Financial Reporting Quality and Uncertainty about Credit Risk among Ratings Agencies

Brian Akins*
Rice University, Jones School of Management
6100 Main Street, 337 McNair Hall
Houston, TX 77005
(713) 348-4253
akins@rice.edu

Abstract

This study finds that better reporting quality is associated with less uncertainty about credit risk as captured by disagreement among the credit rating agencies. The results also show that reporting quality is more important in reducing uncertainty when debt market participants have less access to private information. To mitigate endogeneity concerns, I use the quasi-natural experiment induced by a change in accounting standards that improved reporting quality. Implementation of the standard led to less disagreement among the rating agencies. Overall, this study contributes to the literature on the impact of reporting quality on debt markets and intermediaries.

Keywords: Financial reporting quality, credit ratings, uncertainty, SFAS 131

First Version: August 2011
Current Version: August 2017

*I am grateful for the advice and comments of my dissertation committee: Joe Weber (chair), John Core, and Rodrigo Verdi. I also appreciate insightful comments from Paul Asquith, Anne Beatty (editor), David De Angelis, Louis Ederington, Eric Floyd, Rich Frankel, Frank Gigler, John Jiang, Derek Johnson, Pepa Kraft, Lynn Li, Bob Lipe, Mike Minnis (discussant), Karen Nelson, Jeff Ng, K. Ramesh, Brian Rountree, Shiva Sivaramakrishnan, Richard Swartz, Ross Watts, Luo Zuo, two anonymous reviewers, and seminar participants at the MIT Sloan School of Management, The Ohio State University, Rice University, Southern Methodist University, the University of Connecticut, the University of Houston, the University of Minnesota, the University of Oklahoma, Washington University in St. Louis, and the 2012 Midyear FARS Meeting. I would like to gratefully acknowledge funding from the Massachusetts Institute of Technology, Rice University, and the Deloitte Foundation. Finally, I would like to thank Cynthia Akins for her endless patience with this project.
Credit rating agencies are central to capital formation, investor confidence, and the efficient performance of the United States economy.

— Subtitle C of Title IX of the Dodd-Frank Act (2010)

I. INTRODUCTION

This study examines the role of financial reporting quality in credit ratings. While a large body of scholarship explores how reporting quality affects equity analysts (Dechow, Ge, and Schrand 2010; Healy and Palepu 2001), little research addresses whether and how it influences credit rating agencies (CRAs). Indeed, one might question the relevance of reporting quality for CRAs because, unlike equity analysts, they enjoy access to private corporate information. Yet financial information publicly reported by firms still plays a significant role in their determinations of bond ratings (Kraft 2015), and covenants in debt contracts are frequently written on this information (Leftwich 1983; Smith and Warner 1979). On top of this, research shows that reporting quality affects covenant usage (Costello and Wittenberg-Moerman 2011; Graham, Li, and Qiu 2008). Because debtholders rely on accounting-based covenants, public reporting should also matter to the CRAs. Consequently, I argue that the quality of these reports is of fundamental interest to CRAs.

From a contracting perspective, the reliability of reported numbers is a fundamentally important aspect of financial reporting quality (Armstrong, Guay, and Weber 2010). Lack of reliability can cause CRAs to differ in their ratings, giving rise to uncertainty with respect to credit risk. Therefore, to the extent CRAs rely on financial reports in issuing their ratings, I hypothesize that reporting quality is an important determinant of credit risk uncertainty as reflected in disagreements among CRAs. Such a hypothesis comports with research suggesting that financial reporting quality affects the extent of consensus among equity analysts, a proxy for
uncertainty regarding firm profitability (Dechow, Ge, and Schrand 2010; Healy and Palepu 2001). Specifically, I posit that reporting quality is negatively associated with credit risk uncertainty.

This link would be tenuous if CRAs relied primarily on the private information they can acquire from corporations. However, not all CRAs have similar access to private information. For example, the two major agencies, Standard and Poor’s (S&P) and Moody’s Investor Service (Moody’s) are known to have such access. But Egan-Jones Ratings Company (EJR) relies primarily on public reports in developing its ratings.¹ This difference provides a unique opportunity to examine the link between reporting quality and credit risk uncertainty.

I use the debt contracting value of accounting (DCV) as a proxy for reporting quality—a measure that captures how well earnings information predicts ratings changes. While studies have defined financial reporting quality variously (Dechow et al. 2010), DCV pertains directly to the CRAs (Ball, Bushman, and Vasvari 2008). To capture uncertainty about credit risk, I use the absolute difference in historical default rates between the ratings issued by Moody’s and S&P.² I expect the leading CRAs to disagree more about an issuer’s default risk when it has lower reporting quality and, consistent with this expectation, find a negative association between DCV and their degree of disagreement. For example, a one standard deviation increase in DCV results in a 0.99 percent decrease in the difference in implied default rates corresponding to ratings issued by different agencies—roughly the difference between an A and an A- rating. These results support the hypothesis that better reporting quality is associated with less credit risk

¹ Regulation Fair Disclosure Rule 102(b)(2) allowed Nationally Recognized Statistical Rating Organizations (NRSROs) continued access to private information provided by management for use in the rating process as long as the ratings were publicized, but it ended access to private information for “investment advisors.” Since EJR did not publicize its ratings, unlike Moody’s and S&P, it was not allowed access to private managerial information.

² I focus mainly on disagreements between Moody’s and S&P to capture uncertainty because over 80% of all rated global bond issues are covered by one or both of these agencies. Fitch only rates 14% of outstanding issues (Langohr and Langohr 2009).
uncertainty. They are robust to including a variety of variables that control for issuing firms’
operating and information environments and to using other reporting quality variables, such as
asymmetric timeliness, the conservatism score, and accrual quality.

I also examine the effect of reporting quality on the disagreements between Moody’s and
S&P and EJR. I find a greater reduction in the disagreement between EJR, which lacks extensive
access to private information, and Moody’s and S&P than between Moody’s and S&P for a
given change in reporting quality. This indicates EJR benefits more from better reporting quality.
Taken together, these results highlight the importance of financial reporting quality in reducing
uncertainty in the capital markets.

Because reporting quality may be correlated with other factors affecting uncertainty, my
results are subject to endogeneity concerns. To address this issue, I examine the extent to which
credit risk uncertainty changes after an exogenous change in reporting quality from the
mandatory adoption of Statement of Financial Accounting Standards (SFAS) 131. Past evidence
indicates that the adoption of SFAS 131 increased reporting quality by improving segment
disclosure (Berger and Hann 2003; Ettredge et al. 2005). This setting therefore allows me to test
a directional prediction with respect to the effects of reporting quality on credit rating
disagreements. It also allows me to conduct a difference-in-differences analysis, since firms with
fewer changes in their number of reporting segments were less affected by SFAS 131. Using a
propensity-score-matched sample, I find less disagreement for firms that increased the number of
segment disclosures by three or more after the implementation of SFAS 131 (a 1.59 percent
difference in implied default rates). With this increase in reporting quality, uncertainty regarding
credit risk assessment declined, thereby providing additional support for my hypothesis.
In related work, Wittenberg-Moerman (2008) uses loan spreads as a measure of information asymmetry and shows that firms with more timely loss recognition have lower information asymmetry in the secondary syndicated loan market. However, loan spreads are also affected by a variety of other important risk factors such as interest rate risk, local tax effects, liquidity, and the effects of common equity risk factors (Bao, Pan, and Wang 2011; Elton, Gruber, Agrawal, and Mann 2001; Longstaff and Schwartz 1995). In contrast, my measure of credit risk uncertainty more directly reflects uncertainty that arises from disagreements among the rating agencies (Morgan 2002), which allows me to focus squarely on the impact of reporting quality.

This study contributes to the literature that examines the effects of reporting quality on information intermediaries. Recent papers examine the determinants of debt analysts’ decisions to initiate coverage and the properties of their recommendations (De Franco, Vasvari, and Wittenberg-Moerman 2009; Johnston, Markov, and Ramnath 2009). I extend this literature by directly considering credit risk, which is the fundamental concern of debt holders. I find evidence consistent with reporting quality reducing disagreement between the leading rating agencies about credit risk, despite their access to private information. I also find that reporting quality matters even more when a CRA lacks access to that information. This result underscores the importance of reporting quality in debt markets, since few participants have access to private information.

This study also contributes to research on the consequences of reporting quality in debt markets. Research shows that better reporting lowers the cost of debt (Bharath, Sunder, and Sunder 2008; Sengupta 1998; Zhang 2008), affects the structure of loan syndicates (Ball et al. 2008), influences loan contract design (Costello and Wittenberg-Moerman 2011; Graham, Li,
and Qiu 2008), lowers spreads for syndicated loans traded in the secondary market (Wittenberg-Moerman 2008), and affects the lease-versus-buy decision (Beatty, Liao, and Weber 2010). My complementary results show that reporting quality plays an important role even for sophisticated information intermediaries with access to private information, thus highlighting the importance of financial reporting quality in reducing uncertainty.

Section II discusses related research. Section III develops my hypotheses. Section IV describes my research design, proxies for credit risk uncertainty and reporting quality, and sample selection. Section V provides the results of my tests. Sections VI and VII contain endogeneity and robustness tests. Section VIII concludes.

II. RELATED RESEARCH

The leading CRAs often disagree about debt ratings. This disagreement is driven, at least in part, by uncertainty about credit risk (Morgan 2002). Research on the outcomes of credit risk uncertainty examines whether ratings disagreement can affect the cost of debt, influence the probability of obtaining a third rating, or impact derivative pricing. Studies find evidence consistent with investors demanding higher yields on bonds rated differently by CRAs (Cheng 2011; Livingston and Zhou 2010). Cheng (2011) finds that Moody’s and S&P are less likely to disagree about bonds issued by banks with greater timeliness and better loan-loss provisioning. My study differs in that I examine whether these effects hold for industrials, and I consider the effects of an accounting standard change. Jewell and Livingston (1998) similarly find that split ratings on bonds issued below investment grade significantly increase the underwriter fees charged to issuing firms. Finally, firms that receive different ratings are more likely to incur the

---

3 Relying on this, Kim, Kraft, and Ryan (2013) develop an industry-level measure of financial statement comparability and use rating disagreements to validate it.
cost of obtaining a third rating, consistent with them attempting to reduce uncertainty (Beattie and Searle 1992; Jewell and Livingston 2000).

III. HYPOTHESIS DEVELOPMENT

The agencies need to determine the likelihood of both future interest payments and timely repayment of principal. Ratings are assigned based on an overall assessment of credit risk, which includes a number of hard and soft adjustments made to the various inputs used (Kraft 2015). Thus credit ratings are a function of hard information derived from adjustments to accounting outputs, soft information, and the discretion analysts have in making these adjustments.

Morgan (2002) develops a model in which uncertainty about default risk leads to ratings disagreements. He hypothesizes that there is greater opacity, creating more uncertainty, surrounding financial firms than other firms. He finds empirical evidence, that is, greater ratings disagreement, supporting this. The U.S. SEC likewise says that one barrier to accurate ratings is the ability of debt market participants to obtain “accurate and reliable information from issuers” (SEC 2003). Thus the quality of information provided by issuers figures prominently in risk assessments. I argue that better reporting decreases uncertainty about credit risk and therefore disagreement about the expected default risk of a bond issue.

H1: Higher reporting quality decreases uncertainty about credit risk.

There are at least three reasons why this hypothesis may not hold. First, higher reporting quality may allow the agencies to make more precise forecasts. If CRAs employ different models, more precise forecasts may lead to a divergence in their opinions. For example, the models may differentially weight components of disclosure. Thus higher reporting quality could

4 Hard adjustments are modifications made to reported accounting numbers for ratio analysis, such as the capitalization of off-balance sheet debt. Soft adjustments compensate for qualitative factors affecting credit risk, such as the perceived quality of a firm’s management and accounting. Both types of adjustments tend to lower bond ratings (Kraft 2015).
increase their disagreement (Lang and Lundholm 1996). Second, the agencies may focus on the reported accounting numbers without significantly adjusting for the quality of those numbers. Some firms behave as though market participants, including CRAs, fixate on reported numbers (Engel et al. 1999). And empirical evidence suggests this is true and consequently the CRAs fail to recognize or adjust for reporting quality (Demirtas and Cornaggia 2013; Jung et al. 2013). Thus reporting quality may have no effect on disagreement between the leading CRAs.

Finally, the relation between reporting quality and uncertainty about credit risk could also depend on the extent to which market participants have access to private information and how that information is used. Regulation Fair Disclosure (Reg FD) Rule 102(b)(2) allowed certified rating agencies, such as Moody’s and S&P, to retain access to private information provided by management, conditional on their ratings being made publicly available. Thus, during my sample period Moody’s and S&P could use private information to mitigate the role of reporting quality in their assessment of credit risk. In the extreme, if the agencies have different private information sets, this diversity of information could lead to an association opposite of that hypothesized. If agency analysts assume that the quality of their private information is correlated with that of public information, they may place more weight on the former when reporting quality is high, leading to greater ratings divergence.

In contrast, when private information is limited, investors must rely more on public information. When relying on public information exclusively, the perceived quality of that

---

5 Harris and Raviv (1993) and Kandel and Pearson (1995) model scenarios in which increased disclosure creates divergent beliefs because users interpret the information differently.
6 Ederington (1986) investigates the possibility that S&P and Moody’s weight identical factors differently but finds no evidence of this. However, their practices could have since changed.
7 It may seem unlikely that the agencies possess different private information sets. But this is quite possible if one agency is being paid for its ratings and the other is issuing unsolicited ratings, limiting its access to private information.
information is likely to be more important. Hence reporting quality is expected to matter more to those with less access to private information. This leads to my second hypothesis.

\textit{H2: Reporting quality is relatively more important in reducing uncertainty about credit risk when rating agencies have less access to private information.}

\textbf{IV. RESEARCH DESIGN AND SAMPLE SELECTION}

\textit{Proxy for Uncertainty}

I use bond-level, rather than firm-level, ratings to identify disagreement, for two reasons. First, Moody’s and S&P rarely initiate simultaneous changes in ratings, impeding determination of whether a rating split stems from this asynchronicity or from uncertainty about credit risk. Thus the initial rating of a debt instrument provides an opportunity to examine disagreement because both agencies make a simultaneous judgment about credit risk. Second, Moody’s and S&P use different criteria for firm-level credit ratings. Moody’s evaluates both risk of the firm defaulting and the expected loss given default (LGD) when developing firm-level credit ratings for speculative grade firms. In contrast, S&P considers only default risk for firm-level ratings. However, both of them evaluate the risk of default and the LGD when developing bond-level ratings, making these more comparable than firm ratings.

Morgan (2002) investigates whether there is more uncertainty about credit risk for financial institutions than for other industries using disagreement about credit ratings. I follow his empirical tests by estimating the following model.

\[ \text{Disagreement} = F(\text{reporting quality}, \text{bond-level controls}, \text{firm-level controls}, \text{year fixed effects}, \text{industry fixed effects}) + \epsilon. \]

I add reporting quality and a variety of firm-level controls to this baseline model.
I use the difference in implied default risk (DefaultDiff) indicated by the two ratings a bond receives to determine the extent of disagreement about credit risk between the agencies. I choose this, rather than the number of notches between ratings, since default risk increases exponentially as ratings decrease. The number of notches fails to capture this nonlinearity. To calculate DefaultDiff, I use the historical default rates on corporate bonds for each letter rating by the respective credit agencies. Appendix A contains the average historical default rates for corporate bonds by Moody’s (S&P) by rating from 1983 (1981) through 2008. I take the absolute difference in these rates, setting the difference equal to zero for bonds with equivalent ratings, to capture the difference in expected default probabilities (DefaultDiff).

For example, Boeing issued 30-year senior notes on August 7, 1991, and these notes were rated AA by S&P and Aa3 by Moody’s (equivalent to an AA- on the S&P scale). Thus S&P viewed Boeing more favorably than Moody’s did, indicating uncertainty surrounding the credit risk of this firm. The historical default rate for bonds rated AA by S&P is 0.72 percent, while the default rate for bonds rated Aa3 by Moody’s is 3.14 percent, implying that DefaultDiff would be 2.42 percent for the Boeing bond.

**Empirical Test for Hypothesis 1**

I estimate the following regression in a Tobit specification using my disagreement proxy to determine whether increasing reporting quality reduces the extent of credit risk uncertainty.

\[ DefaultDiff_t = \alpha + \beta_1 DCV_{t-1} + \Sigma \beta_j Controls_{j,t-1} + \epsilon_t. \]  

I include industry fixed effects in all of my tests, since defaults cluster by industry and Morgan (2002) finds significant differences in credit risk uncertainty across industries. Because I use a

---

8 While it would be ideal to have ratings from 1985–2008, the period of my sample, these periods are the closest to that one reported by the agencies.
Tobit model, the industry fixed effects are included as the industry averages for each variable (Wooldridge 2002). I also include year fixed effects and cluster standard errors by firm and year. My hypothesis predicts a statistically significant negative coefficient for $\beta_1$, indicating the reporting quality measure is associated with less uncertainty about credit risk.

**Empirical Test for Hypothesis 2**

For my second hypothesis—that reporting quality matters more for debt market participants who have less access to private information—I would ideally use the previously described test with an interaction term between reporting quality and a proxy for the amount of private information available to CRAs. Unfortunately, I do not have an empirical measure capturing this distribution of private information. So to test this hypothesis, I use ratings issued by Egan-Jones, which lacks the access to private information from management enjoyed by S&P and Moody’s, despite becoming an NRSRO, because it did not publish its ratings. Thus I study the difference in the effect of reporting quality on uncertainty when the CRAs with access to private managerial information disagree with one without it.

Because of data constraints, my research design for this test differs from those in the rest of my study in two ways. First, I use firm-level ratings because EJR does not issue bond-level ratings. Second, I use S&P’s historical default rates by rating to proxy for EJR’s since EJR does not provide these and EJR’s ratings are closer to S&P’s than to Moody’s. EJR also includes S&P’s ratings in its data set as a benchmark for comparison. I compare yield spreads for senior debt issued by firms rated by EJR to those issued by S&P-rated firms, taking yields from the TRACE data set beginning in April of 2003, when Phase II of the bond transaction reporting was initiated, to have sufficient yield data. I use Treasury spreads from Datastream and examine the yield on the most senior bond per firm on a quarterly basis through the end of my sample. I find
significant differences between EJR and S&P’s yield spreads in only three of 15 credit ratings categories. Admittedly, this assumes that similar yield spreads imply similar default rates. Though I cannot mirror my sample period for this test because of data constraints, it supports the reasonability of using S&P’s default rates for EJR to capture the nonlinearity expected in defaults.

Another issue to address under this research design is identifying a time when I can be confident that a disagreement about ratings stems from uncertainty rather than to differential timing in ratings adjustments. To address this issue, I examine ratings when the firm issues new, rated debt since the agencies are then likely to reevaluate the credit profile of the firm. These research design adjustments make my dependent variable noisier than that in my primary tests.

My sample period for this test begins in 2000. I drop observations where there is more than a three-notch difference between S&P’s and EJR’s ratings, as these likely capture timing differences in ratings adjustments, leaving 867 observations. For these observations, I determine the difference between S&P’s and Moody’s default rates. I also calculate the difference between the implied default rates for EJR’s rating and the average of Moody’s and S&P’s ratings and include these as additional observations for a total of 1,734 observations (867×2). Thus I have two observations for each firm and point in time in this test—one where the dependent variable is the difference in S&P and Moody’s implied default rates and one where it is the difference between EJR’s and the average of S&P and Moody’s rates. I estimate my base regression (Equation 1) with an indicator variable \((EJR)\) equal to one if the dependent variable is the difference between EJR and the other agencies and zero if it is the difference between S&P and
Moody’s. I include an interaction term between $EJR$ and $DCV$, which I expect to be significantly negative, if reporting quality is incrementally important for agents lacking access to private information.

**Independent Variables**

**Proxy for Reporting Quality**

I choose a reporting quality proxy used in the debt literature for my empirical examination—the debt contracting value of accounting ($DCV$). Conceptually, $DCV$ captures how well changes in reported earnings predict rating downgrades, that is, the relevance of earnings for forecasting downgrades (Ball et al. 2008). This measure is the Somer’s D goodness of fit statistic from a regression of downgrades on quarterly earnings changes. A higher $DCV$ suggests better reporting quality, as it indicates that earnings better predict downgrades. Prior literature shows that this metric relates to syndicated loan structure, the inclusion of accounting-based performance pricing, and the probability of contract renegotiation (Ball et al. 2008; Dou 2016).

I modify the $DCV$ as calculated by Ball et al. (2008) so it does not use forward-looking data and estimate their model using instrument-level ratings over five-year rolling periods. This weights the measure such that firms with more public debt issues have a greater impact on the proxy. However, it does not bias the measure in a particular direction and allows more observations for calculating the $DCV$ using only past data. I estimate the variable from 1983-2007, as Moody’s moved to a notched rating system in 1982. Because of the move, I cannot

---

9 Because I am basically using two different dependent variables in this test, I conduct additional robustness tests comparing the economic significance of a change in reporting quality between S&P and Moody’s and between EJR and those two agencies when they agree. I find a greater reduction in the difference in default rates associated with a one standard deviation change in reporting quality for the test comparing EJR to S&P and Moody’s.

10 Somer’s D is the difference between the percentage of pairs of concordant observations and that of discordant observations, where a pair is formed by matching a downgrade observation with an observation that is not a downgrade. As an example, for a sample of 60 total observations, 10 of which are downgrades, there would be 500 (50 × 10) pairs used to calculate Somer’s D. A pair is concordant if the model predicts a higher probability of downgrade for the downgraded observation than for its paired observation (Somers 1962).
differentiate whether a ratings change in 1982 is a downgrade or a refinement attributable to this change in methodology.

Controls

I follow Morgan (2002) by controlling for firm size, asset types, and bond features, such as maturity, face value, and average rating. The expected coefficient on maturity is uncertain.\footnote{While it initially seems evident that greater uncertainty would be associated with longer maturities, research has shown that, for high-yield instruments, longer maturities are actually associated with lower yields (Langohr and Langohr 2009). This is consistent with longer maturities signaling a better high yield issuer.} I expect credit risk uncertainty to increase with the face value of the bond\footnote{Morgan (2002) finds the opposite result in his early tests, but he uses the face value of the bond to proxy for firm size, which I include as a control.} and with lower ratings. Additionally, I use the number of covenants in the bond contract as a control for corporate governance. Covenants are more likely to be used in contracts with firms needing greater monitoring (Graham et al. 2008; Costello and Wittenberg-Moerman 2011). Thus the number of covenants captures the lender’s perception of the quality of the borrower’s corporate governance (Li, Tuna, and Vasvari 2014).

I also follow Morgan’s (2002) later tests and control for firm asset mix by including asset tangibility. I control for additional firm characteristics. I expect performance and size (leverage) to be negatively (positively) associated with uncertainty. Firms with high market-to-book ratios derive much of their market value from growth options, which are difficult for outsiders to value (Smith and Watts 1992). However, conservatism also leads to the systematic understatement of the firm book value, relative to market value, and may reduce information asymmetry about the firm (Roychowdhury and Watts 2007; Watts 2003). Thus I make no prediction as to how the market-to-book ratio should affect uncertainty.
Sample Selection

I use Moody’s Investors Service’s historical ratings and Standard and Poor’s RatingsXpress to construct a corporate bond sample for domestic issuers in U.S. dollars from 1985 through 2008.13 Again, I choose 1985 because Moody’s began using notched ratings in 1982, and I want to ensure that I am not classifying this transition as a rating change in my calculation of DCV. To be included in the sample, a bond must have an initial rating from both CRAs at or within seven days of the issuance date listed in the Moody’s data set. Following Morgan (2002), I drop all bonds with significant equity features, equipment trusts, lease obligations, and asset-backed securities. After matching bonds to firms in Compustat using CUSIP, ticker, firm name, and gvkey, I have an initial sample of 11,848 bonds from 1,888 firms.14 After excluding financial firms and utilities, I am left with 4,865 bonds from 1,206 firms.

I obtain bond covenant data from Mergent’s Fixed Income Securities Database (FISD). After eliminating observations without the required financial information for my reporting quality and control variables, I am left with 2,619 bonds from 875 firms. I find that a significant number of bonds are issued by the same firms on the same day; the only differences are in their face value and maturity. I aggregate these bonds, as they most likely represent different tranches of the same issue. The final sample consists of 1,959 bonds representing 875 firms.

13 Although Mergent’s Fixed Income Securities Dataset (FISD) contains ratings from both Moody’s and S&P, I use the original databases because they are more complete. Moreover, the ratings data in the FISD dataset were entered by hand and contain errors. For example, FISD commonly misses rating changes that occurred at the same time as a change in watch list status. More relevant to this study, it was common for FISD to assign a firm-level rating or a rating from another instrument issued by the same firm to a bond if S&P or Moody’s did not rate that issue before the beginning of 2006. Hence FISD records bond ratings for many issues that were not actually rated.
14 These numbers are consistent with the work of Cantillo and Wright (2000), who find that slightly less than 15% of Compustat firms have publicly issued debt. Over my sample period, this would be about 3,300 firms. Additionally, Jewell and Livingston (2000) find that, in March of 1997 (about the midpoint of my sample period), 61.9% of outstanding corporate debt issues were rated by both Moody’s and S&P. If this percentage is representative of the number of firms as well, this would indicate about 2,000 firms from my sample period.
Sample Description

Table 1 presents summary statistics (Panel A) and Pearson correlations (Panel B) for the sample. The variables are defined in Appendix B and are winsorized at the 1 percent and 99 percent levels. Almost 50 percent of my sample is split rated. Of the split rated bonds issued, 505 bonds are rated higher by S&P, and 427 are rated higher by Moody’s. At the letter level (untabulated), there are 178 bonds rated higher by S&P and 148 rated higher by Moody’s. This relatively symmetric distribution is not consistent with split ratings being explained by the CRAs using different ratings scales. The mean implied difference in default rates based on the ratings given by Moody’s and S&P (DefaultDiff) is 4.20 percent, and the standard deviation is 7.32.

The average debt contracting value of accounting information is high, 0.59, compared to the average in Ball et al. (2008), 0.36, indicating that earnings for the issuing firms predict ratings downgrades well. This difference results from calculating the DCV using bond-level rather than firm-level data, as I find a DCV of 0.29 when using firm-level data spanning my entire period. The bonds in my sample have about four covenants each. They have an average maturity of 10.91 years and a face value of $199.24 million. The average of the Moody’s and S&P ratings for bonds in the sample is 8.49, which is between a Baa1 and a Baa2 on Moody’s scale and an BBB+ and a BBB on S&P’s. Firms have a mean leverage just over 30 percent, indicating that they are not highly levered. Asterisks next to the split-sample mean indicate significant differences between the nonsplit- and split-sample means as determined by a clustered t-test. DCV, average rating, and firm size are significantly lower for split-rated bonds. Panel B displays the Pearson correlations for the variables used in this study; boldfaced numbers indicate correlations significant at the 5 percent level. Six of my nine control variables are correlated with my proxy for uncertainty about credit risk.
Table 2 displays the number of bonds with each Moody’s and S&P rating. For example, there are 31 bonds rated AA by S&P and Aa3 by Moody’s. The diagonal entries in the matrix are the bonds that are not split rated. The off-diagonal entries are the number of split rated bonds with the corresponding Moody’s and S&P ratings. Across the bottom (right side) of Table 2, I report the percentage of splits by the S&P (Moody’s) rating. The average percentage of splits rises quickly and then levels out as the ratings scale descends.

V. RESULTS

Hypothesis 1 – Reporting Quality and Uncertainty

Table 3 reports the results from my primary test examining whether reporting quality reduces credit risk uncertainty. A one standard deviation difference in $DCV$ is associated with a 0.99 percent difference in the default rate implied by the two agencies. To put this in the perspective of bond ratings, there is a 0.68 percent difference between the average historical default rates of AAA and AA rated corporate bonds, a full letter difference at the high end of the ratings scale. There is a 1.93 percent difference in implied default rates between an A- (A3) and a BBB+ (Baa1) rated bond, the average in my sample. This finding is consistent with reporting quality reducing uncertainty as captured by CRAs’ disagreement about default risk.

Uncertainty about credit risk also increases with the number of covenants in the bond contract and the market-to-book ratio. It decreases with asset tangibility and higher credit ratings. For comparison, a one standard deviation difference in asset tangibility is associated with a 1.09 percent difference in implied default rate, and a one notch difference in the average rating is

---

15 One of the concerns raised about using $DCV$ is that it may simply capture an industry effect (Beatty 2008). Consequently, I include industry fixed effects in my model. This is also important because defaults tend to cluster by industry.
associated with a 1.53 percent difference. The results are robust to including an indicator variable for non-investment grade debt, further controlling for the nonlinearity in implied default rates.

**Hypothesis 2 – The Role of Private Information**

In Table 4, I report results from the private information tests and their significance following Ai and Norton (2003) and Erkens (2011). The statistically significant mean interactive effect of -2.08 indicates that an increase in \( DCV \) is associated with less disagreement between the certified agencies and EJR than between the certified agencies. Overall, reporting quality is associated with a more significant reduction in uncertainty between the agencies with access to private managerial information and EJR than the reduction in uncertainty between S&P and Moody’s, consistent with my second hypothesis. These results were obtained despite this test having a noisier proxy for uncertainty.

**VI. ENDOGENEITY**

**The Effect of Changes in Reporting Quality on Credit Risk Uncertainty**

Because reporting quality is a choice variable, it may be correlated with other factors that lead to disagreement about credit risk. For example, firms with low reporting quality may be more likely to shop for ratings, whereby they engage the agency they believe to be more likely to give them a higher rating or even try to influence an agency to do so (Kronlund 2017). This could lead to the paid CRA assigning an artificially high rating while another CRA assigns a lower rating, resulting in a split. Using \( DCV \), which is calculated at the industry level, should help mitigate these concerns, but to further address endogeneity, I consider whether an accounting standard change shown to increase reporting quality affects credit risk uncertainty. If reporting quality affects credit risk uncertainty, then changes in reporting quality originating outside of the firm’s control, as captured by SFAS 131, should impact disagreement between
CRAs. Although accounting standard changes are not necessarily exogenous, they are likely outside the control of any one firm.

Even though the generalizability of these tests may be limited due to sample composition (i.e., not all firms have multiple segment disclosures), those firms with these characteristics tend to be larger and have better information environments, which is where I would least expect to find results. The difference-in-differences research design allows a much cleaner method of establishing causality than using a shock that affects all firms simultaneously. I also perform several internal validity checks to address concerns about the research design choice.

Research shows that SFAS 131 impacted financial reporting quality. Before the standard, which applied to financial statements for periods beginning after Dec. 15, 1997, firms reported data disaggregated by industry, with considerable flexibility in how industry was defined. SFAS 131 changed the condition of disaggregation to that of how management internally designates business units. This increased disaggregation, and research finds that the standard also increased information and facilitated monitoring (Berger and Hann 2003; Ettredge et al. 2005). Though there is disagreement about which type of information was previously hidden, that is, profitable segments operating in noncompetitive industries (Botosan and Stanford 2005) or segments with low profits (Berger and Hann 2007), research consistently finds increased disclosure.

One concern about passing SFAS 131 was that firms previously disclosing geographic segments would no longer be required to do so, and thus the standard change would undercut reporting quality for multinational corporations. However, SFAS 131 did not harm analysts’ forecast accuracy or dispersion for these firms (Hope et al. 2006) and appears to have allowed investors to better price foreign earnings. The literature has consistently found evidence that SFAS 131 improved reporting quality. Therefore, I expect to see a decrease in disagreement
about credit risk for firms significantly affected by SFAS 131 around its implementation.

**Empirical Test for a Change in Reporting Quality**

I estimate the following regression using a difference-in-differences specification on a propensity-score-matched sample.

\[
DefaultDiff_t = \alpha + \beta_1 \text{Segments}_t + \beta_2 \text{SFAS131}_t + \beta_3 \text{Segments}_t \times \text{SFAS131}_t + \sum \beta_j \text{Controls}_{j,t-1} + \epsilon_t, \quad (2)
\]

where *Segments* is an indicator variable equal to one if the number of segments increased by three or more after the implementation of SFAS 131 and zero otherwise. Thus my test group consists of firms significantly impacted by SFAS 131. My control group consists of a matched sample of less affected firms. *SFAS131* is an indicator equal to one if that same annual report was issued after SFAS 131 took effect and zero otherwise.\(^{16}\)

This regression does not include year fixed effects since *SFAS131* would simply be a linear combination of these variables in the post period. Therefore I include a time trend variable (*Trend*) to capture the time effect.\(^{17}\) *Trend* is equal to 1 for debt issued in 1985, 2 for 1986, etc. I have no prediction for \(\beta_2\) because firms with more segments are likely to be larger and have better information environments but also to be more complex. Since SFAS 131 improved reporting quality, I expect \(\beta_3\) to be significantly negative.

**Results for Changes in Reporting Quality and Uncertainty**

Table 5 reports summary statistics for the matched sample for the SFAS 131 test. I match on *AvgRate, TotalCovs, MTB, Size*, and *Tangibility* using a greedy match algorithm. Bonds in the

---

\(^{16}\) In untabulated tests, I examine the effects of SFAS 131 on *DCV* in the broader Compustat sample. Specifically, I estimate a difference-in-differences regression for SFAS 131 using my firm controls for the full sample period, excluding the first five years after the standard change because *DCV* is calculated over five-year periods. For the treatment group, *DCV* increased after the implementation of SFAS 131 at the 5% significance level. These results are robust when estimating the regression within my sample.

\(^{17}\) The results in these tests are stronger without the inclusion of the time trend.
treatment sample are issued by firms that have lower leverage than those issuing debt in the control group. Otherwise, there are no significant differences in variables across the subsamples. When I also match on Leverage, sample size drops, and the covariate balance is actually worse. However, Leverage is not significant in any specification in the entire study and is therefore unlikely to drive the results.

I report the results of the SFAS 131 tests in Table 6. Consistent with my prediction, I find less of a difference in implied default rates (a mean interactive effect of -1.59) for new debt issues from firms with increased segment disclosure after the implementation of 131, that is, firms that increased the number of segments disclosed by three or more.\(^{18}\)

Since the parallel trend assumption is untestable, Roberts and Whited (2013) suggest choosing internal validity checks. I use two. First, I report that my groups are well balanced with the exception of Leverage, which does not affect inferences. Second, I conduct falsification tests. I replace the SFAS 131 indicator variable with indicators for the dates five years before and after the standard change took effect and redo my SFAS 131 tests. I fail to find results for either test. My results are also robust to the inclusion of DCV. This evidence is all consistent with firms whose reporting quality was improved by SFAS 131 having less uncertainty about credit risk.

**VII. ROBUSTNESS**

*Tests Ensuring DCV is not Capturing Other Latent Constructs*

My dependent variable, DefaultDiff, is correlated with credit risk proxied by AvgRate. To ensure that my results are not simply capturing credit risk, I estimate my primary regression (Equation 1) by ratings class and report the results in Table 7. I categorize observations into

\(^{18}\) These results are robust to using a threshold greater than three, and they are qualitatively similar when using one or two as the cutoff. However, the covariate balance between the treatment and control groups is best when using three as the threshold.
groups by their average rating and find my results to be robust in three of the five broad ratings classes. Moreover, my results are robust in the highest ratings classes, which is inconsistent with them being driven by the correlation between DefaultDiff and credit quality.

I then construct an indicator variable (Split) equal to one if the ratings on a new bond issue are split and zero otherwise. I also construct a variable (Notches) capturing the number of notches between the S&P and Moody’s ratings for a bond issue. Neither of these proxies is significantly correlated with credit quality. The correlation of Split (Notches) with DefaultDiff is 0.14 (0.10). I report the marginal effects from a probit regression with Split as my independent variable in Panel A of Table 8. In Panel B of the same table, I report the coefficients from an ordered probit on Notches. DCV relates negatively to both proxies, again suggesting that my primary results are not simply capturing credit quality.

Next, I control for additional features of the firm’s operating and information environments to rule out the possibility that DCV captures these constructs. I control for the firm’s operating cycle, Altman’s (1968) Z-score, the standard deviation of cash flows from operations, the number of equity analysts following the firm, analyst forecast dispersion, the standard deviation of daily returns, and the standard deviation of the ratings received on all bonds issued by the firm in the calendar year. I also control for debt seniority. Including these variables does not significantly affect my primary results (H1) or those testing differential access to private information (H2).

Tests Using Other Measures of Reporting Quality

In Table 9, I examine the effect of other reporting quality variables, specifically, asymmetric timeliness and accrual quality, on disagreement about credit risk. The literature argues that asymmetric timeliness both constrains managerial opportunism, because managers
have incentives to manage earnings upward (Gao 2013), and caters to debtholders’ asymmetric
demand for downside information (De Franco et al. 2009). To proxy for asymmetric timeliness, I
use two variables. I use asymmetric timeliness \((AsymTime)\), from Basu’s (1997) regression
estimated over a 20-year rolling period requiring 10 years of observations (Wittenberg-Moerman
2008). I also rely on the \(Cscore\) developed by Khan and Watts (2009) as a method to instrument
for Basu’s (1997) conservatism measure. Although there is debate about whether conservatism
represents accounting quality (Gigler et al. 2009; Guay and Verrecchia 2006), I employ these
measures as they are commonly used in the debt literature (Donovan, Frankel, and Martin 2015;
Wittenberg-Moerman 2008; Zhang 2008).

I then follow Bharath et al. (2008) in measuring accounting quality \((AQ)\) as the first
principal component of three abnormal accrual models, those used by Teoh et al. (1998),
Dechow et al. (1995), and Dechow and Dichev (2002). After taking the absolute value of the
abnormal accruals from each of the three models, I standardize the measures within sample and
run a principal component analysis. I use the equations generated from this analysis to calculate
\(AQ\) and multiply it by negative one so that it is increasing in reporting quality. Consistent with
my results using \(DCV\), I find that one standard deviation difference in \(AsymTime\) \((Cscore, AQ)\) is
associated with a 0.23 percent (0.01 percent, 0.65 percent) difference in the default rate implied
by the two agencies.

\textit{Tests Ensuring Results are not Driven by Differences in Ratings Models}

I conduct several tests to ensure that my results are not the outcome of the CRAs using
different rating models. I redo the tests of H1, H2, and the endogeneity test using signed
dependent variables that capture how much greater Moody’s implied default rate is than S&P’s,
rather than the absolute value of this difference. I do this to address the possibility that one of the
agencies systematically weights reporting quality more heavily in ratings determinations than the other. For example, if Moody’s weights reporting quality more heavily than S&P, Moody’s will systematically rate poor reporting quality firms lower than S&P would. DCV is not statistically significant in this test. Furthermore, I do not find significant results when examining the segment disclosure tests reported in Table 6. These tests support the likelihood that my results capture the impact of reporting quality on uncertainty.19

Finally, I test the robustness of my second hypothesis (H2) concerning private information using EJR’s credit ratings. Additional factors affect disagreement between EJR and the other two agencies. First, EJR is paid by investors, rather than issuers, and issuer-paid agencies tend to give higher ratings. So EJR may issue systematically lower ratings (Bruno, Cornaggia, and Cornaggia 2012; Strobl and Xia 2012). Second, Beaver, Shakespeare, and Soliman (2006) find evidence consistent with Moody’s being more conservative with ratings changes than EJR, which could imply that EJR may have systematically different ratings. To address this possibility, I conduct a clustered t-test and find no systematic difference between EJR and S&P’s ratings for my sample. Additionally, results in this setting could be capturing incentive or other differences if they are correlated with reporting quality. Consequently, I re-estimate my tests using the signed difference between implied default rates and fail to find results, which is inconsistent with the results being driven by differential pay models or ratings scales.

EJR ratings also tend to be timelier, more symmetric, and subject to faster reversals (Beaver et al. 2006; Bruno et al. 2012). Conceptually, because EJR is timelier (on average) than

19 I also find generally robust results when using different 10-year transition matrices for gathering default rates. However, I do not conduct my tests using default rates over shorter periods than this because these are frequently zero, which significantly reduces variation in my dependent variable. In further tests, inferences are unaltered when I drop the restriction that DefaultDiff is equal to zero for bonds with the same rating by both S&P and Moody’s.
the other agencies and does not have access to private information, better $DCV$ may allow EJR to make ratings changes even more quickly. Thus better reporting quality may induce, rather than reduce, disagreement between EJR and the other CRAs, resulting in a positive association between $DCV$ and disagreement. So I control for the difference in ratings volatility for EJR and the average of the ratings volatility for S&P and Moody’s over the previous five years.

I also estimate a fully interacted model to address the concern that my results may be driven by EJR using a different ratings model than S&P and Moody’s. I continue to find the interaction between $EJR$ and $DCV$ significant at the 5 percent level. I then repeat the analysis using a split indicator capturing whether EJR disagrees with S&P and Moody’s about the firm credit rating and find robust results. Estimating an ordered probit with the number of notches between EJR’s rating and the average rating of S&P and Moody’s ratings also produces a negative coefficient on the interaction, though this one is not statistically significant. Overall, these tests support the hypothesis that ratings quality becomes incrementally important in reducing credit risk uncertainty when agencies have less private information (H2).

Overall, my results are robust to a variety of different controls and specifications. Furthermore, results are not present in tests not expected to be significant (i.e., signed dependent variables, time-shifted segment disclosure tests, etc.), indicating that the tabulated findings are not reflecting spurious correlations. Finally, the tests related to segment disclosures indicate that endogeneity is not likely to be biasing the results.

**VIII. CONCLUSION**

I study whether reporting quality reduces uncertainty about credit risk by examining disagreement between the two major credit ratings agencies, Moody’s and S&P. I find that increasing the debt contracting value of accounting information is associated with less
disagreement about the implied probability of bond default based on historical rates. This is consistent with greater reporting quality reducing uncertainty and facilitating consensus among rating agencies about credit risk. In subsequent tests, I use ratings data from EJR and find that the association between reporting quality and credit risk uncertainty is generally greater when agents have less access to private information.

I also examine the effect of a change in accounting standards to alleviate concerns about endogeneity. I find that, after the FASB issued SFAS 131, there was a decrease in disagreement about credit risk for firms that increased segment disclosures—that is, those with improved reporting quality. This corroborates my earlier results. Overall, this paper presents evidence consistent with better reporting reducing uncertainty, even for informed information intermediaries with access to private information.
Appendix A: Historic Corporate Default Rates by Rating

This table contains the average default rates by ratings category for corporate bonds by Moody’s (S&P) from 1983 (1981) through 2008.

| Moody’s/S&P | Average Default Rate |
|-------------|----------------------|
| Aaa/AAA     | 0.43                 |
| Aa1/AA+     | 0.77                 |
| Aa2/AA      | 1.11                 |
| Aa3/AA-     | 2.11                 |
| A1/A+       | 2.92                 |
| A2/A        | 3.67                 |
| A3/A-       | 4.77                 |
| Baa1/BBB+   | 6.70                 |
| Baa2/BBB    | 8.19                 |
| Baa3/BBB-   | 10.88                |
| Ba1/BB+     | 18.07                |
| Ba2/BB      | 26.14                |
| Ba3/BB-     | 35.22                |
| B1/B+       | 39.65                |
| B2/B        | 45.21                |
| B3/B-       | 49.23                |
| Caa1/CCC+   | 56.60                |
Appendix B: Variable Definitions

| Variable                  | Definition                                                                                           |
|---------------------------|------------------------------------------------------------------------------------------------------|
| Accounting Quality (AQ)   | The first principal component of three abnormal accrual models (Bharath et al. 2008).                |
| Asymmetric Timeliness (AsymTime) | $\beta_3$ from Basu’s (1997) regression:  

$$E_t = \beta_0 + \beta_1 D R_t + \beta_2 R_t + \beta_3 R_t \times D R_t + \epsilon_t,$$

where $E$ is earnings scaled by the lagged market value of equity, $R$ is the annual return compounded beginning four months after the fiscal year-end, and $D$ is an indicator variable equal to one when $R$ is negative. |
| Average Rating (AvgRate)  | I map the ratings assigned by the agencies to a numerical scale such that a lower number corresponds to a higher credit rating (1=AAA=Aaa, 2=AA+=Aa1). The average rating is the average of the two ratings given to the bond by Moody’s and S&P. |
| Conservatism Score (Cscore) | The following regression is estimated annually:  

$$E_t = \beta_1 + \beta_2 D_t + R(\mu_1 + \mu_2 MVE_t + \mu_3 MTB_t + \mu_4 Le v_t)$$

$$+ D R(\lambda_1 + \lambda_2 MVE_t + \lambda_3 MTB_t + \lambda_4 Le v_t)$$

$$+ (\delta_1 MVE_t + \delta_2 MTB_t + \delta_3 Le v_t + \delta_4 D_t MVE_t + \delta_5 D_t MTB_t$$

$$+ \delta_6 D_t Le v_t) + \epsilon_t,$$

where $MVE$ is the natural log of the market value of equity, $MTB$ is the firm’s market-to-book value of equity, and $Le v$ is leverage. The coefficients from this regression are substituted into $Cscore = \lambda_1 + \lambda_2 MVE_t + \lambda_3 MTB_t + \lambda_4 Le v_t$. |
| Debt Contracting Value of Accounting Information (DCV) | The Somers’ D goodness of fit statistic from the following probit regression, which is estimated over rolling five-year periods by industry (two-digit SIC code) since estimating the regression by firm would severely limit the sample size due to the requirement of having credit downgrades:  

$$Downgrade_{t,i} = \alpha + \beta_1 \Delta E_{t-1,i} + \beta_2 \Delta E_{t-2,i} + \beta_3 \Delta E_{t-3,i} + \beta_4 \Delta E_{t-4,i}$$

$$+ \epsilon_i,$$

where $Downgrade$ is an indicator variable equal to one if firm $i$ experiences a ratings downgrade from Moody’s over the quarter $t$ and $\Delta E_{t-s}$ is the seasonally adjusted change in quarterly earnings over total assets in the $s^{th}$ prior quarter. |
| Default Difference (DefaultDiff) | The difference between historical default rates for the ratings issued by S&P and Moody’s on new debt issuances. |
| Face Value (Face)          | The log of the face value of the bond.                                                               |
| Variable                  | Definition                                                                 |
|--------------------------|-----------------------------------------------------------------------------|
| Leverage                 | The ratio of the sum of long-term debt and the current portion of long-term debt to total firm assets. |
| Market-to-Book           | \( MTB \) The ratio of the fiscal year-end market value of equity to the book value of equity. |
| Maturity                 | \( Maturity \) The natural log of the number of years from bond issuance until the principal is to be repaid. |
| Notches                  | \( Notches \) The number of notches between the S&P and Moody’s ratings given to a bond. |
| Return on Assets         | \( ROA \) Earnings before interest and taxes, i.e., earnings independent of leverage, scaled by the average firm assets over the year. |
| SFAS 131                 | \( SFAS131 \) An indicator equal to one if the most recent annual report, released at least three months before the debt issue, was issued after SFAS 131 took effect and zero otherwise. |
| Segments                 | \( Segments \) An indicator variable equal to one if the number of disclosure segments increased by three or more from the year before the implementation of SFAS 131 to the year after and zero otherwise. |
| Size                     | \( Size \) The natural log of the firm’s total assets in millions of dollars. |
| Split                    | \( Split \) An indicator variable equal to one if the bond is split rated and zero otherwise. |
| Tangibility              | \( Tangibility \) The ratio of net PPE plus inventory to total assets (Costello and Wittenberg-Moerman 2011). |
| Total number of covenants| \( TotalCovs \) The total number of covenants included in the bond contract. |
References

Ai, C., and E. Norton. 2003. Interaction terms in logit and probit models. *Economic Letters* 80(1): 123–129.

Altman, E. 1968. Financial ratios, discriminant analysis and the prediction of corporate bankruptcy. *Journal of Finance* 23(4): 589–604.

Armstrong, C., W. Guay, and J. Weber. 2010. The role of information and financial reporting in corporate governance and debt contracting. *Journal of Accounting and Economics* 50: 179–234.

Ball, R., R. Bushman, and F. Vasvari. 2008. The debt-contracting value of accounting information and loan syndicate structure. *Journal of Accounting Research* 46(2): 247–287.

Bao, J., J. Pan, and J. Wang. 2011. The illiquidity of corporate bonds. *The Journal of Finance* 66(3): 911–946.

Basu, S. 1997. The conservatism principle and the asymmetric timeliness of earnings. *Journal of Accounting and Economics* 24(1): 3–37.

Beattie, V., and S. Searle. 1992. Bond ratings and inter-rater agreement. *Journal of International Securities Markets* 6: 167–172.

Beatty, A. 2008. Discussion of "The debt-contracting value of accounting information and loan syndicate structure." *Journal of Accounting Research* 46(2): 289–295.

Beatty, A., S. Liao, and J. Weber. 2010. Financial reporting quality, private information, monitoring and the lease-versus-buy decision. *The Accounting Review* 85(4): 1215–1238.

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

Berger, P., and R. Hann. 2003. The impact of SFAS No. 131 on information and monitoring. *Journal of Accounting Research* 41(2): 163–223.

Berger, P., and R. Hann. 2007. Segment profitability and the proprietary and agency costs of disclosure. *The Accounting Review* 82(4): 869–906.

Bharath, S., J. Sunder, and S. Sunder. 2008. Accounting quality and debt contracting. *The Accounting Review* 83(1): 1–28.
Botosan, C., and M. Stanford. 2005. Managers' motives to withhold segment disclosures and the effect of SFAS No. 131 on analysts' information environment. *The Accounting Review* 80(3): 751–771.

Bruno, V., J. Cornaggia, and K. Cornaggia. 2012. The information content of credit ratings: compensation structure does matter. Working paper, University of Indiana.

Cantillo, M., and J. Wright. 2000. How do firms choose their lenders? An empirical investigation. *Review of Financial Studies* 13(1): 155–189.

Cheng, L. 2011. Loan loss provisioning and differences of opinion. Working paper, University of Arizona.

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

Dechow, P., and I. Dichev. 2002. The quality of accruals and earnings: the role of accrual estimation errors. *The Accounting Review* 77(s-1): 35–59.

Dechow, P., W. Ge, and C. Schrand. 2010. Understanding earnings quality: a review of the proxies, their determinants and their consequences. *Journal of Accounting and Economics* 50(2-3): 344–401.

Dechow, P., R. Sloan, and A. Sweeney. 1995. Detecting earnings management. *The Accounting Review* 70(2): 193–225.

De Franco, G., F. Vasvari, and R. Wittenberg-Moerman. 2009. The informational role of bond analysts. *Journal of Accounting Research* 47(5): 1201–1248.

Demirtas, K., and K. Cornaggia. 2013. Initial credit ratings and earnings management. *Review of Financial Economics* 22: 135–145.

Donovan, J., R. Frankel, and X. Martin. 2015. Accounting conservatism and creditor recovery rates. *The Accounting Review* 90(6): 2267–2303.

Dou, Y. 2016. The debt-contracting value of accounting numbers and financial covenant renegotiation. Working paper, New York University.

Ederington, L. 1986. Why split ratings occur. *Financial Management* 15(1): 37–47.

Elton, E., M. Gruber, D. Agrawal, and C. Mann. 2001. Explaining the rate spread on corporate bonds. *Journal of Finance* 56(1): 247–277.

Engel, E., M. Erickson, and E. Maydew. 1999. Debt-equity hybrid securities. *Journal of Accounting Research* 37(2): 249–274.
Erkens, D. 2011. Do firms used time-vested stock-based pay to keep research and development investments secret? *Journal of Accounting Research* 49(4): 861–894.

Ettredge, M., S. Kwon, D. Smith, and P. Zarowin. 2005. The impact of SFAS No. 131 business segment data on the market's ability to anticipate future earnings. *The Accounting Review* 80(3): 773–804.

Gao, P. 2013. A measurement approach to conservatism and earnings management. *Journal of Accounting and Economics* 55(2-3): 251–268.

Gigler, F., C. Kanodia, H. Sapra, and R. Venugopalan. 2009. Accounting conservatism and the efficiency of debt contracts. *Journal of Accounting Research* 47(3): 767–797.

Graham, J., S. Li, and J. Qiu. 2008. Corporate misreporting and bank loan contracting. *Journal of Financial Economics* 89(1): 44–61.

Guay, W., and R. Verrecchia. 2006. Discussion of an economic framework for conservative accounting and Bushman and Piotroski. *Journal of Accounting and Economics* 42(1-2): 149–165.

Harris, M., and Raviv, A. 1993. Differences of opinion make a horse race. *Review of Financial Studies* 6(3): 473–506.

Healy, P., and K. Palepu. 2001. Information asymmetry, corporate disclosure, and the capital markets: a review of the empirical disclosure literature. *Journal of Accounting and Economics* 31(1-3): 405–440.

Hope, O., W. Thomas, and G. Winterbotham. 2006. The impact of nondisclosure of geographic segment earnings on earnings predictability. *Journal of Accounting, Auditing, & Finance* 21(3): 323–346.

Jewell, J., and M. Livingston. 1998. Split ratings, bond yields, and underwriter spreads. *Journal of Financial Research* 21(2): 185–204.

Jewell, J., and M. Livingston. 2000. The impact of a third credit rating on the pricing of bonds. *The Journal of Fixed Income* 10(3): 69–85.

Johnston, R., S. Markov, and R. Ramnath. 2009. Sell-side debt analysts. *Journal of Accounting and Economics* 47(1-2): 91–107.

Jung, B., N. Soderstrom, and Y. Yang. 2013. Earnings smoothing activities of firms to manage credit ratings. *Contemporary Accounting Research* 30(2): 645–676.

Kandel, E., and Pearson, N. 1995. Differential interpretation of public signals and trade in speculative markets. *Journal of Political Economy* 103(4): 831–872.
Khan, M., and R. Watts. 2009. Estimation and empirical properties of a firm-year measure of accounting conservatism. *Journal of Accounting and Economics* 48(2-3): 132–150.

Kim, S., K. Kraft, and S. Ryan. 2013. Financial statement comparability and credit risk. *Review of Accounting Studies* 18(3): 783–823.

Kraft, P. 2015. Rating agency adjustments to GAAP financial statements and their effect on ratings and credit spreads. *The Accounting Review* 90(2): 641–674.

Kronlund, M. 2017. Do bond issuers shop for favorable credit ratings? Working paper, University of Illinois at Urbana-Champaign.

Lang, M., and R. Lundholm. 1996. Corporate disclosure policy and analyst behavior. *The Accounting Review* 71(4): 467–492.

Langohr, H., and P. Langohr. 2009. *The rating agencies and their credit ratings: what they are, how they work, and why they are relevant*. London: John Wiley & Sons.

Leftwich, R. 1983. Accounting information in private markets: evidence from private lending agreements. *The Accounting Review* 58(1): 23–42.

Li, X., I. Tuna, and F. Vasvari. 2014. Corporate governance and covenants in debt contracts. Working paper, London Business School.

Livingston, M., and L. Zhou. 2010. Split bond ratings and information opacity premiums. *Financial Management* Summer: 515–532.

Longstaff, F., and E. Schwartz. 1995. A simple approach to valuing risky fixed and floating rate debt. *Journal of Finance* 50(3): 789–819.

Morgan, D. 2002. Rating banks: risk and uncertainty in an opaque industry. *The American Economic Review* 92(4): 874–888.

Roberts, M., and T. Whited. 2013. Endogeneity in empirical corporate finance. In *Handbook of the Economics of Finance*, Vol. 2, edited by G. Constantinides, R. Stulz, and M. Harris, 493–572. Amsterdam: Elsevier.

Roychowdhury, S., and R. Watts. 2007. Asymmetric timeliness of earnings, market-to-book, and conservatism in financial reporting. *Journal of Accounting and Economics* 44(1-2): 2–31.

Securities and Exchange Commission. 2003. Report on the role and function of credit rating agencies in the operation of the securities markets. Washington, D.C.

Sengupta, P. 1998. Corporate disclosure quality and the cost of debt. *The Accounting Review* 73(4): 459–474.
Smith, C., and J. Warner. 1979. On financial contracting: an analysis of bond covenants. *Journal of Financial Economics* 7(2): 117–161.

Smith, C., and R. Watts. 1992. The investment opportunity set and corporate financing, dividend, and compensation policies. *Journal of Financial Economics* 32(3): 263–292.

Somers, R. 1962. A new asymmetric measure of association for ordinal variables. *American Sociological Review* 27(6): 799–811.

Teoh, S., I. Welch, and T. Wong. 1998. Earnings management and the underperformance of seasoned equity offerings. *Journal of Financial Economics* 50(1): 63–99.

U.S. House of Representatives. 2010. The Dodd–Frank Wall Street Reform and Consumer Protection Act [H. R. 4173]. 111 Cong., 2nd Sess. Washington, D.C.

Watts, R. 2003. Conservatism in accounting, Part I: explanations and implications. *Accounting Horizons* 17(4): 207–221.

Wittenberg-Moerman, R. 2008. The role of information asymmetry and financial reporting quality in debt trading: evidence from the secondary loan market. *Journal of Accounting and Economics* 46(2-3): 240–260.

Wooldridge, J., 2002. *Econometric analysis of cross-sectional and panel data*. Cambridge, Mass.: MIT Press.

Zhang, J., 2008. The contracting benefits of accounting conservatism to lenders and borrowers. *Journal of Accounting and Economics* 45(1): 27–54.
## Table 1: Summary Statistics

### Panel A: Descriptive Statistics

| Variable               | Full Sample | Nonsplit Sample | Split Sample |
|------------------------|-------------|-----------------|--------------|
|                        | Mean        | STD             | Mean         | STD          | Mean        | STD          |
| Disagreement proxy     |             |                 |              |              |             |              |
| DefaultDiff            | 4.195       | 7.323           | 0.000        | 0.000        | 8.401***    | 8.491        |
| Reporting quality measure |             |                 |              |              |             |              |
| DCV                    | 0.592       | 0.258           | 0.613        | 0.251        | 0.570**     | 0.264        |
| Bond-level controls    |             |                 |              |              |             |              |
| Maturity               | 2.390       | 0.563           | 2.378        | 0.579        | 2.402       | 0.566        |
| Face                   | 19.110      | 0.760           | 19.096       | 0.718        | 19.124      | 0.801        |
| AvgRate                | 8.489       | 3.987           | 8.376        | 4.270        | 8.602***    | 3.681        |
| TotalCovs              | 3.795       | 3.980           | 3.923        | 4.052        | 3.666       | 3.905        |
| Firm-level controls    |             |                 |              |              |             |              |
| Tangibility            | 0.554       | 0.200           | 0.558        | 0.206        | 0.549       | 0.195        |
| ROA                    | 0.109       | 0.053           | 0.106        | 0.053        | 0.112       | 0.052        |
| Size                   | 8.098       | 1.550           | 8.195        | 1.620        | 8.002***    | 1.471        |
| Leverage               | 0.308       | 0.139           | 0.304        | 0.139        | 0.311       | 0.139        |
| MTB                    | 2.400       | 1.677           | 2.306        | 1.631        | 2.494       | 1.717        |

Panel A presents summary statistics on the variables of interest used in this study. The full sample size is 1,959 bonds, the nonsplit sample size is 932, and the split-rated sample size is 1,027. ***, **, and * denote significant differences in the means of the nonsplit and split samples at the 1%, 5%, and 10% levels, respectively. DefaultDiff is the difference in the default rates implied by the two credit ratings. DCV is the Somers’ D from the estimation of a probit of downgrades on seasonally adjusted quarterly earnings. Maturity is the natural log of the number of years from bond issuance until the principal is to be repaid. Face is the natural log of the face amount of the bond. AvgRate is the average of the Moody’s and S&P credit ratings. TotalCovs is the total number of covenants included.

### Panel B: Pearson Correlations

|                | DefaultDiff | DCV    | Maturity | Face      | AvgRate   | TotalCovs | Tangibility | ROA       | Size       | Leverage | MTB   |
|----------------|-------------|--------|----------|-----------|-----------|-----------|-------------|-----------|------------|----------|-------|
| DefaultDiff    | 1           |        |          |           |           |           |             |           |            |          |       |
| DCV            | -0.05       | 1      |          |           |           |           |             |           |            |          |       |
| Maturity       | -0.00       | 0.03   | 1        |           |           |           |             |           |            |          |       |
| Face           | -0.06       | -0.09  | -0.02    | 1         |           |           |             |           |            |          |       |
| AvgRate        | 0.24        | -0.10  | -0.12    | 0.08      | 1         |           |             |           |            |          |       |
| TotalCovs      | 0.15        | -0.02  | -0.07    | 0.12      | 0.31      | 1         |             |           |            |          |       |
| Tangibility    | -0.02       | 0.19   | 0.21     | -0.19     | -0.03     | 0.01      | 1           |           |            |          |       |
| ROA            | -0.05       | 0.06   | 0.12     | -0.02     | -0.31     | -0.08     | 0.10        | 1         |            |          |       |
| Size           | -0.19       | 0.06   | 0.02     | 0.19      | -0.71     | -0.19     | -0.11       | 0.03      | 1          |          |       |
| Leverage       | 0.13        | -0.05  | -0.07    | 0.02      | 0.40      | 0.18      | -0.01       | -0.24     | -0.16      | 1        |       |
| MTB            | 0.00        | -0.11  | -0.04    | 0.19      | -0.00     | 0.11      | -0.14       | 0.34      | -0.10      | 0.06     | 1     |

Panel A presents summary statistics on the variables of interest used in this study. The full sample size is 1,959 bonds, the nonsplit sample size is 932, and the split-rated sample size is 1,027. ***, **, and * denote significant differences in the means of the nonsplit and split samples at the 1%, 5%, and 10% levels, respectively. DefaultDiff is the difference in the default rates implied by the two credit ratings. DCV is the Somers’ D from the estimation of a probit of downgrades on seasonally adjusted quarterly earnings. Maturity is the natural log of the number of years from bond issuance until the principal is to be repaid. Face is the natural log of the face amount of the bond. AvgRate is the average of the Moody’s and S&P credit ratings. TotalCovs is the total number of covenants included.
in the bond contract. *Tangibility* is the ratio of net PPE plus inventory to total assets. *ROA* is equal to earnings before interest and taxes scaled by the average firm assets over the year. *Size* is the natural log of the firm’s total assets in millions of dollars. *Leverage* is the ratio of the sum of long-term debt and the current portion of long-term debt to total firm assets. *MTB* is the ratio of the market value to the book value of equity. Panel B provides the Pearson correlations for the variables of interest employed in the study. Boldfaced numbers denote a statistically significant correlation at the 5% level.
Table 2: Bond Ratings Distribution

| Moody’s | AAA | AA+ | AA | AA- | A+ | A- | BBB+ | BBB | BBB- | BB+ | BB | BB- | B+ | B | B- | CCC+ | CCC |
|---------|-----|-----|----|-----|----|----|------|-----|------|-----|----|----|----|--|--|---|-----|-----|
| Aaa     | 59  | 2   | 4  |     |    |    |      |     |      |     |    |    |    |  |  |   |     |     |
| Aa1     | 5   | 11  | 12 |     |    |    |      |     |      |     |    |    |    |  |  |   |     |     |
| Aa2     | 2   | 2   | 57 | 6   | 3  | 1  |      |     |      |     |    |    |    |  |  |   |     |     |
| Aa3     | 8   | 31  | 38 | 14  | 2  | 5  |      |     |      |     |    |    |    |  |  |   |     |     |
| A1      | 3   | 30  | 92 | 56  | 6  |    |      |     |      |     |    |    |    |  |  |   |     |     |
| A2      | 1   | 14  | 71 | 137 | 29| 2  |      |     |      |     |    |    |    |  |  |   |     |     |
| A3      | 8   | 37  | 67 | 28  | 9  |    |      |     |      |     |    |    |    |  |  |   |     |     |
| Baa1    | 1   | 4   | 23 | 64  | 28| 9  |      |     |      |     |    |    |    |  |  |   |     |     |
| Baa2    | 9   | 30  | 71 | 13  |    |    |      |     |      |     |    |    |    |  |  |   |     |     |
| Baa3    | 15  | 25  | 68 | 9   | 3  | 5  |      |     |      |     |    |    |    |  |  |   |     |     |
| Ba1     | 5   | 18  | 10 |     | 8  | 2  |      |     |      |     |    |    |    |  |  |   |     |     |
| Ba2     | 2   | 17  | 9  | 34  | 8  | 10 | 2    |     |      |     |    |    |    |  |  |   |     |     |
| Ba3     | 9   | 9   | 38 | 20  | 5  |    |      |     |      |     |    |    |    |  |  |   |     |     |
| B1      | 3   | 2   | 13 | 16  | 135| 37 | 22   |     |      |     |    |    |    |  |  |   |     |     |
| B2      | 2   | 3   | 26 | 47  | 43 | 11 | 1    |     |      |     |    |    |    |  |  |   |     |     |
| B3      | 1   | 26  | 20 | 93  | 6  | 6  | 0.39 |     |      |     |    |    |    |  |  |   |     |     |
| Caa1    | 2   | 2   |    |     |    |    |      |     |      |     |    |    |    |  |  |   |     |     |
| Caa2    | 2   | 1   | 4  |     |    |    |      |     |      |     |    |    |    |  |  |   |     |     |

| % Split | 0.11 | 0.52 | 0.47 | 0.57 | 0.51 | 0.42 | 0.52 | 0.54 | 0.49 | 0.47 | 0.74 | 0.51 | 0.48 | 0.38 | 0.58 | 0.43 | 0.90 | 0.64 |

This table shows the number of observations for each Moody’s and S&P rating and the percentage of bonds split by rating.
Table 3: Credit Risk Uncertainty and Reporting Quality

| Predicted |  |
|-----------|---|
| $DCV$    | -3.83** |
| Maturity | 0.31 |
| Face     | -0.23 |
| AvgRate  | 1.53*** |
| TotalCovs| 0.52*** |
| Tangibility | -5.44* |
| ROA      | 4.99 |
| Size     | 0.17 |
| Leverage | 0.30 |
| MTB      | 0.15 |
| Constant | 31.20 |

Pseudo $R^2$ (%) 4.64
Observations 1,959
Year FE Yes
Industry FE Yes

This table presents the results from estimating the following Tobit regression from 1985–2008 for 1,959 observations.

$$\text{DefaultDiff}_t = \alpha + \beta_1 DCV_{t-1} + \Sigma \beta_j \text{Controls}_{j,t-1} + \epsilon_t,$$

where $\text{DefaultDiff}$ is the difference in the default rates implied by the two credit ratings. $DCV$ is the Somers’ D from the estimation of a probit of downgrades on seasonally adjusted quarterly earnings. $Maturity$ is the natural log of the number of years from bond issuance until the principal is to be repaid. $Face$ is the natural log of the face amount of the bond. $AvgRate$ is the average of the Moody’s and S&P credit ratings. $TotalCovs$ is the total number of covenants included in the bond contract. $Tangibility$ is the ratio of net PPE plus inventory to total assets. $ROA$ is equal to earnings before interest and taxes scaled by the average firm assets over the year. $Size$ is the natural log of the firm’s total assets in millions of dollars. $Leverage$ is the ratio of the sum of long-term debt and the current portion of long-term debt to total firm assets. $MTB$ is the ratio of the market value to the book value of equity. All regressions include year and industry fixed effects, and standard errors are clustered by firm and year. Significance levels are based on two-tailed tests. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Electronic copy available at: https://ssrn.com/abstract=2375976
Table 4: Credit Risk Uncertainty and Reporting Quality
With Varying Private Information

| Predicted                     |       |
|-------------------------------|-------|
| DCV                          | -     |
| EJR                          | ?     |
| DCV × EJR                    | -     |
| Mature                       | ?     |
| Face                         | +     |
| AvgRate                      | +     |
| TotalCovs                    | +     |
| Tangibility                  | -     |
| ROA                          | -     |
| Size                         | -     |
| Leverage                     | +     |
| MTB                          | ?     |

| Mean Interactive Effect (FRQ × EJR) |       |
|-------------------------------------|-------|
| Pseudo R² (%)                       | 6.17  |
| Observations                        | 1,734 |
| Year FE                             | Yes   |
| Industry FE                         | Yes   |

This table presents the results from estimating the following Tobit regression from 2000–2008 for 1,734 (867 × 2) observations.

\[
\text{DefaultDiff}_t = \alpha + \beta_1 \text{DCV}_{t-1} + \beta_2 \text{EJR} + \beta_3 \text{DCV}_{t-1} \times \text{EJR} + \sum \beta_j \text{Controls}_{j,t-1} + \epsilon_t,
\]

where DefaultDiff is the difference in the default rates implied by the firm-level ratings issued by S&P and Moody’s if EJR is equal to zero and between EJR (using S&P’s default rates) and the average of Moody’s and S&P’s if EJR equals one. DCV is the Somers’ D from the estimation of a probit of downgrades on seasonally adjusted quarterly earnings. Maturity is the natural log of the number of years from bond issuance until the principal is to be repaid. Face is the natural log of the face amount of the bond. AvgRate is the average of the Moody’s and S&P credit ratings. TotalCovs is the total number of covenants included in the bond contract. Tangibility is the ratio of net PPE plus inventory to total assets. ROA is equal to net income scaled by the average firm assets over the year. Size is the natural log of the firm’s total assets in millions of dollars. Leverage is the ratio of the sum of long-term debt and the current portion of long-term debt to total firm assets. MTB is the ratio of the market value to the book value of equity. All regressions include year and industry fixed effects and standard errors are clustered by firm and year. Significance levels are based on two-tailed tests. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Electronic copy available at: https://ssrn.com/abstract=2375976
Table 5: Matched Sample Summary Statistics for SFAS 131 Tests

| Variable          | Full Sample |           | Test Sample |           | Control Sample |           |
|-------------------|-------------|-----------|-------------|-----------|---------------|-----------|
|                   | Mean | STD | Mean | STD | Mean | STD |
| Disagreement proxy|     |     |     |     |     |     |
| DefaultDiff       | 4.402| 7.402| 4.339| 7.531| 4.464| 7.276|
| Bond-level controls|     |     |     |     |     |     |
| Maturity          | 2.367| 0.538| 2.358| 0.543| 2.375| 0.533|
| Face              | 19.175| 0.845| 19.160| 0.824| 19.192| 0.864|
| AvgRate           | 9.453| 4.081| 9.427| 4.536| 9.484| 4.057|
| TotalCovs         | 4.276| 4.380| 4.273| 4.536| 4.279| 4.222|
| Firm-level controls|     |     |     |     |     |     |
| Tangibility       | 0.543| 0.213| 0.539| 0.198| 0.546| 0.227|
| ROA               | 0.105| 0.066| 0.105| 0.062| 0.104| 0.070|
| Size              | 7.728| 1.520| 7.753| 1.567| 7.703| 1.477|
| Leverage          | 0.322| 0.159| 0.307| 0.152| 0.337**| 0.164|
| MTB               | 2.894| 2.991| 2.692| 2.683| 3.102| 3.292|

This table presents summary statistics on the variables of interest for the matched samples used in the SFAS 131 tests. The full sample size is 1,238 bonds, with 619 bonds in each subsample. Bonds in the test sample are those issued by firms which increased the number of their segment disclosures by three or more following the implementation of SFAS 131. The control sample is a propensity-score-matched sample. ***, **, and * denote significant differences between the test and control samples using a clustered t-test at the 1%, 5%, and 10% levels, respectively. DefaultDiff is the difference in the default rates implied by the two credit ratings. Maturity is the natural log of the number of years from bond issuance until the principal is to be repaid. Face is the natural log of the face amount of the bond. AvgRate is the average of the Moody’s and S&P credit ratings. TotalCovs is the total number of covenants included in the bond contract. Tangibility is the ratio of net PPE plus inventory to total assets. ROA is equal to earnings before interest and taxes scaled by the average firm assets over the year. Size is the natural log of the firm’s total assets in millions of dollars. Leverage is the ratio of the sum of long-term debt and the current portion of long-term debt to total firm assets. MTB is the ratio of the market value to the book value of equity.
Table 6: Credit Risk Uncertainty and Accounting Standard Change

|                           | Predicted |         |
|---------------------------|-----------|---------|
| Segments                  | 1.16      | (0.44)  |
| SFAS131                   | 7.32      | (0.45)  |
| Segments × SFAS131        | -3.19***  | (-4.27) |
| Maturity                  | 1.52      | (0.43)  |
| Face                      | -0.19     | (-0.25) |
| AvgRate                   | 1.33***   | (5.81)  |
| TotalCovs                 | 0.69      | (0.47)  |
| Tangibility               | -3.80     | (-0.39) |
| ROA                       | -6.89     | (-0.72) |
| Size                      | 0.30      | (0.35)  |
| Leverage                  | 3.02      | (0.37)  |
| MTB                       | 0.36      | (0.43)  |
| Trend                     | -0.76***  | (-5.13) |
| Constant                  | 34.06     | (0.41)  |
| Mean Interactive Effect   | -1.59***  | (-4.26) |
| (Segments × SFAS131)      |           |         |
| Pseudo R² (%)             | 3.10      |         |
| Observations              | 1,238     |         |
| Industry FE               | Yes       |         |

This table presents the results from estimating the following Tobit regression from 1985–2008 for 1,238 observations.

\[ \text{DefaultDiff} = \alpha + \beta_1 \text{Segments}_t + \beta_2 \text{SFAS131}_t + \beta_3 \text{Segments}_t \times \text{SFAS131}_t + \Sigma \beta_j \text{Controls}_{j,t-1} + \epsilon_t, \]

where DefaultDiff is the difference in the default rates implied by the two credit ratings. Segments is an indicator variable equal to one if the number of disclosure segments increased by three or more from the year before the implementation of SFAS 131 to the year after and zero otherwise. SFAS131 is an indicator variable equal to one if the debt was issued after SFAS 131 took effect. Maturity is the natural log of the number of years from bond issuance until the principal is to be repaid. Face is the natural log of the face amount of the bond. AvgRate is the average of the Moody’s and S&P credit ratings. TotalCovs is the total number of covenants included in the bond contract. Tangibility is the ratio of net PPE plus inventory to total assets. ROA is equal to earnings before interest and taxes scaled by the average firm assets over the year. Size is the natural log of the firm’s total assets in millions of dollars. Leverage is the ratio of the sum of long-term debt and the current portion of long-term debt to total firm assets. MTB is the ratio of the market value to the book value of equity. Trend is a time trend variable set equal to 1 for debt issued in 1985, 2 for 1986, etc. The regression includes industry fixed effects, and standard errors are clustered by firm and year. Significance levels are based on two-tailed tests. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.
Table 7: Credit Risk Uncertainty and Reporting Quality by Rating Class

| Rating  | Coefficient | t-stat | Pseudo R² (%) | Observations |
|---------|-------------|--------|---------------|--------------|
| AAA     | -1.28***    | (-2.85)| 27.55         | 289          |
| AA+     |             |        |               |              |
| AA      | -2.19***    | (-2.62)| 11.49         | 582          |
| AA-     |             |        |               |              |
| A+      |             |        |               |              |
| A       | -3.16**     | (-1.96)| 6.68          | 375          |
| A-      |             |        |               |              |
| BBB+    |             |        |               |              |
| BBB     | -1.85       | (-0.65)| 6.27          | 220          |
| BBB-    |             |        |               |              |
| BB+     |             |        |               |              |
| BB      | -0.76       | (-0.54)| 5.16          | 493          |
| BB-     |             |        |               |              |
| B+      |             |        |               |              |
| B       |             |        |               |              |
| B-      |             |        |               |              |
| CCC+    |             |        |               |              |
| CCC     |             |        |               |              |

This table presents the results from estimating the following Tobit regression from 1985–2008 for 1,959 observations by credit class.

\[ \text{DefaultDiff}_i = \alpha + \beta_1 \text{DCV}_{t-1} + \sum \beta_j \text{Controls}_{j,t-1} + \epsilon_t, \]

where \( \text{DefaultDiff} \) is the difference in the default rates implied by the two credit ratings. \( \text{DCV} \) is the Somers’ D from the estimation of a probit of downgrades on seasonally adjusted quarterly earnings. The regressions include the following control variables: \( \text{Maturity}, \text{Face}, \text{AvgRate}, \text{TotalCovs}, \text{Tangibility}, \text{ROA}, \text{Size}, \text{Leverage}, \) and \( \text{MTB} \). \( \text{Maturity} \) is the natural log of the number of years from bond issuance until the principal is to be repaid. \( \text{Face} \) is the natural log of the face amount of the bond. \( \text{AvgRate} \) is the average of the Moody’s and S&P credit ratings. \( \text{TotalCovs} \) is the total number of covenants included in the bond contract. \( \text{Tangibility} \) is the ratio of net PPE plus inventory to total assets. \( \text{ROA} \) is equal to earnings before interest and taxes scaled by the average firm assets over the year. \( \text{Size} \) is the natural log of the firm’s total assets in millions of dollars. \( \text{Leverage} \) is the ratio of the sum of long-term debt and the current portion of long-term debt to total firm assets. \( \text{MTB} \) is the ratio of the market value to the book value of equity. Observations are categorized into groups by the average of their S&P and Moody’s ratings. All regressions include year and industry fixed effects, and standard errors are clustered by firm and year. Significance levels are based on two-tailed tests. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.
### Table 8: Split Indicator and Number of Notches between Ratings for Credit Risk Uncertainty and Reporting Quality

#### Panel A: Split Indicator and Reporting Quality

|                  | Predicted  |
|------------------|------------|
|                  | 0.12**     |
|                  | (-1.98)    |
| Maturity         | -0.00      |
|                  | (-0.19)    |
| Face             | 0.06***    |
|                  | (3.31)     |
| AvgRate          | 0.01       |
|                  | (1.05)     |
| TotalCovs        | 0.00       |
|                  | (1.06)     |
| Tangibility      | -0.09      |
|                  | (-0.82)    |
| ROA              | 0.44*      |
|                  | (1.94)     |
| Size             | -0.02      |
|                  | (-1.45)    |
| Leverage         | 0.04       |
|                  | (0.34)     |
| MTB              | -0.00      |
|                  | (-0.19)    |
| Pseudo R² (%)    | 4.10       |
| Observations     | 1,959      |
| Year FE          | Yes        |
| Industry FE      | Yes        |

Electronic copy available at: https://ssrn.com/abstract=2375976
Panel B: Number of Notches between Ratings and Reporting Quality

|        | Predicted   |
|--------|-------------|
|        | -0.28**     |
|        | (-2.03)     |
| DCV    |             |
| Maturity| 0.03        |
|        | (0.49)      |
| Face   | 0.10**      |
|        | (2.17)      |
| AvgRate| 0.02        |
|        | (1.48)      |
| TotalCovs| 0.02***    |
|        | (2.41)      |
| Tangibility | -0.36*   |
|        | (-1.75)     |
| ROA    | -0.41       |
|        | (0.83)      |
| Size   | -0.04       |
|        | (-1.09)     |
| Leverage | 0.10      |
|        | (0.39)      |
| MTB    | 0.00        |
|        | (0.13)      |

| Pseudo R² (%) | 3.86 |
| Observations  | 1,959 |
| Year FE       | Yes  |
| Industry FE   | Yes  |

This table presents the marginal effects (coefficients) from estimating the following probit (ordered probit) regression from 1985–2008 for 1,959 observations.

\[
\text{Split}_t = \alpha + \beta_1 \text{DCV}_{t-1} + \Sigma \beta_j \text{Controls}_{j,t-1} + \varepsilon_t,
\]
\[
\text{Notches}_t = \alpha + \beta_1 \text{DCV}_{t-1} + \Sigma \beta_j \text{Controls}_{j,t-1} + \varepsilon_t,
\]

where \( \text{Split} \) is an indicator variable equal to one if the bond is split rated and zero otherwise. \( \text{Notches} \) is the number of notches between the S&P and Moody’s ratings for a bond. \( \text{DCV} \) is the Somers’ D from the estimation of a probit of downgrades on seasonally adjusted quarterly earnings. \( \text{Maturity} \) is the natural log of the number of years from bond issuance until the principal is to be repaid. \( \text{Face} \) is the natural log of the face amount of the bond. \( \text{AvgRate} \) is the average of the Moody’s and S&P credit ratings. \( \text{TotalCovs} \) is the total number of covenants included in the bond contract. \( \text{Tangibility} \) is the ratio of net PPE plus inventory to total assets. \( \text{ROA} \) is equal to earnings before interest and taxes scaled by the average firm assets over the year. \( \text{Size} \) is the natural log of the firm’s total assets in millions of dollars. \( \text{Leverage} \) is the ratio of the sum of long-term debt and the current portion of long-term debt to total firm assets. \( \text{MTB} \) is the ratio of the market value to the book value of equity. All regressions include year and industry fixed effects, and standard errors are clustered by firm and year. Significance levels are based on two-tailed tests. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.
Table 9: Credit Risk Uncertainty and Other Measures of Financial Reporting Quality

| Predicted | AsymTime | Cscore | Cscore | AQ |
|-----------|----------|--------|--------|----|
| FRQ       | -0.82*** | -0.13**| -0.17***| -0.39*** |
| Maturity  | -0.11    | 0.43   | -0.13  | -0.13 |
| Face      | 0.39     | -0.08  | 0.39   | 0.34 |
| AvgRate   | 1.39***  | 1.46***| 1.41***| 1.41*** |
| TotalCovs | 0.50**   | 0.58***| 0.52** | 0.50** |
| Tangibility| -5.66*  | -6.14* | -5.96* | -5.61* |
| ROA       | 15.08    | 20.91**| 16.86  | 15.92 |
| Size      | -1.02    | -0.85  | -0.92  |         |
| Leverage  | 7.39     | 6.41   | 7.07   |         |
| MTB       | 0.16***  | 0.08   | 0.17***|         |
| Constant  | -9.27    | -18.31 | -36.40 |         |
| Pseudo R² (%) | 6.48 | 5.93 | 6.47 | 6.51 |

This table presents the results from estimating the following Tobit regression from 1985–2008 for 890 observations.

\[
Default Diff_t = \alpha + \beta_{FRQ} F_RQ_{t-1} + \sum \beta_j Controls_{j,t-1} + \varepsilon_t,
\]

where DefaultDiff is the difference in the default rates implied by the two credit ratings. FRQ is one of three proxies for financial reporting quality: AsymTime, Cscore, or AQ. AsymTime is asymmetric timeliness calculated as \( \beta_3 \) from a Basu (1997) regression. Cscore is another measure of asymmetric timeliness developed by Khan and Watts (2009). AQ is the first principal component of three abnormal accrual measures (Bharath et al. 2008). Maturity is the natural log of the number of years from bond issuance until the principal is to be repaid. Face is the natural log of the face amount of the bond. AvgRate is the average of the Moody’s and S&P credit ratings. TotalCovs is the total number of covenants included in the bond contract. Tangibility is the ratio of net PPE plus inventory to total assets. ROA is equal to earnings before interest and taxes scaled by the average firm assets over the year. Size is the natural log of the firm’s total assets in millions of dollars. Leverage is the ratio of the sum of long-term debt and the current portion of long-term debt to total firm assets. MTB is the ratio of the market value to the book value of equity. All regressions include year and industry fixed effects, and standard errors are clustered by firm and year. Significance levels are based on two-tailed tests. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.