FINANCIAL REPORTING QUALITY AND UNCERTAINTY ABOUT CREDIT RISK AMONG THE RATINGS AGENCIES

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ABSTRACT

I study whether financial reporting quality resolves uncertainty about credit risk by examining how it affects disagreement between rating agencies. I find better reporting quality is associated with less uncertainty about credit risk as captured by disagreement about ratings between the agencies. Further, my results are consistent with reporting quality becoming more important in reducing uncertainty when an agency does not have access to private information. Finally, I examine whether SFAS 142, which ended goodwill amortization and requires managerial estimates to determine potential impairments of goodwill, affected uncertainty about credit risk. I find increased uncertainty between agencies about the goodwill account for firms with significant goodwill after the implementation of SFAS 142. I contribute to the literature on the role of reporting quality in debt markets and on debt market information intermediaries.

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1. Introduction

This study examines whether financial reporting quality reduces uncertainty about credit risk. Uncertainty reduces the ability of lenders and other debt market participants to accurately assess credit risk. I examine uncertainty in a setting of privately informed information intermediaries - the credit ratings agencies (CRAs). The ratings agencies play an important role in debt markets by reducing information asymmetry between investors and borrowers, allowing borrowers greater access to the debt markets, and providing contractible measures (ratings) of credit risk. By studying the impact of reporting quality on credit risk uncertainty, I provide evidence of one mechanism through which reporting quality affects fixed income investors, borrowing firms, and those who rely on ratings for contracting and regulatory purposes.

I hypothesize that financial reporting quality is negatively associated with uncertainty about credit risk among CRAs. This occurs because higher quality reporting allows the CRA's to better assess the borrower's ability to make periodic interest payments and repay loan principal at maturity. Furthermore, earnings that communicate negative information about performance constrain managerial opportunism (Watts 2003), which likely reduces uncertainty about credit risk. This hypothesis, however, is not without controversy. As detailed in Section 2, support for the null hypothesis of no relation between reporting quality and credit risk uncertainty might arise, among other reasons, because rating agencies have access to private information and may rely on it more heavily than on public financial reporting quality. Thus, the relation between reporting quality and uncertainty about credit risk is ultimately an empirical question.

To proxy for uncertainty about credit risk among the rating agencies, I use disagreement between agencies over their ratings for new debt issuances (hereafter, labeled as split rated debt). When the CRAs have differing views regarding the credit risk of the firm, they issue split ratings. For example, Darden Restaurants Incorporated issued five year senior notes on October 10, 2007, rated BBB+ by Standard and Poor's (S&P) and Baa3 by Moody's Investor Service (Moody's), which is equivalent to a BBB- on the S&P scale. Thus, S&P views Darden as being of higher credit quality than Moody's does, which indicates more uncertainty surrounding the credit risk of this firm than identical ratings would. More recently, S&P downgraded the sovereign debt of the United States while Moody's reaffirmed its AAA rating. One reason given for the disagreement was that the agencies held differing beliefs about how quickly the U.S. government needed to reduce its debt obligations (Appelbaum 2011; Indiviglio 2011).

I focus on whether better reporting quality reduces the uncertainty about corporate credit risk among rating agencies. I use an indicator variable (*Split*), equal to one if the two major rating agencies, Moody's and S&P, issue different ratings for a particular bond, and zero if it receives the same rating from both.[1] I also use the difference in the historical default rates for each agency implied by these differing ratings (*DefaultDiff*) to capture the extent of disagreement between CRAs. The historical default rate for bonds

[1] I focus on disagreement between Moody's and S&P to capture uncertainty because over 80% of all rated global bond issues are rated by one or both of these. Fitch is a remote third in this market, rating about 14% of outstanding issues (Langohr and Langohr 2009). Further demonstrating the dominance of Moody's and S&P, the bond indices are often based on ratings classes, and it was not until the end of 2004 that the Merrill Lynch and Lehman Brothers indices began to use Fitch ratings in addition to Moody's and S&P to determine ratings classes. Moreover, prior research has found that Fitch systematically issues higher debt ratings than Moody's and S&P (Bongaerts et al. 2012; Cantor and Packer 1997), calling into the question the comparability of their rating scales and methodologies.

rated BBB+ by S&P is 7.83%, while the default rate for bonds rated Baa3 by Moody's is 9.47%, indicating *DefaultDiff* would be 1.64% for the Darden bond above. Both measures are, to some extent, analogous to forecast dispersion among equity analysts. When there is greater uncertainty about credit risk, the agencies are more likely to disagree and have greater disagreement about the credit ratings they issue.

To capture reporting quality, I focus on metrics that communicate how well earnings convey negative news. Specifically, I use asymmetric loss recognition, proxied by both *AsymTime* and the *Cscore* (Basu 1997; Khan and Watts 2009), and the debt contracting value of accounting information (*DCV*; Ball et al. 2008). These measures are appropriate for a debt market setting because asymmetric timeliness captures how quickly earnings communicate the negative information reflected in stock returns and the *DCV* communicates how well earnings predict rating downgrades. Conveying bad news is particularly important to bondholders whose fixed claims on firm assets are more sensitive to negative than to positive news (Leftwich 1983; Watts 1993, 2003).

To provide evidence on my hypotheses, I obtain a sample of 898 bonds from 1985-2008 rated by both Moody's and S&P at issuance. I then conduct two tests on the effect of reporting quality on credit risk uncertainty. First, I examine the effects of reporting quality proxies on credit risk uncertainty. I find a negative association between reporting quality and the incidence of split rated debt. Specifically, an increase in *AsymTime*, *Cscore*, and *DCV* is associated with a decrease in the probability of a firm issuing split rated debt. In economic terms, a one standard deviation increase in *AsymTime* (*Cscore*, *DCV*) results in a 1.40% (1.62%, 8.15%) decrease in the probability

of the firm issuing split rated debt, and a 0.29% (0.03%, 0.74%) decrease in the difference in implied default rates. These results are consistent with the hypothesis that better reporting quality is associated with less rating agency uncertainty about credit risk.

In supporting analysis, I study a circumstance in which reporting quality should become more important in reducing uncertainty. I examine disagreement between the two primary rating agencies and Egan-Jones Ratings Company (EJR), which does not have access to private information. I find reporting quality is generally more important (has greater economic effects) in reducing uncertainty about credit risk when a rating agency lacks access to private data.

While my primary tests allow me to predict the directional effect of reporting quality on uncertainty, there is an endogeneity concern. Since reporting quality is a choice variable, it may be correlated with other factors affecting uncertainty. To address this, I conduct a second set of tests examining the extent to which credit risk uncertainty changes after the mandatory adoption of the SFAS 142, using it as an exogenous shock to reporting quality. The FASB argued this change would increase reporting quality, but research suggests the opposite (Li and Sloan 2011; Muller et al. 2010; Ramanna and Watts 2011). Thus, this test has the advantage of allowing me to abstract from my endogeneity issue, but it does not allow me to make a directional hypothesis. It also allows me to conduct a difference-in-difference analysis since firms without goodwill were unaffected by SFAS 142. Consistent with the new standard obfuscating credit risk, I find that significant goodwill is associated with greater uncertainty after the adoption of SFAS 142. Specifically, I find a 1.04% increase in the difference in implied default rates

associated with the goodwill account for firms with goodwill comprising at least 10% of assets after the implementation of SFAS 142.

Finally, I conduct a series of robustness tests. I find my results robust to including a variety of variables controlling for various aspects of the issuing firms' operating and information environments. I also find evidence that my results examining the effect of SFAS 142 are not due to a time trend in uncertainty associated with goodwill. And I conduct cross-sectional tests finding reporting quality to be incrementally associated with a reduction in uncertainty when the issuing firm has not been recently evaluated by the ratings agencies. All of these results support my argument that reporting quality actually causes reductions in uncertainty about credit risk.

This study contributes to two streams of the literature. First, it contributes to research on the consequences of reporting quality in debt market settings. Previous studies show that better reporting quality lowers the debt cost of capital (Bharath et al. 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 et al. 2008), and lowers spreads for syndicated loans traded in the secondary market (Wittenberg-Moerman 2008). While Wittenberg-Moerman (2008) uses spreads in her study, which allows her to show reporting quality reduces uncertainty about a number of important risk factors, using disagreement about credit ratings allows me to focus exclusively on uncertainty about credit risk. Thus, my results complement this research, providing evidence that reporting quality plays an important role even among rating

agencies - fairly sophisticated information intermediaries with access to private information.

Second, this study contributes to the literature examining the effects of reporting quality on information intermediaries. Recent papers look at the determinants of debt analysts' decisions to initiate coverage and properties of their recommendations (De Franco et al. 2009; Johnston et al. 2009). While extensive research examines how reporting quality affects disagreement among equity market intermediaries (Dechow et al. 2010; Healy and Palepu 2001), much less is known about disagreement among intermediaries in the debt markets. This study is akin to research that looks at forecast dispersion as a proxy for disagreement among equity analysts (Lang and Lundholm 1996). However, rather than examine disagreement about earnings, I look directly at credit risk, about which debt holders ultimately care. I find evidence that reporting quality affects the ability of the agencies to rate credit risk despite having access to proprietary information. This is important because numerous parties depend on the CRAs to be able to accurately discern and communicate credit risk, and their ability to do so is affected by reporting quality.

In Section 2, I discuss related research and develop my hypotheses. Section 3 describes my research design and proxies for credit risk uncertainty and reporting quality. I detail my sample selection in Section 4. Section 5 discusses the results from my tests, and I conclude in Section 6.

2. Related Research and Hypothesis Development

2.1. Related Research

2.1.1. The Credit Ratings Agencies

As stated in Subtitle C of Title IX of the Dodd-Frank Act, "credit rating agencies are central to capital formation, investor confidence, and the efficient performance of the United States economy" (2010). Because of their prominence, chief financial officers have stated that credit ratings are one of their greatest concerns when obtaining financing (Graham and Harvey 2001). The ratings provided by the CRAs are used by fixed income investors, regulators, and contracting agents. Previous research establishes that rating changes communicate important information to investors and affect returns (Hand et al. 1992; Goh and Ederington 1993; Kliger and Sarig 2000; Dichev and Piotroski 2001). The reduction in information asymmetry provided by credit ratings increases the ability of firms to raise debt capital, which increases their propensity to undertake real investment (Tang 2009). Lenders use these ratings to identify different states of the world and write more complete contracts. For example, loan contracts often include ratings triggers or performance pricing grids based on credit ratings. They also commonly feature clauses that trigger accelerated repayment or increased collateral requirements when credit risk, measured by ratings, increases. Moody's reports that in 2001, 87.5% of firms rated Ba1 or higher had ratings-based contract provisions (Coppola and Stumpp 2002).

Ratings issued by S&P and Moody's are not only used in investment decisions and contracting but also in regulation. Both S&P and Moody's are certified ratings agencies, or Nationally Recognized Statistical Ratings Organizations (NRSROs). Ratings

issued by NRSROs are commonly used in regulatory settings. A variety of national and state legislative acts and other regulatory standards have come to rely on the designation since it was introduced in 1975 (SEC 2003). As of 2003, credit ratings were referenced in at least 8 federal statutes, 47 federal regulations, and over 100 state-level laws and regulations (Covitz and Harrison 2003).

Although the agencies publish their rating methodologies, 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 in the ratings process (Kraft 2011).[2] Thus, credit ratings can be viewed as a function of hard information derived from adjustments to accounting outputs, soft information, and the discretion of the rating analysts used in making these adjustments.

The agencies often disagree about credit ratings despite their importance, and this disagreement is driven, at least in part, by uncertainty about credit risk (Morgan 2002). In my empirical tests, I follow Morgan (2002) and subsequent papers by using the issuance of split rated debt as a proxy for uncertainty about credit risk. Morgan (2002) develops a model of the rating process in which the true default risk of a bond is uncertain and increased uncertainty results in more split ratings and more lopsided splits. Since Morgan (2002), several empirical papers have used split ratings or prediction models of split ratings to proxy for uncertainty about credit risk (Asquith et al. 2005; Drucker and Puri 2009; Mansi et al. 2004).

[2] Hard adjustments are modifications made to reported accounting numbers for ratio analysis such as the capitalization of off balance sheet debt. Soft adjustments are made to 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 2011).

Several empirical papers examine the causes and consequences of split ratings. Ederington (1986) argues that split ratings are random rather than the outcome of different ratings scales or standards. However, Billingsley et al. (1985) argue that split ratings occur because the agencies disagree about the default risk of a bond issue. Other studies argue and find evidence that disagreements about credit ratings occur, at least in part, because of asset opacity. Morgan (2002) finds that more opaque bank assets such as trading assets and loans increase the uncertainty about the bank's credit risk. Livingston et al (2007) extend these findings by showing that measures of asset opaqueness such as the proportion of assets that are intangible, market-to-book ratio, and size also affect uncertainty about credit risk for nonfinancial firms.[3]

Research on the outcomes of credit risk uncertainty examines whether split ratings affect the cost of debt, influence firms to obtain a third rating, or potentially impact derivative pricing. Early studies examining whether split ratings affect yields on new debt produced mixed results (Billingsley et al. 1985; Jewel and Livingston 1998; Perry et al. 1988; Reiter and Zeibart 1991). However, more recent studies find evidence consistent with investors demanding a higher yield on split rated bonds (Cheng 2011; Livingston and Zhou 2010). Furthermore, Jewell and Livingston (1998) find that split ratings on bonds issued below investment grade significantly increase underwriter fees charged to issuing firms. Firms that receive split ratings are also more likely to incur the cost of obtaining a third rating, consistent with the idea that split ratings indicate

[3] However, they do not control for industry effects, the primary variable of interest in Morgan's (2002) study. Furthermore, they fail to control for a number of bond features that Morgan finds significantly related to split ratings, most importantly the level of credit ratings (except in one specification), which I find to be correlated with both of my dependent variables and all of my control variables except for two, suggesting the possibility of a correlated omitted variable bias in their study.

uncertainty and that firms attempt to reduce this by obtaining an additional rating (Beattie and Searle 1992; Jewell and Livingston 2000). Finally, Livingston et al. (2008) find that split rated bonds have higher ratings volatility, which could lead to the mispricing of credit spread options and increases value-at-risk (VaR) in some risk management models.

2.1.2. Reporting Quality and Uncertainty

Prior research has studied the impact of reporting quality on uncertainty, with greater emphasis on uncertainty in equity markets. For instance, reporting quality (broadly defined) has been shown to be associated with lower information asymmetry (Leuz and Verrecchia 2000), lower idiosyncratic volatility (Rajgopal and Venkatachalalm 2011), and lower dispersion among analyst earnings forecasts (Lang and Lundholm 1996). Far fewer papers have studied the role of reporting quality in mitigating uncertainty in debt markets. A notable exception is a study by Wittenberg-Moerman (2008), which shows that firms with higher reporting quality have lower information asymmetry in the secondary syndicated loan market. My study complements and extends hers. Her study relies on a proxy of uncertainty based on debt market investors, while this study relies on proxies based on debt market intermediaries, specifically the CRAs. This is analogous to the distinction between bid-ask spreads and forecast dispersion documented in equity markets. While Wittenberg-Moerman (2008) shows that better reporting quality reduces uncertainty for loan market participants, we do not yet have evidence on the effect of reporting quality on uncertainty about credit ratings. This is important because, as discussed above, credit ratings provide information to financial markets (Holthausen and Leftwich 1986; Hand et al. 1992), are used to write more

complete contracts (Coppola and Stumpp 2002), and are employed extensively in regulation (Covitz and Harrison 2003).

Furthermore, bond and loan prices contain information about much more than just credit risk (Frost 2007). For example, fixed income prices also reflect interest rate risk, local tax effects, liquidity, and the effects of common equity risk factors (Bao et al. 2011; Elton et al. 2001; Longstaff and Schwartz 1995). In contrast, CRAs focus more singularly on credit risk (Johnston et al. 2009). Thus while using empirical tests employing loan spreads capture uncertainty about a variety of important risk factors, using disagreement about credit ratings allows me to concentrate on uncertainty about credit risk. Hence, my results complement Wittenberg-Moerman's (2008) research, providing evidence that reporting quality plays an important role even among credit rating agencies.[4]

2.2. Hypotheses Development

2.2.1. The Effect of Reporting Quality on Credit Risk Disagreement

The CRAs consider the informativeness of the firm's accounting system when determining ratings, implying reporting quality affects the level of ratings issued (S&P 2006). However, one barrier to accurately determining credit risk is the ability of the ratings agencies to obtain "accurate and reliable information from issuers" (SEC 2003). Thus, the quality of information provided by issuers is important in being able to assign accurate ratings. I argue that reporting quality not only impacts the level of credit ratings,

[4] In a contemporaneous paper, Cheng (2011) finds that Moody's and S&P are less likely to disagree about bonds issued by banks with greater timeliness and more valid loan loss provisioning. My study differs from his in that I examine whether these effects hold for industrials and I examine the effects of an accounting standard change.

but also that it affects uncertainty about credit risk and therefore disagreement about the expected default risk of a bond issue.

In particular, I argue that when earnings better communicate negative information about firm performance and value, the rating agencies are better able to evaluate the downside risk of the debt issuing firm. The asymmetric payoff function of debt holders leads them to have a greater concern with the downside risk of their investments and generates an asymmetric demand for negative information (De Franco et al. 2009). When earnings more rapidly incorporate losses, agency analysts have greater certainty about the liquidation value of the firm and know it is less likely that the firm has pending negative information yet to be recognized. Furthermore, more conservative reporting helps constrain managerial opportunism that may lead to inflated earnings and asset valuations. Thus, this constraint also reduces uncertainty about potential managerial opportunism and is valued by both contracting and regulatory agents who rely on credit ratings (Watts 2003). Based on these arguments, I expect earnings that capture negative information in a timely manner to help reduce uncertainty about credit risk for ratings analysts. Since analysts at Moody's and S&P have less uncertainty about the firm's credit profile, they are less likely to disagree about ratings. My first hypothesis is stated below.

H1: Higher reporting quality decreases uncertainty about credit risk.

While this may initially seem obvious, there exist at least two reasons why this hypothesis may not hold. First, it is possible that increasing reporting quality could create greater disagreement about credit risk between the agencies (Harris and Raviv 1993; Kandel and Pearson 1995; Lang and Lundholm 1996). If the agencies are employing

models that differentially weight the components of disclosure, higher reporting quality may actually increase their disagreement about credit risk. Ederington (1986) investigates the possibility that S&P and Moody's weight identical factors differently and finds no evidence to support this. However, he makes his examination at the letter (AA versus A) rather than the notch (AA versus AA-) level, and this practice could have changed since his study was conducted.

Second, Regulation Fair Disclosure Rule 102(b)(2) allows credit rating agencies to continue having access to private information for use in the ratings process as long as their ratings are made publicly available.[5] Unlike bond analysts working for brokerage firms, analysts at S&P and Moody's continue to receive information through both public and private channels. Thus, in addition to publicly available information that other bond analysts and fixed income investors have, they also have access to private information provided through meetings with firm management. This private information often includes more detailed breakdowns of performance, discussion of potential capital expenditure plans, and financial projections. Because the analysts incorporate this private information in their credit analysis, it is possible that the quality of public information has little effect on their final assessment of credit risk.

Building on this argument, I also hypothesize that the relationship between reporting quality and uncertainty about credit risk will depend on the extent to which rating agencies have access to private information. Since the agencies make assessments based on a mix of public and private information, it is likely that they rely more heavily

[5] This allowance was revoked by Section 939B of the Dodd-Frank Wall Street Reform and Consumer Protection Act of 2010, effective October 4, 2010.

on public information when they have little or poor private information. When relying more on public information, the perceived quality of that information is likely to be more important to the analysts. Hence, reporting quality is likely to be more important to ratings analysts when public information is their only source of information for developing credit ratings. This leads to my second hypothesis.

H2: Reporting quality is relatively more important in reducing uncertainty about credit risk when rating agencies do not have access to private information.

2.2.2. The Effect of SFAS 142 on Credit Risk Disagreement

One possible concern with my study is that since reporting quality is a choice variable, it may be correlated with other factors leading to disagreement about credit risk, such as the extent to which management shares private information with the rating agencies. Specifically, managers who are quicker to recognize negative information in their financial reports may also be quicker to share private information about their firm with rating analysts. Moreover, low reporting quality firms may be more likely to shop for ratings, a process in which they attempt to engage an agency they believe is more likely to give them a higher rating or even to unduly influence one agency to do so (Kronlund 2011).[6] In this case, the solicited rating is likely to be higher than an unsolicited rating, resulting in greater disagreement between the agencies.[7] To address these concerns, I consider whether a particular change in accounting standards

[6] Jiang et al. (2011) find evidence that S&P's ratings became less conservative relative to Moody's after switching from an investor-pay to an issuer-pay model. Though not addressing ratings shopping, this is consistent with raters being influenced by firms paying to be rated.

[7] Most ratings are solicited, particularly for firms as large as those in my sample. However, since Moody's does not report whether a rating is solicited or not, it is possible that bond ratings in my sample represent a mixture of solicited and unsolicited ratings (Kronlund 2011).

hypothesized to impact reporting quality affected uncertainty about credit risk. If reporting quality affects credit risk uncertainty, then changes in reporting quality originated outside the firm's control should still result in an impact on disagreement between the CRAs. No change in accounting standards is entirely exogenous, but standard changes are likely outside the control of a single firm.

I choose to examine the impact of SFAS 142 because both FASB and prior research argue that this standard affected reporting quality and because of data availability. Prior to the introduction of SFAS 142, goodwill was amortized over a period of up to 40 years and assessed for impairment if there was an event which may have caused impairment of its associated assets. SFAS 142 requires goodwill to be allocated to specific business units, and it is no longer amortized but only reduced through impairment. The FASB argued that this change would increase the economic accuracy of the accounting treatment of goodwill, i.e. increase reporting quality.

Credit ratings analysts argued that SFAS 142 had the potential to make goodwill less informative, decrease company comparability, and reduce managerial discipline (Burke et al. 2001). Although goodwill likely represents little value to debt holders in liquidation (Holthausen and Watts 2001; Kothari et al. 2010), analysts explained that goodwill represents "true value" to a firm because it is expected to generate future cash flows.[8] Previous research finds that debt holders are more likely to include goodwill in net worth covenants when borrowers have it (Frankel et al. 2008)[9] and that Moody's

[8] The agencies do, however, place greater emphasis on cash flow analysis, particularly for non-financial firms.

[9] Beatty et al. (2008) also find results consistent with this though they are careful to point out that it is possible covenant tightness may be adjusted to discount the value of goodwill.

neither frequently nor significantly adjusts goodwill in calculating ratios for use in ratings analysis (Kraft 2011), consistent with goodwill representing future economic value to the firm. Second, analysts noted that most companies chose to amortize over the maximum allowable period, 40 years. Since firms are unlikely to apply the impairment test uniformly, the new standard would decrease company comparability, which is important to analysts.

Finally, analysts argued that SFAS 142 could remove the managerial discipline imposed by the regular amortization of goodwill since the new impairment process gives significant discretion to managers (Burke et al. 2001). Kothari et al. (2010) argues that managerial discipline may explain the presence of goodwill on the balance sheet for so many years, despite its lack of value in the event of default. The presence of goodwill on the balance sheet increases the denominator in calculations of ROA and ROE, making managers responsible for the full cost of their acquisitions. Furthermore, periodic amortization of goodwill "likely serves a related role in making management accountable for acquisitions by allocating the cost of these acquisitions to expense, even though this allocation is *ad hoc*" (Kothari et al. 2010, 263). Failing to recognize goodwill write-offs leads to inflated goodwill accounts and earnings. This in turn leads to deflated leverage ratios since the offsetting entry for a goodwill reduction is made to shareholders' equity.

While the FASB indicated this change in goodwill accounting would benefit stakeholders by providing them with a more economically accurate presentation of goodwill, it is not evident this has not been the outcome of the change. Several academic studies show that managerial incentives have affected the adoption and application of the

fair value impairment process under SFAS 142 (Beatty and Weber 2006; Li and Sloan 2011; Li et al. 2011; Muller et al. 2010; Ramanna and Watts 2011). Frankel et al. (2008) find that debt contracts increasingly exclude goodwill for net-worth determination after the adoption of SFAS 142. Furthermore, the SEC recently moved to require greater disclosure about the fair value process to determine goodwill and the assumptions used in that process in the MD&A section of firm financial reports, arguing that greater transparency is needed to accurately assess the value of goodwill. If this change in reporting standards increased (decreased) the difficulty of valuing goodwill, there would be an increase (decrease) in the disagreement about default risk between the ratings agencies related to the goodwill account. I hypothesize that SFAS 142 affected credit quality uncertainty but do not make a directional hypothesis because of the disagreement about whether it improved or worsened reporting quality.

H3: There is a change in uncertainty about credit risk associated with goodwill after the implementation of SFAS 142.

3. Research Design

3.1. Split Rated Debt and Empirical Tests

I examine reporting quality proxied by asymmetric timeliness (*AsymTime*), the *Cscore* (Khan and Watts 2009), and the Debt Contracting Value (*DCV*) of accounting information from Ball et al. (2008). I discuss each of these measures explicitly after describing my empirical tests.

I use bond-level rather than firm-level ratings to identify disagreement about credit risk for two reasons. First, Moody's and S&P rarely initiate simultaneous changes in firm or instrument-level credit ratings making it difficult to determine whether a rating is split because of asynchronous changes or because of uncertainty about credit risk. Furthermore, firm-level initial ratings from S&P and Moody's may not be issued concurrently. Thus, the initial rating of a debt instrument provides a natural time to examine disagreement because both agencies make a simultaneous judgment about credit risk. Second, Moody's and S&P use different criteria for establishing firm-level credit ratings. Moody's evaluates both the 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 CRAs evaluate the risk of default and the LGD when developing bond-level ratings. Thus, bond ratings are more comparable than firm ratings.

Morgan (2002) investigates whether financial institutions are more likely to have split rated debt than firms in other industries. I follow Morgan (2002) in designing my empirical tests by estimating the following model:

$$\text{Disagreement} = F(\text{reporting quality, bond-level controls, firm-level controls, year fixed effects, industry fixed effects}) + \varepsilon$$

I add reporting quality and a variety of firm-level controls to Morgan's basic model.

I use two proxies to capture disagreement. First, I use an indicator variable (*Split*) equal to one if the bond is split rated and zero otherwise. Second, 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 moving down the ratings scale. The number of notches between ratings 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 historical default rates for corporate bonds by Moody's and S&P for each letter rating from 1970 through 2006 taken from the Municipal Bond Fairness Act. I extrapolate the historical letter default rates to get the default rates for the notched ratings, for example AA+ and AA-. Then I take the difference in these rates, setting the difference equal to zero for bonds with equivalent ratings, to capture the difference in expected default probabilities (*DefaultDiff*). The difference in implied default rates conveys more information than the indicator variable, which merely indicates the presence but not the extent of disagreement.

I estimate the following regression using both of my disagreement proxies for each of the financial reporting quality (*FRQ*) variables to determine whether increasing reporting quality reduces the extent of credit risk uncertainty.

$$Disagree_t = \alpha + \beta_1 \, FRQ_{t-1} + \Sigma \, \beta_j \, Controls_{j,t-1} + \varepsilon_t \qquad (1)$$

where *Disagree* is *Split* in a probit regression and *DefaultDiff* in a Tobit specification.[10] I include industry fixed effects in all of my tests since defaults cluster by industry and Morgan finds significant differences in credit risk uncertainty across industries. Since I use probit and Tobit models, the industry fixed effects are included as the industry

[10] I use a Tobit regression for *DefaultDiff* because the dependent variable, the difference in implied default risk, is constrained between 0 and 100 and is equal to 0 for over half of my observations.

averages for each variable (Wooldridge 2002). I also include year fixed effects and cluster standard errors by firm and year. In the above regression, the coefficient of interest is β_1. A statistically significant negative coefficient for β_1 indicates that the reporting quality measure is associated with less uncertainty about credit risk. Based on my hypotheses, I expect β_1 to be negative for both asymmetric timeliness proxies and the debt contracting value of accounting information.

For my second hypothesis, that reporting quality becomes more important for agencies without access to private information, I would ideally use the same test with an interaction term between reporting quality and a proxy for the amount of private information that the CRAs have. Unfortunately, I do not have an empirical measure capturing this distribution of private information. I can, however, use ratings issued by Egan-Jones, which does not have access to private information to attempt to investigate this hypothesis. So, I study the magnitude of the effect of reporting quality on uncertainty when an outside agency without access to private information, EJR, disagrees with the CRAs that do have access to private information.

Due to data constraints, my research design for this test differs from that in the rest of my study in two ways. First, I use firm-level rather than bond-level ratings since EJR does not issue bond-level ratings. Second, I use S&P's historical default rates by rating to proxy for those of EJR since EJR does not provide these and EJR's ratings are closer to S&P's than to Moody's. A third issue to address under this research design is identifying a point in time when I can be reasonably assured that a disagreement about ratings is due to uncertainty rather than to differential timing in ratings adjustments. To

address this issue, I look at the firm-level ratings when the firm issues rated debt since the agencies are likely to reevaluate the credit profile of the firm at this point. Overall, these necessary research design adjustments make my dependent variable noisier for this test than in my primary test.

My sample period begins in 1999, and I drop observations where there is more than a three-notch difference between S&P's and EJR's ratings as these are likely to capture timing differences in ratings adjustments. I only keep observations for which S&P and Moody's issue the same ratings leaving me with 285 observations. I examine whether reporting quality reduces disagreement between EJR and both S&P and Moody's using the same regression (Equation 1) that I used to test my first hypothesis. I rely on *DefaultDiff* in this and all subsequent tests because it is a more meaningful measure than the split indicator. I compare the magnitude of the effects of a one standard deviation change in reporting quality on *DefaultDiff* in these regressions to those from my primary tests.

To test whether SFAS 142 affected the informativeness of goodwill for assessing credit risk, I estimate the following regression using two difference-in-differences specifications. I consider whether credit risk uncertainty was affected for firms with significant goodwill and for firms likely to need goodwill impairments.

$$DefaultDiff_t = \alpha + \beta_1\, Goodwill_{t-1} + \beta_2\, SFAS142_t + \beta_3\, Goodwill_{t-1} \times SFAS142_t + \Sigma\, \beta_j\, Controls_{j,t-1} + \varepsilon_t \qquad (2)$$

where *Goodwill* is either *Goodwill1* or *Goodwill2*. *Goodwill1* is an indicator variable equal to one if goodwill on the most recent balance sheet at least three months prior to the

debt issue is 10% or more of total assets and zero otherwise. Thus, my test group in my first difference-in-differences consists of firms with significant goodwill. My control group consists of all other firms in my sample, which would not have been affected by SFAS 142 since they do not have significant goodwill. *Goodwill2* is an indicator variable equal to one if the firm had goodwill on the balance sheet relatively more likely needing impairment and zero otherwise. Following Beatty and Weber (2006), I consider goodwill likely to need impairing if it is greater than the difference between the market and book value of equity. Since there is likely to be a significant difference between firms with and without goodwill, I use firms with goodwill on their balance sheets unlikely to need impairing as my control group for this sample. *SFAS142* is an indicator equal to one if that same annual report was issued after SFAS 142 went into effect and zero otherwise. This regression does not include year fixed effects since *SFAS142* 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.[11] Trend is equal to 1 for debt issued in 1985, 2 for 1986, etc. While I make no prediction about the sign of β_1, β_3 will be significantly different from zero if the change in the accounting treatment of recorded goodwill after the introduction of SFAS 142 affected uncertainty about credit quality.

3.2. Measures

3.2.1. Proxies for Reporting Quality

Asymmetric timeliness and the debt contracting value of accounting capture how earnings information appropriates bad news from market returns and how earnings

[11] The interaction term is still statistically significant in these tests without the inclusion of the trend variable.

changes predict credit risk deteriorations. Because managers are expected to be forthcoming with good news but reluctant to disclose bad news, a commitment to the timely recognition of losses improves the transparency of the information environment (Armstrong et al. 2010). This commitment is desired in a debt contracting setting because of the asymmetric information and loss functions of the contracting parties (Watts 2003). Specifically, managers have access to private information that outsiders do not, and managers have limited downside loss to their personal wealth. Consistent with this argument, Wittenberg-Moerman (2008) finds that timely loss recognition decreases bid ask spreads, her proxy for information asymmetry, in the secondary syndicated loan market. LaFond and Watts (2008) find evidence consistent with conservatism reducing information asymmetry in equity markets. Firms that have been more conservative prior to issuing debt have financial statements that facilitate the CRAs' estimation of the lower bound of the liquidation value of the firm's assets.

To proxy for asymmetric timeliness, I use two variables. First, I use asymmetric timeliness (*AsymTime*), calculated as β_3 from Basu's (1997) regression (Equation 3), which captures how quickly positive and negative news from returns is reflected in earnings.

$$E_i = \beta_0 + \beta_1 D_i R_i + \beta_2 R_i + \beta_3 R_i \times D_i R_i + \varepsilon_i \qquad (3)$$

where E is earnings scaled by the lagged market value of equity, R is the annual return compounded beginning four months after fiscal year end, and D is an indicator variable equal to one when R is negative. I estimate the equation by firm over a 20 year rolling period requiring 10 years of observations.

I also rely on the *Cscore* developed in Khan and Watts (2009) as a method to instrument for Basu's (1997) conservatism measure. It allows me to proxy for conservatism at the firm-year level even for firms that do not have negative annual equity returns as is required for estimating the Basu measure. To calculate the measure, the following regression is estimated annually:

$$E_i = \beta_1 + \beta_2 D_i + R_i(\mu_1 + \mu_2 MVE_i + \mu_3 MTB_i + \mu_4 Lev_i) + D_i R_i(\lambda_1 + \lambda_2 MVE_i + \lambda_3 MTB_i + \lambda_4 Lev_i) + (\delta_1 MVE_i + \delta_2 MTB_i + \delta_3 Lev_i + \delta_4 D_i MVE_i + \delta_5 D_i MTB_i + \delta_6 D_i Lev_i) + \varepsilon_i \quad (4)$$

where *MVE* is the natural log of the market value of equity, *MTB* is the firm's market to book value of equity, and *Lev* is leverage. The coefficients from Equation (4) are substituted into Equation (5) to derive the firm-level annual *Cscore*.

$$Cscore = \lambda_1 + \lambda_2 MVE_i + \lambda_3 MTB_i + \lambda_4 Lev_i \quad (5)$$

The debt contracting value of accounting information (*DCV*) is introduced in Ball et al. (2008). Conceptually, the *DCV* captures how well changes in reported earnings predict rating downgrades, i.e. the relevance of earnings for forecasting downgrades. This measure is based on a goodness of fit statistic from a regression of downgrades on quarterly earnings changes. Poor goodness of fit, *DCV*, reflects the poor net outcome of the relevance and reliability of earnings for predicting downgrades. A higher *DCV* suggests better reporting quality since it indicates accounting earnings better predict rating downgrades.

DCV is the Somers' D goodness of fit statistic from the following probit regression, which is estimated 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:

$$Downgrade_{t,i} = \alpha + \beta_1 \Delta E_{t-1,i} + \beta_2 \Delta E_{t-2,i} + \beta_3 \Delta E_{t-3,i} + \beta_4 \Delta E_{t-4,i} + \varepsilon \qquad (6)$$

where *Downgrade* is an indicator variable equal to one if firm i experiences a ratings downgrade over the quarter t and ΔE_{t-s} is the seasonally adjusted change in quarterly earnings over total assets in the sth prior quarter.[12]

I modify the *DCV* variable as calculated by Ball et al. so that it does not use forward looking data. I estimate the model (6) using instrument-level ratings over five year rolling periods. This effectively weights the measure such that firms with more outstanding public debt have a greater impact on the proxy. However, it does not bias the measure in a particular direction and allows me more observations to calculate the *DCV* using only backward looking data. I estimate equation (6) for 1983-2007, taking 1983 as the first year for the estimation since Moody's moved to a notched rating system in 1982. Because of the move, I cannot differentiate whether a rating change in 1982 is a downgrade or whether it is a refinement attributable to this change in ratings methodology.

3.2.2. Controls

Morgan (2002) includes bond features, firm size, and asset types as controls in his tests examining whether banks have greater credit risk uncertainty than other firms. I

[12] Somers' 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 Somers' 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).

follow his work and control for the maturity, face value, and the average rating of the bond issues. *Maturity* is the natural log of the number of years from bond issuance until the principal is to be repaid, and its expected coefficient is uncertain.[13] I expect credit risk uncertainty to be increasing in the face value (*Face*) of the bond, and use the log of the face value as a control. 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. 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 (*AvgRate*) is the average of the two ratings given to the bond by Moody's and S&P. Additionally, I use the number of covenants (*TotalCovs*) included in the bond contract as a control for corporate governance as it is important to bond holders. Covenants are more likely to be used in debt contracts with firms needing greater monitoring (Graham et al. 2008; Costello and Wittenburg-Moerman 2011). Thus, the number of covenants captures the lender's perception of the quality of the borrower's corporate governance (Li et al. 2010).

I also follow Morgan's (2002) later tests and control for firm asset mix by including the tangibility of the firm's assets (*Tangibility*). I follow Costello and Wittenberg-Moerman (2011) and calculate *Tangibility* as the ratio of net PPE plus inventory to total assets and expect it to be negatively correlated with uncertainty. I also control for firm performance. *ROA* is equal to net income scaled by the average firm

[13] While it initially seems evident that greater uncertainty would be associated with longer maturity debt, prior research has shown that for high-yield debt instruments, longer maturities are actually associated with lower, not higher, yields (Langohr and Langohr 2009). This is consistent with longer debt maturity signaling a good firm.

assets over the year and is expected to be negatively associated with uncertainty since there may be greater uncertainty about the credit profile of poorly performing firms. Additionally, I include controls for size, leverage, and market-to-book. Large firms have more developed information environments, and I expect credit risk uncertainty to decrease in firm size. *Size* is measured as the natural log of the firm's total assets in millions of dollars. A more highly levered firm has higher interest payments that must be made relative to its assets and is likely to have more uncertainty about its ability to make these payments. *Leverage* is the ratio of the sum of long-term debt and current portion of long-term debt to total firm assets. Finally, I include the market-to-book ratio (*MTB*) as a control because firms with a high *MTB* ratio 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 its market value and reduces 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. *MTB* is the ratio of the fiscal year end market value of equity to the book value of equity. Because *Cscore* is a linear combination of *Size*, *Leverage*, and *MTB*, I do not include these control variables in the regressions with *Cscore* as my proxy for reporting quality.

4. Sample Selection and Description

4.1. Sample Selection

I use Moody's Investors Service historical ratings and Standard and Poor's RatingsXpress to construct a bond sample for 1985 through 2008. 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*. These databases contain the historical corporate bond ratings, rating outlooks, and credit watch activities initiated by these agencies.[14] To capture uncertainty about credit risk, I compare the initial rating of corporate bonds issued by domestic firms in U. S. dollars. To be included in the sample, a bond must have an initial rating from both Moody's and S&P at or within seven days of issuance. I drop all bonds with special features since differences in ratings for these issues may reflect disagreement about the features rather than credit risk. 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.[15]

Morgan (2002) finds that disagreement about bonds issued by financial firms and utilities to be significantly different than that about bonds from industrials. He argues and

[14] Although Mergent's Fixed Income Securities Dataset (FISD) contains bond 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 was entered by hand and contains errors. For example, FISD commonly misses ratings 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 a particular issue prior to the beginning of 2006. Hence, FISD records bond ratings for a number of issues that were not actually rated.

[15] These numbers are consistent with 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, Jewel and Livingston (2000) find 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.

finds evidence that the mix of opaque assets held by banks leads to greater uncertainty about credit risk than for other firms. Moreover, reporting quality studies generally exclude financials because their reporting differs significantly from that of industrials. So I exclude financials from my sample. Morgan also notes that utilities have a much lower incidence of split rated debt than industrials and attributes this to their high concentration of fixed assets, oversight by regulatory agencies, and exogenous cash flows which reduce agency problems.[16] Hence, I do not expect reporting quality to have significant impact on disagreement about the credit risk of their debt issues. Finally, Compustat does not record goodwill for utilities. Therefore, I exclude utilities from the sample leaving 4,865 bonds from 1,473 firms.

I obtain bond covenant data from Mergent's Fixed Income Securities Database (FISD), and after cutting on the required financial information for my reporting quality and control variables, I am left with 1,333 bonds from 372 firms. I find a significant number of bonds are issued by the same firms on the same day with only their face value and maturity differing. To avoid biasing my tests, I aggregated these bonds since they most likely represent different tranches of the same issue for a total of 898 bonds representing 372 firms.

4.2. Sample Description

Table 1 presents summary statistics (Panel A) and Pearson correlations (Panel B) for the sample. The variables are winsorized at the 1% and 99% levels. Almost 50% of

[16] Consistent with utilities being rated differently, S&P states that it considers implicit government support when rating utilities (2004), and Vazza et al. (2007) show that the utilities had the lowest default rate of all industries from 1981 through 2006.

my sample is split rated (*Split*). Of the split rated bonds issued, there are 223 bonds rated higher by S&P and 217 rated higher by Moody's. At the (untabulated) letter level, there are 82 bonds rated higher by S&P and 82 rated higher by Moody's. Given this symmetric distribution, split ratings do not seem to be explained by the CRAs using different ratings scales. The mean implied difference in default rate based on the ratings given by Moody's and S&P (*DefaultDiff*) is 2.11%, and the standard deviation is 4.39.

The average debt contracting value of accounting information is high, 0.55, compared to the average in Ball et al. (2008), 0.36, indicating that earnings for the issuing firms predict ratings downgrades well. This difference may result from calculating the *DCV* using bond-level rather than firm-level data. The bonds in my sample have about three covenants each. They have an average maturity of 10.48 years and face value of $197.85 million. The average of the Moody's and S&P ratings for bonds in the sample are 7.59, which is between a A3 and a Baa1 on Moody's scale and an A- and a BBB+ on S&P's. Firms in the sample have mean leverage under 30%, indicating they are not highly levered. Asterisks next to the split sample mean indicate statistical differences between the non-split 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 with bold numbers indicating correlations significant at the 5% level. *DCV* is negatively correlated with *Split*. This provides limited evidence for my first hypothesis that reporting quality reduces uncertainty about credit risk. *TotalCovs* is positively correlated with both *Split* and *DefaultDiff* suggesting that poorer corporate governance increases uncertainty

about credit risk. Four (six) of my nine control variables are correlated with my proxy for uncertainty about credit risk, *Split* (*DefaultDiff*), and all of my variables are correlated with *AvgRate* except *Maturity* and *Tangibility*.

Table 2 provides the distribution of bond ratings in my sample. It displays the number of bonds with each Moody's and S&P rating. For example, there are 19 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 each corresponding Moody's and S&P rating. I only have two splits in my sample for which the ratings are more than three notches apart. Across the bottom of the table, I report the percent of splits and average *DefaultDiff* by S&P rating. The average percentage of splits rises quickly and levels out going down the ratings scale, while *DefaultDiff* generally increases.

5. Results

5.1. Primary Results

Table 3 reports the results from my primary tests examining whether reporting quality reduces credit risk uncertainty. Panel A contains the results when using *DefaultDiff* as my independent variable. A one standard deviation difference in *AsymTime* (*Cscore*, *DCV*) is associated with a 0.29% (0.03%, 0.74%) difference in the default rate implied by the two agencies.[17] To put this in the perspective of bond ratings, there is a 0.45% difference on average between the historical default rates of AAA and

[17] One of the concerns raised about using *DCV* is that it may simply be capturing an industry effect (Beatty 2008). I include industry fixed effects in my model to address this concern.

AA rated corporate bonds, a full letter difference at the high end of the ratings scale. This finding is consistent with my first hypothesis that reporting quality reduces the CRAs' credit risk uncertainty as captured by their disagreement about default risk. Also, uncertainty about credit risk is increasing in the face value of the debt, the number of covenants included in the bond contract, and the market-to-book ratio. It is decreasing in asset tangibility and with higher credit ratings. For comparison, a one standard deviation difference in asset tangibility is associated with a 0.84% to 0.97% difference in implied default rate, and a one notch difference in the average rating is associated with a 0.90% to a 0.95% difference.

In Panel B, I report the marginal effects from a probit regression with *Split* as my independent variable. I find that when *Cscore* and *DCV* proxy for reporting quality they are associated with less uncertainty about credit risk. A one standard deviation increase in an issuer's *Cscore* (*DCV*) is associated with a 1.62% (8.15%) increase in the probability of the issued debt being split rated. My inferences with *AsymTime* are consistent with these findings but not statistically significant. Again, I find that uncertainty is increasing in the face value of the debt and decreasing in the issuing firm's asset tangibility. *TotalCovs* also comes out strongly significant in the regressions with each covenant included in the bond contract associated with a 2% increase in the probability that the bond will be split rated, consistent with poor corporate governance contributing to uncertainty even after lenders have attempted to control for it by including covenants in the debt contracts.

In Table 4, I examine whether reporting quality is more important in reducing credit risk uncertainty when a rating agency does not have access to private information. I find that increases in each of my reporting quality proxies are associated with less disagreement between S&P and EJR. To assess whether the reduction is greater in this specification than in my baseline tests, I examine the effect of a one standard deviation change for each of my proxies on the difference in implied default rates. A one standard deviation increase in *AsymTime* (*Cscore*, *DCV*) is associated with a 0.39% (1.18%, 0.56%) decrease in implied default rates. Thus, I find the effect of reporting quality to be stronger in this setting than it is when examining differences between S&P and Moody's for two of my three proxies. I find these results despite having a noisier proxy for uncertainty in this test. The sample for the EJR test is smaller than the one used in the primary test. To ensure the differences in effects are not driven by the difference in samples, I re-run the main test using firm level ratings for the same sample of 285 firms used in the H2 test. In this case, I find even smaller effects. Specifically, the effects are 0.12, 0.06, 0.00, and 0.04. Using this sample as a benchmark continues to support the increased importance of reporting quality when an agency has less private information. Hence, reporting quality is associated with a more significant reduction in uncertainty between the agencies with access to private information and EJR than between S&P and Moody's. This evidence is generally consistent with my hypothesis that reporting quality is more important in reducing uncertainty when the agencies have to rely completely on public information in determining ratings.

Since it is possible that reporting quality is correlated with the issuing firm's willingness to share private information with the CRAs or ratings shopping, I examine whether uncertainty about the goodwill account changed after SFAS 142 was implemented. I report the mean of the interactive effects and their significance following Ai and Norton (2003) and Erkens (2011) in Table 5.[18] I find a 1.04% (mean interactive effect) increase in the difference in implied default rates associated with the goodwill account for firms with significant goodwill after the implementation of SFAS 142.[19] I also find a significant increase in uncertainty about credit risk for bonds issued after SFAS 142 by firms likely to need a goodwill impairment. Specifically, there is a 3.5% difference in the implied default risk associated with the goodwill account in the ratings issued by S&P and Moody's for these firms over firms with goodwill less likely to need impairment after SFAS 142. These results are consistent with SFAS 142 having an impact on accounting quality which affected uncertainty about credit risk and with SFAS 142 obfuscating rather than clarifying the economic value of goodwill.

5.2. Robustness

In robustness tests, I examine whether my results hold for other measures of reporting quality commonly used in debt market settings and attempt to further establish causality for my hypotheses. First, in Table 6, I examine the effect of timely gain

[18] See Appendix B of Erkens (2011) for a discussion of the calculation of the mean interactive effects and their significance.

[19] Because SFAS 141 ended pooling contemporaneously to the implementation of SFAS 142, I examine whether my results may be attributable to a large increase in the amount of goodwill recorded as a result of acquisitions rather than to its informativeness. I find that goodwill only increased from 16.7% to 18.1% of assets on average for firms in my sample with goodwill on their balance sheets after SFAS 141. Thus, it is unlikely that my results are attributable to a change in the amount of goodwill rather than its informativeness.

recognition and overall timeliness on the extent of disagreement about credit risk. Ball and Shivakumar (2006), Guay and Verrecchia (2006), and Wittenberg-Moerman (2008) argue that timely gain recognition and overall timeliness are expected to make earnings more informative. My baseline results suggest that neither of these measures is associated with less uncertainty for ratings analysts. The importance of these constructs is expected to increase for high yield bonds since their returns are more affected by the upside news of the firm than the returns of investment grade bonds. I examine these constructs in a sub-sample of high-yield bonds and again fail to find results (Table 6, Panel B). Also because timely loss recognition is frequently examined in the debt market literature, I conduct my tests using this measure and find that my results generally hold in Table 7.

Next, I conduct a series of robustness tests to better establish the causality of my results. First, I drop the restriction that *DefaultDiff* equals zero when Moody's and S&P agree to address the concern that the agencies' scales may not be equivalent. I find consistent results when not setting *DefaultDiff* equal to zero for bonds with the same rating (Table 8). I control for features of the firm's operating and information environments to rule out the possibility that my reporting quality variables are capturing these constructs in Table 9. I control for debt seniority (Panel A), the firm's operating cycle (Panel B), Altman's (1968) Z-score (Panel C), the number of equity analysts following the firm (Panel D), and analyst forecast dispersion (Panel E). I also control for the standard deviations of ratings received on all bonds issued by the firm in the calendar year (Panel F), daily returns (Panel G), and cash flow from operations (Panel H). Including these variables does not significantly affect my results though including the

standard deviation of cash flow from operations in my regressions weakens the statistical strength of my test using the EJR data (Panel I).

I conduct tests to ensure that *Cscore* and *AsymTime* capture asymmetric timeliness. In Table 10, I find my results robust to including the controls that form *Cscore*, *Size*, *Leverage*, and *MTB*, consistent with my *Cscore* results not simply capturing the effect of these features on uncertainty. I only find a variance inflation factor of 2.00 in a linear version of my primary test indicating that collinearity is not a significant problem when including these controls.

Dietrich et al. (2007) and Patatoukas and Thomas (2011) argue that the Basu measure is biased. Patatoukas and Thomas (2011) find it is affected by deflated earnings and the variance of stock returns. However, Ball et al. (2010, 2011) argue that the measure is well specified and that including firm fixed effects removes these biases. Therefore, I make several attempts to address these concerns. First, I include return on assets in my primary tests and the standard deviation of returns in further tests and find robust results. Second, I include firm fixed effects and also find robust results for each test investigating my hypotheses (Table 11). Furthermore, I find that *AsymTime* loads significantly when using *Split* as my dependent variable in my base test, a stronger result than I have in my primary tests.

I conduct two further tests examining my results using the EJR data. In my primary tests, I keep only observations for which S&P and Moody's agree to examine the difference between privately informed and non-privately informed agencies. However, I obtain qualitatively similar or robust results when I drop this restriction, reported in Table

12. This is stronger than my primary result. As another robustness check, I repeat my primary tests using Moody's and S&P firm-level ratings for companies also rated by EJR over this time period and report these results in Table 13. My results show smaller or statistically insignificant coefficients for my reporting quality proxies than those in my primary results reported in Table 3. Using this sample as a benchmark continues to support the increased importance of reporting quality when an agency lacks private information.

Next, I replace the SFAS 142 indicator variable with indicator variables for the dates five years before and five years after the standard change went into effect and conduct my SFAS 142 tests again. Consistent with my results in Table 5 not simply capturing a time trend for the effect of goodwill on uncertainty, I fail to find results in either of these tests in Table 14. My SFAS 142 results are also robust to including my reporting quality proxies in the regressions as presented in Table 15.

If reporting quality reduces uncertainty about credit risk, it should become more important in doing so when the agencies have not evaluated the credit risk of the issuing firm recently. As long as the firm has issued rated debt in the past, the agencies would have developed an assessment of the firm's credit profile. The more recent this assessment was made, the more heavily CRAs can rely on it. If the firm has not had a rating or credit watch change recently, the agencies are forced to completely reevaluate the firm to determine its risk profile. I argue that reporting quality will become incrementally important to the extent that this occurs.

To test this, I employ an interaction term, *SinceLast*, in my primary regressions. *SinceLast* is the average of the number of years since any of the firm's debt last had a rating or credit watch change by S&P and Moody's. If a firm has not issued debt rated by one of the agencies before, I set the time of its last credit evaluation from that agency equal the agency maximum in my sample. Table 16 reports results from this test. The mean interactive effect is negative for each of my reporting quality proxies (*AsymTime* -0.004, *Cscore* -0.67, and *DCV* -0.16) and statistically significant. Thus, it appears that reporting quality is incrementally associated with a reduction in uncertainty the longer it has been since the firm's last credit rating or watch list status change, further supporting the causality of my earlier conjectures.

Finally, I conduct all tests using signed dependent variables capturing how much greater Moody's implied default rate is than S&P's, rather than the absolute value of the difference and report the results in Table 17. I do this to address the possibility that one of the agencies systematically weights reporting quality more heavily in ratings determination 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. Both agencies would increase a firm's rating as it improves its reporting quality, but Moody's will increase the rating more since it weights reporting quality more heavily. Therefore, better reporting quality would reduce the distance between the two ratings simply because of the differential weights assigned to it, not necessarily because it reduces uncertainty. I do not find any of my reporting quality variables to be statistically significant. Furthermore, I do not find significant results when examining goodwill

around SFAS 142. These tests support that my primary results capture the impact of reporting quality on uncertainty.

6. Conclusion

I study whether reporting quality reduces uncertainty about credit risk by examining disagreement between the two major credit ratings agencies, Moody's and Standard and Poor's. I find that increasing measures of asymmetric timeliness and the debt contracting value of accounting information are associated with a lower incidence of split rated debt and less disagreement about the implied probability of bond default based on historical default rates. This is consistent with greater reporting quality reducing uncertainty and better enabling the CRAs to reach a consensus on credit risk. In subsequent tests, I use ratings data from EJR to find the effects of reporting quality on credit risk uncertainty are generally greater when a rating agency does not have access to private information.

I also examine the effect of a change in accounting standards on credit risk uncertainty to alleviate the concern that my proxies for reporting quality may be capturing management's willingness to share private information with the CRAs or the agencies catering to low reporting quality firms. I find that after the FASB issued SFAS 142 there was an increase in disagreement about credit risk associated with the goodwill account for firms with substantial goodwill and for firms with goodwill likely needing impairment relative to other firms with goodwill. This corroborates my earlier results.

Overall, this paper presents evidence consistent with higher reporting quality reducing uncertainty about credit risk for informed information intermediaries with access to private information in the debt market. I leave to future research to investigate the effects of reporting quality on the forecasts of other, non-credit rating agency, debt analysts.

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Appendix A: Historic Corporate Default Rates by Letter Rating

Moody's/S&P	Average Default Rate
Aaa/AAA	0.56
Aa/AA	1.01
A/A	2.10
Baa/BBB	7.47
Ba/BB	24.53
B/B	48.53
Caa-C/CCC-C	69.19

Table 1: Summary Statistics

Panel A presents summary statistics on the variables of interest used in this study. The full sample size is 898 bonds, the non-split sample size is 453, and the sample size for the split rated is 445. ***, **, and * denote significant differences in the means of the non-split and split samples at the 1%, 5%, and 10% levels, respectively. *Split* is an indicator variable equal to one if the bond is split rated and zero otherwise. *DefaultDiff* is the difference in the default rates implied by the two credit ratings. *AsymTime* is asymmetric timeliness calculated as β_3 from a Basu (1997) regression. *Cscore* is another measure of asymmetric timeliness developed in Khan and Watts (2009). *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 current portion of long-term debt to total firm assets. *MTB* is the ratio of the market value to the book value of equity. *Goodwill1* is an indicator variable equal to one if the firm has goodwill greater than or equal to 10% of its assets and zero otherwise. *Goodwill2* is an indicator variable equal to one if the issuing firm has goodwill likely needing impairment on its balance sheet and zero otherwise. Panel B provides the Pearson correlations for the variables of interest employed in the study. Bold numbers denote a statistically significant correlation at the 5% level.

Panel A: Descriptive Statistics

	Full Sample		Non-Split Sample		Split Sample	
Variable	Mean	STD	Mean	STD	Mean	STD
Disagreement proxies						
Split	0.496	0.500	0.000	0.000	1.000***	0.000
DefaultDiff	2.211	4.393	0.000	0.000	4.461***	5.378
Reporting quality measures						
AsymTime	0.027	0.280	0.021	0.287	0.033	0.272
Cscore	0.003	0.095	0.001	0.091	0.004	0.099
DCV	0.549	0.263	0.587	0.251	0.511***	0.270
Bond-level controls						
Maturity	2.349	0.670	2.312	0.680	2.388	0.659
Face	19.103	0.895	19.059	0.913	19.148	0.876
AvgRate	7.587	3.716	7.086	3.856	8.097***	3.500
TotalCovs	3.112	3.526	2.837	3.280	3.393*	3.742
Firm level controls						
Tangibility	0.525	0.192	0.540	0.191	0.510	0.193
ROA	0.059	0.047	0.059	0.046	0.059	0.048
Size	8.393	1.479	8.629	1.593	8.153***	1.311
Leverage	0.267	0.124	0.261	0.126	0.274	0.122
MTB	2.433	1.765	2.372	1.753	2.496	1.777
Goodwill1	0.254	0.435	0.208	0.406	0.301**	0.459
Goodwill2	0.055	0.229	0.036	0.186	0.074*	0.263

Panel B: Pearson Correlations

	Split	*DefaultDiff*	*AsymTime*	*Cscore*	*DCV*	*Maturity*	*Face*	*AvgRate*	*TotalCovs*	*Tangibility*	*ROA*	*Size*	*Leverage*	*MTB*
Split	1													
DefaultDiff	**0.51**	1												
AsymTime	0.02	0.03	1											
Cscore	0.05	**0.20**	0.06	1										
DCV	**-0.15**	-0.06	0.04	-0.05	1									
Maturity	0.06	-0.01	-0.01	-0.04	0.00	1								
Face	0.05	0.07	-0.04	-0.06	**-0.15**	-0.01	1							
AvgRate	**0.14**	**0.42**	**0.11**	**0.65**	**-0.18**	-0.05	**0.16**	1						
TotalCovs	**0.08**	**0.13**	0.01	**0.20**	-0.01	0.01	**0.22**	**0.33**	1					
Tangibility	**-0.08**	0.00	**-0.07**	0.05	**0.37**	**0.20**	**-0.22**	-0.06	-0.01	1				
ROA	-0.00	**-0.18**	-0.01	**-0.44**	0.00	0.04	0.04	**-0.39**	**-0.09**	-0.05	1			
Size	**-0.16**	**-0.22**	**-0.09**	**-0.54**	**0.12**	**-0.16**	**0.23**	**-0.55**	**-0.09**	**-0.11**	**0.09**	1		
Leverage	0.05	**0.17**	0.06	**0.40**	**0.13**	-0.06	0.01	**0.37**	**0.15**	**0.09**	**-0.38**	**-0.07**	1	
MTB	0.03	**-0.10**	0.02	**-0.31**	**-0.11**	-0.04	**0.19**	**-0.14**	**0.11**	**-0.21**	**0.40**	0.04	0.00	1

Table 2: Bond Ratings Distribution

This table shows the number of observations for each Moody's and S&P rating.

	Standard and Poor's																	
Moody's	AAA	AA+	AA	AA-	A+	A	A-	BBB+	BBB	BBB-	BB+	BB	BB-	B+	B	B-	CCC+	CCC
Aaa	**42**		4															
Aa1		**4**	4															
Aa2		1	**53**	5	3													
Aa3			19	**7**	10		4											
A1			4	21	**55**	38	6											
A2				1	28	**59**	20	3										
A3					8	30	**49**	26	2									
Baa1						1	19	**27**	29	2								
Baa2							3	14	**53**	10								
Baa3								4	16	**30**	6							
Ba1								1	5	7	**7**	2						
Ba2										3	7	**11**	4	3	1			
Ba3											2	5	**19**	5	9			
B1											2	4	9	**18**	5	1		
B2														6	**10**	9	**4**	
B3														1		**13**	1	1
Caa1																2	**1**	
Split	0.00	0.20	0.37	0.79	0.47	0.54	0.51	0.64	0.50	0.42	0.71	0.50	0.41	0.45	0.60	0.48	0.83	1.00
DefaultDiff	0.00	0.11	0.28	0.81	0.53	0.68	1.62	2.95	2.31	3.33	5.59	2.41	2.97	6.25	7.66	7.41	15.81	17.24

Table 3: Credit Risk Uncertainty and Reporting Quality

This table presents the results from estimating the following Tobit (probit) regression from 1985-2008 for 898 (880) observations.

$$Disagree_t = \alpha + \beta_1 FRQ_{t-1} + \Sigma \beta_j Controls_{j,t-1} + \varepsilon_t$$

where *Disagree* is *DefaultDiff* is in Panel A and *Split* in Panel B. *DefaultDiff* is the difference in the default rates implied by the two credit ratings. *Split* is an indicator variable equal to one if the bond is split rated and zero otherwise. *FRQ* is one of three proxies for financial reporting quality, *AsymTime*, *Cscore*, or *DCV*. *AsymTime* is asymmetric timeliness calculated as β_3 from a Basu (1997) regression. *Cscore* is another measure of asymmetric timeliness developed in Khan and Watts (2009). *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 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 reports the marginal effects from the probit regression. 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 * denotes significance at the 1%, 5%, and 10% levels, respectively.

Panel A: *DefaultDiff* as a proxy for uncertainty

	AsymTime	*Cscore*	*DCV*
FRQ	**-1.02*** **	**-0.29*** **	**-2.83** **
	(-2.68)	**(-2.74)**	**(-2.02)**
Maturity	-0.19	-0.15	-0.26
	(-0.48)	(-0.41)	(-0.65)
Face	1.13**	1.01**	1.13**
	(2.51)	(2.49)	(2.48)
AvgRate	0.95***	0.93***	0.90***
	(5.63)	(6.65)	(5.45)
TotalCovs	0.19***	0.18**	0.21***
	(4.52)	(2.26)	(4.85)
Tangibility	-4.72*	-5.07**	-4.40*
	(-1.94)	(-2.10)	(-1.80)
ROA	3.42	6.09	2.85
	(0.45)	(0.89)	(0.37)
Size	-0.10		-0.11
	(-0.29)		(-0.32)
Leverage	1.10		1.86
	(0.35)		(0.60)
MTB	0.29***		0.28***
	(4.17)		(4.32)
Constant	-48.82	-27.05	-36.37
	(-1.55)	(-0.52)	(-1.18)
Pseudo R-sq (%)	6.76	8.39	6.94
Observations	898	898	898

Panel B: *Split* as a proxy for disagreement

	AsymTime	*Cscore*	*DCV*
FRQ	**-0.05**	**-0.17****	**-0.31*****
	(-0.60)	**(-2.14)**	**(-2.84)**
Maturity	0.01	0.01	-0.00
	(0.14)	(0.32)	(-0.01)
Face	0.06**	0.04	0.06*
	(2.10)	(1.49)	(1.94)
AvgRate	0.02	0.03***	0.01
	(1.57)	(3.43)	(1.24)
TotalCovs	0.02**	0.02***	0.02**
	(2.18)	(2.72)	(2.35)
Tangibility	-0.37**	-0.38***	-0.33*
	(-2.03)	(-2.63)	(-1.83)
ROA	0.57	0.83	0.52
	(0.97)	(0.54)	(0.88)
Size	-0.04		-0.03
	(-1.39)		(-1.35)
Leverage	0.17		0.25
	(0.76)		(1.12)
MTB	0.02		0.02
	(0.95)		(0.93)
Pseudo R-sq (%)	9.56	9.14	10.58
Observations	898	880	898

Table 4: Credit Risk Uncertainty and Reporting Quality in the Absence of Private Information

This table presents the results from estimating the following Tobit regression from 1999-2009 for 285 observations.

$$DefaultDiff_t = \alpha + \beta_1 FRQ_{t-1} + \Sigma \beta_j Controls_{j,t-1} + \varepsilon_t$$

where *DefaultDiff* is the difference in the default rates implied by the firm-level ratings issued by S&P and EJR. *FRQ* is one of three proxies for financial reporting quality, *AsymTime*, *Cscore*, or *DCV*. *AsymTime* is asymmetric timeliness calculated as β_3 from a Basu (1997) regression. *Cscore* is another measure of asymmetric timeliness developed in Khan and Watts (2009). *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 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 * denotes significance at the 1%, 5%, and 10% levels, respectively.

	AsymTime	*Cscore*	*DCV*
FRQ	**-1.61*** **	**-10.24** **	**-2.44*** **
	(-2.84)	**(-2.35)**	**(-4.68)**
Maturity	-0.57	-0.79	-0.60
	(-1.36)	(-1.60)	(-1.45)
Face	0.30	0.74	0.28*
	(1.60)	(1.45)	(1.65)
AvgRate	1.74**	1.49*	1.68*
	(1.98)	(1.96)	(1.93)
TotalCovs	0.31***	0.28***	0.32***
	(6.96)	(5.88)	(6.46)
Tangibility	3.25	1.08	3.61
	(1.05)	(0.36)	(1.19)
ROA	-2.83	-11.59	-4.04
	(-0.24)	(-1.17)	(-0.35)
Size	1.81		1.76
	(1.64)		(1.62)
Leverage	-17.86		-18.13
	(-0.81)		(-0.61)
MTB	0.09***		0.08***
	(3.01)		(2.89)
Constant	-39.17	-33.21	-27.09
	(-1.01)	(-0.77)	(-0.54)
Pseudo R-sq (%)	5.86	5.02	5.91
Observations	285	285	285

Table 5: Credit Risk Uncertainty and SFAS 142

This table presents the results from estimating the following Tobit regression from 1985-2008 for 898 (368) observations in Column I (II).

$$DefaultDiff_t = \alpha + \beta_1\, Goodwill_{t-1} + \beta_2\, SFAS142_t + \beta_3\, Goodwill_{t-1} \times SFAS142_t + \Sigma\, \beta_j\, Controls_{j,t-1} + \varepsilon_t$$

where *DefaultDiff* is the difference in the default rates implied by the two credit ratings. *Goodwill* is *Goodwill1* (*Goodwill2*) in Column I (II). *Goodwill1* is an indicator variable equal to one if the firm has goodwill greater than or equal to 10% of its assets and zero otherwise. *Goodwill2* is an indicator variable equal to one if the issuing firm has goodwill likely needing impairment on its balance sheet and zero otherwise. *SFAS142* is an indicator variable equal to one if the debt was issued after SFAS 142 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 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 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 * denotes significance at the 1%, 5%, and 10% levels, respectively.

	I	II
Goodwill1	0.93	
	(1.13)	
Goodwill2		1.22
		(0.58)
SFAS142	0.29	1.96
	(0.21)	(1.03)
Goodwill1 × SFAS142	**1.93***	
	(1.80)	
Goodwill2 × SFAS142		**7.94****
		(2.25)
Maturity	-0.33	-1.16
	(-0.76)	(-1.63)
Face	0.84*	1.26**
	(1.87)	(2.37)
AvgRate	0.95***	0.72***
	(5.61)	(2.87)
TotalCovs	0.17	0.20**
	(1.48)	(2.35)
Tangibility	-3.56	0.32
	(-1.43)	(0.11)
ROA	3.92	21.06
	(0.53)	(1.26)
Size	0.03	-0.09
	(0.08)	(-0.17)
Leverage	-0.18	-1.94
	(-0.05)	(-0.47)
MTB	0.26	0.05
	(1.40)	(0.22)
Trend	-0.43***	-0.44***
	(-4.40)	(-3.24)
Constant	-46.57	-83.01***
	(-1.29)	(-3.30)
Mean Interactive Effect	**1.04***	
(*Goodwill1 × SFAS142*)	**1.81**	
Mean Interactive Effect		**3.50****
(*Goodwill2 × SFAS142*)		**(2.18)**
Pseudo R-sq (%)	5.95	7.69
Observations	898	368
Year FE	Yes	Yes
Industry FE	Yes	Yes

Table 6: Credit Risk Uncertainty and Reporting Quality for Timely Gain Recognition and Overall Timeliness

This table presents the results from estimating the following Tobit regression from 1985-2008 for 898 (213) observations in Panel A (B).

$$DefaultDiff_t = \alpha + \beta_1 FRQ_{t-1} + \Sigma \beta_j Controls_{j,t-1} + \varepsilon_t$$

where *DefaultDiff* is the difference in the default rates implied by the two credit ratings. *FRQ* is one of two proxies for financial reporting quality, *TGR* or *Timeliness*. *TGR* is timely gain recognition calculated as β_2 from a Basu (1997) regression. *Timeliness* is the R^2 from the Basu (1997) regression. *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 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 A reports the results for the full sample. Panel B reports the results for the high yield sub-sample. 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 * denotes significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Full Sample

	TGR	*Timeliness*
FRQ	**-1.78**	**-1.86**
	(-0.49)	**(-1.05)**
Maturity	-0.15	-0.16
	(-0.36)	(-0.39)
Face	1.14**	1.18***
	(2.50)	(2.62)
AvgRate	0.92***	0.93***
	(5.45)	(5.56)
TotalCovs	0.19***	0.20***
	(4.48)	(4.57)
Tangibility	-4.65*	-4.64*
	(-1.91)	(-1.91)
ROA	2.64	3.02
	(0.35)	(0.40)
Size	-0.13	-0.17
	(-0.35)	(-0.46)
Leverage	1.24	0.94
	(0.39)	(0.30)
MTB	0.27***	0.26***
	(4.07)	(3.77)
Constant	-56.75*	-47.56
	(-1.77)	(-1.51)
Pseudo R-sq (%)	6.81	6.77
Observations	898	898

Panel B: High Yield Sample

	TGR	*Timeliness*
FRQ	**-1.84**	**-4.73**
	(-0.24)	**(-1.03)**
Maturity	-2.40	-2.58
	(-0.75)	(-0.82)
Face	1.03***	1.22***
	(3.14)	(3.46)
AvgRate	1.51**	1.49**
	(2.26)	(2.24)
TotalCovs	0.46**	0.49**
	(2.10)	(2.17)
Tangibility	-7.74	-8.08
	(-1.08)	(-1.18)
ROA	8.17	8.05
	(0.42)	(0.42)
Size	-0.23	-0.21
	(-0.19)	(-0.17)
Leverage	6.87	5.99
	(0.90)	(0.79)
MTB	-1.26	-1.45
	(-1.22)	(-1.40)
Constant	-139.65**	-120.76**
	(-2.57)	(-2.16)
Pseudo R-sq (%)	6.45	6.28
Observations	213	213

Table 7: Credit Risk Uncertainty and Reporting Quality for Timely Loss Recognition

This table presents the results from estimating the following Tobit (probit) regression from 1985-2008 for 898, 880, and 285 observations in the first column of Panels A and C, Column 2 of Panel A, and Panel B.

$$Disagree_t = \alpha + \beta_1 TLR_{t-1} + \Sigma \beta_j Controls_{j,t-1} + \varepsilon_t$$

where *Disagree* is *DefaultDiff* is in the first column of Panel A and Panels B and C. It is *Split* in the second column of Panel A. *DefaultDiff* is the difference in the default rates implied by the two credit ratings. *Split* is an indicator variable equal to one if the bond is split rated and zero otherwise. *TLR* is timely loss recognition calculated as the sum of β_2 and β_3 from a Basu (1997) regression. *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 current portion of long-term debt to total firm assets. *MTB* is the ratio of the market value to the book value of equity. *SinceLast* is the average of the number of years since any of the firm's debt was last rated or put on credit watch by S&P and Moody's. Column 2 of Panel A reports the marginal effects from the probit regression. Panel B presents the results when comparing ratings from EJR and the agencies with access to private information. Panel C presents cross-sectional results examining the importance of reporting quality dependent on the time since the agencies last examined a firm's credit risk profile. 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 * denotes significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Base Tests

	DefaultDiff	*Split*
FRQ	**-0.87****	**-0.08**
	(-2.18)	**(-0.93)**
Maturity	-0.18	0.01
	(-0.44)	(0.14)
Face	1.13**	0.06**
	(2.54)	(2.11)
AvgRate	0.94***	0.02
	(5.64)	(1.59)
TotalCovs	0.20***	0.02**
	(4.61)	(2.19)
Tangibility	-4.70*	-0.37**
	(-1.93)	(-2.01)
ROA	3.33	0.56
	(0.44)	(0.96)
Size	-0.11	-0.04
	(-0.30)	(-1.41)
Leverage	1.12	0.17
	(0.36)	(0.76)
MTB	0.28***	0.02
	(4.20)	(0.95)
Constant	-49.17	
	(-1.55)	
Pseudo R-sq (%)	6.75	9.64
Observations	898	898

Panel B: Comparing Ratings from EJR and the rating agencies with access to private information

TLR	**-2.38*** **
	(-4.67)
Maturity	-0.54
	(-0.77)
Face	0.30
	(1.61)
AvgRate	1.77**
	(2.01)
TotalCovs	0.33***
	(7.86)
Tangibility	3.18
	(1.03)
ROA	-1.60
	(-0.14)
Size	1.85*
	(1.69)
Leverage	-17.71
	(-0.73)
MTB	0.09***
	(3.07)
Constant	-40.12
	(-1.09)
Pseudo R-sq (%)	6.00
Observations	285

Panel C: Reporting Quality and Credit Risk under Time since Last Examined

TLR	**-2.03*** **
	(-3.25)
SinceLast	-0.01
	(-0.19)
TLR × SinceLast	**0.60**
	(0.07)
Maturity	-0.21
	(-0.53)
Face	1.12**
	(2.50)
AvgRate	0.95***
	(5.61)
TotalCovs	0.20***
	(4.03)
Tangibility	-4.66*
	(-1.93)
ROA	3.25
	(0.43)
Size	-0.10
	(-0.29)
Leverage	1.31
	(0.42)
MTB	0.30***
	(4.40)
Constant	-62.65*
	(-1.70)
Mean Interactive Effect	**0.27**
(*TLR × SinceLast*)	**(0.07)**
Pseudo R-sq (%)	6.80
Observations	898

Table 8: Credit Risk Uncertainty and Reporting Quality with an Unconstrained Dependent Variable

This table presents the results from estimating the following Tobit regression from 1985-2008 for 898 (285) observations for Panels A and C (B).

$$DefaultDiff_t = \alpha + \beta_1 FRQ_{t-1} + \Sigma \beta_j Controls_{j,t-1} + \varepsilon_t$$

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 *DCV*. *AsymTime* is asymmetric timeliness calculated as β_3 from a Basu (1997) regression. *Cscore* is another measure of asymmetric timeliness developed in Khan and Watts (2009). *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 current portion of long-term debt to total firm assets. *MTB* is the ratio of the market value to the book value of equity. *SinceLast* is the average of the number of years since any of the firm's debt was last rated or put on credit watch by S&P and Moody's. Panel A reports the results from the base test. Panel B presents the results when comparing ratings from EJR and the agencies with access to private information. Panel C presents cross-sectional results examining the importance of reporting quality dependent on the time since the agencies last examined a firm's credit risk profile. 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 * denotes significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Base Tests

	AsymTime	*Cscore*	*DCV*
FRQ	**-0.47*** **	**-3.30*** **	**0.25**
	(-3.28)	**(-3.83)**	**(0.41)**
Maturity	-0.14	-0.11	-0.12
	(-1.04)	(-1.02)	(-0.94)
Face	0.28*	0.35**	0.29*
	(1.77)	(2.22)	(1.81)
AvgRate	1.02***	0.89***	1.02***
	(14.89)	(11.72)	(14.90)
TotalCovs	-0.00	-0.03	-0.01
	(-0.07)	(-0.50)	(-0.10)
Tangibility	-0.37	0.64	-0.40
	(-0.37)	(0.68)	(-0.40)
ROA	-3.23	-7.42*	-3.28
	(-0.86)	(-1.94)	(-0.87)
Size	0.37***		0.37***
	(2.60)		(2.59)
Leverage	-0.46		-0.52
	(-0.32)		(-0.37)
MTB	0.11***		0.11***
	(3.19)		(3.14)
Constant	-26.51**	-23.73**	-27.42**
	(-2.11)	(-2.35)	(-2.16)
Pseudo R-sq (%)	15.12	15.15	15.13
Observations	898	898	898

Panel B: Comparing Ratings from EJR and the rating agencies with access to private information

	AsymTime	*Cscore*	*DCV*
FRQ	**-1.61*** **	**-28.10***	**-2.44*** **
	(-2.84)	**(-1.73)**	**(-4.89)**
Maturity	-0.57	-0.69	-0.60
	(-1.36)	(-1.48)	(-1.45)
Face	0.30	0.83	0.28
	(0.81)	(1.53)	(0.78)
AvgRate	1.74**	1.40*	1.68*
	(1.98)	(1.87)	(1.93)
TotalCovs	0.31***	0.26***	0.32***
	(6.96)	(3.92)	(6.46)
Tangibility	3.25	1.15	3.61
	(1.05)	(0.39)	(1.19)
ROA	-2.83	-8.29	-4.04
	(-0.24)	(-0.86)	(-0.35)
Size	1.81*		1.76
	(1.65)		(1.62)
Leverage	-17.86		-18.13
	(-0.81)		(-0.61)
MTB	0.09***		0.08***
	(3.01)		(2.89)
Constant	-39.17	-33.70	-27.09
	(-1.01)	(-0.87)	(-0.54)
Pseudo R-sq (%)	5.88	4.61	5.91
Observations	285	285	285

Panel C: Reporting Quality and Credit Risk under Time since Last Examined

	AsymTime	*Cscore*	*DCV*
FRQ	**-0.65***	**-1.96****	**-0.26****
	(-1.81)	**(-2.00)**	**(-2.51)**
SinceLast	-0.02	-0.01	-0.01
	(-0.59)	(-0.34)	(-0.50)
FRQ × SinceLast	**0.22**	**-0.49*****	**-0.00****
	(0.77)	**(-2.93)**	**(-1.99)**
Maturity	-0.14	-0.18	-0.12
	(-1.05)	(-1.37)	(-0.91)
Face	0.28*	0.35**	0.29*
	(1.73)	(2.13)	(1.80)
AvgRate	1.02***	0.97***	1.01***
	(14.91)	(14.58)	(14.99)
TotalCovs	-0.01	-0.02	-0.01
	(-0.16)	(-0.31)	(-0.16)
Tangibility	-0.32	-0.38	-0.37
	(-0.33)	(-0.39)	(-0.37)
ROA	-3.05	-5.54	-3.35
	(-0.83)	(-1.62)	(-0.89)
Size	0.36**		0.35**
	(2.55)		(2.50)
Leverage	-0.51		-0.57
	(-0.36)		(-0.40)
MTB	0.11		0.11
	(1.39)		(1.39)
Constant	-34.45***	-24.58**	-29.67**
	(-2.60)	(-2.13)	(-2.38)
Mean Interactive Effect	**0.18**	**-0.26****	**-0.00****
(*FRQ* × *SinceLast*)	**(0.76)**	**(-2.52)**	**(-1.97)**
Pseudo R-sq (%)	15.31	15.12	15.21
Observations	898	898	898

Table 9: Credit Risk Uncertainty and Reporting Quality controlling for Additional Features of Firm Operating and Information Environments

This table presents the results from estimating the following Tobit regression from 1985-2008 for 898 (285) observations for Panels A through H (I).

$$DefaultDiff_t = \alpha + \beta_1 FRQ_{t-1} + \Sigma \beta_j Controls_{j,t-1} + \varepsilon_t$$

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 *DCV*. *AsymTime* is asymmetric timeliness calculated as β_3 from a Basu (1997) regression. *Cscore* is another measure of asymmetric timeliness developed in Khan and Watts (2009). *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 current portion of long-term debt to total firm assets. *MTB* is the ratio of the market value to the book value of equity. *Seniority* is an indicator variable equal to one if the debt being issued has seniority and zero otherwise. *OpCycle* is the firm's operating cycle. *Zscore* is Altman's (1968) Z-score for predicting bankruptcy. *Following* is the number of equity analysts following the firm in the previous year. *Dispersion* is the dispersion of equity analysts' forecast over the previous year. *σ(Rate)*is the standard deviation of the credit ratings received on all new debt issues from the firm over the previous year. *σ(Ret)*is the standard deviation of the firm's daily stock returns over the previous year. *σ(CFO)*is the standard deviation of cash flows from operations over a five year period. Panels A through H present results from the base test controlling for additional variables. Panel I examines the effect of reporting quality on the difference between EJR ratings and ratings from the agencies with access to private information while controlling for cash flow volatility. 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 * denotes significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Controlling for Debt Seniority

	AsymTime	*Cscore*	*DCV*
FRQ	**-0.98*** **	**-1.55*** **	**-2.78** **
	(-2.73)	**(-2.48)**	**(-1.99)**
Maturity	-0.28	-0.24	-0.34
	(-0.72)	(-0.62)	(-0.88)
Face	1.13**	1.06***	1.14**
	(2.56)	(3.08)	(2.53)
AvgRate	0.87***	0.88***	0.82***
	(5.09)	(5.75)	(4.96)
TotalCovs	0.20	0.20**	0.21*
	(1.62)	(2.42)	(1.71)
Tangibility	-4.46*	-4.67**	-4.18*
	(-1.87)	(-2.54)	(-1.74)
ROA	2.69	4.70	2.22
	(0.35)	(0.83)	(0.29)
Size	-0.09		-0.10
	(-0.27)		(-0.29)
Leverage	1.01		1.77
	(0.33)		(0.57)
MTB	0.26		0.25
	(1.43)		(1.39)
Seniority	-3.61*	-3.80***	-3.66*
	(-1.76)	(-2.89)	(-1.79)
Constant	-44.30	-30.31	-33.19
	(-1.36)	(-1.43)	(-1.07)
Pseudo R-sq (%)	6.97	6.84	7.15
Observations	898	898	898

Panel B: Controlling for Operating Cycle

	AsymTime	*Cscore*	*DCV*
FRQ	**-0.96*** **	**-1.53*** **	**-2.61* **
	(-2.61)	**(-2.89)**	**(-1.85)**
Maturity	-0.21	-0.15	-0.26
	(-0.52)	(-0.40)	(-0.64)
Face	1.12**	1.06***	1.13**
	(2.49)	(3.05)	(2.49)
AvgRate	0.95***	0.96***	0.90***
	(5.65)	(6.11)	(5.48)
TotalCovs	0.20	0.20**	0.21*
	(1.63)	(2.40)	(1.70)
Tangibility	-4.92**	-5.19***	-4.59*
	(-2.03)	(-2.80)	(-1.88)
ROA	1.99	4.40	1.68
	(0.26)	(0.76)	(0.22)
Size	-0.09		-0.10
	(-0.24)		(-0.28)
Leverage	1.07		1.77
	(0.35)		(0.57)
MTB	0.29*		0.28
	(1.65)		(1.58)
OpCycle	-0.97	-1.04	-0.85
	(-1.27)	(-1.59)	(-1.11)
Constant	-74.89*	-50.43*	-50.70
	(-1.89)	(-1.95)	(-1.21)
Pseudo R-sq (%)	6.87	6.70	6.99
Observations	898	898	898

Panel C: Controlling for Altman's Z-score

	AsymTime	*Cscore*	*DCV*
FRQ	**-0.99*** **	**-0.43*** **	**-2.61* **
	(-2.95)	**(-2.69)**	**(-1.90)**
Maturity	-0.23	-0.23	-0.29
	(-0.56)	(-0.59)	(-0.71)
Face	1.04**	1.09***	1.06**
	(2.37)	(3.14)	(2.38)
AvgRate	0.97***	0.95***	0.93***
	(5.89)	(6.09)	(5.70)
TotalCovs	0.20*	0.20**	0.21*
	(1.68)	(2.50)	(1.77)
Tangibility	-4.20*	-4.55**	-3.94
	(-1.76)	(-2.47)	(-1.64)
ROA	-7.04	-5.20	-7.46
	(-0.85)	(-0.76)	(-0.91)
Size	0.09		0.08
	(0.26)		(0.22)
Leverage	3.58		4.25
	(1.09)		(1.29)
MTB	0.26		0.25
	(1.44)		(1.41)
Zscore	1.39**	1.15***	1.37**
	(2.47)	(2.86)	(2.49)
Constant	-35.11	-22.59	-27.47
	(-1.12)	(-1.04)	(-0.89)
Pseudo R-sq (%)	7.13	6.93	7.26
Observations	898	898	898

Panel D: Controlling for Analyst Following

	AsymTime	*Cscore*	*DCV*
FRQ	**-1.02*** **	**-3.62*** **	**-2.81** **
	(-2.64)	**(-2.45)**	**(-2.00)**
Maturity	-0.12	-0.14	-0.18
	(-0.31)	(-0.38)	(-0.48)
Face	1.20***	1.24***	1.20***
	(2.76)	(3.47)	(2.73)
AvgRate	0.91***	0.89***	0.86***
	(5.54)	(5.74)	(5.35)
TotalCovs	0.18	0.19**	0.19
	(1.56)	(2.28)	(1.65)
Tangibility	-4.14*	-4.63**	-3.81
	(-1.71)	(-2.50)	(-1.56)
ROA	2.64	4.40	2.05
	(0.34)	(0.76)	(0.26)
Size	0.23		0.22
	(0.60)		(0.58)
Leverage	0.36		1.10
	(0.11)		(0.35)
MTB	0.37**		0.36**
	(2.03)		(1.98)
Following	-0.10**	-0.08**	-0.10**
	(-1.97)	(-2.20)	(-2.03)
Constant	-49.94	-30.84	-36.99
	(-1.58)	(-1.38)	(-1.22)
Pseudo R-sq (%)	6.97	6.79	7.16
Observations	898	898	898

Panel E: Controlling for Analyst Dispersion

	AsymTime	*Cscore*	*DCV*
FRQ	**-0.90****	**-2.38*****	**-3.28****
	(-2.16)	**(-2.79)**	**(-2.31)**
Maturity	-0.15	-0.11	-0.24
	(-0.39)	(-0.30)	(-0.62)
Face	1.30***	1.21***	1.28***
	(3.04)	(3.56)	(2.94)
AvgRate	1.00***	1.00***	0.95***
	(5.70)	(6.27)	(5.53)
TotalCovs	0.08	0.09	0.10
	(0.66)	(1.02)	(0.78)
Tangibility	-5.24**	-5.46***	-4.91**
	(-2.15)	(-3.00)	(-2.01)
ROA	0.18	3.53	-0.98
	(0.02)	(0.61)	(-0.13)
Size	-0.10		-0.11
	(-0.28)		(-0.31)
Leverage	-0.43		0.24
	(-0.14)		(0.07)
MTB	0.27		0.27
	(1.59)		(1.60)
Dispersion	-21.79	-20.61	-22.60
	(-1.25)	(-1.24)	(-1.33)
Constant	-46.22	-32.15	-34.81
	(-1.47)	(-1.45)	(-1.17)
Pseudo R-sq (%)	7.22	7.10	7.44
Observations	854	854	854

Panel F: Controlling for the Rating Volatility

	AsymTime	*Cscore*	*DCV*
FRQ	**-1.10*** **	**-1.20*** **	**-2.79** **
	(-3.49)	**(-2.85)**	**(-2.00)**
Maturity	-0.20	-0.13	-0.25
	(-0.47)	(-0.34)	(-0.61)
Face	1.11**	1.03***	1.11**
	(2.51)	(2.96)	(2.46)
AvgRate	0.94***	0.96***	0.89***
	(5.62)	(5.81)	(5.43)
TotalCovs	0.19	0.19**	0.20
	(1.57)	(2.31)	(1.63)
Tangibility	-4.45*	-4.81***	-4.16*
	(-1.80)	(-2.60)	(-1.68)
ROA	2.75	5.30	2.16
	(0.36)	(0.92)	(0.28)
Size	-0.11		-0.13
	(-0.30)		(-0.36)
Leverage	1.12		1.86
	(0.36)		(0.60)
MTB	0.28		0.27
	(1.57)		(1.49)
σ(Rate)	-0.98	-0.45	-0.80
	(-0.94)	(-0.40)	(-0.79)
Constant	-23.53	-29.10	-6.75
	(-0.65)	(-1.36)	(-0.20)
Pseudo R-sq (%)	6.84	6.70	7.01
Observations	898	898	898

Panel G: Controlling for the Return Volatility

	AsymTime	*Cscore*	*DCV*
FRQ	**-1.01*** **	**-0.98*** **	**-2.83** **
	(-2.78)	**(-2.64)**	**(-2.02)**
Maturity	-0.20	-0.14	-0.26
	(-0.48)	(-0.36)	(-0.65)
Face	1.13**	1.07***	1.14**
	(2.50)	(3.06)	(2.49)
AvgRate	0.96***	1.00***	0.92***
	(5.45)	(5.80)	(5.30)
TotalCovs	0.19	0.19**	0.20*
	(1.58)	(2.32)	(1.68)
Tangibility	-4.65*	-4.92***	-4.34*
	(-1.92)	(-2.66)	(-1.78)
ROA	3.06	5.85	2.49
	(0.41)	(1.02)	(0.33)
Size	-0.12		-0.13
	(-0.33)		(-0.36)
Leverage	1.10		1.84
	(0.35)		(0.59)
MTB	0.29		0.28
	(1.59)		(1.57)
σ(Ret)	-19.36	-12.52	-21.71
	(-0.37)	(-0.30)	(-0.41)
Constant	-50.63*	-38.96*	-39.35
	(-1.66)	(-1.83)	(-1.31)
Pseudo R-sq (%)	6.83	6.64	6.97
Observations	898	898	898

Panel H: Controlling for the Cash Flow Volatility

	AsymTime	*Cscore*	*DCV*
FRQ	**-1.00*** **	**-1.49*** **	**-2.81** **
	(-2.64)	**(-2.83)**	**(-2.00)**
Maturity	-0.19	-0.14	-0.25
	(-0.45)	(-0.36)	(-0.62)
Face	1.11**	1.03***	1.11**
	(2.46)	(2.95)	(2.42)
AvgRate	0.95***	0.97***	0.90***
	(5.57)	(5.67)	(5.39)
TotalCovs	0.19	0.19**	0.20
	(1.54)	(2.27)	(1.62)
Tangibility	-4.64*	-4.87***	-4.33*
	(-1.89)	(-2.62)	(-1.76)
ROA	3.47	5.78	2.89
	(0.46)	(1.00)	(0.38)
Size	-0.10		-0.11
	(-0.28)		(-0.31)
Leverage	1.08		1.84
	(0.35)		(0.59)
MTB	0.28		0.27
	(1.56)		(1.52)
σ(CFO)	2.99	5.37	3.22
	(0.32)	(0.63)	(0.34)
Constant	-31.82	-22.96	-20.90
	(-0.79)	(-0.96)	(-0.56)
Pseudo R-sq (%)	6.78	6.64	6.96
Observations	898	898	898

Panel I: Reporting Quality and Credit Risk Comparing Ratings from EJR and the rating agencies with access to private information while controlling for the Cash Flow Volatility

	AsymTime	*Cscore*	*DCV*
FRQ	**-1.72*** **	**-25.65**	**-1.82**
	(-2.95)	**(-1.63)**	**(-0.80)**
Maturity	-0.57	-0.73	-0.62
	(-1.47)	(-1.60)	(-1.55)
Face	0.20	0.71	0.19
	(0.56)	(1.33)	(0.54)
AvgRate	1.66*	1.27*	1.59*
	(1.86)	(1.71)	(1.80)
TotalCovs	0.27***	0.22***	0.27***
	(6.09)	(3.84)	(6.19)
Tangibility	3.72	2.10	4.12
	(1.19)	(0.75)	(1.35)
ROA	-2.07	-9.09	-4.02
	(-0.18)	(-0.91)	(-0.34)
Size	1.81*		1.75
	(1.65)		(1.59)
Leverage	-16.14*		-16.59*
	(-1.83)		(-1.86)
MTB	0.08***		0.08***
	(2.68)		(2.62)
σ(CFO)	31.66	38.65*	29.43
	(1.62)	(1.96)	(1.51)
Constant	-64.07	-59.54	-46.27
	(-1.30)	(-1.17)	(-0.84)
Pseudo R-sq (%)	6.40	5.29	6.37
Observations	285	285	285

Table 10: Credit Risk Uncertainty and Reporting Quality for *Cscore* including Controls that are Components of *Cscore*

This table presents the results from estimating the following Tobit (probit) regression from 1985-2008 for 898, 880, and 285 observations in the first column of Panels A and C, Column 2 of Panel A, and Panel B.

$$Disagree_t = \alpha + \beta_1 \, Cscore_{t-1} + \Sigma \, \beta_j \, Controls_{j,t-1} + \varepsilon_t$$

where *Disagree* is *DefaultDiff* in the first column of Panel A and in Panels B and C and *Split* in the second column of Panel A. *DefaultDiff* is the difference in the default rates implied by the two credit ratings. *Split* is an indicator variable equal to one if the bond is split rated and zero otherwise. *Cscore* is a measure of asymmetric timeliness developed in Khan and Watts (2009). *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 current portion of long-term debt to total firm assets. *MTB* is the ratio of the market value to the book value of equity. *SinceLast* is the average of the number of years since any of the firm's debt was last rated or put on credit watch by S&P and Moody's. The second column reports the marginal effects from the probit regression. Both 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 * denotes significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Base Tests

	DefaultDiff	*Split*
Cscore	**-0.53*** **	**-0.32*** **
	(-2.74)	**(-2.40)**
Maturity	-0.16	0.01
	(-0.44)	(0.17)
Face	1.06***	0.06**
	(2.90)	(2.05)
AvgRate	0.92***	0.02**
	(8.21)	(1.96)
TotalCovs	0.18**	0.02**
	(2.19)	(2.42)
Tangibility	-4.81***	-0.42***
	(-2.63)	(-2.77)
ROA	3.96	0.67
	(0.64)	(1.32)
Size	-0.08	-0.04*
	(-0.28)	(-1.77)
Leverage	1.73	0.28
	(0.70)	(1.38)
MTB	0.26***	0.01
	(2.99)	(0.74)
Constant	-37.05	
	(-1.14)	
Pseudo R-sq (%)	6.78	9.54
Observations	898	898

Panel B: Comparing Ratings from EJR and the rating agencies with access to private information

	Cscore
FRQ	**-11.85****
	(-1.98)
Maturity	-0.57
	(-1.39)
Face	0.36*
	(1.77)
AvgRate	1.77**
	(2.00)
TotalCovs	0.30***
	(6.38)
Tangibility	3.22
	(1.07)
ROA	-5.09
	(-0.39)
Size	1.33
	(1.24)
Leverage	-16.57
	(-0.72)
MTB	0.08***
	(2.66)
Constant	-44.79
	(-1.08)
Pseudo R-sq (%)	6.58
Observations	285

Panel C: Reporting Quality and Credit Risk under Time since Last Examined

	Cscore
FRQ	**-0.47**
	(-0.95)
SinceLast	0.13*
	(1.82)
FRQ × SinceLast	**-1.87****
	(-2.46)
Maturity	-0.18
	(-0.45)
Face	1.13**
	(2.50)
AvgRate	0.93***
	(5.55)
TotalCovs	0.19***
	(3.78)
Tangibility	-4.69*
	(-1.94)
ROA	2.71
	(0.36)
Size	-0.14
	(-0.38)
Leverage	1.56
	(0.48)
MTB	0.25**
	(2.08)
Constant	-42.76
	(-1.36)
Mean Interactive Effect	**-0.87****
(*FRQ* × *SinceLast*)	**(-2.43)**
Pseudo R-sq (%)	6.83
Observations	898

Table 11: Credit Risk Uncertainty and Reporting Quality for Asymmetric Timeliness with Firm Fixed Effects

This table presents the results from estimating the following Tobit (probit) regression from 1985-2008 for 898, 880, and 285 observations in the first column of Panels A and C, Column 2 of Panel A, and Panel B.

$$Disagree_t = \alpha + \beta_1 FRQ_{t-1} + \Sigma \beta_j Controls_{j,t-1} + \varepsilon_t$$

where *Disagree* is *DefaultDiff* is in the first column of Panel A and Panels B and C. It is *Split* in the second column of Panel A. *DefaultDiff* is the difference in the default rates implied by the two credit ratings. *Split* is an indicator variable equal to one if the bond is split rated and zero otherwise. *FRQ* is one of three proxies for financial reporting quality, *AsymTime*, *Cscore*, or *DCV*. *AsymTime* is asymmetric timeliness calculated as β_3 from a Basu (1997) regression. *Cscore* is another measure of asymmetric timeliness developed in Khan and Watts (2009). *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 current portion of long-term debt to total firm assets. *MTB* is the ratio of the market value to the book value of equity. *SinceLast* is the average of the number of years since any of the firm's debt was last rated or put on credit watch by S&P and Moody's. Column 2 of Panel A reports the marginal effects from the probit regression. Panel B presents the results when comparing ratings from EJR and the agencies with access to private information. Panel C presents cross-sectional results examining the importance of reporting quality dependent on the time since the agencies last examined a firm's credit risk profile. 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 * denotes significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Base Tests

	DefaultDiff	*Split*
AsymTime	**-2.88*** **	**-0.02** **
	(-2.84)	**(-1.98)**
Maturity	0.09	0.01
	(0.23)	(0.30)
Face	0.74	0.04
	(1.23)	(0.72)
AvgRate	0.72**	0.00
	(2.42)	(0.15)
TotalCovs	0.18	0.01
	(1.01)	(1.25)
Tangibility	0.19	0.48
	(0.04)	(1.21)
ROA	-1.15	-0.18
	(-0.11)	(-0.23)
Size	0.17	0.01
	(0.18)	(0.15)
Leverage	11.96**	0.47
	(2.33)	(0.98)
MTB	0.06	0.03
	(0.17)	(0.80)
Constant	-42.08***	
	(-3.65)	
Pseudo R-sq (%)	6.80	0.09
Observations	898	898

Panel B: Comparing Ratings from EJR and the rating agencies with access to private information

AsymTime	**-1.61*** **
	(-2.84)
Maturity	-0.57
	(-1.36)
Face	0.30
	(0.81)
AvgRate	1.74**
	(1.98)
TotalCovs	0.31
	(1.48)
Tangibility	3.25
	(1.05)
ROA	-2.83
	(-0.24)
Size	1.81*
	(1.65)
Leverage	-17.86**
	(-2.02)
MTB	0.09
	(0.81)
Constant	-39.17
	(-1.01)
Pseudo R-sq (%)	5.88
Observations	285

Panel C: Reporting Quality and Credit Risk under Time since Last Examined

AsymTime	**-2.95*** **
	(-5.66)
SinceLast	0.01***
	(5.16)
AsymTime × SinceLast	**0.07**
	(0.09)
Maturity	-0.10
	(-0.24)
Face	0.14**
	(2.55)
AvgRate	0.82***
	(5.71)
TotalCovs	0.05***
	(3.96)
Tangibility	-1.28*
	(-1.83)
ROA	4.35
	(0.16)
Size	1.41
	(1.60)
Leverage	0.75
	(0.32)
MTB	0.29***
	(3.81)
Constant	-41.03***
	(-4.20)
Mean Interactive Effect	**0.02**
(*FRQ* × *SinceLast*)	**0.06**
Pseudo R-sq (%)	3.52
Observations	898

Table 12: Credit Risk Uncertainty and Reporting Quality in the Absence of Private Information for Unrestricted Sample

This table presents the results from estimating the following Tobit regression from 1999-2009 for 562 observations.

$$DefaultDiff_t = \alpha + \beta_1 FRQ_{t-1} + \Sigma \beta_j Controls_{j,t-1} + \varepsilon_t$$

where *DefaultDiff* is the difference in the default rates implied by the firm-level ratings issued by the agencies with access to private information and EJR. *FRQ* is one of three proxies for financial reporting quality, *AsymTime*, *Cscore*, or *DCV*. *AsymTime* is asymmetric timeliness calculated as β_3 from a Basu (1997) regression. *Cscore* is another measure of asymmetric timeliness developed in Khan and Watts (2009). *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 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 * denotes significance at the 1%, 5%, and 10% levels, respectively.

	AsymTime	*Cscore*	*DCV*
FRQ	**-0.82**	**-17.05****	**-2.06**
	(-1.33)	**(-2.16)**	**(-1.22)**
Maturity	-0.46	-0.62	-0.52
	(-1.25)	(-1.58)	(-1.40)
Face	0.01	0.56	-0.01
	(0.03)	(1.32)	(-0.03)
AvgRate	1.43***	1.25***	1.43***
	(4.71)	(4.17)	(4.67)
TotalCovs	0.25**	0.25**	0.24**
	(2.18)	(2.17)	(2.16)
Tangibility	-0.24	-0.67	-0.39
	(-0.11)	(-0.30)	(-0.17)
ROA	-1.52	-5.74	-2.10
	(-0.26)	(-1.10)	(-0.36)
Size	1.30***		1.29***
	(2.73)		(2.67)
Leverage	-5.77		-6.05
	(-1.36)		(-1.42)
MTB	0.19*		0.19*
	(1.75)		(1.77)
Constant	55.75	2.86	52.03
	(0.91)	(0.08)	(0.93)
Pseudo R-sq (%)	5.45	4.95	5.58
Observations	562	562	562

Table 13: Credit Risk Uncertainty and Reporting Quality using Firm-level Ratings for Companies also Rated by Egan-Jones Ratings Company

This table presents the results from estimating the following Tobit regression from 1985-2008 for 552 observations.

$$DefaultDiff_t = \alpha + \beta_1 FRQ_{t-1} + \Sigma \beta_j Controls_{j,t-1} + \varepsilon_t$$

where *DefaultDiff* is the difference in the default rates implied by the two credit ratings, S&P and Moody's. *FRQ* is one of three proxies for financial reporting quality, *AsymTime*, *Cscore*, or *DCV*. *AsymTime* is asymmetric timeliness calculated as β_3 from a Basu (1997) regression. *Cscore* is another measure of asymmetric timeliness developed in Khan and Watts (2009). *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 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 * denotes significance at the 1%, 5%, and 10% levels, respectively.

	AsymTime	*Cscore*	*DCV*
FRQ	**0.58**	**-2.37**	**-1.21***
	(0.80)	**(-0.86)**	**(-1.74)**
Maturity	-0.14	-0.13	-0.15
	(-0.77)	(-0.76)	(-0.81)
Face	-0.37	-0.36*	-0.39
	(-1.43)	(-1.69)	(-1.57)
AvgRate	0.69***	0.67***	0.69***
	(4.32)	(5.79)	(4.47)
TotalCovs	-0.12*	-0.12*	-0.12*
	(-1.88)	(-1.80)	(-1.82)
Tangibility	1.02	0.79	0.80
	(0.77)	(0.60)	(0.62)
ROA	-1.69	-1.41	-2.56
	(-0.38)	(-0.36)	(-0.55)
Size	0.05		0.06
	(0.20)		(0.23)
Leverage	-1.34		-1.32
	(-0.67)		(-0.63)
MTB	0.07		0.08
	(1.19)		(1.32)
Constant	-28.50	3.12	-15.76
	(-0.72)	(0.15)	(-0.49)
Pseudo R-sq (%)	9.85	9.38	9.82
Observations	552	552	552

Table 14: Credit Risk Uncertainty and SFAS 142 – Time Shift Robustness

This table presents the results from estimating the following Tobit regression from 1985-2008 for 898 (368) observations in Column I (II).

$$DefaultDiff_t = \alpha + \beta_1\ Goodwill_{t-1} + \beta_2\ SFAS142_t + \beta_3\ Goodwill_{t-1} \times SFAS142_t + \Sigma\ \beta_j\ Controls_{j,t-1} + \varepsilon_t$$

where *DefaultDiff* is the difference in the default rates implied by the two credit ratings. *Goodwill* is *Goodwill1* (*Goodwill2*) in Column I (II). *Goodwill1* is an indicator variable equal to one if the firm has goodwill greater than or equal to 10% of its assets and zero otherwise. *Goodwill2* is an indicator variable equal to one if the issuing firm has goodwill likely needing impairment on its balance sheet and zero otherwise. In Panel A (B), *SFAS142* is an indicator variable equal to one if the debt was issued in the time period beginning five years before (after) SFAS 142 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 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 current portion of long-term debt to total firm assets. *MTB* is the ratio of the market value to the book value of equity. *Goodwill1* is an indicator variable equal to one if the firm has goodwill greater than or equal to 10% of its assets and zero otherwise. *Goodwill2* is an indicator variable equal to one if the issuing firm has goodwill likely needing impairment on its balance sheet and zero otherwise. *SFAS142* is an indicator variable equal to one if the debt was issued after SFAS 142 took effect. *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 * denotes significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Replacing Date of SFAS 142 with Date Five Years Earlier

	I	II
Goodwill1	1.27	
	(1.03)	
Goodwill2		1.26
		(0.60)
SFAS142	-2.56	-3.48
	(-1.61)	(-1.60)
Goodwill1 × SFAS142	**0.33**	
	(0.20)	
Goodwill2 × SFAS142		**3.72**
		(1.06)
Maturity	-0.30	-1.03
	(-0.71)	(-1.50)
Face	0.91**	1.28**
	(2.06)	(2.37)
AvgRate	0.95***	0.72***
	(5.62)	(2.92)
TotalCovs	0.13	0.16
	(1.11)	(1.06)
Tangibility	-3.82	-0.02
	(-1.57)	(-0.01)
ROA	3.32	16.31
	(0.45)	(1.39)
Size	-0.02	-0.06
	(-0.06)	(-0.12)
Leverage	-0.46	-1.86
	(-0.14)	(-0.44)
MTB	0.28	0.09
	(1.55)	(0.38)
Trend	-0.23**	-0.09
	(-2.13)	(-0.62)
Constant	-49.04	-89.50***
	(-1.37)	(-3.40)
Mean Interactive Effect	**0.02**	
(*Goodwill1 × SFAS142*)	**0.03**	
Mean Interactive Effect		**1.61**
(*Goodwill2 × SFAS142*)		**(1.05)**
Pseudo R-sq (%)	5.96	7.50
Observations	898	368
Year FE	Yes	Yes
Industry FE	Yes	Yes

Panel B: Replacing Date of SFAS 142 with Date Five Years Later

	I	II
Goodwill1	1.45	
	(1.61)	
Goodwill2		2.41
		(1.40)
SFAS142	2.42	2.37
	(0.95)	(1.62)
Goodwill1 × SFAS142	**0.37**	
	(0.14)	
Goodwill2 × SFAS142		**4.96**
		(1.41)
Maturity	-0.26	-1.01
	(-0.66)	(-1.45)
Face	0.91**	1.31**
	(2.05)	(2.41)
AvgRate	0.95***	0.75***
	(5.70)	(2.98)
TotalCovs	0.17	0.20
	(1.48)	(1.25)
Tangibility	-3.88	0.41
	(-1.59)	(0.13)
ROA	1.99	13.94
	(0.27)	(1.14)
Size	-0.02	-0.06
	(-0.05)	(-0.11)
Leverage	-0.43	-2.16
	(-0.13)	(-0.51)
MTB	0.29*	0.09
	(1.65)	(0.39)
Trend	-0.43***	-0.37***
	(-5.58)	(-3.76)
Constant	-47.37	-77.87***
	(-1.31)	(-2.81)
Mean Interactive Effect	**0.01**	
(*Goodwill1 × SFAS142*)	**(0.14)**	
Mean Interactive Effect		**2.20**
(*Goodwill2 × SFAS142*)		**(1.38)**
Pseudo R-sq (%)	6.00	7.44
Observations	898	368
Year FE	Yes	Yes
Industry FE	Yes	Yes

Table 15: Credit Risk Uncertainty and SFAS 142 Controlling for Reporting Quality

This table presents the results from estimating the following Tobit regression from 1985-2008 for 898 (368) observations in Panel A (B).

$$DefaultDiff_t = \alpha + \beta_1\, Goodwill_{t-1} + \beta_2\, SFAS142_t + \beta_3\, Goodwill_{t-1} \times SFAS142_t + \beta_4\, FRQ_{t-1} + \Sigma\, \beta_j\, Controls_{j,t-1} + \varepsilon_t$$

where *DefaultDiff* is the difference in the default rates implied by the two credit ratings. *Goodwill* is *Goodwill1* (*Goodwill2*) in Panel A (B). *Goodwill1* is an indicator variable equal to one if the firm has goodwill greater than or equal to 10% of its assets and zero otherwise. *Goodwill2* is an indicator variable equal to one if the issuing firm has goodwill likely needing impairment on its balance sheet and zero otherwise. *SFAS142* is an indicator variable equal to one if the debt was issued after SFAS 142 took effect. *FRQ* is one of three proxies for financial reporting quality, *AsymTime*, *Cscore*, or *DCV*. *AsymTime* is asymmetric timeliness calculated as β_3 from a Basu (1997) regression. *Cscore* is another measure of asymmetric timeliness developed in Khan and Watts (2009). *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 current portion of long-term debt to total firm assets. *MTB* is the ratio of the market value to the book value of equity. *Goodwill* is *Goodwill1* in Panel A and *Goodwill2* in Panel B. *Goodwill1* is an indicator variable equal to one if the firm has goodwill greater than or equal to 10% of its assets and zero otherwise. *Goodwill2* is an indicator variable equal to one if the issuing firm has goodwill likely needing impairment on its balance sheet and zero otherwise. *SFAS142* is an indicator variable equal to one if the debt was issued after SFAS 142 took effect. *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 * denotes significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Full Sample

	AsymTime	*Cscore*	*DCV*
Goodwill1	-0.17	-0.09	-0.19
	(-0.16)	(-0.09)	(-0.18)
SFAS142	0.38	0.03	-0.11
	(0.21)	(0.02)	(-0.06)
Goodwill1 × SFAS142	**3.93****	**3.57****	**3.97****
	(2.26)	**(2.06)**	**(2.34)**
FRQ	-0.08***	-2.28*	-2.89**
	(-2.75)	(-1.85)	(-2.06)
Maturity	-0.03	-0.03	-0.07
	(-0.07)	(-0.08)	(-0.18)
Face	0.25	0.32	0.24
	(0.59)	(0.79)	(0.54)
AvgRate	0.87***	0.87***	0.84***
	(4.95)	(5.60)	(5.01)
TotalCovs	0.09	0.09	0.10
	(0.76)	(0.76)	(0.86)
Tangibility	-2.40	-2.34	-2.15
	(-0.93)	(-0.92)	(-0.83)
ROA	3.76	2.26	3.76
	(0.49)	(0.34)	(0.49)
Size	0.13		0.12
	(0.36)		(0.33)
Leverage	0.13		0.86
	(0.04)		(0.26)
MTB	0.01		0.01
	(0.09)		(0.04)
Trend	-0.46***	-0.41***	-0.41***
	(-4.46)	(-4.38)	(-4.40)
Constant	-19.67	-4.77	9.56
	(-0.59)	(-0.13)	(0.28)
Mean Interactive Effect	**1.84****	**1.72***	**1.87****
(*Goodwill* × *SFAS142*)	**(2.14)**	**(2.02)**	**(2.09)**
Pseudo R-sq (%)	5.99	5.89	6.17
Observations	898	898	898

Panel B: Sub-sample Containing Only Firms with Goodwill

	AsymTime	*Cscore*	*DCV*
Goodwill2	1.52	1.38	1.32
	(0.81)	(0.76)	(0.71)
SFAS142	2.18	2.42	1.90
	(1.28)	(1.51)	(1.10)
Goodwill2 × SFAS142	**8.01****	**7.84****	**7.84****
	(2.15)	**(1.98)**	**(2.04)**
FRQ	-1.89	0.20	-1.32
	(-1.22)	(0.05)	(-0.74)
Maturity	-1.13	-1.08	-1.17*
	(-1.57)	(-1.41)	(-1.66)
Face	1.21**	1.26**	1.24**
	(2.28)	(2.29)	(2.33)
AvgRate	0.77***	0.74***	0.72***
	(3.05)	(3.69)	(2.83)
TotalCovs	0.20**	0.21	0.21**
	(2.35)	(1.26)	(2.46)
Tangibility	0.14	0.18	0.41
	(0.05)	(0.06)	(0.14)
ROA	19.88	23.73**	21.23*
	(1.21)	(2.05)	(1.88)
Size	-0.07		-0.05
	(-0.14)		(-0.10)
Leverage	-2.07		-1.52
	(-0.51)		(-0.36)
MTB	0.07		0.04
	(0.30)		(0.20)
Trend	-0.46***	-0.47***	-0.44***
	(-3.44)	(-3.67)	(-3.32)
Constant	-56.84**	-56.84**	-79.39***
	(-2.31)	(-2.31)	(-3.12)
Mean Interactive Effect	-79.51***	**3.71****	**3.48****
(*Goodwill × SFAS142*)	(-3.18)	**(1.96)**	**(1.98)**
Pseudo R-sq (%)	7.83	6.89	7.73
Observations	368	368	368

Table 16: Credit Risk Uncertainty and Reporting Quality under Time since Last Examined

This table presents the results from estimating the following Tobit regression from 1985-2008 for 898 observations.

$$DefaultDiff_t = \alpha + \beta_1 FRQ_{t-1} + \beta_2 SinceLast_t + \beta_3 FRQ_{t-1} \times SinceLast_t + \Sigma \beta_j Controls_{j,t-1} + \varepsilon_t$$

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 *DCV*. *AsymTime* is asymmetric timeliness calculated as β_3 from a Basu (1997) regression. *Cscore* is another measure of asymmetric timeliness developed in Khan and Watts (2009). *DCV* is the Somers' D from the estimation of a probit of downgrades on seasonally adjusted quarterly earnings. *SinceLast* is the average of the number of years since any of the firm's debt was last rated or put on credit watch by S&P and Moody's. *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 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 * denotes significance at the 1%, 5%, and 10% levels, respectively.

	AsymTime	*Cscore*	*DCV*
FRQ	**-1.02***	**-0.59**	**-2.65***
	(-1.70)	**(-0.20)**	**(-1.89)**
SinceLast	0.03	0.03**	0.04
	(0.75)	(2.00)	(0.65)
FRQ × SinceLast	**-0.01****	**-2.05****	**-0.37*****
	(-2.00)	**(-2.45)**	**(-2.75)**
Maturity	-0.19	-0.18	-0.24
	(-0.47)	(-0.45)	(-0.62)
Face	1.09**	1.04**	1.12**
	(2.45)	(2.39)	(2.45)
AvgRate	0.95***	0.97***	0.90***
	(5.62)	(7.08)	(5.41)
TotalCovs	0.19***	0.20***	0.21***
	(3.83)	(4.03)	(4.18)
Tangibility	-4.55*	-5.05**	-4.44*
	(-1.86)	(-2.05)	(-1.81)
ROA	3.12	5.12	2.76
	(0.42)	(0.75)	(0.36)
Size	-0.09		-0.09
	(-0.25)		(-0.26)
Leverage	1.18		1.98
	(0.38)		(0.63)
MTB	0.29***		0.30***
	(4.17)		(4.81)
Constant	-61.53*	-45.13*	-37.21
	(-1.91)	(-1.65)	(-1.22)
Mean Interactive Effect	**-0.00****	**-0.67****	**-0.16****
(*FRQ* × *SinceLast*)	**(-2.00)**	**(-2.42)**	**(-2.44)**
Pseudo R-sq (%)	6.82	6.70	6.98
Observations	898	898	898

Table 17: Different Assessments of Credit Risk and Reporting Quality

This table presents the results from estimating the following Tobit regression from 1985-2008 for 285 observations for Panel B, 368 for Column 2 of Panel C, and 898 for all other tests.

$$DefaultDiff2_t = \alpha + \beta_1 FRQ_{t-1} + \Sigma \beta_j Controls_{j,t-1} + \varepsilon_t$$

where *DefaultDiff2* is the difference in the default rate of Moody's over that of S&P. *FRQ* is one of three proxies for financial reporting quality, *AsymTime*, *Cscore*, or *DCV*. *AsymTime* is asymmetric timeliness calculated as β_3 from a Basu (1997) regression. *Cscore* is another measure of asymmetric timeliness developed in Khan and Watts (2009). *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 current portion of long-term debt to total firm assets. *MTB* is the ratio of the market value to the book value of equity. *SinceLast* is the average of the number of years since any of the firm's debt was last rated or put on credit watch by S&P and Moody's. *Goodwill1* is an indicator variable equal to one if the firm has goodwill greater than or equal to 10% of its assets and zero otherwise. *Goodwill2* is an indicator variable equal to one if the issuing firm has goodwill likely needing impairment on its balance sheet and zero otherwise. *SFAS142* is an indicator variable equal to one if the debt was issued after SFAS 142 took effect. Panel A reports the results from the base test. Panel B presents the results when comparing ratings from EJR and the agencies with access to private information. Panel C presents the results from the SFAS 142 test. Panel D presents cross-sectional results examining the importance of reporting quality dependent on the time since the agencies last examined a firm's credit risk profile. 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 * denotes significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Base Tests

	AsymTime	*Cscore*	*DCV*
FRQ	**0.50**	**2.90**	**-0.37**
	(0.82)	**(1.63)**	**(-0.46)**
Maturity	0.14	0.18	0.13
	(0.96)	(1.22)	(0.85)
Face	-0.19	-0.31	-0.19
	(-0.91)	(-1.49)	(-0.93)
AvgRate	-1.00***	-0.89***	-1.00***
	(-12.35)	(-12.37)	(-12.39)
TotalCovs	-0.05	-0.03	-0.05
	(-0.71)	(-0.48)	(-0.69)
Tangibility	-0.07	0.11	-0.05
	(-0.06)	(0.09)	(-0.04)
ROA	5.96	6.29*	6.07
	(1.44)	(1.68)	(1.46)
Size	-0.45***		-0.44***
	(-2.67)		(-2.64)
Leverage	1.31		1.41
	(0.78)		(0.85)
MTB	-0.24***		-0.24**
	(-2.59)		(-2.55)
Constant	31.86**	25.46*	33.36**
	(2.08)	(1.87)	(2.12)
Pseudo R-sq (%)	10.79	10.54	10.75
Observations	898	898	898

Panel B: Comparing Ratings from EJR and the rating agencies with access to private information

	AsymTime	*Cscore*	*DCV*
FRQ	**0.85**	**0.82**	**0.57**
	(0.86)	**(0.05)**	**(0.31)**
Maturity	0.41	0.31	0.39
	(1.21)	(0.88)	(1.15)
Face	0.08	0.38	0.07
	(0.45)	(1.12)	(0.42)
AvgRate	0.76	0.42	0.76
	(0.79)	(0.53)	(0.79)
TotalCovs	-0.11	-0.13	-0.11
	(-0.60)	(-0.71)	(-0.57)
Tangibility	5.05	3.96	4.80
	(1.61)	(1.59)	(1.53)
ROA	20.47*	22.13**	18.90*
	(1.81)	(2.56)	(1.71)
Size	0.57		0.55
	(0.55)		(0.53)
Leverage	-9.26		-9.37
	(-1.10)		(-1.11)
MTB	0.11		0.12
	(1.18)		(1.27)
Constant	-25.37	12.92	-0.15
	(-0.77)	(0.36)	(-0.01)
Pseudo R-sq (%)	3.15	2.86	3.13
Observations	285	285	285

Panel D: SFAS 142 Tests

	I	II
Goodwill1	2.20	
	(0.85)	
Goodwill2		6.52**
		(2.54)
SFAS142	0.65	0.25
	(0.15)	(0.07)
Goodwill1 × SFAS142	**1.03**	
	(0.31)	
Goodwill2 × SFAS142		**-31.59**
		(1.06)
Maturity	1.20	1.99
	(0.90)	(1.62)
Face	1.69	0.80
	(1.16)	(0.70)
AvgRate	0.43	0.60
	(1.05)	(1.45)
TotalCovs	-0.01	0.05
	(-0.04)	(0.23)
Tangibility	-6.82	-8.76
	(-1.04)	(-1.64)
ROA	18.37	43.93
	(0.79)	(1.58)
Size	-1.76*	-0.59
	(-1.83)	(-0.66)
Leverage	10.69	9.54
	(1.59)	(1.28)
MTB	-1.21	-1.60*
	(-1.52)	(-1.77)
Trend	0.18	0.22
	(0.66)	(0.84)
Constant	-19.63	-71.01
	(-0.27)	(-1.13)
Mean Interactive Effect	**0.16**	
(*Goodwill1 × SFAS142*)	**0.09**	
Mean Interactive Effect		**-14.63**
(*Goodwill2 × SFAS142*)		**(1.05)**
Pseudo R-sq (%)	14.33	18.56
Observations	898	368
Year FE	Yes	Yes
Industry FE	Yes	Yes

Panel D: Reporting Quality and Credit Risk under Time since Last Examined

	AsymTime	*Cscore*	*DCV*
FRQ	**0.63**	**2.80**	**-0.39**
	(0.87)	**(1.42)**	**(-0.48)**
SinceLast	0.02	0.03	0.02
	(0.58)	(0.99)	(0.63)
FRQ × SinceLast	**-0.16**	**0.40**	**-0.13**
	(-0.48)	**(0.41)**	**(-0.92)**
Maturity	0.12	0.16	0.11
	(0.80)	(1.10)	(0.74)
Face	-0.18	-0.30	-0.18
	(-0.90)	(-1.44)	(-0.86)
AvgRate	-0.99***	-0.89***	-0.98***
	(-12.24)	(-12.48)	(-12.40)
TotalCovs	-0.04	-0.03	-0.03
	(-0.57)	(-0.41)	(-0.50)
Tangibility	-0.26	-0.02	-0.20
	(-0.22)	(-0.01)	(-0.16)
ROA	6.09	6.37*	6.24
	(1.47)	(1.67)	(1.48)
Size	-0.41**		-0.42**
	(-2.52)		(-2.55)
Leverage	1.35		1.40
	(0.81)		(0.85)
MTB	-0.22**		-0.22**
	(-2.43)		(-2.31)
Constant	33.97**	27.55**	36.57**
	(2.15)	(2.10)	(2.29)
Mean Interactive Effect	**-0.03**	**0.08**	**-0.02**
(*FRQ* × *SinceLast*)	**(-0.45)**	**(0.38)**	**(-0.82)**
Pseudo R-sq (%)	10.96	10.69	11.04
Observations	898	898	898