EFFECTIVENESS OF CORPORATE CREDIT RATING – STAKEHOLDERS' PERSPECTIVE

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CANDIDATE'S DECLARATION

I hereby certify that the thesis titled "Effectiveness of Corporate Credit Rating – Stakeholders' Perspective", submitted in fulfillment of the requirements for the award of the degree of Doctor of Philosophy is an authentic record of my research work. The research has been carried out under the guidance of Dr. Archana Singh and Prof. Rajan Yadav. Any material borrowed or referred to is duly acknowledged.

The matter presented in this thesis has not been submitted elsewhere in part or fully to any other University or Institute for the award of any degree.

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SUPERVISOR'S CERTIFICATE

This is to certify that the thesis titled "Effectiveness of Corporate Credit Rating – Stakeholders' Perspective" submitted to the Delhi Technological University, Delhi-110042, in fulfillment of the requirements for the award of the degree of Doctor of Philosophy in Management, embodies the original research work carried out by Mr. Chandan Sharma under our supervision. The matter presented in this thesis has not been submitted elsewhere in part or fully to any other University or Institute for the award of any degree, to the best of our knowledge.

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EXECUTIVE SUMMARY

Credit Rating Agencies (CRAs) are key participants in the banking and financial system for estimating risk and its location and distribution. CRAs communicate credit rating as an opinion on the credit quality of the underlying instrument or the issuer, which communicates the relative degree of risk associated with the timely payment of interest and principal on a debt instrument. The key stakeholders for credit ratings are – Credit Rating Agencies (CRAs), Investors, Issuers or Corporates, and Regulators. CRAs assist investors in their decision-making as well as facilitate corporates. Through literature review, it was found that from investors' and regulators' perspectives, credit ratings should be objective, accurate, and timely to aid in appropriate decision-making. Forward-looking information incorporated in credit rating changes is also an important consideration for investors. For CRAs', reputation is important, which in turn depends on the credibility of credit ratings. For corporates, a credit rating should help access capital at competitive rates, which would also influence corporate decision-making. However, there have been several past instances due to which credit rating effectiveness has come into question.

Given that credit rating is an essential consideration for different stakeholders, the study focuses on the effectiveness of credit ratings assigned by CRAs. The scope of the study is primarily on Indian credit rating agencies and their credit rating actions. The study focuses on examining the effectiveness of credit rating for investors by investigating the informational value of credit rating changes and whether credit rating changes indicate the future financial performance of a firm. The study utilizes the operating profit as a proxy of future financial performance to understand how it changes following a change in the firm's credit rating. The study finds that a firm's operating profit witnessed a relative decline in the year after a credit rating downgrade, supporting the assertion by CRAs that they incorporate forward-looking and

non-public information about the firm in their credit rating actions. The findings confirm the long-term effectiveness of the credit rating for investors.

The study also investigates the effectiveness of credit rating in enabling investors to manage the short-term risk of abrupt events. The analysis compares the responsiveness of credit rating viz a viz stock prices post unanticipated external events. The study findings allow investors to observe the lack of sensitivity of credit ratings to external shocks and understand the need to be more vigilant in managing sudden risks and not rely solely on credit ratings. It also helps the investor understand the relative responsiveness of stock prices compared to credit ratings due to external events.

The study also examines the factors impacting the effectiveness of credit rating through a literature review. The study finds the competition among CRAs as one of the drivers of issues plaguing the credit rating industry. The study uses quantitative techniques to check the impact of competition on a firm's credit rating. The study finds that CRAs inflate a firm's credit rating due to competition from other CRAs. Rating shopping is also evident in the credit rating industry, driven by competition between CRAs to gain new clients. The study's findings also indicate that increased competition for large-size firms business leads to CRAs showing leniency when rating such firms.

Overall, the study helps researchers understand the importance of credit rating for stakeholders. It demonstrates the effectiveness of credit rating changes for investors as an indicator of future performance. However, the study showcases the credit ratings' inability to react to sudden changes, even if those are of greater significance for corporates. It shows the reduced effectiveness of credit rating due to the competition between CRAs for business. The study highlights the importance of credit rating actions for investors and managers. It enables them to understand the nature and extent of forward-looking information incorporated in a rating

change. The study has implications for regulators and policymakers for actively monitoring and controlling the competition among CRAs to ensure the accuracy of credit ratings.

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ABBREVIATIONS USED

AIG	American International Group	I.T.	Information Technology
AR	Abnormal Return	ICRA	Investment Information and Credit Rating Agency
CAAR	Cumulative average abnormal return	MCRIL	Micro-Credit Ratings International Limited
CARE	Credit Analysis & Research Ltd.	NSE	National Stock Exchange
CDF	Cumulative density function	OLS	Ordinary Least Square
CMIE	Centre for Monitoring Indian Economy	RBI	Reserve Bank of India
CRA	Credit Rating Agencies	SEBI	Securities and Exchange Board of India
CRA Act	Credit Rating Agency Reform Act	SEC	Securities and Exchange Commission
CRISIL	Credit Rating Information Services of India Limited	SMERA	SME Rating Agency
EBITDA	Earnings before Interest, Depreciation and Tax	SOX Act	Sarbanes-Oxley Act
ESMA	European Securities and Markets Authority	TJCA	Tax Cuts and Jobs Act
HAC	Heteroscedasticity and Autocorrelation Consistent	VIF	Variance Inflation Factor

Chapter 1

Chapter 1: Introduction

1.1 Background

Credit rating agencies (CRAs) play an important role in international and domestic financial systems. Although the exact role of CRAs in the domestic financial systems of different countries may differ, in most larger economies, CRAs are crucial participants in the banking and financial system for estimating risk and its location and distribution. CRAs assist investors in decision-making and facilitate corporates in accessing capital at competitive rates. Consequently, CRAs assist in allocating funds efficiently across the economy by pricing risk appropriately [1].

The three major credit rating agencies - S&P Global Ratings, Moody's Investor Service, and Fitch Ratings[2] – account for a dominant market share in global financial markets for credit rating[3,4]. However, apart from the three CRAs, which account for the credit rating of the bulk of international debt issuances and domestic issuance in the large US and European financial markets, other CRAs operate in specific countries that rate the domestic debt issued in those countries. Since the research focuses on India, it delves deeper into Indian CRAs and their effectiveness in Indian financial system. However, the findings highlighted in the research is applicable to other countries as well and this could be taken as future area of research.

1.2 CRAs and the Indian financial system

CRAs have a limited history in India, with the first CRA - Credit Rating Information Services of India Limited (CRISIL) established in 1987. Later, several other CRAs were established: ICRA, CARE, India Ratings, SMERA, MCRIL, Brickwork, and Infomerics.

In India, till 2007, CRAs' activities were restricted to rating corporate bonds and other niche areas. However, In 2007, the Reserve Bank of India (RBI) introduced the Standardized

Approach (SA) of capital computation for banks' credit risk. As a result, most bank loans have come under credit rating. Besides RBI, SEBI (Securities and Exchange Board of India) also regulated CRAs in India. However, RBI regulation pertains to bank loan rating by CRAs, while SEBI regulates CRAs' role in capital markets in India. SEBI mandatorily requires corporates to get credit ratings of debt instruments issued in the Indian capital market.

In India, seven CRAs have been accredited by the SEBI – for assigning credit ratings to domestic capital market issuance by firms[5]. RBI has also accredited these seven rating agencies to assign credit ratings to bank loans[6], which banks utilize for risk-weighting their disbursed loan for capital adequacy purposes. However, the top four agencies (CRISIL, ICRA, CARE, and India Ratings) account for over 88% of the Indian credit rating market.

Table 1.1: Credit Rating Agencies accredited by RBI and SEBI in India

Acuite Ratings & Research Limited
Brickwork Ratings India Private Limited
CARE Ratings Limited
CRISIL Ratings Limited
ICRA Limited
India Ratings And Research Pvt. Ltd. (Formerly Fitch Ratings India Pvt. Ltd.)
Infomerics Valuation And Rating Pvt. Ltd.

Source: SEBI, RBI

1.3 Understanding Credit Ratings

CRAs use an alphanumeric symbol to communicate the credit rating of an instrument. CRAs have standardized rating nomenclatures for instruments such as long-term, short-term, medium-term, fixed deposits, and corporate/issuer credit ratings. In the case of domestic corporate credit rating in India, the nomenclature used by CRAs are - AAA, AA, A, BBB, BB, B, C, and D. AAA represents the category of issuers with the least risk of default. In contrast, D represents issuers that are in default or likely to default soon. Internationally, different CRAs use similar or variations of the above credit rating scale. However, SEBI and RBI have standardized rating symbols and definitions across CRAs [7,8]. Thus, each rating symbol across different CRAs amounts to the same level of credit risk and the same degree of safety related to the issuer's ability to timely service financial obligations. Additionally, the CRAs use modifiers of +/- for some categories to indicate the relative degree of risk within each category. However, the credit risk communicated by a domestic/national rating on the scale is significantly different from an international rating.

Table 1.2: Credit rating scales used by CRAs in India

Long-Term Debt Instruments Scale	Short-Term Debt Instruments Scale
AAA	A1
AA	A2
A	A3
BBB	A4
BB	A5
B	
C	
D	

Note 1: Modifiers {"+" (plus) / "-"(minus)} can be used with the rating symbols for the categories AA to C for long-term instruments and for A1 to A4 for short-term instruments.

Note 2: Rating symbols should have CRA's first name as a prefix

Source: SEBI, RBI

CRAs communicate credit rating as an opinion on the credit quality of the underlying instrument or the issuer. Credit rating communicates the relative degree of risk associated with the timely payment of interest and principal on a debt instrument. Thereby, it can be inferred that the key credit metrics of a firm are one of the main determinants of its credit rating. Credit rating is a relative likelihood of an issuer defaulting on a debt instrument compared to other issuers or instruments in the market. Therefore, it can be used as a measure of relative credit risk. As a result, Credit rating help reduce the information asymmetry faced by investors, thus lowering costs for lenders and borrowers. Investors and other market participants may use the ratings as a screening tool to match the relative credit risk of a debt instrument with their risk tolerance or credit risk guidelines in making investment and business decisions. Table 1.3 shows the definition corresponding to each rating level or symbol used by CRAs. All domestic and international CRAs follow a similar definition regarding the credit risk for each rating level.

Table 1.3: Rating Symbols and Definitions for Long Term Debt Instruments

Rating Symbol	Rating Definition
AAA	Instruments with this rating are considered to have the highest degree of safety regarding timely servicing of financial obligations. Such instruments carry the lowest credit risk.
AA	Instruments with this rating are considered to have a 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 an 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 a 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 a moderate risk of default regarding timely servicing of financial obligations.
B	Instruments with this rating are considered to have a high risk of default regarding timely servicing of financial obligations.
C	Instruments with this rating are considered to have a 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

Generally, credit rating is assigned to a debt instrument, not the issuer. The instrument may be a bond or a bank loan, which the CRA rates. However, the credit rating assigned to the debt also reflects the strength and credibility of the issuer. Therefore, it is generally inferred that the issuer of a high-rated instrument is financially sound. Under the credit rating process, a CRA assesses the debt issuer's credit quality using different information sources.

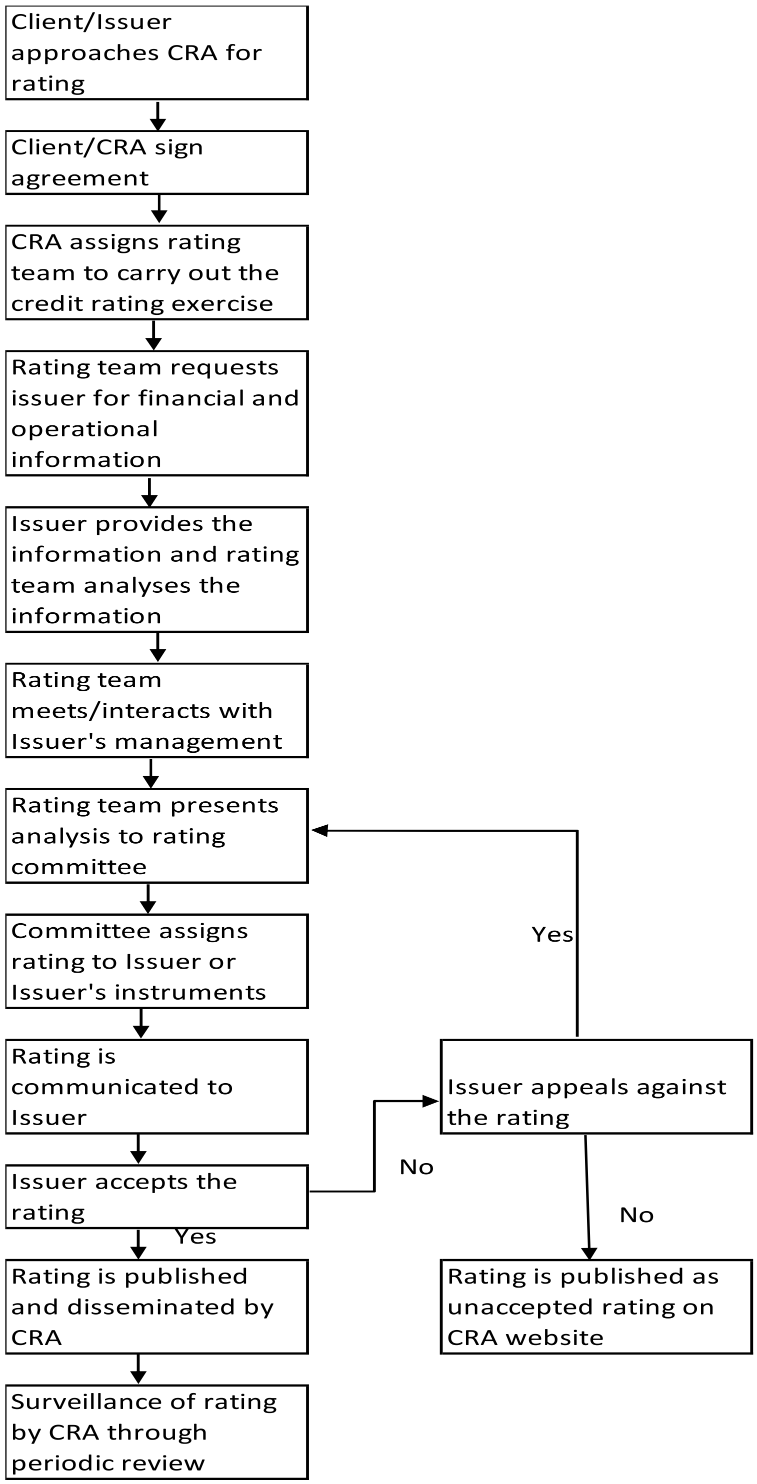
CRAs have specific rating methodologies for rating entities such as non-financial corporates, financial institutions, and public institutions like municipalities, local governments, and sovereign governments [9]. However, the research primarily focuses on the credit rating of non-financial corporates by CRAs, which is more closely related to corporate finance, and also non-financial corporates account for a bulk of CRAs' revenues in India.

1.4 The Rating Process

The credit rating process followed by different CRAs is quite similar. It begins with an entity formally requesting a CRA to assign a rating to the entire entity, a part of its debt, or a new issuance. Once the CRA and the entity agree on the rating exercise, CRA assigns a team of analysts to carry out the rating exercise. The analyst team then coordinates with the entity for the requisite information to carry out the rating exercise. The entity may provide the rating team with material non-public information as part of the rating exercise. In addition, the rating team also has direct access to the senior management of the team and other stakeholders such as bankers and auditors. Based on the information provided, the rating team undertakes necessary due diligence involving the entity's financial, operational, and risk analysis. The rating team presents its analysis to a rating committee constituted by the CRA. The rating committee then finalizes the entity or issuance rating. The finalized rating is communicated to the entity. Once the entity accepts the rating, the rating is published by CRA and disseminated to other stakeholders.

The salient feature of the rating process is that CRAs have access to confidential information and the management of the rated entity and, thus, are in a much better position to determine the creditworthiness of the entity/issuance than a majority of investors. In addition, given a large number of entities/issuances getting rated, the copious amount of information available to investors, and the constantly changing nature of such information, it may become difficult to investors to sift through the entire information and perform the credit risk analysis required for lending to a particular borrower. Thus, the investor dependence on CRAs increases, and CRAs' role in aiding the investor in risk assessment becomes critical. Fig 1.1 shows the overall credit rating process for a CRA.

Figure 1.1: Credit Rating Process



Source: Secondary Research

1.5 CRAs Regulation in India

SEBI and RBI regulate CRAs activities in India. As discussed earlier, SEBI primarily regulates the CRAs' activities related to capital market issuance through the SEBI (Credit Rating Agencies) Regulations, 1999 (CRAs regulations). SEBI has amended the regulations from time to time, depending on the developments and requirements of the Indian financial system. The regulations cover the eligibility criteria of CRAs, and general obligations of CRAs, including code of conduct, disclosure requirement, and accountability. The primary focus of SEBI has been to promote transparency in CRAs working and reduce the conflict of interests and other issues in the credit rating industry.

In India, RBI supervises the use of credit ratings for bank loans. In 2007, RBI made it mandatory for banks to get external credit ratings for loans disbursed to compute risk capital following the Basel II framework [10]. RBI has continued this provision under the Basel III Capital Regulations [11]. Under this regulation, a bank's exposure to a corporate needs to be risk-weighted to calculate capital adequacy requirements. Table 1.4 and Table 1.5 indicate the risk weight applicable to exposure on corporates at different rating levels. It can be seen from Table 1.4 and Table 1.5 that bank has to assign comparatively lower-risk capital for a higher-rated loan, and thus, lending to higher-rated loans is at better pricing. Similarly, higher-rated capital market issuances are considered by investors to be less risky and thus command better pricing.

Table 1.4: Long-term Claims on Corporates – Risk Weights

Long Term Rating	Risk Weight (%)
AAA	20
AA	30
A	50
BBB	100
BB & Below	150
Unrated	100

Source: RBI

Table 1.5: Short-term Claims on Corporates – Risk Weights

Short Term Rating	Risk Weight (%)
A1+	20
A1	30
A2	50
A3	100
A4 & D	150
Unrated	100

Source: RBI

The research focuses on all types of long-term corporate ratings issued by CRAs to achieve the research objectives. In India, ratings assigned by CRAs to different corporate instruments (in the absence of credit enhancement) are the same and depend on the corporate credit risk. Thus, there is no difference in the credit risk of a capital market instrument and a corporate bank loan. In India, bank loans accounted for around 45% of the aggregate debt of non-financial corporates in 2018. The share of capital market issuances accounted for around 38% of the aggregate debt, with promoters, inter-corporate, and foreign currency loans accounting for the remaining debt of non-financial corporates[12]. Thus, bank loans remain the largest source of funding for non-financial corporates. Therefore, this research looks at the credit rating of bank loans and corporate debt issuance to understand the effectiveness of CRAs.

1.6 Issues in the Credit Rating Industry

CRAs' role in the financial system is under constant scrutiny due to investors' and banks' dependence on credit ratings. Investors use the credit rating assigned by CRAs to estimate and mitigate their portfolio risk. An incorrect risk assessment by CRAs could lead to disastrous consequences for affected investors and potentially snowball into a devastating impact on the financial system.

CRAs have faced criticism for being slow to react or foresee the risk in their credit ratings. Although criticism has focused on CRAs' oversight, some have also attributed CRAs' failures to conflict of interest issues plaguing the credit rating industry. In the past, CRAs' mistakes have led to an increased risk to the financial system and put the economic growth of the affected country at peril. Several mistakes by CRAs have caught the attention of investors and regulators and damaged their reputations. The first significant event was that of Enron in 2001, where CRAs downgraded Enron's credit rating by multiple notches, from investment grade to speculative grade, four days before the company filed for bankruptcy[13]. The Enron bankruptcy was the largest in the U.S. until the Worldcom bankruptcy in 2002.

CRA downgraded the credit rating to junk grade 42 days before the bankruptcy filing in the Worldcom case [14]. The size and impact of these bankruptcies led to authorities examining the role of CRAs. CRAs were questioned for being passive and missing the warning signs, despite having access to the company's non-public information and senior management.

Following the Enron and Worldcom debacle, The Sarbanes–Oxley (SOX) Act was passed in 2002. The SOX Act required the Securities and Exchange Commission (SEC) to monitor CRAs' activities. Subsequently, the U.S. Congress passed the Credit Rating Agency Reform Act in 2006 ('CRA Act'). The Act focused on increasing the quality of credit rating by CRAs by increasing competition, transparency, and accountability in the credit rating industry [13]. Following the enactment of the CRA Act, the SEC brought in several regulations to keep a check on CRAs' activities leading to increased compliance and disclosure requirements for CRAs.

However, despite the steps taken, the massive scale of the global financial crisis of 2008 again highlighted that issues plaguing the credit rating industry had remained unresolved. The global financial crisis caused an unprecedented shock to the World economy. It resulted in an estimated USD6-14 trillion loss of output to the US economy alone [15], with a similar impact on other countries.

From 2006-08, CRAs abruptly downgraded subprime structured securities that had been granted AAA rating or a very high investment grade rating [16]. The quantum of the downgrade and its effect could be estimated from the fact that during 2007 Moody's downgraded 83% of USD869bn mortgage securities rated AAA in 2006[17]. Thus, CRAs inflated mortgage-based securities' and their derivatives' credit ratings, leading investors and financial institutions to believe these as safe investments. Besides this, CRAs' delay in downgrading the credit rating of financial institutions with high exposure to these securities and their derivatives drew criticism. CRAs were too slow in downgrading financial institutions such as Lehman Brothers and AIG. AIG rating was kept at the AA rating level till Jan 2008 and then abruptly downgraded to BBB level over 2008-09, despite adequate warning signs in the mortgage-based securities market over 2006-07[18,19]. In the case of Lehman Brothers, CRA rated the company at rating level 'A' till a few days before its bankruptcy in September 2008 [20].

The unprecedented nature and size of the global financial crisis led to another investigation into the role of CRAs by the authorities. Authorities concluded that CRAs' erroneous ratings were a driving force being the financial crisis. CRAs rating methodology or models did not adjust to incorporate the decline in housing prices leading to inflated ratings. In addition, the business model of the industry and the lack of oversight pushed CRAs to assign and maintain skewed ratings to drive up their market share.

The Dodd-Frank Act was passed in 2010 due to authorities' investigation into the financial crisis. The Act created the Office of Credit Ratings at the SEC, giving SEC additional oversight authority, including levying fines and even deregistering CRAs for providing erroneous ratings. It also attempted to decrease investors' reliance on CRAs' ratings and make CRAs more liable for their actions [21]. Similarly, the European Securities and Markets Authority (ESMA) was created in 2011 to monitor CRAs' activities and bring transparency and accountability [2].

In 2013, the U.S. government filed a civil lawsuit against S&P 2013 for defrauding investors by inflating ratings. The lawsuit was settled in 2015, with S&P agreeing to pay USD1.375bn [22]. Similarly, Moody's settled its lawsuits relating to its role in providing credit ratings for mortgage-based securities by agreeing to pay $814mn in settlement charges in 2017 [23]. In 2013, S&P and Moody settled lawsuits related to ratings assigned in the run-up to the financial crisis with investors [24].

Similar issues have arisen in the domestic credit rating market in India. Corporate failures in India have also caught rating companies off guard. Defaults at companies including Amtek Auto, Dewan Housing Finance Corp., Cox & Kings Ltd. Etc. have occurred even though long-term ratings indicated a very low to moderate risk of non-payment [25]. The commonality was a sudden default or severe downgrade of a high-rated entity or instruments in each instance. SEBI has also brought several amendments from time to time in response to the failures of CRAs in India. In 2010, SEBI increased the disclosures, audit, and compliance requirements for CRAs[26]. Similarly, amendments have been brought in by SEBI in 2012, 2016, and 2018 to increase transparency in the working of CRAs and ensure timely action by CRAs. SEBI has also initiated actions against domestic CRAs for erroneous ratings, which the CRAs settled by paying fines[27–29].

1.7 Motivations for the study

Credit rating is an important consideration for different stakeholders enabling the mitigation of individual and systemic risks. However, several instances have raised doubt regarding the effectiveness of credit ratings assigned by CRAs. Thus, it becomes important to understand the effectiveness of credit ratings for stakeholders. Corporates, CRAs, regulators, and investors are the prominent stakeholders of credit rating in the financial system. The study focuses on investors' perspectives, as they are the most important stakeholder in the entire chain, and the primary purpose of credit rating is to aid investors' decision-making.

1.8 The Present Study

The study focuses on achieving its key objectives through an empirical analysis of the credit rating of corporates in India. The study looks at the effectiveness of corporate credit rating as an indicator of future financial performance for investors (long-term) and the effectiveness of credit ratings acting as an early warning signal for investors in the face of sudden shocks/events (short-term). The study also analyses the impact of competition among CRAs on credit rating effectiveness.

1.9 Relevance of the Study

The study contributes to understanding the informational value of credit rating actions of CRAs. The study has implications for investors, analysts, and managers as it analyzes whether credit rating has forward-looking information and whether changes in credit ratings need to be accounted for in decision-making. The study findings have even more relevance in emerging economies where investor disclosures by many firms may be less or absent. The study also investigates how issues in the credit rating industry impact firms' credit rating effectiveness. The study has important implications for regulators and investors. The regulator needs to monitor the issues in the credit rating industry and their impact on rating quality. The study also highlights to investors whether they can rely solely on credit ratings for risk estimation in light of issues in the credit rating industry.

1.10 Thesis Organization

The Thesis has been organized into seven chapters. These chapters are briefly introduced at the beginning of each section.

- Chapter 1: Introduction
- Chapter 2: Literature Review
- Chapter 3: Research Methodology
- Chapter 4: Corporate credit rating as an indicator of future financial performance
- Chapter 5: Corporate credit ratings as an early signal for corporate performance in the face of external events/shocks
- Chapter 6: Impact of competition among CRAs on credit rating effectiveness
- Chapter 7: Conclusion, Implications, and Limitations

Chapter 2

Chapter 2: Literature Review

2.1 Introduction

Credit Rating Agencies (CRAs) allow investors to understand the changing information of many firms. CRAs play a crucial role in helping investors analyze a borrower's credit risk to make more informed investment decisions. However, there has been debate about the informational value of credit ratings, with some researchers pointing to the limitations of credit ratings. CRAs' actions have come under the scrutiny of investors and regulators several times. The main reason for such issues in the rating industry is the issuer-paid revenue model CRAs follow and the competition between CRAs to gain market share and increase revenues. To understand the effectiveness of credit ratings for stakeholders and issues related to competition in the credit rating industry and to identify research gaps, the literature review section has been divided into the following themes:

1. Understanding the effectiveness of credit ratings for stakeholders'
2. Informational value and forward-looking nature of credit ratings with respect to a corporate financial performance
3. Effectiveness of credit ratings as an early signal for corporate performance in the face of external events/shocks
4. Issues in the credit rating industry and the role of competition among CRAs

2.2 Understanding the effectiveness of credit ratings for stakeholders'

Extensive literature has focussed on examining the effectiveness of credit rating for stakeholders. Credit rating guide and influence the decision-making of their stakeholders. Researchers have identified various stakeholders associated with credit ratings and classified them into various groups based on the purpose and scope of their research, focusing on a specific set of stakeholders. In their research, Duff & Einig (2009) focused on four key stakeholder groups to capture credit rating quality[30]: debt issuers, non-issuing financial managers, investors, and other interested parties. Lagner & Knyphausen-Aufseß (2012) classified the stakeholders into four groups – Investors, Issuers, CRA, and regulators – to identify key themes from the literature on the role of ratings[9].

In terms of understanding the effectiveness of credit rating, Bonsall et al. (2015) measured the effectiveness of credit ratings as rating accuracy and how accuracy varies over a period[31]. Roychowdhry & Srinivasan (2019) interpreted effectiveness as the ability of credit ratings to meet their intended objectives[32].

For this study, the effectiveness of credit rating relates to their ability to fulfil their desired role and functions for different stakeholders. The main stakeholders for credit ratings are – Credit Rating Agencies (CRAs), Investors, Issuers, and Regulators. Researchers have found that investors have a strong interest in credit ratings as a source of additional information[28,33]. Credit ratings also act as a signal of the future financial health of firms for investors. Additionally, from investors' and regulators' perspectives, credit ratings should be objective, accurate, timely, and transparent to perform the desired role of risk mitigation [2,30,34,35].

Similarly, CRAs' objective of maintaining and enhancing their reputation depends on whether the investors' objective is effectively met by credit rating[36–38]. From a corporate or issuer perspective, credit rating's influence on corporate decision-making[39–43] can reflect credit rating's effectiveness.

Table 2.1 summarizes the aspects through which researchers measure the effectiveness of credit ratings. It also summarizes stakeholders that researchers have focussed on in recent literature on credit rating. The table also captures key factors that researchers believe impact the effectiveness of credit rating.

Table 2.1: Inferences from recent literature on credit ratings

Year	Paper	Author	Stakeholders' perspective involved	Measure of Effectiveness	Factors impacting Effectiveness
2022	Does competition improve sovereign credit rating quality?	Vu, Huong Alsakka, Rasha ap Gwilym, Owain	CRAs, Investors, Regulators	Rating Objectivity, Accuracy	Competition, Market Share
2021	Stakes Sensitivity and Credit Rating: A New Challenge for Regulators	Booth, Anthony de Bruin, Boudewijn	CRAs, Investors, Regulators	Rating Accuracy, Timeliness	Legal requirement
2021	Negative news and the stock market impact of tone in rating reports	Loffler, Gunter Norden, Lars Rieber, Alexander	Investors	Informational value, forward-looking information	
2021	What moves stock prices around credit rating changes?	Even-Tov, Omri Ozel, Naim Bugra	Investors	Informational value, forward-looking information	
2021	Competition, communication and rating bias	Farkas, Miklós	CRAs, Investors	Rating Objectivity	Issuer-pay business model
2020	Credit rating and competition	Camanho, Nelson Deb, Pragyan Liu, Zijun	CRAs, Investors, Regulators	Rating Objectivity	Competition

Year	Paper	Author	Stakeholders' perspective involved	Measure of Effectiveness	Factors impacting Effectiveness
2020	Peer firms' credit rating changes and corporate financing	Hung, Chi Hsiou D. Naeem, Shammyla John Wei, K. C.	Corporates, CRAs, Investors	Impact on corporate decision making	
2020	Short-term competition and long-term convergence between domestic and global rating agencies: Evidence from China	Tian, Wei Zhou, Xiangyun Tian, Yixiang Meng, Wei	CRAs, Investors, Regulators	Rating accuracy	Regulations, Competition
2019	Rating and capital structure: How do the signs affect the speed of adjustment?	Samaniego-Medina, Reyes di Pietro, Filippo	Corporates, Investors	Impact on corporate decision making	
2019	Do upgrades matter? Evidence from trading volume	Brogaard, Jonathan Koski, Jennifer L. Siegel, Andrew F.	Investors	Informational value, forward-looking information	
2019	The Role of Gatekeepers in Capital Markets	Roychowdhury, Sugata Srinivasan, Suraj	CRAs, Investors, Regulators	Rating Objectivity, Accuracy	Financial reporting quality, Issuer-pay business model
2019	Do analysts really anchor? Evidence from credit risk and suppressed negative information	Ashour, Samar Hao, (Grace) Qing	Investors	Informational value, forward-looking information	
2019	Does competition affect ratings quality?	Bae, Kee Hong Driss, H. Roberts, Gordon S.	CRAs, Investors, Regulators	Rating Objectivity	Competition

Year	Paper	Author	Stakeholders' perspective involved	Measure of Effectiveness	Factors impacting Effectiveness
	Evidence from Canadian corporate bonds				
Year	**Paper**	**Author**	**Stakeholders' perspective involved**	**Measure of Effectiveness**	**Factors impacting Effectiveness**
2019	The effect of reputation shocks to rating agencies on corporate disclosures	Sethuraman, Mani	CRAs, Investors	Rating accuracy, Informational value	CRA Reputation
2019	Bond yield and credit rating: evidence of Chinese local government financing vehicles	Luo, Hang Chen, Linfeng	Investors	Bond Yields	CRA Size
2019	The case for a European rating agency: Evidence from the Eurozone sovereign debt crisis	Altdörfer, Marc De las Salas Vega, Carlos A. Guettler, Andre Löffler, Gunter	CRAs, Investors, Regulators	Rating Objectivity	CRA Reputation
2019	CRA Reputation and Bond Yield: Evidence from the Chinese Bond Market	Hu, Xiaolu Huang, Haozhi Shi, Jing Wang, Hua	CRAs, Investors	Bond Yields	CRA Reputation
2019	Why performativity limits credit rating reform	Stellinga, Bart	CRAs, Investors, Regulators	Rating Objectivity	Regulations
2019	Are inflated domestic credit ratings relative to global ratings associated with peer firms' investment decisions? Evidence from Korea	Oh, Kwang Wuk Kim, Hyun Ah	Corporates, Investors	Impact on corporate decision making	Competition

Year	Paper	Author	Stakeholders' perspective involved	Measure of Effectiveness	Factors impacting Effectiveness
2019	A hard nut to crack: Regulatory failure shows how rating really works	Mennillo, Giulia Sinclair, Timothy J.	CRAs, Investors, Regulators	Rating objectivity	Regulations
2018	Is less information better information? Evidence from the credit rating withdrawal	Salvadè, Federica	CRAs, Investors	Informational value	Issuer-pay business model
2018	Examining the Behavior of Credit Rating Agencies Post 2008 Economic Turmoil	Uslu, Çağrı L.	Investors	Rating Accuracy	Reputation, Financial Crisis
2018	The role of credit ratings on capital structure and its speed of adjustment: an international study	Wojewodzki, Michal Poon, Winnie P.H. Shen, Jianfu	Corporates, CRAs, Investors	Impact on corporate decision making	Financial System
2018	What role does the investor-paid rating agency play in China? Competitor or information provider	Huang, Yu-Li Shen, Chung-Hua	CRAs, Investors	Rating Accuracy	Competition
2018	Are Chinese credit ratings relevant? A study of the Chinese bond market and credit rating industry	Livingston, Miles Poon, Winnie P.H. Zhou, Lei	CRAs, Investors	Bond Yields	Reputation

2017	The potential of conflicts of interest arising in the activities of credit rating agencies in Ukraine	Rebryk, Mykhailo Rebryk, Yuliia Sokol, Sergii Kozmenko, Yevhenii	CRAs, Regulators	Rating Objectivity	Conflict of Interest

2.3 Informational value and forward-looking nature of credit ratings with respect to a corporate financial performance

There has been debate about credit rating's informational value, with some researchers pointing to the limited informativeness of credit rating. Pinches & Singleton (1978) found that rating changes do not convey new information and considerably lag changes in a firm's financial and operational performance[45]. Partnoy (2005) highlighted that CRAs do not provide valuable information and that regulatory licenses drive their importance[46]. Several researchers have raised questions about credit rating quality due to the conflict of interest faced by CRAs because of the issuer-pay business model[2,47].

2.3.1 Credit rating changes and the reaction of stock and bond prices to them

Researchers have highlighted credit ratings' non-public and valuable informational content [48–50]. Credit rating changes will impact the firm's issued instruments only if they contain price-relevant and non-public information unavailable to investors from other sources. Researchers have studied the credit rating's informational value through the impact of credit rating changes on bonds and stock prices.

CRAs state that their ratings are forward-looking opinions on borrowers' credit risk[51,52]. Thus, a change in the borrower's credit risk due to a corresponding change in credit rating can explain the impact on the borrower's bond prices. However, empirical research on the impact of rating changes on bond prices has given mixed results regarding credit ratings' informational value.

Weinstein (1997) found no evidence of an impact on bond prices due to rating change, with any bond price change happening at least 6 to 18 months before the rating change[53], while Katz (1974) found that bond prices reacted to credit rating change with a lag of around two months[54]. Kliger and Sarig (2000) found that credit rating changes contain valuable information regarding the firm, and changes in rating, even though not accompanied by a fundamental change in issuers' risk, impact the firm's debt and equity value[55].

Researchers have also attempted to understand credit ratings' informational value by analyzing the impact of credit rating changes on stock market returns. Some researchers have found that rating upgrades had no impact on stock returns, while downgrades lead to abnormal negative stock returns for stocks listed on the American and European stock exchanges[56,57]. Jorion and Zhang (2007) reported that rating downgrades significantly impact stock returns, but rating upgrades significantly impact stock returns only for lower-rated firms for stocks listed on American stock exchanges[58]. Bissoondoyal-Bheenick and Brooks (2015) drew similar conclusions for stocks of Australian and Japanese stock exchanges[59]. Agarwal et al. (2016) found that the linguistic tone in credit rating action reports has an informational value that can affect stock returns and predict rating changes[60]. Yang et al. (2017) reported that stocks in the Korean stock market witnessed abnormal returns around upgrades and downgrades of credit ratings, but the effect was more pronounced around downgrades[61]. Löffler et al.(2021) suggested that the negative tone of credit rating reports significantly affects the adverse reaction of the stock market to negative news[62]. However, some researchers have found that stock prices react to upgrades and downgrades in credit rating[61,63].

Afik et al. (2014) reported no response in Israel's stock and bond markets following credit rating announcements[64]. Rhee (2015) underlined that credit ratings have little new informational value, and CRAs primarily perform an information sorting function[65].

Kenjegaliev et al.(2016) reported that credit ratings have no informational value, as seen from stock returns of large-capitalized companies in the German stock market[66].

Moreover, CRAs highlight that their rating process involves extensive interaction with the firm's management enabling them to incorporate non-public information into the firm's ratings and provide forward-looking ratings[67–69]. Researchers also show that firm management provides non-public information for credit rating, especially negative information[70,71]. It is evident from the literature that the informational relevance of credit ratings is still an unresolved question, with literature both supporting and questioning this aspect of credit rating. However, assuming rating changes contain forward-looking information, the exact nature of the information is not explicit in the literature.

2.3.2 Nature of information incorporated into credit rating changes

To understand information incorporated in credit rating changes that causes a change in stock prices, one must understand the drivers of stock price changes. The reasons for abnormal stock returns after a credit rating change announcement, as evident from the literature, are 1) investors' expectations due to a change in the cost of capital due to a change in the cost of debt of the firm from the rating upgrade or downgrade and 2) investors' expectations regarding changes in earnings or cash flows of the firm in the future. Goh & Ederington (1999) also suggested that the stock market considers downgrades as providing information on interest cost and future earnings before interest[70]. Chen, Da, and Zhao (2013) have also explained that investors expect changes in the discount rate or cash flows to result in abnormal returns due to a change in credit rating[72].

Researchers have also found that future earnings are the most crucial predictor of stock returns in the long run [73]. This implies that any abnormal stock price reaction to the rating change could be related to an expectation of change in the firm's future earnings by investors. Regarding credit rating changes and their impact on stock prices, several studies have documented the impact of credit rating changes on the cost of borrowing for a firm, which ultimately affects the cost of capital and stock prices of the firm [41,74].

Some researchers have also analyzed the information value of credit rating in relation to earnings forecasts or future performance. Ederington & Goh (1998) highlighted that quarterly earnings reported within a month of bond downgrades witnessed a decline, while there was a negligible change in actual earnings following upgrades[75]. Chou (2013) investigated the informational value in credit ratings in relation to the firm's future earnings and found that stock returns of rated firms better reflect future earnings than non-rated firms[76]. Moreover, the paper found that future earnings are incorporated in stock returns to a greater extent after rating changes. Sharma et al. (2018) reported that a rating downgrade implies deterioration, while an upgrade indicates improvement in an insurer's financial strength[77]. Jeppson et al.(2018) reported that the accuracy of the future earnings forecast of a firm could be determined based on the rating level, with a higher rating meaning low dispersion and a more accurate earnings forecast[78].

2.4 Effectiveness of credit ratings as an early signal for corporate performance in the face of external events/shocks

Extensive research has analyzed the change in stock prices in the short term due to new information/events. There have also been several studies on bond price reactions to external events/shocks. The reaction of stock or bond prices indicates such events' likely impact on firm's future earnings or financial performance or stability. However, there is a lack of literature on how credit ratings react to unanticipated external events.

The earliest study on stock price reaction was conducted by Fama et al. (1969), analysing the information implicit in a stock split[79]. Since then, several studies have analyzed the impact of such external shocks/events on stock prices in the short term. Cummins & Lewis (2003) found that insurance companies' stock prices declined after the World Trade Centre attack[80]. Chesney et al. (2011) found that the airline and insurance industries are more prone to terrorist incidents, whereas the banking industry is less impacted by terrorist incidents but is highly susceptible to financial crashes[81]. Zhang & Sun (2009) highlighted the impact of the financial crisis in the United States on China's and Hong Kong Special Administrative Region's (SAR) stock market[82].

Anoop et al. (2018) found a negative impact of demonetization on the Indian stock market and an asymmetrical impact on different sectors[83]. Jawed et al. (2019) highlighted the positive impact of demonetization on IT/ITES, Pharmaceuticals, and Consumer Durables stocks while significantly negatively impacting the banking and financial services sector[84]. Dharmapala & Khanna (2019) found a significant positive impact on banks and state-owned enterprises[85].

Cayon et al. (2016) found no impact of the global financial crisis on Columbian local bond markets. Similarly, researchers have investigated the impact of different events on bond prices[87–89].

Increased uncertainty leading to a sudden change in investors' mood could explain the immediate impact of such exigencies on the stock market[71]. Understanding the impact of such events could enable investors to predict stock prices in the future[90]. In addition, as highlighted earlier, researchers have also found that future earnings are the most crucial predictor of stock returns in the long run [73]. This implies that any abnormal stock price reaction could be related to expectations of change in the firm's future earnings.

This study looks at three unanticipated events or external shocks to understand the reaction of credit ratings across different sectors following the event. The study also compares credit rating and stock price reactions to look at their relative sensitivity and ability to signal investors about the events' likely impact on corporate performance. As corporate bond trading in India is very illiquid, the study could not analyze bond prices' reactions to these events. Credit rating, stock price and bond price are publicly available proxies for a firm's future corporate performance. The main focus here is to understand whether credit rating and stock price changes are early indicators of a sudden change in a firm's future financial performance driven by unanticipated external factors. The subsequent sections present a brief background on the COVID-19 lockdown, Corporate tax cut, India-China conflict, and related literature review. The reason for taking these three events was that they are rare events likely to impact a country's economy and its corporates significantly. The events have happened in the recent past in India, and limited study is available to understand the impact of such events on corporates.

The first event, COVID-19, as an event, can be considered unique in recent history, with limited parallels available for an external shock that impacted economies worldwide with consequent fallout for companies. The global financial crisis of 2008 had a similar impact on the stock market, but the impact was driven primarily by the liquidity shock caused by the bankruptcies of large banks. However, in the case of infectious disease, the perception created in the public's mind regarding the contagious nature of disease also leads to a drastic reduction in demand in sectors where people-to-people contact is required[91]. COVID-19 uniqueness also stems from the immediate disruption of demand and supply across industries due to the lockdown initiated by countries.

Researchers have conducted several studies to analyze the impact of communicable diseases on impacted countries. Nippani & Washer (2004) studied the impact of the Severe Acute Respiratory Syndrome (SARS) outbreak in 2003 on the stock markets of affected countries and found no impact on two of the eight countries affected, i.e., China and Vietnam[92]. Chun-Da Chen et al. (2009) highlighted the contrasting impact of the SARS outbreak in 2003 on different industries in Taiwan's stock market[93]. Keogh-Brown & Smith (2008) found that the actual economic impact of SARS on affected countries was much less than estimates at the time of the disease outbreak[94]. Garrett (2007) found that the 1918 pandemic led to a short-term negative impact on service and entertainment industries in the US, while healthcare-related businesses witnessed an increase in revenue[95].

Some studies have analyzed the impact of COVID-19 on the global economy. Ali et al. (2020) found a decline in global financial markets and commodities like gold as COVID-19 spread across geographies[96]. However, Chinese markets saw an early recovery due to prompt actions by the government. Liu et al. (2020) found a negative impact of the COVID-19 outbreak on stock markets in 21 countries[97]. He et al. (2020) found a heterogeneous impact of COVID-19 on stocks of different industries in Chinese stock markets[98]. Gössling, Scott, & Hall (2020) looked at the impact of COVID-19 on the global tourism industry and the possible long-term transformation that the industry may undergo[99]. McKibbin & Fernando (2020) analyzed the impact of COVID-19 on the global economy and financial markets[100].

The initial period of the spread of COVID-19 was filled with uncertainties related to the infectious nature of the disease and the likely response required to contain the spread[101].The initial expectation that the vaccine would likely be available after a year further caused panic among investors. The stalling of economic activity due to the lockdown initiated in March 2020 caused varying degrees of disruption across industries in various countries. Thus, the impact of such uncertainty and the lockdown on corporates was likely to be significant.

The second event deals with the tax cut announcement in India. Tax cuts can be a valuable tool to stimulate economic activity[102] and increase capital investment[103]. Changes in tax policies can impact overall firm value and thus impact corporate policies [104]. Corporate tax rates can influence companies' decision-making while evaluating locations to start operations. Other factors being similar across locations, a company will opt for a location with a lower tax incidence. To lower taxes, multinational companies shift their revenues from subsidiaries operating in high-tax countries to subsidiaries in low-tax countries with negligible operations[105,106]. Thus, governments also try increasing competitiveness by decreasing their corporate tax rate and attracting foreign corporations to invest in their countries[107].

As corporate tax rate changes impact future earnings and valuation, companies' stock prices will likely react to such a change[108]. Corporate tax rate cuts have been rare among the world's major economies in the past decade. Thus, limited recent literature analyzes such tax-related events' impact on stock markets. One such event was the U.S. Tax Cuts and Jobs Act of 2017 (TJCA), in which the U.S. government reduced the corporate tax rate to a flat 21%, along with a reduction in individual income tax[109]. Wagner (2018a) studied the impact of TJCA on stocks and found that corporate taxes impacted stock valuations, with highly taxed firms witnessing higher returns in the U.S. stock market, on the expectation of lower corporate tax, before the enactment of TCJA[110]. Kalcheva et al. (2020) found a differential impact of TJCA on the stock returns of companies with different financial leverage and growth prospects in the U.S[111].

Gaertner et al. (2020) studied the impact of TJCA on the different countries' stock markets and found that Indian stock markets experienced a positive return from U.S. tax reform[112]. Overesch & Pflitsch (2021) found that European companies operating in the U.S. witnessed significant positive returns due to the tax cut, while European firms in competition with U.S. firms benefitting from the tax cut witnessed significantly lower returns[113]. Selamat et al. (2017) found that corporate tax changes directly impact firms' share prices in China[114]. However, there is little research exploring the stock market and credit rating reactions to the tax-cut announcements by the Government of India. As the tax cut announcement was unanticipated[115], the research investigates the short-term changes in stock prices and credit ratings in response to the announcement.

On September 20, 2019, the Government of India announced an overhaul of corporate tax rates through the Taxation Laws (Amendment) Ordinance 2019 to make certain amendments to the Income-tax Act 1961 and the Finance (No. 2) Act 2019[116]. The following were the salient features of the amendment related to corporate tax –

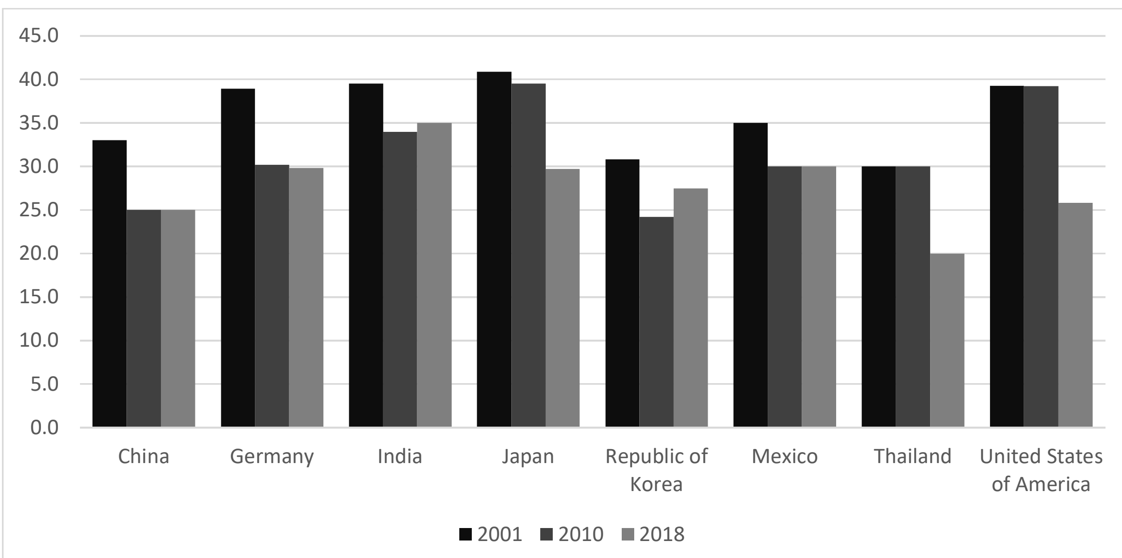
1. The government gave existing companies the option of paying a lower corporate tax rate of 22% with an effective tax rate of 25.17%, including surcharge and cess. However, the companies will have to forego the various exemptions/incentives they were availing of earlier or continue using existing exemptions and pay the older corporate tax rate.

2. The government announced that any new domestic company incorporated on or after October 1, 2019, making new investments in manufacturing and commencing production on or before March 31, 2023, could pay income tax at 15% with an effective tax rate of 17.01%.

The government's main motive behind the corporate tax cut was to attract investment and boost economic growth[117].

These tax reforms were likely to increase India's competitiveness in the global economy[117]. The trade war between U.S. and China, leading to several companies looking for alternatives, also drove the timing of the tax cut announcement. Several countries have taken tax cut measures in the past in order to attract investment. Fig 2.1 shows the trend in the corporate tax rate of selected countries. The data clearly shows that corporate tax rates in India were the highest among the major manufacturing hubs globally, leading to the government announcement on tax cuts, especially after the corporate tax cut announcement in the U.S. in 2017.

Figure 2.1: Trend in Corporate Tax rates in select countries



Source: taxfoundation.org

The third events deal with the potential conflict between China-India following border clashes in 2020. Potential conflicts/wars can create uncertainty about a country's prospects and growth, resulting in an increased risk for investors. Thus, a potential conflict/war will likely impact the nation's financial markets [118]. Understanding market reaction to a potential conflict/war scenario will enable investors to make informed decisions in the future. Several studies have examined the impact of wars or conflicts on the economy or stock market of the nations involved. Amihud and Wohl (2004) observed that the market expectation of the fall of Saddam Hussein had a significant and positive effect on stock prices[119]. Rigobon & Sack (2005) found that the increased risk of war in Iraq in 2003 caused a decline in U.S. stock prices[120]. Schneider and Troeger (2006) observed that the stock market reacted adversely to conflicts/wars[121]. However, certain conflicts that help reduce uncertainty can also result in a positive reaction from stock markets. Kollias, Papadamou, and Stagiannis (2010) examined the impact on Tel Aviv Stock Exchange indices due to Israel's attack on Gaza Strip in 2008 and found that the stock index witnessed significant negative abnormal returns immediately after the attack[122]. Omar, Wisniewski, and Nolte (2017) concluded through analysis of 64 events of international conflict that U.S. and international equities showed a statistically significant abnormal negative return in the period around the conflicts[123]. The research investigates the short-term changes in stock prices and credit ratings in response to the China-India limited conflict.

China and India share a 3,440 KM-long disputed border[124]. Unresolved border issues have been a source of friction between the two countries. However, the border remained largely peaceful over the past four decades until June 2020[125]. With the buildup by the Chinese military near the Line of Actual Control (LAC) from April 2020, the Indian troop buildup also began. Skirmishes along the eastern Ladakh border between the two countries began in the first week of June 2020, culminating in violent clashes on June 15, 2020, which resulted in fatalities for both Indian and Chinese armies. This further increased the tension between the two countries and the possibility of limited military conflict.

2.5 Literature review of issues in the credit rating industry and the role of competition among CRAs

Credit rating by CRAs is mandatory for a corporate to borrow money through capital markets and even from a bank in several countries [126]. Credit rating determines the borrowing rate of corporate[127] and lenders' capital requirements in certain countries[128]. Thus, credit rating plays an essential role in the fair pricing of risk in the financial system. However, large-scale corporate defaults and financial crises have raised questions about CRAs' credit rating accuracy and a possible upward bias in credit rating[31,129,130].

The main reason for issues in the rating industry is the issuer-paid revenue model followed by CRAs and their competition to gain market share and increase revenues. The primary source of revenue for CRAs is the fee receipt for the rating service. The prevalent model in rating markets is the 'Issuer-pays' model, in which the issuer/firm pays CRA to rate the issuer's bond/debt. The issuer-pays model leads to a conflict of interest for the CRAs. CRAs are looking to increase revenue by providing rating services to new debt issuers and gaining more business from existing issuers. The impact of this conflict of interest on CRAs' rating becomes more severe due to other CRAs competing for the same rating business. The conflict of interest and competition could lead to rating inflation, i.e., CRAs assigning higher ratings to firms, which is not commensurate with issuers' creditworthiness and rating shopping, i.e., firms moving from one CRA to another to get better ratings. Several researchers have highlighted that CRAs face a conflict of interest between providing informative ratings to investors and satisfying issuers' rating preferences [2,47,131,132]

2.5.1 Competition among credit rating agencies

The competition among firms operating in an industry is natural in the modern-day economy, where government intervention or control is minimal in businesses. The competition among firms has several benefits, such as higher quality products or services at lower prices for end customers and improved business efficiency [133,134]. However, in the absence of relevant checks in critical industries such as financial systems, unwanted effects of competition can have a contagion effect on the economy. The adverse consequences of the financial industry competition, including the credit rating industry, were seen in the 2008 financial crisis in the U.S., which led to a worldwide economic crisis [135–137]. The research section focuses on the competition among Credit Rating Agencies (CRAs), which are vital in estimating risk in today's financial system.

2.5.2 Impact of competition on the effectiveness of credit rating agencies

Competition among companies is natural in any industry, but unchecked competition in the credit rating industry leads to rating shopping by issuers and inflation of ratings by CRAs[138–140]. The adverse impact of competition among CRAs is visible even in the domestic rating market. Park and Lee (2018) analyzed the Korean domestic rating market and found that CRAs and firms' actions can lower credit rating quality in a competitive market[141]. Singh and Chavan (2020) highlighted that credit ratings sometimes lag the asset quality of borrowers in India, raising concerns about the rating quality of Indian CRAs[142]. The competition could result in CRAs assigning inflated ratings to a firm[143,144] as well as the tendency of firms to do rating shopping, i.e., move from one CRA to another to get a higher rating[145,146].

2.6 Research Gaps

Literature is relatively silent on the exact nature of information incorporated into credit rating changes about the company's future financial performance as measured by a firm's operating profit or earnings. Thus, the first gap that the research focuses on is whether credit rating changes directly convey forward-looking information about a change in a firm's future financial performance.

Existing literature primarily analyzes the information value of credit ratings by investigating stock returns or equity analyst earnings forecasts[61,147,148]. However, there has been minimal research on the information credit rating changes directly incorporate about future financial performance. The research aims to analyze whether credit rating actions by CRAs incorporate forward-looking and non-public information about future financial performance and the nature of such information, if any. The research investigates whether credit rating changes provide investors with crucial information regarding changes in a firm's future earnings or cash flow by analyzing the firm's operating profit a year after the credit rating change.

The second gap that the research focuses on is whether credit ratings and stock prices of firms react to the unique events mentioned earlier in the literature review section. Thus, acting as a warning signal for the investors. As corporate bond trading in India is very illiquid, the author could not analyze bond prices' reactions to these events. The author has not found a detailed study investigating the impact of mentioned events on credit ratings and stock prices of firms in various industries in India.

The third gap that the research focuses on is analyzing the issues of rating inflation and rating shopping among CRAs due to competition in the credit rating industry. Regulators have brought in several changes to address rating inflation by CRAs and rating shopping by issuers. However, despite the regulator's continued focus on improving credit ratings' reliability, the above issues continue in the credit rating industry.

Most researchers have indirectly analyzed the impact of competition on rating agencies. Several researchers have studied the competition among CRAs using a theoretical model with assumptions regarding the credit industry. Bolton et al. (2012) used a model to analyze the impact of competition on credit rating and found that competition reduces efficiency, increases rating shopping, and could result in rating inflation[143]. Camanho et al. (2020) used a theoretical model to analyze competition among CRAs and found that competition exacerbates the rating inflation effect in the credit rating industry[47]. K. Kari Lee & Schantl (2019) used a model to analyze how the dynamics between competition among CRAs and their gatekeeper's role impact rating inflation in the industry[149].

Some researchers have used market share data as a proxy for competition to understand its impact on credit ratings. Vu et al. (2022) used market share data to investigate the impact on sovereign ratings due to competition between CRAs and concluded that competition lowers the quality of the ratings[150]. Flynn & Ghent (2018) reported that incumbent CRAs inflate ratings as the market share of new entrants increases[151]. Becker et al. (2011) used an increase in Fitch's market share to measure increased competition and found that the rating quality of CRAs declined as the market share of Fitch increased[152]. However, Bae et al. (2015) contradicted the above finding and concluded that controlling for unobservable industry effects, there is no linkage between competition measured by Fitch market share and rating inflation[37]. Beatty et al. (2019) found that Moody's and Fitch, following the recalibration of their municipal debt rating scale in 2010, increased the credit rating of municipal bonds without a change in credit quality, resulting in increased market share [144]. However, this study attempts to directly analyze whether competition impacts the rating actions of CRAs by using dual ratings, i.e., multiple CRAs rating a firm as a measure of competition among CRAs.

Chapter 3

Chapter 3: Research Methodology

3.1 Introduction

This chapter of the study outlines the key objectives of the research. The chapter also elaborates on the research design used for the study. The research design explains the sample size and period used to achieve the specific objectives of the research. The statistical model used to achieve a particular objective is specified wherever applicable. The chapter specifies the variables used in each statistical model and highlights past literature where such variables have been used. The chapter also describes the techniques for processing, analyzing and interpreting the data.

3.2 Scope & Objectives of the Study

The scope of the study was primarily on Indian credit rating agencies and their credit rating actions. The study included credit ratings assigned by four major rating agencies – Crisil, ICRA, CARE, and India Ratings. The study was focused on domestic/national credit ratings of non-financial firms in India. The credit rating used in the study represents the Long term rating assigned to the firm's debt, whether bank loan or capital market debt. The instrument's long-term rating is based on the credit risk assessment of the instrument's issuer. The study's main purpose was to analyze the effectiveness of credit rating for stakeholders and how it is impacted due to competition among CRAs. The objectives are as follows:

1. To analyze the effectiveness of corporate credit rating as an indicator of future financial performance for investors
2. To analyze the effectiveness of corporate credit ratings as an early warning signal for corporate performance in the face of external events/shocks
3. To analyse the impact of competition among CRAs on credit rating effectiveness

3.3 Research Design for the Study

3.3.1 Sample for the study

The study used secondary data, primarily corporate credit ratings, stock prices, and financial data, to achieve its objectives. As per each of the objectives, the data points have been customized. The data and methodology employed for each objective are explained in subsequent sections.

3.3.2 Sources of Data for the study

The financial and credit rating data of Indian firms are sourced from the Centre for Monitoring Indian Economy's ProwessIQ Database. Several Indian studies have used the above database [84,153,154]. The data on daily stock prices and Indices have been collected from the National Stock Exchange (NSE) of India Ltd and the Centre for Monitoring Indian Economy (CMIE) – ProwessIQ Database. The data on Index constituents have been collected from the National Stock Exchange (NSE) of India Ltd. The data on firm ownership has been collected from ProwessIQ Database.

3.4 Data and Methodology

3.4.1 Objective: To analyze the effectiveness of corporate credit rating as an indicator of future financial performance for investors

3.4.1.1 Data & Summary Statistics

This objective was fulfilled by utilizing firms' financial and credit rating data. The credit rating used represents the Long term rating assigned to the firm's debt, whether bank loan or capital market debt. If the firm has multiple rating actions in a year, the last credit rating in the year to determine the credit rating action during the year. The instrument's long-term rating is based on the credit risk assessment of the instrument's issuer.

The study period was FY10-FY19, driven by the RBI regulation on bank loan rating coming into effect from FY08 and the availability of relevant data. The sample consists of all firms for which credit rating was available in the database except financial firms during the study period (National Industrial Classification Code 64000-66999). The reason for excluding financial firms is that net interest margin changes primarily drive earnings or cash flows in such companies. Hence, these companies' profitability measures are inherently different from non-financial corporates, as reflected in CRAs' different rating methodologies for financial and non-financial corporates.

Table 3.1: Category Wise distribution of firm-year observations with rating changes

Rating Category	**AAA**	**AA+**	**AA**	**AA-**	**A+**	**A**
No. of Observations	8	30	70	141	205	290
Percentage of Total observations	0.16	0.6	1.39	2.81	4.08	5.77
Rating Category	**A-**	**BBB+**	**BBB**	**BBB-**	**BB+**	**BB**
No. of Observation	381	522	508	506	466	439
Percentage of Total observations	7.59	10.39	10.11	10.07	9.28	8.74
Rating Category	**BB-**	**B+**	**B**	**B-**	**C**	**D**
No. of Observation	283	191	195	111	84	593
Percentage of Total observations	5.63	3.8	3.88	2.21	1.67	11.81

Note: The sample period spans from 2010 to 2019.

The summary of the data taken for the study is shown in Tables 3.1 and 3.2, and summary statistics for the data are shown in Table 3.3. The sample contained 5,023 firm years in which rating changes occurred during the study period. Table 3.1 shows the rating category-wise distribution of firm years in which rating change occurred. 55.4% of total firm-year observations of rating change were related to a rating upgrade. In Table 3.1, an observation falls into a specific category based on its rating following credit rating action. Table 3.2 shows the Year-wise distribution of rating change segregated into upgrade and downgrade. The rating transition observations were equitably distributed across multiple years.

Table 3.2: Year Wise Distribution of firm-year observations with rating changes

	Frequency		Percent	
Year	**Downgrade**	**Upgrade**	**Downgrade**	**Upgrade**
2010	109	54	4.9	1.9
2011	88	217	4.0	7.7
2012	200	194	9.0	6.9
2013	418	161	18.8	5.7
2014	288	336	13.0	12.0
2015	218	544	9.8	19.4
2016	291	462	13.1	16.5
2017	252	360	11.4	12.8
2018	235	325	10.6	11.6
2019	121	150	5.5	5.4
Total	**2,220**	**2,803**	**100**	**100**

Note: The sample period spans from 2010 to 2019.

Table 3.3 shows the summary statistics for the sample. The sample period contained many observations where data points related to relevant variables included in the analysis may not be available. The years in which data were missing for fields required to calculate the variables used in the study's empirical tests had been omitted.

Table 3.3: Year Wise Sample Summary Statistics of firm-year observations

	Leverage*			$NetEBITDA_{it}$*		
Year	**N**	**Mean**	**Std. Dev.**	**N**	**Mean**	**Std. Dev.**
2010	4975	0.001	0.030	2	0.077	0.119
2011	5253	0.417	1.400	4	-0.085	0.137
2012	5765	0.540	1.159	4489	0.019	0.087
2013	5984	0.549	1.005	5405	0.019	0.082
2014	6496	0.608	2.592	5712	0.020	0.084
2015	6491	0.590	5.249	6158	0.014	0.080
2016	6328	0.407	11.355	6163	0.013	0.079
2017	5878	0.605	5.302	5830	0.014	0.080
2018	5046	0.808	26.983	4962	0.013	0.081
2019	3085	0.611	4.747	3079	0.019	0.087

Note: The sample period spans from 2010 to 2019; refer to Table 3.5 for variable definition*

3.4.1.2 Methodology

Under this objective, the aim was to check whether credit rating changes directly convey forward-looking information about a change in a firm's future financial performance. Here, change in profitability was used as a proxy for the firm's future financial performance. It was measured as a change in the firm's EBITDA relative to the firm's assets. EBITDA was taken as a measure of profitability because it is not impacted by interest outflow/cost of capital/financial policy and changes in the firm's tax and depreciation accounting.

The study deployed a two-sample t-test t to compare the future change in operating profit when there was no rating change with cases where the ratings changed (upgraded or downgraded). This was done to check whether there was a significant difference in the mean operating profit change ($NetEBITDA_{it}$; (EBITDAit-$EBITDA_{it-1}$)/Total $Assets_{it-1)}$ of the three groups. For this purpose, Group 1 was firm years, where Dug_dg=0, i.e., when there was no rating change in the previous year, 2) Group 2 firm years, where Ddg = 1, i.e., when the firm saw a rating downgrade in the previous year and 3) Group 3 firms, where Ddg = 1, i.e., when firm saw a rating upgrade in the previous year. The two-sample t-test was conducted year-wise across the sample period.

Pooled time-series cross-section regression was also used to test the hypotheses related to the objective. The study's methodology and approach are similar to several other papers on credit rating explained below [40,155,156].

Kisgen (2006) deployed pooled time-series cross-section regression using Net Debt Issuance ((ΔD_{it} - $\Delta E_{it)}$/A_{it} between time t-1 & t) as the dependent variable. Credit rating categories dummy (related to plus or minus sign) was used as an independent variable with control variables related to firms (Sales (ln($Sales_{i,t-1}$), Profitability ($EBITDA_{i,t-1}/A_{i,t-1}$) and leverage $D_{i,t-1}/(D_{i,t-1} + E_{i,t-1})$)). Kisgen (2009) deployed pooled time-series cross-section using Net Debt Issuance ((ΔD_{it} - $\Delta E_{it)}$/A_{it} between time t-1 & t) as the dependent variable[157]. Change in credit rating (whether upgrade or downgrade) was used as a dummy independent variable with control variables related to firms (sales, profitability, leverage and z-score). Kemper & Rao (2013) extended Kisgen (2006) methodology with a larger sample and introduced another independent variable related to a firm's external financing needs[156,157].

In the regression deployed to test the objective, Net Debt Issuance (ΔD_{it} - $\Delta E_{it)}$/A_{it} between time t-1 & t as dependent variables, dummy variables related to credit rating changes (downgrade or upgrade) were used as independent variables, while control variables were related to the firm's sales, leverage, and profitability. The firm-specific characteristics were controlled using control variables similar to prior research [155,156,158–160]. The definitions of dependent, independent, and control variables are summarized in Table 3.4. The explanatory variable was winsorized at their 1% and 99% percentiles to eliminate outliers. Several other papers have done the winsorization of data [161–164]. The informational content of credit rating change was tested across rating categories and sample years to confirm the findings further.

Table 3.4: Variable Definitions

Variables	Formula	Definitions
Dependent Variable		
$NetEBITDA_{it}$	$(EBITDA_{it}-EBITDA_{it-1})/$ Total $Assets_{it-1}$	$EBITDA_{it}$ = Earnings before Interest, Depreciation and Tax for firm i at time t Total $Assets_{it-1}$ = total assets for firm i at time t-1
Independent Variable		
D_{ug}	Value of 0 or 1	dummy variable for firms that have received a upgrade in credit rating in year t-1
D_{dg}	Value of 0 or 1	dummy variable for firms that have received a downgrade in credit rating in year t-1
D_{ug_dg}	Value of 0 or 1	dummy variable for firms that have received a upgrade or downgrade in credit rating in year t-1
Control Variable		
Leverage	(Total $Debt_{it-1}$)/ (Total $Debt_{it-1}$ + $Equity_{it-1}$)	Total $Debt_{it}$ = book long-term debt plus short-term book debt for firm i at time t-1 $Equity_{it}$ = book value of shareholders' equity for firm i at time t-1
Profitability	$(EBITDA_{it-1})$/ (Total $Assets_{it-1}$)	$EBITDA_{it-1}$ = Earnings before Interest, Depreciation, and Tax for firm i at time t-1 Total $Assets_{it-1}$ = total assets for firm i at time t-1
Size	$\ln(Sales_{it-1})$	$Sales_{it-1}$ = Sales for firm i at time t-1
K_{it-1}	a*Leverage + b*Profitability +c*Size	Represents set of control variables for firm i at time t-1

3.4.1.2.1 Pooled time-series cross-section regression

Regression analysis studies the dependence of a dependent variable on one or more explanatory variables to estimate the value of a dependent variable in terms of independent variables. In pooled regression, the data has elements of both time series and cross-section data.

The ordinary least square regression could be applied in the absence of heteroscedasticity, autocorrelation, and multicollinearity in the data. However, in the case of large samples, using robust standard errors such as White's heteroscedasticity-consistent standard errors take care of heteroskedasticity, while HAC (heteroscedasticity and autocorrelation consistent) standard errors, such as Newey-West standard errors, take care of both heteroskedasticity and autocorrelation in the data [165]. The presence of multicollinearity in the data can be tested using the Variance inflation factor (VIF).

3.4.1.2.2 Two sample t-test

A t-test is used to compare the means of two groups. It can be used in hypothesis testing to determine whether two groups are different from one another. If the groups are derived from a single population, a paired t-test is used. However, If the groups come from two different populations, a two-sample t-test is used.

To test the difference between these two groups using a t-test, null and alternative hypotheses are used, which are as follows:

- The null hypothesis (H0) is that the difference between group means is zero.
- The alternate hypothesis (Ha) is that difference is different from zero.

It may be noted that as per central limit theorem distribution of sample means approximates a normal distribution as the sample size gets larger (n>30), regardless of the population's distribution.

3.4.2 Objective: To analyze the effectiveness of corporate credit ratings as an early signal for corporate performance in the face of external events/shocks

3.4.2.1 Data & Summary Statistics

Under this objective, the focus was on understanding the impact of certain events on companies using credit ratings and stock prices. As corporate bond trading in India is very illiquid, the study could not analyze bond prices' reactions to these events. For Event 1, Credit rating changes of companies in the NIFTY 500 Index, which credit rating agencies in India have rated, were investigated. The changes in these companies' credit ratings were analysed from the event day to six months after the event. The reason for taking only six months was that the objective focussed on whether credit ratings act as an early indicator of the impact of such sudden events on corporates. Nifty 500 companies were grouped into 19 sectors, as per the classification by NSE, to determine whether credit ratings witnessed change across sector companies due to these external events.

In order to analyze the reaction of stock prices, sample data consisted of the daily adjusted closing price of stocks between 01 May 2019 and 30 September 2020 on NSE and an industry-wise analysis of stock price reactions of companies of Nifty 500 was conducted. The Nifty 500 represents the top 500 companies based on full market capitalization from companies listed on NSE and meeting specific liquidity criteria. Table 3.5 shows these companies grouped into 19 sectors as per the classification by NSE[166].

Table 3.5: Industry Classification of Nifty 500 Companies

S.No	Industry	Number of Firms	Percentage of Total
1	Automobile	29	5.9
2	Cement & Cement Products	15	3.1
3	Chemicals	22	4.5
4	Construction	29	5.9
5	Consumer Goods	72	14.7
6	Fertilisers & Pesticides	12	2.5
7	Financial Services	81	16.6
8	Healthcare Services	7	1.4
9	Industrial Manufacturing	48	9.8
10	IT	23	4.7
11	Media & Entertainment	11	2.2
12	Metals	21	4.3
13	Oil & Gas	18	3.7
14	Paper	2	0.4
15	Pharmaceuticals	41	8.4
16	Power	13	2.7
17	Services	29	5.9
18	Telecom	7	1.4
19	Textiles	9	1.8

Source: National Stock Exchange of India Limited

For Event 2, the impact of corporate tax announcements on companies' credit rating and stock returns in different industries, which are part of the Nifty 100 Index, was analysed. NIFTY 100 Index consists of the top 100 companies representing significant sectors of the Indian economy, accounting for 76.8% of the free-float market capitalization of the stocks listed on the NSE[167]. The changes in the credit rating of rated companies in Nifty 100 for six months following the event date were analysed. The data for stock prices were collected from 1 August 2018 to 31 December 2019. The financial data for companies taken for tax rate analysis was for FY19. As per the classification by NSE[167], the Nifty 100 index constituents were classified into 17 industries. However, industries with only one company in the Nifty 100 index were grouped into the Miscellaneous industry group. Table 3.6 shows these companies grouped into a total of 14 industry groups.

Table 3.6: Industry-Wise Classification of Nifty 100 Companies

S.No	Industry	Percentage of Firms
1	Automobile	9.1%
2	Cement & Cement Products	5.1%
3	Construction	2.0%
4	Consumer Goods	16.2%
5	Financial Services	20.2%
6	IT	6.1%
7	Metals	7.1%
8	Oil & Gas	8.1%
9	Pharmaceutical	11.1%
10	Power	4.0%
11	Services	2.0%
12	Telecom	2.0%
13	Consumer Services	3.0%
14	Miscellaneous	4.0%

Source: NSE India

For Event 3, the abnormal return of major indices listed on the National Stock Exchange Limited's (NSE) exchange in India due to the conflict between China and India in 2020 was analysed. The selected indices have been developed using a free-float market capitalization-weighted methodology with maximum weightage of individual security fixed in some indices. The indices selected are shown in Table 3.7. Credit rating changes of firms in industry groups of the Nifty 500 index, which indirectly represents these indices, were also analyzed.

Table 3.7: Description of NSE Indices

S.No	Index	Description
1	Nifty 50	Top 50 companies based on market capitalization from stock listed on NSE meeting specific criteria
2	Nifty 500	Top 500 companies based on market capitalization from stock listed on NSE meeting specific criteria
3	Nifty Auto	Top 15 Stocks belonging to the automobile sector meeting specific criteria
4	Nifty Bank	Top 12 Stocks belonging to the banking sector meeting specific criteria
5	Nifty FMCG	Top 15 Stocks belonging to Fast Moving Consumer Goods Sector meeting specific criteria
6	Nifty Infrastructure	Top 30 Stocks belonging to the infrastructure sector meeting specific criteria
7	Nifty I.T.	Top 10 Stocks belonging to the I.T. sector meeting specific criteria
8	Nifty MNC	Top 30 stocks in which the foreign shareholding is over 50% and/or the management control is vested in the foreign company
9	Nifty Pharma	Top 10 Stocks belonging to the Pharma sector meeting specific criteria
10	Nifty Midcap 150	Top 150 mid-size companies ranked 101-250
11	Nifty Smallcap 250	250 small size companies representing companies ranked 251-500

The sample data consisted of daily closing of NSE stock indices for May 01, 2019, and September 30, 2020.

3.4.2.2 Methodology

Under this objective, a change in the credit rating of corporates within six months after the event was used to analyze the event's impact on corporates. If a corporate faced rating action by multiple agencies during the observation period, the rating action where the company witnessed a rating change by a CRA was selected. The study also used the event study methodology to analyze the impact of these events on the corporates using stock returns. Event study methodology has been widely used to understand the impact of events or new information on the valuation or prices of assets[168]. The event study technique's main idea is that the abnormal returns (ARs) on the firm security prices can determine the relevancy of any unexpected event for firms. The AR on the security of the firm i at time t can be calculated using the following equation:

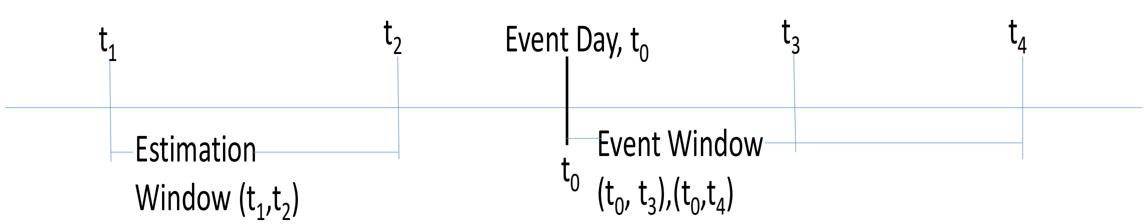
$AR_{it} = R_{it} - ER_{it}$

where R_{it} is the actual return on the security due to an event, ER_{it} is the expected return on the stock in the absence of an event.

The study used a Market-adjusted model to calculate the stock's expected return, the most popular model used in event studies[169].

For Event 1, the return on the Nifty 500 Index was used as a proxy for the market return. The event study methodology requires 1) an estimation window: a period that is used to estimate the parameters for the Market Model to calculate the expected returns for the stock of a firm, 2) Event date: the announcement date of the event or day '0' and, 3) Event window: the period in which impact of the event on stock price is examined as shown in Figure 3.1.

Figure 3.1: Event Study Timeline



For Event 1, the actual lockdown announcement by the Government of India was on 24 March 2020, at 8 PM IST, and hence 25 March 2020 was taken as the event date for lockdown. To analyze the impact of Event 1 on various industries using credit rating, the proportion of companies undergoing credit rating change in a particular industry till six months after the lockdown announcement on 25 March 2020 was analyzed. If a significant portion of the industry witnessed rating action, it was concluded that the lockdown had impacted the industry. A more extended period to investigate credit rating action was taken due to the lower sensitivity of credit rating to such sudden shocks compared to stock prices. This is because credit rating primarily focuses on debt serviceability compared to stock returns that are more linked to earnings or net profit change. The reason for taking only six months period was that the objective focused on whether credit ratings act as an early indicator of the impact of such sudden events on corporates. The changes in the credit rating of Nifty 500 firms were observed and analyzed from 25 March 2020 (event date) to 30 September 2020.

To calculate stock's expected return for event study methodology, the study considered the estimation window of 170 days, ending 30 days before the event day. The estimation period range was in line with other event studies based on daily returns. Nifty 500 firms that came out with an Initial public offering during and after the estimation window were dropped, leaving 486 firms. The study used five-event windows to fully understand the impact of the event on the stock prices – (-20,0 days), (-5,0 days), (0,1 days), (0,5 days), and (0,20 days).

The event window (-5,0) was more critical as the partial lockdown announcement after the stock market's closing on 19 March 2020 built in the expectation that the Government of India would soon announce the nationwide lockdown as had happened in other countries. Besides, the government announced a fiscal stimulus on 26 March 2020, one day after lockdown initiation. This provided confidence to the investors regarding the government's readiness to come out with measures to tackle the negative impacts of the lockdown on the economy. Thus, making the event window (-5,0) important for understanding the impact of the lockdown announcement.

The CAAR (Cumulative average abnormal return) of firms in an industry group was calculated by aggregating the average abnormal return of securities in the index group over the event window.

$$\mathrm{CAAR}(t_1, t_2) = \sum_{t=t_1}^{t=t_2} 1/N \sum_{i=1}^{N} AR_{it}$$

Here t_1,t_2 is the event window, N is the number of securities in the industry group, AR_{it} is the abnormal return on the security i at time t.

Two types of tests– parametric and non-parametric – can be used to test the statistical significance of abnormal returns during the event window. For Event 1, the adjusted BMP (Boehmer, Masumeci, and Poulsen) parametric test[170] and the Generalized Rank non-parametric Test[171] were used due to their robustness over other parametric and non-parametric tests.

Similarly, for Event 2, the changes in the credit rating of Nifty 100 firms were observed and analyzed from 20 September 2019 (event date) to 31 March 2020. For calcualting stock returns for Event 2, the study used the market-adjusted model[172] to calculate the stock's expected return for the event study. The Nifty 500 index was used as the market return in the market-adjusted model. The announcement date of the tax cut, 20 September 2019, was used as the 'event date' or day '0'. Five Event windows were selected – ((-2,0 days); (-1,0 days); (0,0 days); (0,1 days); (0,2 days)) - to measure the impact of tax cut on stock prices. As the government announcement of the tax cut came at 12:00 PM on 20 September 2019 between the market trading hours, the event window of (0,1) days became more important to understand the short-term impact on the market. The estimation window used to calculate the expected return had been taken from '-5' to '-165' days. Firms for which stock price data was not available for the entire duration of the event window were dropped from the event study leaving 99 firms from Nifty 100.

For Event 3, changes in the credit rating of Nifty 100 firms were observed and analyzed from 16 June 2020 (event date) to 31 December 2020. To analyze stock return, the index expected return was calculated using the market-adjusted model[172] with Nifty 500 index as the market return (R_m). News regarding the deadly clash between two countries broke out on June 16, 2020. This date was the 'event date' or day '0'. Three Event windows – ((0,3 days); (0,5 days); (0,15 days) – were taken to measure the impact of the conflict on Nifty indices. The estimation window used to calculate the expected return has been taken from '-16' to '-200' days to remove the effect on stock indices of skirmishes between the two countries in the buildup to the deadly clash on June 15, 2020. For Event 3, A parametric test was utilized to test abnormal returns' statistical significance during the event window[170].

3.4.2.2.1 Parametric and non-parametric tests

Abnormal returns from event studies can be used to analyze whether the mean of the distribution of abnormal returns is different from zero (with statistical significance), implying whether abnormal returns due to an event are significantly different from the expected return in the absence of the event. The same is done through hypothesis testing using significance tests that are classified into parametric and nonparametric tests. Parametric tests assume that a firm's abnormal returns are normally distributed, whereas nonparametric tests do not involve any such assumptions.

Several researchers have focussed on comparing different significance tests for an event study. It has been found that nonparametric tests tend to be more potent than parametric tests, with the generalized rank test (GRANK) being one of the most powerful significance tests.

3.4.2.2.2 Model for expected returns

The stock's expected return can be estimated using different models such as the Single Index Model, Market Adjusted Model, Historical Mean Model, and Multifactor Model. The Market Model estimates the parameters using Ordinary Least Square (OLS) regression over the estimation period.

$ER_{it} = \alpha i + \beta_i * R_{mt}$

where ER_{it} is the expected return on the security, α_i, β_i are the parameters of OLS, and R_{mt} is the market return.

3.4.3 Objective: To analyse the impact of competition among CRAs on credit rating effectiveness

3.4.3.1 Data & Summary Statistics

The objective was fulfilled by utilizing firms' credit rating and financial information data. The credit rating of firms used in the study represents the Long term rating assigned to the firm's long-term bank loans or capital market debt. The study utilized the rating action of CRAs from FY08-FY20 for analysis as RBI regulation on bank loans rating came into existence from FY08. The sample firms included all firms for which credit rating is available in the database except financial firms (National Industrial Classification Code 64000-66999). The reason for excluding financial firms was that such firms' credit ratings are driven by significantly different factors than non-financial firms. If a firm does not witness a credit rating action in a period from a CRA, the previous period's credit rating given by CRA was taken as the firm's outstanding rating from the CRA for analysis.

The rating-wise and year-wise sample distribution taken in the study is shown in Table 3.8 and Table 3.9. The sample contained 14,561 firm years of observations. These observations correspond to the rating given to firms by CRA 'A', as the study primarily focuses on the impact of competition on ratings assigned by CRA 'A'. Sample observations were equally divided between investment grade (above BB+ rating) and non-investment grade (below BBB- rating) observations. The observations were distributed normally with a peak at the boundary of the investment-grade rating of BBB-. Firm-year observations in which dual ratings were present, i.e., one or more agencies were rating along with CRA 'A', were around 22% of total observations.

Table 3.8: Rating Category Wise Sample Distribution

Rating Category	**AAA**	**AA+**	**AA**	**AA-**	**A+**	**A**
No. of Observations	208	111	491	502	730	640
Percentage of Total observations	1.4	0.8	3.4	3.5	5.0	4.4
Dual Rating Percentage	70.7	43.2	36.0	29.3	21.1	29.1
Rating Category	**A-**	**BBB+**	**BBB**	**BBB-**	**BB+**	**BB**
No. of Observations	872	1044	1379	1765	1428	1292
Percentage of Total observations	6.0	7.2	9.5	12.1	9.8	8.9
Dual Rating Percentage	25.2	21.5	21.1	21.4	19.6	18.7
Rating Category	**BB-**	**B+**	**B**	**B-**	**C**	**D**
No. of Observations	861	979	604	243	102	1310
Percentage of Total observations	5.9	6.7	4.2	1.7	0.7	9.0
Dual Rating Percentage	18.2	18.0	23.7	24.7	26.5	18.4

Table 3.9 shows rating distribution across different years. The number of observations was lower in the years immediately after the regulation of credit rating for bank loans was implemented in 2008. However, from 2012 the number of observations was equally distributed at around 10% each year. The percentage of firm ratings in which dual agencies were present is more than 20% in almost all years.

Table 3.9: Year Wise Sample Distribution

Year	Frequency	Percentage	Dual Ratings Percentage
2008	2	0.0	50.0
2009	11	0.1	63.6
2010	11	0.1	72.7
2011	647	4.4	15.3
2012	1,499	10.3	17.3
2013	1,755	12.1	19.8
2014	1,864	12.8	21.9
2015	1,857	12.8	24.5
2016	1,757	12.1	26.5
2017	1,547	10.6	24.1
2018	1,574	10.8	25.9
2019	1,578	10.8	25.3
2020	459	3.2	14.6
Total	**14,561**	**100.0**	**22.6**

3.4.3.2 Methodology

Under this objective, whether competition leads to rating inflation and rating shopping in the credit rating industry was tested. Multiple approaches were adopted to achieve this objective. The study analyzed the rating inflation tendency of one of the top four domestic CRA (designated as CRA 'A') due to competition from the other three of the top four domestic CRAs (designated as CRA ‘1’, ‘2’ and ‘3’). The tendency of issuers to indulge in rating shopping due to competition was investigated by analyzing the initial ratings given by other CRAs (CRA ‘1’, ‘2’, and ‘3’) to firms already rated by CRA 'A' and vice versa. The study used t-tests and regression techniques to empirically analyze the impact of competition among CRAs on firms' credit ratings.

Within this objective, the key credit metrics of leverage (Debt/EBITDA), interest coverage (EBITDA/Interest Expenses), and financial metrics of profitability (EBITDA/Sales) and sales of firms with or without dual ratings were analyzed. Several studies have highlighted that these financial metrics have a significant relationship with credit rating [159,173,174]. These financial metrics were winsorized at their 1% and 99% percentiles to eliminate outliers. For this purpose, The firms were divided into two groups – 1) Group 1 -where only CRA'A' is the rating firm, and 2) Group 2 – dual ratings, i.e., one or more CRA is the rating firm along with CRA' A'. A two-sample t-test was used to compare the mean credit metrics of the two groups. In case of rating inflation, credit metrics of group 2 (dual ratings) will invariably be worse off than group 1. The two-sample t-test was done across rating categories. Rating Category 'C' and 'D' were not included in the analysis. This was because the firms with these ratings have a very high risk of default or are expected to be in default [7]and timely servicing of debt rather than financial metrics is the primary driver for firms rated at this level.

In addition, the study used Ordinary Least Squares (OLS) regression and Ordered Probit regression to test rating inflation hypotheses related to the objective. These techniques have been employed in several previous credit ratings-related papers [141,159,175]. Ordered probit models are well-suited for discrete outcomes having a natural ordering but where the difference between different outcomes may not linear[176]. The OLS and ordered probit regression test were deployed with credit rating as the dependent variable and dual rating dummy as the independent variable along with other control variables to analyze the presence of rating inflation i.e. higher rating of firm by CRA 'A' due to other CRAs (CRA '1', '2' and '3') rating the firm.

The regression employed control variables of Size, Leverage, Profitability, and Interest Coverage to account for firm-specific characteristics driving the firm's rating, as used in several other studies [155,158,159]. As explained earlier, rating levels C and D were excluded from the analysis. The definitions of dependent, independent, and control variables are summarized in Table 3.10. The dependent variable CRit was generated by converting the firm's credit rating into numerical values as per Table 3.11.

Table 3.10: Variable Definitions

Variables	Formula	Definitions
Dependent Variable		
CRit	Value 1 to 18	CR_{it} is the credit rating of firm i at time t at CRA 'A'
Independent Variable		
CRA^jD	Value of 0 or 1	dummy variable for dual rating, which takes a value '1' if CRA j gives a rating to firm i at time t, which has also been rated by CRA 'A' and '0' otherwise
Control Variable		
Leverage	(Total $Debt_{it}$)/ (Total $Debt_{it}$ + $Equity_{it}$)	Total $Debt_{it}$ = book long-term debt plus short-term book debt for firm i at time t $Equity_{it}$ = book value of shareholders' equity for firm i at time t
Profitability	($EBITDA_{it}$)/ (Total $Assets_{it}$)	$EBITDA_{it}$ = Earnings before Interest, Depreciation and Tax for firm i at time t Total $Assets_{it}$ = total assets for firm i at time t
Size	ln($Sales_{it}$)	$Sales_{it}$ = Sales for firm i at time t
Interest Coverage	($EBITDA_{it}$)/ (Interest $Expense_{it}$)	EBITDA divided by total finance expenses of firm i at period t

Table 3.11: Table for Rating Scale conversion to Numerical Scale

Rating Level	Numerical Value
AAA	1
AA+	2
AA	3
AA-	4
A+	5
A	6
A-	7
BBB+	8
BBB	9
BBB-	10
BB+	11
BB	12
BB-	13
B+	14
B	15
B-	16
C	17
D	18

In order to test rating shopping, i.e. the tendency of a new CRA to assign a higher initial rating to a firm where another CRA was already rating, the difference between the credit rating given by CRA 'A' and the initial rating assigned by other CRAs was analysed. In addition, the difference between the credit rating given by other CRAs and the initial rating by CRA 'A' was analysed. If rating shopping occurs, the difference in both cases would invariably be positive. In addition, in most observations, the new CRA rating should be higher whether CRA 'A' or CRA '1', '2' or '3' are assigned the initial rating.

In addition, the study used Ordinary Least Squares (OLS) regression and Ordered Probit regression to test rating shopping hypotheses related to the objective. In this, the difference in credit rating (converted to numerical scale) of a firm i at time t by CRA' j' and CRA 'A' as the dependent variable, $D.CR_A^i$, and a dummy, ICR_{it}^j , as the independent variable with other firm-specific control variables. ICR_{it}^{j} takes a value '1' if a firm i gets a rating assigned by CRA 'A', when CRA 'j' as already rating it'.

3.4.3.2.1 Probit Regression

If the dependent variable is qualitative, using OLS will result in predicted probabilities going beyond the range [0,1]. However, nonlinearity in parameters is required to get predicted probabilities of dependent variables within sensible values, which is impossible with OLS. Therefore, an alternative specification such as Probit Model is used when the dependent variable is categorical.

The probit model is based on the standard normal cumulative density function (CDF), which is defined as

$$F(Z) = \int_{-\infty}^{z} (2\pi)^{1/2} e^{-z^2/2} dz$$

Where Z is a standardized normal variable and e is the base of the natural log

3.5 Conclusion

This chapter of the study elaborated on the research objectives of the study. In addition, the chapter explained the data sources, sample size, study period, sample summary, methodology, and dependent and independent variables involved in regression equations used to achieve the study's objectives. Chapters 4-6 discuss the results from the analysis conducted for each of the three objectives mentioned in this chapter.

Chapter 4

Result & Discussion - I

Chapter 4: Analyzing the effectiveness of corporate credit rating as an indicator of future financial performance for investors

4.1 Introduction

This section analyzes whether a credit rating change indicates the direction of a firm's future operating profits and whether any relationship exists between the change in credit rating and future operating profits. It analyzes the forward-looking nature of credit rating changes across rating categories, sample years, and multiple levels of rating change.

4.2 Inference on Future Operating Profit from Credit Rating change

The following hypotheses were used to test whether credit rating change in a firm indicates the direction of a firm's future operating profits:

Hypothesis 1: Credit rating changes do not contain any information regarding the future operating profit of a firm.

Hypothesis 1a: Credit rating downgrades do not contain any information regarding the future operating profit of a firm.

Hypothesis 1b: Credit rating upgrades do not contain any information regarding the future operating profit of a firm.

If no relationship exists, then a rating upgrade should not be followed by an improvement in profit relative to cases where no rating change (affirmation) occurs, while a rating downgrade should not result in a relative deterioration in profit.

In order to test these hypotheses, a year-wise comparison of $NetEBITDA_{it}$ for firm years when no rating change was in the previous year compared to the rating being downgraded or upgraded in the previous year was done. $NetEBITDA_{it}$ is the change in EBITDA for firm i from t-1 to t period divided by the firm's total assets at time t-1. Table 4.1 shows the mean and median values of $NetEBITDA_{it}$ for three scenarios 1) Group 1 firm years, where Dug_dg=0, i.e., when there was no rating change in the previous year, 2) Group 2 firm years, where Ddg = 1, i.e., when firm saw a rating downgrade in the previous year and 3) Group 3 firms, where Ddg = 1 when firm saw a rating upgrade in the previous year. A two-sample t-test was then used to compare the mean $NetEBITDA_{it}$ between the three groups. If there was no information contained in the rating change regarding future operating profit, then the mean $NetEBITDA_{it}$ of group 1 (Dug_dg =0) should be equal to group 2 (Ddg = 1) and group 3 (Dug = 1).

Table 4.1: Year Wise mean and median of $NetEBITDA_{it}$ for firm years in Group 1 (rating affirmation), Group 2 (rating downgrade), and Group 3 (rating upgrade)

Previous Year	$NetEBITDA_{it}$ (percentage)								
	Group 1 (Dug_dg =0)			Group 2 (Ddg =1)			Group 3 (Dug =1)		
	N^	Mean	Median	N	Mean	Median	N	Mean	Median
2010	4	-8.47	-6.42						
2011	4219	2.03	1.46	73	-0.25**	0.89	197	0.3	0.67
2012	5032	1.96	1.07	192	1.36	0.33	181	-0.06	1.1
2013	5165	2.09	1.18	395	1.22**	0.49	152	1.83	1.2
2014	5563	1.5	0.86	272	0.22***	0.12	323	0.29	0.54
2015	5423	1.39	0.76	206	0.36*	0.07	534	0.68	0.5
2016	5128	1.43	0.7	271	1.27	0.47	431	1.32	0.78
2017	4431	1.33	0.86	215	0.02**	0.09	316	1.38	1.18
2018	2717	1.87	1.13	146	2.37	1.37	216	1.64	1.37

*Note: ^ N stands for the number of firm-year observations. * , **, and *** indicate significance at the 0.1, 0.05, and 0.01 levels, respectively. The significance level in the Table relates to the two-sample t-test between Group 1 - Group 2 and Group 1 - Group 3, as explained in the text.*

As per Table 4.1, it is clear that the mean and median of $NetEBITDA_{it}$ in Group 2 are lower than in Group 1 in almost all the years except 2018. Group 2 $NetEBITDA_{it}$ lower than group 1 by 0.5% in 6 out of 8 years. A two-sample t-test for comparison between the mean of NetEBITDAit of the two groups indicated that the mean $NetEBITDA_{it}$ of Group 2 is significantly lower than Group 1 (level of significance of t-test is indicated in Table 4.1 under Group 2) in 5 out of 8 years. This means that following a downgrade, the incremental change in EBITDA was more likely to be lower than that in affirmation.

The mean of NetEBITDAit in Group 1 was higher than Group 3 in almost all the years except 2017. However, the two-sample t-tests indicated that the mean NetEBITDAit of Group 1 was never significantly higher than Group 3. Thus, there was no information in rating upgrades about a relative improvement in future operating profit.

The following regressions were also used to test hypothesis 1:

$NetEBITDA_{it} = \alpha + \beta_0 D_{ug\_dg} + \xi_{it}$ ....(1)

$NetEBITDA_{it} = \alpha + \beta_1 D_{ug\_dg} + \pi K_{it-1} + \xi_{it}$ ....(2)

$NetEBITDA_{it} = \alpha + \beta_2 c + \beta_3 D_{dg} + \xi_{it}$ ....(3)

$NetEBITDA_{it} = \alpha + \beta_4 D_{ug} + \beta_5 D_{dg} + \pi K_{it-1} + \xi_{it}$ ....(4)

These equations test whether a firm's rating change in a particular year contains any information regarding its operating profit in the next period. Thus, in these equations, the dummy and control variables are for the firm at t-1. At the same time, $NetEBITDA_{it}$ is the change in EBITDA for firm i from t-1 to t period divided by the firm's total assets at time t-1. For a rating to contain forward-looking information, the implication is that a firm witnessing a downgrade (upgrade) in credit rating should exhibit a relative deterioration (improvement) in operating profit in the next year compared to rating affirmation.

In these tests, the null hypothesis is that ratings are not forward-looking in nature, i.e., $\beta_0, \beta_1, \beta_2, \beta_3, \beta_4, \beta_5, = 0$. This would mean no valuable and relevant information about the future change in the firm's operating profit in a credit rating action. Equations (2) and (4) contain firm-specific control variables, which are absent in Equations (1) and (3). The results of the tests are shown in Table 4.2.

Table 4.2: Inference on operating profit from credit rating changes

Dependent Variable: $EBITDA_{it}$				
	1	2	3	4
Constant	0.017^{***}	0.043^{***}	0.017^{***}	0.043^{***}
	(0.000)	(0.002)	(0.000)	(0.002)
Dug_dg	-0.008^{***}	-0.005^{***}		
	(0.001)	(0.001)		
Ddg			-0.008^{***}	-0.016^{***}
			(0.002)	(0.002)
Dug			-0.008^{***}	0.002
			(0.002)	(0.002)
Leverage		-0.000		-0.000
		(0.000)		(0.000)
Size		-0.001^{***}		-0.001^{***}
		(0.000)		(0.000)
Profitability		-0.170^{***}		-0.173^{***}
		(0.009)		(0.009)
N	41804	38563	41804	38563

*Note: The sample period spans from 2010 to 2019. *, **, and *** indicate significance at the 0.1, 0.05, and 0.01 levels, respectively. Errors are White's consistent standard errors inserted in parentheses.*

Columns 1,2, 3 and 4 represent equations (1), (2), (3), and (4), respectively. As per the results in Table 4.2, null hypothesis 1 and sub-hypothesis 1a were rejected at a 1% level, while the test failed to reject sub-hypothesis 1b. The result supported the existing research on investors' informational value of credit rating. It indicated that a credit rating change contains forward-looking information regarding a firm's operating profit. It also augmented the existing research about credit rating changes' valuable nature as an indicator of a change in the firm's future cash flow and profitability.

As per the results, the inclusion of the control variables in column 3 and column 4 changed the significance of Dug. This proved that control variables were significant and needed to be considered when considering the relation between credit rating action and subsequent change in a firm's operating profit. In columns 3 & 4, the Ddg variable was significant and negative, indicating that firms operating profits were likely to see a relative decline a year after a credit rating downgrade compared to operating profit change following affirmation. A firm’s EBITDA relative to assets witnessed an average 1.6% relative decline following a downgrade compared to affirmation. The results were robust using HAC (heteroscedasticity and autocorrelation consistent) standard errors [165] with a similar Ddg variable's coefficient value. This further supported the results obtained through the two-sample t-test that a downgrade in the rating is likely to be followed by a relative decline in the firm's operating profit in the following year. The results are also consistent with Table 4.1, indicating limited informational content in rating upgrades regarding future operating profit.

Although the Dug variable was not significant, the Dug variable's coefficient was positive, indicating that an upgrade in the credit rating indicated that operating profit is likely to improve next year for the firm compared to rating affirmation. The insignificance of the Dug variable could be due to CRAs' tendency to follow a conservative approach while moving credit rating to a higher level [177,178]. This is due to CRAs' likely concern about a sudden or rapid deterioration in the firm's credit quality from a higher rating level, which can have reputational effects. Consequently, CRAs may delay a rating upgrade resulting in no significant operating profit change after an upgrade. At the same time, CRAs are relatively quicker to downgrade credit ratings because of negative news. The selective bias of management in releasing good news to investors early and withholding bad news, which is then communicated through CRA rating action, can also explain this discrepancy [75,179]. Firms' earnings management to delay earnings decreases could also be a reason behind this informational asymmetry between credit rating upgrade and downgrade [180,181]. CRAs most likely see through such earnings management and adjust the ratings downwards before the firm witnesses a complete earnings reversal [182]. Thus, earnings decline continues even after a downgrade, although part of the decline may have happened before the downgrade.

The significance of the Dummy variable related to the rating downgrade indicated that the downgrade's informational content is higher over the upgrade. This relates well with existing literature that highlights that a rating downgrade significantly impacts stock returns, while rating upgrades have limited or no impact on stock returns, indicating a higher informational content of rating downgrade over upgrade[56,57,59,70]. Baghai et al. (2014) highlighted CRAs increasing conservatism in assigning credit ratings over the years, which could manifest in delayed upgrades and relatively quicker downgrades[177]. Ederington & Goh (1998) also reported that nearby quarterly earnings of a firm fall after a downgrade, while there is no such impact of a rating upgrade[75]. Goh & Ederington (1999) assertion that investors view downgrades as providing information on likely future earnings before interest charges (operating profit), not just interest charges, supports the study's findings[70].

4.3 Inference on Future Operating Profit across Rating Categories

This sub-section evaluates whether the informational content of a change in credit rating, from the perspective of a firm's future operating profits, is different when the rating of a firm lies in investment or non-investment grade. The hypotheses are mentioned below:

Hypothesis 2: Credit rating changes do not contain any information regarding the future operating profit of a firm rated in the investment-grade category.

Hypothesis 2a: Credit rating downgrades do not contain any information regarding the future operating profit of a firm rated in the investment-grade category.

Hypothesis 2b: Credit rating upgrades do not contain any information regarding the future operating profit of a firm rated in the investment-grade category.

Hypothesis 3: Credit rating changes do not contain any information regarding the future operating profit of a firm rated in the non-investment grade category.

Hypothesis 3a: Credit rating downgrades do not contain any information regarding the future operating profit of a firm rated in the non-investment grade category.

Hypothesis 3b: Credit rating upgrades do not contain any information regarding the future operating profit of a firm rated in the non-investment grade category.

Table 4.3: Inference on operating profit from credit rating changes in Investment Grade and Non-Investment Grade

Dependent Variable: $NetEBITDA_{it}$				
	Investment Grade		**Non-Investment Grade**	
	1	2	3	4
Constant	0.033^{***}	0.033^{***}	0.048^{***}	0.048^{***}
	(0.004)	(0.004)	(0.003)	(0.003)
Dug_dg	-0.000		-0.015^{***}	
	(0.002)		(0.002)	
Ddg		-0.009^{***}		-0.019^{***}
		(0.003)		(0.003)
Dug		0.003		-0.010^{***}
		(0.002)		(0.003)
Leverage	0.001	0.001	-0.000	-0.000
	(0.001)	(0.001)	(0.000)	(0.000)
Size	-0.001^{**}	-0.001^{**}	-0.002^{***}	-0.002^{***}
	(0.000)	(0.000)	(0.000)	(0.000)
Profitability	-0.110^{***}	-0.115^{***}	-0.184^{***}	-0.184^{***}
	(0.016)	(0.016)	(0.011)	(0.011)
N	10813	10813	27750	27750

*Note: The sample period spans from 2010 to 2019. * , **, and *** indicate significance at the 0.1, 0.05, and 0.01 levels, respectively. Errors are White's consistent standard errors inserted in parentheses.*

Table 4.3 shows the test results on the informational content of credit rating action in investment and non-investment grade rating categories. The observations are classified as investment or non-investment grades based on the instrument's rating after credit rating action. The results show that the information value of ratings, in terms of indication of future change in operating profit, persists across the investment and non-investment grade rating categories. As per the results in Table 4.3, Hypotheses 2a, 3, 3a, and 3b are rejected at a 1% level, while null hypotheses 2 and 2b are not rejected.

The Ddg variable was significant in the investment and non-investment grade rating categories. The Ddg coefficient indicated that, on average, operating profit/assets witnessed a relative decline of 0.9% and 1.9% in investment grade and non-investment grade categories, respectively, a year after the downgrade of credit rating compared to rating affirmation. Thus, the extent of change in operating profit was greater for a non-investment-grade rating than for an investment-grade rating following a credit downgrade. The lower coefficient could be explained by CRAs defining investment-grade credit ratings as comparatively lower credit risk [183,184]. Therefore, even with a relatively lower operating profit decline, CRAs tend to be more prompt in revising the credit ratings in the investment-grade category as it carries higher reputation risk. Baek & Cursio (2016) observed a similar differential behaviour of investment and non-investment-rated firms to capital structure adjustment when faced with credit rating change[185]. Jorion & Zhang (2007) findings also supported a different reaction of investment and non-investment rated firms' stock prices to rating changes, with lower-rated firms witnessing larger price reactions to a rating change[58].

The Dug variable was insignificant in the investment-grade category, with a positive coefficient indicating that the change in operating profit is positive a year after the rating upgrade. In the non-investment grade category, the Dug variable was significant, with the coefficient carrying a negative sign. However, as the ratings in default categories are driven primarily by servicing the debt on time [183,184], the results for the non-investment grade category were calculated after removing the default category observation. As a result, the Dug variable became insignificant, similar to what was seen in the investment-grade category. The above results were robust using HAC (heteroscedasticity and autocorrelation consistent) standard errors.

Table 4.4: Inference on Operating Profit from credit rating changes across rating categories

	AA	A	BBB	BB	B	C
Dug_dg	-0.005	0.005	0.000	-0.002	-0.010^{**}	-0.027^{*}
	(0.005)	(0.003)	(0.002)	(0.003)	(0.005)	(0.016)
Ddg	0.004	-0.008	-0.007^{*}	-0.005	-0.019^{**}	-0.036^{**}
	(0.010)	(0.006)	(0.004)	(0.004)	(0.008)	(0.017)
Dug	-0.007	0.009^{***}	0.004	0.001	-0.003	-0.015
	(0.005)	(0.003)	(0.003)	(0.003)	(0.005)	(0.023)

*Note: The sample period spans from 2010 to 2019. * , **, and *** indicate significance at the 0.1, 0.05, and 0.01 levels, respectively. Errors are White's consistent standard errors inserted in parentheses.*

Table 4.4 shows the results of the test in different rating categories. The sample size is reduced in each rating category, due to which the power of a test is reduced. Still, Ddg was significant in 3 out of 6 rating categories. The results showed that the coefficient of Ddg was negative across rating categories which is in line with the previous results. The result indicated that CRA's downgrade of credit rating indicated a relative decline in a firm's future operating profit across different rating categories. Although Dug was insignificant in 5 out of 6 rating categories, the Dug variable's coefficient was positive in 3 out of 6 categories, accounting for a majority (81.56%) of rating upgrade observations.

4.4 Inference on Future Operating Profit across Years

This sub-section evaluated whether the informational value of credit rating persists across sample years. Table 4.5 indicates that the informational value of credit rating downgrade is evident across the years. The coefficient of Ddg was negative across all eight years, indicating that across the sample years the downgrade of credit rating provides a forward-looking view to the investors about the relative decline in operating profit in the subsequent year. Ddg was significant at a 1% level for 4 out of 8 years and 7 out of 8 years at 10% level. The coefficient of Dug was positive in 4 out of 8 years. Dug was significant at a 5% level in two out of 8 years in the sample period. Thus, the informational content of the downgrade was much higher than an upgrade throughout the study period.

Table 4.5: Inference on operating profit from credit rating changes across Years

	2011	2012	2013	2014	2015	2016	2017	2018
Dug_dg	-0.014***	-0.010**	-0.006	-0.009***	-0.006**	0.002	-0.003	0.003
	(0.005)	(0.004)	(0.004)	(0.003)	(0.003)	(0.003)	(0.004)	(0.005)
Ddg	-0.029**	-0.012*	-0.012***	-0.017***	-0.022***	-0.013**	-0.021***	-0.006
	(0.012)	(0.006)	(0.004)	(0.005)	(0.006)	(0.006)	(0.006)	(0.007)
Dug	-0.009	-0.008	0.010	-0.003	-0.001	0.011***	0.009**	0.009
	(0.006)	(0.005)	(0.008)	(0.004)	(0.003)	(0.004)	(0.004)	(0.006)

*Note: The sample period spans from 2010 to 2019. * , **, and *** indicate significance at the 0.1, 0.05, and 0.01 levels, respectively. Errors are White's consistent standard errors inserted in parentheses.*

4.5 Inference on Future Operating Profit by the extent of Credit Rating Change

This sub-section attempts to evaluate whether the extent of the credit rating action, represented by the number of notches or levels of the rating change, by CRAs conveys different information about the firm's future change in operating profit.

The results are summarized in Table 4.6. The results show that a downgrade of credit rating action signals a likely decline in future operating profit for one notch, two notches, or a three-notch downgrade, with the Ddg variable being significant for all three types of rating action. However, the coefficient of Ddg increased with the extent of credit rating action. The downgrade of one, two, or three notches indicated an average decline in operating profit/assets of 1%, 1.7%, and 3.1%, respectively. Thus, higher severity of downgrade by a CRA indicated a higher relative decline in operating profit/assets in the future year. More severe rating actions were not considered as those may be caused by factors not related to financial performance and may be considered rare occurrences. The Dug variable, although insignificant, is positive for one and two-notch upgrades in rating.

Table 4.6: Inference on operating profit due to different degrees of credit rating changes

	Change of Rating by 1 level	**Change of Rating by 2 levels**	**Change of Rating by 3 levels**
Dug_dg	0.000	-0.007	-0.019
	(0.003)	(0.006)	(0.015)
Ddg	-0.010^{**}	-0.017^{**}	-0.031^{*}
	(0.004)	(0.008)	(0.016)
Dug	0.005	0.001	-0.002
	(0.004)	(0.006)	(0.016)

*Note: The sample period spans from 2010 to 2019. * , **, and *** indicate significance at the 0.1, 0.05, and 0.01 levels, respectively. Errors are White's consistent standard errors inserted in parentheses.*

4.6 Conclusion

The chapter investigated the forward-looking information incorporated in credit rating changes regarding a firm's future operating profits. The study utilized t-tests to compare the future change in operating profit of two groups of firms (with or without rating change). The study also utilized regression to empirically analyze whether credit rating changes contain any information regarding a firm’s future operating profit. The results showed that operating profit is likely to see a relative decline a year after a downgrade of credit rating. In contrast, no such effect was visible following a credit rating upgrade. The effect of downgrades was visible across investment and non-investment grades and individual years of the study.

Chapter 5

Result & Discussion - II

Chapter 5: Analyzing the effectiveness of corporate credit rating in estimating the impact of external events on Corporates

5.1 Introduction

The section attempts to investigate the short-term impact of unanticipated external events on various industries in India using firms' credit ratings and stock returns. It analyzes a firm's credit rating and stock price sensitivity to unanticipated external events. The key objective is to analyze whether investors could use credit rating to manage their risk in an abrupt event. The analysis compares the responsiveness of credit rating viz a viz stock prices to unanticipated external events.

5.2 Credit rating changes and stock reactions following Lockdown due to Covid-19 in 2020

Table 5.1 shows the industry-wise distribution of credit rating actions among the Nifty 500 companies for six months following the lockdown announcement. The analysis of credit ratings of companies indicated that companies in nine industries did not witness any credit rating change. In contrast, another eight of the remaining industries saw less than 15% of companies witness credit rating changes in the six months following the lockdown announcement. In only two industries out of the nineteen in the Nifty 500, the number of companies witnessing credit rating change was above 15% of the total companies but remained below 30%. Thus, corporate credit ratings did not show any sensitivity to the event. The diminished impact of the lockdown on the credit ratings of companies could be due to the Covid-19 package announced by the Reserve Bank of India following the lockdown leading to a moratorium on interest and principal payment for corporates[186,187]. The measure mitigated the burden of debt servicing on companies.

Table 5.1: Proportion of firms in different industries with credit rating changes in six months following the lockdown announcement on 25 March 2020

Industry	Number of rated companies in Industry in NIFTY 500	Companies with a downgrade of credit rating	Companies with an upgrade of credit rating	Proportion of companies with a credit rating change
Automobile	21	2	1	9.5%
Cement & Cement Products	9	1	0	11.1%
Chemicals	12	0	0	0.0%
Construction	22	3	0	13.6%
Consumer Goods	32	3	1	9.4%
Fertilisers & Pesticides	7	2	0	28.6%
Financial Services	29	1	1	3.4%
Healthcare Services	6	0	1	0.0%
Industrial Manufacturing	19	1	1	5.3%
IT	8	0	0	0.0%
Media & Entertainment	2	0	0	0.0%
Metals	14	2	1	14.3%
Oil & Gas	15	0	1	0.0%
Paper	1	0	0	0.0%
Pharma	17	0	5	0.0%
Power	9	0	0	0.0%
Services	17	2	0	11.8%
Telecom	5	1	0	20.0%
Textiles	5	0	0	0.0%

For Event 1, the results of the event study on industry groups of Nifty 500 are presented in Tables 5.2 and 5.3. It could be seen that 17 out of 19 industry groups witnessed a negative return during the event window of (-5,0). In 10 of the 19 industry groups, the returns were negative and significant at a 10% level. The negative returns on various industries were in line with a drastic dip in demand across industries due to the lockdown and supply-side constraints related to labour and the closure of factories. The significance of returns for the industry group was essentially the same in both the Adjusted BMP test and the Generalized Rank test.

Table 5.2: Impact of Lockdown announcement on the Industry group of Nifty 500 Stocks using Adjusted BMP Test

Industry	**Event Window**				
	CAAR[-20,0]	**CAAR[-5,0]**	**CAAR[0,1]**	**CAAR[0,5]**	**CAAR[0,20]**
Automobile	-11.66%	-8.44%*	-2.78%	-3.92%	-2.64%
Cement & Cement Products	-4.17%	-8.39%**	-2.11%	-0.90%	-4.40%
Chemicals	-2.47%	-2.89%	-1.03%	4.60%	15.33%**
Construction	-15.74%**	-10.09%**	-3.57%	-1.61%	-1.49%
Consumer Goods	-4.61%	-6.66%**	-1.38%	4.09%	2.58%
Fertilisers & Pesticides	-7.60%	-6.12%***	1.69%	6.85%***	16.66%***
Financial Services	-19.11%***	-12.80%***	-0.65%	0.49%	-1.50%
Healthcare Services	5.63%	-3.63%	-3.51%	-3.21%	-7.78%
Industrial Manufacturing	-8.39%*	-9.13%***	-2.48%*	2.52%	3.19%
IT	-6.28%	-1.64%	-2.90%	0.09%	-1.06%
Media & Entertainment	-17.08%***	-1.30%	-3.51%	-1.51%	-1.38%
Metals	-12.15%	-4.72%	-4.51%*	-0.58%	-2.57%
Oil & Gas	-5.65%	-3.87%	-3.32%	2.78%	4.75%
Paper	-28.72%***	-13.47%***	6.92%***	14.97%***	18.23%
Pharmaceutical	10.12%**	1.73%	-4.45%**	2.58%	15.62%***
Power	3.82%	5.84%	-7.68%***	-3.20%	-7.35%
Services	-16.49%***	-10.91%***	-4.29%***	0.21%	-8.39%**
Telecom	0.13%	-3.80%	-4.64%	-3.11%	12.03%
Textiles	-22.74%***	-13.55%***	-7.18%**	-5.10%	-2.04%

*Note: * , **, and *** indicate significance at the 0.1, 0.05, and 0.01 levels, respectively.*

Table 5.3: Impact of Lockdown announcement on the Industry group of Nifty 500 Stocks using Generalized Rank Test

Industry	Event Window				
	CAAR[-20,0]	CAAR[-5,0]	CAAR[0,1]	CAAR[0,5]	CAAR[0,20]
Automobile	-11.66%	-8.44%	-2.78%	-3.92%	-2.64%
Cement & Cement Products	-4.17%	-8.39%*	-2.11%	-0.90%	-4.40%
Chemicals	-2.47%	-2.89%	-1.03%	4.60%*	15.33%**
Construction	-15.74%**	-10.09%**	-3.57%	-1.61%	-1.49%
Consumer Goods	-4.61%	-6.66%*	-1.38%	4.09%*	2.58%
Fertilisers & Pesticides	-7.60%	-6.12%***	1.69%	6 .85%***	16.66%***
Financial Services	- 19.11%***	- 12.80%** *	-0.65%	0.49%	-1.50%
Healthcare Services	5.63%	-3.63%	-3.51%*	-3.21%	-7.78%
Industrial Manufacturing	-8.39%	-9.13%***	-2.48%*	2.52%	3.19%
IT	-6.28%	-1.64%	-2.90%	0.09%	-1.06%
Media & Entertainment	- 17.08%***	-1.30%	-3.51%	-1.51%	-1.38%
Metals	-12.15%	-4.72%	-4.51%*	-0.58%	-2.57%
Oil & Gas	-5.65%	-3.87%	-3.32%	2.78%	4.75%
Paper	-28.72%**	-13.47%**	6.92%**	14.97%**	18.23%
Pharmaceutical	10.12%**	1.73%	-4.45%**	2.58%	15.62%***
Power	3.82%	5.84%	- 7.68%***	-3.20%	-7.35%
Services	- 16.49%***	-10.91%**	-4.29%**	0.21%	-8.39%
Telecom	0.13%	-3.80%	-4.64%*	-3.11%	12.03%*
Textiles	-22.74%**	- 13.55%** *	-7.18%**	-5.10%	-2.04%

*Note: * , **, and *** indicate significance at the 0.1, 0.05, and 0.01 levels, respectively.*

Although not significant, the positive returns on the Pharmaceuticals sector during the event window (-5,0 days) could be explained by the fact that Pharmaceutical companies were likely to benefit due to the emerging opportunities of vaccines for COVID-19 and the demand for related medicines.

In terms of the severity of the impact of the lockdown announcement from 25 March 2020, among the major sectors, the Textile, Financial Services, Construction, and Services sector were the most affected, as seen from significant negative returns in the event window (-5,0). The textile sector faced drastic demand reduction and unavailability of labour due to the lockdown. The Financial Services sector was impacted due to demand issues and the risk of default on loan exposure to firms and individuals. Construction activities came to a standstill, and labour shortages were expected to impact the construction sector negatively. The services sector, including Hotel, Courier, and Airline services, was likely to see a complete demand stalling due to the lockdown.

Industrial Manufacturing, Automobile, and Cement sector were also likely to be impacted by a lack of demand and the closure of factories. However, Chemicals and Pharmaceuticals were less impacted, with demand being primarily insulated. The Telecom sector was expected to see increased demand due to people confined to their homes. This could be seen in the fact that in the event window of (0,20 days) where Chemical, Pharmaceutical, and Telecom sectors witnessed significant positive returns. The Consumer Goods industry group, including consumer durables and FMCG sectors, also witnessed significant negative returns. Fertiliser & Pesticides sector saw a significant negative return during the event window (-5, 0 days). However, the sector saw a higher significant positive return during the event window (0, 20 days) due to the expectation of a limited impact on demand from agriculture activities based primarily out of rural areas. Other sectors, such as Healthcare Services, IT, Media & Entertainment, and the Power sector, saw a mixed impact during the event window, with abnormal returns not being significant.

The results indicated a stark difference in the reaction of credit ratings and stock prices to Event 1. Stock prices' short-term reactions were in line with the event's impact on the various industries, whereas credit ratings were insensitive to the event.

5.3 Credit rating changes and stock reactions following corporate tax cut announcement in 2019

Table 5.4 shows the industry-wise distribution of credit rating actions among the Nifty 100 companies. The analysis of credit ratings of companies indicates that companies in eleven industries did not witness any credit rating change. In comparison, another four industries saw less than 15% of companies witness credit rating change in the six months following the tax cut announcement. In only one industry out of the nineteen in the Nifty 100, the number of companies witnessing credit rating change was above 50%. However, the analysis of credit rating change of corporates in this industry indicated that the change was driven by structural changes rather than tax cut announcements. Thus, similar to Event 1, corporate credit ratings showed insensitivity to Event 2.

Table 5.4: Proportion of firms in different industries with credit rating changes in six months following tax cut announcement on 20 September 2019

Industry	Number of rated companies in Industry in NIFTY 100	Companies with a downgrade of credit rating	Companies with an upgrade of credit rating	Proportion of companies with a credit rating change
Automobile	10	1	0	10.0%
Cement & Cement Products	5	0	0	0.0%
Chemicals	1	0	0	0.0%
Construction	2	0	0	0.0%
Consumer Goods	16	0	1	6.3%
Fertilisers & Pesticides	1	0	0	0.0%
Financial Services	25	2	0	8.0%
Industrial Manufacturing	1	0	0	0.0%
IT	6	0	0	0.0%
Media & Entertainment	1	0	0	0.0%
Metals	7	1	0	14.3%
Energy	10	0	0	0.0%
Pharma	9	0	0	0.0%
Services	3	0	0	0.0%
Telecom	3	2	0	66.7%
Textiles	1	0	0	0.0%

The impact of the tax cut announcement on Nifty 100 stocks is summarized in Table 5.5. As per Table 5.5, around 52.5% of the companies witnessed a positive abnormal stock return in the event window (0,1 day), while the remaining witnessed a negative abnormal return. Around 62.6% of companies witnessed significant (at 10% level) abnormal returns in the event window (0,1 day).

Table 5.5: Summary of Event Study on Nifty 100 Stocks with Event Date as 20 September 2019 and Event Window (0,1) day using Boehmer, Musumeci, Poulsen test

Industry	Number of Companies with Positive CAAR	Number of Companies with Positive CAAR and p-value less than 10%	Number of Companies with Negative CAAR	Number of Companies with Negative CAAR and p-value less than 10%
Automobile	8	3	1	0
Cement	5	4	0	0
Construction	1	1	1	0
Consumer Goods	9	9	7	3
Financial Services	13	10	7	3
It	0	0	6	6
Metals	4	0	3	1
Oil & Gas	5	3	3	1
Pharmaceutical	1	0	10	10
Power	0	0	4	2
Services	1	1	1	0
Telecom	0	0	2	1
Consumer Services	3	2	0	0
Miscellaneous	2	2	2	1

Similar results are obtained in the event study using the Generalised Rank non-parametric test, as shown in Table 5.6.

Table 5.6: Summary of Event Study on Nifty 100 Stocks with Event Date as 20 September 2019 and Event Window (0,1) day using Generalised Rank test by Kolari and Pynnonen

Industry	Number of Companies with Positive CAAR	Number of Companies with Positive CAAR and p-value less than 10%	Number of Companies with Negative CAAR	Number of Companies with Negative CAAR and p-value less than 10%m
Automobile	8	3	1	0
Cement	5	4	0	0
Construction	1	1	1	0
Consumer Goods	9	9	7	3
Financial Services	13	10	7	3
It	0	0	6	6
Metals	4	0	3	1
Oil & Gas	5	3	3	1
Pharmaceutical	1	0	10	10
Power	0	0	4	2
Services	1	1	1	0
Telecom	0	0	2	1
Consumer Services	3	2	0	0
Miscellaneous	2	2	2	1

The event's impact on industries is presented in Table 5.7 and Table 5.8. It can be seen that 9 out of 14 industries saw a positive abnormal return while the remaining witnessed a negative abnormal return. Eight of the industry groups saw significant abnormal returns (at a 10% level) in the event window (0,1 days).

Table 5.7: Event Study of Nifty 100 Industry Groups with Event Date as 20 September 2019 and 5 Event Windows using Boehmer, Musumeci, Poulsen test

	Cumulative average abnormal return (CAAR) of stocks in select event windows				
Industry	**(-2,0)**	**(-1,0)**	**(0,0)**	**(0,1)**	**(0,2)**
Automobile	4.09%***	4.69%***	4.21%***	3.52%***	2.87%**
Cement	3.82%***	3.88%***	4.28%***	4.00%***	2.83%***
Construction	3.55%***	3.16%***	3.12%**	4.40%	2.86%
Consumer Goods	1.47%	1.30%	0.51%	1.79%	2.20%
Financial Services	0.95%**	0.73%*	1.15%**	2.08%**	2.06%**
IT	-6.43%***	-6.15%***	-5.99%***	-11.74%***	-9.80%***
Metals	1.41%	-0.07%	0.36%	-0.80%	-2.50%**
Oil & Gas	0.97%	-0.12%	0.59%	1.50%	1.72%
Pharmaceutical	-2.29%***	-2.51%***	-2.68%***	-6.34%***	-5.63%***
Power	-6.55%***	-6.15%***	-5.48%***	-8.46%**	-8.01%**
Services	-0.06%**	-0.25%	-1.38%	1.73%	2.59%
Telecom	-0.03%	0.20%	-0.55%	-3.59%**	-4.52%***
Consumer Services	5.20%***	3.74%**	3.98%***	5.99%**	5.46%**
Miscellaneous	0.07%	0.43%	-0.13%	1.50%	0.68%

Note: *** indicates p-value < .01, ** indicates p-value <.05, * indicates p-value <.1

Analysis of companies' financials in various industry groups indicates that for the majority of industry groups, which witnessed positive abnormal returns in the event window (0,1 day), the average FY19 tax rate of constituent companies of the industry group was more than the reduced corporate tax rate of 25.17%. Hence, these companies were expected to witness a lower tax outgo and improvement in earnings and valuation due to the tax cut. However, specific industries which were not likely to benefit or were negatively impacted witnessed a negative abnormal return.

Table 5.8: Event Study of Nifty 100 Industry Groups with Event Date as 20 September 2019 and 5 Event Windows using Generalised Rank test by Kolari and Pynnonen

	Cumulative average abnormal return (CAAR) of stocks in select event windows				
Industry	**(-2,0)**	**(-1,0)**	**(0,0)**	**(0,1)**	**(0,2)**
Automobile	4.09%**	4.69%***	4.21%***	3.52%***	2.87%*
Cement	3.82%**	3.88%***	4.28%***	4.00%***	2.83%*
Construction	3.55%**	3.16%**	3.12%**	4.40%	2.86%
Consumer Goods	1.47%	1.30%	0.51%	1.79%	2.20%
Financial Services	0.95%	0.73%	1.15%	2.08%*	2.06%
IT	-6.43%**	-6.15%**	-5.99%**	-11.74%**	-9.80%**
Metals	1.41%	-0.07%	0.36%	-0.80%	-2.50%
Oil & Gas	0.97%	-0.12%	0.59%	1.50%	1.72%
Pharmaceutical	-2.29%*	-2.51%***	-2.68%***	-6.34%***	-5.63%**
Power	-6.55%***	-6.15%***	-5.48%**	-8.46%*	-8.01%*
Services	-0.06%**	-0.25%*	-1.38%	1.73%	2.59%
Telecom	-0.03%	0.20%	-0.55%	-3.59%**	-4.52%**
Consumer Services	5.20%***	3.74%*	3.98%**	5.99%*	5.46%*
Miscellaneous	0.07%	0.43%	-0.13%	1.50%	0.68%

Note: *** indicates p-value < .01, ** indicates p-value <.05, * indicates p-value <.1

The automobile industry saw a significant (at 1% level) CAAR of 3.52% in the event window (0,1 days), as it is likely to benefit immensely from the corporate tax cut. Almost 90% of companies in the automobile industry in Nifty 100 had a higher corporate tax rate than the reduced tax rate of 25.17%. The reduced tax rate of 17.01% on the new manufacturing unit is also likely to boost these companies' investment in manufacturing and make them more competitive than their international peers. Similarly, the Cement industry witnessed a CAAR of 4.0% in the event window due to the tax cuts, with existing corporate tax rates of around 80% of companies in the industry group higher than the reduced level announced. The construction industry also witnessed a CAAR of 4.4% during the event window period, as all the companies in the industry group paid a corporate tax rate of more than 25.17%. Similarly, Oil & Gas saw a positive CAAR of 1.5%, with the tax cut resulting in lower tax rates for almost 60% of companies in the industry groups.

The financial services industry group, which includes banks and other financial services companies, also witnessed a significant CAAR of 2.08% in the event window, as all the companies paid corporate tax of more than 25.17% before the announcement. Due to the tax cuts, an increase in Capex for manufacturing by domestic companies is also likely to improve loan demand for the financial services industry.

The Consumer Services and Consumer Goods industry group saw a positive CAAR of 5.99% and 1.79%, as most companies had paid tax at a higher rate than 25.17% in the past and were likely to benefit from the tax cut.

However, the I.T. (Information Technology) sector witnessed a significant negative CAAR of -11.74% in the event window of (0,1) days, as all the companies in the sector paid lower corporate tax rates than 25.17%. Similarly, the Pharmaceutical and Power sector witnessed a significant negative CAAR of -6.34% and -8.46%, as all the companies in these industries paid a lower corporate tax rate prior to the announcement and thus are not likely to benefit from the tax cut.

Overall, the Short-term reaction of stocks indicates that Sectors such as Automobile, Cement, Construction, Financial Services, Consumer Services, and Consumer Goods are likely to benefit from the tax-cut announcement in the form of lower tax outflows in the future. Some sectors are also likely to benefit from lower taxes on new investments. On the other hand, I.T., Pharma, and Power sectors are not likely to benefit from the announcement or may see an increased tax outflow due to higher tax incidence than their current tax rate. Similar to Event 1, Stock prices' short-term reactions were in line with the Event 2 impact on the various industries, whereas credit ratings were insensitive to the event.

5.4 Credit rating changes and stocks reactions following China-India conflict in 2020

Table 5.9 shows the industry-wise distribution of credit rating actions among the Nifty 500 companies six months following Event 3. Nifty 500 Index encompasses constituents of all the indices used to analyse stock returns.

The analysis of credit ratings of companies for Event 3 indicated that companies in four industries did not witness any credit rating change, while another nine industries saw less than 15% of companies witness credit rating change in the six months following the conflict on June 16, 2020. In only one industry out of the nineteen in the Nifty 500, the percentage of companies witnessing credit rating change was above 50% of the total companies. However, analysing the credit rating change of corporates in this industry indicated that company-specific factors drove the change. Thus, corporate credit ratings remained insensitive to Event 3.

Table 5.9: Proportion of firms in different industries with credit rating changes in six months following the China-India dispute on 16 June 2020

Industry	Number of rated companies in Industry in NIFTY 500	Companies with a downgrade of credit rating	Companies with an upgrade of credit rating	Proportion of companies with a credit rating change
Automobile	29	2	0	6.9%
Cement & Cement Products	15	0	0	0.0%
Chemicals	21	0	2	9.5%
Construction	30	4	1	16.7%
Consumer Goods	73	4	4	11.0%
Fertilisers & Pesticides	12	0	1	8.3%
Financial Services	87	8	3	12.6%
Healthcare Services	7	0	0	0.0%
Industrial Manufacturing	49	2	1	6.1%
IT	27	0	0	0.0%
Media & Entertainment	10	0	1	10.0%
Metals	22	2	2	18.2%
Oil & Gas	18	0	0	0.0%
Paper	2	0	1	50.0%
Pharma	38	0	5	13.2%
Power	15	1	2	20.0%
Services	28	3	0	10.7%
Telecom	7	2	0	28.6%
Textiles	10	1	0	10.0%

Table 5.10 shows the cumulative and average actual return of the indices selected for the study. As per Table 5.10, apart from the Pharmaceutical Index, which witnessed negative returns in the event window (0,15 days), the remaining index had only positive returns. Thus, the overall return of the stock market posts the conflict between China-India was positive.

Table 5.10: Actual Return of Nifty Indices with Event Date as of June 16, 2020, and 3 Event Windows

	Average Actual Return			Cumulative Actual Return		
Index/Event Window (days)	**[0,3]**	**[0,5]**	**[0,15]**	**[0,3]**	**[0,5]**	**[0,15]**
Nifty 50	0.011	0.011	0.006	0.033	0.055	0.087
Nifty 500	0.010	0.011	0.006	0.031	0.056	0.083
Nifty Auto	0.009	0.010	0.007	0.028	0.051	0.111
Nifty Bank	0.017	0.019	0.007	0.051	0.094	0.112
Nifty FMCG	0.002	0.005	0.004	0.005	0.027	0.066
Nifty Infrastructure	0.014	0.013	0.004	0.041	0.063	0.059
Nifty IT	0.001	0.003	0.006	0.003	0.016	0.090
Nifty MNC	0.005	0.008	0.004	0.014	0.038	0.062
Nifty Pharma	0.003	0.009	0.000	0.008	0.043	-0.004
Nifty Midcap 150	0.009	0.012	0.006	0.028	0.060	0.083
Nifty Smallcap 250	0.012	0.014	0.006	0.037	0.072	0.088

Table 5.11 shows the abnormal return of the selected indices over the three event windows, with June 16, 2020, as the event date. As per Table 5.11, only four indices showed positive abnormal returns, while the remaining seven showed negative abnormal returns during the event window (0,15). The Pharmaceutical sector index showed significant negative returns in the event window (0,15). The difference in the abnormal return of different indices can be attributed to the dependency of sectors on the trade between China and India. Pharmaceutical sector in India imports around 70% of its API requirements (Active Pharmaceuticals

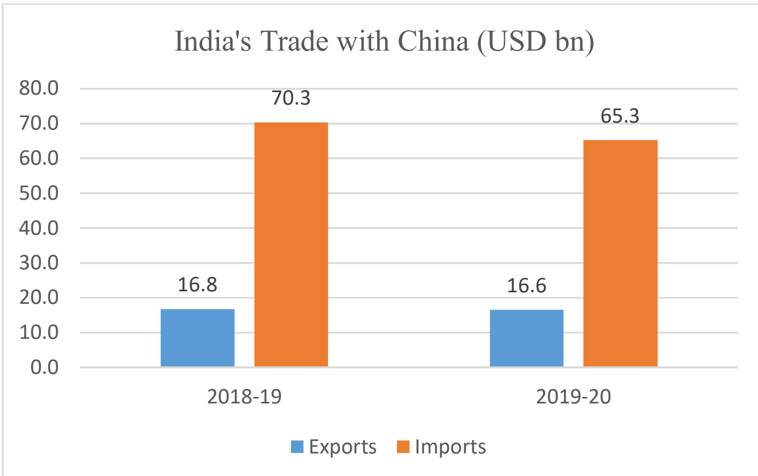
Ingredients) from China. Thus, escalation of conflict between the two nations with possible trade restrictions would negatively impact the Pharmaceutical sector in India [188]. Similarly, the infrastructure sector was likely to be negatively impacted due to the dependency of India's infrastructure players on Chinese equipment, such as solar modules and thermal plant equipment. However, none of the sectors apart from the pharmaceutical sector witnessed a significant positive or negative return over the event period (0,15 days) and thus were unlikely to be impacted by a limited China-India conflict.

Table 5.11: Abnormal return (AR) of Nifty Indices with Event Date as June 16, 2020, and 3 Event Windows using Boehmer, Musumeci, Poulsen test

Index/Event Window (days)	AR[0,3]	AR[0,5]	AR[0,15]
Nifty 50	0.46%	0.088%	0.562%
Nifty 500	0.00%	0.000%	0.000%
Nifty Auto	-0.93%	-1.185%	2.122%
Nifty Bank	3.14%	4.867%**	3.974%
Nifty FMCG	-3.842%*	-4.177%	-2.914%
Nifty Infrastructure	-0.05%	-0.434%	-3.448%
Nifty IT	-3.16%	-4.483%	0.278%
Nifty MNC	-2.734%*	-2.881%	-3.195%
Nifty Pharma	-3.74%	-2.758%	-10.137%*
Nifty Midcap 150	-0.49%	0.097%	-0.290%
Nifty Smallcap 250	-0.25%	0.673%	-0.340%

The limited impact of China – India conflict on Indian markets could be understood from the distribution of the China-India trade. The overall trade between China and India is highly skewed in favour of China, with a trade deficit of USD48.7bn, as shown in Fig 5.1, and as per Indian Ministry of Commerce data, China accounted for only 5.1% of total exports from India.

Figure 5.1: India's Trade with China



Source: Ministry of Commerce, India

Table 5.12 shows India and China's top 5 export and import areas. An analysis of most of the listed Indian companies that were part of selected indices indicates that these companies were not in the production of items exported from India and thus derive minimal revenues from the Chinese market and have a limited import dependency on China. Therefore, except for the Pharmaceutical index, the selected indices did not experience any significant abnormal return due to the China-India conflict.

Table 5.12: Top 5 Import-Exports areas between China-India

Top 5 Exports Areas from India to China		Top 5 Imports Areas to India from China	
Item	% share in Total Exports	Item	% share in Total Imports
Organic Chemicals	16.3	Electrical Machinery, Telecom Equipment	29.3
Ores, Slag and Ash	14.2	Nuclear Reactors & other Mach	19.0
Mineral Fuels, Bituminous Subs.	12.9	Organic Chemicals	12.2
Fish and Crustaceans	8.0	Plastics and Articles	3.9
Electrical Mach, Telecom equipment	5.2	Fertilizers	2.9

Source: Ministry of Commerce, India

5.5 Conclusion

The chapter examined credit ratings' short-term sensitivity to major external events and their effectiveness in indicating the expected impact on corporates due to such events. The sensitivity of credit ratings of firms was compared to that of stock returns. Credit rating changes in the six months following the event were analysed to understand the sensitivity of credit ratings, while event study methodology was used to analyse the responsiveness of stock returns. It was found that the credit ratings of corporates were not impacted due to such events, and investors could not use such credit ratings to understand the risk arising on corporates from such events. On the other hand, stock returns indicated how various sectors are likely to be impacted due to such events.

Chapter 6

Result & Discussion - III

Chapter 6: Analyzing the impact of competition among CRAs on credit rating effectiveness

6.1 Introduction

This section analyzes the impact of competition among CRAs on credit ratings. The objective is to understand whether CRAs engaged in rating inflation when faced with direct competition. In addition, it is analyzed whether rating shopping occurred in the credit rating industry due to competition among CRAs.

6.2 Comparison of key financial metrics of firm rated by multiple CRAs

Under this section, key financial metrics of firms rated by only CRA ‘A’ were compared with those rated by more than one CRA through hypothesis 1. In cases where dual ratings are present, rating inflation could be inferred if firms' key metrics are significantly worse than those rated only by CRA ‘A’ for the same rating category.

Hypothesis 1: There will be no difference in key credit metrics of firms rated by multiple CRAs compared to those rated by a single CRA for the same rating category.

As per hypothesis 1, in case of no rating inflation by CRA 'A', the mean of key credit metrics of firms where more than one CRA (CRA ‘A’ and one or more CRAs) are rating the firm should be equal to those firms in which only CRA 'A' is rating the firms for the same rating category. Hypothesis 1 is tested using a two-sample t-test to check whether the mean credit metrics of the two groups are equal.

Table 6.1 shows the key financial metrics of firms. The firms have been divided into two groups – 1) Group 1 -where only CRA' A' is rating the firm, and 2) Group 2 – dual ratings, i.e., one or more CRA is rating the firm along with CRA' A'. The mean and median leverage of firms, measured as total debt/EBITDA, in Group 2 is higher than in Group 1 firms. This higher leverage of group 2 firms is visible in both investment grade and non-investment grade rating categories. A two-sample t-test found that the mean debt/EBITDA of Group 2 is significantly higher than the mean of Group 1 across rating categories at a 1% level. The mean interest coverage ratio of Group 1 is significantly (at a 1% level) higher than the mean interest coverage ratio of Group 2 in the investment-grade rating category but not in the non-investment-grade rating category. The mean profitability of Group 2 is significantly higher than that in Group 1 (at a 1% level) in both investment and non-investment grade ratings. The mean sales of firms in Group 2 are significantly higher than firms in Group 1 across rating categories. Rating Category 'C' and 'D' have not been included in the analysis. This is because the firms with these ratings have a very high risk of default or are expected to be in default [7]and timely servicing of debt rather than financial metrics is the primary driver of firms rated at this level. CRAs define the investment-grade category ratings as having moderate to the highest level of safety. In contrast, non-investment-grade category ratings are defined as having a moderate to very high risk of default for timely servicing of obligations. Therefore, rating accuracy in the investment-grade category assumes more significance from a risk perspective.

The above analysis indicated that hypothesis 1 is rejected, i.e., the Financial metrics of firms in Group 1 and Group 2 should be equal. The two key credit metrics of firms – leverage and interest coverage - in Group 2 are significantly worse off than in Group 1 – especially across the investment-grade categories. Thus, CRA 'A' assigned a higher rating to a firm with a weaker credit profile when faced with competition in the form of dual ratings. The above analysis confirmed rating inflation by CRAs in India due to competition in the credit rating industry. In addition, the size of firms in Group 2, as measured by sales, is significantly larger than in Group 1, indicating that larger firms are more likely to get inflated ratings due to competition among CRAs. This could be partly explained based on large firms being better positioned to pay fees for credit rating services to multiple CRAs. In addition, large firms have a higher level of debt and thus are likely to pay higher rating fees, as fees are linked to the debt [189,190] and thus are more sought after by multiple CRAs. Jack et al. (2012) concluded that large issuers received more inflated ratings than small hissuers in the U.S. mortgage-backed securities market[191].

Table 6.1: Key Financial Metrics of Firm with or without dual CRAs across rating categories

Key Metrics of Firms						
	Group-1: Firms rated by only CRA 'A'			Group-2: Firms rated by CRA 'A' where at least one more CRA rating is outstanding		
	N	Mean	Median	N	Mean	Median
All Ratings						
Leverage	9174	2.77	2.94	2946	4.34***	3.25***
Interest Coverage	8918	7.19	2.45	2899	5.44***	2.53
Profitability	8719	0.16	0.1	2862	0.18***	0.11***
Sales	8719	6576	1749	2862	27658.15***	4067.5***
Investment Grade Ratings						
Leverage	5064	2.39	2.06	1838	3.79***	2.79***
Interest Coverage	4957	10.96	3.82	1823	7.03***	3.16***
Profitability	4870	0.2	0.12	1807	0.22**	0.13**
Sales	4870	9927.84	**3091.5**	1807	40078.2***	8600.5***
Non-Investment Grade Ratings						
Leverage	4110	3.25	4.07	1108	5.25***	3.94***
Interest Coverage	3961	2.48	1.72	1076	2.74	1.93***
Profitability	3849	0.11	0.08	1055	0.12	0.09**
Sales	3849	2335.13	893.6	1055	6384.58***	1279***
AAA Category						
Leverage	57	1.39	0.21	145	1.01	1.52***
Interest Coverage	57	58.1	28.91	144	24.77***	8.57**
Profitability	57	0.29	0.28	143	0.33	0.2*
Sales	57	120000	97600.2	143	200000***	210000**
AA Category						

Leverage	706	1.73	0.97	356	3.73***	2.48***
Interest Coverage	703	21.93	9.82	356	8.34***	3.93***
Profitability	691	0.25	0.16	355	0.28	0.18*
Sales	691	21962.36	11717.9	355	71207.84***	28982.4***
A Category						
Leverage	1537	2.14	1.67	540	2.98*	2.49***
Interest Coverage	1521	13.49	5.02	540	6.05***	3.5***
Profitability	1507	0.22	0.14	537	0.23	0.14
Sales	1507	9300.54	4183.6	537	20924.05***	9397.5***
BBB Category						
Leverage	2764	2.71	2.72	797	4.86***	3.13***
Interest Coverage	2676	5.64	2.85	783	3.85***	2.46***
Profitability	2615	0.17	0.11	772	0.16	0.11
Sales	2615	4745.22	2122.3	772	10336.69***	3863.05***
BB Category						
Leverage	2270	3.91	3.73	575	4.43	3.56
Interest Coverage	2195	3.07	1.99	560	3.48	2.26***
Profitability	2110	0.11	0.08	546	0.12	0.1***
Sales	2110	2407.05	1019.65	546	6586.07***	1426.1***
B Category						
Leverage	1007	6.04	5.02	311	5.99	4.36***
Interest Coverage	965	2.14	1.58	295	2.36	1.77***
Profitability	952	0.12	0.08	289	0.1	0.07
Sales	952	1229.41	589.3	289	1778.65***	918.4***

*Note: * , **, and *** indicate significance at the 0.1, 0.05, and 0.01 levels, respectively.*

6.3 Effect of competition on the credit rating of a firm by a CRA

Under this section, regression was used to determine whether a CRA provides an inflated rating in the presence of competition. Here, it is directly tested, through hypothesis 2, that a CRA will provide a higher rating, controlling for firm-specific factors, to a firm if other CRAs also rate the same firm.

Hypothesis 2: A CRA rating for a firm is not influenced by another CRA rating of the firm.

Therefore, if hypothesis 2 is rejected, it will mean that CRA 'A' will tend to give a higher rating to a firm if another CRA is also rating the firm. In case of rejection of hypothesis 2, the dummy variable coefficient related to dual ratings in the regression should be of appropriate sign and significant.

As per hypothesis 2, it was tested whether CRA 'A' will tend to give a higher rating if one or more CRA are also rating the firm. The following equation was used to test hypothesis 2:

$$\boldsymbol{CR_{it} = \beta_{\circ} + \beta_1 CRA^j D_{it} + \beta_2 Size_{it} + \beta_3 Leverage_{it} + \beta_4 Profitability_{it} + \beta_5 Interest\ Coverage_{it} + \xi_{it}} \quad \text{..(5)}$$

Where, CR_{it} is the credit rating of firm i at time t at CRA 'A'

$CRA^j D_{it}$ is a dummy variable for dual rating, which takes a value '1' if CRA j gives a rating to the firm i at time t , which has also been rated by CRA 'A' and '0' otherwise

$Size_{it}$, the natural logarithm of total assets of firm i at period t;

$Leverage_{it}$, total debt divided by total debt and total equity of firm i at period t

$Profitability_{it}$, EBITDA divided by total assets of firm i at period t

$Interest\ Coverage_{it}$, EBITDA divided by total finance expenses of firm i at period t

In case CRA 'A' inflates the rating due to competition from other CRAs, then the numerical value of rating of a firm by CRA 'A', which another CRA is rating, will be lower compared to the rating of a firm where CRA 'A' is the only CRA rating the firm, controlling for firm-specific factors. This means that for CRA 'A' to give an inflated rating due to competition, the coefficient of the dummy variable $CRA^j D_{it}$ should be negative and significant.

The OLS and Ordered probit regression results using equation (5) are presented in Tables 6.2,6.3, and 6.4. Table 6.2 shows whether the ratings given by CRA 'A' are inflated when CRA '1' is also rating the same firm. The results show β1, the dummy variable coefficient, for investment and non-investment grade ratings separately.

For non-investment grade category ratings, β_1, the dummy variable coefficient was positive and significant in OLS and ordered probit regression. However, the coefficient is negative and significant at a 1% level for investment grade. The negative coefficient of dummy variables in investment-grade category rating indicates that CRA '1' presence lead to CRA 'A' inflating the issuer rating, i.e., CRA ‘A’ assigned better/higher ratings when faced with direct competition from CRA ‘1’. As discussed earlier, the investment category has more significance than the non-investment category from a risk perspective.

Table 6.2: Impact on Credit Rating of a firm by CRA 'A' due to the presence of CRA' 1'

Dependent Variable: Rating Code, CR_{it}						
	OLS Regression			**Probit Regression**		
	All Ratings	**Investment Grade Ratings**	**Non-Investment Grade Ratings**	**All Ratings**	**Investment Grade Ratings**	**Non-Investment Grade Ratings**
main						
CRA^1D_{it}	0.284***	-0.317***	0.368***	0.080***	-0.155***	0.261***
	(0.078)	(0.076)	(0.066)	(0.028)	(0.037)	(0.048)
Coefficient Economic Size				0.21	-0.377	0.438
Sales	-1.140***	-0.703***	-0.272***	-0.412***	-0.331***	-0.195***
	(0.016)	(0.016)	(0.018)	(0.007)	(0.008)	(0.013)
Leverage	0.409***	0.238***	0.163***	0.143***	0.104***	0.112***
	(0.033)	(0.029)	(0.039)	(0.012)	(0.013)	(0.028)
Profitability	-2.336***	-1.137***	-0.868***	-0.800***	-0.511***	-0.670***
	(0.275)	(0.256)	(0.269)	(0.099)	(0.121)	(0.193)
Interest Coverage	-0.002***	-0.001***	-0.002**	-0.001***	-0.001***	-0.002**
	(0.000)	(0.000)	(0.001)	(0.000)	(0.000)	(0.001)
N	10414	6584	3830	10414	6584	3830

*Note: * , **, and *** indicate significance at the 0.1, 0.05, and 0.01 levels, respectively.*

Table 6.3 shows whether the ratings given by CRA 'A' are inflated when CRA' 2' is also rating the same firm. The results show that for both investment and non-investment grade category ratings, the dummy variable coefficient related to the dual ratings is negative and significant at 1% in both OLS and probit regression. The negative coefficient of the dummy variable related to dual ratings indicates that in the presence of a CRA' 2' rating a firm, CRA 'A' rating for the firm was inflated.

Table 6.3: Impact on Credit Rating of a firm by CRA 'A' due to the presence of CRA '2'

Dependent Variable: Rating Code, CR_{it}						
	OLS Regression			**Probit Regression**		
	All Ratings	**Investment Grade Ratings**	**Non-Investment Grade Ratings**	**All Ratings**	**Investment Grade Ratings**	**Non-Investment Grade Ratings**
CRA^2D_{it}	-0.229**	-0.216**	-0.037	-0.093***	-0.094**	-0.059
	(0.097)	(0.087)	(0.101)	(0.035)	(0.041)	(0.075)
Coefficient Economic Size				-0.243	-0.230	-0.099
Sales	-1.123***	-0.707***	-0.263***	-0.406***	-0.333***	-0.188***
	(0.016)	(0.016)	(0.018)	(0.007)	(0.008)	(0.013)
Leverage	0.415***	0.232***	0.163***	0.145***	0.100***	0.111***
	(0.033)	(0.029)	(0.039)	(0.012)	(0.013)	(0.028)
Profitability	-2.335***	-1.184***	-0.780***	-0.800***	-0.530***	-0.605***
	(0.275)	(0.257)	(0.270)	(0.099)	(0.121)	(0.193)
Interest Coverage	-0.002***	-0.001***	-0.002**	-0.001***	-0.001***	-0.002**
	(0.000)	(0.000)	(0.001)	(0.000)	(0.000)	(0.001)
N	10414	6584	3830	10414	6584	3830

*Note: * , **, and *** indicate significance at the 0.1, 0.05, and 0.01 levels, respectively.*

Table 6.4 shows CRA 'A' rating inflation in the presence of CRA' 3'. The results show that the dummy variable's coefficient related to the dual ratings is negative and significant for all rating categories at a 1% level. Tables 6.2, 6.3, and 6.4 show that CRA 'A' inflated the rating level if another CRA, CRA' 1' or CRA' 2' or CRA' 3', was rating the firm. As per OLS regression, the rating of a firm by CRA 'A' in the presence of other CRAs was 0.21-0.44 notches more than the rating of a firm in which only CRA 'A' assigned the rating, controlling for firm-specific characteristics.

Table 6.4: Impact on Credit Rating of a firm by CRA 'A' due to the presence of CRA' 3'

Dependent Variable: Rating Code, CR_{it}						
	OLS Regression			**Probit Regression**		
	All Ratings	**Investment Grade Ratings**	**Non-Investment Grade Ratings**	**All Ratings**	**Investment Grade Ratings**	**Non-Investment Grade Ratings**
CRA^3D_{it}	-0.449***	-0.438***	0.067	-0.209***	-0.221***	0.033
	(0.145)	(0.125)	(0.173)	(0.053)	(0.060)	(0.126)
Coefficient Economic Size				-0.548	-0.539	-0.056
Sales	-1.121***	-0.703***	-0.264***	-0.405***	-0.331***	-0.189***
	(0.016)	(0.016)	(0.018)	(0.007)	(0.008)	(0.013)
Leverage	0.419***	0.236***	0.163***	0.147***	0.103***	0.112***
	(0.033)	(0.029)	(0.039)	(0.012)	(0.013)	(0.028)
Profitability	-2.349***	-1.194***	-0.785***	-0.808***	-0.538***	-0.612***
	(0.275)	(0.256)	(0.270)	(0.099)	(0.121)	(0.193)
Interest Coverage	-0.002***	-0.001***	-0.002**	-0.001***	-0.001***	-0.002**
	(0.000)	(0.000)	(0.001)	(0.000)	(0.000)	(0.001)
N	10414	6584	3830	10414	6584	3830

*Note: * , **, and *** indicate significance at the 0.1, 0.05, and 0.01 levels, respectively.*

However, to determine the economic impact of dual CRA on a firm's credit rating using the probit model, the study employed the method[1] used by Alp (2013). The economic impact of

[1] In the ordered probit model, the dual rating dummy coefficient estimates, $\boldsymbol{\beta_1}$, are in units of the latent variable $\boldsymbol{CR_{it}}$. To assess the economic impact of the dummy variable on the credit ratings, the coefficient $\boldsymbol{\beta_1}$ is converted to units of rating levels. This is done by dividing the estimated coefficient by the average distance (measured in terms of the latent variable) between the rating categories.

the dummy variable for dual ratings, $CRA^{j}D_{it}$ measures average rating difference between firms rated by CRA 'A' where other CRAs are present (i.e. $CRA^{j}D_{it} = 1$) and where CRA 'A' is the only CRA (i.e. $CRA^{j}D_{it} = 0$). It can be seen that in the case of CRA '1', '2' and '3' presence, CRA 'A' rated firms, on average, are likely to have 0.38, 0.23, and 0.54 levels higher ratings than those firms where CRA 'A' is the only CRA rating the firms. This corresponds to a one-level higher rating by CRA 'A' for approximately one out of every four firms rated along with CRA '2', one out of every three firms rated with CRA '1', and one out of every two firms rated with CRA '3'. The range of dummy variables, $\mathrm{CRA^{j}D_{it}}$,coefficient's economic value for different CRAs could be attributed to the reputational concerns of CRA 'A' viz.a.viz other CRAs in the credit rating industry.

Thus, the results from Tables 6.2,6.3, and 6.4 indicate that hypothesis 2 is rejected, i.e., a CRA rating for a firm is not influenced by another CRA rating, especially in the more critical investment-grade category. The results show that the firm rating given by CRA 'A' was inflated in the presence of other CRAs, as the dummy variable coefficient is negative and significant in all the cases. The findings support the results obtained through a two-sample t-test that CRA 'A' assigned a higher rating to a firm with a weaker credit profile when faced with competition in the form of dual ratings indicating rating inflation due to competition. CRA 'A' actions could be attributed to it providing a higher or equal rating than other CRA to prolong its existing relationship with the firm. The firm may drop CRA 'A' without a higher or equal rating. This corresponds to multiple CRAs rating the firm, improving the firm's rating to a higher but permissible level due to competition as compared to a single CRA-rated firm. Ultimately, the issuer-pays model makes CRA's revenue dependent upon a firm's relationship, and the competition forces CRA to inflate ratings. The findings align with the existing literature that competition among CRAs leads to rating inflation[47,130,143,193].

6.4 Impact on Initial Rating by a CRA due to competition

The tendency of rating shopping by firms can be analyzed using the initial rating assigned by a CRA to a firm when another CRA is already rating the firm. In the case of rating shopping due to competition, the rating assigned by a new CRA will invariably be higher than the current rating. For testing hypothesis 3, the initial rating assigned by other CRAs to a firm rated by CRA 'A' was compared to understand whether other CRAs assign a higher initial rating than the existing rating given by CRA 'A' and vice versa. In addition, hypothesis 3 was tested by using regression to check whether CRA' A' assigns a higher initial rating to firms with existing ratings by other CRAs.

6.4.1 Initial Rating assigned by other CRAs to CRA 'A' rated firms

The rating scale was converted into a numerical scale for this analysis using Table 3.11. Then the initial rating given by other CRAs to a firm was compared with the existing rating given by CRA' A'. The difference between the existing rating given by CRA 'A' and the initial rating assigned by other CRAs was calculated. If rating shopping occurred, the difference would invariably be positive. The summary statistics of this rating difference are presented in Table 6.5. The mean and median difference between CRA 'A' rating and the initial rating by other CRAs are positive for all the CRAs. The difference is also positive for investment and non-investment grade categories with all the CRAs. Table 6.5 shows that CRA 1,2, and 3 assign a higher rating to a firm with an existing rating from CRA 'A' in more than 50% of cases, while a lower rating is assigned in less than 10% of cases. This lends credence to the argument that competition leads to rating shopping in the credit rating industry, i.e., invariably, a firm gets higher than the current rating when it approaches a new CRA for rating. Competition among CRAs to acquire new business from the firm and the Issuer-pays business model is the primary reason for the rating shopping occurring in the credit rating industry.

Table 6.5: Summary of the difference between credit rating of a firm by CRA 'A' and initial rating by other CRAs

				Percentage of observations where new CRA rating is		
	N	**Mean**	**Median**	**Higher**	**Equal**	**Lower**
Comparison of Initial Rating of CRA '1' with Rating of CRA 'A'						
All Rating	367	0.89	1.00	61.04	30.52	8.45
Investment Grade Rating	175	0.61	1.00	50.86	41.14	8.00
Non-Investment Grade Rating	192	1.16	1.00	70.31	20.83	8.85
Comparison of Initial Rating of CRA '2' with Rating of CRA 'A'						
All Rating	304	0.72	1.00	53.62	40.13	6.25
Investment Grade Rating	179	0.30	0.00	37.43	54.75	7.82
Non-Investment Grade Rating	125	1.31	1.00	76.80	19.20	4.00
Comparison of Initial Rating of CRA '3' with Rating of CRA 'A'						
All Rating	167	1.02	1.00	52.10	44.91	2.99
Investment Grade Rating	123	0.58	0.00	39.84	56.91	3.25
Non-Investment Grade Rating	44	2.25	2.00	86.36	11.36	2.27

Table 6.6 shows that CRA 'A' assigned a higher initial rating in more than 50% of cases in which CRA' 1' has an incumbent rating, while in around 10% of cases, it assigned a lower rating. If a firm already has an incumbent rating from CRA' 2' and CRA' 3', CRA 'A' assigned a higher initial rating in around 30% of cases. In comparison, it assigned a lower initial rating in only around 13% of cases. Thus, there was a skew towards CRA 'A' assigning a higher or equal initial rating to firms where other CRA were already present.

Table 6.6: Summary of the difference between the initial rating of a firm by CRA 'A' and rating by other CRAs

				Percentage of observations where new CRA rating is		
	N	**Mean**	**Median**	**Higher**	**Equal**	**Lower**
Comparison of Initial Rating of CRA 'A' with Rating of CRA '1'						
All Rating	503	0.75	1.00	52.3	37.0	10.7
Investment Grade Rating	288	0.73	1.00	53.5	40.6	5.9
Non-Investment Grade Rating	215	0.77	1.00	50.7	32.1	17.2
Comparison of Initial Rating of CRA 'A' with Rating of CRA '2'						
All Rating	251	0.42	0.00	28.3	58.2	13.5
Investment Grade Rating	199	0.43	0.00	26.6	64.8	8.5
Non-Investment Grade Rating	52	0.38	0.00	34.6	32.7	32.7
Comparison of Initial Rating of CRA 'A' with Rating of CRA '3'						
All Rating	104	0.65	0.00	33.7	53.8	12.5
Investment Grade Rating	82	0.62	0.00	28.0	63.4	8.5
Non-Investment Grade Rating	22	0.77	1.00	54.5	18.2	27.3

6.4.2 Initial Rating assigned by CRA 'A' to other CRAs rated firms

Hypothesis 3 was tested using regression, to determine whether the initial rating assigned by CRA' A' to a firm rated by other CRAs was higher, controlling for firm-specific characteristics. The hypothesis is tested using the following equation:

$$\boldsymbol{D.CR_{it}^{j} = \beta_{\circ} + \beta_1 ICR_{it}^{j} + \beta_2 Size_{it} + \beta_3 Leverage_{it} + \beta_4 Profitability_{it} + \beta_5 Interest\ Coverage_{it} + \xi_{it}} \quad \ldots\ldots (6)$$

Where, $D.CR_{it}^{j}$ is the difference in credit rating (converted to numerical scale) of a firm i at time t by CRA 'j' and CRA 'A'

ICR_{it}^{j} is a dummy variable that takes a value '1' if a firm i gets a rating assigned by CRA 'A', when CRA 'j' was already rating it

$Size_{it}$, the natural logarithm of total assets of firm i at period t;

$Leverage_{it}$, total debt divided by total debt and total equity of firm i at period t

$Profitability_{it}$, EBITDA divided by total assets of firm i at period t

$Interest\ Coverage_{it}$, EBITDA divided by total finance expenses of firm i at period t

Control variables are the same as in equation 5. The test employed Ordinary Least Squares (OLS) and Ordered Probit regression. In Case CRA 'A' assigns a higher initial rating to a firm rated by other issuers, then the difference between credit rating by other CRAs and CRA 'A' , i.e., the dependent variable should be positive and the independent dummy variable, ICR_{it}^{j} should be positively correlated to it. The results of equation 6 are shown in Tables 6.7,6.8 and 6.9.

Table 6.7: Rating Shopping: Initial Rating by CRA 'A' to a firm with CRA' 1' as incumbent CRA

Dependent Variable: Rating Difference, $D.CR_{it}^{j}$						
	OLS Regression			**Probit Regression**		
	All Ratings	**Investment Grade Ratings**	**Non-Investment Grade Ratings**	**All Ratings**	**Investment Grade Ratings**	**Non-Investment Grade Ratings**
ICR_{it}^{j}	0.612***	0.345***	0.887***	0.435***	0.380***	0.474***
	(0.098)	(0.093)	(0.207)	(0.060)	(0.076)	(0.100)
Sales	-0.038*	-0.085***	-0.343***	-0.016	-0.067***	-0.142***
	(0.020)	(0.019)	(0.067)	(0.012)	(0.016)	(0.033)
Leverage	-0.020	-0.026	0.647	-0.018	-0.026*	0.314
	(0.024)	(0.018)	(0.484)	(0.014)	(0.015)	(0.230)
Profitability	1.108**	-0.012	6.964***	0.708**	0.268	2.836***
	(0.473)	(0.395)	(1.526)	(0.284)	(0.316)	(0.732)
Interest Coverage	-0.000	-0.000	-0.048**	-0.000	-0.000	-0.020**
	(0.001)	(0.001)	(0.021)	(0.001)	(0.001)	(0.010)
N	1659	1067	592	1659	1067	592

*Note: * , **, and *** indicate significance at the 0.1, 0.05, and 0.01 levels, respectively.*

Table 6.7 shows the coefficient estimates of regression of the dependent variable $D.CR_{it}^{j}$ on the dummy variable ICR_{it}^{j}. The regression has been controlled for firm-specific factors, as per equation 6. Similarly, Table 6.8 and Table 6.9 present coefficient estimates of equation 6. Tables 6.7, 6.8 and 6.9 indicate the tendency of CRA 'A' to assign a higher initial rating in the presence of CRA '1' and CRA '2', respectively.

Table 6.8: Rating Shopping: Initial Rating by CRA 'A' to a firm with CRA' 2' as incumbent CRA

Dependent Variable: Rating Difference, $D.CR_{it}^{j}$						
	OLS Regression			**Probit Regression**		
	All Ratings	**Investment Grade Ratings**	**Non-Investment Grade Ratings**	**All Ratings**	**Investment Grade Ratings**	**Non-Investment Grade Ratings**
ICR_{it}^{j}	0.603***	0.329***	1.125***	0.531***	0.395***	0.793***
	(0.110)	(0.111)	(0.357)	(0.081)	(0.093)	(0.185)
Sales	-0.009	-0.080***	-0.277***	-0.001	-0.070***	-0.057
	(0.021)	(0.022)	(0.099)	(0.015)	(0.018)	(0.052)
Leverage	0.238***	0.202**	-0.124	0.079	0.040	0.130
	(0.088)	(0.084)	(0.937)	(0.064)	(0.069)	(0.442)
Profitability	-2.913***	-2.471***	-3.862	-1.318***	-0.933**	-1.008
	(0.547)	(0.543)	(2.901)	(0.397)	(0.442)	(1.207)
Interest Coverage	-0.001	0.005	-0.114	-0.001	0.002	-0.051*
	(0.003)	(0.003)	(0.102)	(0.002)	(0.002)	(0.026)
N	1048	815	143	1048	815	233

*Note: * , **, and *** indicate significance at the 0.1, 0.05, and 0.01 levels, respectively.*

The coefficient of ICR_{it}^{j} in the OLS regression varies from 0.603 – 1.126 at a significance level of 1% in Tables 6.7,6.8, and 6.9. The dummy variable coefficient is also positive (0.435-0.616) and significant in probit regression. This, along with the positive mean and median rating difference in Table 6.6, implies that CRA 'A' tended to assign a higher initial rating to a firm than its existing rating.

Table 6.9: Rating Shopping: Initial Rating by CRA 'A' to a firm with CRA' 3' as incumbent CRA

Dependent Variable: Rating Difference, $D.CR_{it}^{j}$						
	OLS Regression			**Probit Regression**		
	All Ratings	**Investment Grade Ratings**	**Non-Investment Grade Ratings**	**All Ratings**	**Investment Grade Ratings**	**Non-Investment Grade Ratings**
ICR_{it}^{j}	1.126***	0.881***	1.552	0.668***	0.616***	0.808**
	(0.267)	(0.252)	(1.114)	(0.130)	(0.145)	(0.322)
Sales	0.209***	0.157***	0.160	0.108***	0.085***	0.032
	(0.045)	(0.046)	(0.344)	(0.022)	(0.027)	(0.077)
Leverage	-0.021	-0.055	1.050***	-0.031	-0.047**	0.353*
	(0.042)	(0.037)	(0.381)	(0.020)	(0.020)	(0.192)
Profitability	-0.089	-0.095	-12.211	-0.162	-0.162	-1.076
	(0.844)	(0.738)	(9.097)	(0.394)	(0.402)	(2.392)
Interest Coverage	-0.000	-0.000	0.207*	-0.000	-0.000	0.027
	(0.000)	(0.000)	(0.104)	(0.000)	(0.000)	(0.021)
N	440	364	49	440	364	76

*Note: * , **, and *** indicate significance at the 0.1, 0.05, and 0.01 levels, respectively.*

The economic magnitude of rating shopping can be seen in Table 6.6, which indicates that the initial rating assigned by CRA ‘A’ to a firm, on average, was 0.42-0.75 notches higher than its existing rating by another CRA. Thus, based on these findings, hypothesis 3 was rejected. This could be explained because CRA ‘A’ ability to increase revenue depends on acquiring new firms for ratings due to the issuer-pay model. Therefore, CRA ‘A’ assigns a rating higher than the existing rating of the firm from another CRA to ensure the firm extends the relationship beyond the initial rating. Consequently, the initial rating assigned by a CRA to a firm was generally higher than the firm's existing rating from other CRAs. The results confirm that rating shopping in the credit rating industry stemmed from the competition among rating agencies.

6.5 Conclusion

This chapter analyzed how competition among CRAs impacts firms’ credit ratings. The rating inflation tendency of one of the top four domestic CRA due to competition from the other three and rating shopping in the credit rating industry due to competition was investigated. The study used t-tests and regression techniques to empirically analyze the impact of competition among CRAs on firms' credit ratings. The results showed 1) rating inflation by a CRA due to competition from other CRAs, 2) CRAs' tendency to be lenient when rating large-size firms in the face of competition, and 3) the presence of rating shopping in the credit rating industry.

Chapter 7

Chapter 7: Conclusions, Implications, and Limitations

7.1 Introduction

CRAs' role in risk mitigation in the financial system has become increasingly important, given investors' higher reliance on credit rating for decision-making [194]. The study identifies the aspects of credit rating that are important for stakeholders through literature review. One aspect of the effectiveness of credit ratings is whether credit rating actions contain information about the future financial performance of a corporate. The study investigates the informational value and forward-looking content of credit ratings by analyzing the financial performance of a corporate following a change in its credit rating.

The study also analyzes the sensitivity of credit rating to unanticipated external events and whether credit rating could act as an early warning signal for investors in case of such events. The study compares changes in credit rating to changes in corporate stock price to understand the relative responsiveness of credit rating.

The study also identifies through literature review factors that impact the effectiveness of credit ratings. Within this, the study identifies competition among CRAs as a key reason impacting the effectiveness of credit rating for stakeholders. The study analyzes whether issues in the credit rating industry, such as rating inflation and rating shopping, could be driven by the competition among CRAs.

7.2 Conclusion

This study examines the informational content of credit rating action by CRAs. The study finds that credit rating actions incorporate forward-looking information about a firm's future financial performance as measured by the firm's future operating profit. The results indicate that CRAs' assertion about considering non-public information accessed through interaction with firms' management in their credit rating actions is correct. The findings show that a firm's operating profit is likely to see a relative decline a year after a downgrade of credit rating compared to operating profit change following affirmation. However, a rating upgrade by CRAs is not followed by a similar improvement in operating profit. The results further support the literature that shows a credit rating downgrade has higher information value. Researchers have highlighted that a rating downgrade significantly impacts stock returns, while rating upgrades have limited or no impact, indicating a higher informational content of rating downgrade over upgrade[56,57,59,70]. Baghai et al. (2014) highlighted CRAs increasing conservatism in assigning credit ratings over the years, which could manifest in delayed upgrades and relatively quicker downgrades[177]. Ederington & Goh (1998) also reported that nearby quarterly earnings of a firm fall after a downgrade, while there is no such impact of a rating upgrade[75]. Goh & Ederington (1999) assertion that investors view downgrades as providing information on likely future earnings before interest charges (operating profit), not just interest charges, supports the study's findings[70].

The information asymmetry between downgrades and upgrades could be due to CRAs' likely concern about a sudden or rapid deterioration in the firm's credit quality from a higher rating level, which can have reputational effects. Consequently, CRAs may delay a rating upgrade resulting in no significant operating profit change after an upgrade. At the same time, CRAs are relatively quicker to downgrade credit ratings because of negative news. Thus, earnings decline continues even after a downgrade, although part of the decline may have happened before the downgrade. Jorion & Zhang (2007) explained the asymmetry in stock price reactions to credit rating downgrades and upgrades based on CRAs' greater concern and focus towards identifying deterioration of a firm's credit rather than improvement[58]. The selective bias of management in releasing good news to investors early and withholding bad news, which is then communicated through CRA rating action, can also explain this discrepancy [75,179]. Firms' earnings management to delay earnings decreases could also be a reason behind this informational asymmetry between credit rating upgrades and downgrades [180,181]. CRAs most likely see through such earnings management and adjust the ratings downwards before the firm witnesses a complete earnings reversal [182].

The study shows that credit rating downgrade's information value can be seen across investment and non-investment grades and rating categories. The findings of the study are valid across individual years of the study. The results show that the relative decline in operating profit is likely to be higher if the rating is downgraded to a non-investment grade category. The findings also highlight that a higher level of downgrade indicates a higher relative decline in operating profit in the next year. The findings support the existing literature regarding the informational content of credit rating and provide additional insight into the exact nature of information incorporated in credit rating changes regarding the future operating profit of a firm. The findings are in accordance with results obtained by Ederington & Goh (1998), which indicated that actual quarterly earnings and forecasts fall after the downgrade, while upgrade has no impact on actual earnings[75]. Chou (2013) showed that stock returns of rated firms reflect more future earnings than non-rated firms[76]. Jeppson et al. (2018) reported that the level of rating could predict the accuracy of the future earnings forecast of a firm[78].

The study found that credit ratings are generally less sensitive to external events. There is almost no change in the credit rating of corporates across sectors despite the apparent impact of analysed events were likely to have on corporates performance. Chodnicka-Jaworska (2023) found a delayed reaction of CRAs on the effect of pandemic on European banks[195]. Tran et al. (2021) found that CRAs reviewed sovereign ratings as per their review cycle rather than in response to the sudden changes due to COVID-19[196]. Attig et al. (2021) highlighted that during uncertain times, credit ratings users must evaluate bond issuers' fundamentals since credit ratings are likely to be overoptimistic[197].The stickiness of credit rating in the short term could be attributed to its focus on the long-term debt serviceability of a corporate. Thus, credit ratings are ineffective in the short term as an early warning signal for investors and managers. The study also analyzed the stock returns of corporates and found the heterogeneous impact of analysed events on various sectors in the short term.

The study investigated how competition among CRAs in the credit rating industry impacts firms' credit ratings. The results of this study indicate that competition among CRAs influences firms' credit ratings. The study focuses on empirical analysis of firms' credit ratings given by the top four CRAs in India, focusing on how competition by other CRAs impacts a firm's rating given by CRA 'A'. The study found empirical evidence of rating inflation by a CRA 'A' due to competition from other CRAs. The study's findings also indicate that CRAs tend to be lenient when rating large-size firms in the face of competition. In addition, the results also indicate that competition leads to a firm getting a higher initial rating from a CRA than the firm's existing rating, resulting in rating shopping in the credit rating industry. The study's findings are consistent with prior literature, which highlight that competition among CRAs worsens credit rating quality.[47,141,143,151,152,198]

7.3 Implications

The study contributes to understanding the informational value of credit rating actions of CRAs. The study has implications for investors, analysts, and managers as it confirms that credit rating has forward-looking information, and changes in credit ratings need to be accounted for in decision-making. The study allows investors to understand the changes in the future financial performance of a firm following a credit rating downgrade. Investors and analysts can incorporate credit rating downgrades by CRAs as a key input in a firm's future financial forecast. Investment managers need to monitor credit rating changes in their portfolios to minimize risk, considering the implications of credit rating actions on portfolios' holdings. Analysts and Investment managers can also look at credit rating changes of firms in the same industry and draw a definite conclusion about which firm is likely to see a higher deterioration in performance. The study findings have even more significance in emerging economies where firm investor disclosures may be less or absent. Thus, credit rating changes can be a critical source of forward-looking information for investors in emerging economies.

The study also allows investors to understand the relative responsiveness of changes in credit ratings compared to changes in stock prices due to external events. It enables investors to understand stock market reactions across different industries. It also highlights which sectors are more resilient to such shocks and are likely a better hedge for investors to reduce the risk to their investment when faced with such risks in the future. The study's findings could help policymakers identify segments of the economy that require immediate support due to the disruption from such abrupt events. Investors can observe the lack of sensitivity of credit ratings to such events and understand the need to be more vigilant in managing sudden risks and not rely solely on credit ratings.

The study findings have important implications for regulators and investors. In the past, regulators have sought to address the credit rating industry's issues by increasing competition and allowing more players in the credit rating market. In the U.S., Congress passed the Credit Rating Agency Reform Act in 2006, while in Europe, CRA III regulation, enacted in 2013-14, had provisions for increasing competition in the credit rating industry. In India, three additional CRAs have been accredited for credit rating since 2008. The study's findings indicate that the regulators need to be cautious while allowing more competition in the credit rating industry due to its adverse effects on rating quality. The study informs investors about the hazards of relying solely on credit ratings for risk estimation and the upward bias in large issuers' credit ratings.

7.4 Recommendations

Penalizing CRAs, through monetary fines or temporary suspension, for egregious ratings could be a way to make CRAs more cautious and curb the practice of rating inflation and rating shopping. However, this is more of a reactive approach and needs to be complemented with closer regulatory supervision and increased disclosure requirements to improve transparency and consistency in ratings. Controlling the allocation of cases to different CRAs could help curb rating shopping, as this will restrict firms' movement from one CRA to another for favourable ratings. Periodic rotation of a firm's rating between CRAs could address the rating inflation issue in the industry, with CRAs being aware that their relationship continuance with a firm is independent of the firm’s rating. However, regulators must also strike a balance between supervision and allowing CRA to rate firms freely. A too-conservative approach by CRAs could raise the cost of capital for firms and result in inefficient allocation of resources.

7.5 Limitations & Future Research

The study findings are linked to a CRA's expectation of the future performance of a firm's business. However, credit rating changes by CRA may also be contingent upon a firm specific event occurring and could be reversed by the CRA in case the event does not materialize. Investors must be careful of such instances when using the study's findings for decision-making.

In addition, the study uses non-financial corporate rating data; hence, the findings may not be applicable to credit rating changes in financial corporates and structured finance. Future research can focus on whether credit rating changes in these areas indicate future performance.

Future research can also explore credit rating changes for informational value regarding other aspects of firm performance, such as working capital and interest cost.

The study primarily utilizes data available in the public domain, such as financial information of firms. Additional information, such as issuer fees, could provide more insight into rating shopping and rating inflation trends in the industry.

In addition, Credit Ratings Symbol definitions indicate that financial obligations servicing is the key criteria for assigning a credit rating. Thus, the study has used key credit metrics of firms as a key input to compare credit ratings across CRAs.

The long-term implications of analysed external events on various economic sectors may not align with the study's findings, and researchers need to investigate it to understand the long-term impact of such events. Future research could investigate whether the actual performance of corporates is in line with the study's findings.

Credit rating agencies assert that they rate corporates on a through-the-cycle approach, and the study looked at the immediate or short-term impact on corporates due to specific events. Thus, credit ratings by design may be less reactive in the short term.

The existing competitive dynamics between CRAs may change in the future based on incentives for CRAs to indulge in such practices. Such incentives may arise or disappear based on changes in regulations that may happen from time to time.

The study considers only credit ratings for non-financial corporates, but domestic CRAs also assign ratings in the area of public finance, structured finance, and financial corporates. Future research can focus on how credit ratings in other areas are affected due to competition between CRAs. Future studies can also analyze how the relative market position of a CRA in the industry impacts its response to the competition it faces.

Technological advances are reshaping the dynamics of several industries. Even in the credit rating industry, Machine Learning and neural network-based models can help in bringing efficiency to the credit rating process, particularly in data processing. Machine learning can help incorporate volumes of diverse data into credit ratings which may not be possible by an individual credit analyst, and thus, decision-making can be improved. Machine learning models could also lead to improved credit analysis in segments such as small enterprises that may not appeal to credit rating agencies. However, machine learning-based models are based on historical data, and inadequate data can increase the risk of wrong outcomes regarding discriminatory or unfair credit ratings. In addition, these models are more like black boxes, and assessing them for external stakeholders is not easy. Currently, the criteria for assessment are available for issuers enabling them to understand the process and the rationale behind the final credit rating assigned. However, issuers may be unable to interpret and understand the machine learning-based models, and CRAs may also find it challenging to communicate to issuers the outcome of such models. Thus, future research can focus on how machine learning-based models could lead to changes in the dynamics of the credit rating industry and, at the same time, maintain the regulatory focus on transparency of the credit rating process between issuers and CRAs.

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PhD Scholar's Bio

Mr. Chandan Sharma has joined DTU as Assistant Professor in Feb-2018. He has completed his Post Graduate Diploma in Management (PGDM) from Indian Institute of Management, Indore in 2008 and Bachelor of Engineering from Delhi College of Engineering, University of Delhi in Mechanical Engineering in 2006.

Prior to joining DTU, he has worked in the Financial Services Industry for almost 10 years. He has rich industry experience in both Indian equity and debt markets. He has worked in equity research area during the period May 2008- Mar 2011. During the period Mar 2011-Feb 2018, he was working in corporate credit rating area and has been involved in the credit rating of large domestic corporates. He has extensively engaged Promoters and Senior Management of Corporates as well as market participants such as Domestic Institutional Investors, Foreign Institutional Investors, and Senior Bankers during his stint in the credit rating industry.

List of Publications

Journal Publications

1. Are Credit Ratings forward-looking? - Evidence from India, Kybernetes (Indexed - Scopus, SCIE), **DOI:** 10.1108/K-03-2023-0511
2. Impact of competition in credit rating industry: Evidence from India, Sage Open (Indexed - SSCI, Scopus), **DOI**: 10.1177/21582440221135107
3. Market warnings - learning from short term impact of COVID-19 on stock market constituents, Indian Journal of Finance (Indexed - Scopus, ABDC), **DOI**: 10.17010/ijf/2023/v17i4/170094
4. Impact of India's 2019 Corporate Tax Cut Announcement on the Stock Market, Indian Journal of Finance (Indexed - Scopus, ABDC), **DOI**: 10.17010/ijf/2022/v16i2/162839

Journal Publication (Accepted)

1. An investigation into short term reaction of Indian Stock market to China-India conflict, Journal of Accounting Research and Audit Practices (Indexed - ABDC, UGC CARE List - Group - 1)

International Conference

1. Issuer pay model and the dilemma of rating agencies in India, International Conference on Business and Management, DSM, DTU
2. Analysis of Large Corporate Defaulters in India, International Conference on Green Economy for sustainable growth in Commerce, Science, Technology, Engineering & Management, NSM Degree College, Vile-Parle, Mumbai, India