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ARTICLE

THE IMPACT OF BOND RATING SHOCKS ON MARKET AND FIRM PERFORMANCE IN INDIA

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Abstract

This study attempts to analyse the intensity and impact of credit rating shocks experienced by bond instruments in the Indian market. We work on monthly data on credit ratings assigned by three major credit rating agencies in India- CARE, CRISIL and ICRA. Based on significant rating changes in a single rating revision, we construct the Reputational Shock Index for downgrades, upgrades and overall rating revisions. These indices are built for individual rating agencies and at the aggregate level. Using event study methodology, we aim to analyse the impact of bond rating shocks on firm and market returns. The effect of rating shocks on stock markets can be explained by two prominent theories- The information signalling hypothesis and the Wealth Redistribution Effect. The market-level event study analysis highlights the dominance of the information signalling effect as a negative (positive) response is observed towards downgrades (upgrades) in most cases. The firm-level event study analysis results show a mixed reaction of investors to downgrades and upgrades, but the information signalling effect dominates. The study focuses on the Indian market. Such work can also be extended to other markets to assess the efficiency of credit rating agencies and the market response to rating errors. We recommend the construction of the Reputational Shock Index at the agency and aggregate levels. Our work has important policy implications for bond issuers, credit rating agencies, investors, market regulators, and academicians. The study is unique in constructing the Reputational Shock Index and performing event study analysis at the firm and market level.

Keywords: Bond ratings, Rating downgrades, Reputational shock index, Information signalling hypothesis, Wealth redistribution effect.

1 Introduction

In this study, we analyse the intensity and impact of credit rating shocks experienced by bond instruments rated by three leading rating agencies- CARE, CRISIL and ICRA. A credit rating shock is defined as a severe rating downgrade or upgrade in a single revision. A bond rating shock will likely affect investor behaviour and stock market performance at the macro/micro level. The impact of rating shocks on stock markets can be explained by the following two theories: the Information Signalling Hypothesis and the Wealth Redistribution Effect.

According to the Signalling Hypothesis, additional information about the firm's total value is provided to the market by a rating change. The market may perceive rating change as a signal for change in the issuer's future earnings and cash flows. Thus, a rating downgrade is followed by declining stock prices (Hand, Holthausen and Leftwich, 1992; Elayan et al., 1996; Hite & Warga, 1997; Barron et al., 1997; Dichev & Piotrosky, 2001; Choy et al., 2006; Gropp & Richards, 2001; Benjamin, 2008; Avramov et al., 2009; Chakravarty et al., 2009; Lal & Mitra, 2011) On the other hand, a rating upgrade is followed by rising stock prices (Barron et al., 1997; Gropp & Richards, 2001; Chakravarty et al., 2009; Sehgal et al, 2018). According to the Wealth Redistribution Hypothesis, there is usually a conflict between interests of stockholders and bondholders. Due to their limited liability in a firm, stockholders are tempted to invest in riskier options to earn higher returns. This leads to an increase in the default risk of outstanding bonds, followed by rating downgrades. (Romero and Fernández, 2007). Thus, a decline in the value of bonds is transferred from bondholders to stockholders, causing an increase in stock prices. On the other hand, a rating upgrade would lead to decreasing stock prices. Also, if we view equity shareholders as holding an option on the firm value with a strike price equivalent to the par value of the firm's debt, an increase in the variance of the firm's cash flows would lead to the redistribution of wealth from bondholders to stockholders. (Holthausen and Leftwich, 1986 and Zaima and McCarthy, 1988). Further, the wealth distribution hypothesis is also supported by Goh and Ederington (1993) and Bhoot (1995).

Since both these effects work in the opposite direction, at some point, one of them would dominate and have a positive/negative impact on security prices. Prior research shows that prices are more responsive to downgrades than to upgrades. The present study is a comprehensive attempt to analyse the impact of rating revisions on firms' stock prices and the entire stock market. This is missing in the prior work. Existing literature examines various other aspects of credit ratings and rating changes. Jorion et al. (2005) evaluate the impact of rating changes on security prices in the US market during the Regulation Fair Disclosure period. Kisgen (2009) examine the effect of rating changes on a firm's capital structure. Kaur and Kaur (2011) study the rating methodology of rating agencies in India. Venkatesh and Goswami (2012) work on the understanding and use of ratings for individual and institutional investors in India. Basu et al. (2020) document the impact of rating changes on a firm's voluntary disclosure behaviour. Dawar et al. (2021) analyse the impact of credit rating revisions on prices of common stocks. However, this work is restricted to firm-level analysis. Sehgal et al. (2022) work on estimating an adequate model for determining credit ratings. Artha and Hertikasari (2022) review the existing literature on credit ratings as a moderating variable in the financial system. Nguyen, et al. (2023) estimate the relationship between credit rating downgrades and stock price crash risk across different countries.

In our work, we extend the existing literature. We intend to examine whether the 'Information Signalling Hypothesis' or 'Wealth Redistribution Effect' dominates in the post-rating revision period. Understanding the impact of credit rating revisions is important, as ratings are viewed as an association between borrowers and issuers (Adelson, 2012). Hence, rating agencies have been judged for their role in major economic scandals (Papadimitri et al., 2020).

This study evaluates how stock price responsiveness varies for downgrades and upgrades. For this purpose, we use an event study analysis to measure the impact of reputational shock across the macro and micro levels. This is the unique contribution of our work. Though event studies have been previously employed for various purposes (Gupta & Arya, 2019; Gupta et al., 2022), their application to study the impact of rating revisions on firm and market performance is novel to our paper. At the macro level, we aim to analyse the impact of significant credit rating changes in a month on the overall stock market. We construct a Reputational Shock Index for downgrades, upgrades, and overall rating revisions. These indices are constructed specifically for CARE, CRISIL and ICRA. Composite indices representing major rating revisions made by all three rating agencies are also constructed. Hereafter, Reputational Shock Indices for downgrades, upgrades, and overall rating revisions are represented as RSI-, RSI+, and RSI, respectively. To analyse the market response to downgrades/upgrades, we observe the movement of the NIFTY 200 index before and after specific dates on which major rating downgrades/upgrades are made. These events fall in specific months with the highest RSI- and RSI+ values. At the micro level, we consider significant rating revisions for individual bond issues and assess the movement of stock prices pre- and post-downgrades/upgrades for these specific companies to analyse the investor response. We consider a very short-term window for both macro and micro-level event study analysis. (-1 to +1 days) and a short-term window (-20 to -1 days pre-event and 0 to 20 days post-event). The paper is divided into four sections, including the current one. The next section discusses the materials and methods used. The subsequent section presents results and discussions. The last section concludes with conclusions and managerial implications.

2 MATERIALS AND METHODS

2.1 Data description

For this phase, we will use monthly data on credit ratings assigned by CARE, CRISIL, and ICRA from January 2009 to March 2020. The data is taken from the respective websites of CRAs. Further, we assign cardinal values to these ratings, which range from 1-18, where 1 represents AAA-rated instruments and the riskiest instruments rated D are represented by 18. (Table 1). To observe rating revisions, we look at Notches, which are defined as the difference in cardinal values assigned each month by the same issuer. Monthly downgrades and upgrades can fall in notches ranging from -17 to +17. This data on monthly changes in cardinal values from February 2009 to March 2020 is used to construct the Reputational Shock Indices. For the macro (micro) level event study analysis, we use daily data of closing prices of the NIFTY 200 index (companies that have experienced significant rating shocks). This data is further converted into daily log returns. We use NSE's website and Prowess Database to source this data.

Table 1: Rating classes and their cardinal values

Notes: This table represents the cardinal values assigned to each rating class.

Rating Class	Aaa	aa+	Aa	aa-	a+	A	a-	bbb+	Bbb	by-	bb+	Bb	bb-	b+	B	b-	C	D
Cardinal Value	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18

2.2 Index Construction

For constructing Reputational Shock Indices, a significant rating change is defined as a downgrade/upgrade by three or more notches in a single rating revision. We consider credit ratings from January 2009 to March 2020. Since we are working with the difference in ratings, we obtain index values from February 2009 to March 2020.

RSI—(RSI +) considers all issues falling in +3 to +17 (-3 to -17) notches each month. They were assigned weights from 1 to 15, respectively. Our weighing system gives higher weightage to more considerable rating revisions, as this indicates a more significant error on the part of rating agencies.

The following formula is used to compute RSI-:

$$RSI = \sum_{i=1}^{t} W_i * F_i, \tag{1}$$

where; W_i is the % weight assigned to downgrades from +3 to +17 monthly notches ($i = 1tot$). It is computed as; $(w_n / \sum w) * 100$; where wn is the weight assigned to each notch (i.e. 1 to 15 for notches 3 to 17 respectively), and $\sum w$ is the sum of weights ranging from 1 to 15.
F_i is the % frequency of downgrade cases falling in each notch, ranging from 3-17, each month ($i = 1\ to\ t$). It is computed as; $(f_n / \sum f) * 100$, where f_n is the number of downgrades in each notch, and f is the total number of cases in a particular month ranging from -17 to +17.

Similarly, $RSI+$ is constructed using the following formula

$$RSI+ = \sum_{i=1}^{t} W_i * F_i, \tag{2}$$

where; W_i is the % weight assigned to upgrades ranging from -3 to -17 monthly notches ($i = 1tot$). It is computed as; $(w_n / \sum w) * 100$; w_n is the weight assigned to each notch (i.e. 1 to 15 for notches 3 to 17, respectively), and $\sum w$ is the sum of weights ranging from 1 to 15. F_i is the % frequency of downgrade cases falling in each notch, ranging from 3-17, each month ($i = 1\ to\ t$). It is computed as: $(f_n / \sum f) * 100$, where f_n is the number of downgrades in each notch, and $\sum f$ is the total number of cases in a particular month ranging from -17 to +17. Next, for each month (i), we construct RSI as the weighted average of RSI- and RSI+ using the following formula:

$$RSI_i = (w_{di} * RSI - i) + (w_{ui} * RSI+_i), \tag{3}$$

Where w_{di}= weightage assigned to downgrades in each month (i), which is computed as the total number of downgrades from notch +3 to +17 divided by the summation of cases falling in notch -3 to -17 and +3 to +17.
w_{ui} = weightage assigned to upgrades each month (i), computed as the total number of upgrades from notch -3 to -17 divided by the summation of cases falling in notch -3 to -17 and +3 to +17.
If there are no cases falling in notches, +3 to +17 and -3 to -17, for a particular month, the RSI takes a value of 0.
RSI-i, RSI+i and RSIi, are Reputational Shock Indices for downgrades, upgrades and overall cases for each month (i). These indices are constructed to reflect rating errors made by credit rating agencies. A higher value of the index indicates more fantastic mistakes in assigning ratings. We create all these indices individually for CARE, CRISIL, and ICRA, and a composite index is designed to consider ratings made by all three rating agencies. The methodology used to construct the indices is unique to our work. However, we take inspiration from Goebel and Kemper (2022) to estimate the notches. We use these notches to construct individual and composite indices, which are missing from prior literature. The index developed can be used to identify rating errors and can be used wherever decision choices are based on credit ratings. We extend this methodology to perform macro and micro-level event study analysis, which has not been done comprehensively in past work. This is the unique contribution of our work.

The data for total number of cases falling in each notch for each month is used for index construction. This data is not provided in the text due to paucity of space. However it can be obtained from authors on request.

2.3 Macro-level Event Study Analysis

We now observe the movement of composite RSI- and RSI+ to identify major kinks, which indicates rating mistakes. To analyse the stock market response across significant downgrades and upgrades, we do an event study analysis and observe the Cumulative Abnormal Return (CAR) of NIFTY 200 across a very short-term/short-term window. We first look at the impact of downgrades. Amongst 134 monthly observations (February 2009 to March 2020), RSI- takes values ranging from 0 to 5.32. To look for the impact of downgrades on the stock market, we deep dive into the highest 5% observations, i.e. we specifically focus on seven months with the highest values of RSI-. Within each of these months, we identify the specific dates (treated as a separate event) on which downgrades have taken place and do an event study analysis for each event to understand the market response around these downgrades. For both the time windows, day 0 is defined as the event day, i.e. the date of downgrade, and the estimation period is taken to be -140 to -21 days. CAR is computed from day -1 to +1 for the short-term time window. The long-term window is divided into pre-event (-20 to -1 days) and post-event (0 to +20 days). CAR estimations are done for both of these periods. For the entire period ranging from -140 days to +20 days, daily closing prices are taken, which are further converted into logarithmic returns using the following formula:

$$ln(p_t) - ln(p_{t-1}), \tag{4}$$

where ln(pt) is the natural log of the closing price of NIFTY 200 on day t; $ln(p_{t-1})$ is the natural log of the closing price of NIFTY 200 on day t-1. The mean return across the estimation period (-140 to -21 days) is computed using a simple average of logarithmic returns. For the very short-term window, we estimate abnormal returns (AR) from day -1 to +1 by subtracting the mean return from the actual returns. These are added to obtain CAR for the very short-term window. To estimate the standardised CAR (SCAR), we divide CAR by the standard deviation of ARs from day -6 to +1. We obtain SCAR values for each event within a particular month. Further, we estimate the Cumulative Average Abnormal Return (CAAR) for a specific month using the following formula:

$$CAARm = Wi * CARi, \tag{5}$$

where $CAAR_m$ is the CAAR for each month (m); W_i is the weight assigned to each event (i), which is calculated as the number of issues downgraded on a particular date divided by the total number of issues downgraded in that month; and CAR_i is the Cumulative Abnormal Return for each event (i). Further, the standard deviation for each monthly series is estimated using the Markowitz formula described below. We use this to consider the impact of co-variance between returns, as some dates in a month are very close to each other.

$$\sigma_m = \sqrt{\sum_{i=1}^{N} w_i^2 * \sigma_i^2 + \sum_{i=1}^{N}\sum_{\substack{j=1 \\ i \neq j}}^{N} w_i\, w_i\, \sigma_{ij}} \tag{6}$$

Where s_m is the standard deviation of CAAR for each month (m); W_i is the weight assigned to each event (i), which is calculated as the number of issues downgraded on a particular date divided by the total number of matters downgraded in that month; si is the standard deviation of CAR for each event (i); s_{ij} is the co-variance between CARs for two events (i and j) We now estimate each month's SCAAR (Standardised CAAR) by dividing the CAAR by the standard deviation.

For the short-term window, we divide our observation period into pre-event and post-event. The mean return across the estimation period (-140 to -21 days) is computed using a simple average of logarithmic returns. For the pre-event period (post-event), we estimate abnormal returns (AR) from day -20 to -1 (0 to 20) by subtracting the mean return from the actual returns. These are cumulated to obtain the CAR for the short-term window. To estimate the standardised CAR (SCAR), we divide CAR by the standard deviation of ARs for the same period.

Next, we observe values of RSI+ to estimate the market response to upgrades. Over 134 months, it ranges from 0 to 1.82. The movements in RSI+ are less volatile than those in RSI-, which shows that major corrections by rating agencies have been made on the downside. Thus, we analyse the market response to upgrades only for two months (top 2% values) with the maximum value of RSI+, as the index takes a minimal value (less than 1) for all other months. The event study analysis for very short-term and short-term upgrades is done like for downgrades.

2.4 Micro-Level Event Study Analysis

After analysing the market-wide response to rating errors, we now evaluate individual issues and the stock prices of companies that have bond issues that have experienced major rating revisions. Particularly, we look at issues that have been downgraded/upgraded by 8 and above notches, and have been a part of NSE 200 at any point of time over the past one year before the rating correction. We choose 8 notches as the cut-off point as we focus on a change of greater than equal to 50% of the maximum notch size of 17. Issues of certain companies that have not been a part of NSE 200 have also experienced major rating shocks. We consider these issues also in our analysis. However, for such companies we only consider issues that have been downgraded/upgraded by more than 12 notches, where 12 is taken to represent greater than equal to 75% of the maximum notch size. An event study analysis is done for all the dates on which such rating corrections have been made. We do a separate analysis for downgrades and upgrades.

Based on the above-mentioned criterion, we have identified 17 (3) significant downgrades (upgrades) done across 10 (2) dates/events. As mentioned earlier, the event date is defined as day 0, the estimation period is -140 to -21 days. A very short-term analysis of CAR is done for -1 to +1 days. The short-term window is divided into pre event (-20 to -1 days) and post event (0 to +20 days) period. Log returns for individual companies and NIFTY 200 are computed from their closing prices. We use the market model to compute the expected returns using the following equation:

$$R_{xi} = \alpha_X + \beta_X R_{mi} + e_{xi}, \tag{7}$$

where;
R_{xi} = Return on stock x at time period 'i'
R_{mi} = Return on market index at time period 'i'
α_X, β_X represent the intercept and slope respectively.

α_X and β_X are estimated using the above equation over the estimation period of -140 to -21 days, which are used to calculate daily expected returns for the entire period. Abnormal Returns for very short-term and short-term window are then computed by subtracting expected returns from actual returns for each day. Computation of SCAR for each event for both time windows is done in the same way as discussed previously.

3 RESULTS AND DISCUSSIONS

3.1 Analysis of Reputational Shock Indices

This section reports the volatility of Reputational Shock Indices for CARE, CRISIL, ICRA and the composite indices. We report 2 measures of volatility, namely, standard deviation and range (Table 2). Monthly values of RSI-, RSI+, and RSI for all three rating agencies and the composite values are graphically represented in Figure 1, 2, and 3 respectively. Indices for downgrades range from 0 to 9.40/1.65/5.88/5.32 for CARE/CRISIL/ICRA/composite index. Standard deviation in these indices is found to be 1.31, 0.21, 0.80, 0.74 respectively. Indices for upgrades range from 0 to 3.29/0.52/6.25/1.82 for CARE/CRISIL/ICRA/composite index. Standard deviation in these indices is found to be 0.34, 0.06, 0.86, 0.19 respectively. The value of RSI ranges from 0 to 9.40/1.65/6.25/5.32 for CARE/CRISIL/ICRA/composite index. Standard deviation in these indices is found to be 1.32, 0.21, 1.16, 0.75 respectively. Our results show that maximum volatility is experienced by RSI- for CARE and RSI+ for ICRA.

We now focus on the composite index for downgrades and upgrades to see the impact of rating errors made collectively by CARE, CRISIL and ICRA. We identify events leading to spikes in its value and analyse the market response around these events. This is discussed in the following section.

Table 2: Volatility measures for Reputational Shock Indices (RSI)

Notes: This table shows two measures of volatility-standard deviation and range for RSI (downgrades), RSI (upgrades) and RSI (overall rating revisions) for all three rating agencies and for the composite index. These indices have further been represented as RSI-, RSI+ and RSI respectively.

	CARE			CRISIL			ICRA			COMPOSITE		
Index	RSI-	RSI+	RSI	RSI-	RSI+	RSI	RSI-	RSI+	RSI	RSI-	RSI+	RSI
Volatility	1.31	0.34	1.32	0.21	0.06	0.21	0.80	0.86	1.16	0.74	0.19	0.75
Range	9.40	3.29	9.40	1.65	0.52	1.65	5.88	6.25	6.25	5.32	1.82	5.32

3.2 Macro Level Event Study Analysis

The composite value of RSI- ranges from 0 to 5.32. Out of 134 monthly observations, we look at the highest 7 values (i.e. 5% of the total observations). These 7 months are further a collection of events (specific dates) on which downgrades have taken place. Table 3- Panel A shows the number of events in each of these months and the number of issues downgraded on each date.

The composite value of RSI+ ranges from 0 to 1.82. Since there is not much variation in the monthly values of this index, we analyse only the top 2% of 134 monthly observations. We focus on 2 months, which are further a collection of events (specific dates) on which upgrades have taken place. Table 3- Panel B shows the number of events in each of these months and the number of issues upgraded on each date.

Firstly, we analyse the market response to downgrades. Very short-term analysis shows that CAAR values for 4 months

Fig. 1: Monthly Index values of RSI (downgrades)

Notes: This figure represents the monthly values of RSI- for CARE, CRISL, ICRA and the composite index.

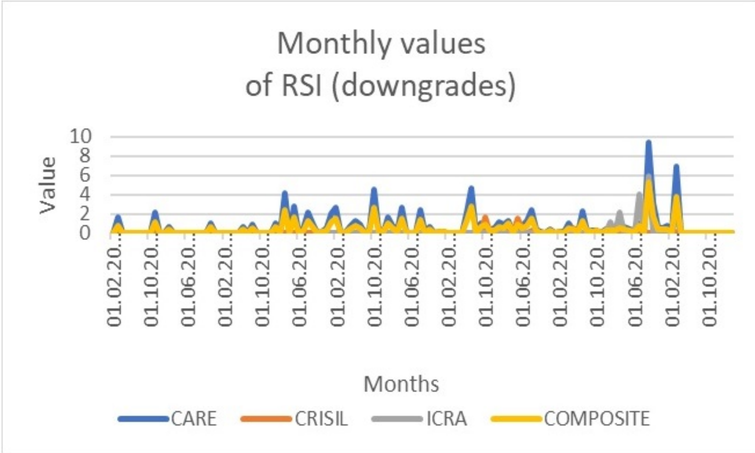


Fig. 2: Monthly Index values of RSI (upgrades)

Notes: This figure represents the monthly values of RSI+ for CARE, CRISL, ICRA and the composite index.

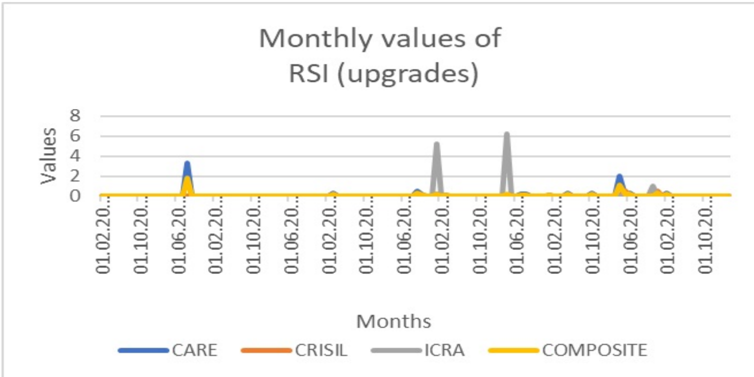
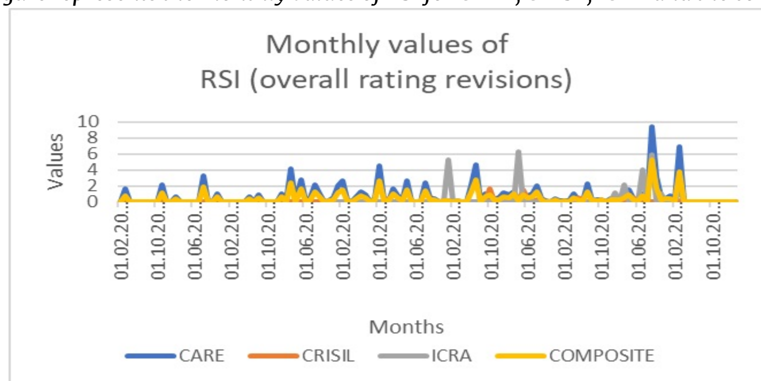


Fig. 3: Monthly Index values of RSI (overall rating revisions)

Notes: This figure represents the monthly values of RSI for CARE, CRISL, ICRA and the composite index.



(September 2018, March 2019, March 2012, October 2018, May 2012) are significantly negative. This negative response of market to rating downgrades shows the dominance of information signalling effect. However, in the month of March 2019, we observe a significantly positive CAAR showing the presence of wealth redistribution effect. When we analyse the CAAR for short-term period, we find a significantly negative value of CAAR for 3 months (September 2018, March 2012, May 2012) in the post event period. However, the CAAR values in the pre-event period show that the market could correctly predict downgrades only in 2 months (September 2018 and May 2012). The wealth redistribution effect is found to dominate in 2 months (March 2019 and October 2013), where CAAR values are significantly positive in the pre and post event period. Next, we analyse the market response to upgrades. CAAR values are not found to be significant in the very short-term period. Looking at the short-term period, we observe significantly positive CAAR values for both the months in

Table 3: Description of downgrade and upgrade events for Macro level event study analysis

Notes: This table shows specific events (dates) on which downgrades and upgrades have taken place and the number of downgrades and upgrades on each date. We take into consideration 7 months having the highest values of composite RSI (downgrades), and 2 months having the highest values of composite RSI (upgrades).

Panel A- Downgrade cases

Months with highest values of composite RSI-	Value of RSI-	Number of events (dates) in each month on which downgrades have taken place	Date of downgrade in the month	Number of issues downgraded
Sep-18	5.32	4	5th	1
			6th	1
			10th	8
			28th	7
Mar-19	3.77	10	4th	2
			6th	23
			11th	2
			13th	3
			15th	2
			20th	1
			25th	1
			27th	5
			28th	1
			31st	4
Jul-15	2.7	3	2nd	1
			9th	2
			23rd	8
Oct-13	2.57	3	1st	1
			8th	5
			17th	1
Mar-12	2.36	2	2nd	2
			15th	4
Oct-18	1.69	5	5th	4
			12th	2
			15th	1
			19th	2
			30th	1
May-12	1.61	2	7th	2
			16th	1

Panel B - Upgrade cases

	Very Short- Term period			Short- Term period (Pre- Event)			Short- Term period (Post- Event)		
	CAAR	Standard Deviation	SCAAR	CAAR	Standard Deviation	SCAAR	CAAR	Standard Deviation	SCAAR
Aug-10	0	0	-0.59	0	0	1.26	0.06	0.01	10.93
Apr-18	0.01	0.01	1.96	-0.02	0.01	-3.26	0.03	0	9

the post-event period, indicating the presence of information signalling effect. However, our results show that investors could not anticipate the upgrades correctly as, CAAR takes a significantly negative value in one period and an insignificant value in another period.

3.3 Micro Level Event Study Analysis

In this section, we analyse the movement of stock prices of individual companies whose bond issues have experienced a significant rating shock. As mentioned in the earlier section, we focus on issues that have been downgraded/upgraded by 8 and above notches, and have been a part of NSE 200 at any point of time over the past one year before the rating correction. Issues of certain companies that have not been a part of NSE 200 have also experienced major rating shocks. We consider these issues also in our analysis. For such companies we only consider issues that have been downgraded/upgraded by more than 12 notches. Based on this criterion, we have identified 10 events for downgrades and 2 for upgrades. Table 5-Panel A and B represent the number of issues downgraded and upgraded respectively on each of these dates/events. It is observed that maximum rating errors have been made by CARE on the downside as well as on upside.

Further, to test the significance of our results, we observe the standardised values of CAR. Our analysis is done on 5% level of significance. We compute the SCAR for each date on which significant downgrades/upgrades have taken place.

Firstly, we analyse the impact of downgrades (Table 6-Panel A). On looking at the very short-term window, we find that CAR values for 4 events (1 event) are significantly negative (positive), indicating the dominance of information signalling

Table 5: Description of downgrade and upgrade events for Micro level event study analysis

Notes: This table shows specific events (dates) on which significant downgrades and upgrades have taken place. It also represents the number of downgrades on each date.

Panel A - Downgrade cases

Date of Downgrade (Event date)	07-05-2012			11-07-2013			11-03-2016			28-09-2018
	2	1	1	1	2	1	1	1	2	3

Panel B - Upgrade cases

Date of Upgrade (Event date)	04-04-2018	
	2	1

effect. The analysis on short-term window shows that 3 post-event CAR values are significantly negative, indicating the presence of information signalling effect. However, we find a significantly positive CAR value for 1 event in the post-event period, indicating the presence of wealth redistribution effect. Investors were unable to predict the impact of downgrades correctly in most of these cases, as seen by the SCAR values in the pre-event period.

Now, we analyse the response of upgrades (Table 6-Panel B). CAR values for very short-term period are not significant for both the events. However, in the short-term window, for both the events, we find a significantly negative CAR value in the pre and post event period. A negative response to upgrades indicates the dominance of wealth redistribution effect in short-term period. SCAR values in the pre-event period indicate that market was able to predict these values correctly.

Table 6: Results of Micro level Event Study Analysis for downgrades and upgrades

Notes: This table reports Cumulative abnormal return (CAR), Standard deviation and Standardised Cumulative abnormal return (SCAR) for 10 and 2 events (dates) on which significant downgrades and upgrades have taken place respectively. Results are reported for very short-term period and pre-event and post-event for short-term period.

Panel A - Downgrade cases

	Very Short-Term period			Short- Term period (Pre- Event)			Short- Term period (Post- Event)		
	CAR	Standard Deviation		CAR	Standard Deviation	SCAR	CAR	Standard Deviation	SCAR
07-May-12	0.02	0.03	0.6	-0.14	0.02	-6.81	0.02	0.02	1.1
26-Feb-13	-0.02	0.01	-1.53	0.05	0.02	3.15	-0.05	0.02	-2.56
04-Jun-13	-0.17	0.03	-5.54	-0.15	0.03	-4.83	-0.08	0.04	-2.17
11-Jul-13	-0.01	0.07	-0.12	0.38	0.04	9.01	-0.43	0.03	-13.85
13-Aug-14	-0.09	0.02	-4.53	-0.17	0.02	-7.31	-0.05	0.04	-1.52
23-Jul-15	-0.05	0.03	-1.63	0.04	0.03	1.53	0.05	0.06	0.94
11-Mar-16	-0.09	0.03	-3.51	-0.01	0.02	-0.34	0.04	0.04	0.97
11-Apr-18	0.08	0.02	4.07	-0.01	0.04	-0.13	0.04	0.02	1.73
31-Jul-18	-0.07	0.02	-3.8	-0.04	0.02	-2.06	0.14	0.03	5.53
28-Sep-18	0.18	0.1	1.84	0.1	0.07	1.39	0.13	0.08	1.65

Panel B - Upgrade cases

	Very Short-Term period			Short-Term period (Pre- Event)			Short-Term period (Post-Event)		
	CAR	Standard Deviation		CAR	Standard Deviation	SCAR	CAR	Standard Deviation	SCAR
04-Apr-18	0	0.02	0.18	-0.12	0.02	-5.18	-0.12	0.02	-6.42
09-May-18	-0.04	0.03	-1.24	-0.05	0.02	-2.59	-0.11	0.02	-4.92

Our results of macro and micro level analysis show a mix of information signalling and wealth redistribution effect. However, there is more dominance of the former effect. These results find support in existing literature, as various studies support the presence of both the effects in different markets. In prior work, we find considerable evidence to support the information signalling hypothesis. (Hand, Holthausen and Leftwich, 1992; Elayan, Maris and Young, 1996; Hite and Warga, 1997; Barron, Clare and Thomas, 1997; Dichev and Piotrosky, 2001; Choy, Gray and Ragunathan, 2006; Gropp and Richards, 2001; Benjamin, 2008; Avramov et al. 2009; Chakravarty, Chiyachantana and Lee, 2009; Lal and Mitra, 2011; Sehgal et al., 2018). Wealth redistribution effect is also supported in past studies (Holthausen and Leftwich, 1986; Zaima and McCarthy, 1988, Goh and Ederington, 1993; Bhoot, 1995; Romero and Fernández, 2007).

4 CONCLUSIONS AND MANAGERIAL IMPLICATIONS

The macro level (market level) event study analysis highlights the dominance of information signalling effect, as a negative (positive) response is observed towards downgrades (upgrades) in most of the cases. However, market is responsive only to downgrades in the very short-term period. Results of micro level (firm level) event study analysis show a mixed reaction of investors to downgrades and upgrades. Investors are responsive only towards downgrades in the very short-term period, and the response is found to be mostly negative. This indicates the dominance of information signalling effect. In the short-term period, investors respond negatively to upgrades, highlighting the presence of wealth redistribution effect. For downgrades in the short-term period, response to most of the events is not significant. However, in certain cases, investors respond negatively to downgrades. Thus, we observe a mix of information signalling effect and wealth redistribution effect, though the former dominates. Various studies in the past have found the presence of both effects across different markets, justifying the relation between credit ratings and investor response.

However, such work for the Indian market is negligible. Moreover, prior work focuses primarily on the micro level analysis. Dawar et al. (2021) report positive abnormal returns around upgrades in India. They find downgrades to be statistically significant in comparison to upgrades. The present study provides a more comprehensive view by analysing the stock market response at the macro and firm response at the micro level across two different time periods for major credit rating changes in India. Our study has important commercial and economic implications for bond issuers, credit rating agencies, and investors. At the policy level, there are pertinent implications for the market regulator. Further, the results are relevant for academic purposes.

Companies raising funds from the public should be cognizant of the market's reaction to such rating shocks. Significant rating changes are likely to have implications for raising further capital from the public, as well as it impacts the existing valuation of the firm. Hence, issuer firms must be cautious of maintaining their financial stability. Also, significant downgrades/upgrades in ratings are indicative of rating errors. This signals that the credit rating agencies haven't performed their analysis prudently. Such repetitive events lead to loss of investors' faith. Hence, investors would give lesser credence to the rating agencies making such errors, and they can choose to rely on rating agencies according to their efficacy. Also, the prediction of rating shocks can have considerable implications for investors' portfolio construction strategies.

If such significant rating shocks are observed repeatedly, there can be negative implications for the society in the form of depressed markets and loss of investor faith. This can lead to unrest for small investors also as they actively invest in the market through debt funds. Further, to avoid the repeated occurrence of such shocks, the market regulator must put the concerned rating agencies under surveillance. This will help in maintaining investors' faith in the financial markets.

We suggest the construction and analysis of 'Reputational Shock Indices' to understand the investor response around such events indicating reputational distress. Such indices should be maintained at the agency level and at the aggregate level by the financial regulator. This would encourage credit rating agencies to take a self-disciplinary action for maintaining rating quality and work towards adopting better rating models and processes.

Lastly, the study reveals results that are beneficial for the academic community. Academic research can delve into the reasons leading to rating errors on the upside and downside. The work can be extended to other markets also to understand which credit rating agency works the best in different markets.

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