The Financial Crisis and Corporate Credit Ratings

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ABSTRACT

Credit ratings on many financial instruments failed to accurately portray default risk before the global financial crisis. I find no decline in the performance of *corporate* credit ratings during or after the crisis, indicating that the failures of ratings on financial instruments were due to conditions unique to the rating agencies' financial instruments divisions. Rather, the preponderance of tests indicate that corporate credit rating performance improves after the crisis, consistent with the rating agencies positively responding to public criticism and regulatory pressures. At the same time, I find evidence of sophisticated market participants decreasing their reliance on corporate credit ratings after the crisis. Consistent with theoretical models of reputation cyclicality, a likely explanation is that the rating agencies suffer spillover reputation damage from their failed ratings on financial instruments. My study informs regulators, practitioners, and academics about the performance of corporate credit ratings during and after the crisis, and provides novel empirical evidence consistent with reputation concerns affecting credit rating usage decisions.

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1. INTRODUCTION

Credit ratings on mortgage-backed securities (MBSs) and collateralized debt obligations (CDOs) significantly underestimated default risk before July 2007. Mass downgrades of these ratings, starting in July 2007, triggered fire sales in debt markets and served as "the most immediate trigger to the [ensuing] financial crisis" (US Senate 2011, 45). Studies indicate that these ratings failures were at least partially due to mistakes by credit rating agency (CRA) personnel.[1] As described by a Moody's executive, "These errors [on MBSs and CDOs] make us look either incompetent at credit analysis, or like we sold our soul to the devil for revenue, or a little bit of both" (US Senate 2011, 245). Since 2007, the Dodd-Frank Act and a host of SEC regulations have been enacted with the aim of preventing recurrences of such widespread rating failures.

There is little doubt that the performance and usage of ratings on MBSs and CDOs sharply declined during the financial crisis, but the fate of nonfinancial corporate credit ratings is less clear.[2] This paper investigates two research questions. First, did the performance of corporate credit ratings decline, improve, or stay the same during and after the financial crisis? Second, was there a coincident change in debt market participants' use of corporate ratings after the crisis?

Section 3.1 discusses reasons to expect a decline, no change, or an improvement in the performance of corporate credit ratings during and after the financial crisis. In summary, performance would likely decline if (i) the misaligned incentives and control weaknesses that led to the failed ratings of MBSs and CDOs also undermined corporate rating quality, (ii) if the crisis

[1] The discussion and analyses herein pertain to S&P, Moody's, and Fitch, which controlled 97% of the regulated US rating industry through 2013 (SEC 2014). See Benmelech and Dlugosz (2010), Griffin and Tang (2011), Ashcraft, Goldsmith-Pinkham, and Vickery (2010), White (2010a), US Senate (2011), and US House (2008) for discussion of the CRAs' failures of ratings on MBSs and CDOs during the crisis.

[2] Like the CRAs, I use the term "corporate" credit ratings to refer to nonfinancial corporations.

triggered a flight of talent or resources from the CRAs' corporate ratings divisions, or (iii) if public criticism and new regulations caused the CRAs to issue overly conservative ratings. It is also plausible that public criticism and regulatory pressure motivated the CRAs to improve corporate rating quality. Finally, it is plausible that, because corporations are rated by separate departments within the CRAs and have different economics and incentives from ratings on MBSs and CDOs, the performance of corporate credit ratings did not change during or after the crisis.

I investigate the performance of corporate credit ratings in the "pre-crisis" period (2004–June 2007) relative to the "during-crisis" period (July 2007–June 2009) and "post-crisis" period (July 2009–2013). I evaluate relative accuracy using cumulative accuracy profiles; absolute accuracy based on types I and II errors; stability based on rating volatility, reversals, and the prevalence of large downgrades; and timeliness based on pre-default rating levels. My primary tests are based on bond-level credit ratings measured on an annual basis.

Tests of relative accuracy find statistically and economically significant increases in cumulative accuracy profiles between the pre-crisis and both the during- and post-crisis periods, consistent with improvements in rating performance. Univariate and regression analyses find mixed evidence of either an improvement or no change in absolute accuracy, stability, and timeliness between the periods. There is virtually no evidence of a decline in rating performance. Tests on a sample of credit rating change and confirmation announcements find similar results. In sum, the data are consistent with the CRAs maintaining or improving rating quality in response to negative publicity and increased regulatory pressures during and after the financial crisis.

I next turn to my second research question about whether market participants alter their use of corporate credit ratings after the crisis. Because there is no change or an improvement in observable rating performance, one might expect no change or an increase in rating usage. However, because true rating quality is revealed only in hindsight, credit rating usage is thought to be heavily determined by perceptions of quality—that is, reputation—which may or may not align with currently observable performance (White 2001). The CRAs acknowledge that their reputations with regards to ratings on MBSs and CDOs were hurt by the crisis. For example, in 2008 congressional testimonies, the chief officers of all three major CRAs attested to the statement that “incredible failures” had “screwed up the ratings [on MBSs and CDOs] so as not to be believable anymore.” Congressman Chris Shays summarized the views of many market participants: “[The CRAs] have no brand, they have no credibility whatsoever. I can’t imagine any investor trusting them” (US House 2008, 188–189 and 102). The CRAs’ failures on MBSs and CDOs plausibly had a spillover effect that caused market participants to question the quality of corporate credit ratings, especially since both kinds of ratings share the same brands and are visually identical. Theoretical models by Mathis, McAndrews, and Rochet (2009), among others, show that market participants can decrease their usage of credit ratings for extended periods after reputation damaging events, even despite coincident improvements in observable rating performance.

My empirical tests focus on the use of corporate ratings in debt contracting. These tests exclude the during-crisis years to allow time for market participants to observe rating performance during the crisis before making informed usage decisions afterward as well as to reduce concerns about confounding events. I first gauge the use of ratings in debt contracting based on value-relevance tests of the strength of the relation between corporate ratings and loan spreads. Specifically, I regress loan interest spreads on the firm’s credit rating, the rating interacted with an indicator for the post-crisis period, controls, and firm and year-quarter fixed effects. If market participants decrease their reliance on corporate ratings, I expect to observe a corresponding decrease in the strength of the relation between those ratings and loan spreads. My second group of contracting tests gauge usage more directly by examining the likelihood of a loan contract containing a rating-based performance pricing provision (PPP).

Both sets of tests find evidence of significant declines in the use of corporate credit ratings after the financial crisis, consistent with the CRAs suffering reputation damage. Two sets of cross-sectional tests further support this inference. First, I find evidence that market participants begin to resume their use of corporate credit ratings in the latter half of the post-crisis period, consistent with gradual reputation recovery after a period of strong performance. Second, despite no evidence of differences in the performance of ratings from Fitch versus S&P and Moody's, I predict that Fitch experiences a lesser decline in reputation because it played a smaller role in market participants' losses from relying on MBS/CDO credit ratings, and because crisis-related criticism focused more on S&P and Moody's. Consistent with this prediction, I find that the use of Fitch ratings declines less than the use of ratings from S&P and Moody's. Finally, robustness tests find no evidence of declines in the use of accounting data in debt contracting after the crisis, indicating that market participants do not decrease their reliance on public information in general. While it is empirically difficult to identify exactly why market participants decrease their reliance on corporate ratings despite no decline in rating performance, these findings are consistent with theory-based predictions that the CRAs experienced crisis-related reputation damage.[3]

[3] A possible alternate explanation is that the crisis altered market participants' risk preferences is such a way as to cause a decline in rating usage and the cross-sectional results I document. Although I'm not aware of theory predicting such a change in preferences, readers should consider alternate explanations when interpreting my findings.

My findings both complement and reinterpret a recent study by Dimitrov, Palia, and Tang (2015). Dimitrov et al. (2015) find that the information content of corporate ratings for debt and equity prices declines following the passage of the Dodd-Frank Act, which roughly coincides with my "post-crisis" period. My study reinforces their findings in this regard by drawing similar inferences based on debt contracting tests, the advantages of which are discussed in Section 4.2. However, my paper and theirs reach starkly different conclusions as to why this decline in rating usage occurs. Dimitrov et al. (2015) find an increase in type II rating errors (i.e., "false warnings") after the crisis and therefore conclude that the Dodd-Frank Act caused the CRAs to become overly conservative, decreasing ratings' usefulness in market pricing.[4] I reexamine rating performance using a much more comprehensive battery of tests, focusing not only on absolute accuracy but also on multiple measures of relative accuracy, stability, and timeliness. Collectively, my tests find no decline or an improvement in rating performance during and after the crisis. I therefore reinterpret the results of Dimitrov et al. (2015) by attributing market participants' decreased use of corporate ratings not to Dodd-Frank undermining rating quality, but rather to the CRAs suffering crisis-related reputation damage.

My findings should inform academics and regulators considering the role of regulation in the credit rating industry as well as market participants deciding how much to rely on corporate ratings in debt contracting and pricing. Federal lawmakers and regulators continue to dissect what went wrong in the financial crisis and evaluate further reforms to improve rating quality. Proposals include measures to both strengthen and repeal parts of the Dodd-Frank Act (US House 2011; Columbus Dispatch 2011). My findings should aid regulators in this process by

[4] Dimitrov et al. (2015) also find a decline in credit rating levels after the crisis, which is generally consistent with my results in Section 3.3.5. However, by itself, it is not clear whether a decline in rating levels indicates an improvement or decline in rating quality. The Internet Appendix provides a detailed analysis of the conflicting results of type II errors between my paper and Dimitrov et al. (2015).

reducing concerns that the failures of ratings on MBSs and CDOs were caused by endemic problems in the rating industry that went beyond ratings on financial instruments, as well as concerns that Dodd-Frank undermined corporate rating quality. Regarding academics, an ongoing debate regards the extent to which market forces are sufficient to incentivize high-quality credit ratings, and whether rating regulation increases or decreases market efficiency.[5] Again, my findings should inform this debate by offering evidence that market forces likely did not undermine corporate rating quality during the crisis, and by reducing concerns that new regulations hurt corporate rating quality after the crisis. Finally, my findings should better inform market participants' decisions about whether to rely on credit ratings versus costlier independent analysis in contracting and pricing decisions.

Beyond the financial crisis, my study contributes to a large literature studying the role of reputation in the rating industry. Numerous papers argue that a strong reputation is a necessary condition for market participants to use credit ratings; indeed, reputation is often cited as the critical factor that maintains integrity in the CRAs' oligopolistic, issuer-pays business model (White 2010a). A contrarian argument is that CRAs are uninformative aggregators of public information, in which case usage of their ratings has less to do with reputation and more to do with contracting and regulatory convenience (Partnoy 1999, 2006). To date, there is limited empirical evidence of a relation between rating reputation and usage, likely because reputation is difficult to isolate from actual rating quality. Documenting divergent trends in rating usage and performance following a plausible reputation shock lends empirical support to analytical models showing the important role that rating reputation plays in rating usage decisions.[6]

[5] For examples, see White (2006, 2010b), Partnoy (1999, 2006), Schwarcz (2002), Cheng and Neamtiu (2009), Hunt (2009), Darbellay and Partnoy (2012), Opp, Opp, and Harris (2013), and Dimitrov et al. (2015).
[6] Jaballah (2012) and Bedendo, Cathcart, El-Jahel, and Evans (2013) find declines in the information content of corporate credit ratings for debt and equity prices during the crisis, which they attribute to damaged reputation. Han,

2. INSTITUTIONAL DETAILS

2.1 Credit Rating Quality and Reputation

The quality of a credit rating is a function of its accuracy, timeliness, and stability in measuring default risk (Cheng and Neamtiu 2009). The CRAs' highest priority is that ratings should provide an accurate relative ordering of firms' default risks at a given date (Cantor and Mann 2003; Mann and Metz 2011; Altman and Rijken 2004). However, absolute accuracy is important for contracting and regulations; that is, securities with high (low) ratings should default less (more) frequently. Timely ratings respond quickly to changes in default risk and anticipate defaults. Stable ratings reflect long-term economic conditions and have low volatility, which is desirable in contracting and regulation.

Because the major CRAs use private information from managers in forming rating opinions, it is difficult to evaluate rating quality in real time. Even ex post evaluations of rating quality are delayed because actual defaults are idiosyncratic and can take many years to occur (Ashcraft and Schuermann 2008; White 2001; Becker and Milbourn 2011). Thus, as with any product where quality is initially unobservable, users' demand for credit ratings depends on the CRAs' reputations (Nelson 1970).[7] Also, because ratings are often used for long-term purposes such as in loan covenants, user demand is based on expectations about quality extending several years into the future.

Reputations are especially fragile in the credit rating industry because the CRAs face several incentives to underinvest in, or even intentionally reduce, rating quality. First, the major CRAs' issuer-pays business model incentivizes optimistically biased ratings to cater to fee-paying

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Pagano, and Shin (2012) find that the yields on Japanese bonds rated by major US CRAs increase during the crisis, which is again attributed to US CRAs' damaged reputations. However, none of these papers examine changes in rating usage in relation to changes in performance, which is an essential comparison for isolating changes in reputation from actual quality.

[7] Credit ratings are paid for by debt-issuing firms. Ratings are used or consumed by market participants, for purposes including contracting and evaluating default risk.

customers. Second, before the Dodd-Frank Act of 2010, the CRAs were largely immune from civil litigation over rating failures (White 2010a). Third, fee-paying debt-issuers' demand for credit ratings is highly inelastic because the CRAs are a regulated oligopoly, their ratings are used extensively in regulations and investment policies, and there are few substitute summary measures of default risk (White 2013; Rhee 2015). Thus the CRAs' revenues are unlikely to suffer in the short run even if rating quality declines.

The CRAs have long argued that concerns about protecting their reputations are sufficient to offset their incentives for providing low-quality ratings (White 2010a). Still, it is well known that a rational seller will only provide a high-quality product as long as the value of maintaining its reputation exceeds the short-term gains from delivering a low-quality product (Klein and Leffler 1981; Shapiro 1983; Bolton, Freixas, and Shapiro 2012). In financial markets, Benabou and Laroque (1992) show that intermediaries can repeatedly build up and cash in on reputation. In the rating industry in particular, Mathis et al. (2009) show that misaligned incentives, combined with information asymmetry about rating quality, lead to "confidence cycles" in which CRAs slowly develop reputations, subsequently earn profits while reducing quality, and eventually experience sudden reputation loss when defaults occur. Importantly, Mathis et al. (2009) discuss how information asymmetry about rating quality can cause reputation damage to persist, despite observably strong rating performance. Models by Bar-Isaac and Shapiro (2013), Bolton et al. (2012), and Opp et al. (2013) also show that ratings are cyclical and co-vary with the business cycle, such that the CRAs improve rating quality and build reputation during recessions, only to lower quality during booms. Consistent with rating quality being initially unobservable, the CRAs earned record revenues in the mid-2000s while delivering inflated ratings on MBSs and CDOs.

2.2 Credit Ratings and the Financial Crisis

<<< INSERT FIGURE 1 ABOUT HERE >>>

Figure 1 depicts key events in the credit rating industry in the years surrounding the financial crisis. Following criticism of the CRAs for being slow to identify credit concerns with Enron and Worldcom, the Sarbanes-Oxley Act of 2002 mandated that the SEC investigate the role of CRAs in capital markets. SEC and congressional investigations culminated in the passage of the Credit Rating Agency Duopoly Relief Act in September 2006, the primary objective of which was to improve rating quality through increased competition and SEC oversight. Cheng and Neamtiu (2009) and Alp (2013) find significant improvements in the observable performance of corporate credit ratings starting in 2002, indicating that criticism and regulatory concerns motivated the CRAs to improve rating quality long before the 2006 Act.

In the mid-2000s, the major CRAs earned record revenues in rating MBSs and CDOs, many of which were engineered to receive AAA ratings. Increases in mortgage delinquencies began in late 2006, and later investigations revealed that senior CRA managers were aware of the need to downgrade their MBS and CDO ratings no later than early 2007. But it wasn't until July 2007 that they began mass downgrades of MBS and CDO ratings, many of which were less than a year old. The downgrades caused selloffs and led to a collapse in the MBS and CDO markets. As an example of the scope of the downgrades, over two years 90% of the CDOs issued with AAA ratings between 2005 and 2007 had been downgraded, with 80% reaching speculative-grade status (US Senate 2011). The historic prevalence of downgrades from AAA to junk status was far below 1% (Standard & Poor's 2012). The CRAs have acknowledged that these downgrades and the ensuing crisis badly damaged their reputations with regards to ratings on MBSs and CDOs (US House 2008).

The mass downgrades in July 2007 evoked harsh criticism and prompted an SEC investigation. An SEC report from July 2008 documents numerous weaknesses in the CRAs' processes but stops short of alleging intentional misconduct. The report also proposes a host of policies aimed to "increase transparency in the ratings process and to curb practices that contributed to recent turmoil in the credit market" (SEC 2008, 4). Many of the proposed policies pertain to ratings on both financial products and corporations, and the report praises the CRAs for already taking actions to address the identified problems. The SEC's proposed rules were formally adopted in 2008 and 2009.

The US Congress commenced its own investigations in October 2008, with the aim of assessing the CRAs' culpability in the financial crisis and developing reforms beyond the powers of the SEC. The congressional investigation concluded with a scathing assessment of the CRAs in April 2011. In the meantime, in June 2009, the Department of the Treasury proposed a series of bills designed to reform and restore faith in the US financial system, including greater oversight of the CRAs and reduced reliance on credit ratings in federal regulations (US Dept. of Treasury 2009). Ninety percent of the Treasury's proposals ended up in the Dodd-Frank Wall Street Reform and Consumer Protection Act, passed in July 2010 (Office of the Press Secretary 2010). The SEC did not adopt many of the reforms mandated by Dodd-Frank until several years later.[8]

In February 2015, S&P agreed to pay $1.4 billion to settle cases brought by the US Department of Justice and numerous state regulators regarding its failures of ratings on MBSs and CDOs. Justice's investigation into Moody's continues (McLaughlin, Schoenberg, and Harris 2016). Recent annual reports from Moody's and McGraw Hill (S&P's parent) note that the

[8] See https://www.sec.gov/spotlight/dodd-frank/creditratingagencies.shtml for information on the Dodd-Frank Act requirements that have been adopted to date (accessed March 2016). In June 2013, several SEC commissioners publicly expressed their frustration with the slow implementation of Dodd-Frank requirements (Lynch 2013).

companies continue to defend against investigations and lawsuits stemming from the financial crisis. Among the most significant civil cases settled thus far were those brought by CalPERS against S&P and Moody's, resulting in settlements of $125 million and $130 million, respectively, in 2015 and 2016.

3. CORPORATE RATING PERFORMANCE BEFORE/DURING/AFTER THE CRISIS

This section first discusses reasons for expecting a decline, increase, or no change in corporate credit rating performance before moving on to empirical tests. My analysis compares the pre-crisis period to (i) during the crisis, (ii) after the crisis, and (iii) the combined during and after periods. I identify the beginning of the financial crisis as July 2007, the month in which the CRAs began large-scale downgrades of ratings on MBSs and CDOs. As there is no official crisis end date, I select June 2009 because it coincides with the introduction of legislation that would later become the Dodd-Frank Act and because it marks the end of the US recession (NBER 2014). The during-crisis period is defined as July 2007 through June 2009.[9]

3.1 Reasons for Expecting a Decline, Improvement, or No Change in Rating Performance

There are several reasons to expect that the performance of corporate credit ratings declines during or after the financial crisis. One possibility is that, as predicted by models of rating cyclicality discussed in Section 2, the CRAs underinvested in rating quality in the boom years leading up to the crisis, or that misaligned incentives caused the CRAs to intentionally lower their rating standards. Unobservable declines in rating quality could have begun before the crisis and, once the economy faltered, these low-quality ratings would have begun to underperform. A second possibility is that the high-profile failures of ratings on MBSs and CDOs during the crisis

[9] Robustness tests in the Internet Appendix examine rating performance using a financial crisis end date as of the passage of the Dodd-Frank Act on July 21, 2010. All tests continue to find unchanged or improved rating performance during and after the crisis.

caused the CRAs to reallocate resources from their corporate rating divisions to the structured finance divisions, causing a decline in corporate rating quality. A related possibility is that negative publicity deterred people from working for the CRAs, causing a decline in quality due to a lack of talented analysts. As the CRAs' negative publicity persisted well after the crisis ended, a lack of talent could hurt rating quality long after the crisis ended. Fourth, since the CRAs potentially face asymmetric penalties for optimistic versus pessimistic ratings, they plausibly became overly conservative after the crisis and issued pessimistically biased or overly volatile ratings (Goel and Thakor 2015; Dimitrov et al. 2015).

An alternative outcome is that intense public criticism, regulatory scrutiny, and legal challenges threatened the CRAs' livelihoods and motivated them to improve corporate rating quality during and after the financial crisis. They could improve rating quality by investing more in human capital, increasing the rigor and frequency of rating reviews, or more carefully selecting clients. External pressures likely motivated the CRAs to implement improvements immediately upon the onset of the crisis, long before the passage of regulations requiring them to do so. For example, a 2008 SEC report praises the CRAs for already implementing proposed reforms, even though the SEC didn't officially adopt the regulations until late 2008 and 2009. Observing an increase in rating quality would also be consistent with the aforementioned theoretical models showing that the CRAs improve rating quality following rating failures and during recessions.

Finally, there are several reasons to expect that the issues giving rise to the failures of ratings on MBSs and CDOs had no impact on the quality of corporate credit ratings, in which case there could be no change in corporate rating performance. First, the CRAs had over 100 years of experience rating corporations but just 10 years of experience rating MBSs and CDOs before the crisis, so the processes and models for rating corporations were likely superior. Second, ratings on MBSs and CDOs are more opaque than corporate ratings, so the CRAs may have let the quality of MBS and CDO ratings deteriorate more than that of corporate ratings. For example, information about corporations is available from firm disclosures and analyst reports, while prospectuses for MBSs and CDOs often lack detail about underlying assets and few other sources of information are available. Third, MBSs and CDOs are often rated by only one CRA, which allows for rating shopping and pressures raters to provide optimistic assessments (Benmelech and Dlugosz 2010). Corporate rating shopping is less problematic because most corporations are rated by multiple CRAs (Bongaerts, Cremers, and Goetzmann 2012).

3.2 Data and Sample Selection

My performance tests evaluate ratings for nonfinancial corporations for 2004 through 2013. The sample starts in 2004 to postdate changes in rating performance following Sarbanes-Oxley. I construct a "defaults sample" that includes defaults occurring from 2005 through 2013, matched to outstanding credit ratings as of one year beforehand. The "defaults" sample starts in 2005 so that the matched rating is outstanding during 2004. For tests involving both default and nondefault bonds, my primary "all ratings" sample follows Cheng and Neamtiu (2009) and Bonsall (2014) in including all outstanding ratings, regardless of whether the rating changes during a period. Specifically, the "all ratings" sample consists of ratings measured on yearly rolling windows ending on June 30. The performance of nondefault bonds is evaluated based on the bond's credit rating as of July 1 of the preceding year. Given the sample start of 2004, the first annual set of nondefault bonds is evaluated as of June 30, 2005, matched to credit ratings as of July 1, 2004. For bonds that default during the yearly window, the bond is matched to its credit rating as of one year before the default date.

An alternative approach to constructing a sample of default and nondefault bonds is to examine just credit rating announcements (i.e., upgrades, downgrades, new ratings, and explicit reaffirmations). However, because a rating that does not change during a period is implicitly reaffirmed, examining a sample of just rating announcements potentially provides an incomplete view of rating performance. For example, if accuracy is measured based solely on rating announcements, a CRA could improve its accuracy statistics by simply not updating ratings it is unsure about. Still, for robustness purposes, I perform tests using a "rating announcements" sample restricted to upgrades, downgrades, new ratings, and explicit reaffirmations issued during 2004 through 2012. The "ratings announcements" sample ends in 2012 to provide sufficient data for measuring rating performance over the subsequent year.

Data on bond terms, defaults, and credit ratings for S&P, Moody's, and Fitch are obtained from Mergent FISD. Each bond-CRA combination is treated as a unique observation. The CRAs' letter ratings are converted to a numeric system shown in Panel B of Appendix A, whereby 20 indicates the safest rating. Default ratings are dropped because they are assigned ex post. I merge FISD with Compustat using the linking table from Kerr and Ozel (2015) and Even-Tov (2015).[10] I require that each bond has FISD and Compustat data needed for control variables. I exclude financial firms with SIC codes 6000–6999. Panel A of Table 1 summarizes each sample before, during, and after the crisis.

<<< INSERT TABLE 1 ABOUT HERE >>>

3.3 Empirical Analysis

My tests follow Cheng and Neamtiu (2009) and Bonsall (2014) and are in the spirit of the criteria of Cantor and Mann (2003) and Mann and Metz (2011). First, I use cumulative accuracy

[10] Kerr and Ozel (2015) and Even-Tov (2015) match FISD to Compustat based on CUSIP, company name, industry membership, and other identifying information, taking into account name changes, mergers, and spinoffs.

profiles to evaluate relative accuracy. Second, I evaluate absolute accuracy based on types I and II error rates. Third, I test various measures of stability. Fourth, I test the timeliness of downgrades in relation to defaults. All regression tests use the following model:

$$\begin{aligned} \textit{Performance} \quad &= \beta_1(\textit{DURING or POST or DURING\&POST}) + \Sigma\beta_k \textit{CONTROLS} \\ &+ \Sigma\beta_k \textit{INDUSTRY} + \varepsilon. \end{aligned} \tag{1}$$

Performance is one of the measures of rating performance discussed below. Model (1) is estimated as a logit (OLS) for indicator (continuous) *Performance* measures. In comparing pre-crisis rating performance with performance during (after) the crisis, model (1) includes a *DURING* (*POST*) indicator variable and excludes post-crisis (during-crisis) observations. Models comparing pre-crisis performance to the combined during- and after-crisis period retain all observations and include a *DURING&POST* indicator.

CONTROLS are defined in Appendix A and summarized in Panel B of Table 1. Similar to Cheng and Neamtiu (2009), all models include indicators for which CRA issues the rating; firm characteristics including size, book-to-market, and leverage; an indicator for negative retained earnings; and the recent 30-year bond return. Also like Cheng and Neamtiu (2009), *CONTROLS* include a variety of bond characteristics that likely affect *Performance* and may systematically vary across time. Tests of rating stability further control for the credit rating level. Unlike Cheng and Neamtiu (2009), I do not include additional macroeconomic controls for the S&P index level, S&P index return, or recent default rate because these variables correlate with *DURING* at up to 91%. I do not include returns-related controls because doing so eliminates defaulting firms that cease trading before default. However, controlling for stock volatility and macroeconomic conditions produces results that are qualitatively unchanged in most cases.[11] Untabulated Fama-

[11] I use the term "qualitatively unchanged" to mean that the results under discussion are of the same sign as the reference tests and are significant at 10% or better. If the reference results are insignificant, "qualitatively unchanged" means that the additional results are also insignificant.

French 12 *INDUSTRY* fixed effects control for fixed industry characteristics and control for potential biases caused by changes in the sample industry composition over time. Except in the cumulative accuracy profile analyses, test statistics are based on standard errors clustered by both firm and year-quarter-industry to adjust for likely serial and cross-sectional correlation.[12]

3.3.1 Tests of Relative Accuracy

<<< INSERT TABLE 2 ABOUT HERE >>>

Cumulative accuracy profiles plot the cumulative percentage of sample bonds on the horizontal axis against cumulative percentage of defaults on the vertical axis. The area under the curve (AUC) is a measure of how well the relative ordering of ratings corresponds with the actual defaults. Table 2 presents AUCs for three comparison sets: (i) pre-crisis versus during-crisis, (ii) pre-crisis versus post-crisis, and (iii) pre-crisis versus combined during/post-crisis. The first (second) column is based on the “all ratings” (“announcements”) sample. In all cases, the AUCs are significantly larger during and after the crisis than before, which is consistent with an improvement in relative accuracy.

3.3.2 Tests of Absolute Accuracy

<<< INSERT TABLE 3 ABOUT HERE >>>

A type I error is a missed default, which I define as a defaulting bond that has an investment-grade credit rating one year before its default date. A type II error is a false warning, which I define as a bond that has a speculative-grade rating but does not default within the year. The type I error rate is the count of type I errors divided by the count of all defaults. The type II error rate is the count of type II errors divided by the count of all nondefaults. Tests of type I (type II) errors use the “default” sample (“all ratings” and “announcements” samples). Table 3 Panel A

[12] Clustering by only firm often produces substantially larger test statistics. I cluster by year-quarter-industry instead of year-quarter or year-month because the latter specification have fewer than 20 clusters in certain tests.

finds that the type I error rate decreases significantly from 0.271 before the crisis to 0.000 during and afterward. The type II error rate in the “all ratings” sample decreases significantly from the pre-crisis period to the post- and during/post-crisis periods. The type II error rate in the announcements” sample decreases significantly in all three comparison periods.

Table 3 Panel B tabulates logistic regressions of indicators for type II errors among non-defaulting bonds. Logit regressions of type I errors are not estimable because there are zero type I errors during or after the crisis. The type II error regressions present a more mixed view than the univariate tests. The “all ratings” sample finds a significant decline in type II errors after the crisis, and the “announcements” sample finds significant declines in both the post-crisis and during/post-crisis periods. However, the “all ratings” sample finds a significant increase in type II errors during the crisis, while the “announcements” sample finds an insignificant decrease.

Overall, the results in Panels A and B find evidence of a significant decline in type I errors in all three comparison periods and a decline in type II errors after the crisis, consistent with improved absolute accuracy. Results for the during-crisis period are more mixed.

3.3.3 Tests of Rating Stability

I evaluate three measures of rating stability. In the “all ratings” sample, rating volatility is calculated as the standard deviation of ratings outstanding during the year preceding the default date or year-end date. Volatility in the “announcements” sample is measured over the year following the rating announcement. Calculating volatility requires at least two ratings during the year. The second measure is an indicator for rating reversals. In the “all ratings” sample, a reversal is when the rating is both upgraded and downgraded within the year. In the “announcements” sample, a reversal is a downgrade followed by an upgrade within one year or vice versa. Movements to and from a default rating are dropped in calculating volatility and reversals. The third measure is an indicator for large downgrades. In the “all ratings” sample, a large downgrade is when a rating decreases by more than three levels from the beginning to end of the year. Sample size is reduced in analyzing large downgrades due to missing data on year-end credit ratings. In the “announcements” sample, a large downgrade is a downgrade announcement of more than three levels. Decreases (increases) in volatility, reversals, or large downgrades are consistent with an improvement (decline) in credit rating stability.

<<< INSERT TABLE 4 ABOUT HERE >>>

The univariate results in Panel A of Table 4 find that, in both the “all ratings” and “announcements” samples, there are significant declines in volatility and large downgrades between the pre- and post-crisis periods but no changes during the crisis. The “all ratings” sample finds a significant decline in reversals during the crisis, while the “announcement” sample finds significant declines in all three periods. None of the univariate tests find evidence of significant increases in volatility, reversals, or large downgrades.

Regression results in Panel B find significant declines in volatility after the crisis. Results in Panel C find a significant decline in reversals only during the crisis in the “all ratings” sample. Panel D finds evidence of significant declines in large downgrades in the post-crisis and during/post-crisis periods. None of the regression tests find evidence of increases in volatility, reversals, or large downgrades. Collectively, the results in Panels A through D are consistent with no change or an improvement in rating stability during and after the crisis.

3.3.4 Tests of Timeliness in Relation to Defaults

<<< INSERT TABLE 5 ABOUT HERE >>>

I use two sets of tests to evaluate rating timeliness. The first is based on the logged number of days between the date of the last speculative-grade rating and the eventual default (variable

DAHEAD), whereby longer lead-times are consistent with more timely rating actions. Univariate tests in Panel A of Table 5 and regression tests in columns (i) through (iii) of Table 5 Panel C find significant increases in *DAHEAD* in all three comparison periods, consistent with an improvement in rating timeliness.

My second set of tests is based on the average rating levels leading up to a default, whereby lower ratings further in advance of default are consistent with more timely downgrades. Panel B of Table 5 finds average rating levels among defaulting firms at various intervals in advance of default: one year, 270 days, 180 days, 90 days, 30 days, and just prior. Rating levels are significantly lower during and after the crisis over all intervals, consistent with rating downgrades among defaulting bonds being timelier. For brevity, regression tests are based on the weighted average rating over the year leading up to default (variable *WRATE*). Columns (iv) through (vi) of Panel C of Table 5 find that *WRATE* are significantly lower in the during-crisis and combined during/post-crisis periods. In sum, the tests in Table 5 are generally consistent with an improvement in rating timeliness during and after the crisis.

3.3.5 Tests of Average Rating Levels

My performance tests do not focus on rating levels for two reasons. First, because credit ratings are designed to be relative measures of default risk, rating levels are not intended to have a fixed relation with default risk over time. This is especially true when changes in risk stem from market-wide conditions (Amato and Furfine 2004; Ashcraft et al. 2010; S&P 2011a, 2011b). Second, and as discussed by Bonsall (2014), it is not clear in isolation whether an increase or decrease in rating levels indicates an improvement or decline in rating quality. For example, observing a decline in rating levels would be consistent with improved quality if accompanied by better performance but a decline in rating quality if accompanied by worse performance. Still, I analyze credit rating levels for descriptive purposes.

<<< INSERT TABLE 6 ABOUT HERE >>>

Untabulated univariate tests indicate that the average credit rating level is unchanged or increases between the pre- and post-crisis periods. However, bond ratings are significantly affected by bond and firm characteristics. Following Becker and Milbourn (2011), Table 6 models firms' credit rating levels using OLS regressions with firm fixed effects. In addition to the standard *CONTROLS*, I include accounting regressors known to affect rating levels: return on assets, capital intensity, interest coverage, an indicator for loss firms, cash flow to debt ratio, current ratio, and current accruals. Sample size is reduced due to the additional data requirements, but untabulated results excluding accounting variables produce qualitatively unchanged results, as do untabulated ordered logit models that replace firm fixed effects with industry fixed effects. Four of six regressions in Table 6 find significant declines in rating levels, while the remaining two find no change.

3.4 Discussion

Table 1 Panel C summarizes the tests of rating performance. The CRAs' primary objective is that credit ratings should provide a relative ordering of default risks at a given point in time. In this regard, my tests are uniformly consistent with improvements in relative accuracy during and after the crisis. Tests based on the "defaults sample" are also quite uniform in finding evidence of improved absolute accuracy and timeliness during and after the crisis. The remaining results are more mixed. The tests are generally consistent with improved absolute accuracy and stability after the crisis. Some tests find evidence of improved absolute accuracy and stability during the crisis, while others find no change, and one test finds a decline in absolute accuracy. On balance, most tests indicate that rating performance improves, and there is virtually no evidence of a decline in performance.

4. RATING USAGE BEFORE AND AFTER THE CRISIS

My analyses of credit rating usage examine changes from the pre-crisis to post-crisis periods. I exclude the during-crisis years for two reasons. First, doing so allows market participants time to observe the performance of corporate ratings during the crisis before making informed decisions afterward. Second, uncertainty and market disruptions during the crisis potentially confound tests of rating usage.

4.1 Reasons to Expect Inconsistent Trends in Rating Performance and Usage

Given that the tests in Section 3 find no change or an improvement in observable rating performance, one might expect to see no change or an increase in market participants' rating usage. However, extreme information asymmetry in the rating industry can lead to long-lasting disconnects between observable performance and perceptions of quality (i.e., rating reputation). For the reasons discussed in Sections 2 and 3.1, it is likely that the financial crisis caused market participants to doubt the CRAs' abilities or integrity with respect to corporate ratings. If so, this reputation damage likely drove down rating usage despite no observable decline in performance.

Reduced reliance on corporate credit ratings due to reputation concerns could be a rational response to increased uncertainty or to receiving new information about the CRAs' abilities and incentives. It is also possible that market participants decreased their dependence on ratings due to overreactions to reputation concerns. Dichev and Piotroski (2001) document systematic underreactions to rating downgrades, indicating that the information is not always efficiently impounded in prices. They speculate that this inefficiency could be caused by optimistic biases, but other possible behavioral explanations are that market participants anchor on initial credit rating assignments, misjudge the low unconditional probability of default, or are inattentive to rating announcements (Barberis and Thaler 2003; Lim and Teoh 2010). These inefficiencies are likely compounded by reputation concerns, similar to the finding of Ng, Tuna, and Verdi (2013) that underreactions to management forecasts are amplified when the forecasts are viewed as being less credible. The possibility of unwarranted reputation "spillover" from the failures of ratings on MBSs and CDOs to perceptions of corporate rating quality is especially plausible because both types of ratings share the same corporate branding and are visually identical (i.e., share the same letter system), meaning that consumers' experiences with one product are likely to transfer to the company's other products (Sullivan 1990; Aaker and Keller 1990; Park, Milberg, and Lawson 1991).

4.2 Empirical Predictions

My analyses of rating usage focus on debt contracting rather than debt pricing (e.g., in pricing bonds or credit default swaps). The former has several advantages over the latter. First, because the use of credit ratings in debt buying and selling decisions is often mandated by firms' internal policies and government regulations, credit ratings and debt prices can be highly correlated even if users perceive ratings as lacking information value. Thus gauging perceptions of rating quality based on pricing value-relevance tests can be misleading. Second, pricing value-relevance tests are sensitive to changes in the liquidity and efficiency of debt markets, while the use of credit ratings in debt contracting operates over longer horizons and is less sensitive to market volatility. Third, lenders can obtain private information from managers in contracting, meaning that they can better substitute away from using credit ratings if the crisis raises concerns about rating quality. Still, tests in the Internet Appendix draw similar conclusions based on tests of rating usage in credit default swap pricing.

Similar to Beaver, Shakespeare, and Soliman (2006) and Becker and Milbourn (2011), my first tests infer usage based on the value-relevance of ratings for loan contract spreads. If market participants decreased their reliance on corporate ratings after the crisis, I expect to observe a corresponding decrease in the strength of the relation between ratings and loan spreads.

My second tests more directly examine the use of credit ratings in debt contracts. Credit ratings are often used in performance pricing provisions (PPPs), which are clauses that tie a loan's interest rate to the firm's financial condition. PPPs can also be based on a financial statement ratio or other metric. The choice between using a rating- versus nonrating-based PPP depends in part on the perceived qualities of the underlying data (Costello and Wittenberg-Moerman 2011). If market participants decrease their use of credit ratings, I expect a corresponding decrease in the prevalence of rating-based PPPs after the crisis.[13]

4.3 Debt Contracting Value-Relevance Tests

Data on loan contracts are sourced from DealScan for 2004 through 2012. Table 7 details the sample refinement. Each loan must be in US dollars, syndicated in the United States, matched with a Compustat GVKEY, and for a nonfinancial firm.[14] I drop loans initiated during the crisis. I further require nonmissing DealScan data for the loan amount, maturity, and interest spread. Because loan-specific ratings are often unavailable for private loans, I match each loan to the most recently issued firm-level credit rating from S&P, Moody's, or Fitch. Credit ratings are obtained from Capital IQ and Mergent FISD. For Mergent FISD data, I use senior, unsecured bond ratings to approximate the firm-level credit rating (Jorion et al. 2005; Beaver et al. 2006).[15]

[13] My choice to examine the use of credit ratings in PPPs is primarily driven by data availability. Credit ratings are used in other ways in debt contracting, both directly within a debt contract as well as indirectly through lenders' policies and procedures. If data were available, examining such uses would be another interesting way to examine the effects of the financial crisis on rating usage.

[14] GVKEY mappings are kindly provided by Michael Roberts, building on data used in Chava and Roberts (2008).

[15] Using Mergent FISD is necessary to obtain Fitch and Moody's ratings, which are not available in Capital IQ. Firm-level ratings must be approximated because FISD contains only bond-level ratings. Like Beaver et al. (2006) and Jorion et al. (2005), I limit the FISD bonds to only senior, unsecured US issues, excluding Yankee, preferred,

I also drop observations with insufficient Compustat data.

<<< INSERT TABLE 7 ABOUT HERE >>>

Individual loans are often part of a package of loans made to a single firm, and the loans within a package often have similar terms. I reduce concerns about repeated similar observations by retaining only loans within a package that have unique interest spreads. In cases where several loans have the same spread, I keep the loan with the longest maturity and largest face value. Finally, to reduce concerns about pre/post-crisis changes in the sample composition, I require that each firm be present in both periods. The final sample consists of 4,022 loans. Sample averages are provided in Panel B of Table 7. My tests are based on the following OLS model:

$$Ln(SPREAD) = \beta_1 RATING + \beta_2 RATING*POST + \Sigma\beta_k CONTROLS + \Sigma\beta_k FIRM + \Sigma\beta_k QUARTER + \varepsilon. \quad (2)$$

Ln(SPREAD) is the logged interest spread at the debt issuance.[16] *CONTROLS* for loan characteristics include the amount, maturity, number of lenders, and indicator variables for whether it is a revolving loan or an institutional loan, and whether the lead arranger has recent experience with the borrower. Firm *CONTROLS* include log of total assets, return on assets, leverage, and a binary variable equal to one if the firm has CDS trading anytime up to three months after the loan agreement date. *FIRM* and *QUARTER* fixed effects absorb all constant firm characteristics and common market trends as well as the *POST* main effect. I expect β_1 to be negative, consistent with higher-rated firms having lower spreads. $\beta_2 > 0$ would be consistent with a decline in rating relevance in the post-crisis period.

<<< INSERT TABLE 8 ABOUT HERE >>>

Columns (i) and (ii) of Table 8 estimate (2) without and with controls. β_2 is significantly

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exchangeable, enhanced, and private placement bonds. For firms with multiple bonds, I create a single rating history for each CRA by retaining only the bond with the most recent rating at any given point in time.

[16] Consistent with Valta (2012), Graham, Li, and Qiu (2008), and Chava, Livdan, and Purnanandam (2009), *SPREAD* is logged to mitigate right skewness and approximate a more normal distribution.

positive in both columns, consistent with ratings becoming less value-relevant after the crisis. Results are qualitatively unchanged in column (iii) including *POST*CONTROLS* interactions, which allow for different slopes for each control variable in the post-crisis period. These results are consistent with decreased usage of credit ratings in contracting after the crisis.

4.4 Debt Contracting PPP Tests

Since loans without a PPP differ substantially from loans with one (Asquith, Beatty, and Weber 2005), my PPP test sample retains only loans with at least one PPP. Retaining only loans with a PPP also avoids assuming that loans missing from DealScan's "Performance Pricing" file do not have a PPP.[17] The resulting sample includes 1,364 loans (Panel A, Table 7). Sample averages are in Panel B of Table 7. My test of PPP usage is based on the following regression:

$$PP\_RATING = \beta_1 POST + \Sigma\beta_k CONTROLS + \Sigma\beta_k FIRM + \varepsilon. \qquad (3)$$

PP_RATING is a binary variable equal to one if the loan has a rating-based PPP. All other variables are as previously defined. I estimate (3) using OLS to accommodate a large number of fixed effects, but using a logit model replacing firm with industry fixed effects produces qualitatively unchanged results (untabulated). $\beta_1 < 0$ would be consistent with lenders decreasing their use of rating-based PPPs after the crisis.

<<< INSERT TABLE 9 ABOUT HERE >>>

Columns (i) and (ii) of Table 9 tabulate results without and with controls. The *POST* coefficients are significantly negative. Column (iii) finds qualitatively unchanged results when untabulated interactions between *CONTROLS*POST* are included. In sum, these data are consistent with a decline in rating usage in debt contracting after the crisis.

4.5 Robustness Test: Is There a Decline in the Use of Other Public Information?

[17] My DealScan PPP data does not identify whether the PPP is based on a specific CRA's ratings. Lenders may decrease their use of PPPs based on a rating from a major CRA and instead use PPPs based on a rating from a minor CRA. If this occurs, it biases against finding a decline in the use of rating-based PPPs.

The decline in rating usage could be due to market participants relying less on public information in general, as opposed to shunning credit ratings in particular. I address this concern by comparing the change in the usage of credit ratings after the crisis to the change in the usage of another source of public information: accounting data. Results detailed in the Internet Appendix find that the value-relevance of accounting-based Altman z-scores for loan contract spreads does not change or even increases after the crisis. These results provide no indication that the observed declines in rating usage stem from market participants eschewing public information in general.

4.6 Cross-sectional Test: Does Rating Usage Begin to Recover?

Models of rating cyclicality predict that reputation eventually recovers after a period of strong performance. Although reputation recovery repair can take years, evidence of it may arise by the end of my sample in December 2012. Or, since investigations and regulatory reforms were continuing through 2012, the CRAs' sullied reputations plausibly persist through the end of my sample. However, observing a growing decline in usage after the crisis could indicate that my results are driven by reasons unrelated to the crisis.

<<< INSERT TABLE 10 ABOUT HERE >>>

Results in Table 10 modify each usage test to include the indicator *POST2*, which takes the value of one for the period starting July 2011. The *POST2* main effect or interaction estimates the incremental difference in post-crisis usage in the latter part of the post-crisis period relative to the earlier part. If rating usage begins to recover, the *POST2* coefficients or interactions should have the opposite sign of the *POST* coefficients. Controls are untabulated for brevity. The value-relevance tests in Panel A find a significant recovery in the *POST2* period. For the PPP usage tests in Panel B, *POST2* is of the correct sign but insignificant at conventional levels (p = 0.189

two-tailed). In sum, these results are generally consistent with the CRAs gradually regaining their reputations over time.

4.7 Cross-sectional Test: Fitch vs. S&P and Moody's

This section investigates the prediction that Fitch suffered less of a decline in reputation than S&P and Moody's as a result of the crisis and, accordingly, that the use of Fitch's corporate ratings declined less. Pre-crisis ratings on financial instruments issued by the three CRAs were correlated at up to 98% (Benmelech and Dlugosz 2010), and there is little evidence of material differences in how the three CRAs' ratings on MBSs and CDOs performed during the crisis. Analyses in the Internet Appendix also fail to find consistent differences in how the S&P and Moody's versus Fitch's corporate credit ratings changed before and after the crisis. Despite similar changes in rating performance, my prediction that Fitch suffers less reputation damage is based on three interrelated observations: (i) Fitch likely had a weaker reputation prior to the crisis; (ii) market participants likely experienced smaller losses from relying on Fitch's pre-crisis ratings on MBSs and CDOs; and (iii) crisis-related criticism and regulatory scrutiny in the United States has been focused on S&P and Moody's. I expand upon these observations in the following paragraphs.

In a sample mostly predating the crisis, Bongaerts et al. (2012) find that Fitch's ratings are used more for certification purposes than to inform users about default risk. This finding indicates that Fitch likely has a weaker pre-crisis reputation than S&P or Moody's with regard to providing measures of default risk. That is, if users perceived Fitch's ratings as having been of equal quality to those of S&P and Moody's, then Fitch's ratings should have had equally strong associations with market prices (which Bongaerts et al. (2012) do not find). This same finding indicates that market participants likely experienced fewer losses from relying on Fitch's pre-crisis ratings on MBSs and CDOs, as well as because Fitch rated fewer asset-backed securities than S&P and Moody's (SEC 2008). Fitch's smaller pre-crisis role is reflected in the popular press. *The Wall Street Journal*, for example, published 0.6 articles per year about Fitch from 2004 through June 2007 while simultaneously publishing 5.4 and 2.3 articles per year about S&P and Moody's, respectively. (See the Internet Appendix for details.) Smaller losses from relying on Fitch ratings likely also contribute to why Fitch appears to have avoided US federal charges for its ratings on MBSs and CDOs, as well as why CalPERS settled litigation with Fitch for $0 in damages while settling with S&P and Moody's for over $125 million each.

That market participants experienced fewer losses from relying on Fitch ratings likely also contributes to why S&P and Moody's have received more criticism for their roles in the financial crisis. For example, a 2011 Senate report concludes that all three CRAs' ratings were badly flawed, but the body of the report mentions Fitch just 34 times while mentioning S&P and Moody's more than 400 times each. Similarly, US crisis-related press coverage tends to jointly criticize S&P and Moody's while only occasionally mentioning Fitch. As an example, *The Wall Street Journal* published 24.8 and 29.8 articles per year about S&P and Moody's, respectively, during and after the crisis, while publishing just 1.7 articles per year about Fitch. Also, analysis in the Internet Appendix finds the tone of articles about S&P and Moody's becomes significantly more negative from before to during and after the crisis, while the tone of media articles about Fitch does not change.

Combined, these observations indicate that Fitch likely not only had less reputation to lose but also experienced less of a reputational shock. If so, I expect Fitch to experience a smaller decline in reputation after the crisis than S&P and Moody's. Accordingly, there should be a lesser decline in the usage of Fitch's ratings.

<<< INSERT TABLE 11 ABOUT HERE >>>

Table 11 analyzes changes in debt contracting value-relevance. The sample is limited to 1,447 contracts with ratings from both Fitch and at least one of S&P or Moody's. *RATING_SP/Moody* is the most recent rating assigned by S&P or Moody's before the contract date. *RATING_Fitch* is the most recent rating from Fitch. In column (i), β_1 is considerably larger than β_2, consistent with S&P/Moody's ratings being more value-relevant before the crisis. Both β_3 and β_4 find significant declines in value-relevance for S&P/Moody's and Fitch ratings after the crisis, but the bottom rows of Panel A find the decline for S&P/Moody's are significantly larger. Results are qualitatively unchanged in column (ii) with untabulated *CONTROLS*. Similar analysis cannot be performed for the PPP tests since I cannot identify which CRA's rating is used in the PPP. In sum, the results in Table 11 indicate that the value-relevance of ratings from S&P and Moody's decline more than Fitch's ratings after the crisis, consistent with S&P and Moody's experiencing a greater decline in reputation.

4.8 Discussion

Together, the body of results indicates that debt market participants reduce their use of credit ratings after the crisis. The Internet Appendix provides additional analyses and robustness tests supporting this conclusion. Observing a decline in rating usage despite no change or an improvement in rating performance is consistent with market participants decreasing their rating usage due to the CRAs suffering crisis-related reputation damage. Cross-sectional tests in Sections 4.6 and 4.7 support this interpretation.[18]

5. CONCLUSION

[18] One alternate explanation could be that the SEC's certification of smaller rating agencies allowed market participants to substitute away from relying on the major CRAs, although this is somewhat unlikely since the major CRAs still controlled 97% of the market through 2013 (SEC 2014). Further, because my PPP tests include PPPs using any CRA's rating, this explanation is inconsistent with my finding of a decline in rating-based PPPs.

This study documents divergent trends in the performance and usage of corporate credit ratings following the global financial crisis. Across a battery of tests, the preponderance of evidence indicates that corporate rating performance improves during and after the crisis, consistent with the CRAs positively responding to public criticism and regulatory pressures. At the same time, I find evidence that market participants decrease their reliance on corporate ratings in debt contracting after the crisis. These results are consistent with the CRAs suffering spillover reputation damage as a result of their failures of ratings on MBSs and CDOs, as well as with theoretical models in which reputation concerns can lead to extended periods when there is a disconnect between rating performance and usage.

My study provides two main contributions. First, my findings of no change or an improvement in rating performance during and after the crisis should inform academics and regulators debating the role of regulation in the credit rating industry, as well as market participants deciding how much to rely on corporate ratings in decision-making. In particular, my findings should help assuage concerns that the financial crisis and related regulations undermined the quality of corporate credit ratings. Second, beyond the specific context of the financial crisis, my study contributes to a lengthy literature examining the role of reputation in the credit rating industry. Documenting divergent trends in rating usage and performance following a plausible reputation shock provides empirical evidence consistent with analytical models of the important role that reputation plays in rating usage decisions.

REFERENCES

Aaker, D. A., and K. L. Keller. 1990. Consumer evaluations of brand extensions. *The Journal of Marketing* 54 (1): 27–41.

Alp, A. 2013. Structural shifts in credit rating standards. *The Journal of Finance* 68 (6): 2435–2470.

Altman, E. I., and H. A. Rijken. 2004. How rating agencies achieve rating stability. *Journal of Banking & Finance* 28 (11): 2679–2714.

Amato, J. D., and C. H. Furfine. 2004. Are credit ratings procyclical? *Journal of Banking & Finance* 28 (11): 2641–2677.

Ashcraft, A. B., P. Goldsmith-Pinkham, and J. I. Vickery. 2010. *MBS Ratings and The Mortgage Credit Boom*. Available at http://papers.ssrn.com/sol3/papers.cfm?abstract_id=1615613.

Ashcraft, A. B., and T. Schuermann. 2008. Understanding the securitization of subprime mortgage credit. *Foundations and Trends in Finance* 2 (3): 191–309.

Asquith, P., A. Beatty, and J. Weber. 2005. Performance pricing in bank debt contracts. *Journal of Accounting and Economics* 40 (1-3): 101–128.

Bar-Isaac, H., and J. Shapiro. 2013. Ratings quality over the business cycle. *Journal of Financial Economics* 108 (1): 62–78.

Barberis, N., and R. Thaler. 2003. A survey of behavioral finance. *Handbook of the Economics of Finance*, vol. 1, edited by G.M. Constantinides, M. Harris and R. Stulz, 1053–1128. Philadelphia: Elsevier Science.

Beaver, W., C. Shakespeare, and M. Soliman. 2006. Differential properties in the ratings of certified versus non-certified bond-rating agencies. *Journal of Accounting and Economics* 42 (3): 303–334.

Becker, B., and T. Milbourn. 2011. How did increased competition affect credit ratings? *Journal of Financial Economics* 101: 493–514.

Bedendo, M., L. Cathcart, L. El-Jahel, and L. Evans. 2013. The credit rating crisis and the informational content of corporate credit ratings. Available at SSRN 1729231.

Benabou, R., and G. Laroque. 1992. Using privileged information to manipulate markets: Insiders, gurus, and credibility. *The Quarterly Journal of Economics* 107 (3): 921–958.

Benmelech, E., and J. Dlugosz. 2010. The credit rating crisis. In *NBER Macroeconomics Annual 2009*, vol. 24, edited by D. Acemoglu, K. Rogoff, and M. Woodford, 161–207. Chicago: University of Chicago Press.

Bolton, P., X. Freixas, and J. Shapiro. 2012. The credit ratings game. *The Journal of Finance* 67 (1): 85–112.

Bongaerts, D., K. Cremers, and W. N. Goetzmann. 2012. Tiebreaker: Certification and multiple credit ratings. *The Journal of Finance* 67 (1): 113–152.

Bonsall, S. B. 2014. The impact of issuer-pay on corporate bond rating properties: Evidence from Moody's and S&P's initial adoptions. *Journal of Accounting and Economics* 57 (2): 89–109.

Cantor, R. M., and C. Mann. 2003. Measuring the performance of corporate bond ratings. *Moody's Investor Services Special Comment*, March. Available at http://papers.ssrn.com/sol3/papers.cfm?abstract_id=996025.

Chava, S., D. Livdan, and A. Purnanandam. 2009. Do shareholder rights affect the cost of bank loans? *Review of Financial Studies* 22 (8): 2973–3004.

Chava, S., and M. R. Roberts. 2008. How does financing impact investment? The role of debt covenants. *The Journal of Finance* 63 (5): 2085–2121.

Cheng, M., and M. Neamtiu. 2009. An empirical analysis of changes in credit rating properties: Timeliness, accuracy and volatility. *Journal of Accounting and Economics* 47 (1-2): 108–130.

Columbus Dispatch. 2011. Stivers slams section of financial reform law (March 20). Available at http://stivers.house.gov/news/documentsingle.aspx?DocumentID=250285.

Costello, A. M., and R. Wittenberg-Moerman. 2011. The impact of financial reporting quality on debt contracting: Evidence from internal control weakness reports. *Journal of Accounting Research* 49 (1): 97–136.

Darbellay, A., and F. Partnoy. 2012. Credit rating agencies and regulatory reform. *Research Handbook on the Economics of Corporate Law*, edited by C.A. Hill, B.H. McDonnell. Cheltenham, UK: Edward Elgar Publishing.

Dichev, I. D., and J. D. Piotroski. 2001. The long-run stock returns following bond ratings changes. *The Journal of Finance* 56 (1): 173–203.

Dimitrov, V., D. Palia, and L. Tang. 2015. Impact of the Dodd-Frank Act on credit ratings. *Journal of Financial Economics* 115 (3): 505–520.

Even-Tov, O. 2015. Can the bond price reaction to earnings announcements predict future stock returns? Doctoral dissertation, University of California at Los Angeles.

Goel, A. M., and A. V. Thakor. 2015. Information reliability and welfare: A theory of coarse credit ratings. *Journal of Financial Economics* 115 (3): 541–557.
Graham, J., S. Li, and J. Qiu. 2008. Corporate misreporting and bank loan contracting. *Journal of Financial Economics* 89 (1): 44–61.
Griffin, J. M., and D. Y. Tang. 2011. Did credit rating agencies make unbiased assumptions on CDOs? *American Economic Review* 101 (3): 125–130.
Han, S. H., M. S. Pagano, and Y. S. Shin. 2012. Rating agency reputation, the global financial crisis, and the cost of debt. *Financial Management* 41 (4): 849–884.
Hunt, J. P. 2009. Credit rating agencies and the "worldwide credit crisis": The limits of reputation, the insufficiency of reform, and a proposal for improvement. *Columbia Business Law Review* 2009 (1): 109–209.
Jaballah, J. 2012. Impact of the subprime crisis on the reputation of rating agencies. Paper Read at EFMA Annual Conference, School of Economics and Business, Barcelona, Spain, June 27–30.
Jorion, P., Z. Liu, and C. Shi. 2005. Informational effects of regulation FD: Evidence from rating agencies. *Journal of Financial Economics* 76 (2): 309–330.
Kerr, J. N., and N. B. Ozel. 2015. Earnings announcements, information asymmetry, and timing of debt offerings. *The Accounting Review* 90 (6): 2375–2410.
Klein, B., and K. Leffler. 1981. The role of market forces in assuring contractual performance. *Journal of Political Economy* 89 (4): 615–641.
Lim, S. S., and S. H. Teoh. 2010. Limited attention. In *Behavioral finance: Investors, Corporations, and Markets*, edited by H.K. Baker and J. F. Nofsinger, Hoboken, NJ: John Wiley.
Lynch, S. 2013. SEC frustrated over pace of U.S. financial crisis reforms. *Reuters* (July 12).
Mann, J., and A. Metz. 2011. Measuring the performance of credit ratings. *Moody's Investor Services Special Comment*, November. Available at https://www.moodys.com/Pages/GuideToDefaultResearch.aspx.
Mathis, J., J. McAndrews, and J. C. Rochet. 2009. Rating the raters: Are reputation concerns powerful enough to discipline rating agencies? *Journal of Monetary Economics* 56 (5): 657–674.
McLaughlin, D., T. Schoenberg, and A. Harris. 2016. Moody's fate in subprime probe to be decided soon by US. *Bloomberg* (February 25). Available at http://www.bloomberg.com/news/articles/2016-02-25/moody-s-fate-in-subprime-probe-said-to-be-decided-soon-by-u-s.
Moody's. 2013. *About Moody's Ratings*. Available at http://www.moodys.com/ratings-process/How-to-Get-Rated/002001 (last accessed July 18, 2013).
National Bureau of Economic Research (NBER). 2014. *US Business Cycle Expanstions and Contractions.* Accessed January 2014. Available at http://www.nber.org/cycles/cyclesmain.html.
Nelson, P. 1970. Information and consumer behavior. *Journal of Political Economy* 78 (2): 311–329.
Ng, J., İ. Tuna, and R. Verdi. 2013. Management forecast credibility and underreaction to news. *Review of Accounting Studies* 18 (4): 956–986.
Office of the Press Secretary. 2010. Remarks by the president on Wall Street reform. Speech delivered at South Lawn, the White House, Washington D.C., June 25. Available at https://www.whitehouse.gov/the-press-office/remarks-president-wall-street-reform-1.
Opp, C. C., M. M. Opp, and M. Harris. 2013. Rating agencies in the face of regulation. *Journal of Financial Economics* 108 (1): 46–61.
Park, C. W., S. Milberg, and R. Lawson. 1991. Evaluation of brand extensions: The role of product feature similarity and brand concept consistency. *Journal of Consumer Research* 18 (2): 185–193.
Partnoy, F. 1999. The Siskel and Ebert of financial markets: Two thumbs down for the credit rating agencies. *Washington University Law Quarterly* 77: 619–712.
Partnoy, F. 2006. How and why credit rating agencies are not like other gatekeepers. *San Diego Legal Studies Paper*. No. 07-46. Available at http://ssrn.com/abstract=900257.
Rhee, R. J. 2015. Why credit rating agencies exist. *Economic Notes* 44 (2): 161–176.
Schwarcz, S. L. 2002. Private ordering of public markets: The rating agency paradox. *University of Illinois Law Review* 2002(1): 1–28.
Securities and Exchange Commission. 2008. Summary Report of Issues Identified in the Commission Staff's Examination of Select Credit Rating Agencies. Available at https://www.sec.gov/news/studies/2008/craexamination070808.pdf.
Securities and Exchange Commission. 2014. Annual Report on Nationally Recognized Statistical Rating Organizations.
Shapiro, C. 1983. Premiums for high quality products as returns to reputations. *The Quarterly Journal of Economics* 98 (4): 659–679.

Standard & Poor's. 2011a. *Credit Rating Definitions & FAQs*. Available at http://www.standardandpoors.com/ratings/definitions-and-faqs/en/us (last accessed May 6, 2011).
Standard & Poor's. 2011b. *Ratings Behavior over Time*. Available at http://www2.standardandpoors.com/aboutcreditratings/ (last accessed May 6, 2011).
Standard & Poor's. 2012. *Default Study: Global Structured Finance Defaults 1978-2011: Credit Quality Fell for Fifth Consecutive Year in 2011*. Available at https://www.standardandpoors.com/ja_JP/delegate/getPDF?articleId=1498583&type=COMMENTS&subType=.
Sullivan, M. 1990. Measuring image spillovers in umbrella-branded products. *Journal of Business* 63 (3): 309–329.
US House of Representatives, Committee on Oversight and Government Reform. 2008. Credit Rating Agencies and the Financial Crisis. Washington D.C.: US Government Printing Office. Available at https://house.resource.org/110/org.c-span.281924-1.pdf.
US House of Representatives, Committee on Oversight and Government Reform. 2011. Oversight of the Credit Rating Agencies Post-Dodd-Frank. Washington D.C.: US Government Printing Office. Available at https://www.gpo.gov/fdsys/pkg/CHRG-112hhrg67946/html/CHRG-112hhrg67946.htm.
US Department of Treasury. 2009. Financial Regulatory Reform. A New Foundation: Rebuilding Financial Supervision and Regulation. Available at https://www.treasury.gov/initiatives/Documents/FinalReport_web.pdf.
US Senate, Permanent Subcommittee on Investigations, Committee on Homeland Security and Governmental Affairs. 2011. Wall Street and the Financial Crisis: Anatomy of a Financial Collapse. Available at http://www.hsgac.senate.gov//imo/media/doc/Financial_Crisis/FinancialCrisisReport.pdf?attempt=2.
Valta, P. 2012. Competition and the cost of debt. *Journal of Financial Economics* 105 (3): 661–682.
White, L. 2001. The credit rating industry: An industrial organization analysis. Conference on Ratings, Rating Agencies and the Global Financial System. Stern School of Business, New York, June 1.
White, L. 2006. Good intentions gone awry: A policy analysis of the SEC's regulation of the bond rating industry. *New York University Law and Economics Working Papers*. Paper 69. Available at http://lsr.nellco.org/nyu_lewp/69/.
White, L. 2010a. The credit rating agencies. *Journal of Economic Perspectives* 24 (2): 211–226.
White, L. 2010b. Credit-rating agencies and the financial crisis: Less regulation of CRAs is a better response. *Journal of International Banking Law and Regulation* 25 (4): 170–179.
White, L. 2013. An Assessment of the Credit Rating Agencies: Background, Analysis, and Policy. Working paper No. 13-16, Mercatus Center, George Mason University. Available at http://mercatus.org/sites/default/files/White_AssessmentCRAs_v1.pdf.

APPENDIX A: Variable Specifications

Variable details are in Panel A. Continuous variables are winsorized at 1% and 99%. Firm accounting data are measured as of the most recently available quarter-end. Panel B details the conversion of credit ratings letters to numbers.

Panel A: Variable definitions

Variables used in multiple tests	
FIRM	Firm fixed effects.
INDUSTRY	Industry classifications based on Fama-French 12 categories.
DURING	Indicator variable for the period 7/1/2007–6/30/2009. Models including only *DURING* exclude observations after 6/30/2009.
DURING&POST	Indicator for the period 7/1/2007 onward.
POST	Indicator for the period of 7/1/2009 onward. Models including only *POST* exclude observations during the crisis.
POST2	Indicator for the period of 7/1/2011 onward.
QUARTER	Calendar year-quarter fixed effects.
Variables used in rating performance tests	
BOND_CONV	Indicator if the bond is convertible to common stock.
BOND_ENHANCE	Indicator if the bond has a credit enhancement feature.
BOND_MATURITY	Remaining time until bond maturity, in years, logged.
BOND_PUT	Indicator if the bond has a put option.
BOND_REDEEM	Indicator if the bond is redeemable.
BOND_SIZE	Natural log of the bond offering amount.
BONS_SS	Indicator if the bond is senior secured.
DAHEAD	Logged number of days between the default date and last speculative-grade, nondefault rating assigned on or before the default date.
FIRM_BTM	Book value of equity divided by market value of equity.
FIRM_LEV	Total debt scaled by total assets.
FIRM_NEG_RE	Indicator for firms with negative retained earnings.
FIRM_SIZE	Natural log of the firm's market value of equity.
FT_RATING	Indicator for credit ratings issued by Fitch.
LARGE_DGRADE	*All ratings sample:* Indicator if the bond's rating declines by more than three levels from the beginning to end of the year. Requires both a beginning- and end-of-year credit rating. *Rating announcements sample:* Indicator if the bond's rating decreases by more than three levels.
MACRO_BOND30	CRSP 30-year bond annual return.
RATING	*All ratings sample:* Bond-level credit rating one year before the yearly window measurement date or default date. *Rating announcements sample*: The new bond-level credit rating.
REVERSAL	*All ratings sample:* Indicator if the firm's rating is both upgraded and downgraded within rolling yearly window, excluding movements to/from default or "not rated." *Announcements sample:* Indicator if a rating downgrade is followed by an upgrade within one year or vice versa.
MD_RATING	Indicator for credit ratings issued by Moody's.
TYPE I Error	Indicator for defaulting bonds rated as investment-grade one year before the default date.
TYPE I Error rate	The count of type I errors divided by the count of all defaults.
TYPE II Error	*All ratings sample:* Indicator for nondefaulting bonds that have a speculative-grade rating at the beginning of the year. *Announcements sample:* Indicator for speculative-grade ratings that do not default within the following year.
TYPE II Error rate	The count of type II errors divided by the count of all nondefaults.
VOLATILITY	*All ratings sample:* Standard deviation of credit rating levels observed during the yearly window. Requires a minimum of two outstanding ratings, excluding default ratings. *Announcements sample:* Standard deviation of credit rating levels observed during the year following the announcement date. Requires a minimum of two outstanding ratings, excluding default ratings.
WRATE	Weighted average rating level during the year prior to default. Excludes default and "not rated" ratings.
Variables used in loan contracting tests	

FIRM_CDS_AVAIL	Indicator if the firm has available credit default swaps before or up to three months after the loan date.
FIRM_LEV	Total debt scaled by total assets.
FIRM_ROA	Trailing four quarters income before extraordinary items scaled by total assets.
FIRM_SIZE	Natural log of the firm's total assets.
INST_INVST	Indicator if the loan's type is term loan B, C, or D.
LENDERS	Count of lenders participating in the loan.
LOAN_SIZE	Natural log of the loan amount.
MATURITY	Natural log of the number of months between the loan issue date and maturity.
PP_RATING	Indicator if the loan has a PPP based on a credit rating. Requires nonmissing data in the DealScan Performance Pricing file.
RELATION	Indicator if one of the lead arrangers was a lead arranger for the same borrower within the last five years.
REVOLVER	Indicator for revolving loans.
SECURED	Indicator if the loan is backed by collateral.
SPREAD	Logged interest rate spread over LIBOR, in basis points, inclusive of fees. DealScan variable All_In_Drawn.
RATING	The firm's most recently assigned credit rating from S&P, Moody's, or Fitch as of the loan date.
RATING_SP/Moody	The firm's most recently assigned credit rating from S&P or Moody's as of the loan date.
RATING_Fitch	The firm's most recently assigned credit rating from Fitch as of the loan date.

Panel B: Credit rating numerical conversions

Group	Numeric Rating	S&P	Moody's	Fitch
Investment Grade	20 (safest)	AAA	Aaa	AAA
	19	AA+	Aa1	AA+
	18	AA	Aa2	AA
	17	AA-	Aa3	AA-
	16	A+	A1	A+
	15	A	A2	A
	14	A-	A3	A-
	13	BBB+	Baa1	BBB+
	12	BBB	Baa2	BBB
	11	BBB-	Baa3	BBB-
Speculative Grade	10	BB+	Ba1	BB+
	9	BB	Ba2	BB
	8	BB-	Ba3	BB-
	7	B+	B1	B+
	6	B	B2	B
	5	B-	B3	B-
	4	CCC+	Caa1	CCC+
	3	CCC	Caa2	CCC
	2	CCC-	Caa3	CCC-
	1 (riskiest)	CC, C	Ca, C	CC, C
In default (assigned ex post)	0	D		D, DD, DDD

FIGURE 1: Timeline of Key Events Affecting the Credit Rating Agencies

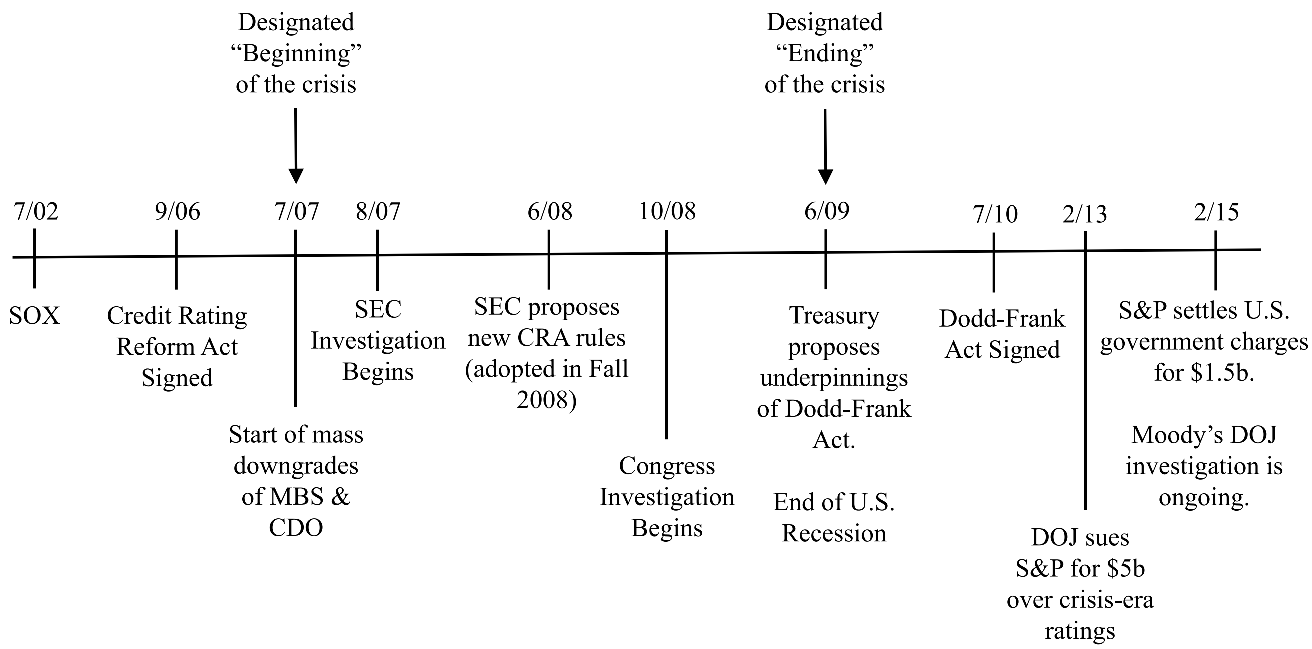

TABLE 1: Summary Information – Rating Performance Samples

The rating performance tests use three samples. The "defaults sample" includes defaulting bonds. The "all ratings sample" includes all bonds, measured annually and including ratings that do and do not change in a given period. The "announcements sample" includes only bonds with rating upgrades, downgrades, initiations, or explicit reaffirmations. See Section 3 for further discussion and Appendix A for variable definitions. Panel A details the three sample sizes. Panel B provides sample averages for control variables. Panel C summarizes results of tests presented in Tables 2 through 6.

Panel A: Samples by period

	Pre-Crisis (2004 – 6/2007)	**During-Crisis (7/2007 – 6/2009)**	**Post-Crisis (7/2009 – 2013)**	**Total**
Defaults sample	303	320	188	811
All ratings sample	49,111	27,965	53,578	130,654
Announcements sample	25,390	14,694	24,969	65,053

Panel B: Sample averages

	Defaults Sample	**All Ratings Sample**	**Announcements Sample**
RATING	Not Used	11.04	10.30
MD_RATING	0.39	0.38	0.28
FT_RATING	0.21	0.23	0.41
FIRM_SIZE	5.25	8.81	8.79
FIRM_LEV	0.78	0.36	0.37
FIRM_NEG_RE	0.85	0.27	0.31
FIRM_BTM	-45.33	0.37	0.31
BOND_SIZE	12.13	12.17	12.48
BOND_CONV	0.09	0.08	0.06
BOND_SS	0.07	0.06	0.05
BOND_ENHANCE	0.31	0.16	0.20
BOND_PUT	0.05	0.09	0.06
BOND_REDEEM	0.76	0.81	0.80
BOND_MATURITY	1.77	1.92	2.08
MACRO_BOND30	0.14	0.09	0.09

Panel C: Performance tests results summary

+ Indicates results consistent with a significant **improvement** in rating performance
0 Indicates results consistent with **no change** in rating performance
– Indicates results consistent with a significant **decline** in rating performance
? Indicates results providing an ambiguous inference about changes in rating performance

	Defaults Sample		
Comparison Period	**During**	**Post**	**During & Post**
Tests of Absolute Accuracy (Table 3)			
Type I errors – univariate	+	+	+
Tests of Rating Timeliness (Table 5)			
Days ahead of default – univariate	+	+	+
Days ahead of default – regression	+	+	+
Pre-default rating levels – univariate	+	+	+
Pre-default rating levels – regression	+	0	+

	All Ratings Sample			Announcements Sample		
Comparison Period	**During**	**Post**	**During & Post**	**During**	**Post**	**During & Post**
Tests of Relative Accuracy (Table 2)						
Cumulative accuracy profiles	+	+	+	+	+	+
Tests of Absolute Accuracy (Table 3)						
Type II errors – univariate	0	+	+	+	+	+
Type II errors – regression	–	+	0	0	+	+
Tests of Rating Stability (Table 4)						
Volatility – univariate	0	+	0	0	+	+
Volatility – regression	0	+	0	0	+	0
Reversals – univariate	+	0	0	+	+	+
Reversals – regression	+	0	0	0	0	0
Large downgrades – univariate	0	+	+	0	+	+
Large downgrades – regression	0	+	+	0	+	+
Tests of Rating Levels (Table 6)	?	?	?	?	?	?

TABLE 2: Relative Accuracy Tests

This table reports tests of differences in areas under the curve (AUC) of cumulative accuracy profiles from the pre-crisis period to each comparison period. All tests comparing the before-crisis to during-crisis (post-crisis) period exclude observations in the post-crisis (during-crisis) period. Results in the first (second) column use the all ratings (announcements) sample. *** indicates significance at 1%, ** at 5%, * at 10%.

	Cumulative Accuracy Profile – Area Under Curve	
Sample	**All Ratings**	**Announcements**
Pre-Crisis	0.782	0.900
During-Crisis	0.930	0.948
Difference	**0.148**	**0.048**
Chi-Squared	[100.73]***	[52.57]***
Post-Crisis	0.923	0.961
Difference	**0.141**	**0.061**
Chi-Squared	[84.78]***	[77.57]***
During- & Post-Crisis	0.929	0.957
Difference	**0.147**	**0.057**
Chi-Squared	[101.10]***	[78.39]***

TABLE 3: Absolute Accuracy Tests

A type I error is defined as a defaulting bond that has an investment-grade credit rating one year before its default date. The type I error rate is the count of type I errors divided by the count of all defaulting bonds. A type II error is defined as a bond that has a speculative-grade credit rating but does not default within the year. The type II error rate is the count of type II errors divided by the count of all nondefaulting bonds. Panel A tabulates univariate tests of error rates. Panel B tabulates the results of logistic regressions of type II errors among non-defaulting bonds:

$$Type\ II\ Error = \beta_1(DURING\ or\ POST\ or\ DURING\&POST) + \Sigma\beta_k CONTROLS + \Sigma\beta_k INDUSTRY + \varepsilon.$$

All tests comparing the before-crisis to during-crisis (post-crisis) period exclude observations in the post-crisis (during-crisis) period. See Appendix A for variable specifications. Standard errors are clustered by firm and industry-year-quarter in all tests. *** indicates significance at 1%, ** at 5%, * at 10%.

Panel A: Univariate tests – types I and II error rates

	Type I Error Rate	**Type II Error Rate**	
Sample	**Defaults Sample**	**All Ratings Sample**	**Announcements Sample**
Pre-Crisis	0.271	0.415	0.492
During-Crisis	0.000	0.381	0.394
Difference	**-0.271**	**-0.034**	**-0.098**
	[-4.49]***	[-1.12]	[-2.60]***
Post-Crisis	0.000	0.337	0.378
Difference	**-0.271**	**-0.078**	**-0.114**
	[-4.49]***	[-2.53]**	[-3.71]***
During- & Post-Crisis	0.000	0.352	0.384
Difference	**-0.271**	**-0.063**	**-0.108**
	[-4.49]***	[-2.36]**	[-3.68]***

Panel B: Logit regressions – type II errors among non-defaulting bonds

Sample	(i) **All Ratings**	(ii) **All Ratings**	(iii) **All Ratings**	(iv) **Announce.**	(v) **Announce.**	(vi) **Announce.**
DURING	0.247			-0.229		
	[2.98]***			[-1.59]		
POST		-0.307			-0.435	
		[-3.09]***			[-2.98]***	
DURING&POST			-0.119			-0.398
			[-1.27]			[-3.08]***
MD_RATING	0.127	0.135	0.120	0.190	0.183	0.125
	[2.31]**	[2.69]***	[2.58]**	[1.83]*	[1.78]*	[1.40]
FT_RATING	-0.066	-0.066	-0.073	-0.477	-0.571	-0.568
	[-0.86]	[-0.87]	[-1.04]	[-4.43]***	[-6.24]***	[-6.21]***
FIRM_SIZE	-0.985	-1.110	-1.064	-1.097	-1.270	-1.219
	[-10.88]***	[-12.52]***	[-12.52]***	[-13.32]***	[-14.96]***	[-15.02]***
FIRM_BTM	0.228	0.266	0.245	0.195	0.286	0.226
	[5.63]***	[5.68]***	[5.97]***	[2.85]***	[3.06]***	[3.13]***
FIRM_LEV	3.250	3.297	3.176	3.902	4.316	3.916
	[4.21]***	[5.04]***	[4.65]***	[5.05]***	[6.13]***	[5.64]***
FIRM_NEG_RE	1.423	1.354	1.336	1.384	1.401	1.371
	[5.14]***	[6.27]***	[6.18]***	[5.45]***	[6.32]***	[6.48]***
BOND_SIZE	0.083	0.126	0.116	0.258	0.352	0.336
	[1.04]	[1.46]	[1.35]	[3.28]***	[3.98]***	[3.98]***
BOND_CONV	1.263	1.354	1.349	0.924	1.080	1.081
	[7.23]***	[7.80]***	[7.87]***	[4.87]***	[5.61]***	[5.73]***
BOND_SS	-0.404	-0.487	-0.445	-0.022	0.120	0.009
	[-0.98]	[-1.26]	[-1.19]	[-0.07]	[0.35]	[0.03]
BOND_ENHANCE	0.549	0.645	0.625	0.556	0.511	0.526
	[3.44]***	[4.40]***	[4.36]***	[3.39]***	[3.19]***	[3.38]***
BOND_PUT	-0.438	-0.486	-0.445	-0.114	-0.241	-0.158
	[-2.58]***	[-2.75]***	[-2.60]***	[-0.72]	[-1.31]	[-0.93]
BOND_REDEEM	0.435	0.200	0.169	-0.140	-0.380	-0.370
	[2.23]**	[0.95]	[0.86]	[-0.86]	[-2.11]**	[-2.22]**
BOND_MATURITY	-0.351	-0.307	-0.310	-0.093	-0.092	-0.081
	[-5.49]***	[-4.92]***	[-5.40]***	[-1.47]	[-1.47]	[-1.37]
MACRO_BOND30	-0.684	0.006	0.160	-2.325	-0.394	-0.788
	[-3.89]***	[0.05]	[2.03]**	[-3.28]***	[-0.77]	[-1.75]*
Industry Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	76,459	102,227	129,858	38,971	49,535	63,679
Pseudo R^2	0.434	0.468	0.454	0.455	0.503	0.498

TABLE 4: Rating Stability Tests

Rating volatility is the standard deviation of outstanding ratings during a year. Rating reversals are when a bond is both upgraded and downgraded, or vice versa, within a given year. A "large downgrade" is defined as a downgrade of more than three levels. See Appendix A for variable specifications. Panel A tabulates univariate tests. Panel B tabulates the results of OLS regressions of rating volatility. Panel C tabulates the results of logistic regressions of rating reversals. Panel D tabulates the results of logistic regressions of large rating downgrades.

VOLATILITY or REVERSAL or LARGEDGRADE = β_1*(DURING or POST or DURING&POST)* + $\Sigma\beta_k$*CONTROLS* + $\Sigma\beta_k$*INDUSTRY* + ε.

All tests comparing the before-crisis to during-crisis (post-crisis) period exclude observations in the post-crisis (during-crisis) period. Standard errors are clustered by firm and industry-year-quarter in all tests. *** indicates significance at 1%, ** at 5%, * at 10%.

Panel A: Univariate tests

Sample	**All Ratings Sample**			**Announcements Sample**		
	Volatility	**Reversals**	**Large Dgrade**	**Volatility**	**Reversals**	**Large Dgrade**
Pre-Crisis	1.184	0.006	0.017	1.019	0.039	0.03
During-Crisis	1.228	0.003	0.017	0.918	0.029	0.025
Difference	**0.044**	**-0.003**	**0.000**	**-0.101**	**-0.01**	**-0.005**
	[0.54]	[-1.76]*	[0.03]	[-0.91]	[-1.66]*	[-0.53]
Post-Crisis	0.972	0.005	0.003	0.43	0.025	0.005
Difference	**-0.212**	**-0.001**	**-0.014**	**-0.589**	**-0.014**	**-0.025**
	[-2.89]***	[-0.79]	[-3.03]***	[-4.46]***	[-2.52]**	[-3.22]***
During&Post-Crisis	1.074	0.004	0.008	0.622	0.027	0.013
Difference	**-0.11**	**-0.002**	**-0.009**	**-0.397**	**-0.012**	**-0.017**
	[-1.47]	[-1.20]	[-1.90]*	[-3.61]***	[-2.34]**	[-2.16]**

Panel B: OLS regressions – rating volatility

Sample	(i) All Ratings	(ii) All Ratings	(iii) All Ratings	(iv) Announce.	(v) Announce.	(vi) Announce.
DURING	0.079			0.106		
	[1.19]			[1.07]		
POST		-0.166			-0.232	
		[-3.38]***			[-3.29]***	
DURING&POST			-0.074			-0.089
			[-1.34]			[-1.24]
MD_RATING	-0.097	-0.089	-0.057	0.045	-0.013	0.005
	[-1.42]	[-1.67]*	[-1.27]	[0.49]	[-0.15]	[0.06]
FT_RATING	-0.002	0.035	0.031	-0.306	-0.304	-0.308
	[-0.04]	[0.77]	[0.82]	[-3.54]***	[-3.42]***	[-3.46]***
RATING	0.031	0.017	0.019	0.046	-0.018	-0.003
	[1.60]	[0.85]	[1.25]	[4.14]***	[-0.85]	[-0.18]
FIRM_SIZE	-0.068	-0.061	-0.057	-0.075	-0.054	-0.061
	[-1.99]**	[-2.29]**	[-2.43]**	[-1.61]	[-1.21]	[-1.62]
FIRM_BTM	0.004	-0.012	-0.006	0.031	0.055	0.046
	[0.15]	[-0.46]	[-0.24]	[2.40]**	[1.87]*	[3.32]***
FIRM_LEV	0.233	0.225	0.223	-0.042	-0.444	-0.158
	[1.17]	[1.47]	[1.53]	[-0.17]	[-2.37]**	[-0.91]
FIRM_NEG_RE	0.209	0.134	0.126	0.003	0.038	-0.040
	[1.80]*	[1.30]	[1.52]	[0.03]	[0.54]	[-0.55]
BOND_SIZE	-0.076	-0.054	-0.056	-0.033	-0.025	-0.031
	[-3.33]***	[-1.65]*	[-2.70]***	[-1.52]	[-0.79]	[-1.37]
BOND_CONV	-0.037	0.004	-0.007	-0.080	-0.049	-0.078
	[-0.69]	[0.09]	[-0.16]	[-0.97]	[-0.52]	[-1.12]
BOND_SS	-0.147	-0.106	-0.138	0.177	0.036	0.088
	[-1.80]*	[-1.72]*	[-2.38]**	[1.51]	[0.43]	[0.98]
BOND_ENHANCE	-0.050	-0.106	-0.063	0.030	-0.031	0.015
	[-0.82]	[-3.68]***	[-1.51]	[0.52]	[-0.72]	[0.32]
BOND_PUT	0.084	-0.014	0.039	0.213	0.067	0.155
	[1.37]	[-0.28]	[0.83]	[1.72]*	[1.02]	[1.81]*
BOND_REDEEM	0.102	0.055	0.060	0.093	-0.056	-0.041
	[4.81]***	[1.71]*	[2.08]**	[1.75]*	[-1.11]	[-0.83]
BOND_MATURITY	-0.007	-0.000	-0.003	-0.035	0.017	0.004
	[-0.44]	[-0.04]	[-0.24]	[-0.93]	[0.93]	[0.16]
MACRO_BOND30	-0.300	-0.025	0.006	-0.310	-0.334	-0.468
	[-0.76]	[-0.15]	[0.03]	[-0.64]	[-1.39]	[-1.67]*
Industry Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	14,980	18,040	23,939	3,623	4,501	6,104
Adjusted R^2	0.080	0.089	0.061	0.167	0.395	0.279

Panel C: Logit regressions – rating reversals

Sample	(i) All Ratings	(ii) All Ratings	(iii) All Ratings	(iv) Announce.	(v) Announce.	(vi) Announce.
DURING	-0.545			-0.092		
	[-1.75]*			[-0.47]		
POST		-0.259			-0.179	
		[-1.00]			[-1.12]	
DURING&POST			-0.373			-0.162
			[-1.53]			[-1.07]
MD_RATING	-0.012	-0.655	-0.606	0.063	-0.230	-0.167
	[-0.04]	[-2.48]**	[-2.52]**	[0.36]	[-1.39]	[-1.16]
FT_RATING	0.407	-0.189	-0.104	-1.159	-1.242	-1.404
	[1.10]	[-0.56]	[-0.35]	[-4.61]***	[-5.66]***	[-6.92]***
RATING	-0.155	-0.070	-0.092	-0.117	-0.078	-0.109
	[-3.56]***	[-1.75]*	[-2.47]**	[-2.68]***	[-1.78]*	[-3.15]***
FIRM_SIZE	0.004	-0.255	-0.244	-0.119	-0.218	-0.179
	[0.05]	[-2.88]***	[-2.92]***	[-1.53]	[-2.56]**	[-2.84]***
FIRM_BTM	0.021	0.086	0.097	0.011	0.062	0.032
	[0.43]	[0.88]	[1.09]	[0.35]	[1.04]	[1.04]
FIRM_LEV	0.446	0.124	0.414	-0.914	-0.491	-0.667
	[0.81]	[0.27]	[0.99]	[-1.95]*	[-1.12]	[-1.67]*
FIRM_NEG_RE	-0.047	0.411	0.197	0.264	0.219	0.295
	[-0.16]	[1.78]*	[0.84]	[1.22]	[1.15]	[1.75]*
BOND_SIZE	0.227	0.163	0.197	0.085	0.031	0.058
	[4.00]***	[2.36]**	[3.02]***	[1.14]	[0.41]	[0.82]
BOND_CONV	-1.215	-0.648	-0.661	-0.283	-0.260	-0.143
	[-4.93]***	[-2.17]**	[-2.39]**	[-1.46]	[-1.35]	[-0.82]
BOND_SS	0.139	-0.025	-0.011	0.485	0.314	0.291
	[0.43]	[-0.07]	[-0.04]	[2.27]**	[1.54]	[1.58]
BOND_ENHANCE	0.600	0.448	0.529	0.095	0.186	0.137
	[2.88]***	[2.65]***	[3.39]***	[0.74]	[1.51]	[1.28]
BOND_PUT	0.385	0.174	0.114	0.224	0.083	0.053
	[1.28]	[0.60]	[0.41]	[1.25]	[0.41]	[0.29]
BOND_REDEEM	-0.126	-0.420	-0.356	-0.067	0.001	-0.062
	[-0.64]	[-2.21]**	[-1.88]*	[-0.53]	[0.01]	[-0.55]
BOND_MATURITY	0.080	0.146	0.124	0.056	0.002	0.019
	[0.97]	[2.19]**	[1.94]*	[0.95]	[0.03]	[0.36]
MACRO_BOND30	-2.615	-0.945	-1.026	-1.454	-0.819	-0.530
	[-2.02]**	[-1.36]	[-1.39]	[-0.97]	[-1.14]	[-0.69]
Industry Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	77,076	102,689	130,654	28,515	34,579	45,419
Pseudo R^2	0.0830	0.0726	0.0776	0.0880	0.0997	0.113

Panel D: Logit regressions – large downgrades

Sample	(i) **All Ratings**	(ii) **All Ratings**	(iii) **All Ratings**	(iv) **Announce.**	(v) **Announce.**	(vi) **Announce.**
DURING	0.208			-0.116		
	[0.78]			[-0.49]		
POST		-1.422			-1.346	
		[-4.12]***			[-4.07]***	
DURING&POST			-0.577			-0.588
			[-2.09]**			[-2.56]**
MD_RATING	-0.318	-0.586	-0.306	-0.948	-1.241	-0.837
	[-1.19]	[-1.88]*	[-1.27]	[-2.23]**	[-2.25]**	[-2.16]**
FT_RATING	0.296	0.091	0.272	-0.547	-0.540	-0.668
	[1.22]	[0.38]	[1.27]	[-2.13]**	[-1.80]*	[-2.69]***
RATING	0.046	0.052	0.044	-0.431	-0.460	-0.444
	[1.14]	[1.14]	[1.10]	[-6.05]***	[-6.43]***	[-6.36]***
FIRM_SIZE	-0.220	-0.238	-0.271	0.240	0.263	0.204
	[-2.07]**	[-1.89]*	[-2.75]***	[1.99]**	[1.86]*	[1.75]*
FIRM_BTM	-0.017	-0.024	-0.006	-0.049	-0.096	-0.051
	[-0.44]	[-0.80]	[-0.13]	[-1.41]	[-1.41]	[-1.47]
FIRM_LEV	1.122	1.516	1.200	-1.409	-1.621	-1.481
	[1.56]	[1.93]*	[1.80]*	[-1.91]*	[-2.14]**	[-2.22]**
FIRM_NEG_RE	-0.012	-0.020	-0.131	-0.742	-0.717	-0.818
	[-0.03]	[-0.03]	[-0.28]	[-1.87]*	[-1.71]*	[-2.25]**
BOND_SIZE	0.001	-0.049	0.009	-0.191	-0.202	-0.172
	[0.01]	[-0.35]	[0.07]	[-2.61]***	[-3.56]***	[-2.38]**
BOND_CONV	-0.417	-0.586	-0.472	-0.900	-1.061	-0.968
	[-2.41]**	[-2.33]**	[-2.51]**	[-4.03]***	[-4.00]***	[-4.23]***
BOND_SS	-0.574	-0.378	-0.526	-0.271	-0.026	-0.111
	[-1.43]	[-0.75]	[-1.50]	[-0.77]	[-0.05]	[-0.33]
BOND_ENHANCE	0.499	-0.049	0.380	-0.070	-0.491	-0.171
	[1.86]*	[-0.16]	[1.52]	[-0.37]	[-2.13]**	[-0.95]
BOND_PUT	-0.094	-0.312	-0.078	0.331	0.061	0.294
	[-0.46]	[-1.43]	[-0.39]	[1.23]	[0.22]	[1.20]
BOND_REDEEM	-0.415	-0.626	-0.545	0.308	0.343	0.350
	[-2.54]**	[-3.17]***	[-3.05]***	[1.54]	[2.07]**	[1.75]*
BOND_MATURITY	0.324	0.381	0.339	0.154	0.168	0.170
	[3.52]***	[4.28]***	[4.24]***	[1.74]*	[2.05]**	[2.08]**
MACRO_BOND30	-1.810	-1.774	-1.238	-0.059	-0.431	0.273
	[-1.10]	[-1.37]	[-1.27]	[-0.04]	[-0.33]	[0.28]
Industry Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	74,632	98,611	125,794	30,248	36,775	48,363
Pseudo R^2	0.114	0.163	0.111	0.215	0.295	0.230

TABLE 5: Rating Timeliness in Relation to Default

Panels A and C analyze the timeliness variable *DAHEAD*, calculated as the logged number of days between the default and last speculative-grade rating assigned on or before the default. Panel A contains univariate tests, while Panel C tabulates the results of OLS regressions. Panel B reports univariate analysis of differences in average credit rating levels at various intervals during the year leading up to default. Panel D tabulates the results of OLS regressions of the weighted-average outstanding rating level during the year leading up to default.

$$DAHEAD \text{ or } WRATE = \beta_1(DURING \text{ or } POST \text{ or } DURING\&POST) + \Sigma\beta_k CONTROLS + \Sigma\beta_k INDUSTRY + \varepsilon.$$

All tests comparing the before-crisis to during-crisis (post-crisis) period exclude observations in the post-crisis (during-crisis) period. See Appendix A for variable specifications. Standard errors are clustered by firm and industry-year-quarter in all tests. *** indicates significance at 1%, ** at 5%, * at 10%.

Panel A: Univariate tests of DAHEAD

	Average DAHEAD
Pre-Crisis	2.783
During-Crisis	4.526
Difference	**1.743**
	[4.39]***
Post-Crisis	4.035
Difference	**1.252**
	[2.44]**
During & Post-Crisis	4.345
Difference	**1.562**
	[3.99]***

Panel B: Tests of pre-default rating levels

	Time Before Default					
	One-Year	**270 Days**	**180 Days**	**90 Days**	**30 Days**	**Just Before**
Pre-Crisis	6.60	5.88	5.60	5.08	4.47	3.38
During-Crisis	4.12	3.76	3.24	2.97	2.49	2.45
Difference	**-2.48**	**-2.12**	**-2.36**	**-2.12**	**-1.98**	**-0.93**
	[-4.27]***	[-3.41]***	[-4.12]***	[-4.91]***	[-6.32]***	[-2.01]**
Post-Crisis	4.15	3.53	3.22	2.78	2.44	2.23
Difference	**-2.45**	**-2.35**	**-2.38**	**-2.30**	**-2.03**	**-1.15**
	[-3.75]***	[-3.32]***	[-4.02]***	[-4.97]***	[-6.10]***	[-2.40]**
During & Post-Crisis	4.13	3.68	3.23	2.90	2.48	2.38
Difference	**-2.47**	**-2.20**	**-2.37**	**-2.18**	**-1.99**	**-1.00**
	[-4.61]***	[-3.60]***	[-4.29]***	[-5.44]***	[-6.82]***	[-2.23]**

Panel C: OLS regressions – DAHEAD and WRATE

Dependent Var.	(i) **DAHEAD**	(ii) **DAHEAD**	(iii) **DAHEAD**	(iv) **WRATE**	(v) **WRATE**	(vi) **WRATE**
DURING	1.741			-2.536		
	[3.82]***			[-4.77]***		
POST		0.511			-0.002	
		[1.69]*			[-0.00]	
DURING&POST			1.539			-2.007
			[4.55]***			[-4.28]***
MD_RATING	-1.996	-1.518	-1.689	-0.868	-0.562	-0.762
	[-4.05]***	[-2.05]**	[-3.79]***	[-4.04]***	[-3.68]***	[-4.33]***
FT_RATING	-1.774	-0.576	-1.452	0.142	0.061	-0.271
	[-2.51]**	[-1.14]	[-2.54]**	[0.31]	[0.10]	[-0.68]
FIRM_SIZE	-0.101	-0.395	-0.115	0.349	0.802	0.283
	[-0.90]	[-2.54]**	[-1.08]	[1.57]	[2.60]***	[1.58]
FIRM_BTM	-0.000	0.015	0.000	0.002	-0.014	0.002
	[-0.24]	[3.67]***	[0.00]	[0.85]	[-1.88]*	[0.76]
FIRM_LEV	0.389	0.012	0.277	-0.571	-0.014	-0.437
	[1.14]	[0.02]	[1.03]	[-1.20]	[-0.01]	[-1.24]
FIRM_NEG_RE	0.472	-0.607	0.089	0.284	-0.018	-0.121
	[0.59]	[-0.96]	[0.13]	[0.29]	[-0.02]	[-0.13]
BOND_SIZE	0.044	-0.186	-0.026	0.486	0.363	0.377
	[0.35]	[-1.28]	[-0.22]	[3.25]***	[4.07]***	[2.84]***
BOND_CONV	0.206	0.575	0.147	-1.318	0.048	-0.173
	[0.70]	[1.79]*	[0.56]	[-2.39]**	[0.05]	[-0.34]
BOND_SS	0.804	0.608	0.038	-0.057	-0.503	0.623
	[2.15]**	[1.83]*	[0.12]	[-0.08]	[-0.59]	[1.15]
BOND_ENHANCE	0.040	-0.231	-0.012	1.662	2.658	1.443
	[0.14]	[-0.93]	[-0.06]	[1.35]	[2.21]**	[1.46]
BOND_PUT	-0.419	-0.655	-0.428	-0.752	-3.179	-1.704
	[-0.98]	[-1.44]	[-1.04]	[-0.95]	[-1.59]	[-1.54]
BOND_REDEEM	-0.384	0.008	-0.067	1.765	1.643	1.145
	[-1.84]*	[0.06]	[-0.33]	[2.36]**	[2.57]**	[2.43]**
BOND_MATURITY	0.007	0.004	0.020	0.292	0.555	0.347
	[0.09]	[0.05]	[0.29]	[1.71]*	[3.47]***	[1.70]*
MACRO_BOND30	-5.067	-2.394	-3.916	3.037	-2.535	1.841
	[-2.29]**	[-1.59]	[-2.85]***	[0.91]	[-1.30]	[1.04]
Industry Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	606	474	794	623	491	811
Adjusted R^2	0.359	0.256	0.275	0.341	0.376	0.307

TABLE 6: Tests of Credit Rating Levels

$RATING = \beta_1(DURING\ or\ POST\ or\ DURING\&POST) + \Sigma\beta_k CONTROLS + \Sigma\beta_k FIRM + \varepsilon.$

All tests comparing the before-crisis to during-crisis (post-crisis) period exclude observations in the post-crisis (during-crisis) period. The results below use an OLS model and include firm fixed effects; the standard set of controls used in tests of rating performance; and accounting-related controls for return on assets, capital intensity, interest coverage, an indicator for loss firms, ratio of cash flows from operations to debt, quick ratio, and current accruals. The fixed effects and additional accounting controls are untabulated. Standard errors are clustered by firm and industry-year-quarter. See Appendix A for variable definitions. *** indicates significance at 1%, ** at 5%, * at 10%.

	(i)	(ii)	(iii)	(iv)	(v)	(vi)
Sample	All Ratings	All Ratings	All Ratings	Announce.	Announce.	Announce.
DURING	-0.241			-0.239		
	[-4.27]***			[-2.08]**		
POST		-0.301			-0.076	
		[-3.43]***			[-0.84]	
DURING&POST			-0.293			-0.109
			[-4.26]***			[-1.22]
MD_RATING	-0.214	-0.243	-0.209	-0.257	-0.289	-0.270
	[-4.18]***	[-5.95]***	[-5.36]***	[-5.23]***	[-6.50]***	[-6.82]***
FT_RATING	0.132	0.062	0.080	0.290	0.171	0.213
	[2.34]**	[1.18]	[1.58]	[4.53]***	[3.07]***	[3.93]***
FIRM_SIZE	0.429	0.533	0.503	0.807	1.073	0.842
	[6.03]***	[7.48]***	[8.10]***	[9.32]***	[12.54]***	[10.73]***
FIRM_BTM	0.058	0.027	0.022	0.022	0.002	0.017
	[1.41]	[0.54]	[0.66]	[0.56]	[0.03]	[0.49]
FIRM_LEV	-1.388	-1.834	-1.922	-4.379	-2.917	-3.226
	[-2.36]**	[-3.45]***	[-4.42]***	[-5.50]***	[-4.63]***	[-5.60]***
FIRM_NEG_RE	-0.104	-0.357	-0.275	0.057	-0.018	-0.082
	[-0.84]	[-3.25]***	[-2.72]***	[0.23]	[-0.10]	[-0.49]
BOND_SIZE	-0.170	-0.151	-0.143	-0.034	-0.007	-0.003
	[-1.79]*	[-1.78]*	[-1.79]*	[-0.58]	[-0.15]	[-0.06]
BOND_CONV	-0.417	-0.477	-0.459	-0.406	-0.511	-0.490
	[-3.43]***	[-4.59]***	[-4.36]***	[-5.68]***	[-7.04]***	[-6.93]***
BOND_SS	0.744	0.932	0.878	1.103	1.524	1.454
	[2.59]**	[3.86]***	[3.64]***	[5.23]***	[7.94]***	[7.32]***
BOND_ENHANCE	0.598	0.381	0.437	0.349	0.134	0.243
	[2.73]***	[2.54]**	[2.95]***	[3.13]***	[2.39]**	[3.17]***
BOND_PUT	0.181	0.155	0.172	0.100	0.170	0.145
	[2.01]**	[2.02]**	[2.18]**	[1.78]*	[2.99]***	[2.70]***
BOND_REDEEM	0.034	0.001	-0.011	0.034	-0.046	-0.041
	[0.50]	[0.01]	[-0.10]	[0.62]	[-0.63]	[-0.68]
BOND_MATURITY	0.029	0.009	0.008	0.022	0.005	0.008
	[1.32]	[0.44]	[0.41]	[1.01]	[0.29]	[0.48]
MACRO_BOND30	0.326	0.020	0.014	0.807	0.119	0.310
	[2.46]**	[0.19]	[0.13]	[1.68]*	[0.61]	[1.73]*
Firm Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Extra Acct. Controls	Yes	Yes	Yes	Yes	Yes	Yes
Observations	70,206	94,348	119,793	34,827	44,474	57,110
Adjusted R^2	0.883	0.876	0.876	0.899	0.908	0.901

TABLE 7: Summary Information – Loan Contracting Samples

The sample consists of loans from DealScan initiated in 2004–2012. See Section 4 for discussion and Appendix A for variable definitions. Panel A details sample selection. Panel B presents sample averages.

Panel A: Sample selection

	Loans
US Loans; in USD; matched with GVKEY; nonfinancial firms	17,172
Drop: loans originated between July 2007 and June 2009	(2,814)
Drop: loans without spread, maturity, and amount data	(1,690)
Drop: loans without credit rating data	(4,889)
Drop: loans without sufficient Compustat data	(613)
Drop: similar facilities in the same loan package	(1,216)
Remaining Observations	5,950
Value-Relevance Test Sample	
Drop: firms without 1+ loan in each of the pre- and post-crisis periods	(1,928)
Final Sample	**4,022**
PPP Test Sample	
Drop: loans without PPP data	(3,178)
Drop: firms without 1+ loan in each of the pre- and post-crisis periods	(1,408)
Final Sample	**1,364**

Panel B: Sample averages

	Value-Relevance Tests	PPP Tests
POST	0.38	0.37
Ln(SPREAD)	4.96	Not Used
PP_RATING	Not Used	0.64
RATING	9.54	10.52
RELATION	0.63	0.64
INST_INVST	0.20	0.07
REVOLVER	0.67	0.82
SECURED	0.45	0.38
LOAN_SIZE	19.82	20.01
MATURITY	3.90	3.87
LENDERS	10.37	13.63
FIRM_SIZE	8.26	8.43
FIRM_ROA	0.03	0.04
FIRM_LEV	0.38	0.34
FIRM_CDS_AVAIL	0.37	0.42

Table 8: Debt Contracting Value-Relevance Tests

$Ln(SPREAD) = \beta_1 RATING + \beta_2 RATING*POST + \Sigma\beta_k CONTROLS + \Sigma_k FIRM + \Sigma_k QUARTER + \varepsilon.$

SPREAD is the loan contract interest rate spread at the time of issuance. *RATING* is the firm's credit rating. *POST* is an indicator variable for the post-crisis period. All other variables are detailed in Appendix A. Columns (i) and (ii) tabulate results without and with *CONTROLS*. Column (iii) adds additional untabulated regressors for *CONTROLS*POST*. Controls in the interactions are de-meaned so that the main effects can be interpreted at the sample averages. Standard errors are clustered by firm and year-month. *** indicates significant at 1%, ** at 5%, * at 10%.

		(i)	**(ii)**	**(iii)**
RATING	β_1	-0.15	-0.13	-0.12
		[-20.82]***	[-16.73]***	[-14.36]***
RATING * POST	β_2	0.10	0.10	0.08
		[20.75]***	[22.41]***	[12.37]***
RELATION	β_3		-0.04	-0.06
			[-2.84]***	[-2.95]***
INST_INVST	β_4		0.04	0.02
			[1.33]	[0.48]
REVOLVER	β_5		-0.22	-0.22
			[-8.80]***	[-6.41]***
SECURED	β_6		0.09	0.16
			[3.98]***	[5.04]***
LOAN_SIZE	β_7		-0.07	-0.10
			[-5.41]***	[-6.45]***
MATURITY	β_9		-0.01	0.01
			[-0.45]	[0.41]
LENDERS	β_{10}		-0.01	-0.01
			[-5.83]***	[-6.29]***
FIRM_SIZE	β_{11}		-0.03	-0.04
			[-1.34]	[-1.45]
FIRM_ROA	β_{12}		-0.46	-0.63
			[-3.39]***	[-3.14]***
FIRM_LEV	β_{13}		0.01	-0.02
			[0.14]	[-0.27]
FIRM_CDS_AVAIL	β_{14}		0.06	0.03
			[1.29]	[0.66]
Firm & Year-Quarter fixed effects		Yes	Yes	Yes
CONTROLS * POST interactions		No	No	Yes
N		4,022	4,022	4,022
Adjusted R^2		0.83	0.85	0.85

Table 9: Usage of Rating-Based Performance Pricing Provisions

$PP\_RATING = \beta_1 POST + \Sigma\beta_k CONTROLS + \Sigma\beta_k FIRM + \varepsilon.$

PP_RATING is an indicator variable equal to one if loan contract has a PPP based on a credit rating and zero otherwise. *POST* is an indicator variable for the post-crisis period. See Appendix A for other variable definitions. Columns (i) and (ii) tabulate results without and with *CONTROLS*. Column (iii) adds additional untabulated regressors for *CONTROLS*POST*. Controls in the interactions are de-meaned so that the main effects can be interpreted at the sample averages. The models are estimated using OLS. Standard errors are clustered by firm and year-month. *** indicates significant at 1%, ** at 5%, * at 10%.

		(i)	(ii)	(iii)
POST	β_1	-0.044	-0.033	-0.034
		[-3.11]***	[-2.08]**	[-2.11]**
RELATION	β_2		0.013	0.026
			[0.87]	[1.27]
INST_INVST	β_3		0.062	0.016
			[1.16]	[0.28]
REVOLVER	β_4		-0.023	-0.030
			[-0.83]	[-0.95]
SECURED	β_5		-0.243	-0.245
			[-5.30]***	[-4.39]***
LOAN_SIZE	β_6		0.007	0.014
			[0.64]	[1.18]
MATURITY	β_7		-0.014	-0.003
			[-0.97]	[-0.18]
LENDERS	β_8		0.003	0.003
			[2.26]**	[2.15]**
FIRM_SIZE	β_9		0.010	-0.003
			[0.38]	[-0.10]
FIRM_ROA	β_{10}		0.053	0.141
			[0.33]	[0.69]
FIRM_LEV	β_{11}		0.190	0.257
			[2.65]***	[2.55]**
FIRM_CDS_AVAIL	β_{12}		-0.033	-0.011
			[-0.69]	[-0.22]
RATING	β_{13}		0.033	0.032
			[3.37]***	[3.45]***
Firm fixed effects		Yes	Yes	Yes
CONTROLS * POST interactions		No	No	Yes
N		1,364	1,364	1,364
Adjusted or Pseudo R^2		0.783	0.820	0.821

Table 10: Does Rating Usage Begin to Recover?

Column (i) in each Panel re-tabulates the main results from Tables 8 and 9. Column (ii) adds *POST2* and *RATING*POST2* interactions. *POST2* is an indicator that takes the value of one for the period starting July 2011. All other variables and specifications are unchanged, but controls are untabulated for brevity. *** indicates significant at 1%, ** at 5%, * at 10%.

Panel A: Debt contracting value-relevance tests (partial results reported)

		(i) (as in Table 8)	**(ii) (modified)**
RATING	β_1	-0.12	-0.12
		[-14.36]***	[-14.31]***
RATING * POST	β_2	0.08	0.09
		[12.37]***	[11.76]***
RATING * POST2	β_3		-0.02
			[-2.43]**
CONTROLS and fixed effects		Yes	Yes
CONTROLS * POST interactions		Yes	Yes
N		4,022	4,022
Adjusted R^2		0.85	0.85

Panel B: Debt contracting rating-usage tests (partial results reported)

		(i) (as in Table 9)	**(ii) (modified)**
POST	β_1	-0.034	-0.043
		[-2.11]**	[-2.55]**
POST2	β_2		0.027
			[1.31]
CONTROLS and fixed effects		Yes	Yes
CONTROLS * POST interactions		Yes	Yes
N		1,364	1,364
Adjusted R^2		0.821	0.821

Table 11: Decline in Rating Usage – Fitch versus S&P and Moody's

This table includes partial results of debt contract value-relevance tests comparing ratings from Fitch versus ratings from S&P and Moody's. *RATING_SP/Moody* is the most recent rating from S&P or Moody's assigned before the contract date. *RATING_Fitch* is the most recent rating from Fitch. All other variables and specifications are unchanged from Table 8, but controls are untabulated for brevity. *** indicates significant at 1%, ** at 5%, * at 10%.

		(i)	(ii)
RATING_SP/Moody	β_1	-0.128 [-10.48]***	-0.102 [-8.25]***
RATING_Fitch	β_2	-0.037 [-3.74]***	-0.034 [-3.54]***
RATING_SP/Moody * POST	β_3	0.084 [6.17]***	0.078 [5.43]***
RATING_Fitch * POST	β_4	0.029 [2.66]***	0.030 [2.55]**
Fixed Effects		Yes	Yes
CONTROLS		No	Yes
N		1,447	1,447
Adjusted R^2		0.840	0.861
Difference-in-differences	$\beta_4 - \beta_3$	-0.055 [2.37]**	-0.048 [1.94]*