The Financial Crisis and Credibility of Corporate Credit Ratings[☆]

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3 January 2013

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Abstract

Credit ratings on certain structured finance products significantly underestimated default risk prior to the recent financial crisis. Rating agency executives acknowledge that these failures damaged the agencies' credibility with respect to credit ratings on structured finance products. I investigate whether the agencies' credibility with respect to *corporate* credit ratings also suffers as a result of the financial crisis. I document a decline in the information content of corporate credit rating changes from mid-2007 onward, accompanied by a decline in the relevance of credit ratings for debt price levels. At the same time, there is a significant increase in the information content of quarterly earnings releases. These findings are consistent with market participants placing less (more) weight on corporate ratings (accounting information) in debt pricing as corporate credit ratings are viewed as less credible in the post-crisis period. Additional tests are consistent with corporate ratings being viewed as optimistically biased as opposed to simply inaccurate. Most directly, my study provides insight as to the credibility effects of the financial crisis on the credit rating agencies. More broadly, my findings provide new empirical evidence on the relation between credit rating credibility and usage, and also inform the literature about the substitutability between corporate credit ratings and accounting information in debt pricing.

[☆] I thank my dissertation chairpersons, Terry Shevlin and Mark Soliman, for their guidance and mentorship. I also appreciate the support of my other committee members, Bob Bowen, Adam Kolasinski, Dawn Matsumoto, and Ed Rice. Additional thanks to Darren Bernard, Brad Blaylock, Asher Curtis, Kristina Demek, Alex Edwards, Jared Jennings, Semi Kedia, Jennifer Koski, Todd Kravet, Sarah McVay, Shiva Rajgopal, Naomi Soderstrom (discussant), Lloyd Tanlu, Jake Thornock, and workshop participants at the University of Washington, 2012 Western AAA, 2012 AFAANZ Doctoral Symposium, and 2012 UBCOW conference. I acknowledge financial support from the Foster School of Business and the CalCPA Education Foundation. Credit ratings data were kindly provided by Standard & Poor's. Thanks to CMA for generous assistance with their CDS data. A previous version of this paper was awarded Best PhD Paper at the 2012 AAA Western Regional Meeting. Email correspondence: edehaan@uw.edu.

1. Introduction

In July of 2007, the major U.S. credit rating agencies began downgrading $1.9 trillion of structured finance products (e.g., collateralized debt obligations) all the way from AAA to junk status – a set of actions that in large part triggered the ensuing financial crisis (White 2010; U.S. Senate 2011).[1] Regulators, academics, and credit rating agency ("CRA") executives agree that credit ratings on certain structured finance products failed to accurately portray default risk prior to the financial crisis (Benmelech and Dlugosz 2009; Ashcraft et al. 2010; White 2010; Standard & Poor's 2010a; U.S. Senate 2011). Further, in Congressional testimonies, chief officers at all three major U.S. CRAs noted that these rating failures caused them serious credibility damage with respect to their ratings on financial products (U.S. Congress 2008). It is unclear, however, whether the failure of ratings on *structured finance products* also damaged the CRAs' credibility with respect to *corporate* credit ratings. CRA executives argue that the failure of ratings on structured finance products was an isolated set of events caused by uncertainty and inexperience with new financial instruments, in which case the credibility of corporate credit ratings should be untainted. In contrast, critics argue that the financial crisis exposed broad dysfunction in the rating industry that undermines the quality and credibility of all types of credit ratings (U.S. Congress 2008; U.S. Senate 2011). In this paper, I investigate the effects of the financial crisis on the major U.S. CRAs' credibility with respect to corporate credit ratings, as well as how credibility damage alters the use of both corporate credit ratings and accounting information in debt pricing.

Credit ratings are intended to provide a relative ranking of default risk at a given point in time (Altman and Rijken 2004). The "quality" of a credit rating is an increasing function of its accuracy and timeliness in representing relative default risk.[2] Credibility, defined as market participants' expectations about rating quality, plays a critical role in the rating industry for several reasons. First, an ex ante evaluation of credit rating quality is difficult because the CRAs use private

[1] In a normal year, the prevalence rate of downgrades from AAA to junk status is below 1%, if any occur at all (Standard & Poor's 2012). Over 80% of collateralized debt obligations were downgraded from AAA to junk status during the financial crisis (White 2010).
[2] "Accuracy" is the extent to which credit ratings represent default risk. "Timeliness" is the speed with which credit ratings are updated in relation to changes in underlying default risk. Section 2.1 further discusses the purpose and uses of credit ratings.

information from managers in forming rating opinions (the CRAs are not affected by Regulation FD). As with any product where quality is unobservable ex ante, consumer demand is based on prior experience with the seller (Nelson 1970). Second, ex post assessments of rating quality are also difficult because actual defaults are rare, idiosyncratic, and also endogenous to rating downgrades. Thus, credibility in the credit rating industry can take many years to develop (White 2001). Third, the major CRAs' "issuer pays" business model creates a potential conflict of interests whereby the CRAs have incentive to provide low-quality ratings. Fourth, the rating industry is an oligopoly and, therefore, the CRAs need not necessarily compete based on rating quality. Fifth and finally, the courts have held that credit ratings are protected under the first amendment, and therefore, the CRAs have been largely immune from civil litigation over rating failures (Mathis et al. 2009; White 2001, 2010; Bolton et al. 2012; Schwarcz 2002; Ashcraft and Schuermann 2008; U.S. Senate 2011). For these reasons, a market participant's decision about how much to rely on credit ratings in debt pricing is largely based on his *expectations* of rating quality. Said differently, *credibility* is a significant determinant of the demand for, and usage of, credit ratings.[3]

My empirical analysis is based on a maintained assumption that market participants discount low-credibility information in debt pricing decisions. Holthausen and Verrecchia (1988) formalize this intuition in a Bayesian updating model in which market participants assign weights to competing information sources based on expectations about the quality of each data item. Belief revision, and therefore price revision, to a data release depends on the credibility of the new signal relative to all other signals. This theory has been used extensively in the accounting literature as a basis for using price response tests to empirically assess the credibility of accounting reports (Francis et al. 2005; deHaan et al. 2012), management forecasts (Pownall and Waymire 1989; Rogers and Stocken 2005), and equity analyst recommendations (Michaely and Womack 1999; Lin and McNichols 1998).

[3] The credit rating and game theory literatures often uses the term "reputation" to refer to market participants' expectations about rating quality (e.g., White 2001, 2010; Bolton et al. 2012; Mathis et al. 2009; Cheng and Neamtiu 2009; Shapiro 1982, 1983). The accounting and analyst disclosure literatures often use the term "credibility" to refer to the largely synonymous construct of market participants' expectations about information quality (e.g., Pownall and Waymire 1989; Michaely and Womack 1999; Stocken 2000; Francis et al. 2005; Healy and Palelu 2001; Rogers and Stocken 2005). I use the term "credibility" to be consistent with the bulk of the accounting literature, and also to avoid confusion with other definitions of "reputation" used in the consumer and investor psychology literatures.

Consistent with the theory of Holthausen and Verrecchia (1988), a reduction in the credibility of corporate credit ratings after the crisis should alter the relations between corporate ratings and observed debt prices in two ways. First, the information content of corporate rating *changes* for debt prices should decline as market participants reduce the weight placed on credit rating signals. Second, as market participants reduce the weight placed on corporate credit ratings, greater weight will be placed on alternate information in debt pricing. As long as the credit ratings and alternate information do not provide identical signals about default risk, the strength of the relation between corporate ratings and debt price *levels* should also weaken in the post-crisis period. I refer to the strength of the relation between credit rating levels and debt price levels as the "relevance" of corporate credit ratings for debt prices.

I use credit default swap ("CDS") spreads as a liquid measure of debt prices.[4] Univariate and regression analyses indicate that the average information content of corporate credit rating letter changes (e.g., from AAA to AA+) among non-financial firms decreases by up to 46% in the post-crisis period starting in July 2007.[5] The average information content of credit rating status changes (e.g., from neutral to negative outlook) decreases by up to 58%. Similar results are observed for an "uncontaminated" subsample that excludes observations with simultaneous earnings releases, management forecasts, or equity analyst forecast revisions. Although attenuated, debt price responses around all types of rating changes remain statistically significant in the post-crisis period. Thus, the information content tests are consistent with the CRAs suffering partial, but not absolute, loss of credibility with respect to corporate ratings as a result of the financial crisis.

I test for changes in the relevance of corporate credit ratings for debt price levels in two ways. First, the data show that the variance of CDS spreads within each credit rating level (e.g., AAA, AA+, etc.) increases by an average of 336% (median of 209%) after the financial crisis. An increase in intra-rating price variance is consistent with market participants putting less weight on rating signals

[4] Credit default swaps are similar to insurance contracts that pay in the event of a default. CDS spreads (a.k.a. "premiums" or "prices") are used as an empirical proxy for cost of debt. Further detail of CDS and the advantages of using CDS spreads over bond prices are discussed in Section 3.1.
[5] As discussed in Section 3, I exclude financial services corporations in my main analysis, primarily because the U.S. Troubled Asset Relief Program obscured the relations between firms' financial positions and probabilities of default during the crisis. However, untabulated results including financial services firms are generally unchanged.

in debt pricing. Second, I assess relevance based on the frequency of firms with "discordant" and "extreme discordant" credit ratings relative to observed CDS spreads. Figure 1 illustrates "discordant" and "extreme discordant" observations. If credit ratings serve their intended purpose of providing a relative ordering of default risk, ordinal rankings of credit ratings and observed debt prices among firms should be inverse but identical. For example, all firms with a AAA credit rating should have cheaper CDS spreads than all firms with a AA+ rating (the next highest rating level). I define a "discordant" observation as when firm *i* has a higher (i.e., safer) rating than firm *j* but also has a higher (i.e., *more* costly) CDS spread than the minimum CDS among firms with the same rating as firm *j*, and vice versa. An "extreme discordant" observation is when firm *i* has a higher (i.e., safer) rating than firm *j* while also having a CDS spread that is higher (i.e., more costly) than the *median* of all firms with firm *j*'s rating level. The prevalence of discordant and extreme discordant observations increases by an average of 32% and 70.4%, respectively, after the financial crisis. Together with the analysis of intra-rating CDS spread variances, these results are consistent with a decline in the relevance of corporate ratings for debt price levels, and with the CRAs suffering credibility damage with respect to corporate credit ratings as a result of the financial crisis.

My next analysis provides insight as to whether the financial crisis causes market participants to view credit ratings as optimistically biased versus simply of low quality. If ratings are thought to be optimistic, there should be an upward correction of debt prices upon this revelation in the post-crisis period. The data are consistent with this prediction; within each credit rating level, CDS spreads are an average of 227% (median of 161%) higher after than before the crisis.

Finally, I examine the theory that market participants increase their reliance on substitute data as they decrease their reliance on less-credible credit ratings after the crisis. Prior literature has shown that corporate credit ratings are substantially based on accounting fundamentals (e.g., Horrigan 1966, among many others). Also, the private information revealed in accounting reports is potentially impounded in credit ratings before its public release. Thus, if market participants no longer view corporate ratings as being credible after the crisis, it is logical that they will "go to the source" and increase their use of accounting reports. Consistent with this prediction, there is a 19% to

34% increase in the information content of unexpected earnings for CDS spreads between the pre- and post-crisis periods. These results are again consistent with the CRAs suffering credibility damage, and with accounting reports becoming more informative for debt prices during periods when corporate ratings are viewed as less credible.[6]

My study's most direct contribution is to provide evidence on whether the failure of credit ratings on structured finance products damaged the CRAs' credibility with respect to corporate credit ratings. Finding evidence consistent with credibility damage indicates that market participants viewed the failures of ratings on structured finance products not as anomalous events, but rather as symptomatic of broader problems in the credit rating industry.[7] Still, the data are consistent with market participants continuing to use corporate ratings in debt pricing after the crisis (although to a lesser degree), which indicates that the credibility damage is not absolute. Given the central role that the CRAs played in the financial crisis, it is useful to understand market participants' collective opinion about the quality of corporate credit ratings. This study also complements the growing body of literature that examines the operations of capital markets during the turbulent financial crisis years.

My study also has several broader implications that extend beyond the specific context of the financial crisis. First, I contribute to the literature studying the role of credibility in the use of credit ratings by debt market participants. Starting with Katz (1974), there is a long line of research examining the use of corporate ratings in debt markets. Numerous authors within the credit rating literature discuss how credibility (or "reputation," as it is often labeled) is a necessary condition for market participants to use credit ratings; indeed, credibility is often cited as the critical factor that maintains integrity in the CRAs' oligopolistic and issuer-pays business model (see Partnoy 1999 for a discussion). To date, however, there have been few opportunities to examine a well-defined shock to CRA credibility. Observing that there are predictable changes in debt market participants' reliance

[6] The accounting information content tests control for losses and other known determinants. Results are qualitatively unchanged when the information content tests are run separately for positive and negative earnings.

[7] Han et al. (2012) also provide some evidence that could be consistent with credibility damage by showing that yields on Japanese bonds that are rated by S&P and Moody's increase relative to similar Japanese bonds that are rated only by Japanese CRAs. However, evaluating differences in yield means is problematic because the CRAs do not intend for the relation between default risk and credit rating levels to be constant across time, nor do they necessarily attempt to maintain the comparability of their ratings with other CRAs (especially between U.S. and non-U.S. CRAs).

on credit ratings after the crisis provides new empirical evidence to support the often-discussed relation between rating credibility and usage.

Finally, I build on the literatures examining the use of *accounting information* by debt market participants and the substitutability between accounting information and credit ratings. Numerous authors have found that, on average, accounting data are informative for debt prices (see Callen et al. 2009 and Batta et al. 2012 for recent examples in CDS markets). To my knowledge, I am the first to predict and demonstrate temporal variation in the use of accounting reports by debt market participants depending on the strength of the overall debt market information environment (e.g., when credit ratings are less credible). Also, although prior studies have documented that accounting data are used as substitutes for credit ratings in contracting (Asquith et al. 2005; Bhanot and Mello 2006), I provide initial evidence on the substitability between accounting data and credit ratings in debt pricing. Together, these results provide new insights about how and when market participants use accounting information in debt pricing decisions.

2. Hypothesis Development

2.1. Credit ratings and the role of CRA credibility in debt pricing

Standard & Poors ("S&P") describes their issuer credit ratings as "a forward-looking opinion about an obligor's overall financial capacity (its creditworthiness) to pay its financial obligations" (Standard & Poor's 2010c). In short, credit ratings are intended to be a summary measure of default risk. The "quality" of a credit rating is an increasing function of the rating's accuracy and timeliness in measuring default risk. The largest CRAs operate on an "issuer-pays" model whereby firms pay the CRAs to consider both private and public information in forming rating opinions (no payment is required for "unsolicited" credit ratings that consider only public information). The CRA industry is an oligopoly in that the SEC has certified ratings from only a select few agencies for use by regulated financial institutions.[8] During 2010, three U.S. CRAs, Standard & Poor's, Moody's, and Fitch, comprised over 97% of the regulated credit rating industry market share (S.E.C. 2011).[9]

[8] White (2010) notes that economies of scale and importance of reputation capital (a.k.a., credibility) in the CRA industry create natural barriers to entry that would likely result in an oligopoly regardless of regulatory intervention.
[9] Through 2003, Moody's, Standard & Poor's, and Fitch were the only Nationally Recognized Statistical Rating Organizations ("NRSROs"). Seven more CRAs were certified in the mid-2000's, although only one, Egan Jones,

A long-term corporate credit rating consists of two components. The first is based on an ordinal list of roughly 20 levels designated by letter, number, and/or "+" or "-" combinations (e.g., CCC-, BB+, or Ba2). The second component is a "status" modifier that signals a potentially forthcoming rating change (e.g., positive or negative "watch," "outlook," or "review" status). A given rating is intended to represent the same default risk across sectors and regions. However, the major U.S. CRAs allow themselves some flexibility regarding whether ratings represent the same default risk across time (Ashcraft et al. 2010; Standard & Poor's 2011b). The major U.S. agencies follow a "through the business cycle" approach to ratings whereby short-term changes in credit risk are given little weighting (Altman and Rijken 2004). Further, as ratings are intended to be relative rather than absolute measures of default risk, macroeconomic events affecting all firms will not necessarily motivate rating changes as long as the relative ordering of default risk among firms is unchanged (Amato and Furfine 2004).

As discussed by Holthausen and Leftwich (1986), the information contained in credit ratings arises from two sources. First, CRAs are specialists that are able to process data at a lower cost than other market participants. Under this view, CRAs have the potential to increase pricing efficiency by serving as a market intermediary and reducing the need for lenders to undertake costly, independent research. Second, CRAs are not subject to Regulation FD and are usually given access to private information that is not available to other market participants.[10] Jorion et al. (2005) find evidence consistent with this view by demonstrating that equity price responses around credit rating

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actively rates U.S. non-financial corporations (S.E.C. 2011). I do not include Egan Jones in my sample primarily because: (i) Egan Jones ratings serve a fundamentally different purpose than ratings from the major U.S. CRAs; (ii) Egan Jones does not rate structured finance products and operates on an investor-pays business model, so likely has different incentives relating to rating quality; and (iii) Egan Jones received NRSRO status in 2007, and certification plausibly altered the content and usage of its ratings (Beaver et al. 2006). Thus, it is likely that the results of this study do not generalize to smaller CRAs. For these same reasons, Egan Jones ratings are unsuitable control group for difference-in-differences analysis; that is, Egan Jones ratings would likely not satisfy the "parallel trends" assumption necessary for such analysis. See discussion below about using accounting reports as a benchmark for the use of debt-relevant information in debt pricing before/after the crisis.

[10] The CRAs were explicitly exempt from Regulation FD upon its initial adoption. The Dodd-Frank Act eliminated this exemption in October 2010. However, the CRAs argue that, as they do not trade or recommend trades based on private information, they are not subject to Regulation FD with or without the explicit exemption (Gibson Dunn & Crutcher, 2010). To date, there is no indication that the SEC disagrees with the CRAs position.

announcements increase following Regulation FD; a result they attribute to an increase in the amount of private information available to CRAs relative to other market participants.

The CRAs' access to private information makes it difficult to ex ante evaluate the quality of credit ratings in relation to actual default risk. For instance, if a third party attempts to gauge rating quality via an independent default risk assessment, it will be unclear whether any deviation between their assessment and the CRA's rating is due to a CRA's private information or to differences in the interpretation of common information. As such, a debt market participant's decision about how much weight to place on credit rating signals is largely based on his *expectations* of rating quality; that is, rating "credibility." The infrequency and heterogeneity of actual defaults as well as endogeneity between rating downgrades and defaults also obfuscates ex post assessment, which means that credibility in the rating industry takes many years to develop.[11]

2.2. The financial crisis and credibility of corporate credit ratings

There is little debate that credit ratings on structured finance products drastically underestimated default risk prior to the financial crisis (Benmelech and Dlugosz 2009; Ashcrat et al. 2010; White 2010; Standard & Poor's 2010a; U.S. Congress 2008; U.S. Senate 2011). For example, 80% of all of the collateralized debt obligations that were issued with an AAA rating prior to the financial crisis had been downgraded to junk status by July of 2009; in a normal year, the prevalence of such large downgrades is well below 1% (Standard & Poor's 2012). A Moody's managing director described the effects of these downgrades as follows: "In short order, faith in credit ratings [on certain structured finance products] diminished to the point where financial institutions were unwilling to lend to one another. And so we had and are still having a credit crisis" (U.S. Congress 2008, p21). In Congressional testimonies, the chief officers at all three major U.S. CRAs attested to the statement that "incredible failures" had "screwed up the ratings [on structured finance products] so as not to be believable anymore" (U.S. Congress 2008, p188 - 189). It is unclear, however,

[11] For instance, if a firm with the lowest possible rating does not default, it is unclear whether the lack of default is because the firm's condition improved or because the rating was overly pessimistic. The accuracy of ratings for highly rated firms is even more difficult to judge as the default rate among investment-grade corporations is historically lower than 0.15% (Standard & Poor's 2010a). Ratings and defaults are endogenous as downgrading a firm to near-default status increases their costs of transacting with capital markets, suppliers, and customers, thereby pushing the firm closer to default.

whether the failures of ratings on structured finance products also damaged the CRAs' credibility with respect to corporate credit ratings. In the following paragraphs, I discuss arguments both for and against market participants lowering their expectations about the quality of corporate ratings after the crisis.

Regulators and CRA critics argue that the crisis exposed a dysfunctional credit rating industry that had neither the incentive nor ability to produce high quality credit ratings for corporations, structured finance products, or any other type of entity. In 2008, Congressman Shay of the U.S. House Committee on Oversight and Government Reform summarized the views of many regulators: "they have no brand, they have no credibility whatsoever. I can't imagine any investor trusting them" (U.S. Congress 2008, p102). A 2011 U.S. Senate Report and related Congressional Hearings Transcripts (2008) identify a number of causes for the failures of ratings on structured finance products, many of which plausibly also affected the quality of corporate credit ratings. First, the reports present evidence that CRA senior executives were aware of the inflated ratings for at least six months before taking downgrade action – these same individuals were managing the corporate ratings line of business. Second, the reports criticize the inherent conflict of interest in the CRAs' "issuer pays" business model, which led to a "race to the bottom" as "agencies weakened their standards as each competed to provide the most favorable rating to win business and greater market share" (U.S. Senate 2011, p7). Additional contributing factors identified by the reports include inadequate staffing and resources, lax standards, incentive compensation tied to rating quantity over quality, oligopoly power, and a prevailing culture that valued profit over integrity.

Recent academic studies also provide reasons to expect that the problems that led to the failure of ratings on structured finance products likely also affected corporate ratings. Becker and Milbourn (2011) find evidence consistent with increased competition from Fitch in the 1990s and early 2000s resulting in lower quality corporate credit ratings. Seven new CRAs gained certification between 2003 and 2008 and, although their market share is still minute (S.E.C. 2011), the threat of increased competition plausibly lead to declines in the quality of ratings on both structured finance products and corporations. Other studies by Griffin and Tang (2011) and Ashcraft et al. (2010) find evidence consistent with the CRAs intentionally ignoring evidence that their ratings on structured finance products were overstated. If CRA senior management were willing to act negligently or even fraudulently with respect to structured finance products, it is likely that those same senior managers would allow for poor quality ratings on corporations.

To the contrary, CRA executives argue that the failure of ratings on structured finance products was an isolated set of events that is unrelated to the quality of their ratings on corporations (U.S. Congress 2008). The CRA executives' primary argument supporting this position is that their ratings on structured finance products were as accurate as possible given an extremely uncertain information environment. They contend that the post-crisis failure rates among mortgage-backed securities and collateralized debt obligations could not have been predicted. CRA management also point out that the financial firms that simultaneously created and purchased these securities also underestimated their risk, as evidenced by the losses these firms incurred as the financial crisis developed. Finally, the CRAs argue that they had limited experience with providing ratings on the types of products that failed during the financial crisis, whereas they have over 100 years of experience in rating corporations. In sum, the CRAs argue that: (i) no bias or malicious intent was involved with their ratings on structured finance products; and (ii) the rating failures were due to a lack of experience with complex new instruments (U.S. Congress 2008).

As discussed by Hunt (2009) and Ashcraft and Schuermann (2008), it is difficult to draw meaningful inferences about rating quality by studying defaults or rating change frequencies. Still, early ex post evidence provides some indication that credit ratings on corporations were likely not as flawed as those on certain structured finance products. For instance, although the default rate among investment-grade non-financial corporations hit a record high of 0.73% in 2008, this rate is far below the roughly 10% default rate among investment-grade collateralized debt obligations. Also, fewer than 1% of AAA non-financial corporate ratings were downgraded to junk status during 2008-2009, whereas roughly 80% of collateralized debt obligations experienced such a decline (Standard & Poor's 2010a; White 2010). These data must be interpreted with caution as: (i) the investment-grade default rate can be manipulated by the CRAs   downgrading firms to junk status just before the default takes place (but after a forthcoming default is common knowledge), and/or (ii) the absence of large downgrades can also be indicative a large number of over-stated ratings. Several more years of data will be necessary to reasonably evaluate the actual accuracy and timeliness of corporate ratings in predicting defaults before and after the crisis.

2.3. Corporate rating credibility and debt market prices

If market participants share regulators' views that the failures of ratings on structured finance products were symptomatic of broader problems in the credit rating industry, then I expect a decline in the credibility of corporate credit ratings after the financial crisis. Debt market participants discount corporate credit ratings in the post-crisis period and, in turn, I expect to observe less belief revision around rating change announcements. That is, I expect to observe a decrease in the information content of credit rating changes for debt prices (Holthausen and Verrecchia 1988). If, instead, debt market participants view the failure of ratings on structured finance products as anomalous, then I expect no credibility damage and no change in the information content of corporate ratings.[12] Hypothesis 1 in the alternate form:

H1: The information content of corporate credit rating changes for debt prices decreases after the financial crisis.

If credibility damage motivates market participants to decrease their reliance on corporate credit ratings in debt pricing, I expect that they also increase their reliance on alternate data via two mechanisms. First, within a fixed information set, a decrease in the weight placed on credit ratings implicitly increases the *relative* weights placed on select non-rating data (Holthausen and Verrecchia 1988). The second mechanism relates to the role of CRAs as market intermediaries. One reason intermediaries exist is that it is more efficient to centralize data aggregation and assessment with a specialist than it is for each market participant to engage in independent research. As the credibility of an intermediary's research declines, market participants will likely increase their expenditure on performing independent analysis. This analysis will involve increased efforts to extract and analyze

[12] A third possible outcome is that the CRAs did experience credibility damage but were somehow able to immediately and credibly communicate an improvement in rating quality after the crisis. This third outcome is unlikely given the preceding discussion about how CRA credibility is slow to develop, but rapid credibility repair would likely result in no change in rating information content in the post-crisis period.

data from substitute information sources that contain the debt-relevant information previously obtained from credit ratings. As long as the credit rating and substitute information sources do not provide identical signals about default risk, the association between credit ratings and debt price levels will weaken in the post-crisis period. Said differently, the relevance of corporate ratings for observed market prices will decline. Hypothesis 2 in the alternate form is as follows:

H2: The relevance of corporate credit ratings for debt price levels decreases after the financial crisis.

Finally, if the financial crisis causes debt market participants to view corporate ratings as optimistically biased (as opposed to simply inaccurate), there should be an upward correction of debt prices upon this revelation after the crisis. For instance, within a given credit rating level (e.g., AA+), the average debt price will increase between the pre- and post-crisis periods. If the financial crisis causes market participants to view corporate ratings as simply noisy, there should be no change in the average debt price but rather an increase in the variance of debt prices within each rating level. It is important to note that, as credit ratings are intended to be relative rather than absolute measures of default risk, observing an intra-rating increase in debt prices unto itself is not conclusive evidence of revealed a optimistic bias. An increase in intra-rating prices could also be explained by a macroeconomic increase in default risk. Still, such evidence is useful in consideration with H1 and H2. Hypothesis 3 in the alternate form is as follows:

H3: Within each credit rating level, the average debt price increases after the financial crisis.

2.4. Benchmarking against the information content of accounting reports

In motivating H1 and H2, I note that a decline in the credibility of corporate credit ratings will not only cause market participants to decrease the weight placed on credit ratings, but it will also cause them to increase the weight placed on alternate information in debt pricing. There are several reasons to expect that accounting reports are a logical choice for such substitute information. First, prior research has demonstrated that credit ratings are substantially based on accounting data (e.g., Horrigan 1966). For instance, as discussed further below, an ordered logit regression of credit rating levels on accounting fundamentals in my sample yields a pseudo R-squared of roughly 63%. Second, many researchers have demonstrated that accounting reports contain timely information for debt pricing. Third, there is evidence that accounting data are a substitute for credit ratings in debt contracting (Asquith et al. 2005; Bhanot and Mello 2006). Finally, the private information revealed in accounting reports is potentially available to the CRAs ex ante but not to other market participants. Thus, if market participants no longer trust credit ratings they will likely "go to the source" and rely more on the accounting reports themselves. Hypothesis 4 in the alternate form is as follows:

H4: The information content of quarterly accounting reports for debt prices increases after the financial crisis.

Observing an increase in the information content of accounting reports also decreases concerns about three alternate explanations for observing a decline in the information content of credit rating changes after the crisis. The first alternate explanation is that debt prices respond less to all information events in the post-crisis period. This explanation is unlikely as Stulz's (2010) assessment of the financial crisis concludes "the credit default swap market worked remarkably well during much of the crisis" (p79). Further, Shivakumar et al. (2011), among others, find that debt markets respond as expected to non-rating information events during the post-crisis period. Still, demonstrating an increase in the price responses to accounting releases further reduces the likelihood of this alternate explanation.

The second alternate explanation is that a decline in the price reactions to rating changes could be due to the CRAs lowering the threshold by which default risk must change before updating a credit rating. For example, consider the case where the CRAs required that default risk must change by X amount before updating a rating in the pre-crisis period, but after the crisis the threshold is lowered to $X/2$. Ceteris paribus, each post-crisis rating change will contain half the information as did the pre-crisis changes. However, the ratings will actually be timelier and, therefore, of *higher* quality. This alternate explanation is inconsistent with observing a decline in the relevance of credit ratings for debt price levels, as predicted by H2, because a higher-quality rating should have a stronger, not weaker, association with debt price levels. Still, if ratings do become timelier after the crisis, then the information content of accounting reports should simultaneously decline as: (i) more news is usurped by credit ratings, and (ii) market participants decrease the weight placed on accounting reports relative to the now higher-quality ratings. Thus, observing an increase in the information content of accounting reports would further reduce the likelihood that ratings become timelier after the crisis.

A third alternate explanation is that, even though CRA credibility is undamaged, market participants simply demand timelier information after the crisis. If market participants demand timelier information, it is unlikely that they will increase their use of quarterly accounting reports. By definition, quarterly accounting reports are released on a quarterly basis and are unlikely to be the timeliest source of news about recent changes in default risk. Rather, to obtain timelier information market participants will likely increase their reliance on information from other intermediaries or on voluntary firm disclosures. Consistent with this notion, Shivakumar et al. (2011) find that the information content of management forecasts increases after the crisis (the authors specifically focus on forecasts that do not coincide with an earnings release).

3. Data and Sample Selection

My sample period spans January 2004 through December 2010.[13] I use July of 2007 to define the pre- and post-crisis periods as a U.S. Senate (2011) report concludes "the most immediate trigger to the financial crisis was the July 2007 decision by Moody's and S&P to downgrade hundreds of RMBS and CDO securities" (p45).

3.1. Debt market data

I use credit default swap ("CDS") spreads as a measure of debt prices. CDS are akin to insurance contracts against the default of a reference entity. A CDS buyer makes quarterly premium payments to a CDS seller. In the event of default, the buyer typically receives a settlement equal to the difference between the par and market values of the reference entity's debt. CDS are traded over-the-counter with premiums (a.k.a., "spreads" or "prices") expressed in basis points per annum.

CDS spreads have a number of advantages over using bond yields as an empirical measure of debt prices. First and foremost, CDS are more liquid than bonds for many reference entities, which allows for short-window price change studies that are often impractical using illiquid bond data.

[13] These are the earliest and latest dates covered in my CDS dataset.

Blanco et al. (2005), among others, find that CDS spreads lead bond interest rates in price discovery. Second, CDS contracts are highly standardized and not tied to a specific debt issue, whereas bond contracts often involve heterogeneous covenants, terms, and provisions.[14] Finally, unlike bond yields, it is not necessary to deduct an estimated risk-free rate from CDS spreads to measure idiosyncratic default risk (CDS do not involve an upfront redeemable payment, and thus do not require a minimum risk-free rate of return). A limitation of using CDS spreads is that the data are available for a smaller number of firms than are bond yield data.

CDS data are obtained from Credit Market Analysis Limited ("CMA") and consist of end-of-day average buy and sell quotes from 40 investment banks, hedge funds, and asset managers. CMA uses automated and manual controls to eliminate outlier and stale quotes from their end-of-day aggregations.[15] Still, a concern in using CDS quote data is that the quotes may not be representative of actual trade spreads in periods of low liquidity (Lok and Richardson 2011). I take two additional steps to reduce the risk that non-representative quotes bias my findings. First, I limit my sample to five-year, senior CDS contracts as these are the most frequently traded (Zhang et al. 2009). Second, I eliminate all daily CDS observations that are based on fewer than two independent buy quotes.[16]

3.2. Credit ratings data

Standard & Poor's kindly provided data of firm-level credit ratings, including both changes in letter rating levels (e.g., AAA, AA+, etc.) as well as changes in rating outlook and watch statuses (hereafter collectively referred to as "status changes"). Foreign firms are excluded from my sample, as are firms already in default. I also exclude financial services firms, primarily because the U.S. Troubled Asset Relief Program obscured the relations between firms' financial positions and default risk during the financial crisis. However, untabulated analysis including financial services firms produces similar results.

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[14] To eliminate the need for frequent and duplicative contracting, CDS traders typically employ standard contracts as per the Institutional Swaps and Derivatives Association "Master Agreement."

[15] CMA's CDS data are available directly from CMA or via Datastream. Datastream's version of the data is not consistently screened for outlier and stale quotes. The CDS data set obtained directly from CMA is smaller but consists of superior quality quotes.

[16] On days when fewer than two reliable buy quotes are observed from different trading entities, CMA uses a statistical model to estimate appropriate CDS spreads (CMA Datavision 2011). I drop these "derived" spreads from my sample.

A limitation of the Standard & Poor's dataset is that it includes only credit ratings issued by one of the three major CRAs. I use the Mergent Fixed Investment Securities Database ("FISD") to expand the sample to include credit rating letter changes from Moody's and Fitch. As FISD provides bond-specific credit ratings, I follow a similar method as used by Jorion et al. (2005) and Beaver et al. (2006) for approximating the firm-level credit ratings. First, I limit the FISD sample to only senior, unsecured U.S. issues, excluding Yankee, preferred, exchangeable, enhanced, and private placement bonds. Ratings on the retained securities should most closely resemble the firm's overall credit rating. 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. As detailed in Table 1, the various letter classification systems of S&P, Moody's, and Fitch are converted to a consistent numeric system whereby the number 20 indicates the highest (i.e., safest) credit rating for all agencies and the number 1 indicates the lowest non-default rating for all agencies. Ratings 11 and higher are considered investment grade.

The FISD database typically does not include changes in rating statuses that are not accompanied by a change in the underlying letter rating, so I cannot similarly expand the sample of changes in credit rating statuses to encompass all three major CRAs. This sample limitation potentially diminishes the generalizability of my analysis of rating status changes to the other major agencies. However, drawing inference about all three major U.S. agencies based on a single agency's ratings is common in prior literature (Beaver et al. 2006; Ashbaugh-Skaife et al. 2006; Dichev and Piotroski 2001).

As with any information content test, it is possible that the observed price reactions around credit rating changes are actually attributable to other firm-specific information events that happen simultaneously with the rating change. Such contamination is not a validity threat in my pre/post-crisis tests as long as the effects of the contaminating events are similar in both periods. Still, in my information content tests I follow Holthausen and Leftwich (1986) and Hand et al. (1992) in performing sensitivity tests using "uncontaminated" subsamples that eliminate observations with simultaneous information events. I identify simultaneous information events from several sources. I use Compustat and IBES to identify dates on which there are quarterly earnings releases and equity analyst forecast revisions, respectively. As Shivakumar et al. (2011) find that the information content of management forecasts increases during the financial crisis, I also use the First Call database to identify dates on which management forecasts occur.

3.3. Credit ratings sample summary information

Table 1 provides summary information for a sample of month-end CDS spreads matched to the most recently issued credit rating from S&P, Moody's, or Fitch. If a liquid CDS spread is not available as of the last trade day of the month, I use the last observation available within the month. There are a total of 14,059 and 15,277 firm-month observations in the pre- and post-crisis periods, respectively, covering a total of 452 individual firms. The sample is roughly 8% larger in the post-crisis period, primarily due to an increase in the number of liquid CDS quotes available in the CMA dataset. Sensitivity analysis using a consistent sample of firms with data in both the pre- and post-crisis periods is discussed in Section 4.

As detailed in Panel A of Table 2, the sample of credit rating letter changes includes a total of 1,747 observations. Each rating change observation must have liquid CDS quotes for both the day before and day after the change announcement. There are an additional 1,072 changes in credit rating statuses that are not accompanied by a change in the underlying credit rating. These samples consist of 373 and 354 individual firms, respectively (Panel B). Panel A of Table 2 shows that the frequencies of rating changes reach a maximum in 2009, and Panel C shows that the prevalence of downgrades is higher after the crisis. These trends are consistent with a deteriorating economic climate from mid-2007 onward. Panel D of Table 2 presents downgrades and upgrades for the "uncontaminated" subsample of observations without simultaneous earnings releases, management forecasts, or equity analyst forecast revisions. The sample sizes are reduced by roughly 18%, but the distribution between downgrades, upgrades, pre-crisis, and post-crisis is similar to the complete sample.

3.4. Sample of quarterly accounting releases

Testing H4 requires a sample of quarterly accounting releases. Accounting data are obtained from Compustat. Analyst consensus forecasts and actuals are obtained from IBES. CDS data for both the day before and day after the earnings release are required for each observation. Panels A and B of Table 2 include sample information. A total of 7,314 firm-quarter observations (400 unique firms) have the requisite data for the accounting tests described below.

4. Empirical Analysis

4.1. Testing H1 – the information content of credit rating changes.

Similar to Shivakumar et al. (2011), I measure information content as the market-adjusted, three-day percentage change in CDS spread around credit rating changes (ΔCDS^{RATE}). The market adjustment is based on the average percentage change in CDS spread for a matched group of firms, identified as firms in the same CDS spread quintile as the reference firm.[17] Matching based on CDS spread levels removes the effects of macroeconomic news on firms with similar default risk:

$$\Delta CDS_{i,t}^{RATE} = \prod_{t=-1}^{+1}\left(\frac{CDS_{i,t}}{CDS_{i,t-1}}\right) - \prod_{t=-1}^{+1}\left[\frac{1}{M}\sum_{m=1}^{M}\left(\frac{CDS_{m,t}}{CDS_{m,t-1}}\right)\right] \quad \textbf{(1a)}$$

where *i* indexes the firm, *t* indexes the date of the rating change announcement, *CDS* is the firm's CDS spread level, and *M* represents all firms in the same quintile of CDS spreads as the firm with the rating change.[18] ΔCDS^{RATE} and all other continuous variables are winsorized at 2% and 98%.

Considerable variation in the mean and variance of firms' CDS spreads before/after the financial crisis raises concerns that ΔCDS^{RATE} will produce mis-specified test statistics (Boehmer et al 1991). Following Micu et al. (2006) and Jorion et al. (2005), I also employ a measure of *standardized* ΔCDS^{RATE} in my information content tests ($\Delta SCDS^{RATE}$):

$$\Delta SCDS_{i,t}^{RATE} = \frac{\Delta CDS_{i,t}^{RATE}}{\sigma(\Delta CDS_i - \Delta\overline{CDS}_m)\times\sqrt{3}} \quad \textbf{(1b)}$$

[17] In calculating the market adjustment, I require that at least five firms within the reference firm's CDS quintile have valid CDS quote data for both the day before and day after the rating change announcement. Using a value-weighted instead of equal-weighted market adjustment produces unchanged results.
[18] A strict CDS "return" should account for the decrease in contract value due to the passage of time and changes in recovery rates. In practice, though, the change in contract value over a three-day period is negligible and Micu et al. (2006) note that efforts to model the contract value change can result in a noisier measure than assuming a change of zero.

where $\Delta\overline{CDS}_m$ is the average percentage change in CDS spread for firms in the same CDS spread quintile, and σ is the standard deviation operator for daily abnormal CDS spread changes, calculated by calendar quarter. Multiplying the denominator by $\sqrt{3}$ facilitates interpretation of regressor coefficients in terms of standard deviations per day.

Lok and Richardson (2011) recommend that, in some cases, using gross changes in CDS spreads as opposed to percentage changes is a superior measure of change in default risk. I use percentage changes because deflating by a firm's initial CDS spread level reduces econometric concerns due to variation in the volatility and responsiveness of CDS spreads depending on a firm's distance to default. I perform additional sensitivity tests using a specification of standardized change in CDS spread that is identical to (1b) except that it uses gross instead of percentage changes. The correlation between standardized percentage changes and standardized gross changes in CDS spreads is approximately 96%. Untabulated results using standardized gross changes are qualitatively and quantitatively unchanged from those using standardized percentage changes.

4.1.1. Information content tests – univariate analysis

Panel A of Table 3 presents the average ΔCDS^{RATE} around credit rating changes in the pre- and post-crisis periods. Standard errors in tests of differences in means are clustered by firm and date to correct for serially and cross-sectionally correlated residuals. The significance of differences in medians is evaluated based on a Wilcoxon rank sum test. In the pre-crisis period, the mean ΔCDS^{RATE} around combined letter and status downgrades is 0.097, which indicates that rating downgrades are accompanied by a 9.7% increase in CDS spreads. As rating downgrades are intended to reflect an increase in default risk, the positive sign on ΔCDS^{RATE} is as expected. The mean ΔCDS^{RATE} around rating downgrades decreases by a statistically and economically significant 5.2 percentage points (53.2%) in the post-crisis period. The median ΔCDS^{RATE} around combined downgrades also decreases by a statistically significant 21.6%. Still, the net mean and median ΔCDS^{RATE} around rating downgrades remain significantly different from zero in the post-crisis period, which is consistent with corporate ratings still being viewed as at least somewhat credible after the financial crisis.

Looking specifically at rating *status* downgrades, the mean ΔCDS^{RATE} in the pre-crisis period is 0.158, which is considerably higher than the mean ΔCDS^{RATE} around rating *letter* downgrades of 0.067. An untabulated t-test shows that the difference between the status and letter downgrades is highly significant (t = 5.01). The mean ΔCDS^{RATE} around status downgrades decreases by a statistically significant 9.1 percentage points (57.8%) in the post-crisis period. Similarly, the mean ΔCDS^{RATE} around letter downgrades decreases by a significant 3.1 percentage points (46.2%). The decline in the median ΔCDS^{RATE} around status downgrades is attenuated but still significant. The decline in the median ΔCDS^{RATE} around letter downgrades is insignificantly different from zero. Again, the net mean and median ΔCDS^{RATE} around both status and letter downgrades in the post-crisis period remain significantly different from zero.

Turning to upgrades, the mean ΔCDS^{RATE} around all upgrades decreases by a statistically significant 35.7%, from -0.037 before the crisis to -0.024 after the crisis. The median ΔCDS^{RATE} around all upgrades decreases by a larger 44.1%. For upgrades in rating status, the mean ΔCDS^{RATE} decreases by a statistically significant 44.9% while the median ΔCDS^{RATE} decreases by a significant 47.7%. The pre/post-crisis changes in ΔCDS^{RATE} around letter upgrades are attenuated but still significant at a 10% level of confidence.

Panel B of Table 3 repeats the analysis in Panel A after excluding "contaminated" dates on which there are simultaneous accounting releases, management forecasts, or equity analyst revisions. The results are generally unchanged. Panel C of Table 3 repeats the analysis in Panel A but for standardized change in CDS, $\Delta SCDS^{RATE}$. The results are somewhat attenuated but generally unchanged, with the exception that the declines in mean and median reactions to letter upgrades are no longer statistically significant. Finally, Panel D of Table 3 repeats the analysis in Panel C but with the uncontaminated subsample of rating changes. The results are qualitatively unchanged, although significance is reduced to below conventional levels for both status and letter upgrades.

In sum, the data are consistent with an average 36% to 68% reduction in the information content of rating downgrades after the crisis. The results are less uniform for rating upgrades, but the majority of tests are consistent with an average 23% to 45% decline in information content. The results are also consistent with all types of rating changes still containing significant information for debt prices even after the crisis. Collectively, these results are consistent with the CRAs suffering partial, but not complete, loss of credibility as a result of the financial crisis.

4.1.2. Information content tests - regression analysis

In this section, I expand the univariate analysis to control for other variables that likely affect the information content of rating changes for CDS spreads. Closely following Holthausen and Leftwich (1986) and Jorion et al. (2005), I estimate the following regression model separately for downgrades and upgrades:[19]

$$\Delta CDS^{RATE}_{i,t} = \beta_0 + \beta_1 POST + \beta_2 RCHANGE\_BIN_{i,t} + \beta_3 RCHANGE + \beta_4 IGRADE\_BDR_{i,t} + \beta_5 CDS_{i,t\text{-}2} + \beta_6 DAYS_{i,t} + \varepsilon_{i,t} \qquad \textbf{(2)}$$

POST, the variable of interest, is a binary variable for the period starting July 1, 2007. If corporate ratings are viewed as being less credible in the post-crisis period, then I expect the β_1 coefficient to be negative (positive) for downgrades (upgrades).

RCHANGE_BIN is a binary variable equal to one for letter rating changes, and is set to zero for credit rating status changes that are not accompanied by a change in the underlying letter rating. *RCHANGE_BIN* is relevant only for model specifications that combine both changes in rating letters and statuses. If status changes are more informative than letter changes (as shown in the univariate analysis), *RCHANGE_BIN* will be negative (positive) for downgrades (upgrades). *RCHANGE* is the difference between the current letter rating and prior letter rating, and is irrelevant in specifications that include only status changes. I have no ex ante prediction for the sign on *RCHANGE* as a larger rating change could be indicative of either: (i) communicating news about a larger change in default risk, in which case the price response would likely be larger; or (ii) the CRA waiting longer to update the rating, in which case the price response could be smaller. *IGRADE_BDR* is a binary variable equal to one if the rating is on the border of moving between investment and junk-grade

[19] An alternate specification would include both upgrades and downgrades in a single regression, include an upgrades binary variable, and interact each variable with the upgrades binary variable. Combining both downgrades and upgrades in such a model produces unchanged hypothesis test results, but does significantly increase the model's explanatory power; e.g., the R-squared in the first regression in Table 4 increases from 5.4% to over 17%. For ease of presentation and consistency with prior literature, I present separate models.

classification prior to the rating change. β_3 will likely be positive (negative) for rating downgrades (upgrades) as prior studies have found market reactions are larger for ratings on the investment-grade border. CDS_{t-2} is the firm's CDS spread two days prior to the rating change announcement scaled by 1,000, and is included to control for any differences in ΔCDS^{RATE} depending on the firm's distance to default. *DAYS* is the number of days that have elapsed since the firm's last credit rating change, scaled by 100. Standard errors are again clustered by firm and date.

Results of estimating (2) are presented in Panel A of Table 4. Combining both letter and status downgrades in column 1, β_1 on *POST* is -0.054 and significantly negative, indicating that reactions to rating downgrades are, on average, 5.4 percentage points smaller after the crisis. This change is consistent with the 5.2 percentage point decline observed in the univariate analysis (Panel A of Table 3). β_2 on *RCHANGE_BIN* is significantly negative, which is consistent with the univariate analysis in that rating status changes are accompanied by larger price responses than are rating letter changes. β_4 on *IGRADE_BDR* is significantly positive, as expected, which is consistent with larger price responses for firms on the investment-grade border. Columns 2 and 3 indicate that the CDS responses around rating status and letter downgrades decrease by 8.3 and 3.6 percentage points, respectively, which are again highly consistent with the univariate analysis. The models in columns 1 through 3 have explanatory power ranging from 3.3% to 5.4%, which are on par with similar models in Jorion et al. (2005).

For combined letter and status upgrades in column 4, β_1 is again significant and of the expected sign. At 0.017, β_1 indicates that price responses are 1.7 percentage points smaller in the post-crisis period, which is consistent with the 1.3 percentage point reduction observed in the univariate analysis (Panel A of Table 3). The results in columns 5 and 6 indicate that the price responses to separate status and letter upgrades decline by 2.7 and 0.9 percentage points, respectively.

Results from repeating the analyses on the uncontaminated subsample are presented in Panel B of Table 4. The results are generally unchanged, with statistically significant price response declines ranging from 1.1 to 10.3 percentage points. Panels C and D repeat the analysis in Panels A and B, but with $\Delta SCDS^{RATE}$ as the dependent variable. Overall, the results in Panels C and D are consistent with those in Panels A and B, as well as with the univariate results in Table 3. The sole exception is that the reduction in the price responses around letter upgrades in the complete sample (column 6 of Panel C) is no longer statistically significant. Taken together, the results in Table 4 are consistent with significant declines in the information contents of all types of rating changes, and with corporate credit ratings being viewed as less credible in the post-crisis period.

4.1.3. Sensitivity analysis - possible effects of a growing CDS market

The CDS market grew considerably during the mid 2000's, and CDS markets are known to impound debt-relevant information more quickly than bond markets. A plausible alternate explanation for observing a decline in ΔCDS^{RATE} around rating changes is that growth in the CDS market provided a daily indicator of default risk that was not available in the early part of the sample, and therefore allowed market participants to decrease their reliance on information provided by the CRAs. On average, my sample firms have actively traded CDS contracts on 69% of all market days in the pre-crisis period versus 85% of days in the post-crisis period, which is consistent with the CDS market becoming more liquid in the late 2000's.

As a robustness test, I reperform the regression analysis including only the subsample of firms that have actively traded CDS contracts in both the pre- and post-crisis periods. I identify firms with "actively traded" CDS contracts as firms for which there are liquid CDS quotes on at least 50% of trade days in both the pre- and post-crisis periods. This restriction reduces the sample of rating changes by roughly 15% and produces largely unchanged regression results (untabulated). Increasing the threshold to requiring liquid quotes on at least 75% of trade days also produces unchanged results, with the exception that the reduction in information content of credit rating letter downgrades is no longer statistically significant in several specifications. As a post-crisis decline in information content is still observed among firms with actively traded CDS contracts both before and after the crisis, the data do not indicate that growth in the CDS markets is driving the reported results.

4.1.4. Sensitivity analysis - possible effects of a changing sample composition

Panel A of Table 2 shows that the samples of credit rating changes tend to grow over time. This raises a concern that the pre/post-crisis results are biased by a systematic change in the sample composition. Limiting the sample to only firms with at least one rating change prior to 2007 reduces the sample by roughly 16%. Untabulated regression results are similar to those reported in Table 4.

4.2. Testing H2 – the relevance of credit ratings for CDS spread levels

H2 predicts that the strength of the relation between credit ratings and debt price levels decreases after the financial crisis as market participants place greater weight on non-rating information sources. I evaluate H2 in two ways. First, if non-rating information plays a greater role in determining debt prices, then there should be an increase in the variance of debt prices within each credit rating level (i.e., and increase in "intra-rating" variances).[20] Panels A through D of Figure 2 plot the standard deviations of CDS spreads by quarter within credit rating groups. For ease of presentation, the highest credit rating levels 14 through 20 are pooled in Panel A, levels 11 through 13 are pooled in Panel B, levels 8 through 10 are pooled in Panel C, and the lowest ratings 1 through 7 are pooled in Panel D. In each panel, the standard deviation of CDS spreads increases in the third or fourth quarter of 2007 and remains consistently higher throughout the post-crisis period than in the pre-crisis period. Thus, the visual evidence indicates that intra-rating variances of CDS spreads increase after the crisis.

Untabulated Levene and Brown-Forsythe tests show that the intra-rating variances of CDS spreads for pooled post-crisis observations are significantly greater than the intra-rating variances of CDS spreads for pooled pre-crisis observations. However, given that the intra-rating means of CDS spreads are non-stationary across the post-crisis period, calculating the variance of pooled post-crisis CDS spreads is potentially misleading. A more appropriate test to avoid the effects of non-stationary means is to individually calculate the intra-rating variances of CDS spreads for each of the 14 pre-crisis quarters and each of the 14 post-crisis quarters. Table 5 presents the mean and median intra-rating standard deviations for the pre- and post-crisis periods. I require a minimum of five observations within each calendar quarter, so means and medians for rating levels 1, 2, and 19 are missing due to insufficient data. On average, the quarterly standard deviation of CDS spreads

[20] For instance, if credit ratings were the *only* data used in debt pricing and were uniformly interpreted by all market participants, then all firms with the same credit rating would have the same CDS spread. As additional information is considered, the variance in CDS spreads among firms with the same credit rating increases.

increases by 336% between the pre- and post-crisis periods. The increase in medians is similar at 209%. T-tests and Wilcoxon rank sum tests show that the increases in quarterly standard deviations between the pre- and post-crisis periods are highly significant for all rating levels. Thus, the data are consistent with an increase in the variance of CDS spreads within each rating level in the post-crisis period.[21]

My second test of H2 is based on the frequency of firms with “discordant” and “extreme discordant” credit ratings relative to observed CDS spreads. As previously discussed, the CRAs’ only commitment about credit ratings is that they should provide a relative ordering of default risk among firms at a given point in time. If credit ratings serve their intended purpose, higher (i.e., safer) rated firms should have lower (i.e., less costly) CDS spreads. Panel A of Figure 1 provides an illustrative example of credit ratings that perfectly accomplish the CRAs’ stated objective. The horizontal axis is the range of possible CDS spreads from lowest to highest (i.e., cheapest to most costly). Each triangle bounds the population of firms within a given credit rating level. As all of the CDS spreads among the firms with a rating of 10 are cheaper than all the CDS spreads among firms with a rating of 9, the ratings are perfectly concordant relative to observed CDS spreads.

I define a credit rating as being “discordant” with observed CDS spreads when firm *i* has a higher (i.e., safer) rating than firm *j* but also has a *higher* (i.e., more costly) CDS spread than the minimum CDS spread observed among firms with the same rating as *j*, and vice versa. Said differently, firm *i* is “discordant” when its credit rating and CDS spread conflict as to whether it is safer or riskier than firms with a lower credit rating. Panel B of Figure 1 provides an example of discordant credit ratings. As can be seen, some “discordant” firms with a rating of 10 have an observed CDS spread that is higher than the minimum CDS spread observed among firms with a rating of 9. As illustrated in Panel C of Figure 1, I define an “extreme discordant” observation as

[21] As previously discussed, credit ratings actually comprise both a letter rating and an outlook or watch status. Thus, within each rating letter level, there are potentially five sub-categories of ratings: watch negative, outlook negative, neutral, outlook positive, and watch positive. Performing intra-rating variance tests on these finer partitions drastically reduces the number observations that are available within each level in a given quarter. Many levels have fewer than the required minimum of five observations. Still, results using finer partitions produce largely unchanged results for those quarters with sufficient data. Results are also generally unchanged if the intra-rating standard deviations are calculated on a monthly basis, although sample size is again reduced due to a lack of data in certain rating levels.

when firm *i* has a higher (i.e., safer) rating than firm *j* while also having a CDS spread that is higher (i.e., more costly) than the *median* of all firms with firm *j*'s rating level.

In my second test of H2, I use the prevalence of discordant and extreme discordant observations as a measure of the relevance of credit ratings for CDS spread levels. If market participants decrease their reliance on credit ratings after the crisis, the percentages of discordant and extreme discordant observations should increase. Panel A of Table 6 presents the percentages of discordant observations by credit rating level before and after the crisis. I empirically specify a "discordant" observation as having a higher (lower) rating than the benchmark rating level while simultaneously having a CDS spread that is higher (lower) than the benchmark level's 10^{th} (90^{th}) percentile of CDS spreads within the same month. I use the 10^{th} and 90^{th} percentiles instead of the minimum and maximum observed CDS spreads to reduce the effects of outliers.[22] Discordant observations are identified with a binary variable *DISCORDANT* set equal to one. On average across all credit rating levels, 16.3% of observations are discordant in the pre-crisis period as opposed to 21.6% in the post-crisis period, representing an increase of 32%. Looking at the individual credit rating levels, 18 of the 20 levels experience an increase in discordance prevalence in the post-crisis periods.

I first test the significance of the intra-rating increases in discordance rates with t-tests: t-tests for all 20 credit rating levels are highly significant, although two are of the unexpected sign. I perform a second test of significance using logit regressions of *DISCORDANT* on a binary variable *POST*. Standard errors in the logit regression are clustered by firm and month. Rating levels 1 and 2 have insufficient observations for the logit. Of the 18 rating levels with sufficient data, 13 are significant and of the expected sign. Only one is significant of the unexpected sign. Panel B of Table 6 presents similar analysis for extreme discordant observations. Overall, the prevalence of extreme discordant observations increases by 70.4% in the post-crisis period. T-tests show that the differences in means for 15 of 20 rating levels are significant and of the expected signs. Only one test is

[22] Extreme outlier observations have a significant impact on the discordancy rates in both the pre- and post-crisis periods. Still, using the minimum and maximum CDS spreads results in larger increase in discordancy in the post-crisis period than when using the 10^{th} and 90^{th} percentiles (i.e., using the minimum and maximum CDS spreads produces stronger evidence in favor of H2).

significant and of the unexpected sign. Logit regressions produce similar results. Thus, the data show an increase in the discordance between credit rating and CDS levels in the post crisis period, which is consistent with market participants decreasing their reliance on corporate credit ratings as a result of credibility damage from the financial crisis.

5.3. Testing H3 – CDS spreads increase within each rating level

H3 predicts that there is an increase in the average CDS spread within each rating level between the pre- and post-crisis periods. As shown in Panels A through D of Figure 1, the average CDS spread within each rating group increases in third quarter of 2007 and remains higher throughout the post-crisis period than in the pre-crisis period. Table 7 presents the average CDS for each credit rating level before and after the crisis. On average, CDS spreads increase by 227% between the pre- and post-crisis periods. I test the differences in means within each credit rating level using a t-test with standard errors clustered by firm and month, except in testing rating levels 1, 2, and 19 where there are insufficient observations for clustering. The increases in the average CDS spread are highly significant within each credit rating level. Wilcoxon rank sum tests show that the differences in medians are also highly significant.[23] Untabulated results using the natural log of the CDS spread as the dependent variable are also highly significant within each rating level.

The persistent increases in intra-rating CDS spreads observed starting in July 2007 is consistent with the financial crisis causing market participants to view corporate ratings as optimistically biased. However, as noted in Section 2, this pattern should be interpreted with some caution as credit ratings are intended to be relative rather than absolute measures of default risk. As such, an upward shift in CDS spreads for all rating levels could be instead attributed to a macroeconomic increase in default risk.

5.4. Testing H4: the information content of accounting reports

In testing H4, I specifically examine whether the information content of quarterly earnings announcements increases after the financial crisis. Earnings releases often include partial financial

[23] The monthly CDS observations are likely serially as well as cross-sectionally correlated, thereby violating the assumption of independence in the Wilcoxon rank sum test (which likely explains the high z-statistics). Untabulated tests that randomly select one observation per firm from each of the pre- and post-crisis periods, thereby reducing both serial and cross-sectional correlation, produce reduced but still significant z-statistics.

statements and qualitative information (D'Souza et al. 2010), much of which is useful for debt pricing. For instance, accounting measures of leverage, liquidity, and performance have been shown to be informative about default risk and can likely be derived from quarterly earnings releases (Altman 1968; Beaver et al. 2005; Batta 2011). However, tests of the informativeness of multiple accounting variables are limited by researchers' abilities to: (i) design information content tests that incorporate multiple accounting measures, and (ii) model the market's expectation of the non-earnings accounting measures in order to isolate information surprise. I therefore use unexpected earnings (*UE*) as a proxy for the overall information contained in firms' quarterly accounting reports. *UE* is calculated as the difference between IBES actual earnings and the most recent analyst consensus prior to the earnings announcements, scaled by end-of-quarter price. To reduce noise from stale or outlier forecasts, consensus estimates with fewer than two individual forecasts or older than 100 days are eliminated.

Three-day change in CDS spread, ΔCDS^{EA}, is calculated via the same method as ΔCDS^{RATE}. I test for post-crisis changes in ΔCDS^{EA} with the following regression:

$$\Delta CDS^{EA}_{i,t} = \beta_0 + \beta_1 UE_{i,t} + \beta_2 UE_{i,t}{*}POST + \beta_3 POST + \beta_4 CDS_{t-2} + \beta_5 UE_{i,t}{*}CDS_{t-2} + \beta_6 IGRADE\_BDR_{i,t} + \beta_7 IGRADE\_BDR_{i,t}{*}UE_{i,t} + \beta_8 NONLINEAR_{i,t} + \beta_9 LOSS + \beta_{10} LOSS{*}UE + \Sigma\beta_k ADDL\_CONTROLS + \Sigma\beta_k ADDL\_CONTROLS{*}UE + \varepsilon_{i,t} \qquad \textbf{(3)}$$

UE is unexpected earnings, as previously defined. β_1 will be negative if a positive earnings surprise informs market participants about a decrease in default risk, and vice-versa. H4 predicts $\beta_2 < 0$.

CDS_{t-2} is the CDS spread two days prior to the earnings release scaled by 1,000, and is included to control for differences in the relation between earnings news and debt prices depending on the firm's distance to default (Callen et al. 2009; Lok and Richardson 2011). *IGRADE_BDR* is an indicator variable equal to one if the firm is on the border of moving between investment and junk-grade status. Following Lipe et al. (1998), *NONLINEAR* is calculated as *UE* * |*UE*| and is included to capture the nonlinear relation between *UE* and ΔCDS^{EA}.[24] I expect the coefficient on *NONLINEAR* to be positive if the marginal informativeness of earnings is decreasing with *UE* magnitude. *LOSS* is an

[24] An untabulated plot of *UE* and ΔCDS^{EA} shows that the relation between *UE* and ΔCDS^{EA} is nonlinear in that ΔCDS^{EA} wanes with larger earnings surprises, much like the nonlinear relation between *UE* and equity returns.

indicator variable equal to one for negative earnings, and is included to control for potential differences in the informativeness of positive versus negative earnings for debt prices (Easton et al., 2009; Hayn 1995). Each variable is interacted with *UE* to control for its impact on the relation between *UE* and ΔCDS^{EA}. Standard errors are clustered by firm and day.

A large body of literature examines the determinants of the relation between *UE* and equity price changes. Among these known determinants are expected growth and discount rate (Collins and Kothari 1989), size (Easton and Zmijewski 1989), and fiscal quarter (Salamon and Stober 1994). The theoretical relations between equity prices and these variables may not uniformly apply to debt prices, especially given the limited upside advantage to debt holders of increased future cash flows. However, I control for these determinants, collectively *ADDL_CONTROLS*, in an expanded model specification. *SIZE* is measured as the natural log of total assets, *BTM* is book value over market value, *LEV* is total debt over book equity, *FQ4* is an indicator for the fourth fiscal quarter, and *BETA* is the equity market beta calculated over the 252-day period ending five days before the earnings announcement. Again, all variables are included as main effects and interacted with *UE.*

The results of estimating equation (3) are presented in Panel A Table 8. The model in column 1 includes the complete sample of observations and no additional controls. The coefficient β_1 on *UE* is -3.669 and highly significant, indicating that a positive earnings surprise equal to 1% of price is associated with a roughly 3.7% decrease in CDS spread in the pre-crisis period (or, an earnings surprise equal to 100% of price is associated with a 366.9% decrease in CDS spread). The coefficient of interest, β_2 on *UE*POST*, is -0.707 and significantly negative. This is consistent with H4 in that there is a 0.7 percentage point (or -0.707 / -3.669 = 19%) increase in the information content of *UE* for CDS spreads in the post-crisis period. The signs of the control variable coefficients are generally as expected.

Untabulated regressions that include the aforementioned additional controls (*ADDL_CONTROLS*) show that a high correlation between *UE* and *SIZE*UE* causes these variables to have variance inflation factors of 320 and 223, respectively. Thus, all of the continuous *ADDL_CONTROLS* variables are normalized to have a mean (variance) of zero (one) to reduce issues from multicollinearity in the interaction terms. Column 2 in Panel A of Table 8 presents the results of regressions that include the normalized additional controls and interactions with *UE*. The additional controls are untabulated for brevity. Of the additional controls, only the coefficient on *BETA* is statistically significant, but the economic magnitude is small. β_2 on *POST* remains highly significant, which is consistent with H4.

The models in columns 3 and 4 repeat columns 1 and 2 but exclude days on which there are simultaneous credit rating changes, analyst forecast revisions, or management forecasts. 49% of the observations in the complete sample have a simultaneous management forecast, 64% have a simultaneous analyst revision, and 0.8% have a credit rating change. Combined, the sample is reduced by 78%. Still, β_2 in the third column remains highly significant and indicates that there is a larger 9.8 percentage point (or -0.980 / -2.895 = 34%) increase in the information content of *UE* among this subsample. The results in column 4 including the additional controls are similar. Panel B repeats the analysis in Panel A but for standardized change in CDS, $\Delta SCDS^{EA}$. The results in Panel B are largely unchanged. Untabulated results repeating all models in Table 8 separately for positive versus negative earnings are also qualitatively unchanged. In sum, the results are consistent with H4; i.e., that market participants increase their reliance on accounting reports in debt pricing as they decrease their reliance on less credible corporate ratings.

5.4.1. Robustness test – credit ratings contain less accounting information after the crisis

A plausible alternate explanation for finding a decrease in the information content of rating changes accompanied by an increase in the information content of accounting releases is that credit ratings contain less accounting information after the crisis. It is unclear why the CRAs would reduce the amount of value-relevant accounting information in their ratings after the financial crisis. Still, I further rule out this alternate explanation by investigating temporal trends in the explanatory power of accounting variables for credit ratings. My analysis is based on the following ordered logit model, which is similar to the model in Ashbaugh-Skaiffe et al. (2006):

$$RATING_{i,m} = \beta_0 + \beta_1 SIZE_{i,q-1} + \beta_2 ROA_{i,q-1} + \beta_3 LEV_{i,q-1} + \beta_4 CAPINTEN_{i,q-1} + \beta_5 INTCOV_{i,q-1} + \beta_6 CFO\_DEBT_{i,q-1} + \beta_7 ACID_{i,q-1} + \varepsilon \quad \textbf{(4)}$$

RATING is the month-end credit rating. Each rating is matched to its most recently available quarterly accounting information. *SIZE* is the log of total assets; *ROA* is the most recent four quarters' net income before extraordinary items scaled by average total assets; *LEV* is total debt divided by total assets; *CAPINTEN* is net property plant and equipment scaled by total assets; *INTCOV* is the most recent four quarters' net income before extraordinary items scaled by the most recent four quarters' interest expense; *CFO_DEBT* is the most recent four quarters operating cash flows scaled by total debt; and *ACID* is total cash and equivalents divided by total current liabilities. The model is estimated by calendar quarter and for each industry sector. The average pseudo R-squared in the pre-crisis period of 0.62 increases marginally to 0.64 in the post-crisis period. Thus, there is no evidence of a decline in the use of accounting information by rating agencies after the crisis.

7. Conclusion

This study investigates whether the failures of credit ratings on *structured finance products* during the financial crisis also damaged the CRAs' credibility with regards to credit ratings on *corporations*. I document a significant decline in the information content of corporate credit rating changes for CDS spreads in the post-crisis period, accompanied by a significant decline in the relevance of credit ratings for CDS spread levels. These results are consistent with credibility damage causing market participants to reduce their reliance on corporate credit ratings in debt pricing. I also find a significant increase in the average debt price within each credit rating level in the post-crisis period, which is consistent with market participants viewing the pre-crisis ratings as optimistically biased. Finally, I benchmark the information content test results against price responses around accounting releases, and find that the information content of unexpected earnings increases significantly after the crisis. An increase in the information content of accounting releases is consistent with market participants substituting towards using alternate information as they decrease their reliance on less-credible corporate ratings. However, corporate credit ratings still contain significant information content for debt prices even after the crisis, indicating that the credibility damage is less than complete.

My study's most direct contribution is to provide evidence about the effects of the financial crisis on the CRAs' credibility with respect to corporate credit ratings. Finding evidence consistent with credibility damage indicates that market participants viewed the failures of rating on structured finance products not as anomalous events, but rather as potentially symptomatic of broader problems in the credit rating industry.

Beyond the specific context of the financial crisis, my study contributes to the literature that examines the role of credibility in the credit rating industry. Credibility is often cited as a primary determinant of the extent to which market participants rely on credit ratings in decision-making. Credibility is also the critical factor that maintains the integrity of the CRAs' oligopolistic and issuer-pays business model. However, to date there has been little opportunity to examine a well-defined shock to CRA credibility. My study provides new empirical evidence about the effects of credibility damage on credit rating usage, and on the general relations between credit rating credibility and observed debt market prices.

Finally, I build on the literature examining the use of accounting information by debt market participants. To my knowledge, I am the first to document predictable temporal variation in the information content of accounting reports for debt prices depending on the broader debt market information environment (i.e., in periods when credit ratings are less trusted). I also provide new evidence consistent with accounting data being a substitute for credit ratings in debt pricing. These findings provide new insights about how and when market participants use accounting information in debt pricing decisions.

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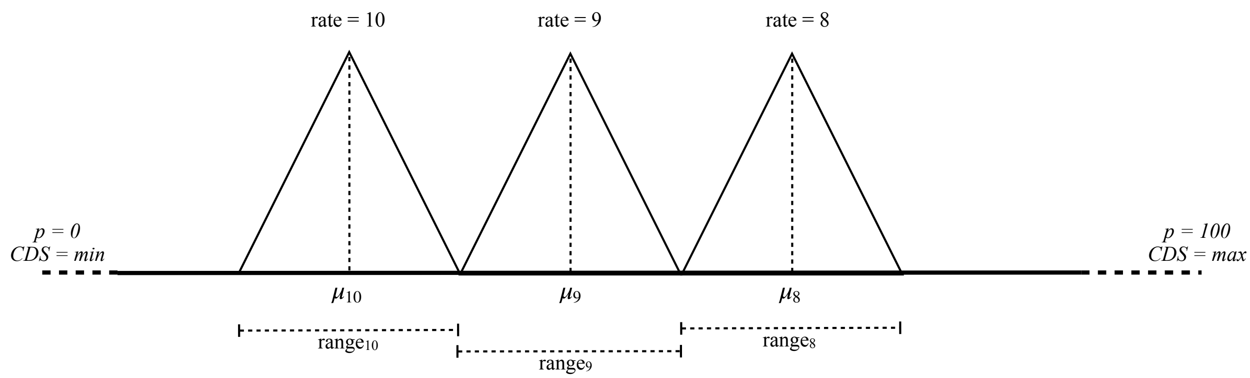
FIGURE 1: Examples of Possible Distributions of Ratings Relative to CDS Spreads

This figure provides illustrative examples of possible distributions of credit ratings relative to observed CDS spreads. The x-axis is a truncated representation of CDS spreads, ranging from the lowest CDS spread for firms with a zero probability (*p = 0*) of default to the highest spreads for firms with a 100% probability of default (*p = 100*). The triangular region underneath each rating bounds the population of CDS spreads within each rating level, where the median spread is μ. A higher numbered rating is intended to represent a safer firm (i.e., lowest probability of default). Ratings 20 – 11 and 7 – 1 are not presented.

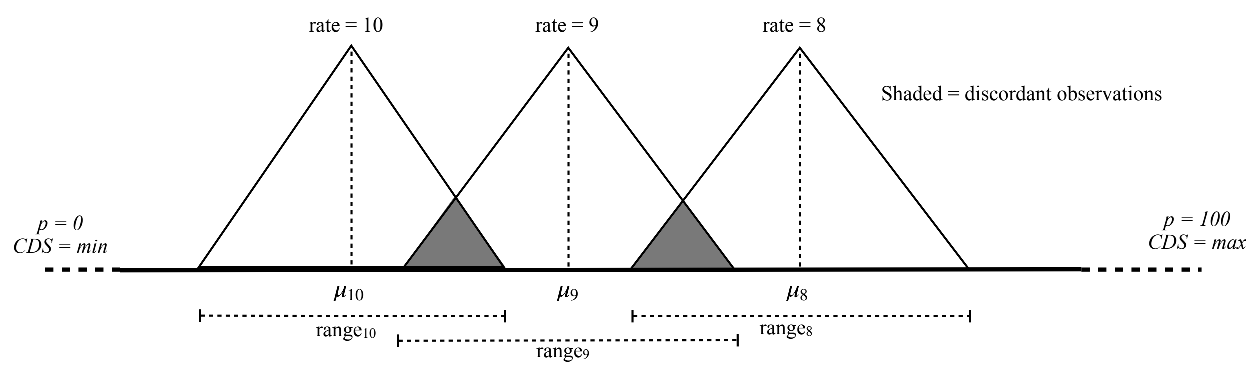
Panel A: Example of ratings that are perfectly concordant relative to CDS spreads

These ratings are perfectly concordant relative to CDS spreads. E.g., all firms with a rating of 10 have lower CDSs spread than all firms with a rating of 9.



Panel B: Example of discordance between credit ratings and CDS spreads

The shaded areas include credit ratings that are discordant with CDS spreads. A "discordant" observation is, for example, a firm with a credit rating of 10 that has an observed CDS spread that is higher (i.e., more costly) than some firms with credit ratings of 9.



Panel C: Example of extreme discordance between credit ratings and CDS spreads

The shaded areas include credit ratings that are "extremely discordant" with CDS spreads. An "extreme discordant" observation is, for example, a firm with a credit rating of 10 that has an observed CDS spread that is higher than the *median* CDS for firms with credit ratings of 9.

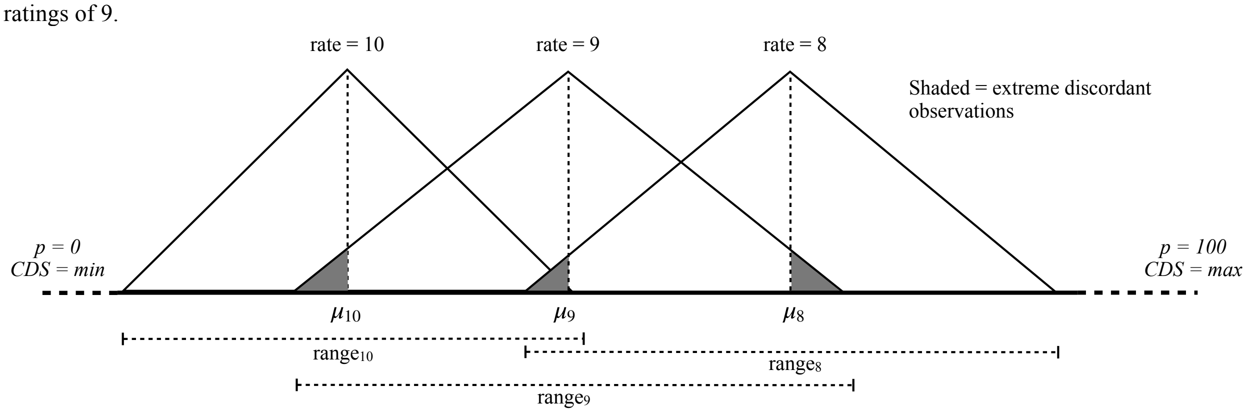
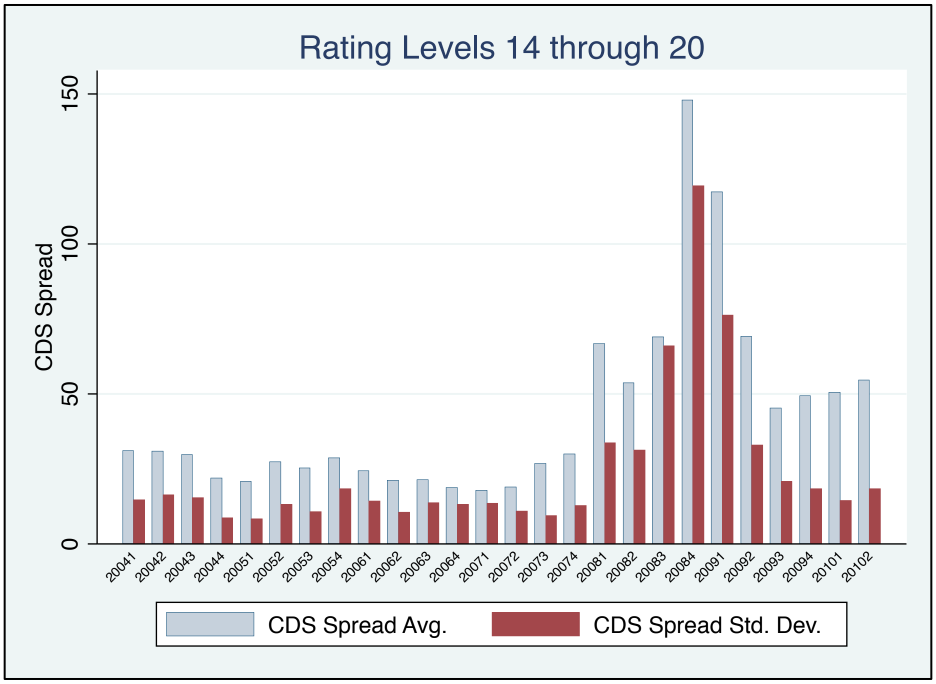


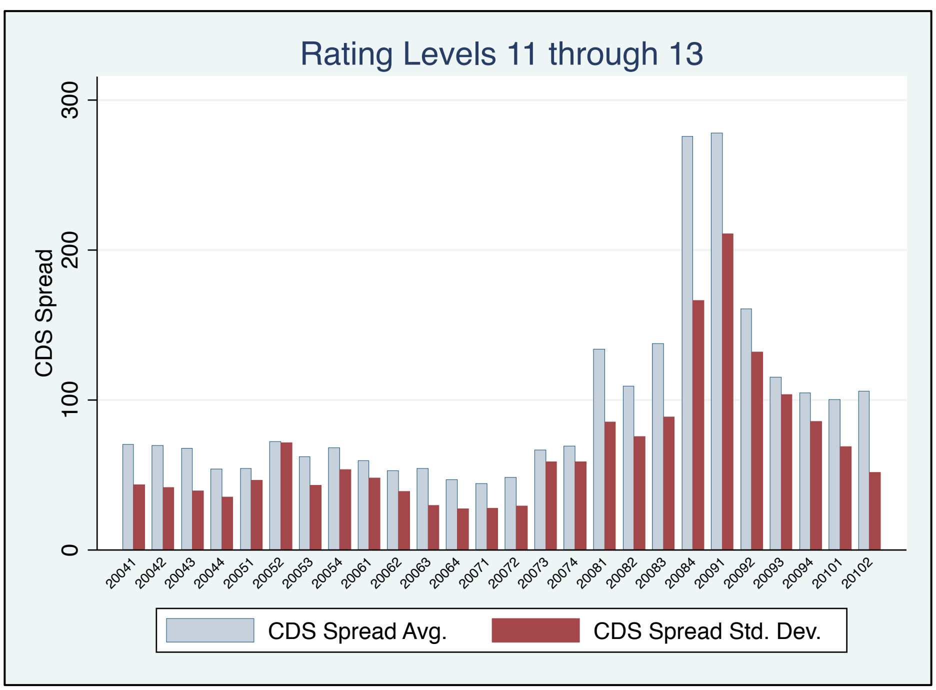
FIGURE 2: Average and Standard Deviation of CDS Spreads by Quarter

The figures below are based on month-end credit default swap (CDS) spreads and credit ratings from 2004 through 2010. For each firm, the last available CDS spread per month is matched to the most recently updated credit rating from S&P, Moody's, or Fitch. CDS spreads are winsorized at 2% and 98%. The plots present quarterly average CDS spreads and standard deviations of CDS spreads within categories of ratings. Panel A groups the highest rating levels 14 through 20, Panel B groups levels 11 through 13, Panel C groups levels 8 through 10, and Panel D groups the lowest ratings 1 through 7. The Y-axis scales vary by panel.

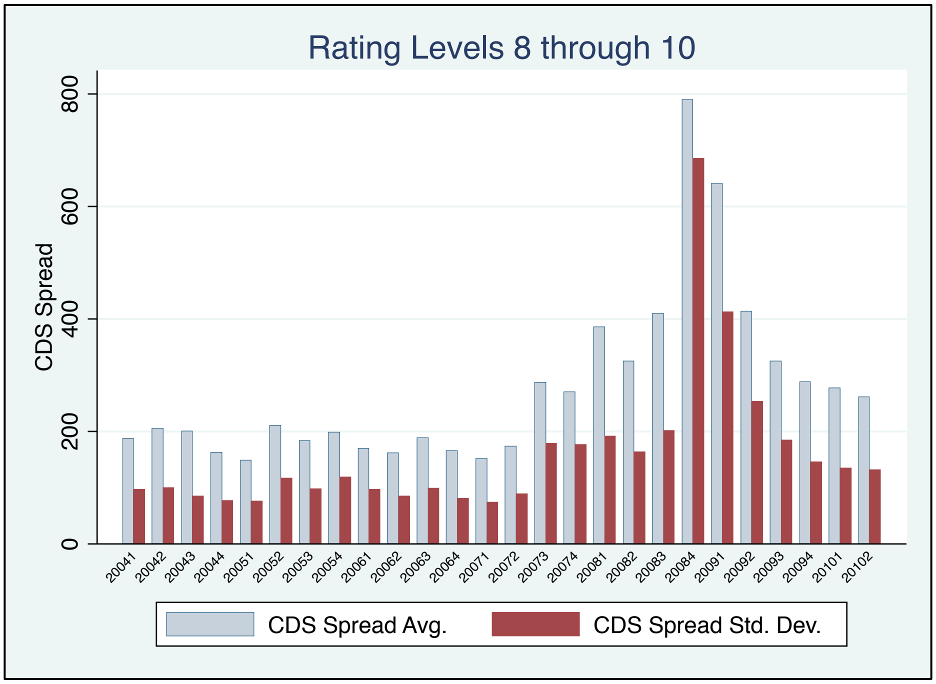
Panel A: Ratings 14 through 20



Panel B: Ratings 11 through 13



Panel C: Ratings 8 through 10



Panel D: Ratings 1 through 7

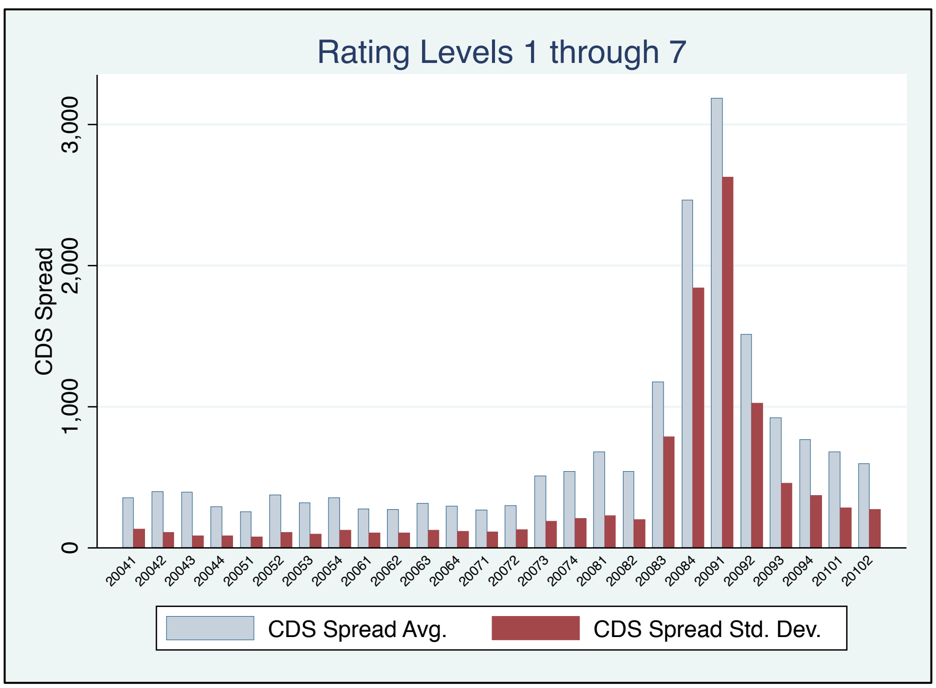


TABLE 1: Summary Information – Sample of Credit Rating Levels Matched to CDS Spreads

The sample of credit rating levels consists of firms' month-end CDS spreads matched to the most recent rating issued by S&P, Moody's, or Fitch. The sample period is 1/1/2004 through 12/31/2010. The demarcation between the pre- and post-crisis periods is 1 July 2007. Industry sector assignments are as per the CDS data provider.

Panel A: Firm-month observations in the pre- and post-crisis periods

S&P and Fitch Letter Rating	Moody's Letter Rating	Numeric Rating	Pre-Crisis	Post-Crisis	Total
AAA	Aaa	20	128	115	243
AA+	Aa1	19	7	18	25
AA	Aa2	18	244	160	404
AA-	Aa3	17	352	307	659
A+	A1	16	552	749	1,301
A	A2	15	1,419	1,561	2,980
A-	A3	14	1,349	985	2,334
BBB	Baa1	13	1,744	1,828	3,572
BBB	Baa2	12	2,608	2,309	4,917
BBB-	Baa3	11	1,656	2,008	3,664
BB+	Ba1	10	944	938	1,882
BB	Ba2	9	930	817	1,747
BB-	Ba3	8	756	982	1,738
B+	B1	7	586	821	1,407
B	B2	6	402	510	912
B-	B3	5	242	530	772
CCC+	Caa1	4	109	344	453
CCC	Caa2	3	26	152	178
CCC-	Caa3	2	2	33	35
CC	Ca and C	1	3	110	113
		Total	**14,059**	**15,277**	**29,336**

Panel B: Number of unique firms in each industry sector

Industry Sector	
Basic Materials	47
Consumer Cyclical	112
Consumer Non-Cyclical	56
Health Care	29
Industrials	54
Oil & Gas	49
Technology	35
Telecommunications	23
Utilities	47
Total Firms	**452**

TABLE 2: Summary Information – Sample of Credit Rating Changes Matched to CDS Spreads

The sample of credit rating letter changes consists of changes in S&P, Moody's, and Fitch corporate ratings from 1/1/2004 through 12/31/2010. The sample of credit rating status changes consists of changes in S&P corporate rating "watch" and "outlook" statuses that are not accompanied by a change in the underlying letter rating. The sample of quarterly accounting releases is based on Compustat and IBES. The demarcation between the pre- and post-crisis periods is 1 July 2007. Industry sector assignments are as per the CDS data provider. The "average magnitude" in Panel C is the number of notches between the current and prior credit rating letter. Average magnitudes are not applicable for rating status changes.

Panel A: Observations by year

Year	Credit Ratings Letter Changes	Credit Rating Status Changes	Quarterly Accounting Releases
2004	141	104	892
2005	194	128	813
2006	300	162	966
2007	302	172	1,148
2008	289	166	1,144
2009	309	186	1,168
2010	212	154	1,183
Total	**1,747**	**1,072**	**7,314**

Panel B: Number of unique firms in each industry sector

Industry Sector	Credit Ratings Letter Changes	Credit Rating Status Changes	Quarterly Accounting Releases
Basic Materials	45	39	44
Consumer Cyclical	89	93	102
Consumer Non-Cyclical	42	42	48
Health Care	29	18	29
Industrials	41	47	50
Oil & Gas	34	34	42
Technology	29	25	32
Telecommunications	24	21	18
Utilities	40	35	35
Total Firms	**373**	**354**	**400**

Panel C: Rating change frequencies and average sizes – complete sample

	Pre-Crisis		Post-Crisis	
	Number	**Avg. Magnitude**	**Number**	**Avg. Magnitude**
Rating Letter Downgrades	456	1.52	641	1.50
Rating Letter Upgrades	333	1.30	317	1.39
Total Rating Letter Changes	**789**		**958**	
Rating Status Downgrades	229	n/a	293	n/a
Rating Status Upgrades	257	n/a	293	n/a
Total Rating Status Changes	**486**		**586**	

Panel D: Ratings change frequencies and average sizes – "uncontaminated" subsample

	Pre-Crisis		Post-Crisis	
	Number	**Avg. Magnitude**	**Number**	**Avg. Magnitude**
Rating Letter Downgrades	377	1.50	548	1.53
Rating Letter Upgrades	296	1.31	282	1.39
Total Rating Letter Changes	**673**		**816**	
Rating Status Downgrades	159	n/a	223	n/a
Rating Status Upgrades	217	n/a	238	n/a
Total Rating Status Changes	**376**		**461**	

TABLE 3: Information Content of Corporate Credit Ratings – Univariate Analysis

Panel A presents mean and median ΔCDS^{RATE} around credit rating changes before and after the financial crisis. ΔCDS^{RATE} is the market-adjusted percentage change in credit default swap (CDS) spread over days t-1 through t+1, winsorized at 2% and 98%. The pre-crisis period spans 2004 – June 2007. The post-crisis period spans July 2007 – 2010. Panel B repeats the analysis in Panel A but excludes dates on which there are simultaneous accounting releases, equity analyst forecast revisions, and/or management forecasts. Panels C and D repeat the analyses in Panels A and B but for $\Delta SCDS^{RATE}$, which is the *standardized* market-adjusted percentage change in CDS. Standard errors in the differences in means tests are clustered by date and firm. Differences in medians are evaluated based on a Wilcoxon rank sum test. ***Indicates significance at 1%, **at 5%, *at 10%.

Panel A: Complete sample – percentage change in CDS (ΔCDS^{RATE})

	Pre-Crisis		Post-Crisis		Difference in Means				Difference in Medians			
	Mean ΔCDS	Median ΔCDS	Mean ΔCDS	Median ΔCDS	Diff.	% Diff.	t-stat		Diff.	% Diff	z-stat	
Downgrades												
All Actions	0.097***	0.026***	0.046***	0.020***	-0.052	-53.2%	-4.72	***	-0.006	-21.6%	-2.40	**
Status Change	0.158***	0.050***	0.067***	0.031***	-0.091	-57.8%	-3.90	***	-0.019	-37.5%	-2.68	***
Letter Change	0.067***	0.017***	0.036***	0.015***	-0.031	-46.2%	-2.57	**	-0.002	-10.3%	-1.05	
Upgrades												
All Actions	-0.037***	-0.028***	-0.024***	-0.015***	0.013	-35.7%	3.26	***	0.012	-44.1%	3.61	***
Status Change	-0.040***	-0.029***	-0.022***	-0.015***	0.018	-44.9%	2.96	***	0.014	-47.7%	3.29	***
Letter Change	-0.034***	-0.027***	-0.025***	-0.016***	0.009	-26.7%	1.71	*	0.011	-41.2%	1.84	*

Panel B: "Uncontaminated" subsample – percentage change in CDS (ΔCDS^{RATE})

	Pre-Crisis		Post-Crisis		Difference in Means				Difference in Medians			
	Mean ΔCDS	Median ΔCDS	Mean ΔCDS	Median ΔCDS	Diff.	% Diff.	t-stat		Diff.	% Diff	z-stat	
Downgrades												
All Actions	0.086***	0.019***	0.036***	0.016***	-0.050	-57.9%	-3.98	***	-0.003	-16.4%	-1.95	*
Status Change	0.162***	0.042***	0.051***	0.022***	-0.111	-68.3%	-3.81	***	-0.020	-47.3%	-2.66	***
Letter Change	0.055***	0.016***	0.030***	0.013***	-0.024	-44.8%	-1.99	**	-0.003	-16.2%	-0.69	
Upgrades												
All Actions	-0.035***	-0.027***	-0.023***	-0.014***	0.012	-33.4%	2.71	***	0.013	-46.9%	3.15	***
Status Change	-0.037***	-0.028***	-0.023***	-0.017***	0.013	-36.5%	2.05	**	0.011	-40.0%	2.35	**
Letter Change	-0.034***	-0.027***	-0.024***	-0.013***	0.011	-30.9%	1.84	*	0.013	-50.9%	2.14	**

Panel C: Complete sample – standardized percentage change in CDS ($\Delta SCDS^{RATE}$)

	Pre-Crisis		Post-Crisis		Difference in Means				Difference in Medians			
	Mean ΔCDS	Median ΔCDS	Mean ΔCDS	Median ΔCDS	Diff.	% Diff.	t-stat		Diff.	% Diff	z-stat	
Downgrades												
All Actions	0.886***	0.399***	0.551***	0.368***	-0.335	-37.8%	-3.48	***	-0.030	-7.6%	-2.19	**
Status Change	1.393***	0.895***	0.865***	0.599***	-0.528	-37.9%	-2.99	***	-0.296	-33.1%	-2.36	**
Letter Change	0.631***	0.247***	0.407***	0.276***	-0.224	-35.5%	-2.00	**	0.028	11.4%	-0.96	
Upgrades												
All Actions	-0.608***	-0.430***	-0.468***	-0.351***	0.140	-23.1%	2.01	**	0.079	-18.4%	1.81	*
Status Change	-0.650***	-0.495***	-0.427***	-0.378***	0.223	-34.3%	2.32	**	0.117	-23.6%	2.22	**
Letter Change	-0.576***	-0.399***	-0.506***	-0.345***	0.070	-12.1%	0.71		0.054	-13.5%	0.05	

Panel D: "Uncontaminated" subsample – standardized percentage change in CDS ($\Delta SCDS^{RATE}$)

	Pre-Crisis		Post-Crisis		Difference in Means				Difference in Medians			
	Mean ΔCDS	Median ΔCDS	Mean ΔCDS	Median ΔCDS	Diff.	% Diff.	t-stat		Diff.	% Diff	z-stat	
Downgrades												
All Actions	0.772***	0.326***	0.445***	0.314***	-0.328	-42.4%	-3.19	***	-0.012	-3.8%	-1.75	*
Status Change	1.332***	0.754***	0.685***	0.448***	-0.647	-48.6%	-3.10	***	-0.306	-40.6%	-2.36	**
Letter Change	0.536***	0.210***	0.344***	0.258***	-0.192	-35.8%	-1.73	*	0.048	22.9%	-0.59	
Upgrades												
All Actions	-0.591***	-0.418***	-0.451***	-0.334***	0.140	-23.7%	1.86	*	0.084	-20.2%	1.67	*
Status Change	-0.604***	-0.446***	-0.443***	-0.393***	0.161	-26.7%	1.51		0.053	-11.8%	1.33	
Letter Change	-0.581***	-0.408***	-0.458***	-0.269***	0.124	-21.3%	1.18		0.139	-34.0%	1.06	

TABLE 4: Information Content of Corporate Credit Ratings – Regression Analysis

Model: $\Delta CDS^{RATE}_{i,t} = \beta_0 + \beta_1 POST + \beta_2 RCHANGE\_BIN_{i,t} + \beta_3 RCHANGE + \beta_4 IGRADE\_BDR_{i,t} + \beta_5 CDS_{i,t-2} + \beta_6 DAYS_{i,t} + \varepsilon_{i,t}$

ΔCDS^{RATE} is the market-adjusted percentage change in credit default swap (CDS) spread over days t-1 through t+1. *POST* is a binary variable for the period starting July 1, 2007. *RCHANGE_BIN* is a binary variable equal to one for letter rating changes and zero for credit rating status changes that are not accompanied by a change in rating letter. *RCHANGE* is the difference between the current letter rating and prior letter rating. *IGRADE_BDR* is a binary variable equal to one if the pre-change rating is on the border of moving between investment and junk-grade classification. CDS_{t-2} is the CDS spread as of two days prior to the earnings announcement, scaled by 1,000. *DAYS* is the number of days since the previous credit rating change, scaled by 100. Continuous variables are winsorized at 2% and 98%. Panel B repeats the analysis in Panel A but excludes dates on which there are simultaneous accounting releases, equity analyst forecast revisions, and/or management forecasts. Panels C and D repeat the analyses in Panels A and B but with the dependent variable $\Delta SCDS^{RATE}$, which is the *standardized* market-adjusted percentage change in CDS. T-statistics in brackets are clustered by firm and day. ***Indicates significant at 1%, **at 5%, *at 10%.

Panel A: Complete sample – percentage change in CDS (ΔCDS^{RATE})

			Downgrades				Upgrades		
	Coef.	H_1	All Changes	Status Changes	Letter Changes	H_1	All Changes	Status Changes	Letter Changes
Intercept	β_0		0.131	0.156	0.044		-0.029	-0.033	-0.029
			[8.27]***	[6.08]***	[4.21]***		[-5.96]***	[-4.81]***	[-4.15]***
POST	β_1	(-)	-0.054	-0.083	-0.036	(+)	0.017	0.027	0.009
			[-4.96]***	[-3.53]***	[-3.11]***		[4.29]***	[4.36]***	[1.71]*
RCHANGE_BIN	β_2		-0.077	n/a	n/a		-0.002	n/a	n/a
			[-5.54]***				[-0.41]		
RCHANGE	β_3		-0.010	n/a	-0.010		0.001	n/a	0.001
			[-1.70]*		[-1.76]*		[0.40]		[0.34]
IGRADE_BDR	β_4		0.048	0.041	0.051		-0.030	-0.026	-0.035
			[3.51]***	[1.45]	[3.36]***		[-6.34]***	[-3.29]***	[-6.00]***
CDS_{t-2}	β_5		0.006	-0.019	0.007		-0.029	-0.044	-0.011
			[1.17]	[-1.46]	[1.39]		[-3.45]***	[-4.02]***	[-0.97]
DAYS	β_6		-0.001	-0.001	-0.002		0.001	0.001	0.001
			[-0.97]	[-0.44]	[-1.91]*		[1.25]	[1.01]	[0.90]
N			1,619	522	1,097		1,200	550	650
Adj. R-Squared			0.054	0.046	0.033		0.047	0.058	0.044

Panel B: "Uncontaminated" subsample – percentage change in CDS (ΔCDS^{RATE})

			Downgrades				Upgrades		
	Coef.	H_1	All Changes	Status Changes	Letter Changes	H_1	All Changes	Status Changes	Letter Changes
Intercept	β_0		0.122	0.166	0.045		-0.024	-0.026	-0.028
			[6.18]***	[5.05]***	[4.56]***		[-4.83]***	[-3.63]***	[-3.74]***
POST	β_1	(-)	-0.056	-0.103	-0.032	(+)	0.016	0.023	0.011
			[-4.47]***	[-3.59]***	[-2.73]***		[3.83]***	[3.44]***	[2.04]**
RCHANGE_BIN	β_2		-0.062	n/a	n/a		-0.004	n/a	n/a
			[-3.94]***				[-0.70]		
RCHANGE	β_3		0.000	n/a	0.001		0.003	n/a	0.003
			[0.10]		[0.24]		[0.75]		[0.66]
IGRADE_BDR	β_4		0.037	0.033	0.038		-0.032	-0.027	-0.037
			[2.61]***	[0.93]	[2.74]***		[-6.19]***	[-3.10]***	[-5.51]***
CDS_{t-2}	β_5		0.009	-0.012	0.009		-0.034	-0.046	-0.018
			[1.68]*	[-0.89]	[1.72]*		[-3.57]***	[-4.16]***	[-1.39]
DAYS	β_6		-0.001	-0.002	0.000		0.000	0.000	0.000
			[-0.51]	[-0.87]	[0.02]		[0.59]	[0.27]	[0.60]
N			1,293	382	911		1,033	455	578
Adj. R-Squared			0.050	0.056	0.021		0.052	0.057	0.051

Panel C: Complete sample - standardized percentage change in CDS ($\Delta SCDS^{RATE}$)

			Downgrades				Upgrades		
	Coef.	**H_1**	**All Changes**	**Status Changes**	**Letter Changes**	**H_1**	**All Changes**	**Status Changes**	**Letter Changes**
Intercept	β_0		1.241	1.401	0.513		-0.451	-0.538	-0.479
			[10.19]***	[7.92]***	[4.63]***		[-5.89]***	[-5.06]***	[-4.38]***
POST	β_1	(-)	-0.301	-0.448	-0.207	(+)	0.222	0.366	0.102
			[-3.05]***	[-2.42]**	[-1.82]*		[3.25]***	[3.69]***	[1.08]
RCHANGE_BIN	β_2		-0.666	n/a	n/a		-0.087	n/a	n/a
			[-5.54]***				[-0.89]		
RCHANGE	β_3		-0.036	n/a	-0.039		0.045	n/a	0.043
			[-0.78]		[-0.86]		[0.74]		[0.69]
IGRADE_BDR	β_4		0.375	0.247	0.438		-0.497	-0.388	-0.594
			[3.30]***	[1.28]	[3.15]***		[-5.96]***	[-3.05]***	[-5.62]***
CDS_{t-2}	β_5		-0.008	-0.178	0.003		-0.574	-0.705	-0.422
			[-0.23]	[-1.47]	[0.09]		[-4.17]***	[-4.22]***	[-1.97]**
DAYS	β_6		-0.009	-0.007	-0.016		0.011	0.015	0.009
			[-0.88]	[-0.43]	[-1.41]		[1.14]	[0.90]	[0.77]
N			1,619	522	1,097		1,200	550	650
Adj. R-Squared			0.046	0.022	0.018		0.041	0.045	0.041

Panel D: "Uncontaminated" subsample - standardized percentage change in CDS ($\Delta SCDS^{RATE}$)

			Downgrades				Upgrades		
	Coef.	**H_1**	**All Changes**	**Status Changes**	**Letter Changes**	**H_1**	**All Changes**	**Status Changes**	**Letter Changes**
Intercept	β_0		1.076	1.353	0.483		-0.394	-0.432	-0.473
			[7.75]***	[6.49]***	[4.54]***		[-4.96]***	[-3.90]***	[-4.01]***
POST	β_1	(-)	-0.321	-0.591	-0.191	(+)	0.226	0.297	0.171
			[-3.03]***	[-2.71]***	[-1.66]*		[3.07]***	[2.70]***	[1.71]*
RCHANGE_BIN	β_2		-0.492	n/a	n/a		-0.106	n/a	n/a
			[-3.81]***				[-0.99]		
RCHANGE	β_3		0.030	n/a	0.031		0.059	n/a	0.057
			[0.77]		[0.79]		[0.95]		[0.90]
IGRADE_BDR	β_4		0.288	0.125	0.348		-0.517	-0.386	-0.626
			[2.40]**	[0.53]	[2.68]***		[-5.83]***	[-2.71]***	[-5.39]***
CDS_{t-2}	β_5		0.017	-0.099	0.022		-0.598	-0.670	-0.514
			[0.45]	[-0.81]	[0.58]		[-4.19]***	[-4.18]***	[-2.20]**
DAYS	β_6		0.000	-0.007	0.003		0.004	0.001	0.006
			[0.02]	[-0.36]	[0.25]		[0.38]	[0.03]	[0.49]
N			1,293	382	911		1,033	455	578
Adj. R-Squared			0.038	0.024	0.011		0.044	0.039	0.048

TABLE 5: Intra-Rating Mean and Median Quarterly Standard Deviations of CDS spreads

The sample herein consists of month-end credit default swap (CDS) spreads from 1/1/2004 through 12/31/2010, matched to the most recently issued credit rating from S&P, Moody's, or Fitch. CDS spreads are winsorized at 2% and 98%. The demarcation between the pre- and post-crisis periods is 1 July 2007. The standard deviation of CDS spreads is calculated by quarter within each credit rating level. Quarters must have a minimum of five observations to be included in the sample. Means and medians of the quarterly standard deviations are presented. "Qtrs" is the number of individual quarters included in the pre- and post-crisis means and medians. A pooled t-test or Satterthwaite test is used to test the differences in means, depending on whether the sample variances are equal or unequal. A Wilcoxon rank sum test is used to assess the difference in medians. ##Indicates that there are insufficient observations for calculating the standard deviation within any quarter of the pre- or post-crisis periods. ***Indicates significance at 1%, **at 5%, *at 10%.

	Pre-Crisis			Post-Crisis			Difference in Means			Difference in Medians		
Rating	Qtrs	Mean Std. Dev.	Median Std. Dev.	Qtrs	Mean Std. Dev.	Median Std. Dev.	Diff.	t-stat		Diff.	z-stat	
20	14	1.2	0.8	14	7.8	5.5	6.6	3.26	***	4.7	4.16	***
19	##											
18	14	2.6	2.2	14	8.7	7.7	6.1	4.75	***	5.5	4.25	***
17	14	7.3	7.0	14	16.1	11.8	8.8	2.80	**	4.8	2.64	***
16	14	7.6	5.3	14	30.1	25.0	22.4	4.26	***	19.7	3.97	***
15	14	11.0	10.5	14	24.9	19.7	13.9	3.37	***	9.2	3.33	***
14	14	14.1	14.7	14	48.5	28.7	34.4	2.42	**	14.0	2.64	***
13	14	24.0	22.7	14	84.9	58.9	60.9	3.45	***	36.2	3.52	***
12	14	32.1	26.9	14	71.5	61.4	39.4	3.83	***	34.5	3.70	***
11	14	51.9	49.0	14	109.3	91.4	57.4	4.13	***	42.5	3.84	***
10	14	71.3	61.6	14	189.4	136.8	118.1	2.78	**	75.3	4.16	***
9	14	83.0	83.5	14	247.2	187.8	164.2	2.59	**	104.3	4.48	***
8	14	99.3	96.3	14	201.9	179.5	102.6	4.20	***	83.3	4.16	***
7	14	103.0	105.5	14	311.4	201.2	208.4	2.84	**	95.6	4.48	***
6	14	93.2	92.5	14	466.0	236.1	372.9	2.83	**	143.6	4.07	***
5	14	92.5	89.8	14	514.5	289.8	422.0	3.24	***	200.0	4.39	***
4	7	89.8	102.1	14	668.1	356.6	578.4	2.74	**	254.5	3.62	***
3	2	45.6	45.6	12	724.7	330.8	679.1	2.56	**	285.2	2.10	**
2	##			##								
1	##			##								
						Avg. Increase =	336%			209%		

TABLE 6: Frequencies of Discordance Between Rating Levels and CDS Spreads

The sample herein consists of month-end credit default swap (CDS) spreads from 1/1/2004 through 12/31/2010, matched to the most recently issued credit rating from S&P, Moody's, or Fitch. CDS spreads are winsorized at 2% and 98%. The demarcation between the pre- and post-crisis periods is 1 July 2007.

See Figure 1 for illustrations of *DISCORDANT* and *DISCORD_EXTRM* observations. A "discordant" observation within each credit rating level is defined as a firm that either has: (i) a higher (i.e., safer) rating than the benchmark rating but a CDS spread that is higher (i.e., more expensive) than the benchmark rating group's 10th percentile CDS spread for the same month; or (ii) a lower (i.e., riskier) rating than the benchmark rating but a CDS spread that is lower (i.e., cheaper) than the benchmark rating group's 90th percentile spread for the same month. Discordant observations are assigned a *DISCORDANT* binary variable of 1, or 0 otherwise. An "extreme discordant" observation within each credit rating level is defined as a firm that either has: (i) a higher (i.e., safer) rating but a CDS spread that is higher (i.e., more expensive) than the benchmark rating group's *median* CDS spread for the same month; or (ii) a lower (i.e., riskier) rating but a CDS spread that is lower (i.e., cheaper) than the benchmark rating group's *median* spread for the same month. Extreme discordant observations are assigned a *DISCORD_EXTRM* binary variable of 1, or 0 otherwise.

"Percentage of Discordant Observations" is the percentage of firms in the pre- and post-crisis periods with *DISCORDANT* = 1. "Percentage Point Change" is the nominal difference in the percentage of extreme discordant observations in the post-crisis period less the percentage in the pre-crisis period. "Diff. Means t-stat" is the t-statistic of a pooled t-test or Satterthwaite test, depending on whether the sample variances are equal or unequal. "Logit z-stat" is the z-statistic from the following logit regression for each rating level:

$$DISCORDANT \text{ or } DISCORD\_EXTRM = \beta_0 + \beta_1 POST + \varepsilon$$

POST is an indicator variable for the post-crisis period. Standard errors are clustered by month and firm. ##Indicates that there are insufficient observations for the Logit regression model. ***Indicates significance at 1%, **at 5%, *at 10%. !!Indicates a decrease rather than increase (as predicted) from the pre- to post-crisis periods.

Panel A: Discordant observations

Rating	Percentage of Discordant Observations Pre-Crisis	Percentage of Discordant Observations Post-Crisis	Percentage Point Change	Percent Change	Diff. Means. t-stat		Logit z-stat	
20	1.0%	6.5%	5.5%	539%	25.22	***	3.92	***
19	0.1%	2.8%	2.7%	3400%	12.67	***	3.71	***
18	4.9%	16.3%	11.4%	232%	32.27	***	5.98	***
17	24.8%	28.9%	4.1%	17%	7.82	***	1.42	
16	19.8%	27.4%	7.5%	38%	14.91	***	2.96	***
15	23.4%	29.1%	5.8%	25%	10.65	***	2.53	**
14	30.8%	39.7%	8.8%	29%	15.24	***	3.37	***
13	38.5%	41.4%	2.9%	7%	4.71	***	1.22	
12	28.7%	40.5%	11.8%	41%	19.45	***	5.30	***
11	24.1%	33.6%	9.5%	39%	16.82	***	4.56	***
10	25.4%	42.3%	16.9%	67%	30.18	***	5.56	***
9	19.9%	24.1%	4.2%	21%	8.51	***	2.24	**
8	31.0%	20.3%	-10.7%	-35%	20.44	***!!	2.56	**!!
7	15.9%	19.2%	3.2%	20%	7.06	***	1.87	*
6	13.0%	15.1%	2.0%	15%	4.89	***	1.18	
5	13.5%	12.1%	-1.4%	-10%	3.41	***!!	0.63	!!
4	9.9%	17.9%	8.1%	82%	19.45	***	3.47	***
3	1.9%	8.7%	6.7%	353%	22.65	***	5.49	***
2	0.0%	1.8%	1.8%	undefined	13.98	***	##	
1	0.0%	3.8%	3.8%	undefined	23.05	***	##	
Avg.	16.3%	21.6%	5.2%	32.0%				

Panel B: Extreme discordant observations

Rating	Percentage of Extreme Discordant Observations Pre-Crisis	Percentage of Extreme Discordant Observations Post-Crisis	Percentage Point Change	Percent Change	Diff. Means. t-stat		Logit z-stat	
20	0.0%	2.0%	2.0%	4517%	17.00	***	3.72	***
19	0.1%	2.8%	2.7%	3383%	12.67	***	3.71	***
18	1.2%	10.4%	9.2%	739%	34.53	***	7.32	***
17	2.3%	8.5%	6.2%	269%	23.65	***	6.54	***
16	4.0%	9.5%	5.6%	140%	18.79	***	4.95	***
15	5.3%	9.4%	4.2%	79%	13.09	***	3.62	***
14	7.7%	13.0%	5.3%	69%	14.48	***	4.35	***
13	9.6%	11.9%	2.4%	25%	6.15	***	1.78	*
12	8.5%	12.0%	3.5%	41%	9.08	***	2.65	***
11	5.9%	9.9%	4.0%	68%	12.04	***	3.52	***
10	4.7%	8.3%	3.6%	75%	12.03	***	3.97	***
9	5.1%	6.4%	1.3%	25%	4.62	***	1.39	
8	5.9%	5.5%	-0.5%	-8%	1.71	*!!	0.56	!!
7	5.1%	4.9%	-0.2%	-3%	0.64	!!	0.22	!!
6	4.2%	4.3%	0.1%	2%	0.30		0.10	
5	3.8%	3.6%	-0.2%	-5%	0.81	!!	0.27	!!
4	4.1%	4.2%	0.2%	4%	0.62		0.18	
3	1.2%	4.0%	2.8%	225%	12.63	***	3.49	***
2	0.0%	1.6%	1.6%	undefined	13.14	***	##	
1	0.0%	1.8%	1.8%	undefined	15.76	***	##	
Avg.	3.9%	6.7%	2.8%	70.4%				

TABLE 7: Intra-Rating Average CDS Spreads

The sample herein consists of month-end credit default swap (CDS) spreads from 1/1/2004 through 12/31/2010, matched to the most recently issued credit rating from S&P, Moody's, or Fitch. CDS spreads are winsorized at 2% and 98%. The demarcation between the pre- and post-crisis periods is 1 July 2007. "N" is the number of monthly observations included in the mean CDS calculation. Standard errors in the differences in means tests are clustered by month and firm where possible. #Indicates that there are insufficient observations for clustering, in which case heteroscedasticity-robust standard errors are used. A Wilcoxon rank sum test is used to assess the difference in medians. ***Indicates significance at 1%, **at 5%, *at 10%.

	Pre-Crisis			Post-Crisis			Difference in Means			Difference in Medians		
Rating	N	Mean CDS	Median CDS	N	Mean CDS	Median CDS	Diff.	t-stat		Diff.	z-stat	
20	128	9.9	9.9	115	37.0	32.8	27.1	9.98	***	22.9	13.37	***
19	7	7.7	7.3	18	34.9	32.7	27.2	6.43	*** #	25.4	3.78	***
18	244	12.2	11.5	160	45.1	42.6	32.9	7.41	***	31.1	16.10	***
17	352	16.4	14.2	307	52.0	45.0	35.6	8.41	***	30.8	20.21	***
16	552	19.5	16.5	749	58.4	47.6	38.9	7.30	***	31.1	27.22	***
15	1,419	24.4	21.7	1,561	62.7	52.2	38.3	7.43	***	30.5	39.07	***
14	1,349	31.4	27.5	985	82.3	58.7	51.0	5.01	***	31.2	30.68	***
13	1,744	43.5	37.5	1,828	106.0	74.5	62.5	5.44	***	37.0	34.78	***
12	2,608	52.8	45.5	2,309	130.4	98.4	77.6	6.65	***	52.9	41.66	***
11	1,656	83.7	71.8	2,008	178.1	138.5	94.4	6.40	***	66.7	31.51	***
10	944	134.8	120.0	938	286.6	221.6	151.8	5.01	***	101.6	19.64	***
9	930	188.4	168.5	817	390.0	315.9	201.5	5.81	***	147.4	21.78	***
8	756	220.4	203.2	982	473.0	406.9	252.6	7.19	***	203.7	24.66	***
7	586	271.3	247.9	821	631.2	535.8	359.9	6.42	***	287.9	23.10	***
6	402	325.1	340.0	510	912.7	650.2	587.6	5.32	***	310.2	21.92	***
5	242	354.8	365.0	530	1,307.3	951.1	952.5	6.30	***	586.1	20.36	***
4	109	342.0	350.3	344	1,394.2	900.7	1,052.2	4.00	***	550.4	13.52	***
3	26	429.6	426.2	152	2,134.0	1,115.9	1,704.4	3.43	***	689.7	7.99	***
2	2	480.0	480.0	33	2,419.4	1,470.2	1,939.4	5.56	*** #	990.2	2.31	**
1	3	465.8	444.9	110	2,698.4	1,476.8	2,232.6	9.76	*** #	1,031.9	2.94	***
					Avg. Percentage Increase =		227%			161%		

TABLE 8: Information Content of Unexpected Earnings for CDS Spreads

$\Delta CDS^{EA}_{i,t} = \beta_0 + \beta_1 UE_{i,t} + \beta_2 UE_{i,t}*POST + \beta_3 POST + \beta_4 CDS_{t-2} + \beta_5 UE_{i,t}*CDS_{t-2} + \beta_6 IGRADE\_BDR_{i,t} + \beta_7 IGRADE\_BDR_{i,t}*UE_{i,t} + \beta_8 NONLINEAR_{i,t} + \beta_9 LOSS + \beta_{10} LOSS*UE + \Sigma\beta_k ADDL\_CONTROLS + \Sigma\beta_k ADDL\_CONTROLS*UE + \varepsilon_{i,t}$

ΔCDS^{EA} is the market-adjusted percentage change in credit default swap (CDS) spread over days t-1 through t+1. *POST* is a binary variable for the period starting July 1, 2007. *IGRADE_BDR* is a binary variable equal to one if the firm is on the border of moving between investment and junk-grade credit rating classification. CDS_{t-2} is the CDS spread as of two days prior to the earnings announcement, scaled by 1,000. *UE* is calculated as actual earnings per share less IBES consensus forecast, scaled by end-of-quarter price. *NONLINEAR* is *UE* * |*UE*|. Loss is an indicator for negative earnings. *ADDL_CONTROLS* are untabulated for brevity and include the natural log of total assets, book-to-market, leverage, an indicator for the fourth fiscal quarter, and equity market beta. Continuous *ADDL_CONTROLS* are normalized to reduce multicollinearity between *UE* and *ADDL_CONTROLS*UE*. All continuous variables are winsorized at 2% and 98%. Panel B repeats the analyses in Panel A but with the dependent variable $\Delta SCDS^{EA}$, which is the *standardized* market-adjusted percentage change in CDS. T-statistics in brackets are clustered by firm and day. ***Indicates significant at 1%, **at 5%, *at 10%.

Panel A: Percentage change in CDS (ΔCDS^{EA})

	Coefficient	**H_4**	**Complete Sample**	**Complete Sample**	**Uncontaminated Subsample**	**Uncontaminated Subsample**
UE (Pre-Crisis)	β_1		-3.669	-3.529	-2.895	-2.844
			[-9.64]***	[-9.04]***	[-4.36]***	[-4.19]***
UE*POST	β_2	(-)	-0.707	-0.705	-0.980	-0.979
			[-3.05]***	[-2.91]***	[-2.90]***	[-2.82]***
POST	β_3		0.005	0.004	0.000	-0.000
			[2.59]***	[2.38]**	[0.01]	[-0.13]
CDS_{t-2}	β_4		-0.014	-0.009	-0.006	0.001
			[-2.54]**	[-1.57]	[-0.65]	[0.11]
$UE*CDS_{t-2}$	β_5		1.089	0.759	0.642	0.592
			[1.75]*	[1.18]	[0.65]	[0.58]
IGRADE_BDR	β_6		-0.006	-0.006	-0.002	-0.001
			[-3.36]***	[-2.73]***	[-0.67]	[-0.27]
IGRADE_BDR*UE	β_7		0.344	0.237	0.778	0.597
			[1.20]	[0.84]	[1.38]	[1.04]
NONLINEAR	β_8		72.781	63.792	49.269	47.767
			[5.52]***	[4.95]***	[2.74]***	[2.59]***
LOSS	β_9		0.008	0.009	0.007	0.007
			[2.94]***	[3.25]***	[1.40]	[1.37]
LOSS*UE	β_{10}		0.662	0.537	0.724	0.662
			[1.82]*	[1.60]	[1.51]	[1.47]
Intercept	β_0		0.000	-0.001	-0.003	-0.005
			[0.02]	[-0.91]	[-1.38]	[-2.13]**
Additional Controls			-	Included	-	Included
N			7,314	7,314	1,639	1,639
Adjusted R-Squared			0.046	0.048	0.060	0.059

Panel B: Standardized percentage change in CDS ($\Delta SCDS^{EA}$)

	Coefficient	H_4	Complete Sample	Complete Sample	Uncontaminated Subsample	Uncontaminated Subsample
UE (Pre-Crisis)	β_1		-72.778	-70.368	-61.489	-61.077
			[-10.48]***	[-9.94]***	[-5.02]***	[-4.83]***
UE*POST	β_2	(-)	-12.617	-11.967	-16.217	-15.947
			[-2.78]***	[-2.54]**	[-2.56]**	[-2.34]**
POST	β_3		0.067	0.061	-0.003	-0.009
			[2.25]**	[1.97]**	[-0.04]	[-0.13]
CDS_{t-2}	β_4		-0.351	-0.255	-0.270	-0.159
			[-3.64]***	[-2.38]**	[-2.00]**	[-0.98]
UE*CDS_{t-2}	β_5		18.931	14.240	13.942	15.766
			[1.68]*	[1.22]	[0.77]	[0.83]
IGRADE_BDR	β_6		-0.105	-0.089	-0.037	-0.017
			[-2.83]***	[-2.25]**	[-0.54]	[-0.23]
IGRADE_BDR*UE	β_7		5.677	4.450	9.666	7.836
			[1.07]	[0.85]	[0.88]	[0.69]
NONLINEAR	β_8		1,482.394	1,356.923	1,115.066	1,096.449
			[6.71]***	[6.25]***	[3.66]***	[3.36]***
LOSS	β_9		0.194	0.207	0.227	0.225
			[3.78]***	[4.09]***	[2.55]**	[2.49]**
LOSS*UE	β_{10}		13.607	11.514	15.672	15.666
			[2.21]**	[1.98]**	[2.13]**	[2.11]**
Intercept	β_0		-0.002	-0.029	-0.063	-0.091
			[-0.08]	[-1.15]	[-1.46]	[-2.02]**
Additional Controls			-	Included	-	Included
N			7,314	7,314	1,639	1,639
Adjusted R-Squared			0.058	0.060	0.070	0.068