TIMER
Technology-Information-Management-Entrepreneurship – Review
E-ISSN: 2584-1602

A Study to Analyse Hit Rate of Credit Rating Agencies in India

Dr. Prashant Ubarhande
Assistant Professor
Symbiosis Open Education Society
Pune, Maharashtra, India
&
Dr. Arti Chandani
Professor
Jaipuria Institute of Management
Lucknow, Uttar Pradesh, India

Abstract

The Credit Rating Agencies (CRAs) are commercial enterprises that provide credit ratings. CRAs assess borrowers for their capacity to repay the debt as well as the credit risk associated with these borrowers. Moreover, no credit rating system is 100% perfect, and the actual predictive ability can be fetched from accuracy study vis-à-vis hit rate or default rate. A clear definition is necessary for computing default rates. The default rates may be computed over varying time frames and potentially exposing such computation in accordance with period-selection bias. CRAs compute default rates using the average cumulative default rate approach and weighted marginal default rate method. The credit rates assigned by different CRAs are not strictly comparable. Hence, there exists a scope to analyse the hit rate of different CRAs for same credit category. This study revealed that, there exists significant difference in the groups for higher rating categories such as AAA, AA, and BBB. Since the groups of higher credit category are significantly different from each other, the higher credit rates assigned by different credit rating agencies are not strictly comparable is justified. Also, credit rates below the median rate assigned by different CRAs can be accepted by lenders without further investigation. The future researchers can take this forward by considering the analysis over more CRAs and inclusion of CRAs across the globe.

Keywords: Hit Rate, Credit Rating Agencies, Gini Coefficient, Lorenz Curve, Random Curve, Ideal Curve.

Introduction

The expansion of financial markets provides wide range of investment options to borrowers and investors. Also, if the borrowers have good reputation and brand value, it becomes difficult for investor to choose among the borrowers. Conversely, increasing cases of interest evasions and financial scams in repayment of debt have increased the importance of valuation of the creditworthiness. Therefore, lenders realized the need for a third party assessment, which can independently assess the creditworthiness of borrowers. CRAs can suffice this requirement of

lenders* and meet investor need of such independent assessment of creditworthiness. The primary function of a credit rate is to provide information with respect to credit risk. Investors use this information to access the creditworthiness and process the debt. Credit rates are assigned using a standard rating scale and are independent of the borrower's profile. The need for credit rating system varies for different stakeholders and depend on the aids it offers to the stakeholders to avail these services.

Credit Rating Agencies (CRAs) are commercial enterprises that provide credit ratings for any company or project or programme that requires financing in the form of loan/debt or any other similar way of financing. CRAs differ from the merchant credit agencies, which typically provide general information on corporations. They are also distinct from a credit bureau, which collects information on corporate or individual credit histories. As per National Institute of Securities Markets, it is also not a credit-evaluating agency, such as a commercial bank's credit department. The CRAs assess the borrowers for their capacity to repay the debt as well as the credit risk associated with these borrowers. All credit rating agencies (CRAs) in India are governed as per SEBI (Credit Rating Agencies) Regulations, 1999. This regulation is a part of the 'Securities and Exchange Board of India Act, 1992'. In India, there are seven credit rating agencies (SEBI). Table 1 represents the seven credit rating agencies of India. The Table 1 includes the information about the prefix to be used (abbreviation) before every rate as per SEBI, the parent company or promotor in India, logo of the respective CRA, its establishment year, location of its headquarter and the source of such information.

Indian credit rating agencies (CRAs) are approved by Reserve Bank of India (RBI) and Securities & Exchange Board of India (SEBI). There are seven CRAs approved by both RBI and SEBI in India. Also, for the comparison of these CRAs, various criteria are identified from the available literature in credit rating domain. These criteria include Gini coefficient (Carvalho et al. 2014; Kramer & Posch, 2019), the time taken to assign the credit rate, revision rate (Pasricha et al. 2017), rate of default (Duan & Li, 2021) and median credit rating (Berndt et al. 2018; Li et al. 2021).

In this study an attempt is made to explore the default rate (also termed as hit rate) of different CRAs. A detailed analysis of default rates over one, two and three years is performed to suggest a check point for lenders before approving the debt of their borrowers. Hit rate is a counter study of accuracy and revision rate of CRAs.

Table 1: Credit Rating Agencies in India

S. No.	Credit Rating Agency	Abbreviation / Prefix	Parent Company	Logo	Year of Establishment	HQ
1.	Credit Rating Information Services of India Limited	CRISIL	S & P Global	CRISIL An S&P Global Company	1987	Mumbai
2.	CareEdge Ratings	CARE	--	CareEdge RATINGS	1993	Mumbai
3.	Investment Information & Credit Rating	ICRA	Moody's	ICRA	1991	Gurgaon

* a

	Agency of India Limited					
4.	India Ratings and Research	Ind-Ra	Fitch Group	India Ratings & Research A Fitch Group Company	--	Mumbai
5.	Brickwork Ratings India Pvt. Ltd.	BWR	--	Brickwork Ratings	2008	Bengaluru
6.	Acuité Ratings & Research Limited	Acuité	SMERA	Acuite RATINGS & RESEARCH	2005	Mumbai
7.	Integrated Financial Omnibus Metrics Research of International Corporate Systems	Infomerics	--		2015	New Delhi

Source: Author's Representation

Accuracy of Credit Rating Agencies

Credit rates has the ability to predict the creditworthiness of borrower and default too. Therefore, the ratings and the default rates are correlated to each other. For instance, if a CRA has default rate of 5% in one year, then 5 companies will default out of 100 companies selected as sample. This situation is represented by a random curve, which is in the form of diagonal straight line. Furthermore, if the ratings can perfectly predict the default status of the companies, then the lowest 5 companies should capture all the defaults in this example. The situation of perfect prediction is represented by an ideal curve. Moreover, no credit rating system is 100% perfect. It is to be noted that actual predictive ability lies between random and ideal curve respectively. The curve represents the actual situation, i.e., lies between random and ideal curve, which is referred to as Lorenz curve. Fig 1 represents these curves. These curves can be used to study the accuracy of rates assigned by different credit rating agencies.

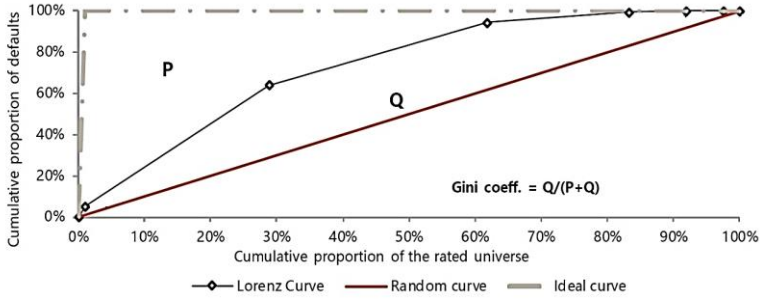


Fig. 1: Lorenz, Random and Ideal Curves
Source: CRISIL

The position of Lorenz curve suggests the accuracy of ratings. The closer Lorenz curve to the ideal curve represents more accuracy of ratings. Also, the accuracy of a credit rating model is measured with the help of Gini Coefficient.
It can be expressed as the ratio of Q (area between the Lorenz and random curves) and P + Q (area between random and ideal curves). Also, from Figure 1 it can be understood that if the value of Q is more, then the Lorenz curve will be near to ideal curve and the model has high accuracy. Gini coefficient ranges between '0' and '1' and if it is closer to '1, it is better.

Fig 2 depicts that CRISIL, CARE, ICRA and Ind-Ra have comparable accuracy. Brickwork has the lowest rating accuracy of 0.32. Gini Coefficient, also called as accuracy ratio, measures the predictive ability of rating. It ranges from 0 to 1, wherein value 1 is the perfect predictor and 0 has no predictive ability. It is to be noted that Ind-Ra is having highest Gini Coefficient of 0.51. However, all other CRAs do have similar coefficient value which indicates the parallel behaviour.

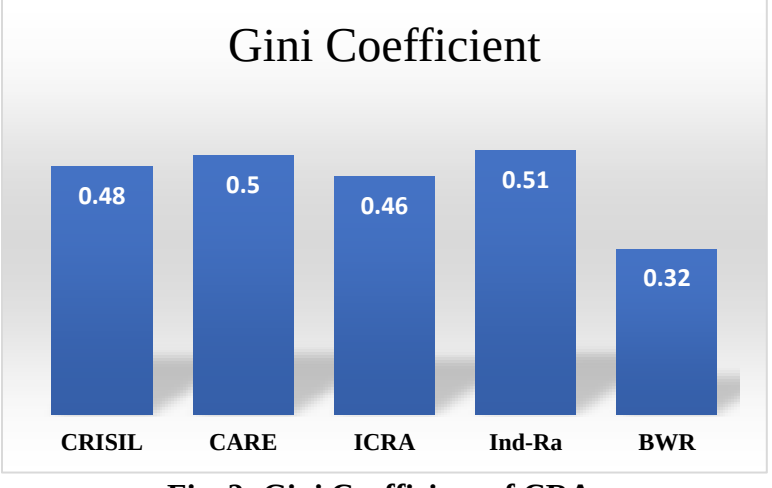


Fig. 2: Gini Coefficient of CRAs
Source: Author's Representation

CRAs have reported that the Covid impact as the major reason for lower accuracy during last three years.

Revision Rate

A rating is an opinion of the rating agency based on data available at the time of evaluation of the company to be rated. However, information can change significantly over time, leading to deviation of the rated company's performance from earlier predictions, affecting future repayment possibilities and necessitating a rating revision. The revision rate of the CRA suggests the rate at which, particular CRA revise the earlier allotted rating due to certain financial event such as payment default or bankruptcy. Rating revisions affect the financial health of the company. Revision in the rating can be either upgrading the existing rating or downgrading the same. Downgrading of credit rating from existing is more important and impacts the capital market more than upgrading (Abad et al. 2019). This study considered the downgrading in the existing rating because downgrading can be used to compare the performance of CRAs (Dawar et al. 2021). Fig 3 represents the revision rate of all CRAs.

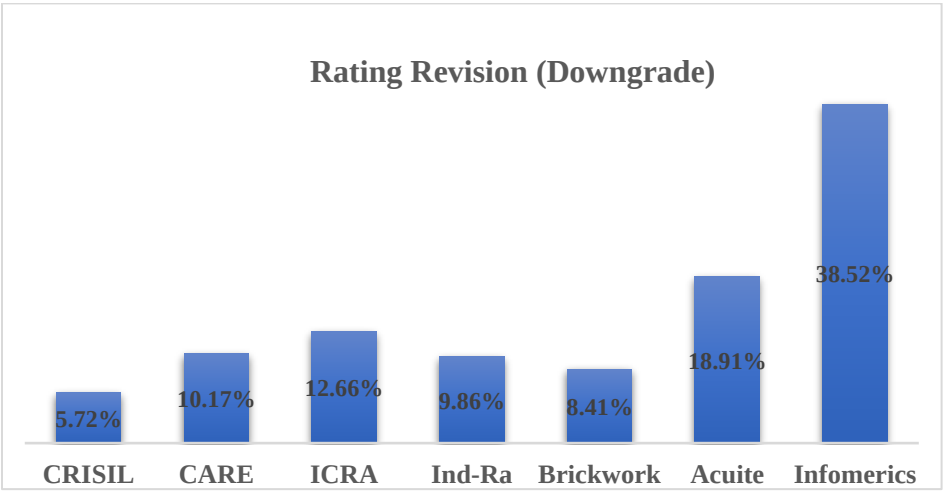


Fig. 3: Revision of Rating (Downgrade) of CRAs
Source: Websites of Credit Rating Agencies, 2021

Infomerics has the highest rating revision as compared to other CRAs of India. Rating revision of the CRA demonstrates the accuracy of rating. It can be understood from Figure 3 that Acuite and Infomerics need to downgrade their ratings more frequently. A downgrade in the rating indicates that the risk of default of the company is higher than what was earlier predicted (SEBI).

Literature Review

Credit Rating Agencies (CRAs) have captured a sizable portion of the attention and glamour in finance domain. Credit rating models cannot predict defaults with 100% accuracy. However, models based on financial data are strong and cannot be replaced (Agarwal & Taffler, 2008). Moreover, the performance of the models can be improved by employing novel methods and implanting relevant data. Subsequently, literature in credit rating domain has been enriched in terms of many innovative methodologies to calculate credit rates. Also, the contribution of CRAs towards structured financial product is limited. In addition to this, dependence on CRAs to determine creditworthiness must be defined by lenders (Tanja et al. 2019). Interestingly, studies have shown that credit rates and tendency to default are inversely proportional (Basil & Elgammal, 2013). To determine creditworthiness, distance-to-default (DD) and probability-of-default (PD) can be compared with total assets (Edmund et al. 2013). Furthermore, to develop credit rating models the methodologies including statistical analysis are common because statistical techniques result in a synergetic output (Thomas, 2000). The seminal literature in the domain of credit rating is given in following table:

Table 2: Seminal Literature in Credit Rating Domain

S. No.	Year	Author(s)	Contribution/Remark
1.	2006	Allen et al. 2006	Companies which defaulted despite having good credit ratings should be further analyzed.

2.	2016	Wu & Wu, 2016	Existing credit rating systems can divide the credit as good or bad. It lacks adequate accuracy in determining creditworthiness of borrowers.
3.	2017	Brocardo et al. 2017	Accurate prediction about creditworthiness is possible if credit rate is based on financial data because the financial data ensures the objectivity.
4.	2019	Guotai & Zhipeng, 2017	Default data can be used as empirical evidence to analyze performance of CRAs.
5.	2020	Chikoore et al. 2020	A method should be accurate in predicting default probabilities.
6.	2021	Pervaiz et al. 2021	Additional verification of rates impacts positively on credit evaluation.

Hit rate or Rate of default for any CRA is defined as the rate at which companies and instruments rated by any CRA defaulted during the period under review. For this analysis, an average rate of default for three years starting 2018 to 2021 is considered. Hit rate or default rate of a CRA is defined as the rate at which companies rated by respective CRA defaulted during any period under study.

The Hit rate represents the number of companies defaulting among rated companies. Also, hit rate is expressed as the percentage of total number of companies rated and it is calculated for each rating category.

Need & Relevance

Analysis of hit rate of different credit rating agencies is performed to study the different meaning a same credit rate carries if it is assigned by different credit rating agency. CRAs compute these credit rates using their own methodology and the weightages to different financial and non-financial factors. Hence, there exists a scope to analyze the hit rate of different CRAs for the same credit category.

This present study intends to reveal that there exists a significant difference in the groups for higher rating categories such as AAA, AA, and BBB. Since the groups of higher credit category are significantly different from each other, the higher credit rates assigned by different credit rating agencies should be reverified. This study shall provide an insight into the fact that higher credit rates assigned by different credit rating agencies should be re-verified.

Objectives

To verify the information of different credit categories and compare different credit rating agencies

To analyze the differences with respect to different credit rating agencies

Methodology

Hit rate of existing credit rating agencies in India is studied by analyzing the rate of default for each category of rating (AAA, AA, etc.) assigned by these agencies over one year, two year and three years. The Fig 4 depicts the methodology carried out for this objective:

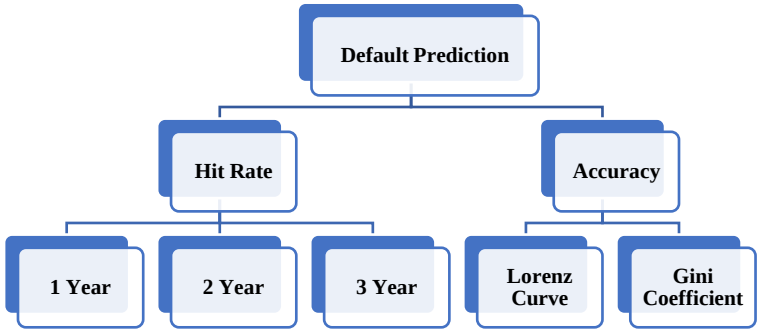


Fig 4: Methodology to Study Hit Rate
(Source: Author's Representation)

To measure default prediction and its accuracy, cumulative accuracy profile (Lorenz Curve) and accuracy ratio (Gini's Coefficient) are studied. In furtherance, to study the hit rate, one-way ANOVA (analysis of variance) has been performed using SPSS thereby the difference in the mean of hit rate is studied and all CRAs were compared for their average default rate called as hit rate for one, two and three years respectively. Also, to study the existing credit rating models proposed in the literature, data from various databases are referred for three financial years (1st April 2018 till 31st March 2021).

Key Variables in Default Rate Computation

Definition of Default: Clear definition of default is quite necessary for computing default rates. For instance, CRISIL Ratings defines default as any missed payment on a rated instrument. It is to be noted that, if a rated debt obligation is not serviced in full by the due date it moves to 'CRISIL D' or an equivalent credit rating. Moreover, credit ratings are opinions on the likelihood of timely repayment of debt and any post-default recovery is not factored into the ratings (CRISIL)

Period of Computation: Default rates can be computed over varying time frames, wherein potentially exposing such computation to understand the period-selection bias. For example, if default rates were published over a period of economic strength, then they would appear to be artificially low and hence, would be of limited use to market participants (CRISIL).

Computation Methodology: Default rates are computed using several methodologies, whereas each one has implications for a numeric outcome. Generally, CRAs such as CRISIL computes default rates using the average cumulative default rate approach and weighted marginal default rate method with a full-year withdrawal adjustment (CRISIL). A 'normalization' of variables should precede any comparison of default statistics across the credit rating agencies (CRAs).

Determinants of Hit Rate

The hit rate of a CRA is calculated for a specific period. Moreover, key determinants of such a hit rate include definition of default, period under consideration and methodology to calculate. A clear definition of default is an important input to determine the hit rate. All credit rating agencies in India categorize defaulted companies as 'D'. The definition of default varies from agency to agency. However, the basis of categorizing any company as a default company is similar i.e., missing payments of debt. Hit rates may be calculated over different time periods as per the policy of CRA. For this study, the hit rate calculated over one, two and three years is considered for analysis. Methodology to calculate the hit rate is common for all CRAs in India and that is cumulative default rate (CDR) approach. CDR is calculated over a period under study such as one, two or three years in this study. CDR is expressed as a ratio of the number of companies defaulting to the number of companies rated at the beginning of the said period (CRISIL).

How are Hit Rates or Default Rates are Used?

The accurate and reliable default rates are critical inputs for all kind of debt market participants' decision, which are as follows:

Pricing Debt: Default rates are the critical inputs in pricing debt instruments or loan exposures. Moreover, default probabilities are associated with ratings, which help the investors and lenders to quantify the credit risk in their debt exposures. Also, to provide inputs on whether and how much to lend, and at what price.

Structuring and Pricing Credit-Enhanced Instruments: The structuring, rating, and pricing of credit-enhanced instruments depend heavily on default rates of the underlying borrowers and securities.

Measuring Credit Risk: Default rates are the key inputs in many quantitative risk assessment models. Moreover, the investors in rated instruments can manage their risk exposures effectively if they have access to reliable default rates.

Indicating Efficacy of The Rating Scale: Credit ratings indicate the probability of default. For instance, if the ratings are reliable, default rates should reduce as one moves up the rating scale. Therefore, default rates can be used to validate rating scales and quantify rating stability.

Hit Rate of CRAs in India

Hit rate published by different CRAs as on financial year ending 31st March 2021 is collected from the websites of respective CRA. Tables 3 to 9 represent the average CDR of different CRAs for one, two and three years.

Table 3: Hit Rate of CRISIL

Rating Category	CRISIL Hit Rate in %		
	One-Year	Two-Year	Three-Year
AAA	0.01	0.07	0.15
AA	0.09	0.25	0.40
A	0.18	0.78	1.50

BBB	0.71	1.91	3.28
BB	2.87	5.57	8.41
B	6.21	11.74	16.03
C	17.25	28.27	36.29

Source: CRISIL

Table 4: Hit Rate of CARE

Rating Category	CARE Hit Rate in %		
	One-Year	**Two-Year**	**Three-Year**
AAA	0.27	0.77	1.43
AA	0.32	1.04	1.54
A	0.53	1.61	3.00
BBB	1.53	3.80	6.03
BB	4.10	7.45	10.32
B	6.56	11.91	15.88
C	25.12	35.12	36.43

Source: CARE

Table 5: Hit Rate of ICRA

Rating Category	ICRA Hit Rate in %		
	One-Year	**Two-Year**	**Three-Year**
AAA	0.10	0.20	0.40
AA	0.10	0.20	0.40
A	0.30	1.10	1.90
BBB	1.70	4.00	6.00
BB	4.50	8.30	11.40
B	6.50	12.00	16.30
C	24.28	35.70	38.47

Source: ICRA

Table 6: Hit Rate of Ind-Ra

Rating Category	Ind-Ra Hit Rate in %		
	One-Year	**Two-Year**	**Three-Year**
AAA	-	0.51	1.06
AA	0.21	0.35	1.71
A	0.22	1.02	2.22
BBB	1.69	5.65	8.91
BB	6.03	9.66	12.03
B	9.82	16.06	18.96
C	42.86	51.24	58.53

Source: India Ratings and Research

Table 7: Hit Rate of Brickwork

Rating Category	Brickwork Hit Rate in %		
	One-Year	**Two-Year**	**Three-Year**
AAA	-	-	-
AA	0.82	1.06	1.29
A	1.11	3.69	6.27
BBB	1.84	4.73	7.62
BB	3.23	6.47	9.71
B	4.39	9.06	13.73

C	23.15	30.33	37.50

Source: Brickwork Ratings

Table 8: Hit Rate of Acuité

Rating Category	Acuité Hit Rate in %		
	One-Year	Two-Year	Three-Year
AAA	-	-	-
AA	0.70	4.20	4.50
A	0.90	1.70	1.90
BBB	1.10	2.90	6.00
BB	1.50	3.90	7.40
B	3.30	8.00	13.80
C	13.80	32.40	57.30

Source: Acuité Ratings

Table 9: Hit Rate of Informerics

Rating Category	Informerics Hit Rate in %		
	One-Year	Two-Year	Three-Year
AAA	-	-	-
AA	6.90	6.15	5.56
A	1.55	1.94	1.93
BBB	0.42	0.42	0.42
BB	2.90	3.61	3.61
B	4.30	4.30	4.30
C	13.04	13.04	13.04

Source: Integrated Financial Omnibus Metrics Research of International Corporate Systems

The hit rate for all seven credit rating agencies given above is collected from the annual reports published by CRAs as per SEBI circular dated 13th June 2019 (SEBI). The tables 10 to 12 gives the year-wise hit rate of different CRAs:

Table 10: Hit Rate of CRAs for One Year

Rating Category	One Year Hit Rate in %						
	CRISIL	CARE	ICRA	Ind-Ra	Brickwork	Acuite	Infomerics
AAA	0.01	0.27	0.10	-	-	-	-
AA	0.09	0.32	0.10	0.21	0.82	0.70	6.90
A	0.18	0.53	0.30	0.22	1.11	0.90	1.55
BBB	0.71	1.53	1.70	1.69	1.84	1.10	0.42
BB	2.87	4.10	4.50	6.03	3.23	1.50	2.90
B	6.21	6.56	6.50	9.82	4.39	3.30	4.30
C	17.25	25.12	24.28	42.86	23.15	13.80	13.04
Average	3.90	5.49	5.35	8.69	4.93	3.04	4.16

Source: Author's Representation

Acuité Ratings has the lowest average hit rate for over one year and Ind-Ra showed the highest hit rate amongst all seven credit rating agencies. Particularly, from the Table 10, it can be concluded that for one-year period CRISIL and Acuité Ratings have the lower hit rate for all the credit categories and India Rating has highest hit rate average of 8.69%.

Table 11: Hit Rate of CRAs for Two Year

Rating Category	Two Year Hit Rate in %						
	CRISIL	CARE	ICRA	Ind-Ra	Brickwork	Acuité	Infomerics
AAA	0.07	0.77	0.20	0.51	-	-	-
AA	0.25	1.04	0.20	0.35	1.06	4.20	6.15
A	0.78	1.61	1.10	1.02	3.69	1.70	1.94
BBB	1.91	3.80	4.00	5.65	4.73	2.90	0.42
BB	5.57	7.45	8.30	9.66	6.47	3.90	3.61
B	11.74	11.91	12.00	16.06	9.06	8.00	4.30
C	28.27	35.12	35.70	51.24	30.33	32.40	13.04
Average	6.94	8.81	8.79	12.07	7.90	7.59	4.21

Source: Author's Representation

Hit rate over the two-year period given in table 11 suggests that Infomerics and India Rating have respectively lowest and highest hit rate average.

Table 12: Hit Rate of CRAs for Three Year

Rating Category	Three Year Hit Rate in %						
	CRISIL	CARE	ICRA	Ind-Ra	Brickwork	Acuité	Infomerics
AAA	0.15	1.43	0.40	1.06	-	-	-
AA	0.40	1.54	0.40	1.71	1.29	4.50	5.56
A	1.50	3.00	1.90	2.22	6.27	1.90	1.93
BBB	3.28	6.03	6.00	8.91	7.62	6.00	0.42
BB	8.41	10.32	11.40	12.03	9.71	7.40	3.61
B	16.03	15.88	16.30	18.96	13.73	13.80	4.30
C	36.29	36.43	38.47	58.53	37.50	57.30	13.04
Average	9.44	10.66	10.70	14.77	10.87	12.99	4.12

Source: Author's Representation

Table 12 suggests that over three-year period, India Rating has the highest hit rate average. Infomerics has the lowest hit rate average for three-year period. India Rating has the highest hit rate over one, two and three-year periods.

Hypothesis & Analysis

Hit rate of all seven credit rating agencies over the period of one, two and three years represents the number of companies defaulted as percentage of total companies rated by respective CRA within one, two and three years respectively. For instance, Acuité Ratings has three year hit rate for AA as 4.50%. This represents that 4.50% of companies rated by Acuité over 10 years has been defaulted within three years of time. It is important to study the hit rates for different CRAs to check the possibility of existence of any relationship between the hit rates of different CRAs and different rating categories.

The Hit rates are calculated by each CRA for different credit rating categories viz. AAA, AA, A, BBB, BB, B and C. All these groups are independent of each other. Therefore, in this

analysis, a parametric test such as one-way ANOVA (Analysis of Variance) is used. Using one-way ANOVA, the difference between means of these rating groups is studied.

Thus, to establish a rationale of this comparison the following hypothesis is constructed:

H_0: There is no significant difference between the hit rate of CRAs.

H_1: There is a significant difference between the hit rate of CRAs.

Hence, to test the above hypothesis, ANOVA or Analysis of Variance is used. The null hypothesis stating no significant differences between the hit rate of CRAs will be rejected if the group mean of hit rate under any credit category is different from overall mean of that credit category. The 'F Test' has been used to determine the significance of differences between the groups, wherein the 'F' value compares the variation in the means of each group to that of variance in the entire group. In this study, the existence of differences between groups represents a property of credit rates assigned by different CRAs indicates that they are not strictly comparable. The table 13 represents the SPSS output of one-way ANOVA.

Table 13: Analysis of Variance - ANOVA

CRAs	Analysis	Sum of Squares	df	Mean Square	F	Significance
AAA	**Between Groups**	0	6	0	7.833	0.001
	Within Groups	0	14	0		
	Total	0.001	20			
AA	**Between Groups**	0.01	6	0.002	19.961	0
	Within Groups	0.001	14	0		
	Total	0.11	20			
A	**Between Groups**	0.002	6	0	1.436	0.0269
	Within Groups	0.003	14	0		
	Total	0.006	20			
BBB	**Between Groups**	0.013	6	0.002	3.191	0.035
	Within Groups	0.009	14	0.001		
	Total	0.022	20			
BB	**Between Groups**	0.005	6	0.001	0.816	0.575
	Within Groups	0.014	14	0.001		
	Total	0.019	20			
B	**Between Groups**	0.026	6	0.004	1.553	0.232
	Within Groups	0.039	14	0.003		
	Total	0.066	20			
C	**Between Groups**	0.098	6	0.016	1.428	0.272
	Within Groups	0.16	14	0.011		
	Total	0.258	20			

Source: SPSS Output

Analysis of variance (ANOVA) output given above advocates that ANOVA is significant for upper credit rates assigned by CRAs. It can also be observed that the test is not significant for the rates below median rating (BB). Therefore, there exists significant difference in the groups for higher rating categories such as AAA, AA, (A) and BBB. Since the groups of higher credit

category are significantly different from each other, the higher credit rates assigned by different credit rating agencies are not strictly comparable is justified. Also, credit rates below the median rate assigned by different CRAs can be accepted by lenders without further investigation.

Observations

ANOVA is significant for the upper credit classes such as AAA, AA and BBB indicating the existence of significant difference between the means of these categories. Therefore, the null hypothesis of non-existence of significant difference is rejected for the higher credit categories and the alternate hypothesis is accepted. Similarly, for lower credit categories—i.e., credit rating below median ratings such as BB, B and C—ANOVA is not significant. The non-significant ANOVA suggests the acceptance of null hypothesis for lower credit categories implying non-existence of significant difference between these groups. ANOVA is reported as non-significant for A credit category.

Suggestions

The present study analysed the hit rate of CRAs, which leads to multiple suggestions to lenders, borrowers, and regulators, which are indicated below:

- Higher credit rates such as AAA, AA and BBB should be further analysed by building an internal evaluation mechanism by the lender.
- Borrowers should check the ratings received by different CRAs for their methodology and the factor coverage.
- Regulators can impose additional verification mechanism if the CRAs are assigning high credit rates.
- The entire study is based on secondary data collected from various websites of different CRAs. Therefore, the future researchers can include the data that are directly available with the regulators for better understanding of CRAs.
- Researchers can take this forward by including the overseas CRAs to understand the global market.

Conclusion

The analysis of CRAs in India reflects a need to develop a default prediction model which provides a basic measure of the creditworthiness of borrowers. The interpretation of ANOVA explains that for the higher credit categories, the lenders should re-verify the credit rates assigned by CRAs. For instance, if a borrower is allotted with AAA or AA rate by different CRAs, then lenders should not completely rely on the same. It has been observed from the results that credit rates of the higher category are comparable. Therefore, an internal assessment system to verify the creditworthiness of borrower with higher credit rates is required. To the contrary, for lower credit categories, lenders can accept these rates assigned by different CRAs as there is no significant difference within the group for such credit category. The present study has attempted to explore the hit rate of different CRAS and its application in financing vis-à-vis debt decisions. Also, this study has led a foundation to analyze the hit rate by studding the hit rate of Indian CRAs.

References

Abad, P., Ferreras, R., & Robles, M.-D. (2019). Informational role of rating revisions after reputational events and regulation reforms. *International Review of Financial Analysis, 62,* 91-103.

Agarwal, V., & Taffler, R. (2008). Comparing the performance of market-based and accounting-based bankruptcy prediction models. *Journal of Banking and Finance, 32*(8), 1541-1551.

Allen, D. E., Powell, R. J., & Singh, A. K. (2006). A dynamic credit ratings model. *Journal of Risk Model Validation, 10*(1), 59-80.

Basil, A., & Elgammal, M. M. (2013). Innovation and credit ratings, does it matter? UK evidence. *Applied Economics Letters, 20*(5), 428-431.

Berndt, A., Douglas, R., Duffie, D., & Ferguson, M. (2018). Corporate credit risk premia. *Review of Finance, 22*(2), 419-454.

Brocardo, M. L., Rolt, C. R. D., Dias, J. D. S., Custodio, R. F., & Traore, I. (2017). Privacy information in a positive credit system. *International Journal of Grid and Utility Computing, 8*(1), 61-69.

Carvalho, P. V., Laux, P. A., & Pereira, J. P. (2014). The stability and accuracy of credit ratings. *SSRN Electronic Journal, 1,* 1-38.

Chikoore, R., Kogeda, O. P., & Ojo. S. O. (2020). Recent approaches to drift effects in credit rating models. *AFRICOMM 2019, 311,* 237-253.

Dawar, G., Bhatia, S., & Bindal, J. P. (2021). Does Credit Rating Revisions Affect the Price of Common Stock: A Study of Indian Capital Market. *Business Perspectives and Research, 0(0).*

Duan, J-C., & Li, S. (2021). Enhanced PD-implied ratings by targeting the credit rating migration matrix. *Journal of Finance and Data Science, 7,* 115-125.

Edmund, A. D., Powell, R., & Singh, A. K. (2013). A dynamic credit ratings model. 20th International Congress on Modelling and Simulation, *MODSIM, 01,* 1291-1297.

Guotai, C., & Zhipeng, Z. (2017). Multi criteria credit rating model for small enterprise using a nonparametric method. *Sustainability, 9(10),* 1-23.

Krämer, W., & Posch, P. N. (2019). Partial orderings of default predictions. In *Applications in statistical computing, 01,* 187-199.

Li, X., Zhang, X., & Zhou, Y. (2021). How do "gatekeepers" affect credit risk? *Journal of Management Science and Engineering*, *6*(3), 295-311.

Pasricha, P., Selvamuthu, D., & Arunachalam, V. (2017, February 10). Markov regenerative credit rating model. *Journal of Risk Finance*, *18*(3), 311-325.

Pervaiz, K., Virglerová, Z., Khan, M. A., Akbar, U., & Popp, J. (2021). Sovereign credit ratings and Asian financial markets. *E+M Ekonomie a Management*, *24*(1), 165-181.

Tanja, V., Riaan, D. J., & Simon, G. (2019). A motivation for banks in emerging economies to adapt agency ratings when assessing corporate credit. *South African Journal of Economic and Management Sciences*, *22*(1), 1-11.

Thomas, L. C. (2000). A survey of credit and behavioural scoring: Forecasting financial risk of lending to consumers. *International Journal of Forecasting*, *16*(2), 149-172.

Wu, H.-C., & Wu, Y.-T. (2016, November). Evaluating credit rating prediction by using the KMV model and random forest. *Kybernetes*, *45*(10), 1637-1651

Webliography

https://www.acuite.in/
https://www.brickworkratings.com/
https://www.careratings.com/
https://www.crisil.com/
https://www.icra.in/
https://www.indiaratings.co.in/
https://www.infomerics.com/
http://www.sebi.gov.in