The Financial Crisis and Credibility of Corporate Credit Ratings

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A dissertation submitted in partial fulfillment of the requirements for the degree of

Doctor of Philosophy

University of Washington

June 2013

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Program Authorized to Offer Degree:

Business - Accounting

University of Washington

Abstract

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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, as well as how credibility damage affects the use of corporate ratings and accounting information in debt pricing. I find evidence consistent with credibility concerns motivating debt market participants to simultaneously decrease their reliance on corporate credit ratings and increase their reliance on accounting data 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 study provides new empirical evidence on the relation between credit rating credibility and usage, and also informs the literature about the substitutability between corporate credit ratings and accounting information in debt markets.

1. Introduction

Regulators, academics, and the credit rating agencies ("CRAs") have found that credit ratings on certain structured finance products (e.g., mortgage-backed securities) significantly underestimated default risk prior to July of 2007, and that the subsequent downgrades of these credit ratings in large part triggered the recent financial crisis (Benmelech and Dlugosz 2009; Ashcraft et al. 2010; White 2010; Standard & Poor's 2010a; U.S. Senate 2011). Further, chief officers at all three major U.S. CRAs have testified that these rating failures caused them serious credibility damage with respect to their ratings on certain financial products (U.S. Congress 2008). It is unclear, however, whether the failure of ratings on <u>structured finance products</u> also damaged the CRAs' credibility with respect to <u>corporate</u> credit ratings. If market participants view the failures of ratings on structured finance products as symptomatic of a corrupt or dysfunctional rating industry, then it is likely that the credibility of corporate credit ratings also suffers as a result of the financial crisis. However, the economics and incentives relating to corporate credit ratings differ from those relating to credit ratings on structured finance products. If market participants view the failures of ratings on structured finance products as being caused by issues specific to that sector, then the credibility of corporate credit ratings is likely unaffected by the financial crisis. 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 how market participants use both corporate credit ratings and accounting information in debt pricing.

I define "credibility" very simply as market participants' expectations about credit rating quality.[1] Credit ratings are intended to provide a relative ranking of default risk at a given point

[1] 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; Shapiro 1982, 1983). The accounting and analyst disclosure literatures often use the term "credibility" to refer to the

in time (Altman and Rijken 2004). Thus, rating "credibility" is increasing with market participants' expectations about the CRAs ability to evaluate relative default risk, as well as the extent to which the CRAs truthfully communicate that risk via their credit ratings. As discussed in detail in Section 2, credibility plays an essential role in the rating industry because: (i) actual rating quality is difficult to observe, both ex ante and ex post; and (ii) the CRAs have incentives to provide low quality and optimistically biased credit ratings. As such, credibility is often cited as the primary determinant of market participants' demand for, and usage of, credit ratings in investment and contracting decisions (White 2001; Partnoy 1999).

Between July of 2007 and July of 2009, the major CRAs downgraded $1.9 trillion of structured finance products from AAA to junk status, including 80% of all outstanding AAA collateralized debt obligations (White 2010). The prevalence of such large downgrades is typically close to 0% (Standard & Poor's 2012). In 2008 Congressional testimonies, the chief officers at all three major CRAs attested to the statement that these "incredible failures…" of ratings on structured finance products "screwed up the ratings so as not to be believable anymore" (U.S. Congress 2008, p188 - 189). At that time, market participants were likely uncertain as to whether the problems that caused the failure of ratings on certain financial products also affected the quality of corporate credit ratings. On one hand, as discussed in detail in Section 2, it is plausible that the failures of ratings on structured finance products were caused by misaligned incentives and weak governance that also undermined the quality of corporate credit ratings. On the other hand, it is also plausible that the failures of ratings on structured finance products were

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synonymous construct of market participants' expectations about information quality (e.g., Pownall and Waymire 1989; Francis et al. 2005; 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.

due to inexperience and lack of transparency specifically related to the financial product sector, and that the quality of corporate ratings was unaffected. The extent to which the credibility of corporate ratings was affected by the financial crisis depends on the extent to which market participants collectively share each of these views.

My empirical analysis is based on a maintained assumption that market participants discount low-credibility information in debt pricing. Thus, the debt market relevance of corporate credit ratings is increasing with rating credibility, where "relevance" is defined as the strength of the relation between an information source and observed market prices.[2] If the credibility of corporate credit ratings suffers after the crisis, market participants place less weight on rating signals and the magnitude of debt price responses around credit rating change announcements declines. Further, as market participants reduce the weight placed on corporate ratings, greater relative weight is placed on alternate information and the relevance of corporate ratings for debt price levels also weakens in the post-crisis period.

While observing a decline in the debt market relevance of corporate ratings between the pre- and post-crisis periods would be consistent with credibility damage, there are many potential alternate explanations for observing such a trend. For instance, significantly reduced liquidity, increased counterparty risk, or increased noise trading could all weaken the relations between debt prices and information sources. Thus, my empirical strategy is to gauge changes in the debt

[2] Holthausen and Verrecchia (1988) formalize this intuition in a Bayesian updating model in which market participants assign weights to competing information sources based on the expected quality (i.e., credibility) 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 market relevance 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).

market relevance of credit ratings in relation to changes in the relevance of a competing information source that does not experience a credibility shock. Difference-in-differences analysis can control for pervasive changes in how debt markets respond to information events. Corporate credit ratings are substantially based on accounting information and, therefore, I argue that accounting reports are a logical alternate source of information for debt pricing. If a decline in the debt market relevance of corporate credit ratings is due to credibility damage, and if accounting reports do not experience a credibility shock, then accounting data will, at a minimum, decline in relevance to a lesser degree than corporate ratings. Depending on the extent of the substitution towards relying on accounting information, the debt market relevance of accounting data may even increase unto itself in the post-crisis period.

I use credit default swap ("CDS") spreads as a liquid measure of a firm's cost of debt, where a higher CDS spread indicates higher risk.[3] Univariate and regression analyses find that the average CDS responses around corporate credit rating downgrades and upgrades declines by up to 58% in the post-crisis period starting in July 2007. Difference-in-differences tests find that CDS responses around quarterly accounting releases decline to a significantly lesser degree than CDS responses around corporate credit rating. Additional regression analysis finds that the informativeness of unexpected earnings (i.e., actual earnings less the consensus forecast) for CDS spreads actually <u>increases</u> by a statistically significant 18% to 28% in the post-crisis period. These results are robust to using a subsample of observations that excludes dates on which there are competing information events, as well as to using a subsample that ensures a balance of similarly sized rating changes and earnings surprises in the pre- and post-crisis periods. Thus, the

[3] 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.

price response tests are consistent with a simultaneous decrease (increase) in the debt market relevance of credit ratings (accounting information), and therefore with the credibility of corporate credit ratings suffering as a result of the financial crisis.

I test for changes in the relevance of corporate credit ratings for debt price levels based on the extent of "discordancy" between credit ratings and observed CDS spreads. Credit ratings reflect the CRA's opinion about the relative ordering of firms' default risks within an economy at a given point in time. At the same time, observed CDS spreads reflect the market's collective opinion about the ordering of default risk. As discussed in detail in Section 4, "discord" between the CRA's ordering and the market's ordering can be used as a measure of the extent to which market participants rely on credit ratings in debt pricing. As debt market participants decrease their reliance on credit ratings, the discordancy between credit ratings and observed debt prices increases. I find that the prevalence of discordancy between credit ratings and CDS spreads is 19.7% in the pre-crisis period versus 25.1% in the post-crisis period, for a statistically significant increase of 5.4 percentage points (or a 27.3% proportional increase). At the same time, there is a small but insignificant decrease in the discordancy between accounting data and CDS spread levels. Difference-in-differences tests confirm that the discordancy between credit ratings and CDS spread levels increases to a significantly greater degree than the discordancy of accounting data. A more stringent measure of "extreme discordant" observations produces similar results. These results are again consistent with a decline in the debt market relevance of corporate credit ratings, and with the credibility of corporate credit ratings suffering as a result of the financial crisis.

Additional 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. 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. However, this result must be interpreted with caution because the CRAs do not intend for ratings to provide absolute measures of default risk. A uniform increase in debt prices could also be consistent with a macroeconomic increase in risk affecting all firms.

I perform a number of robustness tests to reduce concerns about alternate explanations for finding a post-crisis decrease (increase) in the debt market relevance of corporate credit ratings (accounting data). A first alternate explanation is that, during periods of high uncertainty, debt market participants prefer to rely on audited, backward-looking accounting reports rather than on unaudited, forward-looking intermediary reports. I find that the debt market relevance of equity analyst forecast revisions increases by a statistically significant 30% to 42% in the post-crisis period, which is inconsistent with a general shift in demand away from intermediary-provided information. A second alternate explanation is that market participants prefer timelier information in the post-crisis period than in the pre-crisis period, and that accounting reports are potentially a timelier information source than credit ratings. Additional tests find that the relevance of stale accounting information (i.e., accounting information that is more than 90 days old) for debt price levels does not decline in the post-crisis period, which is inconsistent with a demand for timelier information. Additional tests reduce concerns about the effects of growth in the CDS market, changes in the types of firms traded on the CDS market, changes in the way CRAs incorporate accounting information in corporate credit ratings, and changes in the properties of accounting information.

My study's most direct contribution is to provide evidence on whether the CRAs' credibility with respect to corporate credit ratings suffers as a result of the financial crisis. 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.[4] 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 likely 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

[4] 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).

to examine a well-defined shock to CRA credibility. Observing that there are predictable changes in debt market participants' reliance 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; Ball et al. 2008; Costello and Wittenberg-Moerman 2011), I provide initial evidence on the substitability between accounting data and credit ratings in debt pricing. Together, these results provide new insights about a fundamental accounting research question of how and when capital market participants use accounting information in pricing decisions.

2. Hypothesis Development

2.1. Credit ratings and the role of credibility

Standard & Poor's ("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 2010b). 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. 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.[5] During 2010, three CRAs, Standard & Poor's, Moody's, and Fitch, comprised over 97% of the regulated U.S. credit rating industry market share (S.E.C. 2011).[6]

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 2011a, 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,

[5] 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.

[6] 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, 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 operates on an investor-pays business model, so likely has different incentives relating to rating quality; (iii) Egan Jones received NRSRO status in 2007, and certification plausibly altered the content and usage of its ratings; and (iv) Egan Jones plead guilty to filing false registration documents with the S.E.C. in 2008, so Egan Jones' credibility was likely altered differently from the other CRAs (Beaver et al. 2006; S.E.C. 2013). 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.

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).

The information contained in credit ratings arises from two sources. First, CRAs are specialists that are potentially able to process data at a lower cost than other market participants. Under this view, CRAs can increase pricing efficiency by serving as a market intermediary and reducing the need for lenders to undertake costly, independent research (Holthausen and Leftwich 1986). Second, CRAs are usually given access to private information that is not available to other market participants.[7] Jorion et al. (2005) find evidence consistent with this view by demonstrating an increase that the information content of credit rating changes following Regulation FD; a result they attribute to an increase in the amount of private information available to CRAs relative to other market participants.

In addition to providing information about a firm's default risk, credit ratings can also directly impact a firm's default risk in at least two ways. First, private debt contracts often include rating-based covenants or performance pricing provisions, so a change in credit rating can alter a firm's interest payments or other loan conditions. Second, credit ratings are often used in government regulations such as bank capital requirements and, thus, credit rating actions such as a downgrade from investment- to junk-grade status can affect demand for a firm's debt.[8]

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[7] 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, and the CRAs continue to use private information in rating assessments.

[8] The Dodd-Frank Act calls for the removal of references to rating agencies from government regulations. The S.E.C. and F.D.I.C. began to implement such changes in late 2011 and the process continues through 2013. Thus, the removal of ratings from regulations does not impact my sample period.

Credibility plays an essential role in the rating industry because: (i) actual rating quality is difficult to observe, both ex ante and ex post; and (ii) the CRAs have incentives to provide low quality and optimistically biased credit ratings. Ex ante evaluation of credit rating quality is difficult because the CRAs use private information from managers in forming rating opinions, and ex post assessments are difficult because actual defaults are rare, idiosyncratic, and endogenous to rating changes (Ashcraft and Schuermann 2008; White 2001). As with any product where quality is initially unobservable, consumer demand is based on prior experience with the seller (Nelson 1970). Further, because actual rating quality is only observable with a several year delay, numerous years' of experience are likely necessary to alter consumers' views about rating quality. The CRAs have an incentive to provide optimistically biased ratings due to their "issuer pays" business model. The CRAs have limited incentives to maintain rating quality not only because they are an oligopoly and need not necessarily compete based on quality, but also because the CRAs have been largely immune from civil litigation over rating failures (White 2001, 2010; Partnoy 2006; U.S. Senate 2011; Schwarcz 2002).[9] For these reasons, a market participant's decision about how much to rely on credit ratings in debt pricing is largely based on his <u>expectations</u> of rating quality, which may or may not be consistent with the rating's actual quality at a given point in time. Said differently, <u>credibility</u> is a primary determinant of market participants' demand for, and usage of, credit ratings.[10]

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[9] The courts have traditionally found that credit ratings are protected as opinions under the First Amendment and, thus, the CRAs have seldom been held liable for rating errors (Partnoy 2006).

[10] Demand for credit ratings is complicated because the end users of credit ratings (e.g., investors or lenders) are not the fee-paying customers of credit ratings (e.g., firms issuing debt or financial products). Firms have little discretion in purchasing a credit rating due to regulatory requirements and signaling implications. Thus, credibility damage is unlikely to have a short-term effect on the CRAs revenues. Credibility damage *is* likely to have an immediate impact on the demand for credit ratings by end users.

The recent financial crisis is not the first time the CRAs' credibility has been called into question. Concerns that the CRAs' oligopoly power and issuer-pays business model could lead to low-quality or biased ratings have persisted for decades (White 2001, 2010). Most recently prior to the financial crisis, the CRAs were widely criticized for having investment-grade ratings on Enron and WorldCom shortly before their bankruptcies in the early 2000's. Despite these concerns, there is extensive evidence that corporate credit ratings motivate capital market responses, which is consistent with the CRAs having at least some credibility with market participants (see Norden and Weber 2004 for a summary). Jorion et al. (2005) finds increased price responses to credit rating changes after Regulation FD, which indicates that market participants view credit ratings as providing value-relevant information in the years shortly before the recent financial crisis.

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). It is unclear, however, 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.

2.2.1. Reasons why the credibility of corporate ratings is unaffected by the financial crisis

There are several reasons why market participants likely viewed the failures of ratings on structured finance products as anomalous and unrelated to the quality of corporate ratings. The first potential reason is that the CRAs are simply more competent at rating corporations than complex financial instruments. Differences in prior experience support this view: the CRAs had rated corporations for over 100 years and through numerous recessions before the financial crisis, whereas they had fewer than 10 years of experience rating mortgage-based financial products and had yet to weather a serious housing market downturn (as discussed in Ashcraft and Schuermann 2008, securities backed by subprime and Alt-A mortgages existed in relatively small numbers prior to 2001). This view is also consistent with CRA executives' arguments 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).

The second reason why the failure of ratings on financial products was likely unrelated to the quality of corporate ratings is that, due to greater transparency with ratings on corporations, the CRAs had stronger incentives to ensure the accuracy and unbiasedness of their corporate ratings than their ratings on financial products. Ample information about corporations and their assets is available from audited financial statements, voluntary disclosure, and external analyst reports. Quite differently, the prospectuses for structured finance products often lack significant detail about the underlying assets, and few other sources of information about the securities are available. Because thired parties are able to gauge the accuracy of a corporate rating more easily than the accuracy of a financial product rating, the CRAs were plausibly able to let the quality and/or unbiasedness of financial product ratings deteriorate to a greater degree than corporate ratings.

Third, many structured finance products are rated by only a single CRA, which allows for greater "rating shopping" and puts greater pressure on the CRAs to provide optimistic ratings (Benmelech and Dlugosz 2009). Corporations and their debt are nearly always rated by two if not all three major CRAs, reducing pressure on an individual CRA to compete for business, and thereby reducing the pressure to provide biased ratings.

Another likely reason to not expect a decline in the credibility of corporate credit ratings, or even to expect an increase in credibility, is that market participants' believe that: (i) increased public scrutiny incentivizes the CRAs to improve the quality of corporate ratings in the post-crisis period; and (ii) the CRAs are capable of actually improving rating quality should they want to. This scenario is similar to that studied by Cheng and Neamtiu (2009), in which the CRAs appear to improve the quality of corporate credit ratings following the negative scrutiny they received for the Enron and WorldCom bankruptcies.

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 also 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.

2.2.2. Reasons why the credibility of corporate ratings declines after the financial crisis

There are also numerous reasons why market participants likely viewed the failure of ratings on structured finance products as being symptomatic of broad problems in the rating industry that also undermine the quality of corporate ratings. First, congressional investigations and academic studies find evidence indicating that the failures of financial product ratings were not due to a simple inability to evaluate default risk on mortgage-based securities, but were due to gross negligence or even fraud by CRA employees and executives. For instance, Griffin and Tang (2011) and Ashcraft et al. (2010) find evidence consistent with the CRAs intentionally ignoring internally-generated evidence that their ratings on structured finance products were overstated. U.S. Congressional investigators find that senior CRA executives were aware of inflated ratings on financial products at least six months before taking downgrade action (U.S. Congress 2008; U.S. Senate 2011). 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 low quality ratings on corporations.

A second factor is that increased competition from newly certified CRAs in the mid-2000s, combined with the issuer-pays business model, plausibly increased pressure on the major CRAs to provide biased ratings on both structured finance products and corporations. Consistent with this view, Bolton et al. (2012) develop a model in which increased competition leads to biased credit ratings, and Becker and Milbourn (2011) find empirical evidence consistent with increased competition from Fitch in the 1990s and early 2000s resulted in lower quality corporate ratings among the other major CRAs. A 2011 U.S. Senate Report also cites the conflict of interest in the CRAs' business model as a factor leading to the failure of ratings on financial products as it let 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" (p7).

A third potentially relevant factor is that the anti-CRA rhetoric of the media and political leaders caused market participants to question the credibility of corporate credit ratings. In 2008 Congressional hearings, lawmakers' criticisms of the CRAs make little distinction between ratings on structured finance products versus corporations. For instance, Congressman Shay of the U.S. House Committee on Oversight and Government Reform summarized the views of many regulators: "[the CRAs] 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 post-mortem on the role of the CRAs in the financial crisis is more careful in directing its criticism specifically at the CRAs' ratings on structured finance products, but it still identifies a number of factors that plausibly also affected the quality of corporate ratings: 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.

2.3. Corporate rating credibility and debt market relevance

If debt market participants view the failures of ratings on structured finance products as being 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 a decline in the relevance of credit ratings for debt prices. A decline in rating relevance should manifest in two ways. First, the magnitude of debt price changes around credit rating changes declines as rating announcements motivate less belief revision. Second, the strength of the relation between debt price and credit rating levels declines as: (i) 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; and (ii) market participants likely increase their investment in analyzing substitute information sources after the crisis, thereby further increasing (decreasing) the relative weights placed on non-rating data (credit ratings). As long as the credit ratings and non-rating information sources do not provide identical signals about default risk, the association between credit ratings and debt price levels will weaken after the crisis. 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 relevance of corporate ratings. A third possible outcome is that market participants expect that negative publicity and increased scrutiny motivates the CRAs to improve the quality of their corporate ratings in the post-crisis period, thereby causing an increase in the relevance of corporate ratings in debt markets. Hypotheses 1 in the alternate form:

> H1a: The debt market relevance of corporate credit rating changes decreases after the financial crisis.
>
> H1b: The debt market relevance of corporate credit rating levels decreases after the financial crisis.

2.4. Benchmarking against the relevance of accounting information

While a decline in the debt market relevance of credit ratings is consistent with credibility damage, such results could also be due to correlated but unrelated systematic changes in debt markets before/after the financial crisis. Examples of potential correlated changes include significantly reduced market liquidity, increased counterparty risk, or increased noise trading. An effective way to reduce concerns about correlated market-wide changes is to examine the debt market relevance of a non-rating information source in the pre- and post-crisis periods. As discussed in relation to H1, a decline in the credibility of credit ratings will not only reduce the weight placed on rating signals, but will also increase the relative weights placed on select non-rating signals. Thus, data that are a substitute to credit ratings will become more relevant for debt prices after the financial crisis, or at least will decline in relevance to a lesser degree than do credit ratings. However, if the decline in rating relevance is driven by systematic changes in how debt markets respond to all information events, then the relevance of substitute information sources will also decline.

There are several reasons to expect that accounting reports are a logical choice for substitute information in debt pricing. First, prior research has demonstrated that credit ratings are substantially based on accounting data (e.g., Horrigan 1966). 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; Ball et al. 2008; Costello and Wittenberg-Moerman 2011). Finally, the private information revealed in accounting reports is potentially available to the CRAs ex ante but not to other market participants. If market participants no longer trust credit ratings they will likely "go to the source" and rely more on the accounting reports themselves.[11] Hypotheses 2 in the alternate form are as follows:

H2a: The debt market relevance of accounting information changes decreases after the financial crisis to a lesser degree than does the relevance of corporate credit ratings.

H2b: The debt market relevance of accounting information levels decreases after the financial crisis to a lesser degree than does the relevance of corporate credit ratings.

2.5. Are ratings viewed as biased or simply noisy?

As previously discussed, credit ratings lack credibility when the CRAs are thought to be incompetent and/or untruthful. Finding evidence supporting H1 and H2 is consistent with a credit

[11] Other intermediaries such as analysts are another logical source of substitute information and are discussed in more detail in Section 5.

ratings being viewed as noisier signals in the post-crisis period, which indicates that there is a decline in the expected competence of the CRAs. If the financial crisis causes debt market participants to also view corporate ratings as optimistically biased (as opposed to simply inaccurate), there should be an upward correction of cost of debt upon this revelation. For instance, within a given credit rating level (e.g., AA+), the average cost of debt 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 just 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 cost of debt unto itself is not conclusive evidence of a revealed 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 cost of debt increases after the financial crisis.

3. Data and Sample Selection

My sample period spans January 2004 through December 2010. The pre/post-crisis bisection is in July of 2007 – the month in which the CRAs began large-scale downgrades of credit ratings on structured products.[12]

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

[12] 2004 and 2010 are the earliest and latest dates covered in my CDS dataset. A 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).

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. 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. 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.[13] 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

[13] 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.

frequently traded (Zhang et al. 2009). Second, I eliminate all daily CDS observations that are based on fewer than two independent buy quotes.[14]

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.

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.,

[14] 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.

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).

3.3. Credit rating samples 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 5.

As detailed in Panel A of Table 2, the sample of credit rating letter changes includes a total of 1,742 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.

3.4. Accounting samples summary information

Tables 1 and 2 also present summary information for the samples used in performing the accounting-based tests in H2a and H2b. Accounting data are obtained from Compustat. Analyst consensus forecasts and actuals are obtained from IBES. For the levels analysis, the firm-month observations detailed in Panel A of Table 1 are matched to the firms' most recently published accounting data. Accounting data published more than one year prior to the month-end are excluded. As shown in Panel A of Table 1, 25,327 firm-month observations have sufficient accounting data to perform the accounting-based levels tests. Panels A and B of Table 2 show that a total of 7,314 firm-quarter observations (400 unique firms) have the requisite data for the tests of CDS spread changes around earnings announcements. Panel D of Table 2 presents the frequencies negative, zero, and positive earnings surprises in the pre- and post-crisis periods.

3.5. Balanced and uncontaminated subsamples

The "balanced" subsample of credit rating changes presented in Panel C of Table 2 ensures that each rating change from the pre-crisis period is matched to a rating change of the same direction and magnitude in the post-crisis period. The balanced subsample of earnings releases in Panel D of Table 2 ensures that each earnings announcement from the pre-crisis period is matched to an announcement with a similar earnings surprise in the post-crisis period. Earnings surprise is calculated as the IBES actual EPS less the most recent IBES consensus, scaled by end-of-quarter price (see Section 4 for further discussion).[15] Earnings surprises are

[15] Matching based on unscaled *UE* produces largely unchanged results.

matched to the third decimal place. The balanced subsamples are roughly 14% smaller than the complete samples.

The "uncontaminated" subsamples detailed in Panels C and D of Table 2 exclude dates on which there are identifiable simultaneous information events. All dates on which there are simultaneous credit rating changes and earnings releases are dropped, as are days on which management forecasts occur (identified via the First Call database). Dates on which there are more than two equity analyst forecast revisions in the IBES database are also excluded because it is probable that the analysts are responding to an unobserved information event.[16] The uncontaminated subsamples of credit rating and accounting changes are reduced by approximately 14% and 82%, respectively.

4. Empirical Analysis

4.1. Testing H1a: CDS spread changes around credit rating changes.

Similar to Shivakumar et al. (2011), I measure CDS spread responses as the market-adjusted, three-day proportional change in CDS spread around credit rating changes (ΔCDS^{RATE}). The market adjustment is based on the average 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

[16] The sample firms have an average of 14 analysts in any quarter. The choice of excluding days on which there are two revisions is admittedly ad hoc. For the credit rating tests, excluding all days on which there are analyst forecast revisions produces a smaller sample but materially unchanged results. Excluding all analyst forecast revision days from the accounting sample eliminates all but 7% of observations. Results of the accounting tests using just the remaining 7% of observations are directionally unchanged, but significance is reduced to below 10% in several specifications. Eliminating just days on which there are three or four analyst revisions produces results that are largely the same as those reported below.

[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.

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]

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 <u>standardized</u> ΔCDS^{RATE} in my information content tests ($\Delta SCDS^{RATE}$):

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

where $\Delta\overline{CDS}_m$ is the average proportional 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 proportional changes is a superior measure of change in default risk. I use proportional 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

[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.

standardized change in CDS spread that is identical to (1b) except that it uses gross instead of proportional changes. The correlation between standardized proportional 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 proportional changes.

4.1.1. Rating and CDS spread changes – 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. Continuous variables are winsorized at 2% and 98% in all tests.

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 combined letter and status downgrades decreases by a statistically and economically significant 5.4 percentage points (55.7%) in the post-crisis period. The median ΔCDS^{RATE} around combined downgrades also decreases by a statistically significant 24.4%. Still, the net mean and median ΔCDS^{RATE} around combined letter and status downgrades remain significantly different from zero in the post-crisis period, which is consistent with corporate ratings still containing nontrivial information 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. The mean ΔCDS^{RATE} around status downgrades decreases by a statistically significant 9.2 percentage points (58.2%) in the post-crisis period. Similarly, the mean ΔCDS^{RATE} around letter downgrades decreases by a significant 3.4 percentage points (50.7%). 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 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 combined letter and status upgrades decreases by a statistically significant 35.1%, from -0.037 before the crisis to -0.024 after the crisis. The median ΔCDS^{RATE} around combined letter and status upgrades decreases by a larger 44.1%. For upgrades in rating status, the mean (median) ΔCDS^{RATE} decreases by a statistically significant 45.0% (47.7%). The pre/post-crisis changes in ΔCDS^{RATE} around letter upgrades are attenuated but statistically significant.

There is a valid concern that systematic differences in the magnitude of credit rating changes before and after the crisis can bias the univariate price response tests. Thus, Panel B of Table 3 repeats the analysis in Panel A but for a "balanced" subsample of observations with similar magnitude rating changes in both the pre- and post-crisis periods. Another potential concern is that the observed price reactions around credit rating changes are actually attributable to unobserved but simultaneous information events. 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, Panel C of Table 3 repeats the analysis in Panel A after excluding dates on which there are simultaneous accounting releases, management forecasts, or equity analyst revisions (see Section 3 for further discussion). The results in both Panels B and C are generally unchanged from those in Panel A.

Finally, Panel D 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.

In sum, the data are consistent with an average 38% to 71% reduction in the magnitude of CDS spread responses to 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 47% decline in the magnitude of price responses. 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 credibility damage as a result of the financial crisis.

4.1.2. Rating and CDS spread changes - regression analysis

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

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

[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 5.6% to over 17%. For ease of presentation and consistency with prior literature, I present separate models.

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).

LCHANGE_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. *LCHANGE_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, *LCHANGE_BIN* will be negative (positive) for downgrades (upgrades). *LCHANGE* 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 *LCHANGE* 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 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 -0.053 and significantly negative, indicating that reactions to rating downgrades are, on average, 5.3 percentage points smaller after the crisis. This change is consistent with the 5.4 percentage point decline observed in the univariate analysis (Panel A of Table 3). Columns 2 and 3 indicate that the CDS responses around rating status and letter downgrades decrease by 8.2 and 3.5 percentage points, respectively, which are again highly consistent with the univariate analysis. The models in columns 1 through 3 have explanatory power ranging from 3.1% to 5.6%, which is 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 0.019, β_1 indicates that price responses are 1.9 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 2.8 and 1.1 percentage points, respectively.

Results from repeating the analyses on the balanced and uncontaminated subsamples are presented in Panels B and C of Table 4. The results are generally unchanged. The results are also largely unchanged in Panel D when using $\Delta SCDS^{RATE}$ as the dependent variable, with the exception that the reduction in price responses around letter upgrades is no longer statistically significant. Taken together, the results in Table 4 are consistent with significant declines in CDS spread responses to all types of rating changes, and with corporate credit ratings being viewed as less credible in the post-crisis period.

4.2. Testing H1b – The relation between credit ratings and CDS spread levels

H1b 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. My analysis 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 are intended to provide a relative ordering of default risk among firms at a given point in time. At the same time, the market's collective opinion about the relative ordering of default risk is apparent in observed CDS spreads, where the safest firm has the lowest spread. If market participants rely solely on credit ratings in debt pricing, 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 when the CRAs' opinion about the relative ordering of firms' default risk perfectly agrees with the market's collective opinion (i.e., observed CDS spreads). 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 (i.e., the CRAs' opinions) are perfectly concordant with observed CDS spreads (i.e., the market's collective opinions).

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 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 <u>median</u> of all firms with firm *j*'s rating level.

In testing H1b, 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. For empirical purposes, I 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.[20] Discordant and extreme discordant observations are identified with binary variables *DISCORDANT* and *DISCORD_EXTRM* set equal to one, respectively. I require a minimum of three firms within a rating category in a given month to calculate the percentile thresholds. Rating groups 1, 2, and 19 are eliminated due to insufficient data (dropping the minimum three observation criteria to retain these rating groups does not materially change the results).

As shown in Panel A of Table 5, on average across all credit rating levels, 19.7% of observations are discordant in the pre-crisis period as opposed to 25.1% in the post-crisis period, representing an increase of 5.4 percentage points (or a 27.3% proportional change). A t-test of the 17 individual changes indicates that the average 5.4 percentage point increase is highly

[20] 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. That is, using the minimum and maximum CDS spreads produces stronger evidence in favor of H1b and H2b.

significant (t = 3.74, based on White standard errors). Looking within the individual credit rating levels, 15 of the 17 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 with standard errors clustered by firm and month: t-tests for 12 of 17 credit rating levels are statistically significant, although one is 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 again clustered by firm and month, and the results are largely unchanged.

Panel B of Table 6 presents similar analysis for extreme discordant observations. Overall, the prevalence of extreme discordant observations increases by a statistically significant 2.8 percentage points (or a 61.5% proportional change) in the post-crisis period. T-tests and logit regressions show that the differences in means for 11 of 17 individual rating levels are significant and of the expected signs. 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.

4.3. Testing H2a –CDS spread changes around quarterly accounting releases

In testing H2a, I specifically examine whether CDS price responses to quarterly earnings announcements increase after the financial crisis. Earnings releases often include partial financial 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 older than 100 days are eliminated.

4.3.1. Accounting and CDS spread changes - univariate and difference-in-difference analyses

In testing H2a, I examine whether the average three-day change in CDS spread around earnings announcements, ΔCDS^{EA}, declines to a lesser degree than the average ΔCDS^{RATE} around credit rating changes. Negative and positive earnings surprises are assessed separately to be consistent with the analysis in H1a and to facilitate difference-in-differences analysis. Observations with zero earnings surprise are not included in the univariate analysis.

The first line in Panel A of Table 6 re-presents information from Table 3 showing that the average ΔCDS^{RATE} around rating downgrades declines from 0.097 to 0.043 in the post-crisis period. At the same time, the second line of the Panel A of Table 6 shows that the average ΔCDS^{EA} around negative earnings announcements increases by 0.005, from 0.011 to 0.016. An increase in the average ΔCDS^{EA} would be consistent with earnings becoming more, rather than less, relevant after the crisis. However, this increase is insignificant at conventional levels (t = 1.47). The difference-in-differences coefficient, calculated as the change in ΔCDS^{EA} minus the change in ΔCDS^{RATE}, is of interest in testing H2a. If the relevance of earnings decreases to a lesser degree than the relevance of credit rating changes, the difference-in-differences for the bad news events will be positive. As shown in line 3, this is indeed the case: the difference-in-differences coefficient is 0.059 and highly significant.

The results for positive earnings surprises are similar, although the signs are reversed (as expected). The pre/post-crisis increase in ΔCDS^{RATE} (i.e., attenuation toward zero) around rating upgrades is 0.013 (as originally presented in Table 3), as compared to a decline in ΔCDS^{EA} (i.e., absolute growth in price responses) around positive earnings announcements of -0.001. The difference-in-differences -0.014 and statistically significant. Thus, the results for both good and bad news events are consistent with H2a in that the debt market relevance of unexpected earnings declines to a lesser degree than the relevance of credit rating changes.

An obvious concern with the univariate tests is that they do not consider the magnitude of the earnings surprise (i.e., *UE*). Results in Panel B using a "balanced" sample of *UE* and credit ratings, as described in Section 3, are largely unchanged from those in Panel A. Additional tests using the uncontaminated subsample (Panel C) and tests of standardized change in CDS (Panel D) are also largely the same as the results in Panel A.

4.3.2. Accounting and CDS spread changes - regression analysis

The univariate analysis in the previous section provides some indication that the debt market relevance of accounting information increases in the post-crisis period, although the increases are statistically insignificant unto themselves. This section includes additional analysis of ΔCDS^{EA} around earnings announcements that considers *UE* as a continuous variable rather than looking simply at positive versus negative surprises. Observing an increase in the debt market relevance of *UE* would be consistent with market participants substituting towards relying on accounting data as they decrease their reliance on credit ratings. I test for post-crisis changes in ΔCDS^{EA} with the following regression:

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

UE is unexpected earnings, as previously defined. β_1 is the debt market earnings response coefficient ("ERC") in the pre-crisis period, and will be negative if a positive earnings surprise informs market participants about a decrease in default risk, and vice-versa. (β_1 + β_2) is the debt market ERC in the post-crisis period, and β_2 unto itself is the pre/post-crisis change in ERC. β_2 will be negative if market participants increase their reliance on accounting information in the post crisis period.

$CDS_{t\text{-}2}$ and *IGRADE_BDR* are as previously defined. Following Lipe et al. (1998), *NONLINEAR* is calculated as *UE* * |*UE*| and is included to capture the nonlinear relation between *UE* and ΔCDS^{EA}.[21] *LOSS* is an 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). 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

[21] 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.

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 total assets, *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*. *ADDL_CONTROLS* variables are normalized to have a mean (variance) of zero (one) to reduce issues from multicollinearity in the interaction terms.

The results of estimating equation (3) without *ADDL_CONTROLS* are presented in Panel A Table 7. The model in column 1 includes the complete sample of earnings announcements. The coefficient β_1 on *UE* is -3.615 and highly significant, indicating that a positive earnings surprise equal to 1% of price is associated with a roughly 3.6% decrease in CDS spread in the pre-crisis period. The coefficient of interest, β_2 on *UE*POST*, is -0.713 and significantly negative. This is consistent with H2a in that there is a (-0.713 / -3.615 =) 20% increase in the debt market ERC in the post-crisis period.

Columns 2 and 3 of Panel A of Table 7 repeat the analysis in column 1 but for the balanced and uncontaminated subsamples, respectively. Column 4 of Panel A repeats the analysis but with standardized ΔCDS ($\Delta SCDS^{EA}$) as the dependent variable. β_2 on *UE*POST* is significantly negative in all models, indicating an increase in the debt market ERC of between 18% and 28%. Results are largely unchanged in Panel B of Table 7, which is a repeat of Panel A but includes *ADDL_CONTROLS*. Untabulated results repeating all models in Table 7 separately for positive versus negative earnings are also qualitatively unchanged. In sum, the results are consistent with an <u>increase</u> in the debt market relevance of earnings surprises in the post-crisis period, which is consistent with market participants increasing their reliance on accounting information in debt pricing they decrease their reliance on less credible corporate credit ratings.[22]

4.4. Testing H2b – Levels analysis: the relation between accounting data and CDS spread levels

I test the relevance of accounting data for CDS spread levels using a discordancy test similar to that used in H1b. Performing such a discordancy test requires that firms' accounting data are converted into a ranking of default risks that resembles a set of credit ratings. The ideal metric would capture all of the debt-relevant information contained in quarterly accounting reports, and it would accurately represent how market participants use that information in evaluating default risk. As the ideal metric is unavailable, I instead develop a naïve ranking of default risks based on the predicted ratings from an ordered logit model of actual ratings on accounting variables. I refer to this as a "naïve" model as it has several significant limitations: (i) it captures only eight financial statement ratios and ignores all other debt-relevant information available in accounting reports; and (ii) the data for the accounting ratios are lifted directly from the financial statements are do not incorporate common adjustments, such as capitalizing operating leases; and (iii) the variables calculate default risk using an approximation of the CRAs' algorithm for evaluating default risk, which likely differs from the way that market participants use the accounting variables. As such, this model likely serves as a lower bound for assessing the

[22] The regression analysis of accounting relevance is not based on difference-in-differences models because it focuses on a slope parameter (i.e., the coefficient on *UE*POST*) while the regressions of credit rating relevance focus on an intercept shift (i.e., the coefficient on *POST*). Consistent with prior literature, my regressions of credit rating relevance focus on an intercept shift because the large majority of rating changes are just one level (in fact, all status changes are just one level), which means there is little variation in the magnitudes of the rating changes. Conversely, there is a great deal of variation in *UE*, which allows for interpreting a slope coefficient. Combining both forms of analysis in a single regression is possible but the results are difficult to interpret. Still, because the regressions of rating relevance show a significant *decline* while the regressions of accounting relevance show a significant *increase*, there is little concern that the difference-in-differences is anything but significantly positive.

relevance of accounting information for debt prices. Further, if the financial crisis motivates market participants to increase their investment in analyzing default risk, including extracting information from accounting reports, then this model likely understates any post-crisis increase in the relevance of accounting information as it captures only the most basic financial statement data. Thus, using this naïve model likely biases against finding results in support of H2b.[23] The specific model I employ is similar to that in Ashbaugh-Skaife et al. (2006):

$$RATING_{i,m} = \beta_0 + \beta_1 SIZE_{i,q-1} + \beta_2 ROA_{i,q-1} + \beta_3 LEV_{i,q-1} + \beta_4 CAPINTEN_{i,q-1} + \beta_5 INTCOV_{i,q-1} + \beta_6 CFO\_DEBT_{i,q-1} + \beta_7 ACID_{i,q-1} + \beta_8 TCA_{i,q-1} + \varepsilon_{i,m} \qquad \textbf{(4)}$$

The sample for this analysis is the same as that detailed in Table 1 and used in testing H1b, except that the sample size is reduced by roughly 14% due to a lack of accounting data. *RATING* is the firm's month-end credit rating. Each rating is matched to its most recently published 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 interest coverage, calculated as 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; *ACID* is total cash and equivalents divided by total current liabilities; and *TCA* is total current accruals, calculated as the most recent four quarters' net income before extraordinary items less operating cash flows and depreciation, scaled by total assets. The model is estimated by calendar quarter and for each

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[23] An alternate dependent variable might be O-Score (Ohlson 1980). I do not use O-Score primarily because it is highly likely that the relations between accounting variables and default risk change significantly during the financial crisis years and across industries, but the O-Score model coefficients do not vary over time or across industries. Further, using a continuous metric as the dependent variable would require the additional step of arbitrarily dividing predicted values into 20 groupings, which would likely introduce additional noise in my tests.

industry sector. The predicted rating from the logit model, *RATING_PREDICT*, are then used in assessing H2b.

Panel A of Table 8 presents the average coefficients from the 252 individual quarter-industry regressions, along with the results of t-tests that the average coefficients differ from zero. Most average coefficients are of logical signs. An exception is *ACID,* which indicates that a higher cash to current liabilities balance is associated with a worse credit rating. This counterintuitive result is a product of the correlation with other variables; the unconditional correlation between *ACID* and *RATING* is significantly positive (untabulated). Panel B of Table 8 shows that the average pseudo r-squared is 68.4 and 71.5 in the pre- and post-crisis periods, respectively. Panel C of Table 8 presents the distribution *RATING_PREDICT* in the pre- and post-crisis periods. Untabulated results show that 38% of predicted ratings are equal to the firms' actual ratings, and an additional 28% of the predicted ratings are within one level of the actual rating.

Panel A of Table 9 performs discordancy analysis similar to that in Panel A of Table 6, but uses *RATING_PREDICT* instead of the firms' actual credit ratings. Insufficient observations are available to perform the analysis for rating groups 19, 3, 2, and 1. In the pre-crisis period 35.0% of observations are categorized as *DISCORDANT*. In the post-crisis period, the prevalence of *DISCORDANT* predicted ratings <u>decreases</u> to 33.1%, which is consistent with accounting data becoming more relevant for debt prices. However, the overall decrease of -1.8 percentage points is statistically insignificant. Within the individual rating groups, six categories experience a statistically significant decline in discordancy while five categories experience a statistically significant increase. More to the point in testing H2b, Panel B of Table 9 presents the difference-in-differences between the pre/post change for the actual ratings and the pre/post change for the predicted ratings. Overall, the discordancy of actual ratings increases by 5.3 percentage points (column 1, and as originally presented in Panel A of Table 6) while the discordancy of predicted ratings decreases by -1.8 percentage points (column 2, and as originally presented in Panel A of Table 8), for a statistically significant difference-in-differences of -7.1 percentage points (column 3). Within the 16 individual rating categories for which data is available, 10 have significantly negative difference-in-differences coefficients versus just two with significantly positive coefficients.[24]

The results for *DISCORDANT_EXTRM* in Panels C and D of Table 9 are qualitatively the same as the *DISCORDANT* tests. Panel C shows that the overall prevalence of extreme discordant observations among the predicted ratings increases by an insignificant 0.5 percentage points between the pre- and post-crisis periods. Panel D of Table 9 shows that this overall difference-in-differences of -2.4 percentage points is highly significant, and that the difference-in-differences are significantly negative within nine of the 16 individual rating levels. In sum, the discordancy tests are consistent with H2b in that the debt market relevance of accounting information decreases to a lesser degree than the relevance of corporate credit rating levels. In fact, there is no statistically significant change in the relevance of accounting information for debt price levels in the post-crisis period. These results are again consistent with market participants decreasing their reliance on corporate ratings due to credibility damage in the post-crisis period.

[24] The logit model used to test the difference-in-differences within individual rating levels requires an interaction of two binary variables. Ai and Norton (2003) show that interaction coefficients in logit models can have a different sign and/or significance than the cross-partial derivative with respect to the probability of the dependent variable. However, as the difference-in-differences used herein include strictly two binary variables and an interaction (i.e., no continuous variables and no covariates), the concerns raised in Ai and Norton (2003) are not applicable. The overall tests of significance at the bottom of each panel do not involve a logit model.

4.5. 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. Figure 2 presents plots of CDS spread averages and standard deviations by quarter. As can be seen, the mean and standard deviation of CDS spreads within each rating group increases in third quarter of 2007 and remains higher throughout the post-crisis period than in the pre-crisis period. The increased standard deviations are consistent with ratings being viewed as noisier signals in the post-crisis period, while the increased averages are consistent with ratings also being viewed as optimistically biased. Table 10 details 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. 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.[25] Untabulated results using the natural log of the CDS spread as the dependent variable are also highly significant within each rating level. Untabulated tests also show statistically significant increases in the standard deviations of CDS spreads within each rating group.

The increase 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

[25] 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.

upward shift in CDS spreads for all rating levels could be instead attributed to a macroeconomic increase in default risk.

5. Alternate Explanations and Robustness Tests

5.1. The relevance of all intermediary-provided data declines after the crisis

It is plausible that, during periods of high uncertainty, debt market participants prefer to rely on audited, backward-looking accounting reports rather than on unaudited and possibly speculative forward-looking information provided by intermediaries. Such a shift in preferences could explain a decrease (increase) in the relevance of credit ratings (accounting reports) that is unrelated to any change in rating credibility. If there is a uniform shift in preferences away from intermediary-provided data, I expect that the debt market relevance of all intermediaries' reports decline in the post-crisis period. To the contrary, if the post-crisis decline in credit rating relevance is driven by credibility damage, then I expect no change (or even an increase) in the relevance of information provided by other intermediaries.

Prior research has found that equity analyst forecast revisions are informative for debt prices (De Franco et al. 2009; Mansi et al. 2011).[26] I evaluate the pre/post-crisis debt market relevance of equity analyst information using a model similar to equation (4), with the exceptions that: *UE* is replaced by analyst forecast revisions (*REV*); and *LOSS* takes a value of 1 if the analyst's new forecast is for negative earnings (rather than *LOSS* being equal to one for realized negative earnings).[27] Analyst forecasts are matched to the most recently available

[26] I evaluate the relevance of equity analyst reports rather than debt analyst reports because data for the latter is not widely available.
[27] *REV* is calculated as the change in an analyst's forecast from his prior forecast for the same quarter, scaled by price at day (t-2). Current forecasts issued more than 60 days before the earnings announcement are eliminated, as are prior forecasts issued more than 60 days before the current forecast. An average of multiple analysts' *REV* is used on days with more than one analyst revision for the same firm-quarter.

quarterly accounting information, not more than 100 days old. A total of 54,189 firm-day observations are available after intersecting IBES, Compustat, and the CDS data. The first column of Table 11 presents results using the full sample and including *ADDL_CONTROLS*. β_1 on *REV* is -1.464, while β_2 on *REV*POST* is -0.437. Thus, the data are consistent with a (-0.437 / -1.464 =) 30% <u>increase</u> in the debt market relevance of analyst forecast revisions after the financial crisis. Columns 2 through 4 present results of models with a balanced subsample, an uncontaminated subsample, and standardized change in CDS, all of which are consistent with the results in column 1. Untabulated results excluding *ADDL_CONTROLS* are largely unchanged. As such, the data are inconsistent with the alternate explanation of an overall decrease in the relevance of intermediary-provided information after the financial crisis. To the contrary, the data are consistent with an <u>increase</u> in the debt market relevance of analyst forecast revisions, which is consistent with credibility damage causing market participants to selectively shift away from relying on credit ratings and towards relying on substitute data in debt pricing.

<u>5.2. Debt market participants demand more timely information after the crisis</u>

An alternate explanation for a decline in credit rating relevance is that market participants simply demand timelier information in the post-crisis period. Such an explanation is consistent with the increased relevance of equity analyst forecasts discussed in the preceding section. However, this explanation is not consistent with the results of H2b, which show that there is no decline in the relevance of accounting information for CDS spread levels. 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. Thus, if the decline in credit rating relevance is driven solely by demands for timelier information, I would expect to observe a decline in the relation between outstanding accounting information and debt price levels.

I further reduce concerns about demand for timelier information by repeating the levels analysis in H2b but with matching the month-end CDS spreads and credit ratings with accounting data that has been published for a minimum of 90 days (as opposed to the most recent accounting data, as in the original analysis). Untabulated tests show that the relevance of the stale accounting data for CDS levels still declines to a significantly lesser degree than the relevance of current credit ratings. Specifically, the difference-in-differences coefficient for *DISCORDANT* (*DISCORD_EXTRM*) observations is -5.8 percentage points (-2.1 percentage points) with a t-statistic of 2.19 (3.62). Observing that stale accounting information declines in debt market relevance to a lesser degree than corporate ratings is inconsistent with market participants solely demanding timelier information after the crisis.

5.3. Credit ratings contain less accounting information after the crisis

A decrease in the relevance of credit ratings accompanied by an increase in the relevance of accounting releases could be because 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. Further, the analysis of predicted credit ratings in Section 4.4 and Table 8 finds that the explanatory power of accounting information for credit ratings slightly increases in the post-crisis period, from an average pseudo r-squared of 68.4% to 71.5%. Thus, this alternate explanation is inconsistent with the data and seems unlikely.

5.4. 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 of credit rating changes to only firms with at least one rating change prior to 2007 reduces the sample by roughly 16%. Untabulated tests using the consistent subsample are similar to those reported in Tables 3 and 4.

5.5. 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. An 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. As a robustness test, I reperform the regression analysis of H1a 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% but 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 price responses around credit rating letter downgrades is no longer statistically significant in several specifications. As a post-crisis decline in price responses is still observed among firms with actively traded CDS contracts both before and after the crisis, the data are inconsistent with growth in the CDS markets is driving the reported results.

5.6. Change in the nature of the accounting information

It is plausible that a change in the properties of firms' financial statements motivates debt market participants to shift away from relying on credit ratings and towards using accounting information in the post-crisis period. For instance, prior literature has found that the accruals quality and conditional conservatism reduce information asymmetry in debt markets (Francis et al. 2005; Wittenberg-Moerman 2008). I am unaware of systematic changes in accounting standards or practices that would increase the debt market relevance of accounting information in the post-crisis period. Further, untabulated robustness tests find no change in accruals quality among my sample firms, as proxied using *AQ* as in Francis et al. (2005). Untabulated tests find a statistically significant <u>decline</u> in conditional conservatism, as proxied using *CSCORE* as in Khan and Watts (2009). Thus, the data are inconsistent with a change in accounting properties driving my results.

7. Conclusion

This study investigates whether the credibility of corporate credit ratings suffers as a result of the financial crisis, as well as how credibility damage affects the use of both corporate ratings and accounting information in debt pricing. Difference-in-differences analysis finds that the debt market relevance of corporate credit ratings declines to a significantly greater degree than does the relevance of accounting information. Further tests find a stand-alone increase in the relevance of unexpected earnings for debt prices. These results are consistent with credibility damage causing market participants to reduce their reliance on corporate credit ratings and increase their reliance on accounting reports in debt pricing. 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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APPENDIX A: Variable Definitions

Variables used in the empirical tests are detailed below. Accounting data are from Compustat, analyst forecast data are from IBES, credit rating data are sourced from Standard & Poor's and the FISD database, and CDS data are from CMA (see Section 3 for further discussion). All samples span 1/1/2004 through 12/31/2010, with 7/1/2007 demarking the pre- versus post-crisis periods. All continuous variables are winsorized at 2% and 98%.

ΔCDS^{RATE}, ΔCDS^{EA}, ΔCDS^{REV}	Market-adjusted proportional change in CDS spread in the three-day period around information events, as detailed in equation (1a). The ^{RATE} superscript indicates credit rating changes, ^{EA} indicates earnings announcements, and ^{REV} indicates analyst forecast revisions.
$\Delta SCDS^{RATE}$, $\Delta SCDS^{EA}$, $\Delta SCDS^{REV}$	Standardized version of ΔCDS^{RATE}, ΔCDS^{EA}, and ΔCDS^{REV}, as detailed in equation (1b).
ACID	Total cash and cash equivalents divided by total current liabilities.
ADDL_CONTROLS	Group of variables including *SIZE, BTM, LEV, FQ4,* and *BETA*.
BETA	Equity market beta calculated over the 252-day period ending five days before the information event.
BTM	Book value over market value.
CAPINTEN	Net property, plant, and equipment scaled by total assets.
CDS_{t-2}	CDS spread as of two days prior to the information event, scaled by 1,000.
CFO_DEBT	The most recent four quarters operating cash flows scaled by total debt.
DAYS	Number of days since the previous credit rating change, scaled by 100.
DISCORD_EXTRM	Indicator variable equal to one for "extreme discordant" observations. 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.
DISCORDANT	Indicator variable equal to one for "discordant" 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.
FQ4	Indicator variable equal to one for the firm's fourth fiscal quarter.
IGRADE_BDR	Indicator variable equal to one if the firm is on the border of moving between investment- and junk-grade classification prior to the information event.
INTCOV	Interest coverage, calculated as the most recent four quarters' net income before extraordinary items scaled by the most recent four

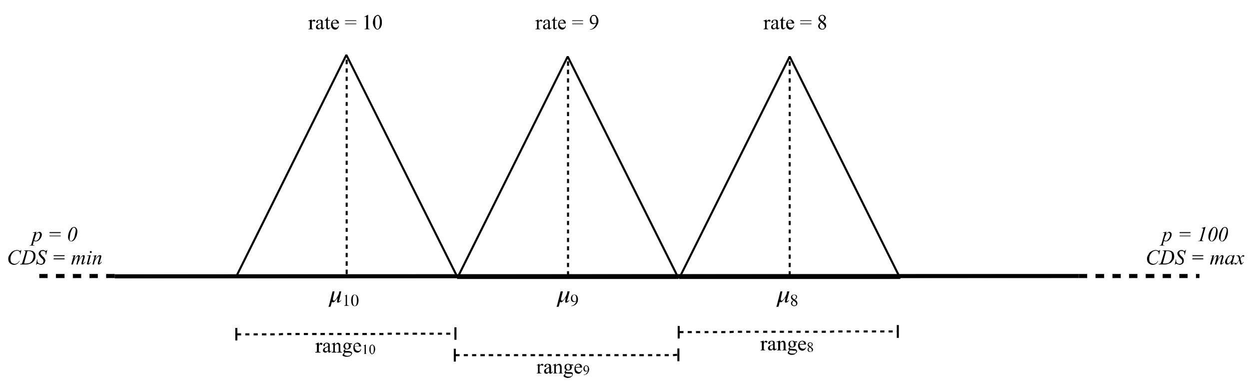
	quarters' interest expense.
LEV	Total debt over total assets.
LOSS	In the tests of earnings announcements, *LOSS* is an indicator variable equal to one if the IBES actual EPS is less than zero. In the tests of analyst forecast revisions, *LOSS* equals one if the new analyst forecast is for negative earnings.
NONLINEAR	$UE * \|UE\|$ for earnings announcements. $REV * \|REV\|$ for analyst forecast revisions.
POST	Indicator variable equal to one for the period starting 7/1/2007.
RATING	The firm's letter credit rating on a scale of 1 (lowest rating) through 20 (highest rating).
RATING_PREDICT	The firm's predicted letter credit rating, as calculated via equation (4).
LCHANGE	The difference between the current letter rating and the previous letter rating. Zero for changes in credit rating status that are not accompanied by a chance in the rating letter.
LCHANGE_BIN	Indicator variable equal to one for letter rating changes and zero for credit rating status changes that are not accompanied by a change in the rating letter.
REV	Analyst forecast revision. Calculated as an analyst's current EPS forecast less his previous forecast for the same quarter, scaled by price at day (t-2). Current forecasts issued more than 60 days before the earnings announcement are eliminated, as are previous forecasts issued more than 60 days before the current forecast. An average of multiple analysts' *REV* is used on days with more than one analyst revision for the same firm-quarter.
ROA	The most recent four quarters' net income before extraordinary items scaled by average total assets.
SIZE	Natural log of total assets.
TCA	Total current accruals, calculated as the most recent four quarters' net income before extraordinary items less operating cash flows and depreciation, scaled by total assets.
UE	Unexpected earnings, calculated as IBES actual earnings per share less IBES consensus forecast, scaled by end-of-quarter price. Consensus forecasts older than 100 days are excluded.

FIGURE 1: Examples of Discordant Credit Ratings and 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., lower probability of default). Ratings 20 – 11 and 7 – 1 are not presented.

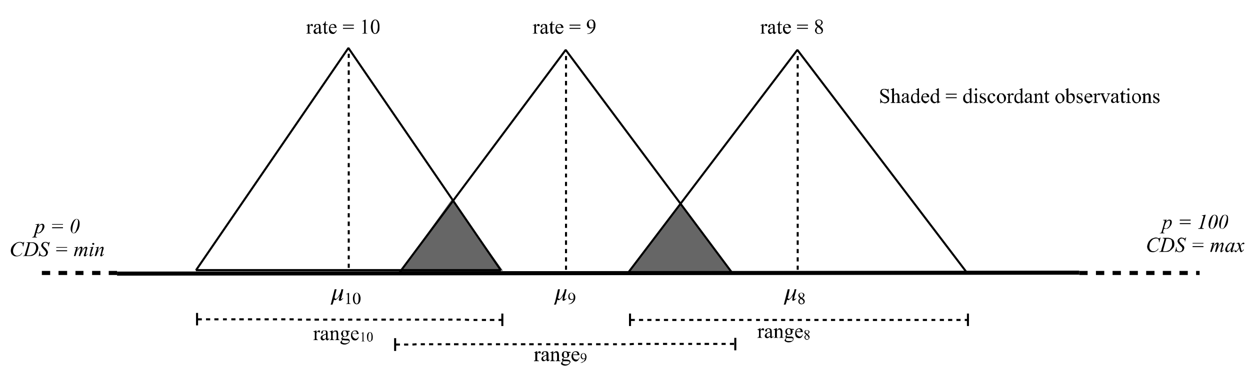
Panel A: Example of ratings that are perfectly concordant relative to CDS spreads

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.

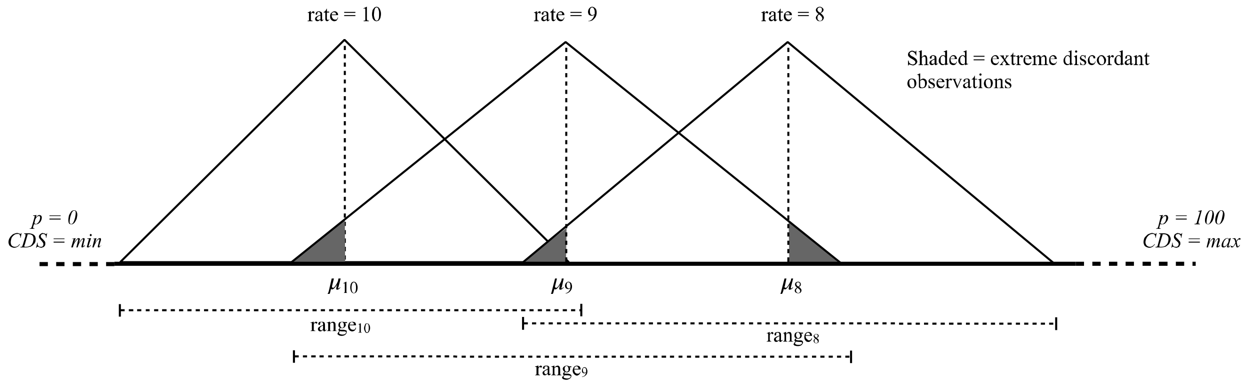
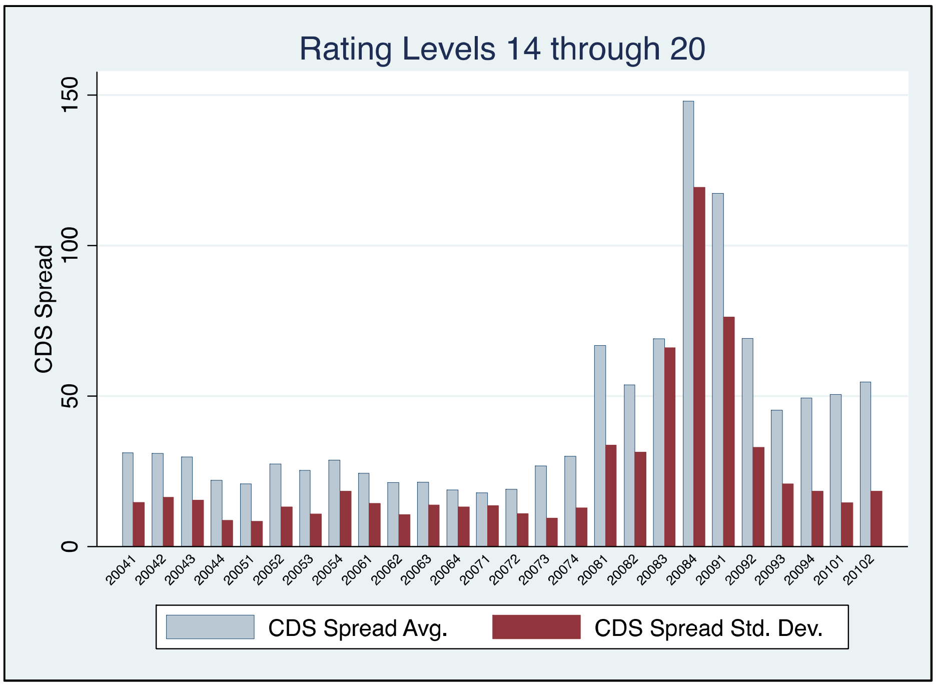


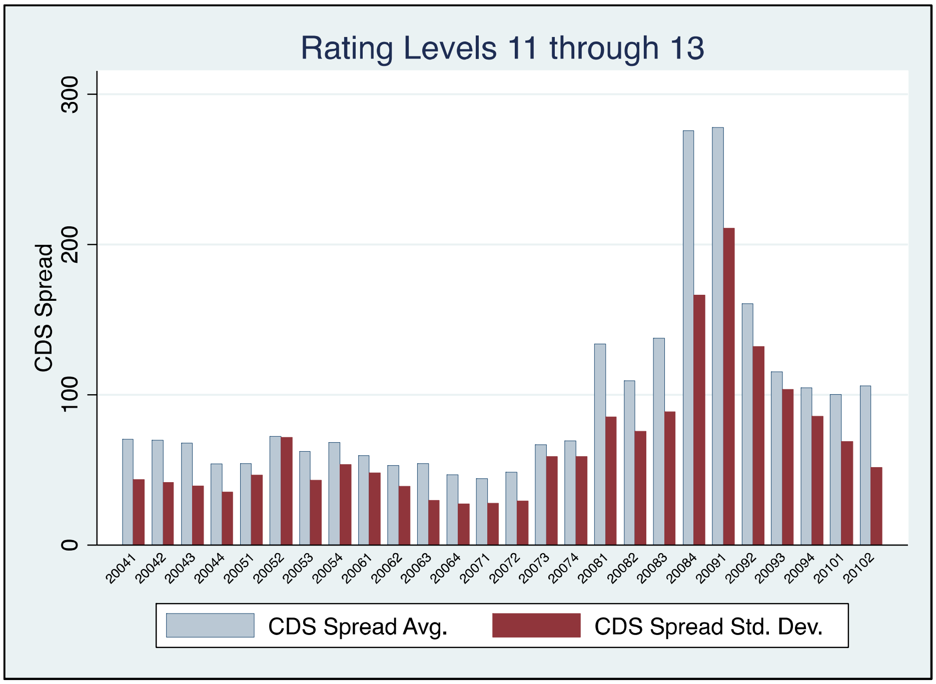
FIGURE 2: Average and Standard Deviation of CDS Spreads by Quarter

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. 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.

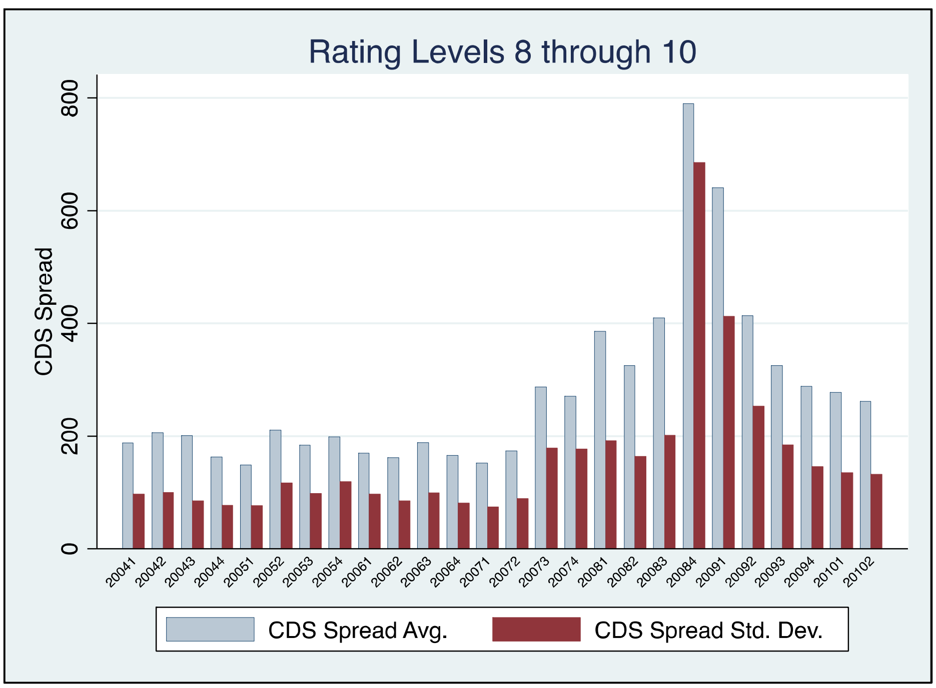
Panel A: Ratings 14 through 20



Panel B: Ratings 11 through 13



Panel C: Ratings 8 through 10



Panel D: Ratings 1 through 7

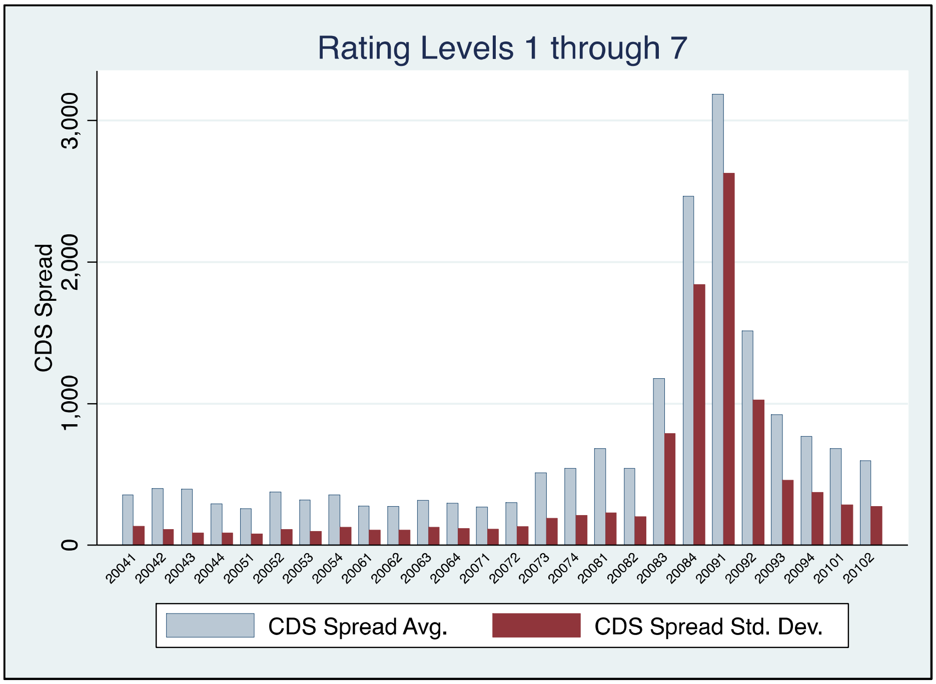


TABLE 1: Summary Information – Sample of Monthly Credit Rating Levels and Accounting Data

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. The "accounting subsample" is limited to only those observations with sufficient financial statement data to perform the accounting discordancy tests described in Section 4.

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	Accounting Subsample
AAA	Aaa	20	128	115	243	239
AA+	Aa1	19	7	18	25	25
AA	Aa2	18	244	160	404	386
AA-	Aa3	17	352	307	659	563
A+	A1	16	552	749	1,301	1,067
A	A2	15	1,419	1,561	2,980	2,612
A-	A3	14	1,349	985	2,334	2,117
BBB	Baa1	13	1,744	1,828	3,572	3,127
BBB	Baa2	12	2,608	2,309	4,917	4,460
BBB-	Baa3	11	1,656	2,008	3,664	3,086
BB+	Ba1	10	944	938	1,882	1,441
BB	Ba2	9	930	817	1,747	1,503
BB-	Ba3	8	756	982	1,738	1,438
B+	B1	7	586	821	1,407	1,231
B	B2	6	402	510	912	790
B-	B3	5	242	530	772	631
CCC+	Caa1	4	109	344	453	347
CCC	Caa2	3	26	152	178	138
CCC-	Caa3	2	2	33	35	30
CC	Ca and C	1	3	110	113	96
		Total	**14,059**	**15,277**	**29,336**	**25,327**

Panel B: Number of unique firms in each industry sector

	Total Sample	**Accounting Subsample**
Basic Materials	47	46
Consumer Cyclical	112	97
Consumer Non-Cyclical	56	53
Health Care	29	29
Industrials	54	50
Oil & Gas	49	49
Technology	35	33
Telecommunications	23	22
Utilities	47	47
Total Firms	**452**	**426**

TABLE 2: Summary Information – Sample of Credit Rating Changes and Earnings Announcements

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. The "balanced" subsample in Panel C ensures that each rating change from the pre-crisis period is matched to a rating change of the same direction and magnitude in the post-crisis period. The "balanced" subsample in Panel D ensures that each earnings announcement from the pre-crisis period is matched to an announcement with the same earnings surprise in the post-crisis period. The "uncontaminated" subsamples exclude dates on which there are simultaneous rating changes, earnings releases, management forecasts, or equity analyst forecast revisions.

Panel A: Observations by year

	Credit Ratings Letter Changes	Credit Rating Status Changes	Quarterly Accounting Releases
2004	141	104	892
2005	193	128	813
2006	300	162	966
2007	302	172	1,148
2008	287	166	1,144
2009	307	186	1,168
2010	212	154	1,183
Total	**1,742**	**1,072**	**7,314**

Panel B: Number of unique firms in each 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 – complete and subsamples

	Pre-Crisis			Post-Crisis		
	Complete Sample	**Balanced Subsample**	**Uncontaminated Subsample**	**Complete Sample**	**Balanced Subsample**	**Uncontaminated Subsample**
Rating Letter Downgrades	455	451	384	637	451	561
Rating Letter Upgrades	333	301	301	317	301	297
Total Rating Letter Changes	**788**	**752**	**685**	**954**	**752**	**858**
Rating Status Downgrades	229	229	165	293	229	222
Rating Status Upgrades	257	257	232	293	257	261
Total Rating Status Changes	**486**	**486**	**397**	**586**	**486**	**483**

Panel D: Earnings announcement frequencies – complete and subsamples

	Pre-Crisis			Post-Crisis		
	Complete Sample	**Balanced Subsample**	**Uncontaminated Subsample**	**Complete Sample**	**Balanced Subsample**	**Uncontaminated Subsample**
Negative Earnings Surprises	793	791	187	1,096	791	329
Zero Earnings Surprises	342	286	42	286	286	42
Positive Earnings Surprises	2,132	2,123	294	2,665	2,123	441
All Earnings Announcements	**3,267**	**3,200**	**523**	**4,047**	**3,200**	**812**

TABLE 3: Relevance of Corporate Credit Rating Changes – Univariate Analysis

The samples of credit rating changes below are detailed in Table 2. Panel A presents mean and median ΔCDS^{RATE} around credit rating changes before and after the financial crisis. ΔCDS^{RATE} is the three-day abnormal change in CDS spread. All variables are further defined in Appendix A. Panels B, C, and D repeat the analysis in Panel A but use the "balanced" subsample, "uncontaminated" subsample, and standardized ΔCDS^{RATE}, respectively. 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

	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***	0.043***	0.019***	-0.054	-55.7%	5.05 ***	-0.006	-24.4%	2.55 **
Status Change	0.158***	0.050***	0.066***	0.031***	-0.092	-58.2%	3.96 ***	-0.019	-37.5%	2.70 ***
Letter Change	0.067***	0.017***	0.033***	0.015***	-0.034	-50.7%	2.88 **	-0.002	-12.7%	1.22
Upgrades										
All Actions	-0.037***	-0.028***	-0.024***	-0.015***	0.013	-35.1%	3.26 ***	0.012	-44.1%	3.61 ***
Status Change	-0.040***	-0.029***	-0.022***	-0.015***	0.018	-45.0%	2.96 ***	0.014	-47.7%	3.29 ***
Letter Change	-0.034***	-0.027***	-0.025***	-0.016***	0.009	-26.5%	1.71 *	0.011	-41.2%	1.84 *

Panel B: Balanced subsample

	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	0.098***	0.026***	0.048***	0.022***	-0.050	-51.0%	4.53	***	-0.004	-14.5%	1.89	*
Status Change	0.158***	0.050***	0.071***	0.034***	-0.087	-55.1%	3.66	***	-0.017	-33.2%	2.12	**
Letter Change	0.067***	0.017***	0.035***	0.016***	-0.032	-47.8%	2.53	**	-0.001	-4.8%	0.98	
Upgrades												
All Actions	-0.037***	-0.029***	-0.023***	-0.014***	0.014	-37.8%	3.17	***	0.014	-49.9%	3.76	***
Status Change	-0.040***	-0.029***	-0.022***	-0.015***	0.018	-45.0%	2.82	***	0.014	-48.7%	3.23	***
Letter Change	-0.035***	-0.028***	-0.025***	-0.014***	0.010	-28.6%	1.82	*	0.013	-48.3%	2.12	**

Panel C: Uncontaminated Subsample

	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	0.083***	0.019***	0.033***	0.015***	-0.050	-60.2%	4.22 ***	-0.004	-23.1%	2.26 **
Status Change	0.155***	0.040***	0.044***	0.018***	-0.110	-71.0%	3.82 ***	-0.022	-54.8%	2.93 ***
Letter Change	0.052***	0.015***	0.028***	0.013***	-0.024	-46.2%	2.07 **	-0.002	-13.8%	0.79
Upgrades										
All Actions	-0.036***	-0.027***	-0.023***	-0.014***	0.013	-36.1%	3.20 ***	0.013	-47.0%	3.66 ***
Status Change	-0.038***	-0.028***	-0.021***	-0.015***	0.018	-47.4%	2.73 ***	0.013	-46.8%	3.16 **
Letter Change	-0.034***	-0.027***	-0.024***	-0.014***	0.010	-29.4%	1.82 *	0.013	-48.1%	2.03 **

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

	Pre-Crisis		Post-Crisis		Difference in Means				Difference in Medians			
	Mean ΔSCDS	**Median ΔSCDS**	**Mean ΔSCDS**	**Median ΔSCDS**	**Diff.**	**% Diff.**	**t-stat**		**Diff.**	**% Diff**	**z-stat**	
Downgrades												
All Actions	0.887***	0.399***	0.529***	0.367***	-0.358	-40.4%	3.77	***	-0.031	-7.9%	2.35	**
Status Change	1.393***	0.895***	0.852***	0.599***	-0.541	-38.8%	3.08	***	-0.296	-33.1%	2.40	**
Letter Change	0.632***	0.248***	0.380***	0.269***	-0.251	-39.7%	2.25	**	0.021	8.4%	1.14	
Upgrades												
All Actions	-0.608***	-0.430***	-0.468***	-0.351***	0.140	-23.0%	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%	2.14	**
Letter Change	-0.576***	-0.399***	-0.506***	-0.345***	0.070	-12.2%	0.71		0.054	-13.5%	0.45	

TABLE 4: Relevance of Corporate Credit Rating Changes – Regression Analysis

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

The samples of credit rating changes are detailed in Table 2. ΔCDS^{RATE} is the three-day abnormal change in CDS spread. *POST* is a binary variable for the period starting July 1, 2007. Other variable definitions are in Appendix A. Panel A presents results using the full sample. Panels B, C, and D repeat the analysis in Panel A but use the "balanced" subsample, "uncontaminated" subsample, and standardized ΔCDS^{RATE}, respectively. T-statistics in brackets are clustered by firm and day. ***Indicates significance at 1%, **at 5%, *at 10%.

Panel A: Complete sample

			Downgrades				Upgrades		
	Coef.	**H_1**	**All Changes**	**Status Changes**	**Letter Changes**	**H_1**	**All Changes**	**Status Changes**	**Letter Changes**
Intercept	β_0		0.131	0.157	0.05		-0.029	-0.031	-0.029
			[8.29]***	[6.12]***	[4.99]***		[-5.85]***	[-4.61]***	[-3.76]***
POST	β_1	(-)	-0.053	-0.082	-0.035	(+)	0.019	0.028	0.011
			[-4.95]***	[-3.52]***	[-3.11]***		[4.62]***	[4.65]***	[2.03]**
LCHANGE_BIN	β_2		-0.072				-0.001		
			[-5.30]***				[-0.14]		
LCHANGE	β_3		-0.008		-0.008		0.001		0.001
			[-1.34]		[-1.34]		[0.25]		[0.22]
IGRADE_BDR	β_4		0.046	0.041	0.049		-0.028	-0.026	-0.029
			[3.20]***	[1.43]	[2.84]***		[-5.02]***	[-3.38]***	[-4.23]***
CDS_{t-2}	β_5		0.002	-0.024	0.003		-0.037	-0.051	-0.019
			[0.41]	[-1.76]*	[0.73]		[-4.24]***	[-4.64]***	[-1.62]
DAYS	β_6		-0.001	-0.001	-0.002		0.001	0.001	0.001
			[-0.95]	[-0.52]	[-1.68]*		[1.26]	[0.88]	[1.03]
N			1,614	522	1,092		1,200	550	650
Adj. R-Squared			0.056	0.049	0.031		0.047	0.067	0.033

Panel B: Balanced subsample

	Coef.	H_1	Downgrades All Changes	Downgrades Status Changes	Downgrades Letter Changes	H_1	Upgrades All Changes	Upgrades Status Changes	Upgrades Letter Changes
Intercept	β_0		0.13	0.159	0.04		-0.029	-0.03	-0.025
			[7.64]***	[5.96]***	[3.14]***		[-5.72]***	[-4.29]***	[-3.27]***
POST	β_1	(-)	-0.052	-0.074	-0.036	(+)	0.019	0.028	0.012
			[-4.77]***	[-3.15]***	[-3.15]***		[4.37]***	[4.24]***	[2.08]**
LCHANGE_BIN	β_2		-0.081				0.004		
			[-4.88]***				[0.57]		
LCHANGE	β_3		-0.01		-0.009		-0.002		-0.003
			[-1.12]		[-1.04]		[-0.53]		[-0.71]
IGRADE_BDR	β_4		0.058	0.044	0.066		-0.028	-0.027	-0.027
			[3.68]***	[1.41]	[3.49]***		[-4.86]***	[-3.35]***	[-3.92]***
CDS_{t-2}	β_5		0.006	-0.031	0.008		-0.035	-0.05	-0.018
			[0.89]	[-2.00]**	[1.25]		[-3.74]***	[-4.05]***	[-1.46]
DAYS	β_6		-0.001	-0.001	-0.001		0.001	0.001	0.001
			[-0.50]	[-0.65]	[-0.68]		[1.16]	[0.65]	[1.12]
N			1,360	458	902		1,116	514	602
Adj. R-Squared			0.059	0.042	0.041		0.045	0.062	0.031

Panel C: Uncontaminated Subsample

	Coef.	H_1	Downgrades: All Changes	Downgrades: Status Changes	Downgrades: Letter Changes	H_1	Upgrades: All Changes	Upgrades: Status Changes	Upgrades: Letter Changes
Intercept	β_0		0.117	0.156	0.045		-0.028	-0.031	-0.029
			[6.19]***	[5.02]***	[4.39]***		[-5.66]***	[-4.36]***	[-3.63]***
POST	β_1	(-)	-0.051	-0.100	-0.028	(+)	0.020	0.029	0.012
			[-4.39]***	[-3.47]***	[-2.48]**		[4.69]***	[4.57]***	[2.14]**
LCHANGE_BIN	β_2		-0.058				-0.002		
			[-3.70]***				[-0.27]		
LCHANGE	β_3		-0.001		-0.001		0.001		0.001
			[-0.20]		[-0.15]		[0.35]		[0.31]
IGRADE_BDR	β_4		0.043	0.042	0.043		-0.027	-0.025	-0.027
			[2.85]***	[1.20]	[2.65]***		[-5.08]***	[-3.09]***	[-4.51]***
CDS_{t-2}	β_5		0.004	-0.018	0.005		-0.037	-0.052	-0.018
			[0.82]	[-1.37]	[1.01]		[-4.15]***	[-4.69]***	[-1.48]
DAYS	β_6		-0.001	-0.001	-0.001		0.001	0.001	0.001
			[-1.02]	[-0.77]	[-1.17]		[1.36]	[0.95]	[1.06]
N			1,332	387	945		1,091	493	598
Adj. R-Squared			0.050	0.060	0.023		0.049	0.073	0.031

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

	Coef.	H_1	Downgrades: All Changes	Downgrades: Status Changes	Downgrades: Letter Changes	H_1	Upgrades: All Changes	Upgrades: Status Changes	Upgrades: Letter Changes
Intercept	β_0		1.225	1.418	0.533		-0.442	-0.512	-0.459
			[10.09]***	[8.01]***	[4.96]***		[-5.77]***	[-4.82]***	[-3.91]***
POST	β_1	(-)	-0.291	-0.442	-0.194	(+)	0.256	0.392	0.146
			[-2.99]***	[-2.41]**	[-1.73]*		[3.60]***	[3.98]***	[1.44]
LCHANGE_BIN	β_2		-0.623				-0.061		
			[-5.15]***				[-0.61]		
LCHANGE	β_3		-0.02		-0.018		0.035		0.034
			[-0.44]		[-0.40]		[0.57]		[0.54]
IGRADE_BDR	β_4		0.439	0.239	0.542		-0.474	-0.4	-0.525
			[3.67]***	[1.25]	[3.52]***		[-5.26]***	[-3.15]***	[-4.61]***
CDS_{t-2}	β_5		-0.044	-0.226	-0.029		-0.709	-0.825	-0.588
			[-1.24]	[-1.79]*	[-0.82]		[-4.90]***	[-4.85]***	[-2.55]**
DAYS	β_6		-0.008	-0.009	-0.013		0.011	0.013	0.01
			[-0.83]	[-0.54]	[-1.17]		[1.13]	[0.76]	[0.91]
N			1,614	522	1,092		1,200	550	650
Adj. R-Squared			0.054	0.026	0.027		0.044	0.055	0.036

TABLE 5: Relevance of Corporate Credit Rating Levels – Discordancy Tests

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. See Table 1 for further detail.

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 10^{th} 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 90^{th} 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 discordant observations in the post-crisis period less the percentage in the pre-crisis period. "Diff. Means t-stat" is the t-statistic from a differences in means test with standard errors clustered by firm and month. "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 significance at 1%, **at 5%, *at 10%. !!Indicates a significant decrease rather than increase (as predicted) from the pre- to post-crisis periods.

At the bottom of each panel is a t-statistic from a test that the average of the 17 percentage point changes differs from zero. ###Indicates significance at 1% based on White standard errors.

Panel A: Discordant observations

Rating	Percentage of Discordant Observations Pre-Crisis	Percentage of Discordant Observations Post-Crisis	Percentage Point Change	Relative Change	Diff. Means. t-stat	Logit z-stat
20	1.0%	8.4%	7.4%	726%	[4.89]***	[4.49]***
19	Insufficient observations					
18	4.9%	16.3%	11.4%	232%	[6.43]***	[5.98]***
17	24.8%	28.9%	4.1%	17%	[1.43]	[1.42]
16	19.9%	27.4%	7.5%	38%	[3.08]***	[2.96]***
15	23.4%	29.1%	5.8%	25%	[2.54]**	[2.53]**
14	30.8%	39.7%	8.8%	29%	[3.36]***	[3.37]***
13	38.6%	41.4%	2.9%	7%	[1.22]	[1.22]
12	28.7%	40.5%	11.8%	41%	[5.29]***	[5.30]***
11	24.1%	33.6%	9.5%	39%	[4.49]***	[4.56]***
10	25.4%	42.3%	16.9%	67%	[5.63]***	[5.56]***
9	19.9%	24.1%	4.2%	21%	[2.25]**	[2.24]**
8	31.0%	20.3%	-10.7%	-35%	[-2.34]**!!	[-2.56]**!!
7	15.9%	19.2%	3.2%	20%	[1.88]*	[1.87]*
6	13.3%	15.1%	1.8%	14%	[1.07]	[1.06]
5	13.5%	12.1%	-1.4%	-10%	[-0.62]	[-0.63]
4	16.8%	17.9%	1.1%	7%	[0.45]	[0.44]
3	2.9%	10.1%	7.2%	247%	[4.71]***	[4.80]***
2	Insufficient observations					
1	Insufficient observations					
Avg.	**19.7%**	**25.1%**	**5.4%**	**27.3%**		
	t-statistic: average change	**different from zero**	**[3.74]###**			

Panel B: Extreme discordant observations

Rating	Percentage of Extreme Discordant Observations Pre-Crisis	Percentage of Extreme Discordant Observations Post-Crisis	Percentage Point Change	Relative Change	Diff. Means. t-stat	Logit z-stat
20	0.04%	2.0%	2.0%	4875%	[3.10]***	[3.65]***
19	Insufficient observations					
18	1.2%	10.4%	9.2%	741%	[6.18]***	[7.32]***
17	2.3%	8.5%	6.2%	269%	[6.12]***	[6.54]***
16	4.0%	9.5%	5.6%	140%	[5.16]***	[4.95]***
15	5.3%	9.4%	4.2%	79%	[3.64]***	[3.62]***
14	7.7%	13.0%	5.3%	69%	[4.20]***	[4.35]***
13	9.6%	11.9%	2.4%	25%	[1.76]*	[1.78]*
12	8.5%	12.1%	3.5%	41%	[2.58]***	[2.65]***
11	5.9%	9.9%	4.0%	68%	[3.29]***	[3.52]***
10	4.7%	8.3%	3.6%	75%	[3.79]***	[3.97]***
9	5.1%	6.4%	1.3%	25%	[1.36]	[1.39]
8	5.9%	5.5%	-0.5%	-8%	[-0.56]	[-0.56]
7	5.1%	4.9%	-0.2%	-3%	[-0.22]	[-0.22]
6	4.2%	4.3%	0.0%	1%	[0.05]	[0.05]
5	3.8%	3.6%	-0.2%	-5%	[-0.27]	[-0.27]
4	4.7%	4.3%	-0.4%	-9%	[-0.51]	[-0.52]
3	0.6%	3.1%	2.4%	387%	[3.00]***	[1.79]*
2	Insufficient observations					
1	Insufficient observations					
Avg.	**4.6%**	**7.5%**	**2.8%**	**61.5%**		
	t-statistic: average change different from zero		**[4.41]###**			

TABLE 6: Relevance of Unexpected Quarterly Earnings Surprises– Univariate Analysis

The samples of credit rating changes and quarterly earnings announcements below are detailed in Table 2. Panel A presents mean and median *ΔCDS* around credit rating changes and quarterly earnings announcements before and after the financial crisis, along with difference-in-differences coefficients. *ΔCDS* is the three-day abnormal change in CDS spread. All variables are further defined in Appendix A. Panels B, C, and D repeat the analysis in Panel A but use the "balanced" subsample, "uncontaminated" subsample, and standardized ΔCDS^{RATE}, respectively. 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

	Pre-Crisis		Post-Crisis			
	Mean ΔCDS	**t-stat**	**Mean ΔCDS**	**t-stat**	**Difference**	**t-stat**
Rating Downgrades (from Table 3)	0.097	[10.04]***	0.043	[8.83]***	-0.054	[5.05]***
Negative Earnings Surprises	0.011	[4.03]***	0.016	[6.15]***	0.005	[1.47]
Difference-in-Differences					**0.059**	**[5.21]*** **
Rating upgrades (from Table 3)	-0.037	[11.62]***	-0.024	[8.14]***	0.013	[3.26]***
Positive earnings surprises	-0.010	[6.77]***	-0.011	[7.82]***	-0.001	[-0.58]
Difference-in-Differences					**-0.014**	**[3.29]*** **

Panel B: Balanced sub-sample

	Pre-Crisis		Post-Crisis			
	Mean ΔCDS	t-stat	Mean ΔCDS	t-stat	Difference	t-stat
Rating Downgrades (from Table 3)	0.098	[9.97]***	0.048	[8.55]***	-0.050	[4.53]***
Negative Earnings Surprises	0.011	[4.02]***	0.015	[5.32]***	0.004	[1.05]
Difference-in-Differences					**0.054**	**[4.59]*** **
Rating upgrades (from Table 3)	-0.037	[10.87]***	-0.023	[7.57]***	0.014	[3.17]***
Positive earnings surprises	-0.010	[6.81]***	-0.007	[5.21]***	0.003	[1.37]
Difference-in-Differences					**-0.011**	**[2.39]** **

Panel C: Uncontaminated sub-sample

	Pre-Crisis		Post-Crisis			
	Mean ΔCDS	t-stat	Mean ΔCDS	t-stat	Difference	t-stat
Rating Downgrades (from Table 3)	0.083	[7.67]***	0.033	[6.95]***	-0.050	[4.22]***
Negative Earnings Surprises	0.011	[2.04]**	0.013	[3.12]***	0.002	[0.26]
Difference-in-Differences					**0.052**	**[3.65]*** **
Rating upgrades (from Table 3)	-0.036	[11.66]***	-0.023	[7.34]***	0.013	[3.20]***
Positive earnings surprises	-0.014	[3.88]***	-0.018	[5.59]***	-0.004	[0.76]
Difference-in-Differences					**-0.017**	**[2.77]*** **

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

	Pre-Crisis		Post-Crisis			
	Mean ΔCDS	**t-stat**	**Mean ΔCDS**	**t-stat**	**Difference**	**t-stat**
Rating Downgrades (from Table 3)	0.887	[11.22]***	0.529	[9.93]***	-0.358	[3.77]***
Negative Earnings Surprises	0.187	[4.10]***	0.242	[5.17]***	0.055	[0.92]
Difference-in-Differences					**0.413**	**[3.80]*** **
Rating upgrades (from Table 3)	-0.608	[12.20]***	-0.468	[8.72]***	0.14	[2.01]**
Positive earnings surprises	-0.200	[8.38]***	-0.25	[9.04]***	-0.05	[1.47]
Difference-in-Differences					**-0.19**	**[2.56]** **

TABLE 7: Relevance of Quarterly Unexpected Earnings – Regression Analysis

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

The samples of earnings announcements are detailed in Table 2. ΔCDS^{EA} is the three-day abnormal change in CDS spread. *UE* is unexpected earnings, as defined in Appendix A. *POST* is a binary variable for the period starting July 1, 2007. *ADDL_CONTROLS* are untabulated for brevity and include *SIZE, BTM, LEV, FQ4,* and *BETA*. Continuous *ADDL_CONTROLS* are normalized to have a mean (variance) of zero (one). Other variable definitions are in Appendix A. Panel A presents the model excluding *ADDL_CONTROLS*, while Panel B includes *ADDL_CONTROLS*. T-statistics in brackets are clustered by firm and day. ***Indicates significance at 1%, **at 5%, *at 10%.

Panel A: Regression Output – basic model (without ADDL_CONTROLS)

	Coefficient	H2a	Complete Sample	Balanced Subsample	Uncontaminated Subsample	Complete Sample $\Delta SCDS^{EA}$
UE (Pre-Crisis)	β_1		-3.615	-3.747	-2.717	-71.798
			[-9.51]***	[-7.56]***	[-4.27]***	[-10.35]***
UE*POST	β_2	(-)	-0.713	-0.791	-0.758	-12.707
			[-3.05]***	[-2.19]**	[-2.54]**	[-2.78]***
POST	β_3		0.005	0.006	0.006	0.076
			[2.86]***	[3.33]***	[1.30]	[2.54]**
CDS_{t-2}	β_4		-0.018	-0.024	-0.025	-0.429
			[-3.39]***	[-4.03]***	[-3.06]***	[-4.47]***
UE*CDS_{t-2}	β_5		1.094	0.651	0.355	18.984
			[1.76]*	[0.85]	[0.40]	[1.68]*
IGRADE_BDR	β_6		-0.006	-0.007	0.003	-0.106
			[-3.40]***	[-3.41]***	[0.66]	[-2.86]***
IGRADE_BDR*UE	β_7		0.363	0.546	1.041	6.013
			[1.26]	[1.18]	[3.11]***	[1.13]
NONLINEAR	β_8		71.233	88.132	60.983	1,454.671
			[5.38]***	[4.87]***	[3.93]***	[6.57]***
LOSS	β_9		0.009	0.010	0.013	0.214
			[3.37]***	[3.52]***	[2.79]***	[4.20]***
LOSS*UE	β_{10}		0.644	0.322	0.398	13.273
			[1.76]*	[0.75]	[0.92]	[2.15]**
Intercept	β_0		0.000	0.001	-0.001	0.003
			[0.19]	[0.68]	[-0.20]	[0.12]
Additional Controls			No	No	No	No
N			7,314	6,400	1,335	7,314
Adjusted R-Squared			0.047	0.037	0.071	0.060

Panel B: Regression Output – with additional controls

	Coefficient	H2a	Complete Sample	Balanced Subsample	Uncontaminated Subsample	Complete Sample $\Delta SCDS^{EA}$
UE (Pre-Crisis)	β_1		-3.418	-3.672	-2.654	-67.928
			[-9.05]***	[-7.32]***	[-4.19]***	[-9.96]***
UE*POST	β_2	(-)	-0.664	-0.836	-0.665	-11.212
			[-2.82]***	[-2.22]**	[-2.05]**	[-2.51]**
POST	β_3		0.005	0.006	0.005	0.071
			[2.73]***	[3.20]***	[1.13]	[2.32]**
CDS_{t-2}	β_4		-0.014	-0.023	-0.019	-0.311
			[-2.24]**	[-3.14]***	[-2.08]**	[-2.73]***
UE*CDS_{t-2}	β_5		0.237	0.399	-0.014	3.136
			[0.37]	[0.46]	[-0.02]	[0.27]
IGRADE_BDR	β_6		-0.006	-0.007	0.003	-0.104
			[-3.13]***	[-3.32]***	[0.62]	[-2.67]***
IGRADE_BDR*UE	β_7		0.501	0.591	1.216	10.262
			[1.71]*	[1.20]	[3.17]***	[1.90]*
NONLINEAR	β_8		50.698	80.335	43.779	1,059.004
			[3.84]***	[4.14]***	[2.59]***	[4.78]***
LOSS	β_9		0.010	0.009	0.013	0.222
			[3.60]***	[3.42]***	[2.76]***	[4.52]***
LOSS*UE	β_{10}		0.598	0.248	0.395	12.859
			[1.75]*	[0.59]	[0.95]	[2.24]**
Intercept	β_0		-0.001	0.001	-0.000	-0.027
			[-0.67]	[0.31]	[-0.14]	[-1.04]
Additional Controls			Yes	Yes	Yes	Yes
N			7,314	6,400	1,335	7,314
Adjusted R-Squared			0.051	0.037	0.074	0.066

TABLE 8: Credit Rating Prediction Model Results

$$RATING_{i,m} = \beta_0 + \beta_1 SIZE_{i,q-1} + \beta_2 ROA_{i,q-1} + \beta_3 LEV_{i,q-1} + \beta_4 CAPINTEN_{i,q-1} + \beta_5 INTCOV_{i,q-1}$$
$$+ \beta_6 CFO\_DEBT_{i,q-1} + \beta_7 ACID_{i,q-1} + \beta_8 TCA_{i,q-1}$$
$$+ \varepsilon_{i,m}$$

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 and accounting data. See Table 1 for further detail. In the ordered logit model above, *RATING* is the firm's credit rating letter at month-end. All other variables are defined in Appendix A. The logit model is estimated by quarter and industry sector, for a total of 252 industry-quarter regressions. Panel A presents the average coefficient estimates along with results of t-tests that the average coefficients differ from zero. Panel B presents average pseudo r-squared fit statistics in the pre- and post-crisis period. Panel C presents the distribution of fitted values from the above model, *RATING_PREDICT*.

Panel A: Average coefficients from models by quarter and industry

	N	Mean Coefficient	t-statistic	Pr > t
ACID	252	-0.941	-3.85	0.000
CAPINTEN	252	-1.956	-1.23	0.219
CFO_DEBT	252	0.306	0.24	0.809
INTCOV	252	0.335	2.16	0.031
LEV	252	-5.572	-2.68	0.008
ROA	252	35.038	9.91	<.0001
SIZE	252	1.293	9.82	<.0001
TCA	252	-11.153	-3.95	0.000

Panel B: Pseudo r-squared from models by quarter and industry

	N	Mean	Min.	Median	Max.	Std. Dev.
Pre-crisis	126	68.4%	35.6%	69.2%	96.1%	13.0%
Post-crisis	126	71.5%	41.6%	72.4%	96.5%	12.9%

Panel C: Predicted ratings (i.e., RATING_PREDICT)

Predicted Rating	**Pre-Crisis**	**Post-Crisis**	**Total**
20	125	118	243
19	6	19	25
18	222	94	316
17	268	180	448
16	267	435	702
15	1,410	1,758	3,168
14	917	477	1,394
13	1,333	1,459	2,792
12	3,599	3,170	6,769
11	1,365	1,992	3,357
10	512	369	881
9	532	797	1,329
8	475	661	1,136
7	511	677	1,188
6	262	240	502
5	197	324	521
4	86	258	344
3	17	88	105
2	0	28	28
1	3	76	79
Total	**12,107**	**13,220**	**25,327**

TABLE 9: Relevance of Accounting Data in Levels – Discordancy Tests

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 and accounting data. See Table 1 for further detail. Accounting-based predicted credit ratings, *RATING_PREDICT*, are calculated using an ordered logit model of firms' month-end actual credit ratings regressed on accounting variables, as discussed in Section 4. *DISCORDANT* and *DISCORD_EXTRM* observations are calculated in the same way as previously defined, but firms' predicted ratings are substituted for actual ratings. See Section 4 and Table 5 for further discussion.

Panel A summarizes the percentage of *DISCORDANT* observations based on *RATING_PREDICT*. "Percentage Point Change" is the nominal difference in the percentage of discordant observations based on *RATING_PREDICT* in the post-crisis period less the percentage in the pre-crisis period. "Diff. Means t-stat" is the t-statistic from a differences in means test with standard errors clustered by firm and month. "Logit z-stat" is the z-statistic from the following logit regression of *DISCORDANT* on an indicator variable *POST*. Standard errors are clustered by month and firm. ***Indicates significance at 1%, **at 5%, *at 10%. At the bottom of Panel A is a t-statistic from a test that the average percentage point change differs from zero (n = 16). ##Indicates significance at 1% based on White standard errors.

Panel B presents difference-in-differences analysis between the pre/post-crisis change in discordant observations based on actual ratings versus the pre/post-crisis change in discordant observations based on predicted ratings. !!Indicates a significantly positive difference-in-differences rather than negative difference-in-differences (as predicted).

Panels C and D repeat the analysis in Panels A and B but for *DISCORD_EXTRM* observations.

Panel A: Discordant observations using accounting-based predicted ratings

Rating	**Percentage of Discordant Observations Pre-Crisis**	**Percentage of Discordant Observations Post-Crisis**	**Percentage Point Change**	**Relative Change**	**Diff. Means. t-stat**	**Logit z-stat**
20	2.1%	9.9%	7.8%	375%	[4.28]***	[4.51]***
19	Insufficient observations					
18	17.0%	13.3%	-3.7%	-22%	[-1.27]	[-1.21]
17	33.1%	18.7%	-14.4%	-43%	[-2.50]**	[-2.69]***
16	46.9%	25.6%	-21.3%	-45%	[-4.99]***	[-5.11]***
15	43.7%	33.7%	-10.0%	-23%	[-3.61]***	[-3.60]***
14	48.2%	44.4%	-3.8%	-8%	[-1.32]	[-1.31]
13	53.4%	47.0%	-6.3%	-12%	[-2.69]***	[-2.67]***
12	50.0%	52.8%	2.8%	6%	[1.20]	[1.19]
11	46.7%	52.8%	6.1%	13%	[2.15]**	[2.14]**
10	45.4%	47.3%	2.0%	4%	[0.51]	[0.51]
9	39.1%	44.0%	4.9%	13%	[1.56]	[1.55]
8	44.6%	32.5%	-12.1%	-27%	[-2.73]***	[-2.76]***
7	35.2%	24.4%	-10.7%	-30%	[-3.69]***	[-3.63]***
6	19.8%	34.5%	14.7%	74%	[3.30]***	[3.51]***
5	21.5%	32.1%	10.7%	50%	[1.85]*	[1.81]*
4	12.8%	17.1%	4.3%	33%	[1.98]**	[1.86]*
3	Insufficient observations					
2	Insufficient observations					
1	Insufficient observations					
Avg.	**35.0%**	**33.1%**	**-1.8%**	**-5.2%**		
	t-statistic: average change different from zero		**[0.74]**			

Panel B: Discordant observations difference-in-differences

Rating	Percentage Point Change Based on Actual Ratings (Panel A of Table 6)	Percentage Point Change Based on Predicted Ratings (Panel A of Table 8)	Difference-in-Differences	Diff-in-Diff OLS t-stat	Diff-in-Diff Logit z-stat
20	7.4%	7.8%	0.4%	[0.27]	[-1.01]
19	Insufficient observations				
18	11.4%	-3.7%	-15.1%	[-4.80]***	[-5.48]***
17	4.1%	-14.4%	-18.5%	[-2.74]***	[-2.90]***
16	7.5%	-21.3%	-28.8%	[-6.98]***	[-7.19]***
15	5.8%	-10.0%	-15.8%	[-6.59]***	[-6.60]***
14	8.8%	-3.8%	-12.7%	[-4.82]***	[-4.92]***
13	2.9%	-6.3%	-9.2%	[-4.14]***	[-4.09]***
12	11.8%	2.8%	-8.9%	[-4.04]***	[-4.41]***
11	9.5%	6.1%	-3.4%	[-1.20]	[-1.83]*
10	16.9%	2.0%	-15.0%	[-3.78]***	[-4.23]***
9	4.2%	4.9%	0.7%	[0.23]	[-0.33]
8	-10.7%	-12.1%	-1.4%	[-0.53]	[0.40]
7	3.2%	-10.7%	-13.9%	[-4.63]***	[-4.55]***
6	1.8%	14.7%	12.9%	[2.85]***!!	[2.59]***!!
5	-1.4%	10.7%	12.1%	[1.93]*!!	[1.84]*!!
4	1.1%	4.3%	3.2%	[1.13]	[1.24]
3	Insufficient observations				
2	Insufficient observations				
1	Insufficient observations				
Avg.	**5.3%**	**-1.8%**	**-7.1%**		
	t-statistic: average DID different from zero		**[2.59]##**		

Panel C: Extreme discordant observations using accounting-based predicted ratings

Rating	**Percentage of Extreme Discordant Observations Pre-Crisis**	**Percentage of Extreme Discordant Observations Post-Crisis**	**Percentage Point Change**	**Relative Change**	**Diff. Means. t-stat**	**Logit z-stat**
20	0.2%	3.0%	2.8%	1769%	[3.32]***	[4.12]***
19	Insufficient observations					
18	2.8%	3.7%	0.8%	29%	[0.75]	[0.78]
17	3.6%	6.2%	2.7%	75%	[2.66]***	[2.68]***
16	9.0%	10.8%	1.8%	20%	[1.08]	[1.06]
15	11.3%	9.3%	-2.0%	-17%	[-1.28]	[-1.30]
14	15.5%	17.4%	1.9%	12%	[1.30]	[1.30]
13	18.2%	16.7%	-1.4%	-8%	[-0.95]	[-0.94]
12	13.2%	14.3%	1.1%	8%	[0.78]	[0.77]
11	13.0%	14.3%	1.3%	10%	[0.91]	[0.91]
10	14.5%	15.6%	1.1%	8%	[0.76]	[0.75]
9	13.8%	13.0%	-0.9%	-6%	[-0.57]	[-0.57]
8	10.3%	9.3%	-1.0%	-9%	[-0.94]	[-0.94]
7	9.4%	8.1%	-1.3%	-14%	[-1.16]	[-1.18]
6	8.2%	7.1%	-1.1%	-13%	[-0.97]	[-1.00]
5	4.8%	4.7%	-0.1%	-2%	[-0.13]	[-0.13]
4	4.6%	6.3%	1.8%	38%	[1.71]*	[1.66]*
3	Insufficient observations					
2	Insufficient observations					
1	Insufficient observations					
Avg.	**9.5%**	**10.0%**	**0.5%**	**4.9%**		
	t-statistic: average change different from zero		**[1.24]**			

Panel D: Extreme discordant observations difference-in-differences

Rating	Percentage Point Change Based on Actual Ratings (Panel A of Table 6)	Percentage Point Change Based on Predicted Ratings (Panel A of Table 7)	Difference-in-Differences	Diff-in-Diff OLS t-stat	Diff-in-Diff Logit z-stat
20	2.0%	2.8%	0.9%	[1.19]	[-1.20]
19	Insufficient observations				
18	9.2%	0.8%	-8.4%	[-5.11]***	[-5.56]***
17	6.2%	2.7%	-3.5%	[-4.12]***	[-3.85]***
16	5.6%	1.8%	-3.8%	[-2.42]**	[-3.36]***
15	4.2%	-2.0%	-6.1%	[-4.71]***	[-5.50]***
14	5.3%	1.9%	-3.5%	[-2.49]**	[-3.56]***
13	2.4%	-1.4%	-3.8%	[-2.37]**	[-2.48]**
12	3.5%	1.1%	-2.4%	[-1.56]	[-1.95]*
11	4.0%	1.3%	-2.7%	[-1.94]*	[-3.00]***
10	3.6%	1.1%	-2.5%	[-1.80]*	[-3.46]***
9	1.3%	-0.9%	-2.2%	[-1.39]	[-1.70]*
8	-0.5%	-1.0%	-0.5%	[-0.44]	[-0.12]
7	-0.2%	-1.3%	-1.1%	[-1.04]	[-0.76]
6	0.0%	-1.1%	-1.1%	[-1.05]	[-0.89]
5	-0.2%	-0.1%	0.1%	[0.09]	[0.14]
4	-0.4%	1.8%	2.2%	[2.51]**!!	[2.49]**!!
3	Insufficient observations				
2	Insufficient observations				
1	Insufficient observations				
Avg.	**2.9%**	**0.5%**	**-2.4%**		
	t-statistic: average DID different from zero		**[3.83]**###		

TABLE 10: 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. See Table 1 for further detail. 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	***
							27.2		***			
19	7	7.7	7.3	18	34.9	32.7		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	***
							1,939.4		***			
2	2	480.0	480.0	33	2,419.4	1,470.2		5.56	#	990.2	2.31	**
							2,232.6		***			
1	3	465.8	444.9	110	2,698.4	1,476.8		9.76	#	1,031.9	2.94	***
						Avg. Percentage Increase =	227%			161%		

TABLE 11: Relevance of Equity Analyst Forecast Revisions

Model: $\Delta CDS^{REV}_{i,t} = \beta_0 + \beta_1 REV_{i,t} + \beta_2 REV_{i,t}{*}POST + \beta_3 POST + \beta_4 CDS_{t-2} + \beta_5 REV_{i,t}{*}CDS_{t-2} + \beta_6 IGRADE\_BDR_{i,t} + \beta_7 IGRADE\_BDR_{i,t}{*}REV_{i,t} + \beta_8 NONLINEAR_{i,t} + \beta_9 LOSS_{i,t} + \beta_{10} LOSS_{i,t}{*}REV_{i,t} + \Sigma\beta_k ADDL\_CONTROLS_{i,q-1} + \Sigma\beta_k ADDL\_CONTROLS_{i,q-1}{*}REV_{i,t} + \varepsilon_{i,t}$

The sample includes analyst forecast revisions between 1/1/2004 and 12/31/2010. Forecast revisions are matched to the most recently available quarterly accounting information, not more than 100 days old. ΔCDS^{REV} is the three-day abnormal change in CDS spread around the forecast revision. *REV* is analyst forecast revision, as defined in Appendix A. *POST* is a binary variable for the period starting July 1, 2007. *ADDL_CONTROLS* are untabulated for brevity and include *SIZE, BTM, LEV, FQ4,* and *BETA*. Continuous *ADDL_CONTROLS* are normalized to have a mean (variance) of zero (one). The balanced subsample ensures that each *REV* observation from the pre-crisis period is matched to a *REV* observation in the post-crisis period. The uncontaminated subsample excludes dates on which there are simultaneous rating changes, earnings releases, or management forecasts. Other variable definitions are in Appendix A. T-statistics in brackets are clustered by firm and day. ***Indicates significant at 1%, **at 5%, *at 10%.

	Coefficient	Complete Sample	Balanced Subsample	Uncontaminated Subsample	Complete Sample $\Delta SCDS^{EA}$
REV (Pre-Crisis)	β_1	-1.464	-1.777	-1.130	-25.242
		[-7.15]***	[-6.00]***	[-6.06]***	[-6.82]***
REV*POST	β_2	-0.437	-0.676	-0.409	-10.033
		[-1.98]**	[-2.48]**	[-1.91]*	[-2.60]***
POST	β_3	0.001	0.001	0.001	0.031
		[1.48]	[1.67]*	[1.68]*	[2.19]**
CDS_{t-2}	β_4	-0.019	-0.024	-0.019	-0.336
		[-6.69]***	[-6.64]***	[-6.82]***	[-7.29]***
REV*CDS_{t-2}	β_5	0.110	0.087	0.046	0.849
		[0.31]	[0.15]	[0.14]	[0.15]
IGRADE_BDR	β_6	-0.002	-0.002	-0.002	-0.044
		[-2.93]***	[-2.50]**	[-2.52]**	[-3.13]***
IGRADE_BDR*REV	β_7	-0.059	-0.489	-0.071	-2.903
		[-0.32]	[-1.66]*	[-0.43]	[-0.96]
NONLINEAR	β_8	31.173	96.716	25.387	678.460
		[3.74]***	[3.19]***	[2.94]***	[4.47]***
LOSS	β_9	0.007	0.006	0.006	0.134
		[4.13]***	[3.89]***	[3.55]***	[4.20]***
LOSS*REV	β_{10}	0.133	-0.021	0.118	3.644
		[0.78]	[-0.07]	[0.73]	[1.22]
Intercept	β_0	0.002	0.002	0.002	0.013
		[3.01]***	[3.25]***	[3.31]***	[1.14]
Additional Controls		Yes	Yes	Yes	Yes
N		54,189	43,495	48,079	54,189
Adjusted R-Squared		0.014	0.012	0.011	0.016