.

To estimate the actual stock return of the security 'i' at time 't' below equation is used:

$$R_{it} = \{P_{it} - (P_{it-1})\} / (P_{it-1})$$

Where "R_{it} is used to represent the actual daily stock return of security 'i' on day 't'. P_{it} is the daily adjusted stock price of the security 'i' at the end of day 't'. P_{it-1} is the daily adjusted stock price of the security 'i' at the end of day 't-1'. Here t-1 is a day before t" (Brenner, 1979; He, P., Sun, Y., Zhang, Y., & Li, T., 2020).

The normal return is also known as actual return. This is return the market receives every day on security/portfolio. The expected return is the method of predicting return by using single index market model. Previous studies suggested that market model has high predicting power and it is the most frequently used model (Brenner, 1979; He, P., Sun, Y., Zhang, Y., & Li, T., 2020). ER of a security is the return that is expected by the market after the occurrence of any event. The ER of the security 'i' at time 't' is represented as $E(R_{it})$ and estimated using below regression equation of single index market model:

$$E(R_{it}) = \alpha_i + \beta_i R_m + \varepsilon$$

Where α_j = intercept (intercept of the regression line)

R_m = The expected market return,

β_j = The slope of the regression

The Market Return (MR) is calculated using, again, single index market model. To predict the ER, market return has significant role and is important to estimate the abnormal return. MR is the expected return that the market can have before the announcement of an event. It is calculated using the following equation:

$$R_{mt} = \{I_t - (I_{t-1})\} / (I_{t-1})$$

Where, R_{mt} shows the daily return of the market index on day 't'.

I_t and I_{t-1} is the closing index value of the market index on the day't' and day 't-1', respectively.

Average Abnormal Returns (AARs) and Cumulative Average Abnormal Returns (CARs)

AARs is the average of aggregate ARs for all N stocks at time 't'. To examine the common response of the stock prices to the event, the daily AR of each day for all of the events of the firms are pooled to examine the "accumulated response" of the event on stock prices. AAR helps to eliminate measuring quirks caused by certain stocks. This aggregate is for the event window of 61 days. The AAR is calculated by dividing the aggregated abnormal daily returns by the sample size (N):

$$\mathbf{AAR} = \frac{1}{\mathrm{N}} \sum_{t=1}^{N} \mathbf{AR_{i,t}}$$

Where, AAR is the Average Abnormal Returns on security at time 't', and N is the number of events. Further, CAAR is calculated using AAR for the events. CAAR is the sum total of AAR of all the event windows. The objective of calculating the AARs and CAARs is to arrive at the cross-sectional and time-series accumulation for the event period.

$$\mathbf{CAAR_T} = \frac{1}{\mathrm{N}} \sum_{t=1}^{N} \mathbf{AAR_{it}}$$

Where, N represents the number of ARs of the firms. In addition to the AAR, the CAAR is a useful statistical study since it allows us to see the aggregate effect of the AR. The CAAR can be extremely valuable, especially if the event's impact within the event window is not primarily on the event date.

Parametric Significance Test

To test the significance of the result "Parametric Significance Test" is necessary. The t-statistic/ z-statistic is calculated to check the statistical significance of AARs and CAARs first for each event window. To get the t-statistics for AARs, standard deviation is calculated for the estimation period of abnormal returns. To get the standard deviation and t-statistics of AAR following formula is used:

$$\mathbf{S.D\ (AAR_t)} = \sqrt{\frac{(\boldsymbol{ARt - AAR})^2}{\boldsymbol{N}}}$$

$$\mathbf{t\ (AAR) = \sqrt{N}\ \frac{AARt}{S.D\ (AARt)}}$$

Where, AR_t = Abnormal Return at time 't'

N = Number of days in estimation window

SD = Standard Deviation

AAR_t = Average Abnormal Return at time 't'

The t-statistics of CAARs is calculated by using following formula:

$$\mathbf{t\ CAAR_t = CAAR_t / (S.D^* (N)\text{^}1/2)}$$

Where, t CAAR is the t statistics of CAAR at time 't'

$CAAR_t$ = CAAR of the event at time 't'

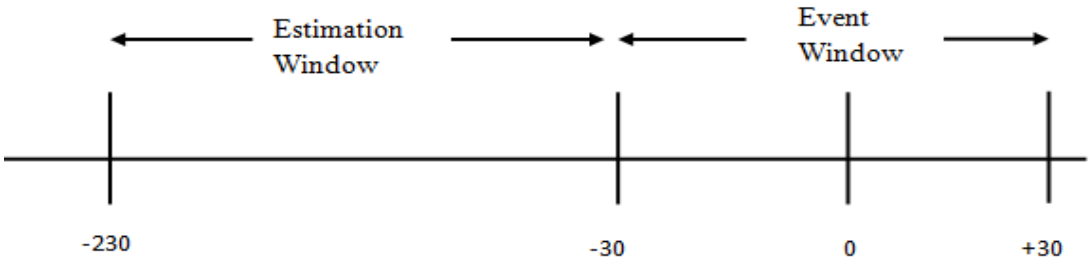
S.D = Standard Deviation of the estimation window

N = Number of days in Window

Estimation and Event Window

As defined earlier, estimation window is used to calculate market return. The estimation window considered for this the study is 200 days i.e., -230 days to -30 days pre-event. The event window considered for study is 61 days. This is used to calculate abnormal return. 0 is considered as event day, -30 pre-event and +30 post event days. This is shown in Figure 3.3 below:

Figure 3. 3 Estimation Window and Event Window of the Study



3.2.2 Data Selection and Preparation

The rating announcements data are collected from ProwessIQ CMIE and CRAs website. Whereas, stock price data are collected from NSE, BSE and ProwessIQ CMIE database. The period of data observation for is from January 2009 to March 2020. In order to examine the effects of rating announcements on the market after GFC, this period is considered to be sufficient. The selection of sample is based on specific characteristics. A firm should be listed in stock exchange so that we can access stock data. The rating announcements made by CRAs for an instrument could be one or more than one. Rating announcements do not have any consistency or limitations. But for the final analysis only one announcement is considered. The samples taken for the study fulfil the below characteristics to be considered for final dataset.

- All the companies (except banks) which are listed in any Indian stock exchange during 2008-2020.
- The rating announcement should be by any domestic CRAs, i.e., ICRA, CRISIL, CARE, India Ratings and BRICKS rating from March 2009 to December 2019.
- Only first rating of the year is considered, non-applicable ratings are removed
- Firms with missing financial data are also eliminated

- The daily stock price data should be accessible at the time of rating announcement
- Companies having a turnover of more than Rs.5 crore are taken
- Only one rating for every event window is considered
- Bond issue with a size of more or at least Rs.1 cr. is included

3.2.2.1 Data Cleaning and Preparation

Initially, the BR announcement data extracted includes the entire announcements. But since many announcements are made for an issuer at the same time, this study has take only one rating announcement made in the event window. Other announcements which fall in the event window are ignored. The issuers who do not meet the required characteristics are removed from the final dataset. The steps taken to ascertain the sample size before cleaning and finalizing data set are recorded in Table 3.11 and the distribution of ratings is shown in chart 3.2, 3.3 and 3.4.

Table 3. 11 Rating Announcements Distribution Step–by-Step

		Initial dataset	After matching Characteristics	Final
Initial	Investment	3436	1921	711
	Speculative	660	618	42
Upgrade		1700	1325	544
Downgrade		2356	1364	714
Re-affirmed		18985	8291	4126
Rating watch		915	375	232
Suspended Rating		438	420	83
Withdraw Rating		1536	630	229

Investment-grade	25999	11507	5863
Speculative Grade	4027	3437	647

The second column of the Table 3.11 represents the total data which are collected from the database (ProwessIQ) for the analysis. But, all the data were not matched with the characteristics of samples. Hence, only the data which matched with the sample characteristics are kept and are shown in third column of the Table 3.11. However, the final samples used for the analysis included only suitable data presented in last column of the Table 3.11.

Chart 3. 2 Distribution of Initial Rating Announcement Dataset

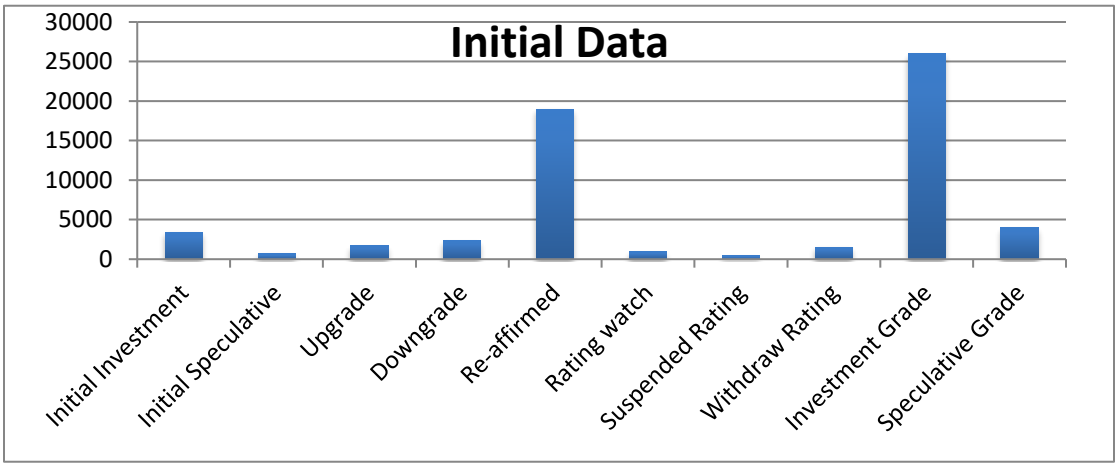


Chart 3. 3 Distribution of Rating Announcement after Meeting Characteristic

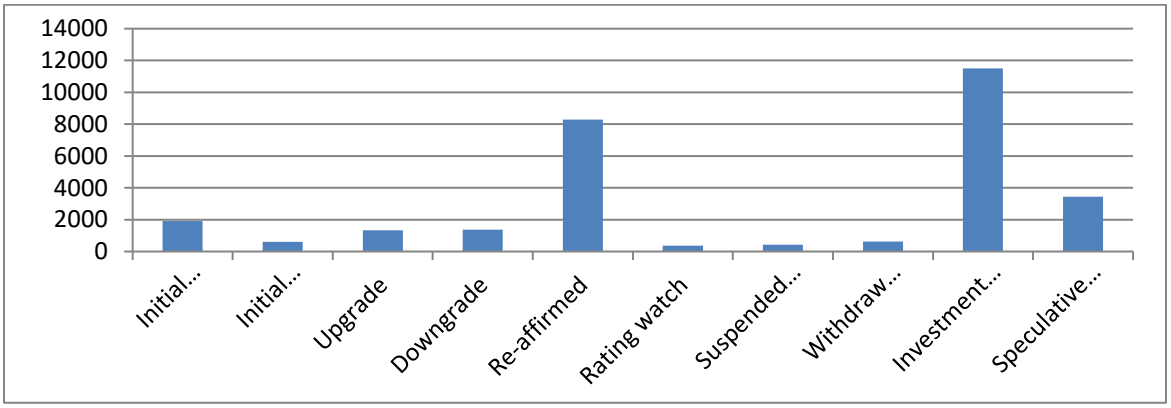
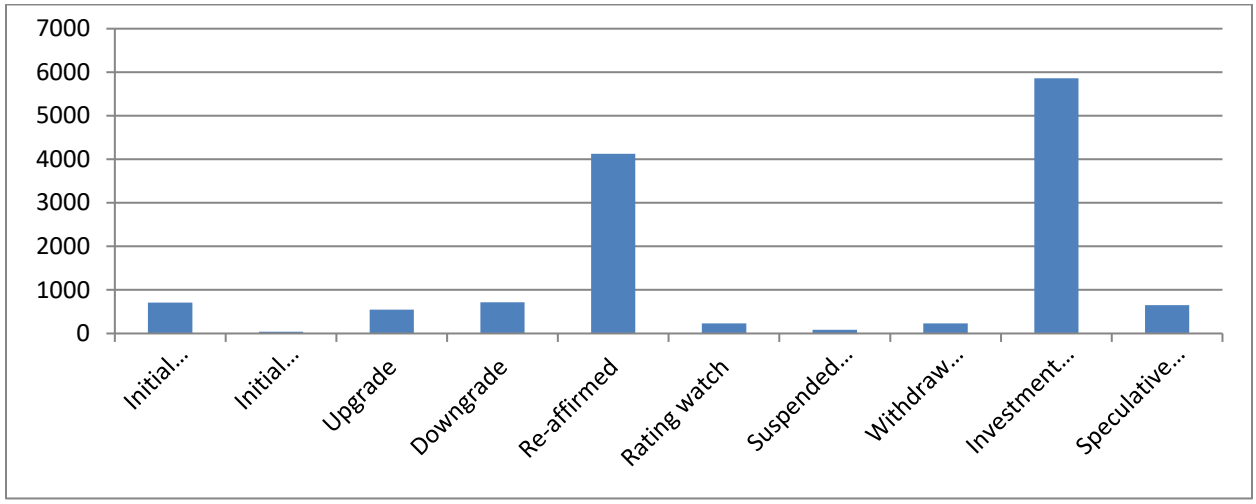


Chart 3. 4 Distribution of Rating Announcement in Final Dataset



Data shown in the table 3.11 and chart 3.1 present the actual rating grades of instruments assigned by CRAs. From the data and graph we can observe that among total rating grades received by the instruments, approximately 86 percent of the rating grades are in investment grade whereas only 14 percent instruments received speculative grade ratings. Similarly, if we will look at the first rating (Initial Rating) assigned to the instruments, approximately 84 percent instruments have received investment grade rating. From the data we can observe the behaviour of CRAs in assigning the rating grades. The Chart 3.3 shows the distribution of rating grades after removing the non-applicable announcements (rating which are not matched with the characteristics of sample). In this also, we can see that number of rating grades that fall under investment grades are much higher in number compared to the rating grades that fall under speculative grade. The distribution of final data used in analysis are shown in last column of Table 3.11 and presented graphically in chart 3.4. Data shows that 90 percent (approximately) of total rating announcements fall under investment-grades; even in the case of the first rating (Initial Rating) 94 percent of the rating fall under investment grade and only 6 percent

(Approximately) were lie in speculative grade. Hence, from the behaviour of data we can say that CRAs are liberal in assigning rating grades.

Summary

The present study is based on secondary data. To predict CR and to calculate Z-score, credit rating data, and the financial variables of a certain period is required. The selected variables of the study are based on the information provided by CRAs on methodology and from the previous literature on the same topic. CR grades and financial variables are extracted from ProwessIQ CMIE database. The time frame considered for the rating prediction is from March 2010 to March 2020. In order to compare the data of different issuers, financial ratios are used instead of using direct financial data. To manage the outliers of raw data, winsorisation is used. The method employed in the study is ordered probit regression. The second part of the study focuses on the effects of rating announcements on stock prices. The relationship between BR announcement and stock price in terms of effect is measured through event study. The rating announcements data are collected from ProwessIQ CMIE and CRAs website. Whereas, stock price data are collected from NSE, BSE and ProwessIQ CMIE database. The period of data observation for is from January 2009 to March 2020.

CHAPTER 4

4. RESULTS AND DISCUSSION

This chapter presents the empirical analysis and the main results. To begin with, this chapter gives the statistical summary of the variables used in the study. The results of both parts of the study are presented in separate sections. The tools used for analysis to achieve the objectives of the study are described in the methodology section. To predict ratings, ordered probit regression is used for CBR data from 2011 to 2019. The results of OPM and pooled OLS are given in section 4.1 with the matrix of actual and predicted ratings. The independent variables in the rating prediction model that provide insights are highlighted. Their effects on the predicted model and sample justification are also presented.

The second part of the study follows the methods discussed in the previous chapter to examine the impact of an event, i.e., a rating announcement on stock price. The result related to abnormal return and Z-statistic are given in section 4.2 for all the CBR announcements between 2009 and 2019. This is done to achieve the second main objective of the study which is to examine whether a rating announcement induces any informational change in the stock market.

4.1 Rating Prediction:

4.1.1 Descriptive Statistics

The statistical data of rating prediction model are derived from secondary data. The data are based on a dataset of 9151 observations of 2645 issuer firms. This section summarises the variables and their respective statistics which are used to predict ratings and to calculate z-scores. The summary is reported in Table 4.1 that demonstrates the statistical description of variables

included in the study on credit rating prediction. The table gives the details of explanatory variables in term of the mean value, the standard deviation of the distribution, minimum and maximum values, and total observations.

Table 4. 1 Descriptive Statistics of Rating Prediction Variables

Variables	Mean	Std. Dev.	Min	Max	Obs
Rating	8.298437	3.737419	1	16	9151
Log Bond	6.360237	2.226693	-2.30259	15.74478	9151
Log TA	8.358736	1.914644	-2.30259	31.20423	9151
Interest Coverage	15.69918	30.07526	-0.02029	129.2118	9151
Equity Ratio	0.362896	0.198501	0.004452	0.782629	9151
Debt Ratio	0.33941	0.216292	4.47E-05	0.79008	9151
Debt-to-Equity	1.418489	1.628138	0	6.592148	9151
Gearing Ratio	27826.51	37066.87	106.8074	105180	9151
Debt-to-Profit	10.60366	290.3196	0	25786.33	9151
Neg. Debt	0.049175	0.216245	0	1	9151
Operating Profit	0.163128	0.164411	-0.01464	0.779199	9151
Net Profit Margin	0.261538	0.400106	-1.32786	1.26317	9151
Current Ratio	1.307084	0.749978	0.229411	3.789892	9151
RE-to-Assets	0.025405	0.046467	-0.10767	0.121876	9151

CA-to-Assets	0.471623	0.239336	0.048384	0.899576	9151
RoABT	0.045862	0.0668	-0.10734	0.199596	9151
Assets Turnover	1.075344	0.830884	0	25.72653	9151
OCF-to-Debt	0.490909	1.031308	-0.54453	4.413844	9151
OCF-to-assets	0.050493	0.08975	-0.17397	0.23854	9151
Rent-to-TA	0.005389	0.008389	0	0.036562	9151
PPE-to-TA	0.255859	0.198435	0	0.676698	9151

Rating is used as a dependent variable in the rating prediction model, whereas in the event study method it is used as an independent variable. Here, ratings represent the actual rating grades assigned to the specified bonds by CRAs. Rating grade has the maximum value of 16 and the minimum is 1. Minimum value indicates highest safety and maximum value indicates highest risk. This has been explained in detail in the methodology section. The summary of rating statistics has a different value for different groups, but the value of other variables, i.e., independent variables is constant. The explanatory variables used for the model are: (1) Natural log value of bond issue (size of bond issue) which has an average value of 6.4 million rupees, (2) Natural log of the book value of total assets having an average value of rupees 8.3 million, (3) Interest coverage ratio, (4) Equity ratio, (5) Debt ratio, (6) Equity to debt ratio, (7) Gearing ratio, (8) Debt-to-profit ratio, (if the value is negative, it is replaced with 0 and added as dummy named Neg. Debt.), (9) Neg. Debt added as a dummy for the Debt-to-profit ratio. If the debt-to-profit ratio value is negative, it is assigned 1 in neg. debt else 0 for the positive Debt-to-profit

ratio. (10) Operating profit, (11) Net profit margin, (12) Current ratio, (13) Retained earnings to total assets, (14) Current assets to total assets, (15) Return on assets before interest and tax, (16) Assets turnover ratio, (17) Operating cash flow to total debt, (18) Operating cash flow to total assets, (19) Total rent expenses to total assets and (20) Total net property, plant, and equipment (PPE) to total assets. The calculation of ratios of explanatory variables is explained in appendix table A.1.

4.1.2 OPM for Group 1

The OPM model is used to describe the dynamics of CR and rating change. This model is used to find out the statistical determinant of risk transfer and to predict rating. The rating codes from 1 to 16 in group 1 are as follows: AAA=1, AA+=2, AA=3, AA-=4, A+=5, ..., B=14, C=15 and D=16. For the lowest grade rating B, C and D, holding sign (+/-) are ignored. The ordered probit regression is estimated for the explanatory variables. The advantage of OPM is that it does not assume the same increase for each rating category. High numbers represent worse rating and low numbers indicate better grades. The coefficient and p-value of ordered probit regression are given in Table 4.2. This shows the significance level of explanatory variables and the significance of the model. The pseudo R^2 is different from the adjusted R^2, and it is used to compare the model and not the percentage of explanatory variable explaining the model. Hence, ordered probit regression explains the significance of the model and the significance level of the explanatory variable.

Table 4. 2 Result of Ordered Probit Regression Group I

Rating	Estimation	Standard error
Log Bond	-0.0705***	0.0076
Log TA	-0.3234***	0.0100
Interest Coverage	-0.0016**	0.0005
Equity Ratio	-0.4874***	0.0982
Debt Ratio	0.4738***	0.0911
Debt-to-Equity	0.0316**	0.0106
Gearing Ratio	0.0000***	0.0000
Debt-to-Profit	0.0001**	0.0000
Neg. Debt	0.9869***	0.0894
Operating Profit	-0.9033***	0.0984
Net Profit Margin	-0.5658***	0.0482
Current Ratio	-0.1006***	0.0199
RE-to-Assets	7.3330***	0.7232
CA-to-Assets	0.7595***	0.0763
RoABT	-7.2842***	0.5026
Assets Turnover	-0.1775***	0.0172
OCF-to-Debt	-0.0375*	0.0166
OCF-to-assets	0.5395***	0.1528
Rent-to-TA	-15.4866***	1.3211
PPE-to-TA	-0.1750*	0.0703
Prob.> chi2		0.0000
Pseudo R2		0.1411

‘****’, ‘**’, ‘*’ significant at 0.001%, .01% and .05%

All the explanatory variables used in the study are statistically significant except for cash ratio, quick ratio, working capital ratio and capital to total assets, which are insignificant. So they are not included in the model. Firms have inferior/lower rating grades, if they hold too much debt, have low interest coverage, pay high rent, have less valuable assets and have less profit. The results are consistent with previous studies. In Table 4.2, the results of ordinal regression are given in log-odds form. The result shows that a decrease in an additional unit of the bond improves the status of rating (from D to AAA) by 0.07 point keeping other variables constant. Similarly, a decrease in one unit of book value of total assets improves the log odds of rating status by 0.32 point. On the other hand decrease in one unit of interest coverage ratio deteriorates the log odds of rating status by 0.002 point and also decrease in one unit of equity ratio deteriorates the log odds of rating status by 0.487 point. Whereas, an increase in the unit of debt ratio increased the log odds in support of improving the rating grades (moves upward from D to AAA) status by 0.474 points, respectively for all other variables, one unit of increase and decrease improves/worsens the rating grades status. The detailed results are presented in Table 4.2.

In brief, the result showed that the CR grades of the instruments are getting worse from AAA to D if the firms have high debt of different kinds, high debt to equity ratio, paying higher rent and having high gearing ratio. The creditworthiness decreases with the increase in the size of bond issues, low interest coverage ratio, low equity ratio and low profit margin (i.e. low value of operating profit, lower net profit margin and low operating profit to total debt), of firm, and so rating grades also decrease. The CR grades improved from D to AAA or got better CR grades with higher value of assets turnover ratio, high value of retained earnings to total assets and having lower value of current assets to total assets ratio, lower debt to profit ratio with exception

of low operating cash flow to total assets ratio. To predict the rating, we calculate the probability for each rating grade through marginal effect method. The slope or marginal effect of each explanatory variable is determined for all the categories of rating grades. The results are tabulated in Table 4.3 and continued in table 4.4.

Table 4. 3 Marginal Effect of Ratings at 1, 2, 3, 4, 5, 6, 7, 8 for Group I

	1	2	3	4	5	6	7	8
Log Bond	0.0008 (7.25)	0.0015 (7.9)	0.0033 8.47	0.0046 8.65	0.0066 8.83	0.0054 8.71	0.0045 8.59	0.0014 6.07
Log TA	0.0035 (11.05)	0.007 13.79	0.0153 17.51	0.0211 18.93	0.0301 20.99	0.0249 19.78	0.0204 18.83	0.0062 7.93
Interest Coverage	0.0001 (3.19)	0.0001 3.23	0.0001 3.25	0.0001 3.25	0.0001 3.26	0.0001 3.26	0.0001 3.26	0.0001 3.07
Equity Ratio	0.0053 4.56	0.0105 4.71	0.023 4.83	0.0319 4.86	0.0453 4.89	0.0376 4.87	0.0308 4.85	0.0094 4.22
Debt Ratio	-0.0051 -4.75	-0.0102 -4.91	-0.0223 -5.05	-0.031 -5.08	-0.044 -5.11	-0.0365 -5.09	-0.0299 -5.07	-0.0091 -4.39
Debt-to-Equity	-0.0003 -2.87	-0.0007 -2.92	-0.0015 -2.95	-0.0021 -2.96	-0.0029 -2.97	-0.0024 -2.96	-0.002 -2.95	-0.0006 -2.77
Gearing Ratio	0 7.21	0 7.79	0 8.28	0 8.4	0 8.55	0 8.46	0 8.4	0 6.11
Debt-to-Profit	0 -3.16	0 -3.21	0 -3.25	0 -3.25	0 -3.26	0 -3.26	0 -3.25	0 -3.05

Neg. Debt	-0.0107 -7.99	-0.0212 -8.91	-0.0465 -9.72	-0.0645 -9.97	-0.0917 -10.25	-0.0761 -10.12	-0.0624 -9.99	-0.019 -6.55
Operating Profit	0.0098 7.25	0.0194 7.81	0.0426 8.34	0.059 8.53	0.084 8.73	0.0697 8.66	0.0571 8.56	0.0174 6.1
Net Profit Margin	0.0061 8.27	0.0122 9.28	0.0267 10.2	0.037 10.49	0.0526 10.81	0.0436 10.65	0.0357 10.51	0.0109 6.71
Current Ratio	0.0011 4.65	0.0022 4.8	0.0047 4.91	0.0066 4.94	0.0093 4.97	0.0078 4.96	0.0064 4.94	0.0019 4.3
RE-to-Assets	-0.0792 -7.79	-0.1576 -8.53	-0.3458 -9.11	-0.4793 -9.25	-0.6815 -9.46	-0.5656 -9.37	-0.4633 -9.33	-0.1409 -6.44
CA-to-Assets	-0.0082 -7.55	-0.0163 -8.32	-0.0358 -8.99	-0.0496 -9.17	-0.0706 -9.37	-0.0586 -9.25	-0.048 -9.14	-0.0146 -6.28
RoABT	0.0787 9.16	0.1565 10.58	0.3435 11.92	0.4761 12.3	0.677 12.79	0.5618 12.52	0.4603 12.29	0.14 7.13
Assets Turnover	0.0019 7.7	0.0038 8.48	0.0084 9.19	0.0116 9.43	0.0165 9.69	0.0137 9.58	0.0112 9.46	0.0034 6.37
OCF-to-Debt	0.0004 2.21	0.0008 2.23	0.0018 2.24	0.0024 2.24	0.0035 2.24	0.0029 2.24	0.0024 2.24	0.0007 2.17
OCF-to-assets	-0.0058 -3.38	-0.0116 -3.43	-0.0254 -3.48	-0.0353 -3.49	-0.0501 -3.5	-0.0416 -3.5	-0.0341 -3.49	-0.0104 -3.24
Rent-to-TA	0.1672 8.15	0.3328 9.25	0.7303 10.25	1.0122 10.55	1.4393 10.89	1.1944 10.64	0.9785 10.38	0.2977 6.6
PPE-to-TA	0.0019 2.43	0.0038 2.46	0.0083 2.47	0.0114 2.48	0.0163 2.48	0.0135 2.48	0.0111 2.47	0.0034 2.37

Table 4. 4 Marginal Effect of Ratings at 9, 10, 11, 12, 13, 14, 15, 16 for Group I

	9	10	11	12	13	14	15	16
Log Bond	-0.0034 -8.28	-0.0074 -8.87	-0.0055 -8.78	-0.0042 -8.67	-0.0026 -8.36	-0.0031 -8.59	-0.0003 -6.17	-0.0015 -8
Log TA	-0.0156 -15.84	-0.0339 -22.43	-0.0255 -20.86	-0.0193 -19.29	-0.0117 -16.51	-0.0142 -18.52	-0.0016 -8	-0.0067 -14.05
Interest Coverage	-0.0001 -3.23	-0.0002 -3.27	-0.0001 -3.27	-0.0001 -3.26	-0.0001 -3.24	-0.0001 -3.26	0 -3.06	0 -3.21
Equity Ratio	-0.0236 -4.8	-0.0512 -4.9	-0.0384 -4.88	-0.0291 -4.86	-0.0176 -4.81	-0.0213 -4.85	-0.0024 -4.25	-0.0101 -4.74
Debt Ratio	0.0229 5	0.0497 5.13	0.0373 5.11	0.0283 5.08	0.0172 5.01	0.0207 5.05	0.0023 4.39	0.0099 4.94
Debt-to-Equity	0.0015 2.95	0.0033 2.96	0.0025 2.96	0.0019 2.95	0.0011 2.94	0.0014 2.96	0.0002 2.81	0.0007 2.94
Gearing Ratio	0 -8.02	0 -8.66	0 -8.6	0 -8.49	0 -8.18	0 -8.35	0 -6.07	0 -7.75
Debt-to-Profit	0 3.23	0 3.27	0 3.27	0 3.26	0 3.24	0 3.25	0 3.05	0 3.22
Neg. Debt	0.0477 9.52	0.1036 10.46	0.0777 10.25	0.0589 9.98	0.0357 9.46	0.0432 9.75	0.0048 6.57	0.0205 9.12
Operating Profit	-0.0437 -8.22	-0.0948 -8.82	-0.0711 -8.7	-0.0539 -8.58	-0.0327 -8.27	-0.0395 -8.47	-0.0044 -6.12	-0.0188 -7.93
Net Profit Margin	-0.0274 -9.94	-0.0594 -11.04	-0.0445 -10.8	-0.0337 -10.51	-0.0205 -9.94	-0.0248 -10.3	-0.0027 -6.72	-0.0118 -9.47

Current Ratio	-0.0049 -4.87	-0.0106 -4.99	-0.0079 -4.98	-0.006 -4.95	-0.0036 -4.89	-0.0044 -4.93	-0.0005 -4.31	-0.0021 -4.81
RE-to-Assets	0.3547 8.81	0.7697 9.66	0.5772 9.55	0.4374 9.37	0.2655 8.96	0.321 9.22	0.0354 6.38	0.1525 8.45
CA-to-Assets	0.0367 8.76	0.0797 9.47	0.0598 9.34	0.0453 9.18	0.0275 8.81	0.0332 9.08	0.0037 6.35	0.0158 8.44
RoABT	-0.3523 -11.31	-0.7645 -13.12	-0.5733 -12.82	-0.4344 -12.44	-0.2638 -11.58	-0.3188 -12.19	-0.0352 -7.17	-0.1515 -10.62
Assets Turnover	-0.0086 -9.07	-0.0186 -9.81	-0.014 -9.62	-0.0106 -9.44	-0.0064 -9.04	-0.0078 -9.31	-0.0009 -6.43	-0.0037 -8.7
OCF-to-Debt	-0.0018 -2.23	-0.0039 -2.24	-0.0029 -2.24	-0.0022 -2.24	-0.0014 -2.24	-0.0016 -2.24	-0.0002 -2.17	-0.0008 -2.22
OCF-to-Assets	0.0261 3.47	0.0566 3.51	0.0425 3.5	0.0322 3.49	0.0195 3.47	0.0236 3.49	0.0026 3.25	0.0112 3.45
Rent-to-TA	-0.749 -9.91	-1.6254 -10.93	-1.2189 -10.73	-0.9237 -10.51	-0.5608 -9.99	-0.6779 -10.42	-0.0748 -6.76	-0.322 -9.49
PPE-to-TA	-0.0085 -2.46	-0.0184 -2.48	-0.0138 -2.48	-0.0104 -2.48	-0.0063 -2.47	-0.0077 -2.48	-0.0008 -2.39	-0.0036 -2.46

Each additional unit of log-bond increases the probability of reporting AAA by 0.08%, AA+ by 0.15%, AA by 0.33%, AA- by 0.46%, A+ by 0.66%, A by 54, A- by 45, BBB+ by 0.14%. But "BBB, BBB-, BB+, BB, BB-, B, C, D" decline by 0.34%, 0.74%, 0.55%, 0.42%, 0.26%, 0.31, 0.03% and 0.15% for every unit increase in the bond value and also for all the variables. The marginal effect of the overall variable is reported in Table 4.5.

Table 4. 5 Marginal Effects for Ordered Probit Regression for Group I

Variables	Rating	z-stat
Log Bond	-.07048532***	-9.28
Log TA	-.32342905***	-12.33
Interest Coverage	-.00159207***	-3.29
Equity Ratio	-.4874177***	-4.97
Debt Ratio	.47380003***	5.2
Debt-to-Equity	.03163799**	2.98
Gearing Ratio	-3.196e-06***	-9.01
Debt-to-Profit	.00012143**	3.29
Neg. Debt	.98687578***	11.03
Operating Profit	-.90330848***	-9.18
Net Profit Margin	-.56575937***	-11.74
Current Ratio	-.10056457***	-5.06
RE-to-Assets	7.3330322***	10.14
CA-to-Assets	.75945395***	9.95
RoABT	-7.2841898***	-14.49
Assets Turnover	-.17749205***	-10.32
OCF-to-Debt	-.03745464*	-2.25
OCF-to-assets	.53950021***	3.53
Rent-to-TA	-15.486567***	-11.72
PPE-to-TA	-.17502925*	-2.49

‘****’, ‘**’, ‘*’ significant at 0.001%, .01% and .05%

With the help of marginal effect and predicted probability for each rating category, the calculation of predicted rating for each category is done. The predicted rating and actual rating grades are tabled in table 4.6. The table proves the difference between predicted and actual rating. We can see that predicted rating grades observed under AAA are less than the actual rating grades awarded by CRAs. In investment-grade rating, the actual rating grades reported are more than predicted rating. Whereas in speculative rating, the number of actual rating grades are lesser than the predicted rating grades. Hence, it indicates that more ratings deserve to be in lower rating grades but CRAs assigned higher rating grades.

Table 4. 6 Actual Ratings and Predicted Ratings for Group I

Rating Grades	Actual Rating	Predicted Rating
1(AAA)	374	359
2 (AA+)	290	267
3 (AA)	423	413
4 (AA-)	485	481
5 (A+)	673	677
6 (A)	637	662
7 (A-)	775	816
8(BBB+)	981	1025

9 (BBB)	1015	1046
10(BBB-)	1060	1066
11 (BB+)	656	642
12 (BB)	505	479
13 (BB-)	342	309
14 (B)	515	439
15 (C)	71	59
16 (D)	349	410

4.1.3 Ordered Probit Regression for Group II

In group II, rating grade is divided into 8 numerical scales. They are as follows: AAA=1, AA+, AA and AA- = 2, A+, A and A- = 2, BBB+, BBB and BBB- = 4, BB+, BB and BB- = 5, B+, B, and B- =6, C=7, D=8. The distance between 1 and 2 is not equal to the distance between 2 and 3, 3 and 4, and so on. The values are ordinal in nature and the distance between them cannot/ need not be the same. The pseudo R2 is 19.74% for group II whereas for group I it is 14.11% which is less. It shows that group II is better than group I in predicting rating. However, in both the groups, all the variables are found to be significant for the model. The details of ordered regression are shown in Table 4.7.

Table 4. 7 Ordered Probit Regression Group II

	Coefficients	Std. Err
Log Bond	-0.0629***	0.0079
Log TA	-0.3114***	0.0104
Interest Coverage	-0.0014**	0.0005
Equity Ratio	-0.5042***	0.1020
Debt Ratio	0.4751***	0.0946
Debt-to-Equity	0.0276*	0.0110
Gearing Ratio	0.0000***	0.0000
Debt-to-Profit	0.0001**	0.0000
Neg. Debt	1.0025***	0.0929
Operating Profit	-0.9028***	0.1024
Net Profit Margin	-0.5698***	0.0500
Current Ratio	-0.0936***	0.0207
RE-to-Assets	6.7768***	0.7549
CA-to-Assets	0.7404***	0.0794
RoABT	-6.8071***	0.5249
Assets Turnover	-0.1801***	0.0179
OCF-to-Debt	-0.0348*	0.0174
OCF-to-assets	0.5315***	0.1591
Rent-to-TA	-14.9280***	1.3781
PPE-to-TA	-0.1796***	0.0732
Prob.> chi2		0.0000

Pseudo R2	0.1974

‘****’, ‘**’, ‘*’ significant at 0.001%, .01% and .05%

Ordered regression is done to test the significance level of the variables at different confidence intervals. The significance level of debt to equity ratio and operating cash flow to total assets is 95%, and the significance level of interest coverage ratio and debt to profit or PBITDA is 99 %. And all other variables significance level is at 99.9 percent. Their probability is estimated after checking the significance of variables marginal effect calculated for each category rating. Table 4.8 shows the predicted probability of each category of rating and the confidence interval. This table shows how the predicted probabilities of the dependent variables of each group change due to the change in the rating value from 1 to 16.

Table 4. 8 Marginal Effect of Ratings at 1, 2, 3, 4, 5, 6, 7 and 8 for Group II

	1	2	3	4	5	6	7	8
Log Bond	0.0008 6.61	0.0086 7.83	0.0144 7.86	-0.0081 -7.56	-0.011 -7.86	-0.0029 -7.55	-0.0003 -5.75	-0.0014 -7.14
Log TA	0.004 11.24	0.0428 23.96	0.0711 25.12	-0.0402 -18.44	-0.0546 -25.87	-0.0145 -18.28	-0.0016 -7.99	-0.007 -13.95
Interest Coverage	0 2.77	0.0002 2.82	0.0003 2.83	-0.0002 -2.81	-0.0002 -2.83	-0.0001 -2.81	0 -2.68	0 -2.78
Equity Ratio	0.0064 4.56	0.0693 4.9	0.1152 4.92	-0.065 -4.84	-0.0884 -4.92	-0.0235 -4.83	-0.0026 -4.24	-0.0113 -4.73
Debt Ratio	-0.0061 -4.64	-0.0653 -4.98	-0.1085 -5	0.0613 4.92	0.0833 5	0.0222 4.9	0.0025 4.29	0.0107 4.79
Debt-to-	-0.0004	-0.0038	-0.0063	0.0036	0.0048	0.0013	0.0001	0.0006

Equity	-2.45	-2.52	-2.52	2.51	2.51	2.51	2.42	2.5
Gearing Ratio	0 7.15	0 8.52	0 8.55	0 -8.13	0 -8.62	0 -8.15	0 -5.99	0 -7.59
Debt-to-Profit	0 -2.71	0 -2.78	0 -2.78	0 2.77	0 2.78	0 2.76	0 2.64	0 2.74
Neg. Debt	-0.0128 -7.99	-0.1378 -10.4	-0.229 -10.53	0.1293 9.9	0.1757 10.5	0.0468 9.63	0.0052 6.53	0.0225 9.04
Operating Profit	0.0115 7.11	0.1241 8.58	0.2062 8.68	-0.1165 -8.27	-0.1582 -8.68	-0.0422 -8.21	-0.0047 -6.02	-0.0203 -7.72
Net Profit Margin	0.0073 8.26	0.0783 10.94	0.1301 11.08	-0.0735 -10.31	-0.0999 -11.08	-0.0266 -10.11	-0.003 -6.67	-0.0128 -9.34
Current Ratio	0.0012 4.24	0.0129 4.49	0.0214 4.5	-0.0121 -4.44	-0.0164 -4.5	-0.0044 -4.43	-0.0005 -3.97	-0.0021 -4.34
RE-to-Assets	-0.0866 -7.34	-0.9315 -8.74	-1.5478 -8.79	0.8742 8.35	1.1877 8.86	0.3164 8.34	0.0354 6.07	0.1522 7.76
CA-to-Assets	-0.0095 -7.34	-0.1018 -9.1	-0.1691 -9.14	0.0955 8.7	0.1298 9.15	0.0346 8.63	0.0039 6.2	0.0166 8.08
RoABT	0.0869 8.93	0.9356 12.34	1.5547 12.45	-0.8781 -11.31	-1.193 -12.58	-0.3178 -11.3	-0.0355 -6.98	-0.1528 -10.02
Assets Turnover	0.0023 7.66	0.0247 9.73	0.0411 9.86	-0.0232 -9.31	-0.0316 -9.83	-0.0084 -9.15	-0.0009 -6.38	-0.004 -8.58
OCF-to-Debt	0.0004 1.98	0.0048 2	0.008 2	-0.0045 -2	-0.0061 -2	-0.0016 -2	-0.0002 -1.95	-0.0008 -1.99
OCF-to-assets	-0.0068 -3.22	-0.0731 -3.33	-0.1214 -3.33	0.0686 3.31	0.0932 3.33	0.0248 3.31	0.0028 3.1	0.0119 3.27

Rent-to-TA	0.1907 7.92	2.0519 10.52	3.4095 10.55	-1.9256 -9.88	-2.6164 -10.56	-0.697 -9.82	-0.0779 -6.6	-0.3352 -9.04
PPE-to-TA	0.0023 2.4	0.0247 2.45	0.041 2.45	-0.0232 -2.44	-0.0315 -2.45	-0.0084 -2.44	-0.0009 -2.36	-0.004 -2.43

The column value 1, 2..., 8 represent the categorical value of rating predicted estimation. With the help of estimated probability, predicted rating is calculated. In Table 4.9 the estimate marginal effect of ordinal regression for all the variables is given together. Z statistic values show that the variables have a significant influence on rating.

Table 4. 9 Marginal Estimation of OPM Group II

Variable	Estimation	z-stat
Log Bond	-.06292041***	-7.97
Log TA	-.31144743***	-30.07
Interest Coverage	-.00142466**	-2.83
Equity Ratio	-.50418131***	-4.94
Debt Ratio	.47506677***	5.02
Debt-to-Equity	.02764915*	2.52
Gearing Ratio	-3.218e-06***	-8.72
Debt-to-Profit	.00010792**	2.78
Neg. Debt	1.002477***	10.79
Operating Profit	-.90280815***	-8.82
Net Profit Margin	-.56975136***	-11.4
Current Ratio	-.09357275***	-4.52

RE-to-Assets	6.7768462***	8.98
CA-to-Assets	.74040078***	9.33
RoABT	-6.8071076***	-12.97
Assets Turnover	-.18005421***	-10.06
OCF-to-Debt	-.03481384*	-2.01
OCF-to-assets	.53152846***	3.34
Rent-to-TA	-14.928012***	-10.83
PPE-to-TA	-.17956077*	-2.45

'****', '**', '*' significant at 0.001%, .01% and .05%

The predicted probability of each rating category is (given) estimated separately and summarized. The tabulated value of predicted rating and actual rating are given in table 4.10. In table 4.10 it is observed that the number of actual rating grades is more than predicted rating grades except for A, BBB and default rating. Actual rating grade which falls in default is lesser in number compared to predicted default rating. Also, the actual ratings assigned by CRAs fall in A and BBB, and are less than the predicted values in the same grade. To sum up, it can be stated that the securities whose creditworthiness fall under default/risk category are awarded safer grades by CRAs. Hence, there is a significant difference between actual rating and predicted rating.

Table 4. 10 Actual Ratings and Predicted Ratings for Group II

Rating	Actual Rating	Predicted Rating
AAA (1)	374	363
AA (2)	1198	1158
A (3)	2085	2158
BBB (4)	3056	3127
BB (5)	1503	1431
B (6)	515	448
C (7)	71	60
D (8)	349	406

4.1.4 Ordered Probit Regression for Group III

In group III, rating grade is divided into three numerical scales. They are as follows: AAA, AA= 1, A, BBB, BB = 2, B, C, D= 3. The distance between 1 and 2 is not equal to the distance 2 and 3. The pseudo R^2 is 26.94 percent for group III whereas for the group I it is 14.11 percent and for group II it is 19.74 percent, which is less. It shows that group III is better than group I and group II in predicting ratings. However, all the variables are found in each group at different significance levels. In group I and group II, the variables operating profit to debt, and net plant property and equipment to total assets are found significant at 95%. And the chi-square statistic

is found to be less than 0.05 in both the groups. Hence, the variables used in the model have explanatory power of dependent variable. But in group III, the variables operating profit to debt, and net plant property and equipment to total assets are found significant at 90%. As was explained earlier, pseudo R2 is different from adjusted R2. Hence, both the pseudo R2 and adjusted R2cannot be interpreted as the same. The details of estimated ordered regression coefficient are presented in Table 4.11 with the statistical significance levels.

Table 4. 11 Ordered Probit Regression Group III

Variables	Coefficients	Std. Error
Log Bond	-0.04110***	0.01000
Log TA	-0.27320***	0.01280
Interest Coverage	-0.00169**	0.00063
Equity Ratio	-0.30754*	0.12820
Debt Ratio	0.44906***	0.11915
Debt-to-Equity	0.03332*	0.01344
Gearing Ratio	0.00000***	0.00000
Debt-to-Profit	0.00010*	0.00005
Neg. Debt	1.37851***	0.11523
Operating Profit	-0.74766***	0.12671

Net Profit Margin	-0.69324***	0.06182
Current Ratio	-0.09581***	0.02587
RE-to-Assets	9.32252***	0.99777
CA-to-Assets	0.78403***	0.09960
RoABT	-7.57345***	0.68998
Assets Turnover	-0.18003***	0.02195
OCF-to-Debt	-0.02063[#]	0.02182
OCF-to-assets	0.47093*	0.20139
Rent-to-TA	-11.4706***	1.75668
PPE-to-TA	-0.05654[#]	0.09180
Prob > chi2		**0.0000**
Pseudo R^2		**0.2694**

'****', '**', '*' '[#]' significant at 0.001%, .01%, .05% and 0.1%

The coefficient of ordinal regression is not useful in calculating the slope of the regression. The slope calculated with marginal effect and predicted probability for rating equal to 1, 2 and 3 separately. Table 4.12 shows the predicted probability estimate for each rating category, and Table 4.13 shows the marginal effect estimate of all variables

Table 4. 12 Predicted Probability Estimation for Rating of Group III

	1	2	3
Log Bond	0.0071 4.11	-0.0032 -3.97	-0.0038 -4.09
Log TA	0.047 19.87	-0.0216 -12.13	-0.0254 -17.82
Interest Coverage	0.0003 2.66	-0.0001 -2.62	-0.0002 -2.65
Equity Ratio	0.0529 2.4	-0.0243 -2.37	-0.0286 -2.39
Debt Ratio	-0.0772 -3.76	0.0355 3.66	0.0418 3.75
Debt-to-Equity	-0.0057 -2.48	0.0026 2.44	0.0031 2.48
Gearing Ratio	0 6.62	0 -6.09	0 -6.52
Debt-to-Profit	0 -2.28	0 2.26	0 2.28
Neg. Debt	-0.2371 -11.63	0.1089 9.2	0.1282 11.27
Operating Profit	0.1286 5.87	-0.0591 -5.48	-0.0695 -5.8

Net Profit Margin	0.1192 10.97	-0.0548 -8.86	-0.0645 -10.67
Current Ratio	0.0165 3.69	-0.0076 -3.6	-0.0089 -3.67
RE-to-Assets	-1.6036 -9.16	0.7366 7.86	0.867 8.93
CA-to-Assets	-0.1349 -7.82	0.0619 6.97	0.0729 7.66
RoABT	1.3028 10.75	-0.5984 -8.77	-0.7043 -10.43
Assets Turnover	0.031 8.1	-0.0142 -7.15	-0.0167 -7.95
OCF-to-Debt	0.0035 0.95	-0.0016 -0.94	-0.0019 -0.94
OCF-to-assets	-0.081 -2.34	0.0372 2.31	0.0438 2.33
Rent-to-TA	1.9731 6.53	-0.9063 -5.98	-1.0668 -6.47
PPE-to-TA	0.0097 0.62	-0.0045 -0.62	-0.0053 -0.62

Table 4. 13 Marginal Effect of OPM Group III

Rating	Coeff.	z-stat
Log Bond	-.04109539***	-4.11
Log TA	-.27319705***	-21.34
Interest Coverage	-.00168756**	-2.67
Equity Ratio	-.30754459*	-2.4
Debt Ratio	.44905746***	3.77
Debt-to-Equity	.03332354*	2.48
Gearing Ratio	-3.087e-06***	-6.65
Debt-to-Profit	.00010445*	2.28
Neg. Debt	1.3785085***	11.96
Operating Profit	-.74765705***	-5.9
Net Profit Margin	-.69323665***	-11.21
Current Ratio	-.09580734***	-3.7
RE-to-Assets	9.3225193***	9.34
CA-to-Assets	.78402927***	7.87
RoABT	-7.5734457***	-10.98
Assets Turnover	-.18002937***	-8.2
OCF-to-Debt	-0.020629#	-0.95
OCF-to-assets	.47093427*	2.34
Rent-to-TA	-11.470555***	-6.53
PPE-to-TA	-0.056544#	-0.62

'****', '**', '*' '#' significant at 0.001%, .01%.05% and 0.1%

Rating is predicted using estimation probability for each category. We find that at 0.05 significance level there is no difference between the predicted rating and actual rating. But, the number of rating grades which fall in risk category is less than actual number of rating grades belonging to risk grade, through predicted probability. Similarly, the rating grades assigned by CRAs which fall under safety zones are more compared to grades in safety zone in predicted rating. As per the model, most of rating grades belong to moderate safety/risk zone. The number of rating grades belonging to each group and predicted ratings of all the groups are given in Table 4.14.

Table 4. 14 Actual Ratings and Predicted Ratings

Rating	Predicted Rating	Actual Rating
1	1567	1,572
2	6623	6644
3	961	935

4.1. 5 Z-Score, Actual Rating and Predicted Rating

Z-score is calculated for all firms and are divided into three categories: safe zone, grey zone and red zone. Safe zone is converted into the numerical digit one, grey zone into two and red zone into three. Similarly, the ratings provided by CRAs are divided into three groups. Grade AAA and AA are assigned as 1, grade A, BBB and BB are assigned 2 and grade B, C, D are assigned 3. The number of actual rating and z-score value are given in Table 4.15.

Table 4. 15 Z-Score and Actual Rating

	Z-score	Actual Rating
1 (Safety Zone)	3535	4581
2 (Grey Zone)	2191	3318
3 (Risk Zone)	3477	1304

The three zones of z-value are considered for calculating rating and for comparing with the actual rating. Confusion matrix is given in table 4.16 for both actual and calculated rating. We can see that the actual rating and calculated rating are equal to 1 is 2108, 2 is 969 and 3 is 788. Whereas actual rating is 1 and calculated is 2 are equal to 969; and actual rating 2 and calculated rating 1 are equal to 1164. The variation between actual rating and calculated rating is found significant at 95%. The variance of the actual rating reported is 0.51, and for calculated rating it is 0.762. The F value (0.673) is less than the F critical value (0.966), and the p-value is significant (0.00). Hence, the rating calculated with z-value is statically significant different from the actual rating. The actual ratings provided by CRAs are more but the grades they gave should be less. According to Altman, the Z-score values of 3477 securities were falling in default zone but only 1304 securities were graded as defaults; and the rest were awarded higher grades. Hence, the ratings assigned by CRAs are less reliable as they are more inclined to award higher grades.

Table 4. 16 Confusion Matrix Actual Ratings and Calculated Ratings

		Calculated Rating		
		1	2	3
Actual Rating	1 (Safety Zone)	2108	969	1504
	2 (Grey Zone)	1164	969	1185
	3 (Risk Zone)	263	253	788

4.2 Impact of CBR Announcement on Stock Price

Using both AAR and CAAR with different windows, the impact of rating announcements on stock prices is studied. The event day is considered as 0 day, pre-announcement days (-30) and post-announcement (+30). So the event window could be considered between window (-30) and (+30). The event date is defined as the day of announcement of ratings by the CRAs.

All the types of rating announcement: Initial, Upgraded, Downgraded, Reaffirmed, Rating watch, Suspended, Withdrawn, Investment-grades and Speculative grades are studied separately. The t-test is used to determine the significance of the test. CAAR and AAR are calculated for all the events.

4.2.1 Initial Rating Announcement

The initial rating announcements are divided into two parts: (a) initial investment rating and (b) initial speculative rating. The results of initial rating announcements are given in the table 4.17.

Panel A indicates the results of investment-grade, whereas panel B indicates the results of speculative grades. CAR is found insignificant for initial investment-grade announcement. The t-statistic is to be found significant after 5 days of announcement, where CAR showed negative return 5 days before the event till the 30th day after the event. The same is not true for initial speculative-grade events. The market return is negative a day before the event,and also 5 to 10 days after the event. The t-statistic is insignificant for all the event windows except for 20 days before the event.

Table 4. 17 CAAR And T-Statistic of Initial Investment-Grade and Initial Speculative-Grade Rating Announcements

Event Window	PANEL A		PANEL B	
	Initial investment-grade		Initial speculative grade	
	CAR	t-stat	CAR	t-stat
T-30, T-11	-0.00917	-2.00814**	0.046784	2.204819**
T-30, T-20	-0.00937	-2.7654**	0.04165	1.455697
T-20, T-10	0.00019	0.05621	-0.00125	-0.05884
T-1, T-10	-0.00257	-0.79422	0.030641	1.514523
T-6, T-10	0.000567	0.248098	0.025341	1.771355*
T-1, T-5	-0.00313	-1.37129	0.0053	0.370505
T-1, T-0	-0.00231	-1.60117	-0.0061	-0.6739

T+0, T+1	-0.00044	-0.30803	0.000554	0.061275
T+1, T+5	-0.00095	-0.41493	0.011783	0.82366
T+6,T+10	-0.00527	-2.30784**	-0.01714	-1.19804
T+1, T+10	-0.00622	-1.92529*	-0.00536	-0.26473
T+10, T+20	-0.01081	-3.18989***	0.005711	0.269149
T+11, T+30	-0.01348	-2.95163***	0.021799	0.761883
T+20, T+30	-0.00504	-1.48623	0.006252	0.294625

'****', '**', '*' significant at 0.001%, .01% and 0.05%

Figure 4.1 presents the graph of abnormal return and CAR of initial investment-grade for pre and post announcement of an event. The graph shows that the AAR on the day before the event and after the event has a negative return. The curve of CAR falls as the days of post-event increase. On the contrary, no significant difference is found for initial speculative rating grade. The abnormal returns for initial speculative-grade ratings are given in figure 4.2, and it is observed that the AAR before and after the event are equal. Before the event CAR was highly positive, but five days before the event and five days after the event, the positive return fell but the abnormal return was positive. Figure 4.3 shows the compared graph of investment event and speculative event of Initial Rating.

Figure 4. 1 Initial Investment-grade Rating Announcements

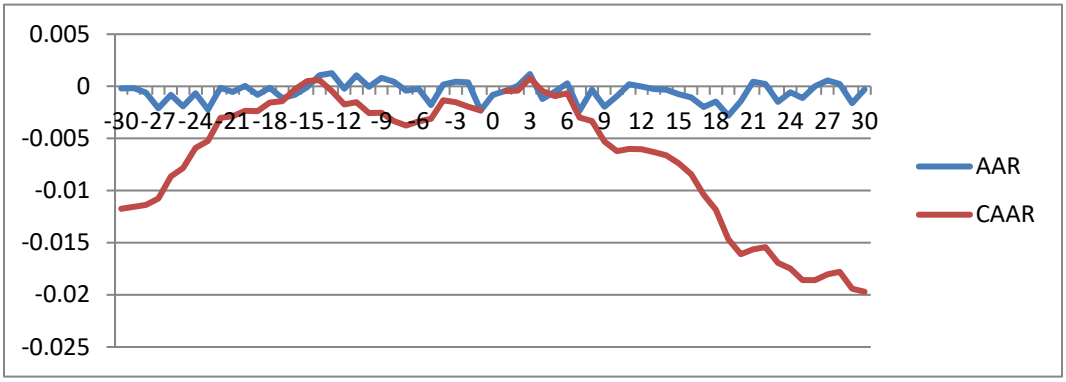


Figure 4. 2 Initial Speculative Grade Rating Announcements

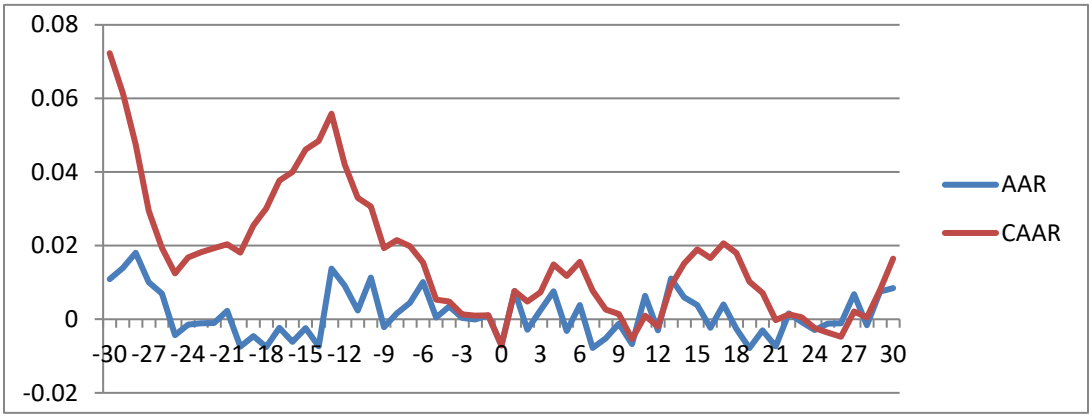
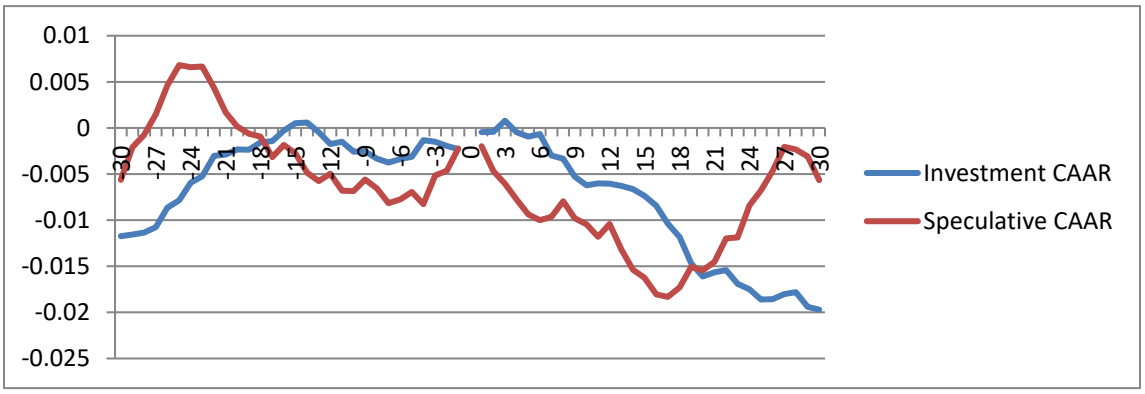


Figure 4. 3 Initial Rating Announcements



4.2.2 Upgrade Rating Announcements

The rating assigned initially may change during the tenor of the bond until maturity. The upgrades in rating grade, such as moving from AA to AAA, BBB to A/AA etc., are called upgraded rating. The results of upgraded event are given in table (4.18). The upgrades in t-statistic which are significant in pre-event and post-event window are: (T-30, T-11), (T-30, T-20), (T-20, T-10), (T-6, T-10), (T+1, T+5), (T+6, T+10), (T+1, T+10), (T+11, T+30) and (T+20, T+30). It is found that the abnormal return is positive after five days of announcement. The statistical significance also remains unchanged irrespective of Pacheco, (2012), Poornima et al., (2016). Figure 4.4 presents the graph of abnormal return and cumulative abnormal return.

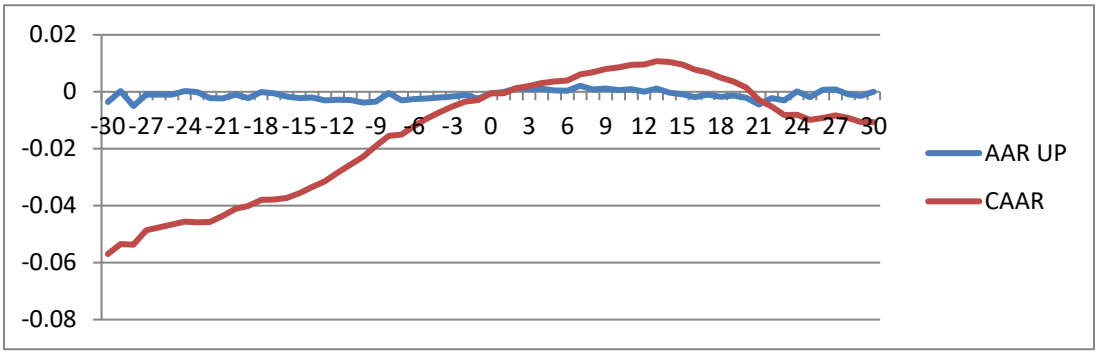
Table 4. 18 CAAR and t-statistic of Upgraded Ratings

Event Window	Upgraded Rating	
	CAAR	t-stat
T-30, T-11	-0.0342	-6.3438***
T-30, T-20	-0.0168	-4.2160***
T-20, T-10	-0.0222	-5.5465***
T-1, T-10	-0.0228	-5.9834***
T-6, T-10	-0.0133	-4.9526***
T-1, T-5	-0.0095	-3.5092***
T-1, T-0	-0.0029	-1.6886*
T+0, T+1	-0.0006	-0.3315
T+1, T+5	0.0036	1.3366
T+6,T+10	0.0050	1.8503*

T+1, T+10	0.0086	2.2535**
T+10, T+20	0.0065	-1.6245*
T+11, T+30	-0.0192	-4.8055***
T+20, T+30	-0.0142	-2.6439***

‘****’, ‘**’, ‘*’significant at 0.001%, .01% and 0.05%

Figure 4. 4AAR and CAAR for Upgraded Rating



4.2.3 Downgrade Rating Announcements

The AAR and CAAR are calculated for downgrade rating announcements and they are reported in the Table 4.19 for different event windows. All the event windows between 30 days before the event and 30 days after the event showed that they are significant except for (T+0, T+1) which are found insignificant. The difference found is statistically significant indicating difference in return at 0.001, 0.01, 0.05 and 0.1 percent level after five days of the event. The market reacted negatively with a downgrade announcement. Figure 4.5 presents the chart of AAR and CAAR for downgraded ratings. Figure 4.6 presents the comparative chart of CAAR for upgraded and downgraded ratings. The result of the study is consistent with results of Choy et al., (2006); and Reddy et al., (2019).

Table 4. 19 CAAR and t-statistic of Downgraded Rating

Downgraded Rating		
Event window	CAR	t-stat
T-30, T-11	-0.0241	-4.2683***
T-30, T-20	-0.0151	-3.6235***
T-20, T-10	-0.0092	-2.2098**
T-1, T-10	-0.0062	-1.5644
T-6, T-10	-0.0054	-1.8993*
T-1, T-5	-0.0009	-0.3131
T-1, T-0	-0.0019	-1.0759
T+0, T+1	-0.0009	-0.5069
T+1, T+5	-0.0054	-1.9199*
T+6,T+10	-0.0061	-2.1679**
T+1, T+10	-0.0115	-2.8905**
T+11, T+30	-0.0101	-2.4228**
T+20, T+30	-0.0118	-2.0937**

‘****’, ‘**’, ‘*’significant at 0.001%, .01% and 0.05%

Figure 4. 5 AAR and CAAR for Downgraded Rating

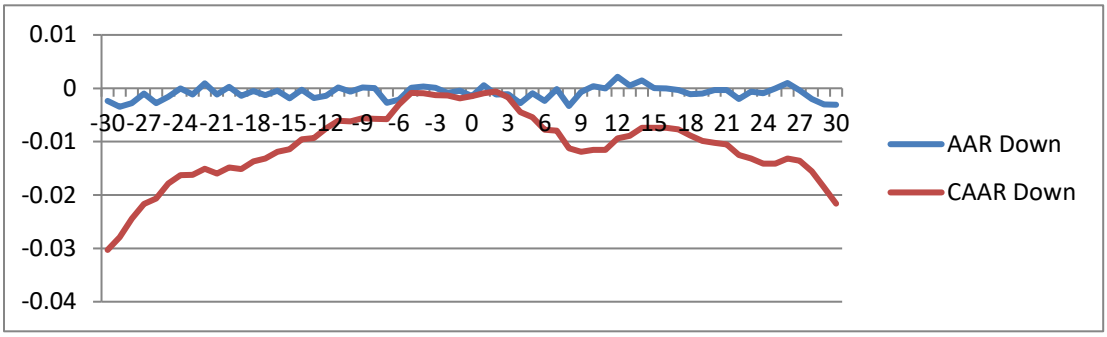
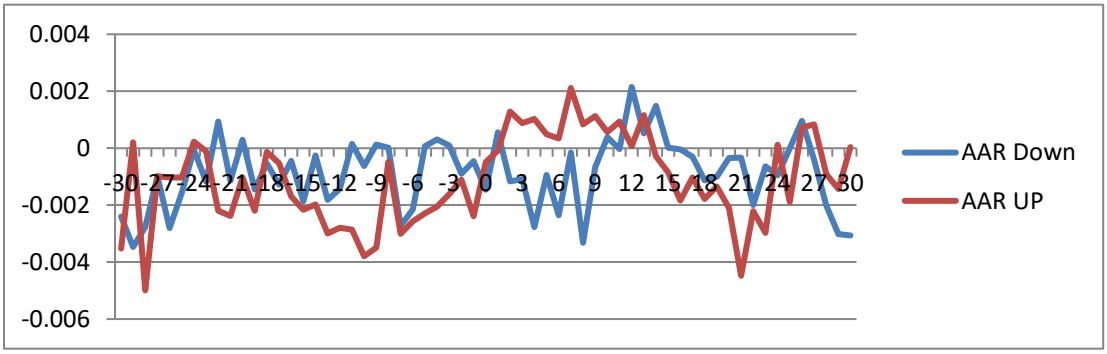


Figure 4. 6AAR and CAAR for Upgraded and Downgraded Rating



4.2.4 Reaffirmed Rating and Rating Watch Announcements

CAAR is calculated for the different event windows for 30 days prior to and after the event. The abnormal return value is not different from zero and it is statistically insignificant for both reaffirmed and rating watch. For event windows (T+0, T+1), the t-statistics are significant, but for all the other event windows they are insignificant for reaffirmed rating. Whereas for rating watch, t-stats for the event windows (T-1, T-5), (T-1, T-0), (T+0, T+1) and (T+1, T+5) are significant. The results are given in table 4.20 and the charts of AAR and CAAR of both reaffirmed rating and rating watch are shown in Figure 4.7 and Figure 4.8. The abnormal return of pre and post-event is negative for both announcements.

Table 4. 20 AAR and t-statistic of Reaffirmed Ratings and Rating Watch

Event Window	Reaffirmed		Rating Watch	
	CAAR	t-stat	CAAR	t-stat
T-30, T-11	-0.0034	-1.6882*	0.0012	0.1481
T-30, T-20	-0.0029	-1.9242*	-0.0050	-0.8252
T-20, T-10	-0.0008	-0.5380	0.0058	0.9498
T-1, T-10	-0.0005	-0.3241	-0.0069	-1.1848
T-6, T-10	-0.0005	-0.5204	0.0001	0.0266
T-1, T-5	0.0001	0.0621	-0.0070	-1.7021*
T-1, T-0	0.0010	1.5587	-0.0060	-2.3206**
T+0, T+1	0.0014	2.1685**	-0.0057	-2.2190**
T+1, T+5	-0.0008	-0.8374	-0.0094	-2.2939**
T+6,T+10	-0.0003	-0.2664	-0.0011	-0.2631
T+1, T+10	-0.0011	-0.7805	-0.0105	-1.8081*
T+10, T+20	-0.0014	-0.9333	-0.0056	-0.9298
T+11, T+30	-0.0018	-1.2082	0.0048	0.7913
T+20, T+30	-0.0006	-0.2843	0.0094	1.1519

‘****’, ‘**’, ‘*’significant at 0.001%, .01% and 0.05%

Figure 4. 7 AAR and CAAR of Reaffirmed Rating

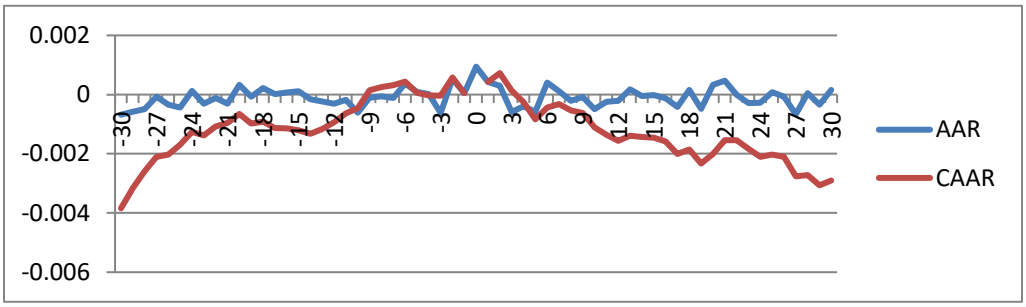
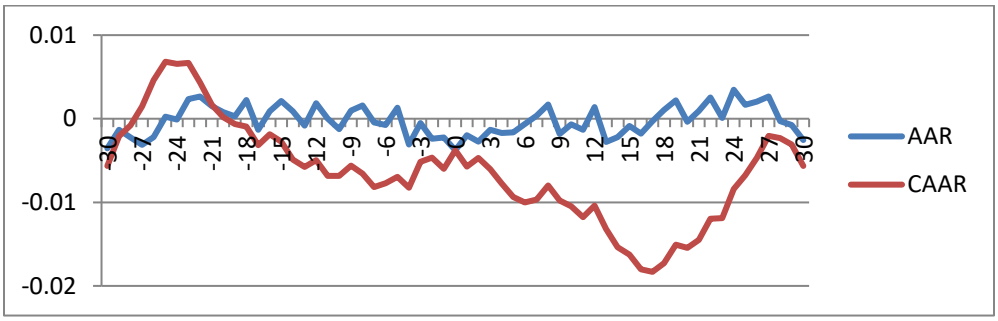


Figure 4. 8 AAR and CAAR of Rating Watch



4.2.5 Suspended and Withdrawn Rating Announcements

CAAR is calculated for the different event windows for 30 days prior to and after the event. The value of abnormal return is equivalent to zero, and it is statistically insignificant for both suspended rating and withdrawn rating. For event windows (T-1, T-10) and (T-6, T-10), t-statistics are significant but for the other entire event windows of suspended rating announcements, the t-statistics are insignificant. Whereas for withdrawn rating, t-statistics for the event windows (T-30, T-11), (T-30, T-20), (T-20, T-10) and (T+11, T+30) are significant. The results are presented in Table 4.21 and the charts of AAR and CAAR for both suspended and withdrawn ratings are shown in Figures 4.9 and Figure 4.10. CAAR shows a positive return for suspended rating and negative for withdrawn rating.

Table 4. 21 CAAR and t-statistic of Suspended and Withdrawn Rating

Event Windows	Suspended		Withdrawn	
	CAAR	t-stat	CAAR	t-stat
T-30, T-11	0.0056	0.2891	-0.0234	-3.2321***
T-30, T-20	-0.0016	-0.1091	-0.0122	-2.2731***
T-20, T-10	0.0049	0.3353	-0.0159	-2.9665***
T-1, T-10	-0.0378	-2.7381***	-0.0061	-1.1863
T-6, T-10	-0.0283	-2.8943***	-0.0046	-1.2671
T-1, T-5	-0.0096	-0.9779	-0.0015	-0.4106
T-1, T-0	0.0022	0.3627	0.0004	0.1702
T+0, T+1	0.0027	0.4385	0.0032	1.3963
T+1, T+5	0.0050	0.5118	-0.0001	-0.0206
T+6,T+10	0.0000	0.0007	-0.0034	-0.9429
T+1, T+10	0.0050	0.3624	-0.0035	-0.6813
T+10, T+20	-0.0058	-0.3972	0.0034	0.6416
T+11, T+30	0.0164	1.1313	-0.0098	-1.8211*
T+20, T+30	0.0232	1.1889	-0.0094	-1.2955

‘****’, ‘**’, ‘*’significant at 0.001%, .01% and 0.05%

Figure 4. 9 AAR and CAAR of Suspended Rating

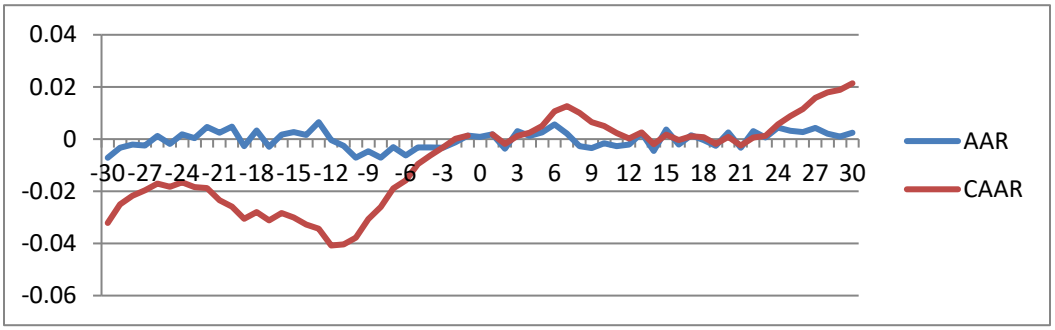
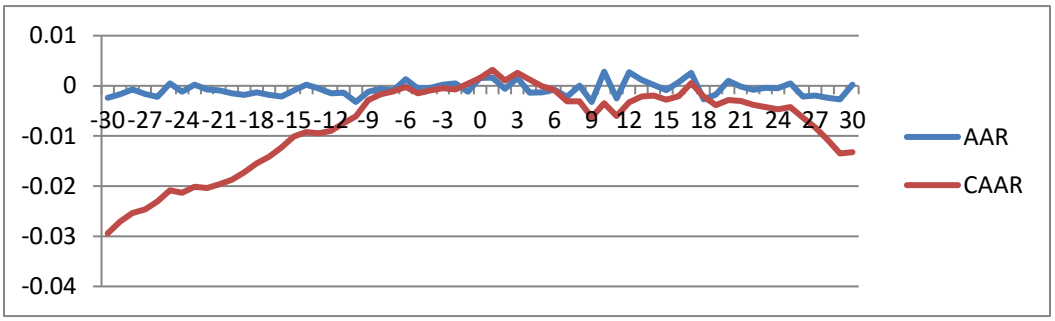


Figure 4. 10 AAR and CAAR of Withdrawn Rating



4.2.6 Investment Grade and Speculative Grade Rating Announcements

The market return is calculated for all the event windows. The abnormal return for one-day post-investment grade rating announcement showed positive return. The cumulative abnormal return is significant for event windows (T+1, T+10), (T+10, T+20), (T+11, T+30) and (T+20, T+30). The difference in returns for the pre and post announcement of investment-grade rating is very less. But the result for speculative rating grade is contradictory to investment-grade rating. The market did not show any reaction to an event. Hence, speculative-grade rating is insignificant for stock return. The results are presented in Table (4.22), and the graphs for CAAR and AAR are given in Figure 4.12 and Figure 4.13 respectively for both investment-grade and speculative-grade ratings.

Table 4. 22 CAAR and t-statistic of Investment Garde and Speculative Grade Rating

Event Window	Investment		Speculative	
	CAAR	t-stat	CAAR	t-stat
T-30, T-11	-0.0069	-3.8278***	-0.0264	-4.1209***
T-30, T-20	-0.0054	-4.0305***	-0.0120	-2.5299***
T-20, T-10	-0.0026	-1.9094**	-0.0147	-3.0976***
T-1, T-10	-0.0033	-2.6145***	-0.0123	-2.7170***
T-6, T-10	-0.0017	-1.9335**	-0.0091	-2.8565***
T-1, T-5	-0.0016	-1.7640*	-0.0032	-0.9859
T-1, T-0	-0.0006	-1.0542	0.0004	0.2143
T+0, T+1	0.0001	0.0925	0.0037	1.8403*
T+1, T+10	0.0021	1.6333*	-0.0028	-0.6119
T+10, T+20	0.0031	2.2874**	-0.0043	-0.9057
T+11, T+30	-0.0058	-4.3603***	-0.0080	-1.6847*
T+20, T+30	-0.0033	-1.8070*	-0.0053	-0.8305

‘****’, ‘**’, ‘*’significant at 0.001%, .01% and 0.05%

Figure 4. 11 AAR and CAAR of Investment-grade Rating

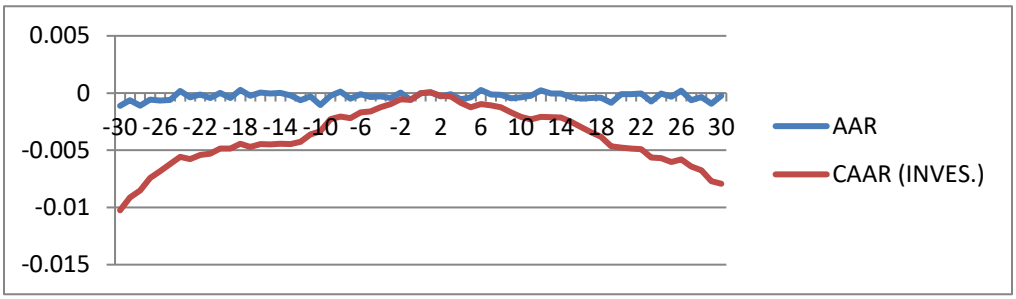
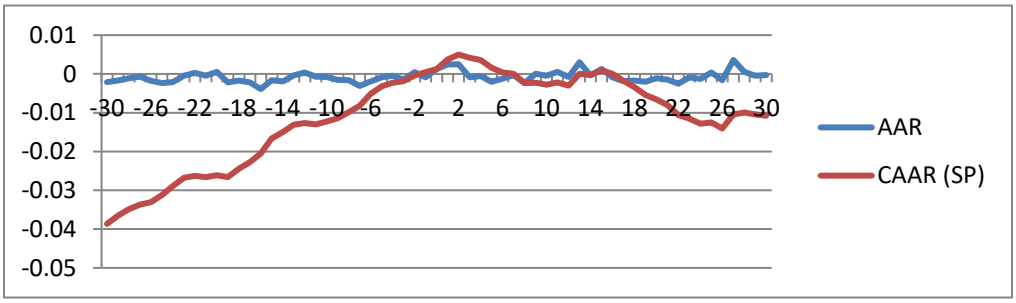


Figure 4. 12 AAR and CAAR of Speculative Grade Rating



4. 3 DISCUSSION

4.3.1 Rating Prediction and Z-score

The variables used to predict rating through ordered probit regression are found significant for the present model. The result showed that predicted ratings for AAA, AA+, AA, and AA- rating grades are less in number compared to actual rating grades provided by CRAs. Whereas the number of rating grades A+, A, A- BBB+, BBB, BBB- and D are more. The results suggest that group I of predicted rating is significant with actual rating. There is a difference between actual rating and predicted rating. The variables used in the model are found to be significant, which are consistent with previous literature (Baghai et al., 2014; Ahn et al., 2019).

The group II of the model has eight rating categories. The result shows that model is significant at 0.001 levels. And the actual ratings are more in AAA, AA, BB and B, whereas the number of A, BBB and D rating grades are more in predicted rating. This shows the leniency of CRAs while rating the default instruments. For Group II (not consistent), the predicted rating is different than the actual rating. Similarly in Group III, the highly-rated ratings (AAA, AA) and moderate safety ratings (A, BBB, BB) are more in actual rating. In contrast, the number of low rated ratings (B, C, D) are more in predicted rating. Hence, the hypothesis of this study is accepted for the predicted and actual rating. There is a difference between actual rating and predicted rating.

Actual rating is compared with the calculated Z-score. The actual rating is divided into three parts to compare with three-zone of Z-score. The result shows that t-statistic is significant at 0.01 percent level and the actual ratings fall more in safe zone whereas according to Z-score more in the distress zone. This is not to suggest that the result showed that the actual rating is wrong. Hence, it would be right to say that some distress zone ratings also have received safe /moderate zone rating.

Rating agencies are engaged in providing rating grades to different instruments. But the ratings provided by CRAs are faulty for few rating grades of bonds. The results suggest that default bonds are rated one or two notches above the default grade whereas other grades are rated one notch above the predicted rating. The Z-score shows more defaults than predicted rating. The default results are consistent with a previous study in the same field (Agarwal and Taffler, 2008). The results contradict with the Alp (2013) for investment-grade rating and speculative-grade rating. Alp (2013) suggested that agencies were strict for investment-grade rating, but the present

study shows that CRAs are lenient for investment-grade ratings, especially for the two upper grades (AAA and A).

The model variables: The results show that the variables: Interest coverage ratio, total assets, debt to PBDITA, Negative debt to PBDITA, rent to total assets and net property, plant and equipment are significant and it is supported by previous studies (Beaver, 1966; Baghai et al., 2014; Vana, 2018; Ahn et al., 2019; Cardarelli, 2020). The other variables: equity ratio, debt ratio, debt to equity ratio, gearing ratio, operating profit, current ratio, retained earnings to total assets, assets turnover, current assets to total assets, operating cash flow to assets are also significant and supported by previous studies (Edmister, 1972; Maher and Sen 1997; Wu et al., 2014; Vana, 2018; Daniel et al.,, 2020; Cardarelli, 2020). However, the results of other variables like quick ratio, working capital ratio, capital to total assets and cash & equivalent to total assets, show that they are insignificant and contradictory to previous studies (Altman 1968; Wu et al., 2014; David, 2018; Bonsal et al., 2019). Apart from all these variables, a new variable is (i.e., size of the Bond issues) is added in the model, which was not yet used in the prediction model. A latest study by Bradford et al., 2019 suggests that a bond's issue's value significantly impacts rating grade. Hence, when bond value is added in the prediction model, it is found to be significant at 0.001 significance level. All other variables are significant at 0.05, 0.01 and 0.001 significance levels shown in Table 4.2, Table 4.7 and Table 4.11 respectively.

4.3.2 Rating Announcement and Impact on Stock Price

Announcement of rating is very sensitive as it provides essential information to the market about instruments. This kind of information should normally affect stock price and stock return in the capital market. A firm needs to borrow money from the market through bonds which are rated by

CRAs. The first rating is called initial rating. This initial rating is later revised according to the performance of a firm and its bonds. If a firm perform better than the expectation of the capital market, its rating is upgraded. Otherwise, it would lead to downgrade rating. However, in a situation where the performance of firm and its bonds are consistent, the same rating is affirmed and as called reaffirmed rating.

The study shows that initial rating grades announcements that fall in investment-grade rating, become significant after six days of the event. The reaction of the market was positive but it was not same for the speculative-grade announcement. The market did not show any response around the events. Hence, the hypothesis for investment-grade rating is accepted whereas for speculative-grade rating the hypothesis is rejected. The market reacted positively after six days of initial investment-grade rating announcement. This result is consistent with the findings of previous studies (Barron et al., 1997; Poon, Chan, & Firth, 2013).

The upgrade of rating is considered as positive information in general for the capital market. The study shows that CAAR reacted positively immediately after the announcement, whereas downgrade rating reacted negatively with the rating. The result of this study is in line with the findings of previous studies (Poornima et al., 2016 and Reddy et al., 2019). The market did not react much with rating watch, reaffirmed rating, suspended rating, and withdrawn rating announcements. Small reactions are observed for rating watch and suspended rating for the event windows (-5, +5). So apart from the windows (-5, +5), all the other windows are found insignificant. Hence, the market did not react with rating announcement and is consistent with the previous study (Poon and Chan, 2008, Agarwal et. al., 2016).

Rating announcements bring new information to the market and affect stock prices. The possible reasons could be; one, the ratings carry internal information of a firm (which is claimed to be CRAs); Two, the ratings does not convey any information, but the announcements has a validation value on the available market information. CRAs claim that they have access to private information of firms and ratings carry new information. The results of initial investment-grade rating, rating upgrade, rating downgrade and investment-grade rating are in line with first reason. Whereas the results of reaffirmed rating, initial speculative-grade rating, withdrawn rating and speculative-grade rating are in line with second reason. However, the cumulative abnormal returns for these announcements are limited, and there are sufficient evidences to show the effect on the market. The results indicate that CRAs carry new information with Initial investment-grade rating, rating upgrade and downgrade. Hence, the information conveyed by the ratings is unknown previously to the market. However, reaffirmed rating, initial speculative-grade rating, withdrawn rating, and speculative-grade rating do not convey new information to the market. Even though results suggest that rating announcements have a minor impact on the stock prices of firms. The results show that CRAs have a significant role in the capital market. Still, before investing, one should look into all the other factors instead of depending on CRAs alone. The results of the study are summarised according to hypotheses below:

- **H_1 : Accepted;** Actual rating grades are higher in number than predicted rating grades.
- **H_{2a} : Accepted**; The number of bonds found in Safe zone under Z-score are lesser than the actual safe rating grades awarded by CRAs
- **H_{2b} : Accepted**; The number of bonds found in distress zone under Z-score are greater than the actual default rating grades assigned by CRAs

- **H_{3a}- Accepted;** The initial investment grade rating associated negatively with CAR is statistically significant.

- **H_{3b} – Rejected;** The result shows that the initial speculative grade rating is statistically insignificant.

- **H_{3c} - Accepted;** The upgrade rating is associated positively with stock return and it is significant.

- **H_{3d}- Accepted;** Downgrade is negatively associated with stock return and it is significant.

- **H_{3e}- Rejected;** Reaffirmed rating is insignificant and it is showed as positive CAR post event.

- **H_{3f}- Accepted;** Rating watch is associated negatively with stock return and it is significant.

- **H_{3g} and H_{3h} – Rejected;** Suspended rating, and Withdrawn rating are statistically insignificant.

- **H_{3h}- Accepted;** Investment grade rating is associated positively with CAR and it is statistically significant

- **H_{3i} – Rejected;** The speculative grade rating is statistically insignificant.

As per CRAs, SEBI and SEC's, the main objective of CRAs is to provide valid opinion on the creditworthiness of the issuers and reduce the information asymmetry between issuers and investors. It is assumed that information gap increases ineffective investment decisions and it

blocks the chance to land good credit. The results of the study are sufficient to prove the information gap. If it exists, the actual rating grade should be reliable and downgrade rating should be done step by step, and the market needs to react with rating announcements. However, results of the first part of the study suggest that rating grades provided by CRAs are a grade or more above the predicted ratings. The results of the second part suggest that stock prices react only for downgrade, upgrade, and initial speculative ratings; and not for all the announcements. However, our logical interpretation of predicted rating result is that all the information of the firms is available in the market. In contrast, results of the second part of the study show that there is an information gap between issuers and investors. Hence, it would be better to say that the investors should look at issuers for all the available information before depending on the ratings.

CHAPTER 5

5. CONCLUSION, LIMITATIONS AND RECOMMENDATIONS

5.1 CONCLUSION

Predicting credit rating of firms could be arrived at using different econometric and statistical tools. Previous studies have used different methods, analysis software and lesser number of variables. Currently, Indian CRAs use twenty categories (including +/-outlook), and actual rating is analysed using different statistical tools and models. Majority of the previous studies have focused on the estimation of rating accuracy provided by CRAs.

The objective of this study is to predict the rating of bonds by using publicly available information. The results of the study have a fairly high accuracy. To achieve the objective of the study, an ordered probit model was used based on financial and economic data provided by issuers to the public every year. The data used for the study is collected from the period 2009 to 2019. It is important to note that if number of years is more, then the repeated variables improve the prediction accuracy. Using an ordered probit model, the study has taken care of the ordinal nature of rating categories.

The independent variables used in the model are issuers' activity, profitability, leverage value, size, cash flow, and liquidity. Ordinal regression is used to check the significance of the model, and the results showed that model is significant at 0.001 percent of the significance level. The study used a new variable called bond size in the model and it is significant at 0.001 level. Predicted rating is found to be conservative for highest safety grades, whereas the frequency of actual rating for highest safety grades is very high in number. Hence, the result suggests that

CRAs are lenient in assigning high-grade rating, and rating can be predicted with publicly available information.

Z-score is calculated for all the issuers whose ratings are already available. Z-score is used widely in the UK and US for predicting the bankruptcy of firms. In this study, z-score is compared with actual rating. Actual rating is categorized into three levels. The result using Z-score to calculate rating suggests that more ratings are found in distress level, whereas in actual rating the more bonds are in for safety level.

The second part of the study examined the impact of rating announcements on stock prices. CRAs announce the different types of rating like Initial, Upgrade, Downgrade, Reaffirmed, Rating Watch, Rating suspended etc for rating instruments. In general, it is perceived that rating carries new information to the market because CRAs use private information of issuers. Hence, the market should react to the rating announcement either positively or negatively according to the type of event. Most of the literature examined the impact of rating change on stock prices, bond prices and capital structure. Some authors have studied the impact of initial rating announcement on stock price. And some authors have studied the impact of rating watch, reaffirmed rating, suspended rating, and withdrawn rating on stock prices. The main objective here is to examine the impact of different rating announcements by CRAs on stock prices.

The result suggests that initial investment-grade rating, rating upgrade, rating downgrade and investment-grade rating are significant. Whereas initial speculative-grade rating, reaffirmed rating and speculative-grade rating are insignificant. Rating watch and withdrawn ratings are significant for specific event windows, i.e., RW for (-5, +5) and withdrawn for (+11, +30). The abnormal return after initial investment-grade rating and rating upgrade is positive. In

comparison, downgrade rating near and after the event has a negative association with the cumulative abnormal return near.

The market reacted positively for Initial investment-grade rating, rating upgrade and investment-grade rating announcements, whereas the market responded negatively for downgrade, withdrawal, and rating watch announcements. These reactions provide evidences that rating carries new information to the market. Contrary to this, there was no reaction by the market for Initial speculative-grade rating, reaffirmed rating, suspended rating, and speculative-grade rating which supported the previous argument that rating did not carry new information. The findings of the study are given below:

- The entities that had distress financial status also received safe rating grades.
- CRAs provide safe rating grades to the default entities.
- Rating Agencies have become liberal in providing high-grade ratings even though the actual values of the instruments are low.
- Sudden changes in bond rating grades occurred due to the liberal nature of CRAs
- Initial speculative grade rating, reaffirmed rating, suspended rating, withdrawn rating and subsequent speculative-grade rating announcements are insignificant and they do not convey any information to the market.
- In predicted rating, grades such as AAA and AA are rare, whereas in actual rating the frequency in which AAA and AA rating grades are awarded is high.
- Initial investment-grade rating is associated positively with cumulative abnormal return and it is significant.

- Initial Investment grade rating, upgraded rating, downgrade rating, rating watch and investment grade rating announcements are significant and informative to the market. These announcements carry new information to the market.
- The data collected and the results of the study show that ratings are positively biased toward the issuers.
- All CRAs who award ratings do not provide informational content to the market.
- The Indian bond market is semi-strong form which is efficient enough to react to some valuable ratings.
- Upgrade rating announcements are associated positively with abnormal return and are significant for stock price.
- Downgrade rating announcements are associated negatively with abnormal return and are significant for stock price.
- Reaffirmed rating announcements showed negative reactions to abnormal return after the event for a few days and are insignificant for stock return.
- Rating watch announcements are associated negatively with abnormal return and are significant for stock price.
- Suspended ratings did not show any reaction to the abnormal return and are insignificant for stock return.
- Withdrawn ratings reported negative to abnormal return after 10 days of the event and are significant for stock price for event windows (+11, +30).
- Investment-grade ratings are associated positively associated with cumulative abnormal return and are significant for stock price.

- Speculative grade ratings did not show any reaction to the abnormal return and are insignificant for stock return.

5.2 Recommendations

The study has contributed to the literature of prediction model and information content of rating in the Indian market. It has also added a variable “bond value” (i.e. size of bond issues) to predict the variables of the model and this step is a contribution to the existing literature on prediction model. None of the studies previously conducted have investigated the effects of bond value/ size of bond issues in rating prediction. This model is used for Indian bond market only, and so it could be extended to other markets. The study started with an objective to study the reasons behind the sudden fall of rating from investment-grade to default. The prediction model revealed that the actual ratings are more in higher grades, whereas predicted rating shows more moderate grades and default grades. The rating predicted through the model for the three groups are categorised on different scales. The study highlighted that for all the groups predicted ratings are stringent to the highest rating grade. The results indicated that actual rating provided by CRAs carries an investment-grade rating, whereas predicted rating carries a speculative-grade rating. This is because of the biased practice of rating shopping. The previous studies on rating in the Indian context also suggest that ratings are biased towards issuers who pay higher fees for ratings. CRAs do not reveal the fees they charge for bond rating. The results clearly indicate that actual ratings are AAA or AA rating but predicted ratings show BBB rating. This shows the bias of CRAs toward the issuers. The same is reported (for) by the default cases explained in the problem statement section of the introductory chapter. Hence, the reason behind the difference in

predicted rating and actual rating can be attributed to rating fees or rewards and private information that were not available for analysis to analysts.

The well-established US-based Z-score model is also used for the study. The result revealed that bonds falling in distress level according to this model are more than actual ratings in distress level. The Z-score is nearer to the predicted rating through OPM. The results of this work have unravelled and shed light on the understanding of rating provided by CRAs. Rating agencies are not doing the work for which were created or established. The results also suggest that investors can use this model to know the creditworthiness of a firm instead of depending solely on CRAs. The researcher has also added to the literature of rating information content in the market. The initial investment-grade rating, rating upgrade, rating downgrade and investment-grade rating announcements carry new information to the market. The study also conducted rating watch and reaffirmed rating analyses which has not been done so far for the Indian bond market. The results of the study showed that reaffirmed rating did not appear to be any significant for abnormal return, so it is not informative to the market. Similarly suspended rating did not appear significant to CAAR and it did not convey information to the market. On the other hand, the results showed that rating watch is significant and informative to the market. Similar to this, suspended rating did not appear significant to CAAR and so not informative to market as well. Likewise, withdrawn rating appears significant near an event and it is informative to the market. This study also conducted the first analysis on the impact of suspended rating and withdrawn rating announcements on stock price.

The results of the study also add to the evidences that CRAs have become charitable in awarding high ratings. The ratings predicted through the financial ratios based model are defined in the methodology chapter. However, the financial ratio based model is criticized for lack of

theoretical foundation. The corporate defaults cannot happen all of a sudden especially for firms with strong profitability and balance sheet. Such sudden collapses are rare and they do not happen without sudden economic and environmental. Despite the widespread criticisms against financial ratio-based model, the model is significant using different statistical tools in practical approach. Also, the ratios of this model are defined by CRAs in their methodologies. The study raised the following questions to the regulators and CRAs- How can the independence autonomy of rating committee be assured? How can conflict of interest for rating agencies be identified, addressed, and disclosed? Should the rating be decided based on a methodology or by a rating committee or by a majority vote of the board directors of rating agencies? Should there be a standard methodology for all CRAs to assign rating grades? The recommendations suggested to regulators, CRAs, investors, and issuers are summarised below:

5.2.1 Recommendations for Regulators

SEBI is the regulator of Indian CRAs. SEBI makes rules and regulations for CRAs. Rating agencies work under the "SEBI (Credit Rating Agencies) Regulation", 1999. The primary objectives of SEBI are to safeguard the right of the investors and monitor stock market activities. But the results of this study are somewhat opposite to the objectives set for CRAs by SEBI. Instead of protecting the investors, CRAs are involved in making profit at the investors' cost. The quality of rating has diminished over the past few decades. The results showed that ratings are biased towards the issuers. The securities rated by Indian CRAs enjoy very high grades. CRAs are making huge profits by charging high fees for ratings and the issuers do not hesitate to offer huge fees to get favourable ratings. This practice has encouraged rating shopping which is not in the best interests of the investors. This has given a negative perception about CR. SEBI should

protect the rights of the investors and properly regulate the rating agencies to ensure quality rating.

CRAs are using their own methods to assign ratings. The different methods used result in different rating grades for the same instrument by different CRAs. This creates confusion among investors about the credibility of an instrument. Therefore, the introduction of a standardised methodology could help investors to trust CR again. Also, CRAs are expanding their businesses with the diversification of their service areas. The additional services offered by CRAs could harm the quality of rating. The regulators need to work on the above stated problem through the results of the study. The study provides few suggestions to the regulators:

- They need to monitor the work ethics of CRAs and tighten the rules.
- To introduce penalties and punitive action to prevent unreliable ratings.
- Discourage the practice of rating shopping as soon as possible
- To tightly regulate or remove the purchase of non-rating services by the issuers from the same CRA to prevent biased ratings and ensure fair ratings.
- To bring in a standard rating methodology.
- To standardise a rating fee depending on the percentage of bond size and also set minimum and maximum fees.
- Regulators can explore the possibility of including the model proposed in the study to assess risk.

5.2.2 Recommendations for Investors

Investors are the pillars of capital market. The investors are dependent on CRAs for the information about the issuer. But this study has revealed that investors are getting punished for

their dependence on CRAs who are providing poor quality rating. The results suggest that investors should look at other information available in the market about the issuers before taking investment decisions. This study provides a model which could help investors in comparing the risks provided by CRAs with rating grade symbol and actual risk hold by securities. The study also suggests that before taking investment decision investors can use the proposed model to know the risks of securities. The recommendations given to the investors based are summarised below:

- Investors should not rely entirely on ratings given by CRAs.
- Investors should also look into other publicly available information apart from rating grades given by CRAs before making investment decisions.

5.2.3 Recommendations for CRAs

CRAs act as mediators between investors and issuers. Their purpose is to protect the investors but the results of the study contradict this role of the CRAs. At the moment, CRAs are driven to make huge profits even at the cost of their reputations by issuing inflated ratings for short term benefits. This behaviour of CRAs has resulted in losses to investors who rely on ratings. CRAs should be fair and transparent in awarding ratings to build the trust of the investors. But as the results of the study suggest CRAs are not transparent. Default disclosure and change in rating should be consistent but in reality it does not happen. The study reveals that ratings given are unreliable and inconsistent. The ratings of few instruments are higher than their actual values. Hence, CRAs need to work on this issue. The practice of awarding high ratings to default zone instruments has harmed the rating industry and even threatened the removal of CRAs from the market.

The rating committee of a rating agency includes CEO, MDs, board members and analysts. Here the analysts play the prime role in awarding rating. The analysts collect all the related information and analyse it, after which they prepare a report and submit to the CEO. The direct reporting of the analysts to CEO can have a negative influence on the quality of rating. The study suggests that instead of reporting to the CEO, the analysts can report straight to the rating committee. Also, there is no quantitative measurement or risk scale used by CRAs. The measurement of risk on numerical metric can improve the transparency of risk associated with each rating grade. CRAs can only give hint about the credibility of instruments without any reliable assessment evidence. Therefore, CRAs should be made accountable for issuing unreliable rating grades. For analysis, CRAs emphasise more on qualitative grades which are again neither reliable nor accurate. Rather they should use quantitative grades. The study presents a few recommendations to CRAs:

- The analysts should report directly to the board members instead of the CEO.
- CRAs should not sacrifice their long-term reputation for short term benefits.
- CRAs should use quantitative scale for each type of risk, and rating should be based on quantitative measures instead of opinions.

5.2.4 Recommendations for Issuers

The results of rating prediction model reveal that issuers are given favourable ratings although they do not deserve. The issuers pay more fees to get inflated rating. Due to this practice, rating announcements did not convey any new information to the market. Reaffirmed rating, rating withdrawal, suspended rating and speculative rating announcement did not convey any new

information. Stock market showed a significant negative reaction for initial investor grade rating. This indicates the negative perception about CR in the market.

In India, either the CRAs approach issuers to give rating business or issuers bargain with CRAs for favourable ratings. The practice of CRAs to assign rating without approaching issuers can help in protecting the interest of the investors. CRAs help in enhancing the reputation of an issuer in the market by awarding high rating grades. A high rating grade means low interest rate and high reputation but a low grade increases the cost of borrowing and decreases an issuer's reputation. However, the present practice of rating shopping and the approach of CRAs of seeking issuers have created a negative perception of CR in the market. A rating issued should always be reliable and accurate for a healthy capital market. Hence, the study recommends that CRAs should stop rating shopping to regain the trust of investors, and issuers should also stop approaching CRAs for favourable ratings.

5.3 Theoretical Contributions to the Study

Previous studies in the same area have highlighted many empirical issues and attempts were also made to address them. Likewise, this study also engaged with issue of predicting rating based on market information. Ordered probit model and Z-score are used to check rating accuracy and event study was used employed to check the impact of rating announcements on stock prices. The core aim in this study was to examine the reliability of rating grades. The reliability was checked by comparing predicted rating and Z-score safety & default zones with actual ratings provided by CRAs. Predicted rating was calculated with the ordered probit regression using publically available information. Also, to check the efficiency of market, event methodology was employed in the study. We have done so by using all the publicly available information.

Accordingly, the first main practical contribution of the present study is that it has provided a rating prediction model for the Indian Bond market. This model can be used further to calculate the risks associated with bonds. Previous studies on rating prediction model were limited to the developed countries. This model can help one to understand default status and also diversify risk in investment. To use this model, one is required to have only basic knowledge of getting financial information of companies/issuers. Prior experience of analysis or financial analytical knowledge not required to use the model. With the help of the proposed model, an investor can know the reliability of ratings provided by CRAs.

The second major contribution of the study is that it has added a new variable to the rating prediction model. The existing model is improved with the addition of bond size issued by the issuer. The rating of different bonds of the same issuers by same the CRAs can be different. Hence, rating grades depend on size of the bond issue and the performance of the bond. This is significant in the proposed model for Indian bond rating.

The last contribution of the present study is that it has provided evidences to prove that Indian stock market is semi-strong one. According to efficient market hypothesis, a market reacts to rating grade announcements. This is possible only when a market is in semi-strong form The results of present study are also supported by a latest research on same area by Xie et al., (2020). The contributions are summarized below:

- Predicted rating model of the bond rating is extended to the Indian market.
- Improved the predicted rating model by adding additional variable, i.e., size of the bond.
- Indian stock market is a semi-strong market.

5. 4 LIMITATIONS

Every research/project conducted by an individual or group has some limitations. The degree and magnitude of the limitations depend on the type of study, methodology employed, study area, nature of data and availability of information. The present study is restricted to the Indian bond market and Indian CRAs. Despite the importance of the study and its contribution to the existing literature, theory, prediction model and impact, it does have some limitations. The study could have been better and it would have been more significant if not for the following reasons:

1. The qualitative variables are not included in the rating prediction model.
2. The sample is limited to the data available in prowessIQ.
3. Only the first rating is considered for the study. Subsequent rating changes could probably have impacted predicted ratings.
4. The study is limited to the Indian bond market. Hence, the results cannot be generalised for other countries or instruments.

5.5 FUTURE SCOPE

The study has revealed a number of interesting and innovative questions. Based on the present study and previous studies on rating prediction, it can be said that this study area has potential for further research. With the available data there is a possibility of improving the model with qualitative variables. This can be done by employing different qualitative variables and using latest analysing software (statistical tools). The present study has presented a holistic result using combined data of all the CRAs. Also there is a probability to examine a result individually for all CRAs. This could help in interpreting the accuracy of rating given by CRAs and the results can

be compared. This will also provide the true working activities of all CRAs separately. The scopes for future research are suggested below:

- The rating model can be used by adding qualitative variables.
- The study can be conducted separately for each CRA, and the result can be compared accordingly.
- Qualitative study can be conducted to understand the impact of the personal relationship between the management teams of issuers and CRAs for biased ratings.

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Appendix A 1.1 Definition of variables

Below table represent the explanations of variable used in the present study. Variables ordered alphabetically

Variables	Explanations
Borrowings	To receive money from another party with the agreement that the money will be repaid.
Capital work-in-progress	Capital work-in-progress is referred to as Assets under Construction and are represented by a specific Asset class. It is an asset on the balance sheet that is not considered to be a final product, but must still be accounted for because funds have been invested toward its production. It is thus a work that has not been completed but has already incurred a capital investment
Cash and cash equivalents	Cash equivalents are short-term, highly liquid investments with a maturity date that was 3 months or less at the time of purchase. In other words, there is very little risk of collecting the full amount being reported. It includes money market accounts U.S. Treasury Bills, commercial paper.
Current Assets	A current asset is an asset that a company holds and can be easily sold or consumed and further lead to the conversion of liquid cash.
Current Liabilities	A current liability, in the accounting context, falls under the broad category of liabilities, which are the financial obligations of a company to another entity. In other words, if a company has partaken in any transaction that has led another entity to have economic or monetary

	expectations from such an organisation, it can be considered as a liability.
Interest expense	Interest expense is the cost of borrowing money during a specified period of time. Interest expense is occurring daily, but the interest is likely to be paid monthly, quarterly, semi-annually, or annually.
Inventories	Inventory is the items that your business has bought with the intention of reselling to customers. The items may be resold without change, or they could be combined into a new product. Inventory refers to all the items, goods, merchandise, and materials held by a business for selling in the market to earn a profit.
Long Term Debt	Also known as long-term liabilities, long-term debt refers to any financial obligations that extend beyond a 12-month period, or beyond the current business year or operating cycle.
Net PPE	Net property plant and equipment (PP&E) are long-term tangible assets that are physical in nature. These are non-current assets that are used in the company's operations for a longer part of the time. They are also called as the fixed assets of the company as it cannot be easily liquidated.
Net sales	Net sales are the portion of a firm's revenues that remain after deducting the allowances for any missing or damaged goods, returns, and the sales discounts. In other words, it's the remaining sales after all returns, discounts, and allowances are removed from the gross number. The gross sales represent the total income a firm earns during a specified period, usually quarter or year, and it includes all the cash, credit card,

	debit card and trade credit sales performed during the period, including the sales allowances and sales discounts.
Net worth	Net worth is the difference between the asset and the liability of a company.
Operating Cash Flow	Operating cash flow or OCF can be simply described as the measure of cash a company generates through its core business operations within a specific time. It helps to analyse if a company is capable enough to generate the required amount of cash flow to maintain and expand its existing business operations.
PBDITA	It is Profit Before Interest, Taxes, Depreciation, and Amortization. The EBITDA metric is a variation of operating income that excludes non-operating expenses and certain non-cash expenses. It is calculated as EBITDA = Net Income + Interest + Taxes + Depreciation + Amortization OR EBITDA = Operating Profit + Depreciation + Amortization
PBIT	It is Profit Before Interest, Taxes. PBIT presents an earning value without the impact of interest and tax rates.
PBT	Profit before tax (PBT) is a line item in the income statement of a company that measures profits earned after accounting for operating expenses like COGS, SG&A, Depreciation & Amortization, etc as well as non-operating expenses like interest expense, but before paying off the income taxes. PBT = Revenue – (Cost of Goods Sold – Depreciation Expense –

	Operating Expense –Interest Expense)
Profit after tax	Profit after tax (PAT) can be termed as the net profit available for the shareholders after paying all the expenses and taxes by the business unit. The business unit can be any type, such as private limited, public limited, government-owned, privately-owned company, etc. Profit After Tax (PAT) = Profit Before Tax (PBT) – Tax Rate
Rent Expenses	Rent expense is an account that lists the cost of occupying rental property during a reporting period. This expense is one of the larger expenses reported by most organizations, after the cost of goods sold and compensation expense. Or *Rent Expense* refers to the cost incurred for the right to use a commercial space or a property belonging to another entity.
Retained profits/losses	A retained profit/loss is a profit/loss incurred by a business, which is recorded within the retained earnings account in the equity section of its balance sheet. The retained earnings account contains both the gains earned and losses incurred by a business, so it nets together the two balances.
Short Term Debt	Short-term debt is the amount of a loan that is payable to the lender within one year. Other types of short-term debt include commercial paper, lines of credit, and lease obligations. The balance in the short-term debt account is a major consideration when evaluating the liquidity of a business. If the proportion of this debt to the amount of liquid assets is too high, an analyst might conclude that the firm is facing a liquidity crisis and so will downgrade its credit rating.

Tangible net worth	Similar to net worth in that it takes into consideration assets and liabilities, your tangible net worth goes one step further and subtracts the value of any intangible assets, including goodwill, copyrights, patents, and other intellectual property. The basic formula for calculating tangible net worth is: Tangible Net Worth = Total Assets - Total Liabilities - Intangible Assets
Total Assets	Assets are defined as resources owned by the company from which future economic benefits are expected to be generated. Total assets are the sum of non-current and current assets, and this total should equal the sum of stockholders' equity and total liabilities combined. Total Assets = Non Current Assets + Current Assets
Total Income	Total Income is a company's total earnings or profit. Net income is calculated by taking revenues and subtracting the costs of doing business, such as depreciation, interest, taxes, and other expenses. The bottom line, or net income, describes how efficient a company is with its spending and managing its operating costs.
Total Liability	Total liabilities are the aggregate debt and financial obligations owed by a business to individuals and organizations at any specific period of time. Total liabilities are reported on a company's balance sheet and are a component of the general accounting equation: Assets = Liabilities + Equity.

APPENDIX A 3.1 Grouping of Rating and Definitions

Rating Grades	Group I	Group II	Group III	Definitions
AAA	1	1	1	Best solvency, lowest risk of in solvency
AA+	2	2		Very good solvency, very low risk of insolvency
AA	3			
AA-	4			
A+	5	3	2	Good solvency, low risk of insolvency
A	6			
A-	7			
BBB+	8	4		Strongly satisfying solvency, low to medium risk of insolvency
BBB	9			
BBB-	10			
BB+	11	5	3	Satisfying solvency, medium risk of insolvency
BB	12			
BB-	13			
B	14	6		Sufficient solvency, higher risk of Insolvency
C	15	7		Barely sufficient solvency, high to very high risk of insolvency
D	16	8		Insufficient solvency, insolvency

APPENDIX A 3.2 Explanation of Ratios Calculated

Below table explained the formula employed to calculate the different financial ratios used in the study

Variable	DEFINATIONS
Rating	Letter grades assigned by CRAs to the instruments/securities. Such as AAA, AA, A……., C, D.
Log Bond	Natural log of size of bond issued by the entities.
Log TA	Natural log of total assets
Interest Cov	Interest coverage ratio is also known as interest coverage, debt service ratio, or debt service coverage ratio. The formula for calculating ICR is: **Interest coverage ratio = EBIT/interest expenses**
Equity Ratio	The equity ratio is an investment leverage or solvency ratio that measures the amount of assets that are financed by owners' investments by comparing the total equity in the company to the total assets. **Equity Ratio = Total Equity / Total Assets** Equity ratio uses a company's total assets (current and non-current) and total equity to help indicate how leveraged the company is: how effectively they fund asset requirements without using debt.
Debt Ratio	Debt ratio is a solvency ratio that measures a firm's total liabilities as a

	percentage of its total assets. In a sense, the debt ratio shows a company's ability to pay off its liabilities with its assets. It is the ratio of sum of Long Term Debt (LTD) and Short Term Debt (STD) and Total Assets
Debt-to-Equity	Also known as leverage ratio that calculates the weight of total debt and financial liabilities against total shareholders' equity. Obtained by dividing the sum of LTD, STD and other debt to shareholders equity i.e., **Debt to Equity Ratio = Total Debt / Shareholders' Equity**
Gearing Ratio	It is the ratio of Total Debt to Tangible Net Worth
Debt-to-Profit	The sum of long- and short-term debt divided by earnings before interest, taxes, depreciation, and amortization; set equal to zero if negative **((LTD + STD) / EBITDA)**
Neg. Debt-to-profit	If Debt-to-profit < 0 the indicator variable assigned 1 else 0
Operating Profit Margin	Operating Profit Margin is the profitability ratio which is used to determine the percentage of the profit which the company generates from its operations before deducting the taxes and the interest and is calculated by dividing the operating profit of the company by its net sales

Net Profit Margin	Net profit margin is calculated by dividing Net Profit by Net Sales
Current Ratio	Current ratio measures the business's ability to pay debts within a year by comparing current assets to current liabilities. It is defined as CA divided by CL
RE-to-Assets	Retained Earnings/Loss Divided by Total Assets
CA-to-Assets	Current Assets Divided by Total Assets
RoABT	Earnings Before Interest and Tax divided by Total Assets
Assets Turnover Ratio	Net Sales Divided by Total Assets
OCF-to-Debt	Operating Cash Flow divided by Total Debt
OCF-to-Assets	Operating Cash Flow divided by Total Assets
Rent-to-TA	Rent expense divided by total assets
PPE-to-TA	Net Plant, Property & Equipment divided by Total Assets

EFFECTIVENESS OF CREDIT RATING: A STUDY OF BOND RATING AND ITS IMPACT ON STOCK PERFORMANCE

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