Capital Market Consequences of Reputation Damage to CRAs: Evidence on Spillover Effects to Bond Issuers

Abstract

We use an unexpected default in the Indian debt market as a shock to the reputation of credit rating agencies (CRAs) to shed light on the spillover effects arising from such reputation loss. The default crisis, dubbed "India's Lehman moment," resulted in widespread criticism of the allegedly irresponsible CRAs, which did not sufficiently forewarn investors about the impending defaults. We find significant negative stock market reactions surrounding the crisis events for non-defaulting issuers rated by tainted CRAs (i.e., those suffering reputation loss). However, we fail to find significant reactions for issuers rated by clean CRAs (i.e., those not suffering reputation loss). We interpret these findings as evidence of a decline in the capital market's perception of the credibility of the CRAs. Further, such negative stock price reactions are more pronounced for issuers rated by tainted CRAs that (i) had greater credit risks or (ii) were more likely to have obtained inflated ratings. Overall, these findings help us establish the spillover effects to issuers resulting from CRAs' loss of reputation.

Keywords: Credit ratings; Credit rating agencies; Reputation; Information intermediaries; Spillover

JEL classification: G24; L14; D62; G14; G20

1. Introduction

Economic theory predicts that credit rating agencies (CRAs) care about their reputation (Sobel 1985; Lizzeri 1999; Mathis, McAndrews, and Rochet 2009; Bolton, Freixas, and Shapiro 2012). CRAs have incentives to invest considerable efforts and resources in building and maintaining their reputation for delivering a superior product. This superior product is widely understood to be a credit rating that accurately reflects the underlying issuer/instrument risk in a timely fashion, even in the absence of regulatory supervision and monitoring of the CRA. CRAs themselves note the importance of reputation as a disciplining mechanism (see comments from S&P[1] and Moody's[2]). Cankaya (2017) even goes on to claim that "[t]he main concern for credit rating agencies is not regulation or government interventions, the only value that matters is the trust of the market participants, which is synonymous with reputation for CRAs." Yet, time and again, CRAs have suffered a significant dent in their reputation because of their inability to provide timely predictions of default events.[3]

A growing body of literature has examined the consequences of such reputation loss for CRAs. The focus of these studies is predominantly on documenting changes in the quality and informativeness of ratings after reputation loss (Cheng and Neamtiu 2009; Dimitrov, Palia, and Tang 2015; deHaan 2017; Sethuraman 2019; Baghai and Becker 2020). However, despite the

[1] "The hallmark of S&P's success in the markets and of our prospects for future success is our reputation for independence and objectivity. Without that reputation, S&P could hardly have achieved its place as one the world's most respected credit rating agencies." (S&P 2006)

[2] According to Moody's, "[W]hat's driving us is primarily the issue of preserving our track record. That's our bread and butter" (Becker and Milbourn 2011).

[3] The East Asian Financial Crisis (1997), bankruptcies of Enron (2001) and WorldCom (2002), and the US subprime crisis (2007) are some prominent examples where CRAs maintained investment grade ratings, AAA in several cases, up until a few days before defaults on the rated products or the rated firms filed for bankruptcy. The Financial Crisis Inquiry Commission non-trivially ascribed the subprime financial crisis to the failures of CRAs and noted that "[t]he three credit rating agencies were key enablers of the financial meltdown" and that "the crisis could not have been marketed and sold without their seal of approval. Investors relied on them, often blindly." The Commission concluded that "[t]his crisis could not have happened without the rating agencies" (Financial Crisis Inquiry Commission 2011).

criticality of a CRA's reputation for the capital markets at large, there is scant direct empirical evidence on the capital market consequences of a loss in the CRA's reputation. We fill this gap in the literature by investigating the *externalities* arising from such reputation-damaging events. Specifically, we examine the stock market reactions of the *corporate issuers* affiliated with the tainted CRAs, i.e., those experiencing reputation loss surrounding the events that led to such loss.[4]

When a bond issuer defaults on its debt repayment obligation, it is expected to have negative shareholder wealth effects due to heightened concerns about its viability and potential financial distress (Griffin, Lont, and McClune 2014; Beneish and Press 1995). It is also likely that the CRAs that rated the defaulting issuer face considerable reputation loss, especially if the issuer had an outstanding investment-grade rating (Cheng and Neamtiu 2009). However, predicting the stock market reactions of firms that did not default but were rated by these CRAs that suffered reputation loss is difficult. The extent to which stock prices of such *non-defaulting* bond issuers are likely to respond to the reputation loss suffered by CRAs depends on whether investors consider the information provided by the CRAs to be incrementally useful in assessing the underlying credit risk of the issuing firm. If credit ratings provide incrementally valuable information to equity investors, for example, by incorporating issuers' material nonpublic information in the credit ratings (Standard & Poor's (S&P) 2015; Jorion, Liu, and Shi 2005), then the inability of a CRA to predict the default by one major issuer will affect investors' beliefs about the probability of default by other issuers. The resulting increase in the information asymmetry will lead to a decrease in stock prices for non-defaulting firms, i.e., a negative spillover.

[4] We also provide some descriptive evidence on the capital market consequences of reputation loss for the CRAs *themselves*. This analysis is admittedly primitive as the number of CRAs is small, to begin with, and only a subset of them is publicly listed.

However, to the extent that market participants conduct their own due diligence and independent credit quality analysis and do not simply rely on the credit ratings assigned by CRAs (House 1995; De Pascalis 2016; Sangiorgi and Spatt 2017),[5] missed defaults by CRAs may not impact the credit risk assessments of equity investors. Investors may also significantly discount the credit ratings if they believe that ratings shopping or catering may have led to inflated ratings (Skreta and Veldkamp 2010; Chakraborty, Saretto, and Wardlaw 2019; Holden, Natvik, and Vigier 2012). Another possibility is that equity investors consider credit ratings uninformative but still use them because of regulatory requirements, private/internal investment mandates, or other asset management policies that prohibit them from holding shares of an issuing firm that does not have a certain minimum rating threshold for its debt instruments (e.g., Kisgen and Strahan 2010; Jeon and Lovo 2013; Cornaggia, Cornaggia, and Hund 2017; Ellul, Jotikasthira, and Lundblad 2011; Chen, Lookman, Schürhoff, and Seppi 2014). This prediction is consistent with the "regulatory license" view of CRAs advanced by Partnoy (1999). Specifically, he posits that CRAs do not necessarily generate more valuable information; rather, they sell valuable regulatory licenses that allow bond issuers cheaper access to financing from institutional investors who can only invest in bonds that carry these licenses. For these reasons, CRA reputation loss may not give rise to spillover effects in the form of negative stock price reactions for non-defaulting issuers. Thus, whether there are *spillover* effects of CRA reputation loss is ultimately an empirical question.

We address this question by examining a major default crisis in the Indian corporate bond market, often referred to as "*India's Lehman moment*" (Rangan 2020).[6] This default relates to the

[5] Investors could also rely on alternate summary measures of credit risk, such as credit spreads. Partnoy (2002) claims that credit spreads are a much superior alternative to credit ratings as they (i) already incorporate the information contained in credit ratings, (ii) are at least as accurate as the credit ratings, and (iii) are determined by the market as a whole thereby minimizing the bias of select individuals/entities.

[6] Just weeks after the crisis unfolded, Kunal Shah, a debt fund manager who oversees nearly $1.7 billion at Mumbai-based Kotak Mahindra Life Insurance Co., commented that "[w]e have not had this kind of a systemic event of this

Infrastructure Leasing and Financial Services (ILFS) Group, a large financial institution funding infrastructure development in India. In September 2018, two ILFS subsidiaries defaulted on their payment obligations on bank loans, inter-company deposits, and commercial papers. These initial defaults triggered a series of other payment defaults by these and other group companies. These defaults had a domino effect on firms in other related sectors, such as housing finance companies and commercial banks, eventually creating a widespread panic in the Indian capital markets.

The ILFS crisis provides a novel setting for us to examine the spillover effects because three CRAs – CARE, ICRA, and INDRA (tainted CRAs, hereafter) attracted severe criticism for maintaining investment grade rating for ILFS up until a few days before default and thereby suffered significant reputation loss. In contrast, four other CRAs - CRISIL, Brickwork, Acuite, and IVR (clean CRAs, hereafter), did not rate ILFS and hence are not expected to have suffered reputation loss. To validate our claim that CRAs that rated ILFS suffered reputation loss, whereas the CRAs that did not rate ILFS suffered no such reputation loss, we look at the stock price reactions of these CRAs on the four event dates relating to the ILFS default in September 2018. We find that stock prices of ICRA and CARE (the listed tainted CRAs) fell by 7.1% and 10.5%, respectively, on the ILFS default dates. This corresponds to a decline in the market value of INR 1.696 billion (approx. US$ 23.4 million) for ICRA and INR 2.289 billion (approx. US$ 31.58 million) for CARE in September 2018. In comparison, CRISIL (the listed clean CRA) did not experience negative abnormal returns during the same time period.[7]

magnitude in the bond market before in India, and so we don't really have a precedent as to how to deal with it." (Bremner et al. 2018). In Sections 2.1 and 2.2, we provide greater institutional details on the Indian CRA market and ILFS crisis, respectively.

[7] INDRA, BRICKWORK, ACUITE, and IVR are not publicly listed CRAs, and hence, we can't document the change in their market values during the ILFS crisis.

This novelty in our research setting, i.e., the presence of a counterfactual, arises because of a particular institutional difference between the markets for credit ratings in the U.S. and India.[8] Specifically, the U.S. credit rating market is dominated by Moody's and S&P, and often both these CRAs rate the debt of the same issuer simultaneously (Bongaerts, Cremers, and Goetzmann 2012; Kedia, Rajgopal, and Zhou 2017; Chen and Wang 2021). However, in the Indian debt market, issuing firms typically get a rating from only one CRA, and even in less frequent cases when ratings are obtained from multiple CRAs, instances of an issuing firm getting ratings from all big-three CRAs are rare (Kallapur, Khizer, Manchiraju, and Vijayaraghavan 2024).[9] This feature of the Indian credit rating market provides us with a counterfactual in our research setting as we have issuers that are rated by *only one* of the tainted or clean CRAs. Thus, we examine the spillover effects arising from CRA reputation loss by comparing the stock price reactions for the non-defaulting issuer clients (i.e., issuers other than ILFS) of the tainted CRAs with the stock price reactions for issuer clients of the clean CRAs around the events that led to CRA reputation loss. Our research setting has another major advantage over the settings used in the extant literature, wherein the events causing reputation loss are often confounded by market-wide regulatory measures initiated in the aftermath of these events (e.g., SOX after the high-profile corporate bankruptcies of Enron and WorldCom, Dodd-Frank after the sub-prime financial crisis). This clustering of confounding events makes it difficult, if not impossible, to causally disentangle the effects of reputation loss from regulatory intervention (Bedendo, Cathcart, and El-Jahel 2018). In

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[8] As we detail in Section 2, it is noteworthy that the overall structure of the ratings market is comparable in the two economies. For instance, in the US, S&P, Moody's, and Fitch are the three major CRAs collectively accounting for almost 96% of the outstanding ratings as of December 31, 2021 (https://www.sec.gov/files/2023-ocr-staff-report.pdf). Likewise, in India, CARE, CRISIL, and ICRA are the three major players, collectively accounting for 84% of the outstanding ratings (Kallapur et al. 2024). There are six (five) other rating agencies operating in the U.S. (India).

[9] In India, 74% of issuers get ratings from *only* one CRA, and no issuer gets ratings from *all* three major rating agencies (i.e., CARE, CRISIL, and ICRA) in our sample.

contrast, our research setting allows a cleaner identification of a spillover effect arising from CRA reputation loss because we focus on a short event window around the ILFS default when no regulatory actions were taken against CRAs. Further, our focal event relates to one defaulting firm (ILFS) as opposed to the market-wide meltdown seen, for example, during the financial crisis.

We find that compared to the bond issuer clients of the clean CRAs (control firms), the bond issuer clients of the tainted CRAs (treated firms) experience an abnormally negative equity market reaction surrounding the key events associated with the reputation loss for CRAs. We interpret these findings as evidence that the equity market believes that, compared to the outstanding ratings issued by clean CRAs, the outstanding ratings issued by tainted CRAs are more likely to be biased upwards. This likely results in an upward revision in the equity investors' assessment of an issuing firm's credit risk and translates into a negative stock price reaction. This novel finding allows us to document the externalities resulting from CRA reputation damage in the capital markets.[10]

In the next set of tests, we exploit cross-sectional variation in our sample to gather insights into which issuers bear a higher burden of spillover costs resulting from the reputation damage of the CRAs. We find that the main effect of the spillover cost, the negative abnormal stock market reaction, is *stronger* for issuer clients that have an outstanding rating close to a key threshold for regulatory and contracting purposes (such as BBB- for separating investment grade from non-investment grade) and for issuer clients whose last rating change was an upgrade. These findings are consistent with the notion that investors are more skeptical of the ratings assigned to such

[10] deHaan (2017) documents a different dimension of spillover where damage to a CRA's reputation in one product market spills over to the CRA's reputation in another product market. Specifically, deHaan (2017) shows that after the CRAs experienced financial-crisis-related reputational harm for their ratings of the *mortgage-backed securities* and *collateralized debt obligations*, market participants questioned the quality of and reduced their usage of *corporate* credit ratings produced by these CRAs.

issuers and, hence, react more negatively. We also predict that the spillover cost is higher for issuers with higher credit risks. We capture credit risk using two different metrics: (a) whether the issuer had a loss in the prior year and (b) the issuer's earnings volatility. Consistent with expectations, we find that issuers with higher credit risks, i.e., those with a presence of loss or higher volatility of earnings, have a *larger* negative market reaction. We interpret these findings as evidence that the spillover effects of the CRA reputation damage are disproportionately higher for tainted CRAs' clients with weaker credit and economic profiles. Finally, we find that the spillover cost is higher for issuers that are a part of a business group. This finding is consistent with the prediction by Bolton et al. (2012) that CRAs are more likely to issue inflated ratings to cater to issuers that are more lucrative for CRAs.

In additional analyses, we examine the responses by the tainted CRAs and their issuer clients to the CRA reputation damage. In the aftermath of the reputation damage to the CRA and spillover costs to its clients, an affected CRA would likely institute substantive changes to mend its reputation by tightening rating standards (Cheng and Neamtiu 2009). However, investing in reputation-building activities is costly, and the CRA could just maintain the status quo.[11] We test these alternate predictions in a difference-in-differences (DID) setting and find that compared to clean CRAs, tainted CRAs, on average, issue more *conservative* ratings subsequent to the ILFS crisis. Specifically, compared to the clean CRAs, tainted CRAs (i) issue lower ratings, (ii) are less likely to commit a *TYPE I ERROR* (missed default), and (iii) are more likely to commit a *TYPE II ERROR (*false warning*)*. Overall, our evidence is consistent with CRAs improving the rating quality after they suffer reputation loss. With respect to issuer responses to CRA reputation loss, we examine whether issuing firms are more likely to move away from the tainted CRAs after the

[11] Worse still, the CRA could loosen its rating standards and *intentionally* issue inflated ratings to cater to existing clients or attract new clients in a bid to protect their industry market share (Baghai and Becker 2020).

ILFS shock. We do not find any such evidence. We posit that the corrective actions taken by the tainted CRAs, such as the tightening of credit ratings, the firing of top management, and greater oversight, might have succeeded in persuading the issuing firms to continue with their CRAs.[12]

Our study contributes to the growing literature that explores the economic consequences of CRA reputation loss. Several studies in this area examine the response of CRAs to events that threaten their reputation (Cheng and Neamtiu 2009; deHaan 2017; Bonsall, Green, and Muller 2018; Baghai and Becker 2020; Dimitrov et al. 2015; Bonsall, Koharki, Kraft, Muller, and Sikochi 2022; Bonsall, Koharki, and Neamtiu 2022). The consensus in this literature is that CRAs improve their ratings quality, i.e., attributes such as accuracy, timeliness, stability, and volatility, in the aftermath of reputation-damaging events such as the corporate scandals and bankruptcies of WorldCom and Enron in the early 2000s and the 2007-08 sub-prime financial crisis.[13] Other studies in this area have also examined the informativeness of credit ratings after CRA reputation loss (Jaballah 2015; Dimitrov et al. 2015; deHaan 2017; Sethuraman 2019). These studies document that CRA reputation loss (restoration) decreases (increases) investor reaction to rating change events. Extending this line of research, Sethuraman (2019) documents that, as investors rely less on credit ratings after the CRA reputation loss, bond issuers increase their voluntary disclosures to reduce information asymmetry in the bond markets, which results from a decline in the informativeness of credit ratings. Thus, while existing research examines the response of CRA and bond issuers to the events of CRA reputation loss, there is no direct evidence on the capital market consequences of CRA reputation loss. We fill this gap in the literature by documenting the

[12] We do acknowledge the possibility that some issuing firms do not switch to a new CRA because of contractual reasons or other market frictions. For instance, an issuer-client of a tainted CRA could be apprehensive about switching to a clean CRA because of potentially worse credit ratings and the ensuing higher costs of capital.

[13] Baghai and Becker (2020), a notable exception, show that S&P, after experiencing significant reputational harm, issued optimistically biased ratings to the issuers to cater to the issuers and win back market share.

spillover effects of such reputation loss for issuing firms rated by tainted CRAs and not for issuing firms rated by clean CRAs.

We also add to the broader literature on spillover effects. The literature in this area has examined information transfers for several focal-firm actions/events, including earnings announcements and management earnings forecasts (e.g., Foster 1981; Baginski 1987; Pandit, Wasley, and Zach 2011), earnings restatements (e.g., Gleason, Jenkins, and Johnson 2008; Akhigbe and Madura 2008; Lee and Lo 2016), distress and bankruptcy filings (e.g., Hertzel, Li, Officer, and Rodgers 2008; Lang and Stulz 1992), and audit failures (e.g., Skinner and Srinivasan 2012; Chaney and Philipich 2002; Krishnamurthy, Zhou, and Zhou 2006; Weber, Willenborg, and Zhang 2008). However, this strand of literature provides limited evidence on the spillover effects in the context of credit rating agencies. Joe and Oh (2018) document spillover effects *within* Korean business groups (i.e., among firms affiliated with the same business group) by using the setting of credit rating change announcements as their proxy for information events. deHaan (2017) shows that the reputation damage CRAs faced in their financial instruments division had negative spillover effects for their corporate ratings division as investors decreased their reliance on these ratings despite an improvement in their quality. We extend this line of research by documenting spillover effects that arise for bond issuers due to the reputation loss suffered by the CRAs. We show that these indirect costs relating to CRA reputation loss are extensive and impact a variety of firms.

2. Institutional Background

2.1. The Indian Credit Ratings Market

As in other major world economies, CRAs play a critical role in the Indian capital market. India has a sizeable corporate debt market where credit ratings are used both in private contracting as well as in instances where regulation imposes the need. [14] For instance, companies issuing bonds are required to have at least one rating by an eligible CRA; mutual funds are permitted to invest in debt securities with a rating of BBB- or better; and banks rely on ratings to calculate risk weights for regulatory capital adequacy purposes. Currently, there are seven CRAs registered with the SEBI, the regulatory body that oversees the functioning of India's capital markets, under the SEBI (Credit Rating Agencies) Regulations, 1999.[15] These are CRISIL Ratings Limited (CRISIL), CARE Ratings Limited (CARE), ICRA Limited (ICRA), India Ratings and Research Private Limited[16] (INDRA), Brickwork Ratings India Private Limited (Brickwork), Acuite Ratings and Research Limited (Acuite), and Infomeric Valuation and Rating Private Limited (IVR). Given the prominence of the CRAs and their pivotal role in the Indian capital markets, the Indian CRAs have been subject to heavy regulation and supervision. As Karminsky, Mistrulli, Stolbov, and Shi (2021) note, the rating market in India is relatively mature, and the regulation of domestic CRAs is constantly benchmarked to those of their international counterparts, particularly in the US and EU. SEBI, India's primary securities market regulator, and RBI, the Indian central bank, jointly regulate and oversee the functioning of the Indian CRAs. The top regulatory features include: (a) demanding registration of the domestic CRAs with the SEBI, (b) requiring compliance with extensive disclosure and performance requirements (e.g., establishment and public disclosure of detailed rating methodologies and training of the key rating personnel), and (c) periodic monitoring and review of the ratings activities by the SEBI.[17]

[14] As of December 2020, the outstanding corporate debt stood at INR 35.1 lakh crores (about USD 450 Bn), which was about 18.2% of India's GDP: https://www.thehindubusinessline.com/opinion/we-need-a-vibrant-corporate-bond-market/article37403478.ece.

[15] SEBI is the Indian equivalent of the Securities Exchange Commission (SEC) of the USA.

[16] Formerly, Fitch Ratings India Private Limited.

[17] https://www.sebi.gov.in/legal/circulars/jun-2017/monitoring-and-review-of-ratings-by-credit-rating-agencies-cras-_35220.html.

There are several noteworthy features of the Indian CRA industry. First, as in the US, the Indian credit ratings market is largely oligopolistic, with CRISIL, ICRA, and CARE – the "big three" collectively holding about 90% of the domestic credit rating market share. Second, the major domestic CRAs are directly affiliated with the three major global/US CRAs – S&P Global, Moody's, and Fitch.[18] As of September 2018, CRISIL is majority (67%) owned by S&P Global Inc., ICRA is majority (51%) owned by Moody's Investor Service Company, and INDRA is a 100% owned subsidiary of the Fitch Group. These affiliations greatly facilitate the transfer of knowledge, analytics, and best practices related to rating methodology, policies, and procedures. For instance, ICRA notes that "Moody's provides enrichment programs to ICRA employees, including access to the financial markets and related courses that are offered as part of the eLearning software licensed by Moody's from Intuition, and provision of financial writing training seminars to designated ICRA employees."[19] Finally, the three largest CRAs — CRISIL, ICRA, and CARE — are publicly traded on the Bombay Stock Exchange Limited (BSE) and the National Stock Exchange of India Limited (NSE), the leading stock exchanges in India. As a result, we can observe the stock price reactions of these CRAs to validate our claim about them suffering reputation loss.

2.2. The ILFS crisis

Infrastructure Leasing and Financial Services (ILFS) Group is an Indian infrastructure development and finance company and has been a major player in the domestic real estate market.

[18] Hung, Kraft, Wang, and Yu (2022) use the term 'Big Three CRAs' to refer to S&P, Moody's, and Fitch, which collectively account for the bulk of the market shares both within and outside the U.S.

[19] https://www.icra.in/Home/Profile

ILFS Limited, a core investment company, serves as the holding company of the ILFS Group.[20,21] ILFS was formed in 1987 by three large Indian public financial institutions: the Central Bank of India, the Housing Development Finance Corporation, and the Unit Trust of India. Over time, its ownership has evolved to include Life Insurance Corporation of India, a public sector undertaking and ILFS's largest domestic investor, and international institutional shareholders such as Orix Corporation (Japan) and Abu Dhabi Investment Authority (United Arab Emirates). As of March 31, 2018, the ILFS Group operated with about 200 subsidiaries and a debt of approximately INR 91,000 crores (USD 14 Bn) and total assets of INR 1.16 lakh crore (USD 17.8 Bn).[22]

ILFS has diversified businesses spanning the transportation, energy, financial services, and real estate sectors. Its principal operations are conducted through its various subsidiaries (direct and indirect), joint ventures, and strategic business alliances. Some of its key subsidiaries include the transportation network company – ILFS Transportation Networks Ltd. (ITNL), the engineering and procurement company – ILFS Engineering & Construction Ltd. (IECCL), and the financial services company – ILFS Financial Services Ltd. (ILFSL). Through its vast network of subsidiaries and affiliates, ILFS has contributed to the development of the Indian economy and capital markets over the last three decades. ILFS and its subsidiaries, such as ITNL and IECCL, have been regulars in the Fortune India 500 rankings. ILFS is also a huge and frequent borrower; Bremner, Joshi, Sanjai, and Bloomberg (2018) estimate that ILFS accounts for about "2% of outstanding commercial paper, 1% of debentures, and as much as 0.7% of banking system loans." ILFS further contributes to the debt markets by providing capital to non-bank lenders. Given its

[20] This section borrows heavily from the draft interim report issued by Grant Thornton, which was hired for a forensic audit (code-named 'Project Icarus') examining the series of ILFS payment defaults and the alleged role of its CRAs.

[21] We use the terms ILFS, ILFS Group, and ILFS Limited interchangeably to refer to the same entity.

[22] https://www.ilfsindia.com/media/2022/annual-report-fy-2018.pdf. Media reports, however, allege that the group under-reported its total assets by about 30%: https://www.financialexpress.com/industry/ilfs-crisis-more-skeletons-out-company-under-reported-assets-by-rs-50-cr/1342376/.

pivotal role in the Indian economy and capital markets, ILFS has been designated as a "Systemically Important Non-Deposit Accepting Core Investment Company."[23]

The earliest harbinger of the ILFS crisis was probably the defaults by ILFS Financial Services, the financial services arm of the ILFS group, on the repayments of commercial papers (CPs) on August 28th, 2018. This issue was rectified within two days, and the company claimed that the defaults were due to some technical errors and not because of liquidity issues. However, soon after, on September 4th, 2018, ILFS defaulted on an INR 1000 crore (USD 140 Mn) short-term loan to the Small Industries Development Bank of India (SIDBI). Concurrently, an ILFS group company also defaulted on an INR 500 crore loan (USD 70 Mn) to the SIDBI. The defaults to the SIDBI were followed by defaults on several CPs on September 14th, 2018. September 17th, 2018 had yet another spate of defaults on CPs and some non-convertible debentures. September 21st, 2018, saw defaults on repayments concerning a letter of credit to the Industrial Development Bank of India (IDBI).

This series of defaults snowballed into a default crisis and sparked panic in the equity and debt markets. ILFS and its subsidiaries, being highly popular among the Indian investing community, were held by more than 30 mutual funds with cumulative holdings valued at approximately INR 2,308 crores (USD 3.26 Bn) at the end of August 2018. As these funds typically rely on the credit ratings provided by the CRAs to value their portfolios, they experienced a substantial fall in their NAVs, ranging from 25 – 100%, in the aftermath of the dramatic and drastic credit rating downgrades of the ILFS group companies (Adajania 2018). Besides, even retail investors were intrigued and impacted by these massive downgrades and the ensuing defaults. For instance, Investor Q, an online community platform where individual finance

[23] https://www.ilfsindia.com/Investors.html

enthusiasts participate in Q&As related to finance and capital markets, received several questions and posts discussing various aspects of the ILFS crisis.[24] Around this time, the crisis had started affecting other companies in the non-banking finance sector. For instance, DSP mutual fund started selling the debt papers of Dewan Housing Finance Corp., an ILFS peer, at a steep discount, signaling the declining market confidence in the debt securities issued by non-banking finance companies at large. To curtail the spread of the crisis and the potential contagion risk, on October 1st, 2018, the Government of India assumed control of ILFS and constituted a new board. The new board was tasked with developing a debt restructuring plan and restoring investor confidence. In addition, the Serious Fraud Investigation Office (SFIO) began a probe into the Group. The government justified its swift action and intervention as being consistent with its mission to protect the public interest and restore confidence in the capital markets.[25]

2.3. Reputation loss for CRAs in the ILFS crisis

Given the stature of ILFS and the importance of the infrastructure sector to the Indian economy, unsurprisingly, this corporate debt crisis attracted heightened regulatory, media, practitioner, and widespread attention. In particular, the failure of CRAs to forewarn these impending defaults has been severely criticized.[26] The CRAs – namely, CARE, ICRA, and INDRA – maintained consistently high ratings for ILFS debt and only started downgrading them in September 2018, after the defaults. In fact, to catch up to the reality of the imminent default, the CRAs had to

[24] Investor Q platform is owned and operated by IIFL Securities Limited (formerly India Infoline Limited), one of the largest independent full-service retail and institutional brokerage houses and an investment advisory firm (https://investorq.com/Views/Home/PrivacyPolicy.html).

[25] https://www.business-standard.com/article/finance/nclt-allows-govt-to-seize-il-fs-new-board-to-elect-chairman-at-next-meet-118100100735_1.html.

[26] https://www.livemint.com/Companies/kDBrz7DB4Ti4Pz2TdxG85N/How-credit-rating-agencies-missed-the-ILFS-crisis.html

downgrade ILFS several notches at once in an unprecedented move.[27] CRAs were also criticized for relying too much on the ILFS management's assertions about debt repayment plans.

The unprecedented and drastic rating downgrade by CRAs from highly rated to default category drew regulatory ire. On December 12th, 2018, SEBI initiated adjudication proceedings against the three CRAs for allegedly assigning inflated ratings to the ILFS group companies. SEBI blamed the "lethargic indifference and needless procrastination and laxity" of the rating agencies in the matter of the ILFS default. On December 26th, 2019, SEBI came up with its Adjudication Order against the CRAs and imposed a fine of INR 2.50 million (approx. 32,000 USD) on each of the CRAs. Subsequently, on September 22nd, 2021, the penalty was increased to INR 10 million (approx. 130,000 USD). In the wake of the increased regulatory scrutiny and widespread negative publicity in the following months, the three tainted CRAs initiated house-cleaning measures. In July 2019, both ICRA and CARE sent their respective managing directors - Naresh Takkar and Rajesh Mokakshi – on leave until further notice.

A highly damaging event for the CRAs in the ILFS saga was the issuance of Grant Thornton's forensic report on August 20, 2019. The 105-page report highlights potential conflicts of interest between rating agencies and ILFS that eventually resulted in "consistently high" ratings.[28] The report alleges, among other things, that ILFS secured "good credit ratings" by engaging in several unethical and questionable activities, including luring the CRAs with expensive villas and football match tickets. If there were any doubts among market participants regarding the foul play by these CRAs, this report put them to rest. Following this report, ICRA

[27] When ICRA downgraded ILFS by at least nine notches from AA+ to BB in September 2018, a fund manager commented, "I have not seen such a sharp rating downgrade in my career. Things will continue to evolve."(Das 2018)

[28] The forensic audit report was produced by Grant Thornton's Project Icarus and was privately shared with the stakeholders https://www.reuters.com/article/india-il-fs-ratings-idINKCN1UG079. An unofficial copy of the report may be accessed here: https://pdfcoffee.com/qdownload/grant-thornton-on-credit-rating-agencies-pdf-free.html.

promptly sacked its Managing Director on August 29th, 2019. A few months later, the Managing Director of CARE also "resigned" on December 20th, 2019.

Overall, the default by ILFS, subsequent regulatory actions, and massive negative business press coverage collectively delivered a severe blow to the reputation of the involved credit rating agencies, who were blamed for assigning very high ratings to the ILFS group entities despite being aware of the weak financials of the group. Since two of the CRAs that rated ILFS and another major CRA that did not rate ILFS are listed companies, we examine their stock price reactions on the event dates pertaining to the ILFS crisis to estimate the economic magnitude of reputation loss. For ease of reference, we list all these events and the corresponding market reaction for CRAs in Appendix A. The market reaction is measured as the 3-day CAR around the event date, following standard event study methodology.[29]

The first five events relate to the defaults by the ILFS group starting on August 28th, 2018, and ending on September 21st, 2018. We find that three of the five default events drew significantly negative market reactions for CARE and ICRA (the listed tainted CRAs) but not for CRISIL (the clean CRA). The total 3-day-CAR across these five events is -7.1% and -10.5% for CARE and ICRA, respectively. In contrast, the total 3-day-CAR for CRISIL for the corresponding period is statistically insignificant. To make sure that the choice of event dates does not influence our results,

[29] For each event in the ILFS crisis, the abnormal return is computed using the market model with an estimation window of 250 days ending before the first event (28th August 2018). The market return is proxied by the return on the NIFTY500 index, which is roughly analogous to the S&P 500 in the U.S. $CAR_{[-1,1]}$ is then computed as the cumulative abnormal return for a CRA aggregated over the three days surrounding each event. We test whether these CARs are significantly different from zero using the standard deviation of prediction errors in the estimation period. We also assess the statistical significance of these abnormal returns using the bootstrap method following Zhang (2007). Specifically, for each event, we first compute the returns of the same number of consecutive non-event days from the one-year window commencing on the date of the first event (sample A). Then, we draw a sample of 10,000 returns (sample B) with replacement from sample A. Finally, we compute the one-tailed p-values as: p = the proportion of observations in sample B with values greater (smaller) than the *event return* if the event return is non-negative (negative). When we use these bootstrapped p-values, there is an overall decline in the level of statistical significance, and four events cease to have a market reaction that is significantly different from zero.

we also look at the overall change in the market values of these CRAs for the entire month of September 2018.[30] We find a decline in the market value of INR 1.696 billion (approx. US$ 23.4 million) for ICRA and INR 2.289 billion (approx. US$ 31.58 million) for CARE in the month of September 2018, respectively. It is pertinent to note that the decline in market values for tainted CRAs is significantly higher than the eventual penalty imposed by regulators (approx. US$ 130,000), suggesting that the negative market reaction predominantly captures reputation loss and not merely potential regulatory penalties.

We also find significant negative stock market reaction around events relating to the (i) start of regulatory actions against tainted CRAs, (ii) CEOs of tainted CRAs being sent on leave, and (iii) release of the forensic report by Grant Thorton.[31] Overall, we find that the listed tainted CRAs – CARE and ICRA – experienced significantly negative market reactions around the key events relating to the ILFS crisis. On the other hand, the market reactions for CRISIL, the clean CRA, are insignificantly different from zero and even positive in some cases. These findings are consistent with our prediction that equity investors price the negative shock to the CRAs' reputation and the resulting potentially negative future business prospects.

[30] Since August 28 was a Friday, the last trading day of the week, and the month of August, our opening stock price for calculating the decline in market value corresponds to the beginning stock price on August 28, 2018. This also allows us to include all five default events in our calculation.

[31] We find no significant market reaction when final regulatory rulings were passed against tainted CRAs or when their CEOs were eventually fired. One possible reason for such insignificant market reactions is that the market already anticipated these ultimate outcomes when the regulatory actions had started and CEOs were sent on leave. Hence, the eventual closure of these events is unlikely to be a surprise for the market.

3. Related literature and hypothesis development

3.1 Importance of reputation for CRAs

Accuracy, timeliness, and stability are some of the key desirable attributes of credit ratings produced by CRAs and used by the market to evaluate a CRA's performance and credibility (Cheng and Neamtiu 2009). The CRAs thus have incentives to build a reputation for quality over time by investing in superlative credit analysis and producing high-quality ratings (e.g., ratings that are unbiased/accurate). A CRA's reputation is also especially valuable because market participants are generally unable to evaluate the quality of the ratings in real time. One reason for this delayed evaluation is that CRAs' credit rating assessments are informed by issuer *nonpublic* information that is unavailable to the market at large.[32] This incorporation of private information is actually a critical factor that enhances the informativeness of the credit ratings (Bonsall 2014; Ahn, Bonsall, and Van Buskirk 2019; Jorion et al. 2005; Bonsall, Koharki, and Neamtiu 2017). Relatedly, several papers show that credit ratings contain value-and credit-relevant information and issuance of (changes to) credit ratings are associated with significant equity and bond market reactions (see, among others, Holthausen and Leftwich 1986; Hand, Holthausen, and Leftwich 1992; Jorion et al. 2005; Cornaggia, Cornaggia, and Israelsen 2018).

Despite the long-term premiums associated with building and maintaining a reputation for issuing high-quality ratings, a CRA could have incentives to *knowingly* produce a sub-par rating vis-à-vis the above attributes, for instance, an upwardly biased rating. CRAs' inherent business

[32] CRAs were expressly exempted from the Regulation Fair Disclosure (2000) requirement of non-selective disclosure of material nonpublic information under Rule 100(b)(2)(iii) and thus continued to receive material nonpublic information from corporate bond issuers in the post-Reg FD period (Jorion et al. 2005). Although the Dodd-Frank Act of 2010 removed this express exemption granted to CRAs, the rating agencies continued to obtain material nonpublic information from the issuers, exploiting another exemption under Regulation Fair Disclosure granted to "a person who expressly agrees to maintain the disclosed information in confidence" under Rule 100(b)(2)(iv) (Ahn et al 2019).

model (“issuer-pay”) is one factor that could induce such CRA behavior (e.g., He, Qian, and Strahan 2012; Jiang, Harris Stanford, and Xie 2012; Bolton et al. 2012). The major global CRAs (S&P, Moody’s, and Fitch) and several other smaller players in the credit ratings market are paid by their customers, i.e., the bond issuers. This business model could cause CRAs’ incentives to be more aligned with the issuers, who generally prefer a *higher* rating, and less aligned with the users, who prefer an *unbiased* rating. Two other notable market features potentially exacerbate this “ratings inflation” practice and a deterioration in ratings quality in general. The extensive use of credit ratings in regulation and investment mandates and the oligopolistic market structure, where a few key CRAs virtually control the market, makes the demand for ratings relatively inelastic (Bolton et al. 2012). As a result, even if ratings quality were to decline, issuers and users would have limited alternatives, so there is no real threat to the future payoffs of CRAs.[33]

Downplaying these incentives and allegations of knowingly producing low-quality ratings, CRAs have always maintained that their reputation and market perception are critical to their existence. Their reputation likely allows them to command a premium, and they would not risk their long-term future payoffs by engaging in an action such as ratings inflation that could jeopardize their reputation for producing accurate and high-quality ratings. For instance, a former executive vice president of Moody’s, Thomas McGuire, stated in 1995 that ‘‘what’s driving us is primarily the issue of preserving our track record. That’s our bread and butter’’ (Becker and Milbourn 2011). Theoretical papers generally support this assertion by CRAs but argue that there are limits to reputation as a disciplining mechanism and that CRAs do trade off the payoffs from

[33] Theory predicts that an increase in competition could actually worsen credit quality (Bolton et al. 2012; Bar-Isaac and Shapiro 2013). For instance, Bolton et al. (2012) posit that an increase in competition could incentivize the issuers to “shop” around for ratings, thereby aggravating the practice of “ratings inflation.” Using the material entry of Fitch as a third rating agency, Becker and Milbourn (2011) provide robust evidence of a decline in the ratings quality of the two incumbents: Moody’s and S&P.

investing in building and maintaining a reputation for a high-quality product (e.g., truthful ratings) with the payoffs from providing a sub-par product such as inflated ratings (Mathis et al. 2009; Bolton et al. 2012; Bar-Isaac and Shapiro 2013). For instance, Mathis et al. (2009) analytically show that the threat of reputation damage ceases to discipline ratings inflation by CRAs when a major source of their income is the rating of complex and non-standard products.

3.2 Consequences of reputation loss

Given that CRA reputation is highly valuable and is an important barometer for the market, a loss in this reputation likely has real consequences for the CRAs and several stakeholders, including the debt issuers (i.e., CRAs' customers who seek ratings) and investors (i.e., the users of ratings). A growing literature has examined the response of CRAs to events that threaten their reputation.[34] The general consensus has been that CRAs improve the quality of their ratings in the aftermath of reputation damage. For instance, Cheng and Neamtiu (2009) show that CRAs respond to the increased regulatory scrutiny and capital market pressure following the Enron and Worldcom scandals by increasing their ratings' timeliness and accuracy while reducing the rating volatility. In a similar vein, Alp (2013) and Baghai, Servaes, and Tamayo (2014) show that there has been a structural shift towards more stringent ratings, especially since 2002. Using the financial crisis setting, where all major CRAs were publicly rebuked for intentionally issuing significantly inflated ratings, deHaan (2017) and Dimitrov et al. (2015) provide evidence that CRAs undertake massive steps to repair their reputations by improving the quality of their ratings.[35] There is also evidence

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[34] Majority of the literature examining consequences of damage to CRA reputation focuses on one of the two settings/events that damaged CRA reputation: (1) high-profile corporate bankruptcies of the early 2000s (e.g., Enron and WorldCom) and (2) sub-prime mortgage crisis in the late 2000s. Following both these events, CRAs drew a lot of negative popular attention, investor criticism, and regulatory pressure.

[35] Dimitrov et al. (2015) find that the CRAs become more conservative in their rating levels, i.e., issue lower ratings to protect their reputation. A side effect of this increased stringency is that there is an increase in false warnings and a decline in the informativeness of ratings.

consistent with CRAs changing their behavior in anticipation of reputational damage. Kraft (2015a) shows that CRAs opportunistically use "soft" rating adjustments to cater to issuers by providing more favorable ratings, but this catering is muted in the presence of high reputational costs. As additional evidence of CRAs responding to potential reputational harm, Kraft (2015b) shows that CRAs are less likely to 'cater' to issuers' demand for inflated ratings in the presence of heightened reputational costs from catering. Bonsall et al. (2018) show that CRAs respond to the heightened reputational risk emanating from the widespread business press coverage of their issuer clients by taking explicit measures such as assigning better rating analysts, resulting in higher-quality ratings. Similarly, Bonsall, Koharki, and Neamtiu (2022) show that the initiation of credit default swaps trading disciplines the CRAs by providing investors with an alternative source of credit risk information. Baghai and Becker (2020), a notable exception in this literature, present robust evidence that S&P issued optimistic (i.e., lower quality) ratings after suffering significant reputation loss. Interestingly, they also find that these strategically *biased* ratings allowed S&P to regain lost market share from its primary competitors - Moody's and Fitch.

The literature has also examined the effects of CRA reputation damage on debt market investors and corporate issuers. Given the large body of evidence suggesting that credit ratings are informative to the market participants (e.g., Hand et al. 1992; Holthausen and Leftwich 1986; Jorion et al. 2005), it is reasonable to argue that debt market participants would likely reduce their reliance on ratings from a CRA whose reputation has been tarnished. In the wake of reputation damage arising from the financial crisis, where the major CRAs issued inflated ratings on *structured* financial instruments, there was a noticeable decline in debt market participants' demand for *corporate* credit ratings produced by these CRAs (deHaan 2017). Notably, the quality of corporate credit ratings did not decline during or after the crisis. Thus, the decrease in the usage of credit ratings could be primarily attributed to the market's *perception* of the impaired quality of the CRAs' outputs. In a similar vein, Jaballah (2015) and Bedendo et al. (2018) find evidence supporting a decreased informativeness of credit ratings, as captured by the equity market reactions to ratings announcements after several CRA reputation-damaging events. The loss in reputation for CRAs also likely affects their issuer clients. Using the setting of high-profile corporate bankruptcies, Sethuraman (2019) documents that bond issuers react to CRA reputation damage by increasing voluntary disclosure to offset the potential increased information asymmetry caused by a decline in the credibility of the credit assessments produced by these CRAs.

3.3 Externalities of damage to CRA reputation

Externalities in capital markets occur when one firm's actions have effects that spill over to economically related firms such as product market rivals, customers, or suppliers ("peer firms"). These spillover effects arise as the *focal* firm's actions convey potentially value-relevant information to investors of the *peer* firms ("information transfers"). For example, the information in the focal firm's actions could (i) pertain to industry-specific economic factors common to all firms within an industry [e.g., weak demand projections/forecasts (Foster 1981)] or (ii) relate to (changes in) business fundamentals or competitive position of the peer firms [e.g., supply chain uncertainty (Pandit et al. 2011)] or (iii) indicate similar forthcoming actions by peer firms [e.g., accounting restatements (Gleason et al. 2008)]. The literature on information transfers has examined such peer-valuation effects for several focal-firm actions/events, including earnings announcements and management earnings forecasts (e.g., Foster 1981; Baginski 1987; Pandit et al. 2011), earnings restatements (e.g., Akhigbe and Madura 2008; Gleason et al. 2008; Lee and Lo 2016), distress and bankruptcy filings (e.g., Hertzel et al. 2008; Lang and Stulz 1992), and audit failures (e.g., Chaney and Philipich 2002; Weber et al. 2008; Krishnamurthy et al. 2006; Skinner and Srinivasan 2012).

We build on this extensive literature and argue that there are potentially significant negative *externalities* of a negative shock to a CRA's reputational capital, such as the public revelation of "ratings inflation." Upon learning about this negative news related to the CRA, investors of the CRA's issuer clients, who are the users of these credit ratings, likely presume that the ratings issued by the *tainted* CRA for their other issuer clients are also likely biased upwards. And so, the investors presumably correct for the "inflated ratings" by relying less on these ratings in their investment decisions and adjusting (upwards) their credit risk assessments of these issuers. Such an increase in risk assessments will lead to a decline in stock prices.

However, this prediction is not without tension, and there are at least three reasons why issuers may not have a negative stock market reaction upon reputation loss for their CRAs. First, several commentators, including scholars, investors, journalists, and regulators, have acknowledged that ratings inflation is rampant (see, among others, Bolton et al. 2012; Coffee 2009; Partnoy 1999; Podkul and Banerji 2019; Hemraj 2015). To the extent investors of these other issuer firms believe that the ratings obtained by their firms are also inflated, these investors may already discount these ratings and impound that information about the adjusted credit risk into the stock prices (Skreta and Veldkamp 2010; Chakraborty et al. 2019; Holden et al. 2012).[36] Second, relatedly, it is possible that equity market participants conduct their own due diligence and independent credit risk assessments and not simply rely on the credit ratings provided by the CRAs (House 1995; De Pascalis 2016; Sangiorgi and Spatt 2017). Partnoy (2017) notes that investors

[36] Using a sample of performance-sensitive debt, Herpfer and Maturana (2021) show that debt market participants such as banks, mutual funds, and loan funds are aware of CRAs' incentives to engage in ratings inflation, and these market participants price the potential ratings inflation, albeit not entirely, at the debt origination.

are well aware that ratings lack information content and are increasingly relying on more information-rich measures such as credit spreads, which are market measures of credit risk, along with fundamental 'bottom-up' credit analyses. Third, even if equity investors find credit ratings uninformative, they may *mechanically* depend on them because of regulatory requirements, private/internal investment mandates and asset management policies. For instance, regulation prohibits several classes of investors, such as pension funds and mutual funds, from holding shares of an issuing firm that does not have a certain minimum rating threshold for its debt instruments (e.g., Kisgen and Strahan 2010; Jeon and Lovo 2013; Cornaggia et al. 2017; Chen et al. 2014). Such requirements create a mechanistic reliance on credit ratings that is not necessarily driven by the underlying informativeness of the ratings. This prediction is consistent with the view espoused by Partnoy (1999) that CRAs have evolved from providers of credit-relevant information to providers of 'regulatory licenses.' By having exclusive rights to distribute these licenses, CRAs have acquired the role of gatekeepers to the bond markets, where the issuers seek these licenses to get access to cheaper financing from institutional investors such as banks, pension funds, insurance companies, and money market funds.

Given the aforementioned reasons, the stock prices might not change upon the public revelation of ratings inflation by CRAs and the ensuing damage to their reputations. Accordingly, we state our first hypothesis in the null form:

H1: During the events relating to a CRA's reputation loss, there is no abnormal stock price reaction for issuer firms that get rated by that (tainted) CRA.

We do not expect that this negative shock to the CRA's reputation would spillover uniformly to all its issuer clients. Specifically, we expect more severe consequences for issuers that investors perceive to have ex-ante obtained inflated ratings from the (now tainted) CRAs. For instance, issuers who are on the cusp of regulatory thresholds (such as investment grade –

speculative grade) likely have incentives to move across such thresholds for potential capital market benefits like higher liquidity, more stability, and lower cost of capital (e.g., Ellul, Jotikasthira, and Lundblad 2011; Kisgen and Strahan 2010; Chen, Lesmond, and Wei 2007). The market would consequently levy much stronger penalties on these firms, suggesting stronger spillover effects for such firms. Accordingly, we predict that:

H2a: The negative stock price reactions are stronger for those clients of tainted CRAs that are suspected of having obtained inflated ratings.

In a similar vein, we expect that issuers with weaker current economic performance and outlook would face more adverse spillover effects. Given the weak fundamentals, the market perceives these issuers as potentially having a higher credit risk profile and more likely to default than what their existing credit ratings imply. For instance, firms making losses and firms that exhibit a higher degree of earnings volatility are more likely to face high bankruptcy and insolvency risks, all else equal (Jung, Soderstrom, and Yang 2013). Accordingly, we predict that:

H2b: The negative stock price reactions are stronger for those clients of tainted CRAs that (i) report a loss or (ii) have higher earnings volatility.

4 Research design and sample selection

4.1 Regression specification

For examination of the spillover effects of CRA reputation damage, the ILFS setting presents a quasi-exogenous shock where the non-ILFS corporate issuer clients of the tainted CRAs (CARE, ICRA, and INDRA) serve as the *treated* group, and corporate issuer clients of other CRAs (CRISIL Brickwork, Acuite, and IVR) serve as the *control* group. We test for the spillover effects of CRA reputation damage by comparing the treatment and control firms' stock market reactions around the key events of the ILFS crisis. Specifically, we estimate the following regression specification:

$$\boldsymbol{CAR = \alpha + \beta_1 * TREAT + \sum Controls + Industry\,FE + \epsilon} \qquad (\mathbf{1})$$

The dependent variable *CAR* is the three-day cumulative abnormal return for an issuer firm centered around the ILFS default crisis event dates (-1, +1). The abnormal returns are measured as the excess over the returns predicted by the market model. The parameters for the market model are estimated over the (-210, -11) interval using the NIFTY 500 index to proxy for market returns.[37] The primary independent variable of interest in equation (1) is *TREAT*, an indicator variable that equals one for an issuer rated by a tainted CRA (i.e., CARE, ICRA, or INDRA) and zero otherwise. A negative coefficient on *TREAT* is consistent with adverse spillover effects arising from reputational shock to CRAs.

We also control for several issuer firm characteristics, including size (measured as the natural log of the *TOTAL ASSETS*), book to market *(BM*), sales growth (*SALES GROWTH*), leverage (*LEVERAGE*), return on assets (*ROA*), earnings volatility (*EARNINGS VOLATILITY*), cash (*CASH*), current ratio (*CURRENT RATIO*), asset tangibility (*TANGIBILITY*), and the median outstanding credit rating (*RATING*). Additionally, we include dummy variables for whether the issuer was affiliated with a business group (*BUSINESS GROUP*), was rated non-investment grade (*NON-INVESTMENT GRADE)*, recently had a rating downgrade (*DOWNGRADE*), recently had a rating upgrade (*UPGRADE*), and was placed on a watchlist (*WATCHLIST).* All the control variables are measured at the beginning of the fiscal year 2019[38], the year in which the ILFS crisis happened. These variables are defined in Appendix A. Finally, we control for the unobserved time-invariant industry-level factors common to all issuer firms within an industry by including the 2-digit SIC industry fixed effects.

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[37] NIFTY 500 is roughly analogous to the S&P 500 in the U.S.

[38] In India, most publicly listed companies follow the fiscal year from April 1st to March 31st for their corporate reporting. This choice aligns their reporting with the financial year for corporate tax and government reporting/budgeting purposes.

4.2 Sample and data

Since the ILFS crisis happened in September 2018, we include all firms in the sample that have (i) daily stock return data available around the key event dates and for the estimation period, (ii) ratings available on their debt instruments, and (iii) accounting data at the beginning of the fiscal year 2019 (the fiscal year in which ILFS crisis happened). We obtain all data on stock prices, credit ratings, fundamental and financial performance, and industry classification from the Prowess database managed by the Center for Monitoring Indian Economy (CMIE). Given its comprehensive coverage and high quality, this database has been extensively used in prior literature (Manchiraju and Rajgopal 2017; Baghai and Becker 2018; Khanna and Palepu 2000; Gopalan, Nanda, and Seru 2007). The aforementioned data restrictions lead to a final sample of 836 unique firms. In our sample, 555 firms (66%) got their debt instruments rated by a tainted CRA (i.e., CARE, ICRA, or INDRA) and hence are classified as treatment firms. On the other hand, 281 firms (34%) obtained ratings for their debt instruments from CRISIL, Brickwork, Acuite, and IVR — the CRAs not implicated in the ILFS crisis — and hence are classified as control firms.

Panel A of Table 1 presents the distribution of sample firms according to the Fama-French 10 industry classification (Fama and French 1997). The manufacturing Group ('3') has the highest proportion for both treated and control firms. Panel B of Table 1 presents the ratings-wise sample distribution. We find that the distribution across broad ratings scales is similar for both treatment and control group firms. For instance, 72% of all treatment firms get a rating of BBB or higher. This is comparable to the control group, where 74% of all firms get BBB ratings or above. We provide summary statistics on the firm characteristics in Table 1, Panel C. The average market capitalization of our sample firms is 840 USD million. About 43% of issuers are part of a business group (*BUSINESS GROUP*), which is a peculiar characteristic of the Indian corporate sector. Our sample consists mainly of profitable firms with an average return on assets of 4% (*ROA*). The mean (median) rating level is 12.22 (13.00), which translates to a letter rating of BBB+ (*RATING*). Additionally, about 36% of our issuer firms are rated non-investment grade (*NON-INVESTMENT GRADE*), i.e., have a rating of BB+ (9) or lower. We also look at the differences in the means and medians of these variables across the treatment and control groups. On average, treatment firms are larger, more leveraged, and less profitable. Given that the treatment and control firms vary on several dimensions, we control for these characteristics in our multivariate analyses.

5 Empirical results

5.1 Spillover effects of CRAs' reputation damage

As discussed earlier, the ILFS crisis provides a unique setting where three major CRAs (CARE, ICRA, and INDRA) allegedly engaged in ratings inflation and subsequently suffered a loss to their reputation. On the other hand, CRISIL, Brickwork, Acuite, and IVR did not provide ratings to ILFS and likely did not face a similar negative shock to their reputations. Thus, our treatment and control groups comprise issuers rated by these tainted and clean CRAs, respectively. It's important to highlight that our control group for the spillover analysis is comprised exclusively of issuers rated by CRISIL. This sample composition results from requiring the issuers to be publicly listed, and the clients of other clean CRAs—namely Brickwork, Acuite, and IVR—are primarily private firms. We begin the examination of the spillover effects arising from CRA reputation damage by comparing the mean 3-day CAR for the treatment and control firms around the key events in the ILFS crisis. Table 2 presents the results from this univariate analysis. We find that the average 3-day CAR is significantly negative for the treatment firms for eight of the thirteen events we examined. In comparison, the average 3-day CAR for control firms is positive for three events, negative for two events, and statistically insignificant for the remaining eight events. We also examine if the average 3-day CAR for treatment firms is significantly more negative than the average 3-day CAR for control firms. We find that for four particular events - (i) default to SIDBI (September 4, 2018), (ii) default on commercial papers (September 14, 2018), (iii) default on non-convertible debentures and commercial papers (September 17, 2018), and (iv) default on the letter of credit (September 21, 2018), the average 3-day CAR for treatment firms is significantly more negative than the average 3-day CAR for control firms.[39]

< Insert Table 2 here >

Table 3 presents the results from examining the spillover effects in a multivariate framework by estimating equation (1). For this purpose, we cumulate the individual abnormal returns for (i) all events and (ii) the events occurring in September 2018 – the month when ILFS defaulted on its debt obligations.[40] The choice to cumulate individual event CARs is motivated by two main reasons. First, the equity market's reaction to an individual event is conditional on the "collective responses" from the prior events in the series (Grewal, Riedl, and Serafeim 2019), so viewing an event in isolation might not capture the entire reaction. Second, aggregation reduces measurement noise in an individual event's abnormal return computation. For instance, if other events unrelated to the ILFS crisis differentially affect the treated and untreated firms on a particular calendar date that coincides with one of the ILFS event dates, the abnormal returns for that specific ILFS event date are likely measured with error. Thus, aggregating abnormal returns across *all* events reduces this event-specific measurement noise.[41] In column (1), where the

[39] We note that the market reaction for treatment firms for one event ("SEBI imposes a fine of 25 L") is positive, but the difference between the market reactions for treatment and control firms is statistically insignificant.

[40] We exclude the default on August 28th, 2018, following ILFS's claims that the default was triggered due to a technical glitch, which was immediately rectified. Including this default event does not change our inferences.

[41] Admittedly, exclusion (inclusion) of relevant (irrelevant) events introduces noise in our (aggregate) measure of CAR and, hence, potentially biases against finding results consistent with our expectations.

dependent variable is CAR cumulated over *all* events, the coefficient on *TREAT* is negative and significant (coefficient = -0.088, p-value <1%). This finding indicates that around key ILFS crisis events, firms rated by CRAs with bad reputations (ICRA, CARE, and INDRA) had an 8.8% greater decline in market value compared to the decline in the market value of firms rated by the CRA with a good reputation (CRISIL). The results are similar in column (2), where the dependent variable is CAR cumulated over events happening in September 2018.[42] Collectively, the findings in Table 3 provide evidence that a negative reputational shock has significant adverse capital market consequences, including *spillover* effects consistent with the capital market placing less confidence in the outputs produced by the tainted rating agencies.

< Insert Table 3 here >

5.2 Cross-sectional variation in spillover effects of CRAs' reputation damage

We then examine the cross-sectional variation in these adverse capital market consequences for issuer firms rated by the tainted CRAs. Our first cross-sectional prediction is that the negative spillover effects would be stronger for firms where the investors perceive the existing ratings as inflated. We measure investors' perception of ratings inflation in several ways. First, we argue that the market participants will be more skeptical of the quality of such ratings for an issuer that obtained an *UPGRADE* in their ratings (compared to *DOWNGRADE*, *RATING WATCH*, or no change). Second, we posit that issuers who received a rating that just meets a critical rating threshold are more likely to be viewed suspiciously. For instance, the Insurance Regulatory and Development Authority of India requires insurance companies to have at least 60% of their holdings in corporate bonds rated AA- or higher. Mutual funds are permitted to invest in debt

[42] In an untabulated analysis, we estimate equation (1) for each event individually. We find a significant coefficient on *TREAT* for all four events happening in September 2018. In our subsequent cross-sectional analyses, we use CAR aggregated for the September 2018 events. Our results hold if we use CAR aggregated for all events.

securities up to a BBB- rating and not below. Thus, all else being equal, issuers will prefer an AA- rating to an A+ rating and a BBB- rating to a BB+ rating. Due to the demand for inflated ratings by issuers close to certain thresholds, rating agencies are more likely to issue inflated ratings to them. To capture these types of issuers, we create an indicator variable *THRESHOLD* that equals one for issuers who receive a rating equal to the minimum rating prescribed for regulatory purposes and zero otherwise. The intuition is that the equity market would be more skeptical of the ratings produced by tainted CRAs for such issuers as these issuers would have had greater incentives to seek inflated ratings and engage in rating shopping (see, e.g., Graham & Harvey, 2001; Kisgen, 2006, 2009). Finally, we also expect that the negative spillover effects faced by the issuer clients of tainted CRAs would be more pronounced for those issuers who belong to a business/corporate group. We create an indicator variable *BG* that equals one for firms belonging to a business group and zero otherwise. We predict that the ratings produced by tainted CRAs for such issuers are more likely to be inflated as CRAs have potentially more to gain by "catering" to such issuers and thereby attracting other affiliates and group companies. This hypothesis builds on the theoretical prediction that a CRA is more likely to inflate an issuer's ratings when an issuer is more important to that CRA (Bolton et al. 2012).

To test this set of hypotheses that relate to the cross-sectional variation of the main result, we augment equation (1) by including indicator variables capturing our predicted variations and interacting them with *TREAT*. A negative and significant coefficient on an interaction term will support our hypothesis that the negative spillover effects of reputation loss will be stronger in firms where investors perceive the existing ratings as inflated. We present the results of this analysis in Table 4. In column (1), we find the coefficient on *TREAT*UPGRADE* is negative and significant (coefficient = -0.074 p-value = 1%), while the coefficients on *TREAT*DOWNGRADE* and

*TREAT*RATING WATCH* are insignificant. This finding indicates that compared to the stock returns of the firms rated by the clean CRAs, the stock returns of firms that received a rating *UPGRADE* by the tainted CRAs fell by 9.4% (-0.054 – 0.073 + 0.043). In column (2), the coefficient on *TREAT*THRESHOLD* is negative and significant (coefficient = -0.046 p-value = 5%), suggesting firms receiving ratings from tainted CRAs in such a way that the ratings are precisely equal to the minimum rating for regulatory purposes, experience 7.5% lower stock returns compared to stock returns of firms that get their rating from the clean CRAs. Finally, in column (3), the coefficient on *TREAT*BG* is negative and significant (coefficient = -0.053 p-value = 1%), indicating that among firms that receive ratings from tainted CRAs, firms belonging to a business group are more likely to experience negative stock returns. Such firms have 10.7% lower stock returns compared to the stock returns of firms rated by the clean CRAs. Overall, the results of this table are consistent with our prediction that negative spillover effects will be more pronounced in firms where investors perceive the ratings to be inflated.

< Insert Table 4 here >

Our second cross-sectional prediction is that the negative spillover effects would be stronger in firms with low and uncertain profitability since the information provided by CRAs will be incrementally valuable for equity investors of these firms. Specifically, we expect that among firms rated by tainted CRAs, those making losses and having high earnings volatility will likely experience more negative stock returns around the ILFS crisis events. To test this prediction, we augment equation (1) with indicator variables to capture (i) loss and (ii) high earnings volatility. We define *LOSS* as an indicator variable that equals one if a firm had reported a loss in the fiscal year ending before the ILFS crisis and zero otherwise. *HIEARNVOL* is an indicator variable that equals one if a firm's earnings volatility is above the median earnings volatility for the sample distribution and zero otherwise. We define earning volatility as the standard deviation of the *ROA* (Net income divided by total assets) over the last five years. These indicators are then interacted with our primary variable of interest, *TREAT*. Negative and statistically significant coefficients on *TREAT*LOSS* and *TREAT*HIGHEARNVOL* would suggest that the stock market levies an *incremental* penalty on issuers with weaker financial performance outlooks and higher credit risks.

Table 5 presents the results of these analyses. In column (1), the coefficient on *TREAT*LOSS* is negative and significant (coefficient = -0.073 p-value = 5%), indicating that among firms that receive ratings from tainted CRAs, firms incurring losses are more likely to experience negative stock returns. These firms have 8.2% lower stock returns compared to the stock returns of firms rated by the clean CRAs. In column (2), we find that the coefficient on *TREAT*HIEARNVOL* is negative and significant (coefficient = -0.133 p-value = 1%), indicating that among firms that receive ratings from tainted CRAs, firms with higher levels of earnings volatility are more likely to experience negative stock returns. These firms have 7.2% lower stock returns compared to the stock returns of firms rated by the clean CRAs. Finally, in column (3), we examine whether the stock returns of firms rated by tainted CRAs are lower than those rated by the clean CRAs if such firms make losses and have high earnings volatility. We find the three-way interaction term *TREAT*LOSS*HIEARNVOL* is negative and significant (coefficient = -0.177 p-value = 1%), indicating that these firms experience 10.7% lower stock returns compared to the stock returns of firms rated by the clean CRA. In summary, the results of this table are consistent with our prediction that the negative spillover effects will be more pronounced in firms where earnings are lower and more volatile.

< Insert Table 5 here >

5.3 Additional analysis

5.3.1 CRAs' response to reputation damage

Given that reputation damage has potential real consequences in terms of a decline in competitive position and loss of market share, it stands to reason that CRAs would react to this reputation damage. There are two possibilities. CRAs could take corrective actions in order to rebuild their reputation by making substantive changes to their internal governance, rating methodology, training of analysts, etc. These changes are likely aimed at improving credit rating quality (and signaling these improvements) to win back or attract new clients and regain market share. Alternatively, CRAs could maintain the status quo of issuing low-quality ratings or even go on to issue more lenient ratings to gain market share in the short run (Baghai and Becker 2020). This strategy by the CRAs is likely aimed at "catering" to issuers who are "shopping" around for better ratings, i.e., upward-biased ratings. The net effect on ratings quality after a negative reputational shock would depend on which of these two forces dominate.

To examine which of these two economic forces influence the CRAs' response to the reputation damage, we use a difference-in-differences design and compare the changes in ratings quality pre- and post-ILFS crisis for the CRAs with bad versus good reputations. Specifically, we estimate the following regression specification using OLS:

$$\begin{aligned} \boldsymbol{RATING\ QLTY} &= \boldsymbol{\alpha} + \boldsymbol{\beta_1} * \boldsymbol{TREAT} + \boldsymbol{\beta_2 POST} + \boldsymbol{\beta_3\ TREAT} * \boldsymbol{POST} \\ &\quad + \boldsymbol{Firm\ FE} + \boldsymbol{Year\ FE} + \boldsymbol{CRA\ FE} + \boldsymbol{\epsilon} \qquad (\mathbf{2}) \end{aligned}$$

In Equation (2), following prior literature (see, e.g., Bonsall et al., 2018; Cheng & Neamtiu, 2009; deHaan, 2017; Dimitrov et al., 2015), *RATING QLTY* is measured as one of the following: (i) *RATING LEVEL,* which is the median of all the ratings an issuer firm receives in a given year across all its instruments aggregated across CRAs, with a value of 19 denoting the highest credit rating "AAA" and a value of one denoting "C-"; (ii) *TYPE I ERROR* is an indicator variable that equals one if an issuer gets an investment grade rating (BBB- or higher) in the year *t* and defaults in the year *t+1*, and zero otherwise; (iii) *TYPE II ERROR* is an indicator variable that equals one if an issuer gets a non-investment grade rating (BB+ or lower) in the year *t* and does not default in the year *t+1*, and zero otherwise. We consider that a CRA gives strict ratings if, all else equal, the CRA gives a lower level of rating or is less likely to commit a *TYPE I ERROR*, which captures a missed default, and more likely to commit a *TYPE II ERROR*, which captures a false warning about future default. *TREAT*, as before, is an indicator variable that equals one for tainted CRAs (ICRA, CARE, and INDRA) and zero otherwise. The sample period for our analysis is September 2015 to September 2021, which covers three years before and three years after the ILFS crisis events of September 2018. *POST* is an indicator variable that equals one for years after the ILFS crisis and zero otherwise. We use issuer-firm fixed effects and year fixed effects to control for firm-specific time-invariant factors and time-varying factors common to all firms (e.g., macroeconomic), respectively.[43] To control for the time-invariant CRA-specific rating philosophy, process, and technology, we include rating agency fixed effects (CRA FE). The primary independent variable of interest is the interaction term *TREAT * POST*. Since our rating quality measures capture the strictness of rating, a negative coefficient on the interaction term when the dependent variable is *RATING LEVEL or TYPE I ERROR* and a positive coefficient on the interaction term when the dependent variable is *TYPE II ERROR* will suggest that the tainted CRAs

[43] In untabulated analyses, we find that our results are not sensitive to the inclusion of control variables such as firm size (LN(TOTAL ASSETS)), profitability (ROA), and leverage (LEVERAGE). These robustness analyses provide us comfort that time-varying changes in issuer credit quality are unlikely to drive the improvement in ratings quality we document. We do not include these control variables in our primary analyses as a considerable proportion of firms in our sample are private/unlisted, and data availability, even for fundamental characteristics, is sparse for these firms.

issue stricter ratings compared to the clean CRAs in the post-ILFS crisis period relative to the period before the crisis.

The sample for this analysis is constructed following the procedure outlined in Baghai and Becker (2018). First, we drop observations if they relate to ratings classified as withdrawn/not meaningful/suspended/issuer not cooperating. Second, since the Prowess database does not have a unique identifier for an issuer's debt security, we drop a rating as a duplicate entry if it has the same value for the combination of the following fields: rating date, rating agency, issuer, security type, issue amount, rating status and rating. Third, we calculate ratings quality measures at the firm-year-rating agency level by considering the median ratings across all instruments for each issuing firm provided by a particular CRA in a given year.[44] Finally, we drop firms rated by multiple CRAs where one or more CRAs are tainted and one or more CRAs are clean, as it is not possible to disentangle the impact of reputation loss on ratings quality for such firms.[45] This process results in a final sample of 42,491 unique firm-year-CRA observations in our sample relating to 11,605 unique firms.[46]

Panel A of Table 6 presents descriptive statistics for our rating quality measures. The average rating level is 10.415, which is just above the investment grade rating threshold. The average likelihood of *TYPE1 ERROR* is 0.40%, which is small, but these are the errors that attract

[44] Prowess database has 90 different instrument types that a firm can issue. Following Baghai and Becker (2018), we include only the most common debt instruments in our analysis. These instruments include – long-term loans, term loans, short-term loans, cash credit, working capital loans, overdrafts, packing credit, fund-based financial facilities/ instruments, bank guarantees, letters of credit, non-fund-based financial facilities/ instruments, commercial papers, debentures/bonds/notes/bills, non-convertible unsecured debentures/bonds/notes/bills, and fixed rate unsecured non-convertible debentures. Together, these 15 instruments comprise approximately 80% of the entire sample. Our results do not change significantly if we take the mean, maximum, or most recent rating for each issuing firm, year, and CRA across all instrument categories. Our results also remain unchanged if we take the median of ratings over all instruments rather than only the top 15.

[45] We lose about 18% of our sample due to this data restriction.

[46] This sample is much bigger in size compared to the sample used in the analysis of spillover effects because a large proportion of this sample comprises unlisted firms. The unlisted firms were not included in the spillover analysis because the capital market consequences of reputation loss can only be determined for listed firms.

the most scrutiny. The average likelihood of *TYPE II ERROR* is 44.40%, which is high and reflects the conservative nature of the ratings. Panel B of Table 6 presents the results from our DID analysis. The dependent variable is *RATING LEVEL*, *TYPE I ERROR,* and *TYPE II ERROR*, in columns (1), (2), and (3), respectively. The coefficient on *TREAT X POST* is negative and significant in columns (1) and (2) and positive and significant in column (3), consistent with rating agencies becoming stricter in their rating assessments. These results suggest that, in the aftermath of the ILFS crisis, compared to clean CRAs, tainted CRAs assign lower ratings, are less likely to commit a *TYPE I ERROR*, and are more likely to commit a *TYPE II ERROR*. Collectively, these findings suggest that CRAs assign stricter credit ratings and improve the quality of their rating output. It is noteworthy that we include issuer-firm fixed effects to address unobserved firm heterogeneity and mitigate the concern that time-invariant issuer-specific characteristics drive the change in ratings quality we document.[47] We also include year fixed effects to capture any economy-wide trends and CRA fixed effects to absorb any rating agency-specific differences in the quality of ratings.

< Insert Table 6 here >

5.3.2 Issuers' response to CRAs' reputation damage

To complement the above analysis, we examine the issuers' response to the CRAs' reputation damage because of the ILFS crisis. The ILFS crisis highlighted the casual attitude and low-quality ratings exhibited by the tainted CRAs, and our evidence shows that the capital market penalized these CRAs as well as their issuer clients. Given the capital market's perception of these CRAs and its low confidence in these CRAs' outputs, current and potential issuers might consider moving

[47] As noted earlier, our results are robust to the inclusion of time-varying issuer characteristics such as size, profitability, and leverage that could be correlated with changes in issuer credit risk and ratings quality.

away from these CRAs to clean CRAs to avoid the negative consequences of being associated with the tainted CRAs. On the other hand, issuers could also gravitate towards these tainted CRAs with the expectation of getting inflated ratings by persuading these CRAs into giving them lax ratings, as in the case of ILFS. In that scenario, these tainted CRAs might have an increase in customer base and attract the clean CRAs' existing clients and new debt issuers.

To test the issuers' response to CRAs' reputation damage, we examine the frequency of a firm changing its CRA over time. Specifically, we create an indicator variable *CHANGE* that equals one if a firm got rated from a tainted CRA (ICRA, CARE, or INDRA) in the year *t* and by a clean CRA (CRISIL, Brickwork, Acuite, or IVR) in the year *t+1*, and zero otherwise. We compare the average value of *CHANGE* in the pre versus post-ILFS crisis period and document the results in Table 7. As shown in panel A, in the pre-ILFS crisis period, the average *CHANGE* is 1.27%, suggesting that 1.27% of issuing firms discontinue their association with the (to-be) tainted CRAs to get their ratings from clean CRAs. This average for *CHANGE* is 1.23% in the post-ILFS crisis period, which is not statistically different from the pre-crisis period average. In Panel B, we show results from a fixed effects regression model where *CHANGE* is estimated as a function of *POST*. Consistent with the results from the univariate analysis, we find an insignificant coefficient on *POST*. Overall, we find that a substantial proportion of issuers do not switch from tainted CRAs to clean CRAs after the loss of CRA reputation.

This analysis also helps address one potential concern with our findings and inferences from Table 6. The concern is that the ILFS crisis could have led to changes in CRAs' clientele, and the changes in ratings we observe are not (entirely) due to changes in CRA rating practices/standards but (at least partially) due to these changes in customer bases. In other words, the concern is that the lower credit ratings assigned by tainted CRAs do not reflect stricter ratings standards/practices but the fact that these tainted CRAs are left with issuers of lower credit quality. In the wake of the reputation damage suffered from the ILFS crisis, the tainted CRAs have limited bargaining power and so are left with these poor-quality issuers because the good-quality issuers probably jumped ship to go to CRISIL and other clean CRAs. The findings in Table 7 help rule out this alternative explanation and give us confidence that the changes in rating quality we observe post-ILFS crisis (reported in Table 6) are more likely to be driven by the changes and improvements in CRAs' rating standards and practices.

< Insert Table 7 here >

6 Conclusion

We examine the economic externalities resulting from a loss in the reputation of credit rating agencies for their issuer clients. We use the massive default in the Indian debt market by an AAA-rated financial institution (ILFS) as a setting where the CRAs suffering reputation damage (tainted CRAs) experience a significant decline in their market values. We find that damage to a CRA's reputation results in significant adverse capital market consequences. Specifically, we show that debt issuers that get ratings from tainted CRAs experience negative stock market reactions around the ILFS default crisis events, suggesting a decline in the capital market's confidence and trust in the tainted CRA's rating outputs. In contrast, around the same events, there are no significant market reactions for issuers that get ratings from the clean CRAs.

We add to the literature examining the economic consequences of a negative shock to CRAs' reputation. Examining CRAs' reputation is important, given the critical role CRAs play as information intermediaries in the smooth functioning of the capital markets (Roychowdhury and Srinivasan 2019). Our results are of potential interest to academics, practitioners, and regulators grappling with issues pertaining to the credit rating market worldwide. One unique aspect of our study is highlighting the unintended consequences for the *clients* of the CRAs. We show that these clients suffer from a taint resulting from a loss of confidence in the CRA.

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Appendix A: Market reactions for CRAs around key events of the ILFS crisis.

This appendix presents the stock market reaction for publicly listed CRAs around events in the ILFS default crisis. For each event in the ILFS crisis, the abnormal return is computed using the market model with an estimation window of 250 days ending before the first event (28th August 2018). The market return is proxied by the return on the NIFTY500 index, which is roughly analogous to the S&P 500 in the U.S. $CAR_{[-1,1]}$ is then computed as the cumulative abnormal return for a CRA aggregated over the three days surrounding each event. *CRISIL* is the clean CRA as it was not involved in rating any ILFS group company, whereas *CARE* and *ICRA* likely got a tainted reputation from allegedly issuing inflated ratings to one or more ILFS group companies. The t-statistics, reported in parentheses below the coefficient estimates, are computed using the standard deviation of the raw returns from the estimation period. ***, **, and * denote estimates that are significantly different from zero at the 1%, 5%, and 10% levels, respectively.

			$CAR_{[-1,1]}$		
S.No.	**Date**	**Event**	**CRISIL**	**ICRA**	**CARE**
1	**2018-08-28**	First Commercial Paper (CP) default	0.009 [0.672]	0.001 [0.115]	-0.006 [-0.428]
2	**2018-09-04**	Default on term loan from Small Industries Development Bank of India (SIDBI)	0.006 [0.459]	-0.025** [-2.125]	-0.029** [-2.002]
3	**2018-09-14**	Another CP Default	0.004 [0.324]	-0.024** [-2.045]	-0.031** [-2.143]
4	**2018-09-17**	More defaults on CPs and non-convertible debentures (NCDs)	0.008 [0.577]	0.007 [0.575]	0.004 [0.261]
5	**2018-09-21**	Defaults on Letter of Credit (LC) to Industrial Development Bank of India (IDBI)	0.009 [0.679]	-0.030** [-2.558]	-0.043*** [-2.904]
6	**2018-12-12**	SEBI starts proceedings against the allegedly involved CRAs	0.027** [1.972]	-0.025** [-2.130]	-0.036** [-2.459]
7	**2019-07-02**	ICRA MD sent on leave	0.001 [0.059]	-0.045*** [-3.801]	0.006 [0.393]

8	**2019-07-18**	CARE MD sent on leave	0.007 [0.549]	0.001 [0.064]	-0.028* [-1.937]
9	**2019-08-20**	Grant Thornton releases final forensic audit report	-0.004 [-0.330]	-0.029** [-2.407]	-0.051*** [-3.450]
10	**2019-08-29**	ICRA MD sacked	0.008 [0.554]	0.018 [1.515]	0.007 [0.453]
11	**2019-12-20**	CARE MD resigns	0.018 [1.307]	0.003 [0.245]	0.005 [0.330]
12	**2019-12-26**	SEBI imposes a fine of 25L each on ICRA, CARE, and INDRA	-0.008 [-0.619]	0.000 [-0.003]	0.003 [0.222]
13	**2021-09-22**	SEBI revised the above penalty to INR 1 crore each	-0.001 [-0.045]	-0.009 [-0.783]	-0.011 [-0.737]

Appendix B: Variable Definitions

Variable Name	**Variable Definition**
BM	The ratio of the book value of equity to the market value of equity of the debt issuing firm.
BUSINESS GROUP	An indicator variable that equals one for issuer firms that belong to a business group and zero otherwise.
CAR	The cumulative abnormal return for an issuer firm aggregated over events relating to the ILFS crisis occurring in September 2018. For computing the expected return, we use the market model and an estimation window of 200 days preceding the month of the first event.
CASH	The total of cash and cash equivalents at the end of the fiscal year of the issuing firm.
CURRENT RATIO	The ratio of the total current assets to the total current liabilities of the issuing firm.
DOWNGRADE	An indicator variable that equals one for issuers who got a rating downgrade in the fiscal year and zero otherwise.
EARNINGS VOLATILITY	The standard deviation of the pre-tax net income before extraordinary items over the preceding five fiscal years.
HIEARNVOL	An indicator variable that equals one for debt issuers with above-median earnings volatility and zero otherwise.
LEVERAGE	The ratio of the total long-term debt to the total assets.
LN(TOTAL ASSETS)	Natural log of one plus the total assets of the debt issuing firm.
LOSS	An indicator variable that equals one for debt issuers who reported a negative ROA and zero otherwise.
RATING	The median of all long-term issue ratings outstanding for an issuer across all instruments and all CRAs in the fiscal year. We assign numerical values to the letter grade ratings, with a value of 19 denoting the highest credit rating "AAA" and a value of one denoting "C-."
NON-INVESTMENT GRADE	An indicator variable that equals one if the average outstanding rating of the issuing firm is less than 10 (BBB-) and zero otherwise. To compute the average outstanding rating, we take an average (median) of all long-term issue ratings of the issuer across all CRAs in the fiscal year.
POST	An indicator variable that equals one for months after September 2018 and zero otherwise.

ROA	The ratio of the pre-tax net income before extraordinary items and the average total assets of the issuing firm.
SALES GROWTH	The ratio of the sales at the fiscal year-end and the sales at the beginning of the fiscal year.
TANGIBILITY	The ratio of the net properties, plants, and equipment (PP&E) to the book value of total assets.
THRESHOLD	An indicator variable that equals one for issuers with a rating exactly equal to AA- (16) or BBB- (10) and zero otherwise.
TREAT	An indicator variable that equals one when the debt issuer is rated by one of the three tainted CRAs (i.e., CARE, ICRA, or INDRA) and zero otherwise
TYPE I ERROR	An indicator variable that equals one if an issuer gets an investment grade rating (BBB- or higher) in the year t and defaults in the year $t+1$, and zero otherwise.
TYPE II ERROR	An indicator variable that equals one if an issuer gets a non-investment grade rating (BB+ or lower) in the year t and does not default in the year $t+1$, and zero otherwise.
UPGRADE	An indicator variable that equals one for debt issuers who got a rating upgrade in the fiscal year and zero otherwise.
WATCHLIST	An indicator variable that equals one for issuers who have been put on ratings watch in the fiscal year and zero otherwise.

Table 1: Descriptive statistics of sample used in spillover analysis.
This table reports the sample distribution. Panel A presents the sample distribution according to the Fama-French 10 industry classification. Panel B presents the sample distribution according to a rating grid with coarse partitions, i.e., excluding the letter ratings suffixed with + or – (e.g., AAA-, BB+). Panel C provides summary statistics relating to the financial characteristics of the full sample and separately for the treatment and control groups of firms. All variables are defined in Appendix A. ***, **, and * denote estimates that are significantly different from zero at the 1% level, at the 5% level, and at the 10% level, respectively.

Panel A – Industry-wise distribution

FF-Industry	Treat		Control		Total	
1	112	20%	53	19%	165	20%
2	36	6%	25	9%	61	7%
3	216	39%	118	42%	334	40%
4	11	2%	5	2%	16	2%
5	35	6%	20	7%	55	7%
6	13	2%	5	2%	18	2%
7	23	4%	7	2%	30	4%
8	32	6%	16	6%	48	6%
9	10	2%	3	1%	13	2%
10	67	12%	29	10%	96	11%
Total	555	100%	281	100%	836	100%

Panel B - Ratings-wise distribution

Rating	Treat		Control		Total	
AAA	6	1%	2	1%	8	1%
AA	161	29%	83	30%	244	29%
A	124	22%	56	20%	180	22%
BBB	109	20%	64	23%	173	21%
BB	94	17%	45	16%	139	17%
B	48	9%	26	9%	74	9%
C	13	2%	5	2%	18	2%
Total	555	100%	281	100%	836	100%

Panel C – Descriptive statistics

	Overall sample (N = 836)			Treatment firms (N = 555)			Control firms (N = 281)				
	Mean	Median	SD	Mean	Median	SD	Mean	Median	SD	Difference in mean T-C	Difference in median T-C
MCAP (INR billion)	57.49	4.94	208.05	46.12	5.08	156.12	79.95	4.30	283.01	-33.83*	0.78
MCAP (USD billion)	0.84	0.07	3.04	0.67	0.07	2.28	1.17	0.06	4.14	-0.49	0.01
BM	0.95	0.54	1.51	0.92	0.56	1.33	0.99	0.48	1.82	-0.07	0.08*
SALES GROWTH	0.04	0.09	0.41	0.01	0.08	0.48	0.08	0.10	0.22	-0.06**	-0.02
LEVERAGE	0.27	0.26	0.18	0.28	0.27	0.18	0.24	0.23	0.18	0.03**	0.04**
ROA	0.04	0.04	0.08	0.03	0.03	0.07	0.05	0.05	0.09	-0.02***	-0.02***
EARNINGS VOLATILITY	0.03	0.02	0.04	0.03	0.02	0.03	0.03	0.02	0.04	0.00	0.00
CASH	0.07	0.03	0.10	0.07	0.03	0.10	0.07	0.03	0.09	0.00	0.00
CURRENT RATIO	1.64	1.35	1.30	1.62	1.33	1.45	1.67	1.39	0.95	-0.05	-0.06***
TANGIBILITY	0.34	0.32	0.20	0.34	0.33	0.21	0.32	0.32	0.19	0.02	0.01
INTEREST COVERAGE	40.83	4.75	221.45	36.03	4.20	222.05	50.33	6.06	220.37	-14.30	-1.86***
BUSINESS GROUP	0.43	0.00	0.50	0.44	0.00	0.50	0.40	0.00	0.49	0.04	0.00
RATING	12.22	13.00	4.27	12.26	13.00	4.25	12.15	13.00	4.32	0.12	0.00
NON-INVESTMENT GRADE	0.36	0.00	0.48	0.36	0.00	0.48	0.36	0.00	0.48	0.00	0.00
UPGRADE	0.16	0.00	0.37	0.18	0.00	0.38	0.13	0.00	0.33	0.05*	0.00*
DOWNGRADE	0.09	0.00	0.29	0.10	0.00	0.29	0.08	0.00	0.27	0.02	0.00
WATCHLIST	0.06	0.00	0.24	0.05	0.00	0.23	0.08	0.00	0.27	-0.03	0.00

Table 2: Spillover effects of the ILFS crisis – univariate analysis

This table presents the results from a simple comparison of the mean 3-day CARs across the treatment and control groups, where CAR is the cumulative abnormal return for an issuer firm around an event in the ILFS default crisis. *TREAT* refers to treatment firms rated by a CRA whose reputation was tainted in the ILFS crisis, i.e., CARE, ICRA, or INDRA. *CONTROL* refers to firms rated by CRISIL. Events relating to the ILFS crisis are outlined in Appendix A. ***, **, and * denote estimates that are significantly different from zero at the 1%, 5%, and 10% levels, respectively.

Sno	Date	Event	*TREAT*	*CONTROL*	*T-C*
1	28-08-2018	First Commercial Paper (CP) default	-0.007***	-0.005	-0.002
2	04-09-2018	Default on term loan from Small Industries Development Bank of India (SIDBI)	-0.008***	0.010***	-0.019***
3	14-09-2018	Another CP Default	-0.011***	0.002	-0.012***
4	17-09-2018	More defaults on CPs and non-convertible debentures (NCDs)	-0.020***	0.011***	-0.031***
5	21-09-2018	Defaults on Letter of Credit (LC) to Industrial Development Bank of India (IDBI)	-0.023***	-0.010***	-0.013***
6	12-12-2018	SEBI starts proceedings against the allegedly involved CRAs	0.005	0.004	0.001
7	02-07-2019	ICRA MD sent on leave	-0.003	-0.006	0.004
8	18-07-2019	CARE MD sent on leave	-0.006**	-0.005	-0.001
9	20-08-2019	Grant Thornton releases final forensic audit report	-0.003	-0.005	0.001
10	29-08-2019	ICRA MD sacked	-0.006***	0.000	-0.006
11	20-12-2019	CARE MD resigns	-0.001	0.003	-0.005
12	26-12-2019	SEBI imposes a fine of 25L each on ICRA, CARE, and INDRA	0.015***	0.016***	-0.001
13	22-09-2021	SEBI revised the above penalty to INR 1 crore each	-0.006***	-0.008***	0.001

Table 3: Spillover effects of the ILFS crisis – regression analysis

This table documents the spillover effects of a negative shock to CRAs' reputational capital. The dependent variable, *CAR*, is the cumulative abnormal return for an issuer firm aggregated over (i) all events relating to the ILFS crisis and (ii) events relating to the ILFS crisis happening in September 2018, in columns 1 and 2, respectively. *TREAT* is an indicator variable that equals one if an issuer is rated by a CRA whose reputation was tainted in the ILFS crisis, i.e., CARE, ICRA, or INDRA, and zero if CRISIL rates the issuer. Events relating to the ILFS crisis are outlined in Appendix A. All control variables are defined in Appendix B. The t-statistics are reported in the parentheses below the coefficient estimates and are based on heteroskedasticity-robust standard errors. ***, **, and * denote estimates that are significantly different from zero at the 1% level, 5% level, and 10% level, respectively.

Dependent variable = CAR	All events (1)	Sep 2018 events (2)
TREAT	-0.088***	-0.063***
	[-4.89]	[-6.17]
LN(TOTAL ASSETS)	0.017**	0.009**
	[2.35]	[2.08]
BM	0.029***	0.010***
	[4.82]	[2.91]
SALES GROWTH	0.017	0.014
	[0.74]	[1.07]
LEVERAGE	0.044	-0.010
	[0.72]	[-0.29]
ROA	-0.160	-0.126
	[-1.12]	[-1.55]
EARNINGS VOLATILITY	0.011	0.126
	[0.04]	[0.88]
CASH	0.147	-0.008
	[1.34]	[-0.13]
CURRENT RATIO	0.000	0.005
	[0.00]	[1.08]
TANGIBILITY	-0.063	-0.025
	[-1.23]	[-0.85]
INTEREST COVERAGE	0.000	-0.000
	[0.20]	[-0.42]
BUSINESS GROUP	-0.059***	-0.045***
	[-3.11]	[-4.13]
RATING	0.006	0.004
	[1.30]	[1.32]
NON-INVESTMENT GRADE	0.033	0.010
	[0.96]	[0.52]
UPGRADE	0.001	-0.006
	[0.04]	[-0.48]
DOWNGRADE	-0.026	0.007
	[-0.83]	[0.38]
WATCHLIST	-0.052	0.003
	[-1.49]	[0.13]
Industry FE	Y	Y
Observations	829	829
Adjusted R-squared	0.093	0.068

Table 4: Market reaction around key events of the ILFS crisis – cross-sectional variation based on perceived inflated ratings.

This table reports the coefficients for linear regression models estimating the spillover effects of a negative shock to CRAs' reputational capital while exploiting the cross-sectional variation in perceived inflated ratings. The dependent variable, *CAR*, is the cumulative abnormal return for an issuer firm aggregated over events relating to the ILFS crisis events happening in September 2018. *TREAT* is an indicator variable that equals one if an issuer is rated by a CRA whose reputation was tainted in the ILFS crisis, i.e., CARE, ICRA, or INDRA, and zero if CRISIL rates the issuer. *UPGRADE* is an indicator variable that equals one for issuers with a rating upgrade in the fiscal year and zero otherwise. *DOWNGRADE* is an indicator variable that equals one for issuers with a rating downgrade in the fiscal year and zero otherwise. *RATING WATCH* is an indicator variable that equals one for issuers placed on ratings watch in the fiscal year and zero otherwise. *THRESHOLD* is an indicator variable that equals one for issuers with a rating exactly equal to AA- or BBB- and zero otherwise. *BG* is an indicator variable that equals one for firms that belong to a business group and zero otherwise. Control variables are the same as those in Table 3, Panel B. For brevity, we do not report the coefficients on control variables. All control variables are defined in Appendix B. The *t*-statistics are reported in the parentheses below the coefficient estimates and are based on heteroskedasticity-robust standard errors. ***, **, and * denote estimates that are significantly different from zero at the 1% level, 5% level, and 10% level, respectively.

Dependent variable = CAR	**(1)**	**(2)**	**(3)**
TREAT	-0.054***	-0.056***	-0.044***
	[-4.65]	[-5.01]	[-3.54]
*TREAT*UPGRADE*	-0.073***		
	[-2.70]		
*TREAT*DOWNGRADE*	-0.010		
	[-0.29]		
*TREAT*WATCHLIST*	0.003		
	[0.08]		
*TREAT*THRESHOLD*		-0.046**	
		[-2.02]	
*TREAT*BG*			-0.053***
			[-2.81]
UPGRADE	0.043*	-0.006	-0.005
	[1.90]	[-0.43]	[-0.36]
DOWNGRADE	0.012	0.008	0.005
	[0.40]	[0.43]	[0.30]
WATCHLIST	0.000	0.003	0.008
	[0.00]	[0.13]	[0.39]
THRESHOLD		0.027	
		[1.51]	
BG	-0.043***	-0.042***	-0.009
	[-3.96]	[-3.90]	[-0.58]
Controls	Y	Y	Y
Industry FE	Y	Y	Y
Observations	835	835	835
Adjusted R-squared	0.063	0.061	0.066

Table 5: Market reaction around key events of the ILFS crisis – cross-sectional variation based on earnings.

This table reports the coefficients for linear regression models estimating the spillover effects of a negative shock to CRAs' reputational capital while exploiting the cross-sectional variation in earnings. The dependent variable, *CAR*, is the cumulative abnormal return for an issuer firm aggregated over events relating to the ILFS crisis events happening in September 2018. *TREAT* is an indicator variable that equals one if an issuer is rated by a CRA whose reputation was tainted in the ILFS crisis, i.e., CARE, ICRA, or INDRA, and zero if CRISIL rates the issuer. *LOSS* is an indicator variable that equals one for issuers who reported a loss and zero otherwise. *HIEARNVOL* is an indicator variable that equals one for issuers with above-median earnings volatility and zero otherwise. Control variables are the same as those in Table 3, Panel B. For brevity, we do not report the coefficients on control variables. All control variables are defined in Appendix B. The t-statistics are reported in the parentheses below the coefficient estimates and are based on heteroskedasticity-robust standard errors. ***, **, and * denote estimates that are significantly different from zero at the 1% level, 5% level, and 10% level, respectively.

Dependent variable = Total CAR for events 2-5	**(1)**	**(2)**	**(3)**
TREAT	-0.056***	-0.030**	-0.034***
	[-5.16]	[-2.58]	[-2.77]
*TREAT*LOSS*	-0.073**		0.040
	[-2.35]		[0.96]
*TREAT*HIEARNVOL*		-0.133***	-0.097***
		[-5.85]	[-3.82]
*TREAT*LOSS*HIEARNVOL*			-0.177***
			[-2.85]
LOSS	0.047		-0.029
	[1.63]		[-0.80]
HIEARNVOL		0.091***	0.068***
		[4.26]	[2.90]
*LOSS*HIEARNVOL*			0.122**
			[2.25]
Controls	Y	Y	Y
Industry FE	Y	Y	Y
Observations	835	835	835
Adjusted R-squared	0.062	0.096	0.103

Table 6: Quality of ratings after the ILFS crisis – DID analysis.

This table reports results from examining changes in rating quality after the ILFS crisis using a DID framework. Panel A of this table presents the descriptive statistics for the ratings quality measures used in the analysis. Panel B shows the results of the regression analysis. Each observation corresponds to a unique firm-rating agency-year. The sample for this analysis comprises 42,491 unique firm-year-CRA observations in our sample relating to 11,605 unique firms. The sample period is from September 2015 to August 2021, three years before and after the ILFS crisis that happened in September 2018. *POST* is an indicator variable that equals one for the time period after September 2018 and zero otherwise. *TREAT* is an indicator variable that equals one if the rating agency is ICRA, CARE, or INDRA (these three agencies rated ILFS debt instruments) and zero otherwise. Firms that get ratings from both treatment and control ratings agencies are dropped from the sample. Rating quality is measured as *RATING LEVEL*, *TYPE I ERROR, and TYPE II ERROR* in columns (1)-(3), respectively. *RATING LEVEL* is the median of all the ratings a firm receives in a given year across all its instruments aggregated across CRAs, with a value of 19 denoting the highest credit rating "AAA" and a value of 1 denoting "C-." *TYPE I ERROR* is an indicator variable that equals one if an issuer gets an investment grade rating in the year *t* and defaults in the year *t+1*, and zero otherwise. *TYPE II ERROR* is an indicator variable that equals one if an issuer gets a non-investment grade rating in the year *t* and does not default in the year *t+1*, and zero otherwise. All control variables are defined in Appendix B. The *t*-statistics are reported in the parentheses below the coefficient estimates and are based on heteroskedasticity-robust standard errors clustered by firm. ***, **, and * denote estimates that are significantly different from zero at the 1%, 5%, and 10% levels, respectively.

Panel A: Descriptive statistics for rating quality measures

	Mean	SD	P25	Median	P75
RATING LEVEL	10.415	4.220	8.000	10.500	13.000
TYPE I ERROR	0.004	0.059	0.000	0.000	0.000
TYPE II ERROR	0.444	0.497	0.000	0.000	1.000

Panel B: Regression analysis

Dependent variable →	**(1)** ***RATING LEVEL***	**(2)** ***TYPE I ERROR***	**(3)** ***TYPE II ERROR***
TREAT X POST	**-0.265*** **	**-0.002***	**0.042*** **
	[-7.07]	**[-1.86]**	**[6.91]**
Firm FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
CRA FE	Yes	Yes	Yes
Observations	40,591	40,591	40,591
Adjusted R-squared	0.852	0.080	0.715

Table 7: Issuers' choice of rating agencies after the ILFS crisis.

This table reports the changes in the choice of rating agencies by issuers before and after the ILFS crisis. Each observation corresponds to a unique firm-year. *CHANGE* is an indicator variable that equals one if a firm got rated from a tainted CRA (ICRA, CARE, or INDRA) in the year *t* and by a clean CRA (CRISIL, BRICKWORK, ACUITE, or IVR) in the year *t+1* and zero otherwise. *POST* is an indicator variable that equals one for the time period after September 2018, i.e., ILFS crisis and zero otherwise. The sample period is from September 2016 to August 2021, i.e., three years before and after the crisis. We require a firm to have at least two years of data during this six-year period. Firms that get ratings from both tainted and clean ratings agencies are dropped from the sample. Panel A presents the univariate analysis, and Panel B shows the regression analysis. The *t*-statistics are reported in the parentheses below the coefficient estimates and are based on heteroskedasticity-robust standard errors, clustered by firm and year. ***, **, and * denote estimates that are significantly different from zero at the 1%, 5%, and 10% levels, respectively.

Panel A: Univariate analysis

	PRE	***POST***	***TOTAL***
CHANGE = 0	20,572 98.73%	17,674 98.77%	38,246 98.75%
CHANGE = 1	263 1.27%	220 1.23%	483 1.25%
TOTAL	20,835 100.00%	17,894 100.00%	38,729 100.00%

Panel B: Regression analysis

Dependent variable →	**(1)** ***CHANGE***
POST	**0.000** **[0.29]**
Firm FE	Yes
Observations	36,680
Adjusted R-squared	-0.017