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Essays on Information and the Bond Market

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ABSTRACT

This dissertation studies the issues on information and the bond market. The first essay examines the incentives of certified credit rating agencies to issue credit watches. The second essay studies how quality of private information of investors affects bond yield spreads. The third essay studies whether more accrual-based income smoothing is related with better or worse bond ratings.

Essay 1: Asymmetric Credit Watches before Downgrades and Upgrades: Evidence on Conservatism of Certified Credit Rating Agencies

Certified credit rating agencies issue credit watches to warn about changes in firms' creditworthiness and possible future rating changes. More rating downgrades are preceded by credit watches than rating upgrades, consistent with the rating agencies being conservative, that is, responding more quickly to bad news than to good news. Downgrades are more likely to be preceded by credit watches than upgrades when (1) the ratings are of investment grade, (2) there are rating triggers, and (3) the issuer's securities-related litigation risk is high. These results suggest that rating agencies' conservatism, like accounting conservatism, is likely motivated by contracting and litigation.

Essay 2: Quality of Private Information and Bond Yield Spreads

Private information of investors could play a different role in the over-the-counter (OTC) market for corporate bonds than in the equity market. In particular, private information could reduce dealer market power and assessed default probability while

having limited effect on creating information asymmetry among mostly institutional investors. We show that precision of both private and public information is *negatively* related to bond yield spreads. There is also a substitution effect between the two sources of information. In addition, we find that the information effect is especially large when bond maturity is relatively short, consistent with the theory of Duffie and Lando (2001). Our results suggest that, when assessing their reporting strategy, managers should not only consider the relation between public and private information, but also weigh the relative importance of the bond and equity markets in each context.

Essay 3: Income Smoothing and Bond Ratings

Accounting accruals affect not only the levels but also the volatility of the reported earnings. We show in this paper that the income-smoothing use of accruals plays a useful role in the debt market. More income smoothing is associated with more favorable bond ratings and larger weight on accruals in bond ratings. These results are consistent with the argument that income smoothing signals superior firm performance. They complement the consistent findings from the equity market on the reward to income smoothing and cast doubt on the recent plea to "stop smoothing earnings" (Jensen, 2005).

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Asymmetric Credit Watches before Downgrades and Upgrades: Evidence on Conservatism of Certified Credit Rating Agencies

Doctoral Dissertation Chapter 1

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ABSTRACT

Certified credit rating agencies issue credit watches to warn about changes in firms' creditworthiness and possible future rating changes. More rating downgrades are preceded by credit watches than rating upgrades, consistent with the rating agencies being conservative, that is, responding more quickly to bad news than to good news. Downgrades are more likely to be preceded by credit watches than upgrades when (1) the ratings are of investment grade, (2) there are rating triggers, and (3) the issuer's securities-related litigation risk is high. These results suggest that rating agencies' conservatism, like accounting conservatism, is likely motivated by contracting and litigation.

Asymmetric Watch Decisions before Downgrades and Upgrades: Evidence on Conservatism of Certified Credit Rating Agencies

1. Introduction

Certified credit rating agencies, especially Moody's and Standard and Poor's (S&P), have been criticized for being slow in updating credit ratings (Hunt 2002).[1] Such criticism reached an all-time high after the major rating agencies assigned investment-grade ratings to companies such as Enron and Worldcom just before their collapses. The lack of responsiveness has been largely attributed to the lack of competition in the oligopolistic rating industry, with Moody's and S&P controlling about 80% of the market share. Some also argue that the lack of independence of certified rating agencies compromise the rating quality. Certified rating agencies rely on issuer fees for the majority of their revenue[2], which raises the concern that conflicts of interest impair the quality of their ratings and cause their slowness to respond (see Frost (2006) for a survey on credit rating agencies). These concerns have led to on-going reforms of the credit rating industry.

Amid the haste to condemn the certified rating agencies, Beaver et al. (2006) point out that rating properties are shaped by the demands of rating users. Ratings from non-certified agencies are used mainly for investment advice; therefore non-certified ratings incorporate both bad news and good news in a timely and symmetric fashion. In

[1] These agencies are certified by the Securities and Exchange Commission (SEC) as the "Nationally Recognized Statistical Ratings Organizations (NRSROs). In 2006, there are five certified agencies: Moody's, Standard and Poor's, Fitch Ratings, Dominion bond Rating Services, and A.M. Best.
[2] For example, about 90 percent of Moody's revenue comes from issuers who pay fees for ratings (SEC 2003). In general, the issuer fees are based on the size of the issuance and the nature of the instrument being rated. They typically include both a fee for the initial rating and an annual maintenance fee.

contrast, certified ratings are used in regulations and contracts in addition to their investment advisory role. Consistent with the contracting role, changes of certified ratings usually lag those of non-certified ratings, and are more responsive to bad news than to good news. In other words, certified rating agencies are conservative. Such conservatism in certified ratings mirrors the conservatism in accounting. Beaver et al. provide a better understanding on how the uses of credit ratings affect the incentives of rating agencies.

In this paper we add to the understanding by examining the credit watches issued by credit rating agencies, which are public announcements that a rating is under active review for a possible change. We study whether rating agencies display conservatism in their decisions to issue credit watches, specifically whether they issue more credit watches before downgrades than before upgrades in response to the asymmetric demands of rating users for good news and bad news. Through credit watches, rating agencies inform the market of the perceived changes in credit risk ahead of possible final rating changes. To a large extent, credit watches themselves are a response of the certified rating agencies to the criticism that they are slow to respond to investors. When there are signs of credit quality changes, credit watches not only provide the information in a more timely fashion, but also avoid the immediate direct consequences of actual rating changes such as mandated portfolio adjustments or triggering rating-based clauses.

Based on an adapted framework for accounting conservatism described in Guay and Verrecchia (2006), we argue that credit watch decisions are likely to embody the conservatism of credit rating agencies. Putting a rating on watch can have at least two costs: the cost of increasing market uncertainty if it turns out that a rating change is unnecessary, and the cost of collecting and examining information during the watch process. Because of these costs, rating agencies have incentives to wait until the information becomes relatively easy to verify. On the other hand, a demand for earlier release of bad news than good news leads rating agencies to issuer more watches before downgrades than before upgrades. The asymmetric demand for good new and bad news can come from the following sources. First, hold-to-maturity bondholders desire to know bad news early to protect their investment. Second, rating downgrades can lead to mandated portfolio adjustments or violation of contract terms. The concerned parties in these cases prefer to know the adverse information early. Third, the litigation environment encourages earlier release of bad news than that of good news. Based on these arguments, we hypothesize that rating agencies are more likely to issue credit watches before downgrades than before upgrades.

Using the credit watch and rating change data from Moody's Investors Service covering 1995-2003, we find that Moody's issues more credit watches before rating downgrades than before rating upgrades. Furthermore, downgrades are more likely to be preceded by credit watches than upgrades when the ratings are of investment grade, when there are rating triggers, and when the issuer's litigation risk is high. Our results provide evidence that contracting and litigation are likely to drive rating agencies to be conservative.

This paper contributes to the literature in the following ways. First, we provide evidence that rating actions are a function of the demands of rating users. This result has implications for the recent reforms on the rating industry. In September 2006, the Senate passed the Credit Rating Agency Reform Act, abolishing the "NRSROs" system. Any rating firms with three years of experience that meet certain standards can register as a "statistical ratings organization". The Act also grants SEC new authority to inspect credit rating agencies. However, as long as regulations and contracts continue to use ratings from certain rating agencies as performance benchmarks, the behavior of these rating agencies will still be affected. Our results suggest that these reforms must consider the economic factors driving the rating properties. Second, this study complements Beaver et al. (2006) paper on asymmetric actual rating changes by certified rating agencies. Beaver et al. compare the actual rating changes from a certified agency (Moody's) with a non-certified agency (EJR) and find that Moody's ratings incorporate bad news sooner than good news. Moody's downgrades lag EJR's downgrades by as little as one month and up to four months, while Moody's upgrades lag EJR's upgrades between five and six months. Moody's downgrades but not upgrades are associated with significant release of information in the marketplace, proxied by changes in stock prices over the three months prior to the rating changes. Third, this study also complements the numerous studies on accounting conservatism by providing evidence that rating agencies' conservatism, like accounting conservatism, is likely driven by contracting and litigation.

The rest of the paper is organized as follows. Section 2 discusses the institutional background. Second 3 develops the hypotheses. Section 4 describes sample selection and variable measurement. Section 5 presents the sample characteristics. Section 6 contains the main results. The conclusion is provided in Section 7.

2. Institutional Background

Credit Rating Agencies and Their Roles

Credit rating agencies assess the relative creditworthiness of debt issuers and their obligations and publish the outcome in the form of ratings. For nearly a century, investors have used credit ratings to facilitate their investment decisions.[3] Rating agencies collect, process, and disseminate information to the general public, thereby serve as an important information intermediary between issuers and investors. This service is particularly valuable to small investors for whom costs are likely to be too high to conduct their own credit analysis. Even institutional investors such as mutual funds use credit ratings as an "input" in their independent credit analysis.

Besides investment advisory role, credit ratings from a handful of certified agencies have been widely used in regulations and private contracts. Regulators employ the certified credit ratings to help monitor the risk of investments held by regulated entities. For example, the Federal Deposit Insurance Act prescribes that corporate debt securities are considered "investment grade" only if they are rated in one of the four highest categories by at least one certified agency (SEC 2003). For another example, congress requires the "mortgage-related-security" to be rated in one of the two highest rating categories by at least one certified agency (Section 3(a)(41) of the Exchange Act, 1984). Prospectus of money market mutual funds may also specify that only securities with certain certified ratings can be purchased (Beaver et al. 2006).

The use of certified ratings also extends to private contracts (Asquith et al. 2005; Doyle 2004; Bhanot and Mello 2006). A bond indenture may include a "rating trigger clause", requiring the debt issuer to prepay part or all of its debt or to increase the coupon rate on its debt if the issuer's credit rating is downgraded to a specified level. Rating

[3]The first credit rating agency, Moody's Investors Service, was incorporated in 1914 and a formal rating department was created in 1922.

triggers are also used in mergers and acquisitions. For example, after the problems with Enron emerged, Dynegy Inc. offered a rescue deal to Enron on the condition that Enron maintained its investment-grade credit rating.

Credit Watches

A credit watch is a public announcement that the rating agency detects a potentially significant change in the issuer's credit quality and is considering revising its rating. Starting from the 1980s, the major certified rating agencies have supplemented rating changes with credit watches as an additional means to convey information.[4, 5] Moody's (1998) states that, "the Watchlist is designed to inform investors of Moody's opinion that the credit quality of an obligation or obligor may be changing, and conveys important credit risk information". Each credit watch has a well-defined and publicly announced beginning and end. A rating can be put on watch for possible downgrade, possible upgrade, or, in rare cases, uncertain direction. Credit watches are concluded either by changing the issuer's credit rating or confirming its existing credit rating. In a few cases, the rating agencies may decide to continue watching the rating or stop evaluating the creditworthiness of the issue (issuer) by withdrawing the rating. During the rating review, rating agencies solicit information from the issuer in order to understand plans either for addressing the problem, or for taking advantage of the opportunities that

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[4] Moody's has been publishing a "Watchlist" of ratings on review since 1985. The Watchlist assignments became formal rating actions after 1991. S&P started the Credit Watch List in 1981. All of the five certified agencies issued credit watches as part of their rating processes.

[5] Rating agencies also issue rating outlooks. A rating outlook is a rating agency's opinion regarding the likely direction of an issuer's credit quality, and therefore its rating, over a medium term (usually 12-18 months). Rating outlooks take the values of positive, negative, stable, and developing. Compared with a rating outlook, a credit watch is a much stronger statement about the future direction a credit rating may take (Moody's 2004).

have inspired the review. The watch process usually takes three months, but can vary from a few days to more than a year.

Credit watches have become important signals of changes in credit risk. Moody's (2004) reports that credit watches improve the credit ratings' performance as predictors of default. Hand et al. (1992) document that both the bond market and the stock market react significantly to credit watch announcements.

Moody's states that a rating may be put on watch in the following scenarios: (1) The issuer has announced plans which Moody's believes would materially affect credit quality, but which are not certain to come to fruition; (2) Trends in the issuer's operations or financial strength may develop that could affect the issuer's willingness and ability to pay its debts on time; (3) An event suddenly occurs which changes the issuer's operating environment, but the magnitude of its effect on the issuer is not clear (Moody's 1998). None of these scenarios suggests that the rating agencies would react to plans, trends, or events with positive effects on creditworthiness differently from those with negative effects. In the following section, we will discuss the forces that drive the conservatism of certified rating agencies.

3. Hypotheses on Conservatism of Certified Rating Agencies

Our arguments on credit rating agencies' conservatism echo those on accounting conservatism (see Ball (2001) and Watts (2003a,b) for debated discussion of accounting conservatism). Accounting conservatism is often defined as the more timely recognition of bad news than good news in earnings, or "anticipating no profit, but anticipating all losses". Guay and Verrecchia (2006) suggest an interpretation of conservatism based on asymmetric costs and benefits of reporting verifiable information. Suppose there are two types of information: easy-to-verify information and difficult-to-verify information. When information is easy to verify, timely recognition for both good news and bad news is preferred and demand for conservatism is low. However, managers have incentives to delay the recognition of difficult-to-verify information until it becomes easy to verify, because it is costly to incorporate such information into the financial reports. [6] Such cost includes higher auditing cost and lower reliability of the financial statements. Some users of financial statements have a higher demand for timely information about losses than about gains. The cost of recognizing difficult-to-verify bad news is (partly) offset by the benefit of catering to the demand of these users, while the cost of recognizing difficult-to-verify good news is not. The consequence is a more timely recognition of bad news than good news. The major motivations for the asymmetric demands for good news and bad news are contracting and shareholder litigation.[7] Debt contracts, for example, make it more important for firms to timely report bad news than good news, because debt holders have fixed claims and therefore are more sensitive to losses than to gains. Litigation cost also creates asymmetric reporting incentives for firms because firms are more likely to be sued when bad news is not incorporated into financial statements than when good news is not incorporated into financial statements.

The economic forces that drive the conservatism in accounting are likely to induce conservatism in certified credit ratings as well. It is reasonable to assume that it is costly for rating agencies to incorporate difficult-to-verify information into rating actions.

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[6] R&D activities, treatment of goodwill, restructuring activities are examples of difficult-to-verify information.

[7] The other two explanations for accounting conservatism are taxation and accounting regulation. Watts (2003a, b) find that the evidence on the effect of taxation and regulation is weaker.

To incorporate such information, the rating agencies will have to make further investigations including acquiring additional information, analyzing and interpreting the information. In addition, rating actions based on difficult-to-verify information have a higher chance of being reversed, leading to costly actions of rating users. Certified rating agencies are expected to satisfy the demands of the rating users and increase their user base. Although they charge the issuers for rating fees, it is reasonable to believe that a wider user base is likely to lead to higher fees they can charge.[8] The demands of rating users are thus expected to influence the actions of rating agencies. An asymmetric demand for good news and bad news from rating users, coupled with the cost of incorporating difficult-to-verify information into rating actions, creates incentives for the rating agencies to be conservative.

The asymmetric demands for good news and bad news of rating users can come from the following sources. First, bondholders who intend to hold the bonds to maturity are likely to have more demand for bad news than for good news. Good news merely verifies their initial judgment and will not prompt any action. Bad news, on the other hand, serves to warn the holders of the necessity to reconsider their portfolios. Bondholders are more sensitive to bad news than to good news also because bonds have more exposure to downside risk but limited upside potentials. Second, certified ratings are used in regulations and private contracts. As most of these regulations and contracts have terms contingent on the issuer maintaining a minimum level of rating, it is more important to timely incorporate bad news into rating actions than to incorporate good

[8] Relying on the issuers for revenue could also cause conflicts of interest. The certified agencies argue that the rating fee from each individual issuer is only a very small percentage of their total revenue, which leaves the rating agencies little incentive to curry the favor of any particular issuers. Covitz and Harrison (2003) find that rating agencies are motivated primarily by reputation-related incentives and find no evidence on conflicts of interest.

news into rating actions. Third, issuer's litigation risk is also likely to have an impact on rating agencies. Even though debt ratings may be constitutionally protected as "free speech" by the First Amendment,[9] when the issuers are sued for providing misleading information to the market, it can still damage the reputation of the rating agencies as an information intermediary (Covitz and Harrison 2003; Partnoy 1999). Given that investors tend to sue only when there is a large negative surprise or a loss (Skinner 1994), rating agencies have incentives to incorporate bad news earlier than good news to avoid the direct litigation cost or the indirect reputation cost.

Credit watch provides a unique setting to study rating agencies' conservatism. A credit watch serves as an early warning to rating users about the changes in credit quality and a possible rating change in the near future. As discussed in Section 2, rating agencies tend to put a rating on watch when it is difficult to verify how and to what extent some plans, events or trends affect the issuer's credit quality. When facing difficult-to-verify information, rating agencies have incentives to delay the decisions until it is clear whether a rating change is necessary. Putting a rating on watch can have at least two costs. First, when it turns out a rating change is unnecessary, a credit watch becomes a "false alarm". Moody's states that it is "cautious about putting ratings under review…in order to avoid unnecessarily increasing uncertainty in the marketplace" (Moody's 1998). Second, after putting a rating on watch, rating agencies must spend costly resources in

[9] In June 1996, one-and-a-half years after Orange County declared bankruptcy, the County sued Standard & Poor's, claiming its 1993 and 1994 ratings of the County's notes and bonds were too high. A federal court in the Ninth Circuit ruled in 1999 that debt ratings issued by rating agencies are not financial advice, and reaffirmed that such ratings are speech that is constitutionally protected under the First Amendment. The court confirmed that rating agencies act as independent evaluators of the creditworthiness of specific debt issues, not as advisors to the issuer of such debt. *County of Orange v. The McGraw-Hill Companies, d/b/a Standard & Poor's Ratings Services*, United States District Court, Central District of California, Case No. SACV 96-0765.

investigations. Given the costs of issuing credit watches and demands from rating users for timelier bad news than good news, we hypothesize that,

H1: Certified rating agencies are more likely to issue credit watches before rating downgrades than before rating upgrades.

We further expect that the asymmetry in watch decisions will be more pronounced in the following scenarios. The first scenario is when the rating is of investment grade. Government regulations often use certified ratings as investment eligibility benchmarks and specify that the regulated entities hold bonds of certain investment-grade categories. The regulations can be considered as contracts between the government and the regulated entities under which the regulated entities will have to sell if the bonds are downgraded below certain level. The cut-off point is usually a relatively low level within investment-grade ratings or between investment and non-investment grade ratings. Bondholders therefore demand timely information when an investment-grade bond has adverse news and faces a possible downgrade. The information demand is especially higher when a possible rating change is from investment grade to non-investment grade ("fallen angel candidate").

The second scenario is when there are "rating triggers". For issuers with contracts including a "rating trigger clause", a rating downgrade can result in significant cost to the issuers. If the rating is downgraded to a pre-specified level, the clause often requires the issuers to pay part or all of the debt before the maturity date or to increase the coupon payment. Credit watches inform the contract holders of the detected changes in credit quality and the possible rating changes. Because it is rating downgrades, not rating upgrades, that can lead to the violation of contracts, demand on early warnings of downgrades is higher.

The third scenario is when the issuer's securities-related litigation risk is high. The litigation environment encourages pessimistic forward-looking information and discourages optimistic forward-looking information. Such an asymmetric effect is more pronounced when the litigation risk is high. For this reason, we expect the rating agencies to issue more downgrade watches than upgrades watches when the issuer is operating in a more litigious environment.

Based the above discussions, we have the following hypothesis:

H2: The asymmetry in watch decisions as described in H1 is more pronounced when (1) the rating is of investment grade, (2) the rating is a "fallen angel candidate", (3) there is a rating trigger, (4) the issuer's litigation risk is high.

Boot et al. (2005) propose a "monitoring" function of credit watches. They model that rating agencies use the watch process to induce recovery efforts from firms. The "monitoring" argument itself cannot explain the asymmetric watch decisions. When there are signs of improvement in credit quality, rating agencies could use the watch process to encourage more creditworthiness-enhancing efforts.

4. Sample Selection and Variable Measurement

Sample

To conduct this study, an ideal sample would include firms whose yet-to-be-verified developments in credit quality suggest possible rating changes. Findings that a rating agency issue more credit watches in cases of adverse developments than in cases of positive developments will provide evidence on the conservatism of the rating agency.

This ideal sample is difficult to acquire. Instead, we use a sample of firms with actual rating changes and examine whether a credit watch is issued before the rating change. These firms have experienced significant developments in credit quality. This sample has two potential problems. First, sometimes rating agencies change a rating without putting it on watch simply because the developments in credit quality are clear and significant enough. However, there is no obvious reason that positive developments are more likely to be clear and significant than negative developments. Therefore, evidence that rating agencies issue more watches before downgrades than before upgrades still supports the notion that rating agencies are conservative. Second, studying the watch decisions using a sample of firms with actual rating changes may introduce sample selection bias. We address this issue in Section 6.

We obtain rating change and credit watch data from Moody's Investors Service. The sample covers the period from 1995 to 2003. There are 4,927 rating changes on issuer ratings or senior debt ratings. Rating actions on subordinated debt or preferred stocks are excluded in the analysis. We match the rating change sample with the credit watch sample to separate them into those that are preceded by watches and those that are not. To be included in the analysis, we also require each observation to have necessary data from Compustat and CRSP to calculate the required variables discussed next. This data requirement reduces the sample size to 2,140 rating changes.

Variable Measurement

Investment Grade and "Fallen Angel Candidate"

Following Moody's practice, we define ratings above "Baa3" as investment grade ratings, and those from "Ba1" to "C' as non-investment grade ratings. "Fallen angel candidates" are defined as ratings one or two notches above the investment-grade threshold, i.e., ratings "Baa3" and "Baa2". Moody's (1997) documents that the majority (88%) of rating changes are within two notches.

Rating Trigger

We obtain the rating trigger data from Mergent Fixed Income Securities Database (FISD) and the Reuters/EJV Database (EJV)[10]. FISD flags bonds with a rating-triggered put provision (rating_decline_trigger_put = "Y"). A put provision typically grants the bondholder the right to sell the issue back to the issuer at a pre-specified price. EJV identifies which bonds have rating-based clauses (credit_sensitive_fl = "Y"). The dummy variable TRIGGER equals to 1 if either of the two databases marks an issuer as having rating-triggers. The credit ratings used as triggers are not necessarily Moody's ratings. Further examination of the FISD data indicates that most triggers are based on ratings from either Moody's or S&P.

Issuer's Litigation Risk

Following Rogers and Stocken (2005), we use the estimated probability of litigation from the following probit model to measure litigation risk. Appendix B details the estimation results.

$$\Pr ob(LAWSUIT_{j,t}) = G(\beta_0 + \beta_1 SIZE_{j,t} + \beta_2 TURNOVER_{j,t} + \beta_3 BETA_{j,t} + \beta_4 RETURN_{j,t} + \beta_5 RET\_STD_{j,t} + \beta_6 RET\_SKEW_{j,t} + \beta_7 RET\_MIN_{j,t} + \beta_8 HIGHRISK\_IND_{j,t} + \varepsilon_{j,t})$$

[10] The author greatly appreciate the access to Reuters /EJV database during her internship at Moody's KMV.

where t = indicator of the calendar quarter t; j = indicator of firm j; LAWSUIT = 1 if Stanford Law School's Securities Class Action Clearinghouse documents a securities class action lawsuit, and zero otherwise; SIZE = log (average daily market capitalization); TURNOVER = average daily number of shares sold / average shares outstanding; BETA = coefficient from market model estimated with daily stock returns and equal-weighted market returns; RETURN = buy-and-hold returns over the calendar quarter; RET_STD = standard deviation of the daily returns; RET_SKEW = skewness of the daily returns; RET_MIN = minimum of daily returns; and HIGHRISK_IND = 1 if the firm is in Bio-technology (SIC 2833-2836), Computer Hardware (SIC 3570-3577), Electronics (SIC 3600-3674), Retailing (SIC 5200-5961), or Computer Software (SIC 7371-7379). The returns data are from CRSP and the industry classification data (SIC) are from Compustat. The model is estimated using all the firm-quarters with available data from the fourth quarter of 1995 to the fourth quarter of 2003. As firms' litigation environment can change over time, we rank the estimated probabilities in percentiles for all firms within each quarter, and use the ranks to measure the relative litigation risk. Higher rank means higher litigation risk.

Control Variables

In the regression analysis, we control for a number of additional variables that can possibly affect rating agencies' watch decisions. Firm size (FIRMSIZE) is measured as the natural log of the issuer's total assets as of the quarter before a rating action (watch or direct rating change). Leverage (LEV) is calculated as the issuer's total liabilities scaled by total assets as of the quarter before a rating action. Systematic risk is measured by the market beta (BETA), estimated as the slope coefficient from the market model; idiosyncratic risk is measured by the variance of the residuals from the market model (MSE). The market model is estimated with daily stock returns and equal-weighted market returns in the quarter prior to the rating action, requiring a minimum of 24 observations. Growth opportunities is measured by the market to book ratio (MTB), calculated as market capitalization divided by book value of equity. Finally, we also control for two industry dummies: financial institutions (FIN_IND for 2-digit SIC 60-69) and regulated firms (REG_IND for 2-digit SIC 40-42, 44-47, 49).

The above factors can have multi-folded effects on rating agencies' watch decisions. For example, larger firms have more investors and therefore possibly higher information demands. However, such effect can be mitigated by the fact that larger firms tend to have more analysts following and institutional holdings, reducing the information demands on credit rating agencies. Similarly, when leverage is higher, debtholders become more sensitive to rating changes, and may demand earlier information. Investors' information demand is also expected to be high for high-risk firms and firms with high growth opportunities.

To control for performance changes, we use change in return on assets (ΔROA) measured as the seasonal change in ROA as of the quarter before a rating action, and change in leverage (ΔLEV) measured similarly. Another firm performance measure is the buy-and-hold size-adjusted stock returns during the 90 days before the on-watch date ($STK\_RET_{[-90,-1]}$). If there is no credit watch, we pick the 90th day before rating change as the "pseudo" on-watch day. The performance change variables may have different impact on downgrade watches and upgrade watches. In the regression analysis, we control for such difference.

5. Sample Characteristics

Table 1 presents the distribution of all firms with rating changes (Panel A) and those with rating changes and other required data (Panel B). Observations are first classified by their rating change directions (downgrade or upgrade), then by their watch directions (no watch, possible downgrade, possible upgrade, uncertain direction). In the first sample, 46% of the downgrades are on the watchlist, and 54% are downgrades without prior watches (i.e., outright downgrades). In the second sample, 52% of the downgrades have been watched first, and 48% are outright downgrades. The data requirements reduce “outright-downgrade” observations slightly more than “downgrade-after-watch” observations. To mitigate the concern that the change in sample composition might affect the results, in the sensitivity test, we construct a sub-sample that mimics the composition of the first sample and re-conduct the analysis. For firms that are upgraded, the compositions are similar between the first sample and the second sample. In both samples, about one-third of the firms are watched before the upgrades. Results in Table 1 are consistent with hypothesis H1 that downgrades are more likely to be preceded by watches than upgrades.

Among the firms that are watched before rating changes, most are watched in the same direction as the rating change direction. The firms watched as “possible upgrade” or “possible downgrade” and eventually changed in the opposite direction, as well as those watched as “uncertain direction”, only account for a very small percentage of the sample. We define a dummy variable WATCH to be equal to 1 if the rating has been watched before being changed and 0 if it is an outright change. Excluding the rating change observations that are watched in the opposite direction or uncertain direction does not affect the results.

Table 2 shows the distribution of the first sample across years. More rating changes are preceded by credit watches in the second half of the sample period than in the first half. Before 1999, the percentage of the watched among the total downgrades ranges from 33% to 40%. This percentage jumps above 40% after 1999, and peaks at 62% in 2002. The percentage of the watched upgrades among the total upgrades increases from 26% in 1995 to 54% in 2000, although it declines to 33% in 2003. The percentage of watched downgrades is greater than the percentage of watched upgrades in all sample years except 2000.

Table 3 presents the stock price behavior around watch-related events. Panel A lists the mean duration of credit watches and the mean three-day stock returns around the on-watch and off-watch (rating change) announcements. Also presented in Panel A are the mean three-day stock returns around the rating change announcements when there are no credit watches. Downgrade watches on average last 100 days, 40 days shorter than upgrade watches. Both downgrade watch and upgrade watch announcements are associated with significant stock market returns (average three-day return of -4.4% and 7.91% respectively). The downgrade announcements after credit watches are associated with significantly smaller negative stock returns compared with outright downgrade announcements (-2.72% versus -4.33%). The upgrade announcements, preceded by credit watches or not, are associated with small and positive stock returns.

Panel B of Table 3 plots the stock returns for the 90 days prior to the on-watch announcements. When there are no credit watches, we take the 90^{th} day before the rating change announcement as the “pseudo” on-watch day. Under the premise that stock returns capture relevant information in a timely manner, we would expect smaller stock returns before the “pseudo” on-watch day for the non-watched groups if the rating changes of these groups are responses to more sudden and significant changes in credit quality. Two interesting observations arise from Panel B. First, there are symmetric market returns before downgrade watches and upgrade watches, in contrast to the asymmetric returns before downgrades and upgrades (see Figure 2, Beaver et al. (2006)). It appears that downgrade watches and upgrade watches are equally timely responses to information release. Second, the non-watched firms have experienced significant changes in stock prices at least 90 days before the rating changes. Had stock returns been the criteria of putting a firm on watch, rating agencies could have issued watches on these non-watched firms as well. The fact that no watches are issued for these firms indicates that there are other effects at work.

Table 4 reports the descriptive statistics of the variables used (see Appendix A for the definitions of these variables). Of all the rating changes with available data, 64.8% are downgrades and 45.8% are watched before. 37.4% of the sample firms are of investment grade before the rating change, with 16.1% being “fallen angel candidates”, that is, one or two notch above the threshold of investment grade. 13% of the sample firms have a rating trigger. LITI_RISK is a rank variable measuring the issuer’s relative securities-related litigation risk with a range from 0.00 to 0.99. Our sample firms have higher relative litigation risk with a mean rank of 0.752. There is on average an increase in leverage and decrease in ROA in the quarter before the rating actions (mean ΔLEV_{-1} 0.014; mean ΔROA_{-1} -0.012), as downgrades are the majority in our sample. Table 5 presents the correlation coefficients among the main variables. DOWNGRADE and WATCH are positively correlated, consistent with H1 that downgrades are more likely to be watched first than upgrades. The four factors under examination are all positively correlated with WATCH as well. The univariate results shed little light on how these factors affect downgrade watches and upgrade watches differently. Next we turn to the multivariate tests.

6. Results

Main Results

We conduct the logit regression analysis using the following models.

$$WATCH = \beta_0 + \beta_1 DOWNGRADE + CONTROLS \tag{1}$$

$$\begin{aligned} WATCH &= \beta_0 + \beta_1 DOWNGRADE + \beta_2 INVEST\_GRADE + \beta_3 FAL\_ANGL\_CAN \\ &+ \beta_4 RAT\_TRIGGER + \beta_5 LITI\_RISK + \beta_6 DOWNGRADE \times INVEST\_GRADE \\ &+ \beta_7 DOWNGRADE \times FAL\_ANGL\_CAN + \beta_8 DOWNGRADE \times RAT\_TRIGGER \\ &+ \beta_9 DOWNGRADE \times LITI\_RISK + CONTROLS \end{aligned} \tag{2}$$

The dependent variable, WATCH, takes the value of 1 if the rating is put on watch before being changed and 0 otherwise. H1 predicts that downgrades are more likely to be preceded by credit watches than upgrades; therefore we expect β_1 to be positive. H2 predicts that four factors lead to a higher demand of bad news and further increase the chances of downgrades being watched: the rating being of investment grade, the rating being a "fallen angel candidate", the existence of a rating trigger, and issuer having higher litigation risk. Therefore, we expect β_6, β_7, β_8, and β_9 to be positive. To the extent that these four factors capture all the forces that cause the conservatism in credit watches, β_1 in Model (2) will no longer be positive.

The control variables include firm size, leverage, BETA, MSE, market to book ratio, and two industry dummies for regulated industry and financial industry respectively, all measured as of the quarter before the rating action. We also control for the firm performance in the quarter before the rating action using the seasonal change in return on assets, the seasonal change in leverage, and the buy-and-hold stock returns. Firm performance may have opposite effects on watch decisions before downgrades and upgrades. For this reason, we include ΔLEV_{-1}, ΔROA_{-1}, $STK\_RET_{[-90,-1]}$ as well as their interaction terms with the DOWNGRADE dummy in the regression model.

The regression results are reported in Table 6. In Column (1) WATCH is regressed on DOWNGRADE without any control variables. The coefficient on DOWNGRADE is positive and significant at the 0.01 level, supporting H1 that downgrades are more likely to be preceded by credit watches than upgrades. Adding the control variables (Column 2) does not affect the magnitude and significance of the coefficients. The performance change variables have mixed effects on the watch decisions. The coefficient on $STK\_RET_{[-90,-1]}$ is positive. The coefficient on DOWNGRADE×$STK\_RET_{[-90,-1]}$ is negative, and the total coefficient on $STK\_RET_{[-90,-1]}$ for DOWNGRADE (the sum of the coefficients on $STK\_RET_{[-90,-1]}$ and DOWNGRADE×$STK\_RET_{[-90,-1]}$) is negative. Firms experience more negative (positive) stock returns are more likely to be watched before downgrades (upgrades). Similarly, firms with larger increases in leverage are more likely to be watched for upgrades but more likely to be directly downgraded (not watched). On the other hand, firms with worse accounting performance (ΔROA_{-1}) are more likely to be watched before upgrades but directly downgraded, while those with better accounting performance are more likely to be directly upgraded or watched before downgrades.

In Column (3) we add the four factors and their interaction terms with DOWNGRADE. The coefficient on DOWNGRADE×INVEST_GRADE is positive and significant at the 0.05 level. More downgrades are preceded by watches than upgrades for investment-grade ratings. The coefficient on DOWNGRADE×FAL_ANGL_CAN is also positive as predicted but not statistically significant. The coefficient on DOWNGRADE × RAT_TRIGGER is positive and significant at the 0.01 level. The existence of rating triggers increases the odds of downgrade watches over upgrade watches. Finally, the coefficient on DOWNGRADE×LITI_RISK is positive and significant at the 0.01 level. For issuers with high litigation risk, more watches are issued before downgrades than before upgrades. Adding these terms into the regression model increases the Pseudo R^2 from 3.9% in Column (1) to 19.8% in Column (3). The coefficient on DOWNGRADE also becomes negative. The result indicates that these four factors are the major forces that make the rating agencies issue more watches before downgrades than before upgrades. Adding control variables as shown in Column (4) has little impact on the results.

In Columns (3) and (4), the coefficients on INVEST_GRADE, FAL_ANGL_CAN, LITI_RISK, and RAT_TRIGGER capture how these factors affect upgrade watch decisions. The coefficient on INVEST_GRADE is positive and significant. It appears that investment-grade bonds are more likely to be watched even before upgrades. The coefficient on LITI_RISK is negative and highly significant. When the issuer's litigation risk is high, the rating agency is unwilling to release good news earlier (putting the rating on upgrade watch). The coefficient on RAT_TRIGGER is also negative and significant at the 0.10 level. The rating agency is less likely to put the rating on upgrade watch when there are rating-based contracts.

Sample Selection Issue

We use a sample of firms with actual rating changes to study the watch decisions. The variables that affect watch decisions can be the same as or correlated with the variables that affect rating change decisions. In this case, estimating Equation (2) yields inconsistent coefficient estimates (see Greene (2000), Chapter 20 for more details).

We use the MLE version of Heckman's (1979) sample selection model to address this issue. Specifically, consider the following two equations.

$$CHANGE^* = \beta X + U_1, \text{ with } U_1 = \delta_1 e_1 + \delta_2 e_2 \qquad (3)$$

$$WATCH^* = \gamma Z + U_2, \text{ with } U_2 = e_2 \qquad (4)$$

where e_1 and e_2 are independent standard normally distributed. We observe the watch action (WATCH=1) only when the latent dependent variable $WATCH^*>0$, otherwise WATCH=0. Similarly, CHANGE=1 when the latent dependent variable $CHANGE^*>0$, otherwise CHANGE=0. We observe a watch decision before a change decision if $WATCH^*>0$ and $CHANGE^*>0$. Define

$$\Phi_1 = \Pr ob(WATCH^* > 0, CHANGE^* > 0 | X, Z)$$

$$\Phi_2 = \Pr ob(WATCH^* \leq 0, CHANGE^* > 0 | X, Z)$$

$$\Phi_3 = \Pr ob(CHANGE^* \leq 0 | X, Z)$$

Then the log likelihood function can be written as

$$L=\sum_{j=1}^{n}(1-CHANGE_j)\times\ln\Phi_3+\sum_{j=1}^{n}CHANGE_j\times WATCH_j\times\ln\Phi_1+\sum CHANGE_j\times(1-WATCH_j)\times\ln\Phi_2$$

The maximum likelihood estimation gives consistent coefficient estimates.

To estimate Equation (3) we construct a sample of control firms without rating changes. To do this, for each firm-year in the original sample, we find a firm without rating change in the same year, with the same first two SIC digits, and with a credit rating no more than three notches from that of the original firm. If there is more than one firm meeting these requirements, we pick the one whose total assets is closest to the original firm. 857 (450) downgrades (upgrades) find a match firm.

The estimation results are reported in Table 7. We conduct the analysis separately for downgrades and upgrades. Column (1) shows the results for downgrade changes. Firms are more likely to be downgraded if they experience more increase in leverage, decrease in ROA, decrease in firm size, increase in MSE, and more negative stock returns. Firms with investment grade ratings and higher litigation risk are also more likely to be downgraded. Column (2) shows the result on watch decision before downgrades. Consistent with Table 6, downgrades are more likely to be watched first if the rating is of investment grade, if there is a rating-trigger, and if the issuer's litigation risk is higher. Results for upgrades are reported in Columns (3) and (4). Firms are more likely to be upgraded if they reduce leverage level, improve ROA, or experience positive stock returns. The counterintuitive result is that firms with higher litigation risk are more likely to be upgraded. We do not have a good explanation for this result. For the watch decision before upgrades, the coefficients on INVEST_GRADE, FAL_ANGL_CAN, and LITI_RISK are insignificant. The coefficient on RAT_TRIGGER is negative and significant at the 0.10 level. Firms with rating triggers are less likely to be watched before an upgrade, consistent with the results from Table 6. Column (5) reports the t-statistic for the difference in coefficients from the two WATCH equations (Columns (2) and (4)). The difference between the coefficients on INVEST_GRADE, RAT_TRIGGER, and LITI_RISK are statistically significant.

In conclusion, controlling the sample selection bias does not qualitatively change our main results. Firms with an investment-grade rating, a rating-based contract, or higher litigation risk are more likely to be watched before downgrades. These variables have little or even opposite impact on upgrade watches. The evidence supports our argument that the regulation/contracting and litigation concerns are the driving forces behind the asymmetric watch decisions before downgrades and upgrades.

Additional Tests

As shown in Table 1, the data availability requirement causes a greater reduction of outright downgrades than of downgrades after watches, which raises the concern on the generalizability of the results. To address this issue, we randomly picked a sub-sample of downgrades after watches so that the proportion of downgrades without watches is the same as that in the big sample, and re-ran the regression analysis. We repeated this process 100 times. The results remained qualitatively unchanged.

Recent studies find that the rating agencies weigh on the corporate governance mechanisms of the debt issuers when evaluating their credit risk (Bhojraj and Sepgupta 2003; Klock et al. 2005). It is an open question whether the quasi-regulatory function of the rating agencies serves as a complement or substitute to debt issuers' governance mechanisms. To the extent that the quality of the issuers' corporate governance affects the cost functions of the rating agencies, it can be related with the watch decisions. To test this conjecture, we construct a firm-level governance index following Gompers et al. (2003) using the data on shareholder rights from Investor Research Responsibility Center. The availability of the governance data significantly reduces the rating change sample to only 698 observations. We do not find any significant association between the governance index and the watch decisions, either because of no relationship between the two or because of the low test power due to the smaller sample size.

7. Conclusion

Certified rating agencies have incentives to be conservative, that is, to react to bad news more quickly than to good news. We hypothesize that rating agencies issue more credit watches before downgrades than before upgrades. We further hypothesize that rating agencies' conservatism in credit watches arises from several sources. First, government regulations often require the regulated entities to hold only investment-grade bonds or even high investment-grade bonds. Investors therefore prefer to know adverse news about investment grade bonds early to avoid the consequence of forced selling. Second, certified credit ratings are also used in private contracts as performance benchmarks. A downgrade could pull the rating trigger and lead to undesirable results. Therefore early recognition of bad news is preferred when the issuer has rating-based contract. Finally, firms are more likely to be sued for failing to timely provide bad news. Incorporating bad news into the rating actions earlier than good news reduces the direct litigation cost and indirect reputation cost when the issuer is sued for providing misleading information. We find that Moody's tends to issue more credit watches before downgrades than before upgrades. Such a tendency is more pronounced when the rating is of investment grade, where there exists a rating trigger, and when the issuer's securities-related risk is high. Our results indicate that rating agencies' conservatism is motivated by contracting and litigation.

While one may question whether Moody's is representative of all certified rating agencies that issue credit watches, prior researchers argue that Moody's is a good substitute for other certified agencies (Dichev and Piotroski 2001; Beaver et al. 2006). Reading the rating policies published by each certified agency also reveals that the major agencies adopt similar procedures and standards, which mitigates the concern that the results in this paper may be agency-specific.

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Appendix A: Variable Definitions

Variable	Definition
WATCH	Dummy variable, 1 if a rating change is preceded by a credit watch, 0 otherwise
DOWNGRADE	Dummy variable, 1 if the rating change is a downgrade, 0 otherwise
INVEST_GRADE	Dummy variable for investment-grade rating, 1 if before the rating action, the rating is of investment grade ("Baa3" to "Aaa"), 0 otherwise
FAL_ANGL_CAN	Dummy variable for candidates of "Fallen Angel", i.e., investment-grade ratings that are one or two notches above the threshold of investment grade, 1 if the rating before the rating action is "Baa3" or "Baa2", 0 otherwise
RAT_TRIGGER	Dummy variable for the existence of a rating trigger
LITI_RISK	Within-quarter percentile rank of estimated litigation probabilities
DURATION	The number of days a rating is on the Watchlist
$RET\_WATCH_{(-1,+1)}$	Three-day size-adjusted buy-and-hold stock returns around the on-watch day
$RET\_\Delta RATING_{(-1,+1)}$	Three-day size-adjusted buy-and-hold stock returns around the rating change day
$FIRMSIZE_{-1}$	Firm size, natural log of total assets as of the quarter before the rating action
LEV_{-1}	Leverage, total liabilities scaled by total assets as of the quarter before the rating action
$BETA_{-1}$	Systematic risk estimated with the market model as of the quarter before the rating action
MSE_{-1}	Idiosyncratic risk estimated with the market model as of the quarter before the rating action
MTB_{-1}	Market to book ratio, market capitalization divided by book value of equity, as of the quarter before the rating action
REG_IND	Dummy variable for the regulated industry, 1 if the 2-digit SIC is 40-42, 44-47, 49, 0 otherwise
FIN_IND	Dummy variable for the financial industry, 1 if the 2-digit SIC is 60-69, 0 otherwise
ΔLEV_{-1}	Seasonal change in leverage in the quarter before the rating action
ΔROA_{-1}	Seasonal change in return on assets in the quarter before the rating action

Appendix B: Estimation of Litigation Risk

Variable	Predicted Sign	Coefficient	Chi-Square
INTERCEPT	+/-	-4.967	3960.29*
SIZE	+	0.152	769.26*
TURNOVER	+	0.114	4.63**
BETA	+	0.017	19.90*
RETURN	-	-0.180	25.52*
RET_STD	+	0.277	0.50
RET_SKEW	-	-0.003	0.08
RET_MIN	-	-2.344	197.04*
HIGHRISK_IND	+	0.248	114.82*
Psuedo R^2			11.43%
N			275,452

This table presents the regression results for the following probit model:

$$\Pr ob(LAWSUIT_{j,t+1}) = G(\beta_0 + \beta_1 SIZE_{j,t} + \beta_2 TURNOVER_{j,t} + \beta_3 BETA_{j,t} + \beta_4 RETURN_{j,t} + \beta_5 RET\_STD_{j,t} + \beta_6 RET\_SKEW_{j,t} + \beta_7 RET\_MIN_{j,t} + \beta_8 HIGHRISK\_IND_{j,t} + \varepsilon_{j,t}$$

where t = indicator of the calendar quarter t. j = indicator of firm j. LAWSUIT =1 if Stanford Law School's Securities Class Action Clearinghouse documents a securities class action lawsuit for that firm-quarter, and 0 otherwise. SIZE is the natural log of the average daily market capitalization. TURNOVER is the average daily number of shares sold divided by the average shares outstanding. BETA is the coefficient from market model estimated with daily stock returns and equal-weighted market returns. RETURN is the buy-and-hold returns over the calendar quarter. RET_STD and RET_SKEW are the standard deviation and skewness of the daily returns, respectively. RET_MIN is the minimum of daily returns. The HIGHRISK_IND dummy variable equals one if the firm is in the industry of Bio-technology (SIC 2833-2836), Computer Hardware (SIC 3570 to 3577), Electronics (SIC 3600-3674), Retailing (SIC 5200 to 5961), or Computer Software (SIC 7371 to 7379). The sample period starts from the fourth quarter of 1995 and ends with the fourth quarter of 2003. There are altogether 278,711 firm-quarter observations. After deleting 3,529 observations with missing explanatory variables, 275,452 observations are used in the regression analysis, among which 1,076 firm-quarters have lawsuits.
*, **, *** denote significance at 1, 5, and 10 percent levels respectively

Table 1: Distribution of Rating Changes across Watch Directions and Change Directions

Panel A: All Firms with Rating Changes

		Watch Direction				
		No Watch	Possible Downgrade	Possible Upgrade	Uncertain Direction	Total
Change Direction						
Downgrade	Number	1756	1486	8	22	3272
	Percentage	*54%*	*45%*	*0%*	*1%*	*100%*
Upgrade	Number	1087	17	536	15	1655
	Percentage	*66%*	*1%*	*32%*	*1%*	*100%*

Panel B: Firms with Rating Changes and Available Data

		Watch Direction				
		No Watch	Possible Downgrade	Possible Upgrade	Uncertain Direction	Total
Change Direction						
Downgrade	Number	665	710	3	9	1387
	Percentage	48%	51%	0%	1%	100%
Upgrade	Number	495	7	243	8	753
	Percentage	66%	1%	32%	1%	100%

Panel A lists the total 4,927 Moody's issuer or senior debt rating changes from 1995 to 2003. Panel B lists the 2,192 rating changes with required data. Observations are first classified according to their change directions, then to their watch directions.

Table 2: Annual Distribution of Watched and Non-Watched Rating Changes

		Downgrade Sample			Upgrade Sample		
		WATCH =0	WATCH =1	Total Downgrades	WATCH =0	WATCH =1	Total Upgrades
1995	Number	129	65	194	132	47	179
	Percentage	66%	34%	100%	74%	26%	100%
1996	Number	114	77	191	163	47	210
	Percentage	60%	40%	100%	78%	22%	100%
1997	Number	137	78	215	162	59	221
	Percentage	64%	36%	100%	73%	27%	100%
1998	Number	218	108	326	156	67	223
	Percentage	67%	33%	100%	70%	30%	100%
1999	Number	194	164	358	113	90	203
	Percentage	54%	46%	100%	56%	44%	100%
2000	Number	218	156	374	93	110	203
	Percentage	58%	42%	100%	46%	54%	100%
2001	Number	332	274	606	109	69	178
	Percentage	55%	45%	100%	61%	39%	100%
2002	Number	243	391	634	60	30	90
	Percentage	38%	62%	100%	67%	33%	100%
2003	Number	171	203	374	99	49	148
	Percentage	46%	54%	100%	67%	33%	100%

See Appendix A for variable definitions.

Table 3: Characteristics of Credit Watches

Panel A: Duration and Announcement Effects

Downgrade Sample

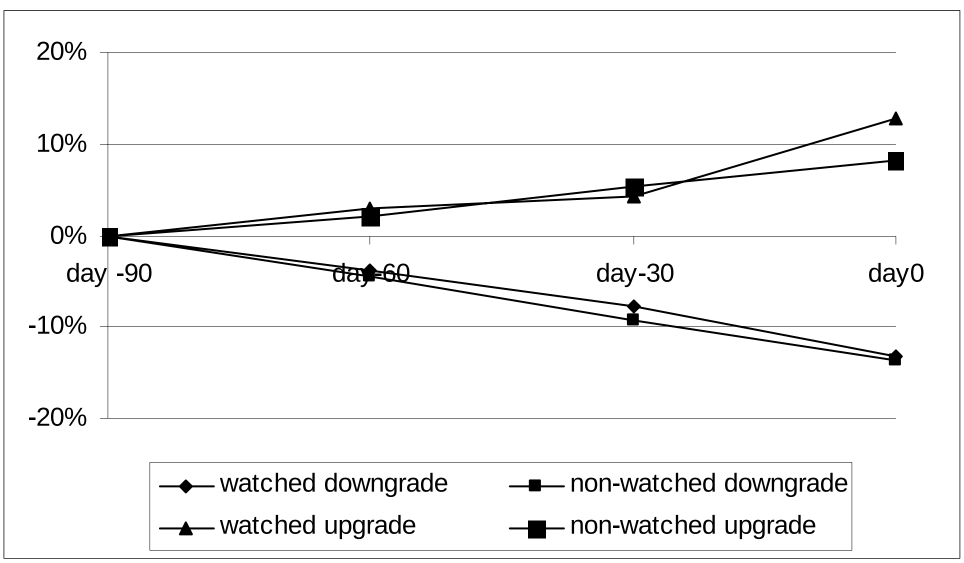
	DURATION (days)	RET_WATCH$_{(-1,+1)}$	RET_ΔRATING$_{(-1,+1)}$
WATCH=1	100	-4.40%*	-2.72%*
WATCH=0	-	-	-4.33%*
Difference	-	-	1.61%**

Upgrade Sample

	DURATION (days)	RET_WATCH$_{(-1,+1)}$	RET_ΔRATING$_{(-1,+1)}$
WATCH=1	140	7.91%*	0.30%
WATCH=0	-	-	0.65%**
Difference	-	-	-0.35%

See Appendix A for variable definitions.
*, **, *** denote significance at 1, 5, and 10 percent levels respectively.

Panel B: Stock Returns before Credit Watches



Day 0 is the on-watch day when there is a credit watch, and the 90th day before the rating change announcement when there is no credit watch.

Table 4: Descriptive Statistics

VARIABLE	MEAN	MIN	Q1	MEDIAN	Q3	MAX	STD
WATCH	0.458	0.000	0.000	0.000	1.000	1.000	0.498
DOWNGRADE	0.648	0.000	0.000	1.000	1.000	1.000	0.478
INVEST_GRADE	0.374	0.000	0.000	0.000	1.000	1.000	0.484
FAL_ANGL_CAN	0.160	0.000	0.000	0.000	0.000	1.000	0.367
RAT_TRIGGER	0.130	0.000	0.000	0.000	0.000	1.000	0.337
LITI_RISK	0.752	0.000	0.630	0.805	0.930	0.990	0.211
ΔLEV_{-1}	0.014	-0.374	-0.036	0.009	0.058	0.401	0.115
ΔROA_{-1}	-0.012	-0.992	-0.015	-0.002	0.004	0.467	0.060
$FIRMSIZE_{-1}$	7.686	4.843	6.681	7.564	8.592	11.031	1.367
LEV_{-1}	0.728	0.303	0.600	0.708	0.823	1.514	0.205
$BETA_{-1}$	0.816	-0.837	0.348	0.724	1.148	3.155	0.716
MSE_{-1}	0.002	0.000	0.000	0.001	0.002	0.016	0.002
MTB_{-1}	2.624	-16.746	0.788	1.670	3.000	37.538	5.667
$STK\_RET\_BW_{[-90,-1]}$	-0.054	-0.773	-0.231	-0.050	0.103	0.978	0.297
REG_IND	0.113	0.000	0.000	0.000	0.000	1.000	0.316
FIN_IND	0.009	0.000	0.000	0.000	0.000	1.000	0.096

See Appendix A for variable definitions.

Table 5: Pearson and Spearman Correlation Coefficients

VARIABLE	WATCH	DOWNGRADE	INVEST_GRADE	FAL_ANGL _CAN	RAT_TRIGGER	LITI_RISK
WATCH	1.000	0.171	0.315	0.128	0.084	0.180
DOWNGRADE	0.171	1.000	0.153	0.015	-0.023	0.003
INVEST_GRADE	0.315	0.153	1.000	0.565	0.077	0.268
FAL_ANGL _CAN	0.128	0.015	0.565	1.000	0.058	0.101
RAT_TRIGGER	0.084	-0.023	0.077	0.058	1.000	0.133
LITI_RISK	0.174	0.049	0.258	0.085	0.127	1.000

Pearson correlation coefficients are listed above the diagonal; Spearman correlation coefficients are listed below the diagonal.

See Appendix A for variable definitions.

Table 6: Logit Analysis of Watch Decisions (N=2,140)

	Dependent variable WATCH =1 if the rating change is preceded by a watch			
VARIABLE	(1)	(2)	(3)	(4)
INTERCEPT	-0.652*	-4.331*	-0.432	-2.571*
DOWNGRADE	0.734*	0.849*	-1.506*	-1.300*
INVEST_GRADE			0.928*	0.622**
FAL_ANGL_CAN			-0.483***	-0.374
LITI_RISK			-0.490	-1.577*
RAT_TRIGGER			-0.325	-0.448***
DOWNGRADE* INVEST_GRADE			0.568**	0.550***
DOWNGRADE* FAL_ANGL_CAN			0.326	0.288
DOWNGRADE* LITI_RISK			2.254*	2.081*
DOWNGRADE* RAT_TRIGGER			1.148*	1.140*
ΔLEV_{-1}		1.361***		1.083
ΔROA_{-1}		-4.086***		-3.397***
$STK\_RET_{[-90,-1]}$		1.080*		1.004*
DOWNGRADE* ΔLEV_{-1}		-2.157**		-2.012**
DOWNGRADE* ΔROA_{-1}		5.333**		4.340***
DOWNGRADE*$STK\_RET_{[-90,-1]}$		-1.630*		-1.844*
$FIRMSIZE_{-1}$		0.493*		0.365*
LEV_{-1}		-0.016		0.369
$BETA_{-1}$		-0.103		-0.020
MSE_{-1}		-93.472*		-49.085***
MTB_{-1}		0.013		0.010
REG_IND		-0.174		-0.337**
FIN_IND		-0.199		-0.243
Pseudo R^2	3.9%	19.8%	20.2%	25.2%

See Appendix A for variable definitions.
*, **, *** denote significance at 1, 5, and 10 percent levels respectively.

Table 7: Watch and Change Decisions based on Heckman's Sample Selection Model

	Downgrade		Upgrade		T-stat for diff in Watch coefficients
VARIABLE	Downgrade or Not (N=1714)	Watch or Not(N=857)	Upgrade or Not(N=900)	Watch or Not(N=450)	
	(1)	(2)	(3)	(4)	(5)
INTERCEPT	-0.393*	-2.447*	-0.901*	-2.840*	0.497
INVEST_GRADE	0.151***	0.702*	-0.200	0.085	2.178**
FAL_ANGL_CAN	-0.067	-0.026	-0.098	0.156	-0.629
RAT_TRIGGER	-0.115	0.443*	0.170	-0.353***	2.972*
LITI_RISK	0.337**	0.441***	1.166*	-0.684	1.823***
ΔLEV_{-1}	1.092*	-0.256	-1.797*	0.531	-0.861
ΔROA_{-1}	-5.026*	-1.143	3.874**	-4.022	1.025
$\Delta FIRMSIZE_{-1}$	-0.623*		0.164		
$\Delta BETA_{-1}$	0.026		0.015		
ΔMSE_{-1}	113.371*		-48.189		
$STK\_RET_{[-90,-1]}$	-0.856*	-0.655*	0.989*	0.495**	-4.291*
REG_IND	0.022	-0.013	0.072	0.081	-0.311
FIN_IND	-0.245	-0.057	0.127	-0.518	0.578
$FIRMSIZE_{-1}$		0.128*		0.325*	-2.176**
LEV_{-1}		0.494**		0.400	0.257
$BETA_{-1}$		0.085		-0.066	1.148
MSE_{-1}		-40.953**		91.358	-1.678***
MTB_{-1}		-0.005		0.005	-1.667***
Log Likelihood	-1567		-841		

See Appendix A for variable definitions.
*, **, *** denote significance at 1, 5, and 10 percent levels respectively.

Quality of Private Information and Bond Yield Spreads*

Doctoral Dissertation Chapter 2

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Quality of Private Information and Bond Yield Spreads

Abstract: Private information of investors could play a different role in the over-the-counter (OTC) market for corporate bonds than in the equity market. In particular, private information could reduce dealer market power and assessed default probability while having limited effect on creating information asymmetry among mostly institutional investors. We show that precision of both private and public information is *negatively* related to bond yield spreads. There is also a substitution effect between the two sources of information. In addition, we find that the information effect is especially large when bond maturity is relatively short, consistent with the theory of Duffie and Lando (2001). Our results suggest that, when assessing their reporting strategy, managers should not only consider the relation between public and private information, but also weigh the relative importance of the bond and equity markets in each context.

Keywords: *Private information, public information, information precision, yield spread, credit ratings*.

Data Availability: *All data are available from public sources*.

JEL classification: G12, G29, M40, M41

Quality of Private Information and Bond Yield Spreads

1. Introduction

In the equity market, private information of investors tends to increase information asymmetry among investors and lead to higher expected returns on equity (Easley et al., 2002; Easley and O'Hara, 2004). Private information could play a very different role in the bond market than in the equity market. Biais and Green (2007) argue that the two markets are different in their microstructures. While stocks are competitively traded on exchanges, bonds are traded in the over-the-counter (OTC) market through bargaining with dealers who act as local monopolies and extract considerable rents (Diamond, 1971; Duffie et al., 2005; Green, 2007). Institutional ownership and trading also dominate the bond market relative to the equity market. These features suggest that private information in the bond market could help strengthen investors' bargaining position in trade negotiations in addition to the conventional role of reducing investors' estimation error about firm value, whereas its effect on creating information asymmetry among (mostly institutional) investors is likely to be limited.

We empirically examine the relation between information quality and bond yield spreads. Assuming that the information environments of financial analysts are representative of the information environments of informed investors, we show that precision of both private and public information is *negatively* related to bond yield spreads. There is also a substitution effect between the two sources of information. In addition, the information effect is stronger when bond maturity is shorter, consistent with the theory of Duffie and Lando (2001).

While some theories argue that information risk is diversifiable and not priced, other theories link information quality to the pricing of risky securities through the effect of estimation risk (uncertainty about asset payoff parameters) and information asymmetry on expected returns. The net effect differs between information from public sources that are available to all investors and information from private channels that are available only to a subset of investors. Public information tends to reduce both estimation risk and information asymmetry among investors, and is thus expected to lower the expected returns.[11] Private information, however, tends to reduce estimation risk but increase information asymmetry among investors. Empirical studies on the effect of private information have generally focused on the equity market and found that higher quality of private information is associated with higher expected returns on equity (e.g., Botosan et al., 2004; Easley et al., 2002; Easley and O'Hara, 2004). This suggests that the information asymmetry effect dominates the estimation risk effect in the equity market. If the same effects carried over to expected returns on debt, one would expect that higher quality of private information is associated with larger bond yield spreads, *ceteris paribus*, since expected returns on debt are a major component of yield spreads. This contrasts to our finding of a negative relation between the two.

Theories directly linking information quality to bond yield spreads have been few and far between even though credit spreads have been extensively studied before. Duffie and Lando (2001) are a notable exception. Incorporating information into a standard structural model for valuing risky debt, they show that more precise information about firm value can reduce the conditional probability of firm value crossing the default threshold and lower credit yield spreads. In addition, such effect is most pronounced

[11] Empirical results appear supportive of this relation: higher quality of public information has been found to be associated with both expected returns on equity (e.g., Botosan, 1997; Frankel et al., 1995; Francis et al., 2004) and expected returns on debt using proxies such as bond yield spreads and bond ratings (e.g., Sengupta, 1998; Francis et al., 2005; Yu, 2005; Wittenberg-Moerman, 2005).

when debt maturity is relatively short. Although Duffie and Lando (2001) use the term "accounting" to refer to the information in their model, information serves the role of changing investors' conditional distribution of firm value and can come from either public or private sources. Their theory suggests that private information in the bond market would help reduce estimation risk and bond yield spreads, especially for short-term bonds.

On the other hand, the effect of private information on creating information asymmetry among investors is likely to be relatively weak in the bond market. This is because the vast majority of bond trading occurs between institutional investors (Biais and Green, 2007). Information asymmetry among them is less of a concern since they are usually better informed. Information asymmetry between them and small investors exists or may even be larger than in the equity market, but its effect on increasing expected returns on debt and consequently bond yield spreads is likely to be small due to limited trading activities by small investors.

Further, private information of bond investors can play a unique role that is absent in the equity market, that is, to mitigate dealer market power and reduce dealer rents. In the OTC market for bonds, trading is a bargaining process between investors and dealers, with dealers in a dominant position due to their monopoly power and information opacity in this market. Even though bonds are less risky than stocks, transaction costs have been higher in the bond market than in the equity market partly because of dealer rents (Edwards et al., 2007). In the trade negotiation process, investors would be in a better bargaining position and obtain better terms when equipped with better information, private or public (Green, 2007). *Ceteris paribus*, bond yield spreads are expected to be lower with lower dealer rents. Overall, the role of private information in reducing the dealer market power-related transaction costs and in reducing estimation risk is likely to more than offset its limited role in creating information asymmetry among investors. Thus, we conjecture that quality of private information is negatively associated with bond yield spreads, especially for bonds with relatively short maturity.

We measure yield spreads for two samples, one of seasoned bonds and one of new bond issuances. We also examine Standard and Poor's (S&P) issuer credit ratings and yield spreads after controlling for credit ratings. To measure quality of information, we use the information precision measures first developed by Barron et al. (1998) and generalized by Gu (2006). These measures are based on the assumption that analyst earnings forecasts reflect both public information shared by all analysts and private information available only to individual analysts and independent of other information. Precision of public and private information is inferred from the observed forecast dispersion, error in the mean forecast and number of analysts.

Our results indicate that precision of both public and private information is negatively related to bond yield spreads. In addition, the interaction of the two precision measures is positively related to yield spreads. That is, the effect of the precision of information from either source is smaller if the precision of information from the other source is higher, suggesting a substitution effect between the two information sources. The results based on the ranked precision measures indicate that, holding public information precision at the median level, an increase of the private information precision from the 25^{th} percentile to the 75^{th} percentile is associated with a decrease of yield spreads of about 117 (54) basis points (BP) without (with) the control variables for seasoned bonds and 65 (21) BP for new bond issuances. The effect of public information is similar in magnitude. When we separate the bonds into different maturity groups, the corresponding impacts of private information for bonds with below-median maturity are 54 and 12 BP higher than for bonds with above-median maturity in the two samples, after controlling for other factors. The results from credit ratings are consistent, with higher precision of both public and private information associated with more favorable credit ratings. The information effect on bond yield spreads holds even after controlling for credit ratings.

Our study contributes to the literature in several ways. First, while some prior studies examine indirectly how the *content* of private information affects bond yield spreads, we are perhaps among the first to study how the *quality* of private information affects bond yield spreads. A common approach in prior studies is to regress credit ratings on publicly known variables and interpret the residuals as reflecting the private information available to credit rating agencies beyond public information. The residuals are then related to yield spreads in a second-stage regression (e.g., Liu and Thakor, 1984). This residual approach is insufficient to study the information quality effect because a positive residual rating can be due to either favorable news content about a firm's higher-than-expected cash flows, or a high quality of news source. Moreover, residual ratings already summarize the information effect, if any, into a directional measure (positive or negative) and are expected to affect bond yield spreads accordingly. We are interested in whether and how private information quality affects bond yield spreads (and credit ratings) in the first place and we use a direct measure of information quality.

Second, we show that, to the extent that bond yield spreads proxy for expected returns on debt, private information affects expected returns on debt differently from expected returns on equity. These results suggest that how information affects the cost of capital depends not only on the quality of information itself but also on the market microstructure in which the information is used. Recent studies in finance have paid increasing attention to the issue of dealer market power in the bond market. For example, larger trade size has been found to be associated with lower bid-ask spread in the bond market but higher bid-ask spread in the equity market. This has been attributed to the different microstructures of the two markets. Our results provide further support along this line and are consistent with the role of private information in facilitating bond trade negotiations.

Third, our study has some interesting implications for firms' disclosure strategy and, together with studies on the equity market, provides a more complete picture of capital market consequences of information quality. For example, Botosan et al. (2004) conclude that managers should consider the relation between public and private information when assessing their disclosure strategies. Our study suggests that managers should further consider the relative importance of the debt and equity markets in each context. This is consistent with the Holthausen and Watts' (2001) argument that one should go beyond the stock market when considering the value relevance of information. For another example, firms' public disclosures often trigger increased search for private information (Barron et al., 2002). The effect of increased private information can more than offset the effect of public disclosures on the expected returns on equity (Botosan et al., 2004). We find that both will lower bond yield spreads.

Finally, our results provide a partial explanation for the rationale behind Regulation Fair Disclosure, which prohibits managers' preferential disclosure of private information to select investors, but grants an exemption to bond rating agencies and allows them to continue receiving private information from managers (Jorion et al., 2005). The regulation is intended to reduce management private communication that presumably increases the information asymmetry among equity investors and thus expected returns on equity. However, continuing to allow such private communication in the bond market could be useful for reducing bond yield spreads, especially when the cost of public disclosure is high (e.g., due to proprietary costs).[12]

The rest of the paper is organized as follows. In the next section we motivate our study and argue why private information is expected to reduce bond yield spreads. Variable measurements are described in section 3. Section 4 provides the descriptive statistics for our samples. Empirical results are discussed in Section 5. Conclusions are drawn in Section 6.

2. Motivation

2.1. Private Information and Dealer Market Power

One of the major differences between the bond market and the equity market is in the microstructures (Biais and Green, 2007). Trading of corporate bonds migrated from NYSE to the dealer-based OTC market in the 1940's, accompanied by an increase in the role of institutional investors. Unlike exchanges for stocks, the dealer market for bonds are much less competitive and dealers have considerable market power in the trade

[12] Although we only examine public debt in this study, this implication is consistent with an explanation for firms' private placements of debt in terms of facilitating private communication and monitoring while avoiding public disclosure.

negotiation process. Dealer market power comes from at least two sources. First, dealers act as local monopolies in setting bond prices (Diamond, 1971). Trading of bonds typically does not occur directly between investors through limit orders, but between investors facing search costs and a few dealers. Second, unlike in the stock market where investors can infer information from past transactions, information on past bond transactions was traditionally not known to investors. Even concurrent bid-ask prices for a same bond across dealers are not observable unless an investor contacts each dealer individually. Thus, information acquisition costs are relatively high. The monopolistic position of dealers in both products and information gives them considerable market power to extract rents. *Ceteris paribus*, bond yields are expected to be higher when dealer market power-related transaction costs are higher.

Dealer market power suggests that information could play a role in the bond market that is absent in the equity market. That is, higher quality of information, *from either public or private sources,* could provide bond investors with more bargaining power in the negotiation with dealers and reduce the transaction costs (Green, 2007). The use of information in mitigating dealer market power can perhaps be best illustrated using the consumer car market as an analogy. Car dealers have long been known to be able to extract considerable rents due to their local monopolistic position in holding the car inventory and superior information about the functions, market conditions, manufacturing and shipping costs, and past transactions of their cars. Consumers are highly advised to conduct their search for such information, either from public or private sources, before approaching the dealer and starting the bargaining process. While the increasing public availability of information such as dealer costs on the internet in recent years has significantly reduced the dealer advantage, additional information through private search and analysis (such as recent deal terms, test driving experience, and driving experience of friends) would further strengthen consumers' bargaining position.

Recent findings in finance on the relationship between trade order size and bid-ask spreads support the importance of dealer market power in the bond market. In the equity market, bid-ask spreads are found to increase in order size. The argument is that the market-maker would infer from a larger order that the investor has superior private information and thus charge a higher spread to protect himself. However, bid-ask spreads are found to decrease in order size in the bond market (Edwards et al., 2007; Harris and Piwowar, 2006; Schultz, 2001). The argument is that a larger order would give the investor more bargaining power when transacting with the dealer (Green et al., 2007) (just like a car buyer is likely to get better terms from dealers if he buys ten cars instead of one). The dealer may still infer from a larger order size that the investor has superior private information, but the private information would work to the advantage of the investor.

Duffie et al. (2005) model the price formation in the OTC market as a randomized matching and bargaining process. When investors have more outside options (e.g., more easily find other investors or have easier access to multiple dealers, just like a car buyer who have better access to other car dealers or other individual sellers, or are more willing to accept substitute brands/models), they are in a better position to bargain with the dealer and receive smaller dealer spreads. Although Duffie et al. do not model the role of information, their study not only illustrates the bargaining nature of bond transactions, but also can be directly extended to cases where investors' outside options depend on the (private or public) information available to them (i.e., how much they know about outside options).

Lack of transparency and higher transaction costs in the bond market compared to the equity market have raised considerable regulatory concerns (Spatt, 2006). A number of actions have been taken to reduce dealer market power. Most notably, NASD has required dealers to report OTC bond transactions through the TRACE (Trade Reporting and Compliance Engine) system since July 2002. It has been shown that bond transaction costs have fallen in recent years (Bessembinder et al., 2006; Goldstein et al. 2007).[13] The regulatory efforts have generally focused on increasing the public availability of past transactions data. In this paper, we examine quality of information about firm fundamentals (earnings). Although public availability of past transactions data would reduce dealers' information advantage, we argue above that private information of investors can serve a similar role in one-to-one negotiations with dealers. Further, we examine a period before the full implementation of TRACE due to data availability to us. That is, we study the cross-sectional variation in information quality holding the information regime constant.

2.2. Private Information and Yields Spreads at Different Maturities

While the role of private information in reducing dealer rents and thus yield spreads has received limited attention before, Duffie and Lando (2001) model from another angle how (accounting) information can reduce yield spreads of risky debt through investors' reduced estimation error about firm value. Relaxing the assumption in

[13] Edwards et al. (2007) show that even as past transactions data became available through the TRACE system, bid-ask spread for a bond trade of retail size was still more than three times as large as bid-ask spread for an equity trade of similar size.

previous structural credit risk models that firm value is always perfectly observed, they show that credit yield spreads are affected by how precise investors' information is about firm value. Imperfect knowledge of firm value induces a non-zero conditional probability of firm value crossing the default threshold even when the bond maturity is 0. *Ceteris paribus*, more precise information decreases the probability and consequently lowers yield spreads. Duffie and Lando (2001, p. 649) point out that this result is analogous to the bond pricing in a Black-Scholes setting where the equity price as a function of asset level is increasing in the volatility of assets and therefore the bond price is decreasing in the volatility of assets. The difference is that the actual asset volatility is held fixed this time, but investors' inferred volatility depends on the precision of information available to them. In addition, Duffie and Lando show that the impact of information on reducing yield spreads depends on the term structure of the bond. It is most pronounced when maturity is short and dissipates as maturity gets longer.

Barclay and Smith (1995) examine the cross-sectional determinants of debt maturity structures and find results consistent with the hypothesis that firms with more information asymmetry (between the firm and investors) are more likely to issue bonds with shorter maturity. Their results suggest that if information helps investors assess firm value at all, the benefit is larger when bond maturity is shorter.

Yu (2005) empirically tests the predictions of the Duffie and Lando theory. Using disclosure rankings by the Association for Investment Management and Research as the measure of accounting information quality, he finds that higher disclosure quality is associated with lower bond yield spreads and such information effect is especially large for short-term bonds.

The Duffie and Lando (2001) study is partly motivated by the previous empirical findings that macroeconomic variables as well as firm-specific accounting variables have predictive power for bond yield spreads, even after exploiting the asset and liability data in structural credit risk models. Although they use the term "accounting" to refer to information, information in their model can be from either public or private sources as long as it helps investors assess the conditional distribution of firm value. Furthermore, the model in Duffie and Lando (2001) is abstracted from the dealer-investor bargaining process. In light of the dealer market considered in Duffie et al. (2005), the use of private information could be especially effective when bond prices are set in one-to-one negotiations relative to cases where prices are set competitively and investors take the prevailing market price.

Previous literature has also long argued that information can reduce investors' uncertainty in assessing the parameters of assets' payoff distributions, that is, estimation risk. To the extent that estimation risk is nondiversifiable and priced, quality of information is negatively related to expected returns because higher quality of information will reduce the premium on estimation risk (see, e.g., Klein and Bawa, 1976; Coles and Lewenstein, 1988; Easley and O'Hara, 2004; Lambert et al., 2007). When applied to the bond market, this line of research also suggests that better private information would be associated with smaller bond yield spreads due to lower expected returns on debt.

2.3. Information Asymmetry and Institutional Investors in the Bond Market

Another line of research on the relation between information risk and expected returns argues that adverse selection arises from information asymmetry among investors.

When information is available only to certain investors but not to others, expected returns are higher because, to compensate for illiquidity or the risk of trading with informed investors, uninformed investors will demand higher returns (see, e.g., Amihud and Mendelson, 1987; Easley et al., 2002; Easley and O'Hara, 2004). This line of research suggests that quality of private information is positively related to expected returns because private information increases the information asymmetry among investors.

In the bond market, however, the information asymmetry effect of private information is likely to be smaller than in the equity market, due to another feature of the bond market microstructure. In particular, the vast majority of investors of US corporate bonds are institutional investors. Based on data from several sources, Biais and Green (2007) report that the household ownership of corporate bonds has been consistently under 20% since the 1950's.[14] Although detailed trading data are lacking, they conjecture that institutional investors account for the majority of the trading activities in the bond market. The institutional investors are usually among the better informed with private information. Their information advantage to small investors may be big, or even bigger in the bond market than in the equity market.[15] However, the information asymmetry among themselves who are the major players in the bond trading activities is not necessarily large. The information asymmetry between institutional investors and small investors may have limited effect on expected returns on debt because small investors have limited

[14] As of the end of 2003, household ownership and financial institutional ownership of corporate bonds are 6.5% and 68.7% respectively, whereas the corresponding ownerships of corporate equity are 41.4% and 48.5% (Federal Reserve statistical release, 2004). Other major owners of bonds are state and local governments and foreign countries.

[15] The bond market is informationally more opaque than the equity market in the sense that information about past transactions such as the timing, amount, price and trader identity is not as readily available in the bond market as in the equity market, especially to small investors (Green et al., 2007). It is less clear, however, whether information about firm fundamentals is also more opaque in the bond market.

trading activities and thus limited exposure to the information asymmetry risk.

In addition, the bond market features a handful of rating agencies that serve as information intermediaries and widely disseminate their ratings to the general public but do not engage in trading of the bonds. Of them, five "Nationally Recognized Statistical Rating Organizations" recognized by the SEC play a quasi-regulatory role as their ratings are explicitly referenced by regulators in numerous federal and state laws and regulations (Beaver et al., 2006). The quasi-regulatory role implies that these rating agencies cannot use their information to selectively serve investors as equity analysts do. In the rating process, the rating agencies often get access to management confidential information (Edenrington and Goh, 1998; S&P, 2003). However, the primary use of the private information is to help the rating agencies reduce estimation risk in assessing firms' creditworthiness instead of creating information asymmetry so that certain investors can take advantage of others.

2.4. Aggregate Information Effect

The aggregate information effect on bond yield spreads depends on the relative importance of the three effects discussed above and depends on whether information is public or private. Higher quality of public information is expected to reduce dealer market power, estimation error about firm value and information asymmetry among investors, hence reduce bond yield spreads. Empirical evidence has been consistent. More voluntary disclosures, higher quality of reported accounting numbers and increased public availability of past transactions data are found to be associated with lower yield spreads and more favorable credit ratings (e.g., Sengupta, 1998; Francis et al., 2005; Yu, 2005; Wittenberg-Moerman, 2005; Bessembinder et al., 2006; Goldstein et al. 2007;

Edwards et al., 2007). Although the dealer market power effect is lacking in the equity market, better public information is also found to be associated with lower expected returns on equity (e.g., Botosan et al., 2004; Frankel et al., 1995; Botosan, 1997; Francis et al., 2004).

Empirical studies on the effect of private information have generally focused on the equity market. Using similar measures to those used in this paper, Botosan et al. (2004) and Kanagaretnam et al. (2006) find that more precise private information is associated with higher expected returns, larger bid-ask spreads and less market depth. These results suggest that the information asymmetry effect of private information dominates the estimation risk effect in the equity market.

Our previous discussion suggests that the information asymmetry effect of private information is likely to be limited in the bond market due to the dominance of institutional investors. The effects of private information in lowering the dealer market power-related transaction costs as well as reducing estimation error about firm value and default probability are likely to be relatively more important.[16] These considerations lead us to conjecture that quality of private information is negatively related to bond yield spreads. The theory of Duffie and Lando (2001) further suggests that this relation is especially strong when bond maturity is relatively short.

We recognize that theoretically a consensus is yet to be reached on whether

[16] The dominance of institutional investors also constrains dealer market power. However, information quality of institutional investors can still vary significantly *across bonds*, leading to different dealer market power and estimation error. Information asymmetry among institutional investors, *for any given bond*, can be limited with either high or low information quality. Thus, cross-sectionally there can be both large variations in the information effects related to dealer market power and estimation error, and small or little variation in the effect related to information asymmetry among investors. Our interest is in the aggregate information effect on bond yield spreads in the cross-sectional setting.

information risk is priced. Recently Hughes et al. (2007) argue that both estimation risk and asymmetric information risk are diversifiable in a large pure exchange economy. Lambert et al. (2007), however, argue that while the effect of information quality on the assessed variance of a firm's cash flows is diversifiable, the effect on the assessed covariances is not. Empirically most studies find that information quality is associated with expected returns. This suggests that either information risks are either nondiversifiable or that investors are under-diversified.

The difficulty in diversifying away estimation risk and information asymmetry risk is especially a concern in the bond market since this market is relatively illiquid with fewer trades by fewer investors compared to the equity market (Biais and Green, 2007).[17] In addition, it is not clear how transaction costs arising from dealer market power can be diversified away since each transaction has to be consummated through the limited number of dealers in this market. The use of better information or larger trade size is precisely to reduce, but probably not eliminate, such dealer-related transaction costs. In other words, even if estimation risk or information asymmetry risk may (or may not) be fully diversifiable, information is still likely to matter in the very process of achieving diversification. At a minimum, whether and how information quality is priced in the bond market remains an empirical question.

3. Variable Measurement

3.1. Bond Yield Spreads

Bond yield spreads (SPREAD) have been examined in many prior studies and are

[17] Based on data in 2003 after the TRACE system took effect, Edwards et al. (2007) find that the median (mean) number of trades per day is 1.1 (2.4) for a bond. Such low liquidity is likely to be already higher than that in our sample period before the installation of the TRACE system.

often interpreted as a proxy for the cost of debt in the accounting literature because expected returns on debt constitute a major component of yield spreads (Mansi et al. 2007; Jiang, 2005; Shi, 2003; Sengupta, 1998). Even though the calculation of yield spreads itself is based on no default, default risk affects bond prices and is incorporated in yield spreads (e.g., Duffie and Lando, 2001). We measure SPREAD for two samples, one of seasoned bonds and one of new bond issuances.

SPREAD of seasoned bonds is obtained from Datastream database.[18] Datastream provides daily bond price information collected by Merrill Lynch. The stated price is an average price across all dealers on the OTC market for a bond (Chen et al. 2007). For each bond, SPREAD is calculated in percentages as the difference between the yield to maturity and the yield of the treasury issues with comparable maturity. We measure SPREAD as of the last day of the third month after the fiscal year end to ensure that accounting information for the year is available to the market. If a yield spread is not available that day, the immediate next available yield spread is used. If a company has more than one bond outstanding in a given year, the yield spread of the most senior bond (best rating) is used. We also use the weighted average of yield spreads over a firm's outstanding bonds, with the market values of the bonds as the weights. The results are qualitatively similar (unreported).[19]

SPREAD of new bond issuances is obtained from Mergent FISD database. We similarly measure SPREAD in percentages as the difference between the offering yield to maturity of new issuances and the yield of the treasury issues with comparable maturity.

[18] We are grateful to Jieying Zhang for generously sharing the data collected from Datastream.
[19] There are about 60 observations with negative yield spreads. We assume they are measured with error and assign a value of zero to them. Our results are not affected if we exclude these observations.

We only use senior and senior subordinated bonds and exclude other subordinated bonds and bonds with asset-backed or credit-enhancement features. For firms with multiple issuances in a given year, we use the yield spread on the issuance with the largest offering amount (Khurana and Raman 2003; Jiang 2005). Since bonds can be issued any time during the year, most control variables for this sample are measured in the year prior to the bond issuance.

The S&P issuer credit ratings (RATING) provide an assessment of bond issuers' overall creditworthiness and are closely related to firms' default risk and interest cost (S&P, 2003; Altman 1992). Factors affecting bond yield spreads are expected to similarly affect credit ratings. We also examine how information quality affects credit ratings and whether the information effect on yield spreads holds after controlling for credit ratings. S&P issuer credit ratings are obtained from Compustat (#280). These ratings are coded from 2 to 21, with 2 representing a rating of AAA and 21 representing a rating of CCC- (code 3 unassigned) in Compustat. We re-code the credit ratings in reverse order from 19 to 1 so that a higher value of RATING represents a more favorable rating.

3.2. Precision of Private and Public Information

To study the effect of information quality on bond yield spreads, one would ideally have quality measures for information in the debt market. The empirical proxies we use are precision of private and public information of financial analysts inferred from their earnings forecasts. The use of analysts' information quality for the debt market can be justified by several considerations. First, it is reasonable to assume that public information is similar in the debt and equity markets. Second, for private information, we are interested in how its *across-firm variation* is related to the *across-firm variation* in bond yield spreads. Comparing two firms, we expect that the one for which financial analysts are able to extract more precise private information is most likely also the one for which bond analysts and investors are able to extract more precise private information. In other words, even though equity investors and bond investors may have different focuses on the content of information, the quality of private information available to them is likely to have similar across-firm variation. What makes our measures work is not the measured values themselves, but their relative ordering across firms. Third, institutional investors are the major clients of financial analysts' research reports. They trade in both the bond and equity markets and are likely to use all available information. Thus, information provided by financial analysts can be directly relevant to the information set of these informed investors and their bond trading activities.[20] To the extent that the information precision measures we use do not capture the relevant information quality in the debt market, the measurement error will bias against our finding of any systematic relation between information precision and bond yield spreads.

Specifically, we measure the precision of analysts' public and private information following the method initially developed by Barron et al. (1998) and generalized by Gu (2006) to infer unobservable properties of the information environment from observed properties of analyst forecasts. Each analyst is assumed to observe two signals about future earnings A: a common prior shared by all analysts that A is normally distributed with mean $\bar{A}$ and precision (inverse of variance) h; a private signal $z_i = A + \varepsilon_i$ available only to analyst i, where ε_i is normally distributed with mean zero and precision s_i, and

[20] Based on private conversation with Scott Richardson of BGI, debt analysts and equity analysts have significant overlap in their research and information generated. Some investment banks have moved toward combining their debt and equity research departments together.

independent of all other information. Analyst i makes forecast of future earnings based on her expectation conditional on her two signals, $F_i = (h\bar{A}+s_iz_i)/(h+s_i)$. Variance of her forecast error is $V_i = 1/(h+s_i)$. Although precision of public and private information (h and s_i) cannot be measured from an individual forecast due to lack of degree of freedom, with multiple forecasts, h and s_i can be measured by utilizing the information in the aggregated forecast properties: the mean forecast error, forecast dispersion, and number of forecasts. In particular, under the assumption that s_i is identical across all analysts (= s), Barron et al. (1998) show that,

$$h = \frac{(SE - D/N)}{\left[(1-1/N)D + SE\right]^2}, \text{ and } s = \frac{D}{\left[(1-1/N)D + SE\right]^2}.$$

where N is total number of analysts making forecasts; SE is variance of error in the mean forecast; D is expected dispersion (sample variance) of the N forecasts.

Gu (2006) relaxes the assumption that all analysts have identical precision of private information and provides the following generalized measures of h and s_i:

$$h = \frac{N(N-1)[SE - D/N]}{N^2\left[(1-1/N)D + SE\right]^2 - \sum_{i=1}^{N} V_i^2}, \text{ and } s_i = \frac{1}{V_i} - h, \text{ for i = 1,…, N.}$$

where V_i is variance of error in the individual forecast by analyst i. The relaxation of the equal private information precision assumption by Gu (2006) is justified by numerous findings that analysts differ systematically in their forecast accuracy, which can only be caused by different precision of their private information (e.g., Mikhail et al., 1997; Jacob et al., 1999; Clement, 1999). We use the generalized Gu measures for our main results and use the Barron et al. measures as a sensitivity check.

Variables of V, V_i and D in the above theoretical measures of h and s_i are in expectations. To obtain empirical measures of h and s_i, we can use their observed realizations as proxies. In particular, we can use squared forecast error $FE_i^2 = (A - F_i)^2$ to proxy V_i, squared error in the mean forecast $(A - \Sigma_i F_i/N)^2$ to proxy SE, and sample variance of the N forecasts $[\Sigma_i(F_i - \Sigma_i F_i/N)^2]/(N-1)$ to proxy D in the expression for h (and s_i). Using realizations in the empirical measures implies that we need to impose additional conditions on our sample. In particular, we require that there must be at least three forecasts available to allow reasonably efficient estimates of forecast dispersion. There must also be at least two forecasts that are not exactly equal to actual earnings (zero forecast errors) since otherwise both the denominator and numerator of h will be zero.

Following Gu (2006), we make several treatments of the empirical measures of h and s_i. First, although h and s_i are positive theoretically, empirical measures using realized values can be negative. In this case, we assume they take a value of zero (i.e., no public or private information). Second, when a forecast error is zero, s_i will be infinity. In this case, we assume that it takes a value that is twice as large as the maximum of the finite measures from the remaining forecasts. Using other reasonable multiples or excluding such observations does not qualitatively affect our results. Third, while h is the same for all analysts, we aggregate s_i by taking the average across analysts, $s = \Sigma_i s_i/N$. Fourth, since the precision measures are skewed, we take their square roots.

Further, since realized values used in the precision measures are subject to random shocks that lead to measurement errors, we take the medians of the precision measures over a window to smooth out the random effects. Because we are interested in the overall information environment and investors' assessment of information quality, we choose an eight-quarter (minimum three) window surrounding the yield spread measurement date to report our main results. In addition to the four quarters prior to the measurement date with realized information precision measures, the four subsequent quarters may also be relevant because they can capture investors' expectation of information quality around the measurement date beyond realized past measures.[21] We denote the final precision measures (medians of square roots of h and s) as PUBLIC and PRIVATE. As we argued earlier, the relative ordering of the precision measures is likely to be more important in our context. We also report results using percentile ranks of the measures in our regressions.

We obtain analyst quarterly earnings forecasts and actual earnings from the First Call Historical Database. To remove the effect of stale forecasts, we require analyst forecasts to be made within 90 days before earnings announcement. To allow for across-firm comparability, we first standardize both the forecast and actual earnings by the stock price at the beginning of quarter, multiplied by 100, before we use them to calculate the precision measures.

3.3. Control Variables

Prior studies have identified a number of other factors that are related to bond yield spreads such as profitability, volatility of profitability, firm size, risk, leverage and interest coverage (e.g., Kaplan and Urwitz, 1979; Campbell and Taksler, 2003). We control for these variables in our tests. For profitability, Gu and Zhao (2006) show that the cash flow and accrual components of earnings take different weights in assessing firms' creditworthiness. Following them, we break the commonly used ROA into two

[21] We also use a four-quarter window prior to yield spread debt measurement date or ending one quarter before the yield spread measurement date. Our results do not change qualitatively. When the means instead of the medians of the precision measures from a window are used, the results are also qualitatively similar.

components: CFO (operating cash flows # 308, divided by average assets #6) and ACCRUAL (income before extraordinary item #18 minus operating cash flows, divided by average assets). For volatility of profitability, prior studies have used volatility of cash flows (Minton and Schrand, 1999) or volatility of earnings (Ahmed et al., 2002). We use volatility of earnings (V_ROA) in this paper, calculated as the standard deviation of return on assets over the 5-year period up to the current year. Using volatility of cash flows does not affect our main results qualitatively.

For other control variables, we measure firm size (SIZE) as the logarithm of total assets and size of the bonds (BONDSIZE) as the logarithm of the par value of the bonds. Leverage (LEV) is measured as the long-term debt (#9) divided by average assets. Interest coverage (INTCOV) is calculated as the ratio of the sum of operating income and interest expense (#178+#15) to interest expense (#15). We estimate equity beta (BETA) from the market model using monthly stock returns and value-weighted market returns in the 5 years up to the current year obtained from CRSP, with a minimum of 24 observations. To capture the idiosyncratic risk, we use the variance of the residuals from the market model (MSE). We use the market-to-book ratio (MB), measured as market capitalization (#199 × #25) divided by book value of equity (#60), to capture firms' growth opportunities as well as accounting conservatism (Ahmed et al. 2002). Negative market-to-book ratios are set to zero. We control for two industry dummies, one for regulated firms (REG for 2-digit SIC 40-42, 44-47, 49), and one for financial firms (FIN for 2-digit SIC 60-69). For yield spreads of seasoned bonds, we also control for bond age (AGE), measured as the logarithm of number of years that the bonds have been outstanding since their issuance. Finally, we use a dummy variable (NONSTR) to control for nonstraight bonds with embedded options (call, convertible, floating rate or zero coupon rate).[22,23]

4. Samples and Descriptive Statistics

Our sample period spans 1993 to 2002. We start from 1993 when First Call's coverage of analyst earnings forecasts stabilized. The seasoned bond sample contains 1,169 observations for 468 firms; the new issuance sample contains 963 observations for 476 firms, and the credit rating sample contains 6,052 observations for 1,366 firms. To mitigate the effect of outliers, we winsorize all variables at the top and bottom 1% level.

Panels A and B of Table 1 provide the descriptive statistics for the two yield spread samples. Descriptive statistics for the credit rating sample are omitted for brevity. Mean (median) SPREAD is 262 (180) BP for seasoned bonds, considerably larger than the 177 (130) BP for new issuances. The difference could reflect different pricing of bonds in the primary and secondary markets and could also be due to other differences in the two largely non-overlapping samples. The mean (median) total assets (ASSET) of these firms are $11.6 (5.2) and $20.2 (5.5) billion, consistent with the notion that corporate bonds are usually issued by relatively large firms. On average, seasoned bonds

[22] For seasoned bonds, nonstraight features as defined by Datastream refer to convertibility in most cases. Datastream does not provide separate information on the call option. For new bond issuances, nonstraight features refer to the call option since no convertible bonds are left in the final sample after merging with other data. This explains the opposite effects of NONSTR on bond yields later.

[23] We do not control for forecast dispersion and number of analysts, which are interpreted as proxies for information risk and related to credit ratings and yield spreads in Mansi et al. (2007). This is because forecast dispersion and number of analysts (and squared forecast errors) are the very inputs in our information precision measures. Hence, using these two variables again as control variables would result in an over-control problem. Forecast dispersion is a joint outcome of uncertainty in public and private information (Gu, 2005). In this sense, our study can be viewed as an extension of Mansi et al. (2007) by tracing forecast dispersion to its root sources and examining which source is contributing to the observed relation between forecast dispersion and yield spreads.

are \$224 million in size (BONDSIZE) and mature in 12.3 years (MATURITY). New issuances are \$359 million in size and mature in 13.5 years. The average credit ratings are about 12, corresponding to a rating of BBB+. The two precision measures (PUBLIC and PRIVATE) are skewed to the right, with the means larger than the medians. As in prior studies, accounting accruals (ACCRUAL) are negative on average due to depreciation expense. The equity beta (BETA) suggests that firms in the seasoned bond sample are less risky than in the new issuance sample. A small number of firms are regulated or in the financial sector.

Table 2 presents the correlations among the variables, with Pearson (Spearman) correlation coefficients above (below) the diagonal, for the seasoned bond sample. The qualitatively similar results for the other two samples are omitted for brevity. Both PUBLIC and PRIVATE are negatively correlated with SPREAD and positively correlated with RATING, suggesting that higher quality of either public or private information is related to lower yield spreads and more favorable credit ratings. The correlation between the two precision measures is relatively high (0.31 and 0.36). It is not clear whether one can subsume the effect of the other or each has its own separate effect when the two are jointly considered. Correlations between the precision measures and other variables suggest that information quality tends to be higher for firms that are larger, have better and less volatile performance, are less risky, have larger market-to-book, and have larger amounts of bonds. The high correlations between the precision measures and many of the control variables suggest that while it may be important to control for other factors, one should also be aware of a possible over-control problem with other variables taking away information quality effects. For example, firm size may be related to yield spreads not because of size *per se*, but because larger firms have higher quality of information. We present results both with and without the control variables.

5. Empirical Results

5.1. Precision of Information and Yield Spreads

Since the yield spread samples are relatively small, we run OLS regressions with pooled observations and control for fixed year effects based on the following model:

SPREAD = b_0 + b_1 PUBLIC + b_2 PRIVATE + b_3 PUBLIC×PRIVATE + b_4 Controls + ε

The regression results for the sample of seasoned bonds are reported in Table 3. For brevity, the coefficients on the yearly dummies are not reported. Before we consider the information precision measures, the results for the control variables are first presented in column 1. They are broadly consistent with prior findings. For example, although both cash flows (CFO) and accruals (ACCRUAL) are negatively related to yield spreads, the weight on CFO is larger than on ACCRUAL, consistent with the lower predictive power of accruals for future cash flows. Yield spreads are smaller if firms are larger, have lower leverage and lower systematic and idiosyncratic risks, and if the bonds are smaller in size, are more recently issued and are convertible.

In columns 2 to 4, we use the raw information precision measures. Column 2 indicates that when only information precision is considered, both PUBLIC and PRIVATE are negatively related to SPREAD. This contrasts to the finding of Botosan et al. (2004) that the univariate relation of private information precision to the expected returns on equity is subsumed and reversed to the opposite direction when public and private information precision measures are jointly considered. In column 3, we include the interaction of the two precision variables to examine if there is any complementary or substitution effect between the two sources of information. The interaction variable takes a significantly positive coefficient. That is, holding the precision of public (private) information constant, higher precision of private (public) information is associated with smaller weight on the precision of public (private) information. Thus, the two sources of information appear to be substitutes. When other control variables are added in columns 4, the information precision measures continue to take significant coefficients.

The results using percentile ranks of the information precision measures are reported in columns 5 to 7. An advantage of using ranks is that the economic impact of information precision on yield spreads can be easily assessed. Note first that in all specifications, the coefficients on PUBLIC and PRIVATE remain negative and significant. By the regression coefficients in column 6, if the precision of public information is held at the median level (rank of PUBLIC = 0.50), an increase in the precision of private information from the 25th percentile to 75th percentile (rank of PRIAVATE from 0.25 to 0.75) would decrease yield spreads by 117 BP (= (-5.680 + 6.683×0.5) × (0.75-0.25)%). Similarly, holding the precision of private information at the median level (rank of PRIVATE = 0.50), an increase in the precision of public information from the 25th percentile to 75th percentile (rank of PUBLIC from 0.25 to 0.75) would decrease yield spreads by 136 BP (= (-6.070 + 6.683×0.5) × (0.75-0.25)%). With the control variables included in column 7, the impacts of information precision are reduced to 54 and 48 BP in the above two scenarios, which are still economically large.

The regression results for the sample of new bond issuances are reported in Table

4. The signs of the coefficient estimates are generally consistent with those reported in Table 3. Notably, the coefficients on the two information precision measures are significantly negative and the coefficient on the interaction variable is significantly positive in all specifications. By the coefficients in columns 6 and 7, holding the precision of public information at the median level, an increase in the precision of private information from the 25th percentile to 75th percentile would decrease yield spreads by 65 (21) BP without (with) the control variables. Similarly, holding the precision of private information at the median level, an increase in the precision of public information from the 25th percentile to 75th percentile would decrease yield spreads by 59 (23) BP without (with) the control variables.

Overall, the results in Tables 4 and 5 suggest that precision of both private and public information is negatively associated with bond yield spreads. The economic impacts are similar in magnitude between the two sources of information, and each serves as a substitute for the other.

5.2. Information Effect at Different Bond Maturities

The Duffie and Lando (2001) theory suggests that the information effect on yield spreads is especially large for short-term bonds. As we argue earlier, information in their model can be both public and private. Thus, the effects of both public and private information documented above are expected to be stronger when bond maturity is relatively short. To test this, we separate each yield spread sample into two groups based on the median maturity of bonds and run regressions for each group. To ensure that changes in percentiles measures represent similar changes in raw values of the information precision for each group so that economic significances can be compared across groups, the percentile rankings are obtained from pooled observations.

In Table 5 for seasoned bonds, the coefficients on PUBLIC and PRIVATE and their interaction in either raw or percentile measures are more than twice as large for bonds with below-median maturities as for bonds with above-median maturities. This result holds without or with the control variables. The differences in the coefficients are significant at the 0.01 level for PRIVATE and at the 0.05 level for PUBLIC and the interaction variable (columns 5 and 10). Using coefficients based on percentile measures and with the control variables to assess the economic significance (column 10), an increase in precision of private information from the 25th percentile to the 75th percentile decreases yield spreads by 54 more BP for short-term bonds than for long-term bonds, holding precision of public information at the median level. Similar impact of public information is 23 more BP for short-term bonds than for long-term bonds.

The results for new issuances reported in Table 6 are qualitatively similar. When the raw measures are used, the differences in coefficients between short-term and long-term bonds are significant at the 0.05 level for PUBLIC and marginally significant at the 0.12 level for PRIVATE (column 5). The differences are significant at the 0.05 or lower level for both these variables in percentile measures (column 10). An increase in PRIVATE and PUBLIC from the 25th percentile to the 75th percentile, holding the other at the median level, decreases yield spreads for short-term bonds by 12 and 27 more BP than for long-term bonds. Overall, these results support the prediction that information effect is stronger when bond maturity is shorter.

5.3. Precision of Information and Credit ratings

Since credit ratings are a categorical variable, we examine the relation between precision of information and credit ratings by ordered-probit regressions based on the following model,

$$\text{RATING} = b_0 + b_1\,\text{PUBLIC} + b_2\,\text{PRIVATE} + b_3\,\text{PUBLIC}\times\text{PRIVATE} + b_4\,\text{Controls} + \varepsilon$$

Compared with the specification earlier, the control variables here do not include the size and age of bonds because these two items are not available from Compustat and the ratings are issuer specific, not bonds specific. The regressions are run for each year during the sample period and the time-series mean coefficients and statistical significance for the means are reported in Table 7 following the Fama-MacBeth procedure.

In the base case of only control variables (column 1), the relations between the control variables and credit ratings are generally as expected. Firms have higher ratings if they have higher profitability and lower volatility, are larger, have higher market-to-book ratio, interest coverage, lower leverage, and lower systematic and idiosyncratic risks. When the two precision variables are considered in column 2, the coefficient estimates on both variables are positive and highly significant. That is, higher precision of either public or private information is associated with more favorable credit ratings. The interaction variable of the two precision measures added in column 3 takes a significantly negative coefficient, again suggesting a substitution effect between the two information sources. When other control variables are included in column 4, the coefficients on the information precision measures and the interaction variable become smaller but remain highly significant. The results using within-year percentile ranks of the precision measures in columns 5 to 7 are qualitatively similar. The coefficients on PUBLIC are slightly larger than those on PRIVATE in all specifications, suggesting that public information is somewhat more important in credit ratings than private information.

5.4. Controlling for Credit Ratings in Yield Spreads

When examining yield spreads above, we intentionally do not include RATING as an explanatory variable for SPREAD, even though credit ratings are an assessment of default risk which should be a determinant of yield spreads. This is because credit ratings themselves are a summary of available information, public and private. Including RATING as an explanatory variable may weaken or even subsume the effect of other information variables even though those variables are the underlying determinants of yield spreads. This is relevant in our setting since PUBLIC and PRIVATE are informational properties that we expect to be considered by credit rating agencies and incorporated in credit ratings. Omitting RATING allows us to capture fully their effect on bond yield spreads (see, e.g., Mansi et al., 2004).

On the other hand, it is possible that RATING do not fully capture the effect of information precision on yield spreads because 1) RATING is a discrete variable with only limited categories, whereas yield spreads and information precision are continuous variables; or 2) credit rating agencies are not fully efficient in processing the relevant information. In either case information precision can affect the yield spreads even after controlling for credit ratings.

In Table 8, we repeat the analysis in Tables 5 and 6 but include credit ratings as an additional variable to control for default risk. Not surprisingly, RATING takes a significantly negative coefficient, indicating that more favorable credit ratings are associated with lower yield spreads. Compared with the results in Tables 5 and 6, the coefficients on PUBLIC and PRIVATE become slightly smaller in magnitude but retain qualitatively similar signs and statistical significance. Except in the case where information precision is measured in raw values, the information effect is significantly stronger for short-term bonds than for long-term bonds. Thus, while the information effect has been partially incorporated by credit ratings as shown in Table 7, information precision continues to affect yield spreads even after controlling for credit ratings.[24]

5.5. Additional Tests

5.5.1. Investment grade vs. noninvestment grade bonds

Firms with investment grade and noninvestment grade bonds may face different information environments and have different information demands. Mansi et al. (2004) find that the relation between auditor quality/auditor tenure and bond yield spreads is more pronounced for noninvestment grade credit ratings. Untabulated results for our samples indicate that precision of both public and private information is significantly lower for noninvestment grade bonds. These firms also tend to have worse performance and higher risks. To examine whether the information effect differs between firms with investment grades and noninvestment grade credit ratings, we separate each of our samples into two subsamples using BBB- as the cutoff point.

[24] Some studies (e.g., Mansi et al., 2004) regress credit ratings on a relevant variable under study first and then use the residuals as an explanatory variable for yield spreads. In this case, the full effect of the relevant variable is captured by its own coefficient while the residual ratings capture the incremental effect of credit ratings. That is, the effect of that variable is first "purged" from credit ratings, leaving the full effect of the variable to itself. Econometrically this is equivalent to the specification in Table 8, with identical coefficients on RATING or the residual ratings. For the full effect of the relevant variable itself, since the residual ratings are, by construction, orthogonal to this variable, omitting the residual ratings has no effect on the inference on the variable. Thus, Tables 5 and 6 without including the residual ratings provide the same statistical inference about the full effect of the relevant variable (PUBLIC or PRIVATE) as including the residual ratings.

We run regressions separately for each subsample and, for brevity, report in Table 9 the results using information precision in percentile measures. In general, the coefficients on the two information precision measures and their interaction are consistent with those for the overall samples. The exception is the case of new issuances with noninvestment grade ratings, where neither PUBLIC nor PRIVATE is significant (column 5). There are, however, only 200 observations in this case. Thus, the insignificance could also be due to low test power. The evidence is mixed with regard to whether the information effect is stronger for a particular subsample. For seasoned bonds and credit ratings, the information effect appears stronger for firms with noninvestment grade ratings. For new bond issuances, the information effect appears stronger for firms with investment grade ratings. We recognize that test power could be low in the analysis here not only because of the small number of observations with nonininvestment grade ratings, but also because information could be most effective in differentiating between, rather than within, investment grade and noninvestment grade firms.

5.5.2. High leverage vs. low leverage

Using investment and noninvestment grade ratings to partition the samples results in skewed subsamples with uneven number of observations. We use leverage as an alternative portioning variable and examine whether the information effect is similar for high leverage and low leverage firms. This analysis can be similarly motivated by the consideration that that high leverage and low leverage firms may have different information demands. Correlation results in Table 2 indicate that higher leverage is associated with lower precision of both public and private information.

For the two yield spread samples, firms are separated into high leverage and low leverage subsamples based on the median of LEV. For the credit rating sample, firms are separated into two subsamples based on the yearly median LEV each year. Only results for information precision in percentile measures are reported in Table 10. The coefficients on PUBLIC and PRIVATE are significant in all cases. The evidence on the relative strengths of the information effect is again mixed. The information effect appears stronger for high leverage firms in the seasoned bond sample but low leverage firms in the new issuance sample. The effect is similar between high leverage and low leverage firms in the credit rating sample.

5.5.3. Barron et al. (1998) measures vs. Gu measures

Botosan et al. (2004) find a positive relation between precision of private information and expected returns on equity using the original Barron et al. measures. It is not clear whether the negative relation between precision of private information and bond yield spreads that we document is sensitive to the different information precision measures used. To explore this issue, we also calculate the Barron et al. measures and use them in our regressions. The results are reported in Table 11. Compared with the corresponding columns 3, 4, 6, and 7 in Tables 3, 4 and 7, the results in Table 11 are qualitatively similar. Never in one case does the coefficient on PRIVATE suggest a positive relation between private information precision and yield spreads. Thus, the result that precision of private information is negatively related to bond yield spreads is not driven by the different measures used.

6. Conclusions

The bond market differs from the equity market in several aspects. In particular, bonds are traded in the OTC market where dealers act as local monopolies. Dealer rents constitute an important component of transaction costs in this market. We argue that private information of investors can help increase their bargaining power when transacting with dealers and reduce the transaction costs. Although private information can increase the information asymmetry among investors, most of the bond trades occur between institutional investors that are usually better informed. The information asymmetry between them and small investors may be large but may not have a large effect on expected returns on debt due to limited activities of small investors in this market. Duffie and Lando (2001) also show that information, public or private, can reduce investors' estimation error about firm value and consequently the assessed default probability, especially when debt maturity is relatively short. The role of privation information in mitigating dealer market power and reducing estimation risk is likely to dominate its limited role of creating information asymmetry among investors, leading to a negative relation between quality of private information and bond yield spreads.

Using the Gu (2006) measures of information precision that are generalized versions of the Barron et al. (1998) measures, we show that higher precision of both public and private information is associated with lower yield spread of both seasoned and newly issued bonds. There is also a significant substitution effect between the two information sources. In addition, the information effect is especially large for short-term bonds. These results hold even after controlling for credit ratings.

The relation between quality of private information and bond yield spreads illustrates the need to consider information effects in the bond market differently than in the equity market and the complexity managers have to face when deciding on their reporting strategies. When public disclosure is costly, should managers resort to more private communication? Should managers be encouraged to make public disclosures that are likely to trigger increased search for private information? Results of this paper suggest that answers to such questions are unlikely to be uniform and depend on how managers weigh the importance of the bond market and the equity market in each context.

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Table 1. Descriptive Statistics

Panel A: Sample for seasoned bonds (nob =1,169)

	Mean	Std. dev.	Q1	Median	Q3
SPREAD	2.621	2.911	1.121	1.803	3.067
RATING	12.375	3.817	10.000	13.000	15.000
PUBLIC	6.661	7.135	1.982	4.261	8.590
PRIVATE	12.136	10.544	3.894	9.494	17.273
CFO	0.099	0.065	0.060	0.095	0.133
ACCRUAL	-0.065	0.064	-0.085	-0.057	-0.032
V_ROA	0.036	0.045	0.013	0.022	0.041
ASSET (in $mil)	11,580.226	25,247.210	2,398.500	5,221.410	13,231.100
LEV	0.322	0.158	0.216	0.296	0.397
INTCOV	6.189	7.017	2.877	4.606	7.081
MSE	0.014	0.015	0.005	0.009	0.015
BETA	0.861	0.602	0.478	0.798	1.100
MB	3.340	4.123	1.493	2.213	3.511
REG	0.150	0.357	0.000	0.000	0.000
FIN	0.014	0.116	0.000	0.000	0.000
BONDSIZE (in $mil)	224.354	222.673	56.007	175.000	300.000
NONSTRT	0.092	0.288	0.000	0.000	0.000
AGE	4.226	3.450	1.400	3.433	6.014
MATURITY	12.299	7.533	6.633	9.262	17.970

Table 1. Continued

Panel B: Sample for new bond issuances (nob = 963)

	Mean	Std. dev.	Q1	Median	Q3
SPREAD	1.765	1.410	0.770	1.300	2.250
RATING	12.142	3.175	10.000	12.000	14.000
PUBLIC	6.648	7.440	1.830	4.017	8.816
PRIVATE	12.822	10.911	4.376	10.004	18.432
CFO	0.092	0.074	0.045	0.091	0.136
ACCRUAL	-0.046	0.060	-0.075	-0.046	-0.016
V_ROA	0.027	0.027	0.009	0.018	0.034
ASSET (in $mil)	20,172.823	62,895.377	2,024.426	5,462.335	14,792.516
LEV	0.283	0.184	0.147	0.261	0.379
INTCOV	7.208	7.673	3.096	5.060	8.219
MSE	0.009	0.009	0.004	0.007	0.011
BETA	0.981	0.522	0.658	0.936	1.241
MB	3.203	2.903	1.572	2.304	3.635
REG	0.118	0.323	0.000	0.000	0.000
FIN	0.111	0.314	0.000	0.000	0.000
BONDSIZE (in $mil)	359.349	317.665	185.000	250.000	400.000
NONSTRT	0.600	0.490	0.000	1.000	1.000
MATURITY	13.508	12.225	7.038	10.016	12.003

In Panel A, SPREAD is the difference, in percentages, between yield to maturity of seasoned bonds calculated from bond trade prices as of the last day of the third month after the fiscal year end and yield of treasury issues with comparable maturity, obtained from Datastream database. In Panel B, SPREAD is the difference between the offering yield to maturity of new bond issuances and yield of treasury issues with comparable maturity, obtained from Mergent FISD database. RATING is S&P's issuer credit rating (Compustat #280) coded 19 to 1 with 19 (1) for the highest (lower) rating; We follow Gu (2006) to calculate the precision of analysts' public and private information h and s (s_i averaged across analysts) for a quarter using price-deflated quarterly earnings forecasts and actual earnings from First Call. PUBLIC and PRIVATE are the medians of the square roots of h and s over the eight quarters (minimum three) around the measurement of SPREAD or RATING. CFO is operating cash flows (Compustat # 308) divided by average assets (#6); ACCRUAL is income before extraordinary item (#18) minus operating cash flows divided by average assets; V_CFO is standard deviation of return on asset in the 5 years up to the current year; LEV is long-term debt (#9) divided by average assets; INTCOV is the ratio of the sum of operating income and interest expense (#178+#15) to interest expense (#15); BETA is equity beta estimated from the market model using monthly stock returns and value-weighted market returns in the previous five years from CRSP (minimum 24 observations); MSE is variance of the residuals from the market model; MB is market capitalization (#199 × #25) divided by book value of equity (#60); REG is an indicator variable for regulated firms (2-digit SIC 40-42, 44-47, 49); FIN is an indicator variable for financial institutions (2-digit SIC 60-69); BONDSIZE is par value of the outstanding bonds or new bonds issued. AGE is the number of years that the bonds have been outstanding since issuance. NONSTRT is a dummy variable that takes the value of 1 if a bond has embedded options (call, convertible, floating rate or zero coupon rate), and 0 otherwise. MATURITY is the bonds' time to maturity in years.

Table 2. Correlation Coefficients: Sample for Seasoned Bonds (nob = 1,169)

	SPREAD	RATING	PUBLIC	PRIVATE	CFO	ACCRUAL	V_ROA	SIZE	LEV	INTCOV	BETA	MSE	MB	REG	FIN	BONDSIZE	LGAGE	NONSTR
SPREAD		-0.56	-0.26	-0.28	-0.34	-0.19	0.29	-0.20	0.38	-0.27	0.41	0.54	-0.13	-0.03	-0.05	0.14	-0.06	0.06
RATING	-0.56		0.28	0.29	0.34	0.13	-0.29	0.38	-0.43	0.34	-0.42	-0.57	0.18	0.12	0.04	-0.22	0.21	-0.29
PUBLIC	-0.33	0.32		0.31	0.30	0.09	-0.12	0.07	-0.19	0.40	-0.13	-0.14	0.36	-0.15	0.11	-0.01	0.03	0.04
PRIVATE	-0.32	0.30	0.36		0.20	0.08	-0.08	0.29	-0.21	0.30	-0.12	-0.23	0.23	-0.09	-0.04	0.01	0.14	-0.03
CFO	-0.31	0.34	0.33	0.20		-0.42	-0.05	-0.06	-0.19	0.48	-0.24	-0.20	0.29	-0.11	-0.05	-0.03	0.07	-0.11
ACCRUAL	-0.09	0.09	0.09	0.09	-0.52		-0.48	0.09	-0.05	0.05	-0.25	-0.25	-0.01	0.11	0.05	-0.04	0.02	-0.14
V_ROA	0.17	-0.25	-0.17	-0.08	0.06	-0.32		-0.18	0.10	-0.09	0.44	0.52	0.11	-0.19	-0.04	0.03	-0.10	0.31
SIZE	-0.25	0.37	0.05	0.28	-0.09	0.11	-0.19		-0.23	0.10	-0.13	-0.35	0.01	0.04	0.08	0.14	0.21	-0.21
LEV	0.33	-0.41	-0.25	-0.24	-0.21	-0.03	0.00	-0.17		-0.39	0.12	0.33	0.01	0.08	-0.11	0.06	-0.17	0.07
INTCOV	-0.43	0.49	0.48	0.37	0.60	0.09	-0.11	0.02	-0.49		-0.09	-0.12	0.27	-0.13	0.14	0.05	0.03	0.01
BETA	0.19	-0.32	-0.15	-0.12	-0.20	-0.06	0.30	-0.09	-0.03	-0.17		0.56	-0.02	-0.30	-0.03	0.08	-0.06	0.40
MSE	0.56	-0.56	-0.16	-0.28	-0.14	-0.21	0.41	-0.31	0.24	-0.23	0.32		-0.03	-0.15	0.00	0.17	-0.20	0.42
MB	-0.39	0.37	0.48	0.33	0.42	0.02	0.04	0.11	-0.20	0.50	-0.10	-0.20		-0.14	-0.01	-0.02	0.03	0.01
REG	-0.04	0.10	-0.11	-0.06	-0.13	0.13	-0.30	0.06	0.14	-0.16	-0.34	-0.23	-0.19		-0.05	-0.15	-0.01	-0.10
FIN	-0.06	0.05	0.09	-0.05	-0.03	0.03	-0.05	0.07	-0.11	0.05	-0.05	0.04	0.01	-0.05		0.05	-0.06	0.06
BONDSIZE	0.16	-0.13	-0.04	0.01	-0.11	-0.04	0.03	0.22	0.12	-0.07	0.01	0.32	-0.04	-0.04	0.08		-0.17	0.04
LGAGE	-0.05	0.27	0.05	0.16	0.10	0.00	-0.07	0.28	-0.15	0.09	-0.06	-0.27	0.08	0.00	-0.08	-0.35		-0.12
NONSTR	-0.14	-0.28	0.04	-0.01	-0.07	-0.07	0.21	-0.20	0.01	-0.05	0.30	0.31	0.01	-0.10	0.06	0.12	-0.17	

Pearson (Spearman) correlation coefficients are above (below) the diagonal. SIZE, BONDSIZE and LGAGE are logarithms of ASSETS, BONDSIZE and AGE in Table 1. For definitions of other variables, see Table 1.

Table 3. OLS Regression Results for Yield Spreads of Seasoned Bonds

	Dependent variable: SPREAD						
Explanatory		PUBLIC/PRIVATE in raw			PUBLIC/PRIVATE in percentiles		
Variables	1	2	3	4	5	6	7
INTERCEPT	2.561*	4.608*	5.088*	2.737*	5.812*	7.328*	4.267*
PUBLIC		-0.082*	-0.158*	-0.050*	-2.677*	-6.070*	-2.923*
PRIVATE		-0.056*	-0.097*	-0.039*	-2.182*	-5.680*	-3.033*
PUBLIC × PRIVATE			0.005*	0.002*		6.683*	3.919*
CFO	-14.771*			-14.042*			-12.847*
ACCRUAL	-10.695*			-10.156*			-9.146*
V_ROA	-3.157***			-3.140***			-3.526***
SIZE	-0.246*			-0.198*			-0.201*
LEV	3.368*			3.179*			2.748*
INTCOV	0.014			0.021***			0.018
BETA	0.942*			0.894*			0.864*
MSE	59.602*			57.342*			54.302*
MB	-0.007			0.004			0.014
REG	0.263			0.177			0.181
FIN	-0.429			-0.425			-0.403
BONDSIZE	0.056***			0.055***			0.051***
LGAGE	0.209*			0.202*			0.190*
NONSTRT	-2.361*			-2.196*			-2.025*
Adjusted R^2	0.494	0.191	0.216	0.503	0.247	0.291	0.523

For variable definitions, see Tables 1 and 2. *, ** and *** indicate significance at the 0.01, 0.05 and 0.10 levels.

Table 4. OLS Regression Results for Yield Spreads of New Bond Issuances

Explanatory Variables	Dependent variable: SPREAD						
		PUBLIC/PRIVATE in raw			PUBLIC/PRIVATE in percentiles		
	1	2	3	4	5	6	7
INTERCEPT	4.408*	3.226*	3.348*	4.460*	3.709*	4.068*	4.782*
PUBLIC		-0.043*	-0.062*	-0.028*	-1.127*	-1.937*	-0.847*
PRIVATE		-0.035*	-0.045*	-0.015*	-1.314*	-2.054*	-0.805*
PUBLIC × PRIVATE			0.001*	0.001*		1.517*	0.780*
CFO	-5.099*			-4.663*			-4.480*
ACCRUAL	-3.069*			-2.725*			-2.706*
V_ROA	3.243*			2.316***			2.021
SIZE	-0.223*			-0.194*			-0.205*
LEV	1.299*			1.260*			1.215*
INTCOV	-0.002			-0.000			-0.000
BETA	0.189*			0.168*			0.173*
MSE	31.691*			29.771*			28.395*
MB	-0.042*			-0.022***			-0.027**
REG	-0.237**			-0.276*			-0.250*
FIN	0.130			0.064			0.073
BONDSIZE	-0.126**			-0.130**			-0.109***
NONSTRT	0.236*			0.239*			0.233*
Adjusted R^2	0.634	0.410	0.419	0.646	0.421	0.431	0.649

For variable definitions, see Tables 1 and 2. *, ** and *** indicate significance at the 0.01, 0.05 and 0.10 levels.

Table 5. OLS Regression Results for Yield Spreads of Seasoned Bonds: Short vs. Long Maturities

	Dependent variable: SPREAD									
	PUBLIC/PRIVATE in raw					PUBLIC/PRIVATE in percentiles				
	1	2	3	4	5	6	7	8	9	10
Maturity	Short	Long	Short	Long	(= 3 – 4)	Short	Long	Short	Long	= (8 – 9)
INTERCEPT	6.199*	3.365*	4.676*	0.395	4.280*	8.924*	4.710*	6.710*	1.441***	5.269*
PUBLIC	-0.220*	-0.087*	-0.080*	-0.021	-0.059**	-7.732*	-3.528*	-3.721*	-1.831*	-1.890**
PRIVATE	-0.157*	-0.042*	-0.068*	-0.018***	-0.050*	-8.031*	-2.852*	-4.333*	-1.826*	-2.508*
PUBLIC × PRIVATE	0.008*	0.002*	0.004*	0.001	0.003**	8.949*	3.594*	5.289*	2.448*	2.841**
CFO			-18.134*	-5.390*	-12.744*			-16.369*	-4.923**	-11.446*
ACCRUAL			-13.139*	-2.269	-10.869*			-11.647*	-2.026	-9.621*
V_ROA			-2.106	-2.119	0.013			-1.766	-3.434	1.668
SIZE			-0.328*	0.055	-0.384*			-0.364*	0.058	-0.422*
LEV			3.686*	2.345*	1.341			3.123*	2.111*	1.012
INTCOV			0.032***	-0.009	0.042***			0.028	-0.011	0.040***
BETA			0.928*	0.692*	0.236			0.913*	0.666*	0.246
MSE			43.024*	59.757*	-16.733			38.575*	56.533*	-17.957
MB			-0.000	0.010	-0.010			0.012	0.019	-0.007
REG			-0.257	0.728*	-0.985*			-0.137	0.672*	-0.809**
FIN			0.070	-0.926	0.996			0.205	-1.116	1.321
BONDSIZE			0.046	0.027	0.019			0.043	0.025	0.018
LGAGE			0.126	0.202*	-0.076			0.126	0.192*	-0.066
NONSTRT			-2.579*	-1.917*	-0.663			-2.312*	-1.760*	-0.552
Adjusted R^2	0.224	0.159	0.546	0.347		0.316	0.201	0.567	0.363	

For variable definitions, see Tables 1 and 2. Bonds are classified into the Short and Long maturity groups based on the median MATURITY of the sample. *, ** and *** indicate significance at the 0.01, 0.05 and 0.10 levels.

Table 6. OLS Regression Results for Yield Spreads of New Bond Issuances: Short vs. Long Maturities

	Dependent variable: SPREAD									
	PUBLIC/PRIVATE in raw					PUBLIC/PRIVATE in percentiles				
	1	2	3	4	5	6	7	8	9	10
Maturity	Short	Long	Short	Long	(= 3 – 4)	Short	Long	Short	Long	= (9 – 8)
INTERCEPT	3.766*	2.944*	5.648*	3.347*	2.301*	4.782*	3.400*	6.235*	3.445*	2.790*
PUBLIC	-0.078*	-0.043*	-0.038*	-0.014***	-0.025**	-2.769*	-1.122*	-1.444*	-0.278	-1.166*
PRIVATE	-0.055*	-0.035*	-0.021*	-0.010**	-0.011	-2.673*	-1.500*	-1.314*	-0.442**	-0.872**
PUBLIC × PRIVATE	0.002*	0.001**	0.001**	0.000	0.001	2.350*	0.770***	1.480*	0.218	1.262**
CFO			-4.643*	-4.592*	-0.052			-4.326*	-4.459*	0.133
ACCRUAL			-2.633**	-3.119*	0.486			-2.573**	-3.107*	0.534
V_ROA			1.853	2.848***	-0.995			1.235	2.805***	-1.570
SIZE			-0.203*	-0.188*	-0.015			-0.216*	-0.190*	-0.026
LEV			1.237*	1.287*	-0.050			1.162*	1.263*	-0.102
INTCOV			-0.004	0.003	-0.006			-0.003	0.002	-0.005
BETA			0.262*	0.030	0.232***			0.283*	0.029	0.253***
MSE			22.433*	38.584*	-16.151			20.136*	37.584*	-17.448***
MB			-0.025	-0.018	-0.007			-0.033**	-0.020	-0.013
REG			-0.393**	-0.145	-0.248			-0.368**	-0.135	-0.234
FIN			0.001	0.228	-0.228			-0.007	0.240	-0.247
BONDSIZE			-0.251**	-0.014	-0.237**			-0.229**	-0.000	-0.229***
NONSTRT			0.249**	0.180**	0.069			0.249**	0.170**	0.079
Adjusted R^2	0.402	0.453	0.636	0.668		0.422	0.463	0.644	0.670	

For variable definitions, see Tables 1 and 2. Bonds are classified into the Short and Long maturity groups based on the median MATURITY of the sample. *, ** and *** indicate significance at the 0.01, 0.05 and 0.10 levels.

Table 7. Ordered-probit Regression Results for Credit ratings (nob = 6,052)

		Dependent variable: RATING					
Explanatory		PUBLIC/PRIVATE in raw			PUBLIC/PRIVATE in percentiles		
Variables	1	2	3	4	5	6	7
PUBLIC		0.054*	0.083*	0.047*	1.200*	2.006*	1.139*
PRIVATE		0.037*	0.053*	0.026*	1.124*	1.953*	0.976*
PUBLIC × PRIVATE			-0.002*	-0.001*		-1.557*	-0.827*
CFO	5.343*			4.651*			4.446*
ACCRUAL	3.631*			2.948*			2.818*
V_ROA	-2.390**			-2.061**			-2.040**
SIZE	0.399*			0.365*			0.373*
LEV	-2.381*			-2.347*			-2.325*
INTCOV	0.004**			0.004**			0.005**
BETA	-0.280*			-0.279*			-0.288*
MSE	-70.821*			-67.743*			-67.619*
MB	0.043*			0.023*			0.029*
REG	0.041			0.170*			0.146*
FIN	0.207*			0.248*			0.235*
Pseudo-R^2	0.680	0.224	0.242	0.701	0.232	0.249	0.702

For variable definitions, see Tables 1 and 2. Regressions are run for each year during 1993-2002. The time-series mean coefficients and statistical significance for the means based on t-statistics are reported. *, ** and *** indicate significance at the 0.01, 0.05, and 0.10 levels.

Table 8. OLS Regression Results for Yield Spreads: Short vs. Long Maturities after Controlling for Credit ratings

	Dependent variable: SPREAD											
	Seasoned Bond Sample						New Bond Issuance Sample					
	PUBLIC/PRIVATE in raw			PUBLIC/PRIVATE in percentiles			PUBLIC/PRIVATE in raw			PUBLIC/PRIVATE in percentiles		
	1	2	3	4	5	6	7	8	9	10	11	12
Maturity	Short	Long	(= 1-2)	Short	Long	= (4-5)	Short	Long	=(7-8)	Short	Long	= (10-11)
INTERCEPT	7.420*	1.628**	5.791*	9.073*	2.395*	6.678*	6.810*	4.322*	2.488*	7.212*	4.358*	2.854*
PUBLIC	-0.062*	-0.016	-0.047	-3.370*	-1.441*	-1.929**	-0.029*	-0.013***	-0.017	-1.077*	-0.195	-0.882**
PRIVATE	-0.060*	-0.019**	-0.041**	-3.931*	-1.710*	-2.221*	-0.017*	-0.009**	-0.008	-1.021*	-0.389**	-0.631***
PUBLIC × PRIVATE	0.004*	0.001	0.003**	5.037*	2.126*	2.911**	0.001***	0.000	0.000	1.032**	0.219	0.813
CFO	-15.348*	-3.752***	-11.596*	-13.864*	-3.550***	-10.314*	-3.025*	-2.913*	-0.112	-2.838*	-2.891*	0.052
ACCRUAL	-12.597*	-1.132	-11.465*	-11.219*	-1.035	-10.184*	-1.730***	-2.007**	0.277	-1.729***	-2.066**	0.337
V_ROA	-2.418	-0.714	-1.704	-2.082	-1.902	-0.180	0.328	1.968	-1.641	-0.076	2.065	-2.141
SIZE	-0.138	0.158**	-0.296**	-0.180***	0.155**	-0.335*	-0.098***	-0.114*	0.016	-0.112**	-0.117*	0.005
LEV	2.475*	1.787*	0.688	2.047*	1.628*	0.418	0.524***	0.773*	-0.249	0.492	0.764*	-0.272
INTCOV	0.052*	-0.006	0.058**	0.048*	-0.008	0.056**	0.006	0.005	0.001	0.006	0.005	0.001
BETA	0.807*	0.510*	0.297	0.791*	0.501*	0.291	0.194**	-0.004	0.198	0.213**	-0.003	0.215***
MSE	29.367*	53.074*	-23.707	26.299*	50.931*	-24.632	8.900	25.932*	-17.032***	7.469	25.668*	-18.200***
MB	0.012	0.020	-0.008	0.025	0.026	-0.001	-0.015	-0.012	-0.003	-0.023	-0.016	-0.007
REG	0.099	0.776*	-0.677***	0.174	0.729*	-0.556	-0.437*	-0.171***	-0.266	-0.417*	-0.161	-0.256
FIN	-0.125	-0.709	0.583	0.065	-0.886	0.951	-0.038	0.220	-0.257	-0.045	0.229	-0.273
BONDSIZE	-0.038	-0.001	-0.037	-0.035	-0.001	-0.034	-0.216**	-0.028	-0.188	-0.200**	-0.018	-0.182
LGAGE	0.144	0.215*	-0.071	0.146	0.207*	-0.061						
NONSTRT	-2.765*	-2.055*	-0.710	-2.499*	-1.919*	-0.581	0.135	0.118	0.017	0.140	0.111	0.029
RATING	-0.276*	-0.125*	-0.151*	-0.260*	-0.116*	-0.144*	-0.168*	-0.111*	-0.057***	-0.161*	-0.108*	-0.053***
Adjusted R^2	0.583	0.373		0.600	0.385		0.666	0.696		0.671	0.697	

For variable definitions, see Tables 1 and 2. Bonds are classified into the Short and Long maturity groups based on the median MATURITY of the sample. *, ** and *** indicate significance at the 0.01, 0.05 and 0.10 levels.

Table 9. Regression Results for Yield Spreads and Credit ratings: Investment Grade vs. Noninvestment Grade Ratings

	Investment Grade Ratings			Noninvestment Grade Ratings		
Dependent variable	SPREAD (Seasoned bonds) (nob = 906)	SPREAD (New issuances) (nob = 763)	RATING (Credit ratings) (nob = 4,199)	SPREAD (Seasoned bonds) (nob = 263)	SPREAD (New issuances) (nob = 200)	RATING (Credit ratings) (nob = 1,853)
Explanatory Variables	1	2	3	4	5	6
INTERCEPT	3.557*	3.499*		9.288*	7.217*	
PUBLIC	-1.063*	-0.794*	0.996*	-4.795*	-0.513	1.181*
PRIVATE	-0.997*	-0.718*	0.730*	-6.559*	0.289	1.313*
PUBLIC × PRIVATE	1.234*	0.799*	-0.755*	7.079**	-0.547	-1.627*
CFO	-4.353*	-4.088*	5.753*	-19.607*	-3.190**	2.802*
ACCRUAL	-2.827*	-3.068*	3.850*	-9.309**	-2.315***	2.182*
V_ROA	-0.555	2.854**	-0.524	-2.063	-1.962	-1.433***
SIZE	-0.172*	-0.135*	0.287*	-0.215	-0.220***	0.283*
LEV	0.361	0.663*	-2.424*	3.415*	-0.230	-0.815*
INTCOV	-0.007	0.003	0.004	0.083	-0.037	0.007
BETA	0.310*	0.104***	-0.106***	0.902**	0.041	-0.126**
MSE	35.018*	22.600*	-113.672*	25.752***	12.452***	-36.566*
MB	-0.008	-0.021**	0.037**	-0.017	-0.043	-0.004
REG	-0.063	-0.171**	0.139*	2.263**	0.052	-0.054
FIN	-0.228	-0.040	0.349*	1.663	0.029	0.326
BONDSIZE	0.025**	-0.028		-0.087	-0.292***	
LGAGE	0.110*			0.364		
NONSTRT	-1.899*	0.083		-1.992*	0.893*	
R^2	0.467	0.544	0.486	0.446	0.631	0.457

For variable definitions, see Tables 1 and 2. PUBLIC and PRIVATE are measured in percentiles. Firms are defined as investment grade if credit ratings are at or above "BBB", and noninvestment grade otherwise. OLS regressions are run with pooled observations for the two yield spread samples. For the credit rating sample, ordered-probit regressions are run for each year during 1993-2002 and the time-series mean coefficients and statistical significance for the means based on t-statistics are reported. *, ** and *** indicate significance at the 0.01, 0.05 and 0.10 levels.

Table 10. Regression Results for Yield Spreads and Credit ratings: Low vs. High Leverage

Dependent variable	Low Leverage			High Leverage		
	SPREAD (Seasoned bonds)	SPREAD (New issuances)	RATING (Credit ratings)	SPREAD (Seasoned bonds)	SPREAD (New issuances)	RATING (Credit ratings)
Explanatory Variables	1	2	3	4	5	6
INTERCEPT	4.968*	3.376*		4.117*	6.372*	
PUBLIC	-2.543*	-0.830*	1.236*	-2.966*	-0.684**	0.940*
PRIVATE	-2.675*	-0.819*	0.966*	-3.002*	-0.587**	0.976*
PUBLIC × PRIVATE	3.520*	0.860*	-0.952*	3.666*	0.435	-0.842*
CFO	-11.279*	-3.182*	4.775*	-12.224*	-5.233*	3.727*
ACCRUAL	-9.530*	-3.116*	2.850*	-8.014*	-2.370**	1.801
V_ROA	3.199***	-1.204	-4.882**	-7.605**	4.686**	-0.470
SIZE	-0.282*	-0.118*	0.384*	-0.175	-0.339*	0.394*
LEV	0.006	0.160	-2.336*	4.016*	0.454	-2.478*
INTCOV	0.005	-0.003	0.003	0.006	-0.011	0.055*
BETA	0.198	-0.047	-0.366*	1.279*	0.331*	-0.250*
MSE	48.853*	50.223*	-90.456*	47.759*	16.574*	-61.918*
MB	0.012	-0.026***	0.049*	0.002	-0.015	0.003
REG	0.012	-0.127	-0.026	0.372	-0.245**	0.333*
FIN	-0.288	-0.024	-0.021	-2.011	-0.123	1.562*
BONDSIZE	0.083***	-0.028		0.021	-0.115	
LGAGE	0.167*			0.197**		
NONSTRT	-2.189*	0.189*		-1.672*	0.231**	
R^2	0.579	0.529	0.677	0.496	0.662	0.701

For variable definitions, see Tables 1 and 2. PUBLIC and PRIVATE are measured in percentiles. Firms are separated into low leverage and high leverage groups based on the median LEV. OLS regressions are run with pooled observations for the two yield spread samples. For the credit rating sample, ordered-probit regressions are run for each year during 1993-2002 and the time-series mean coefficients and statistical significance for the means based on t-statistics are reported. *, ** and *** indicate significance at the 0.01, 0.05 and 0.10 levels.

Table 11. Regression Results Using the Barron et al. (1998) Measures

Dependent variable	SPREAD (Seasoned bonds)				SPREAD (New issuances)				RATING (Credit ratings)			
Explanatory	PUBLIC/PRIVATE in raw		PUBLIC/PRIVAT in percentiles		PUBLIC/PRIVATE in raw		PUBLIC/PRIVAT in percentiles		PUBLIC/PRIVATE in raw		PUBLIC/PRIVAT in percentiles	
variables	1	2	3	4	5	6	7	8	9	10	11	12
INTERCEPT	4.754*	2.810*	7.312*	4.587*	3.202*	4.497*	4.011*	4.874*				
PUBLIC	-0.185*	-0.052*	-7.056*	-3.402*	-0.084*	-0.035*	-2.094*	-0.920*	0.088*	0.044*	1.587*	0.773*
PRIVATE	-0.084*	-0.029*	-5.449*	-2.803*	-0.040*	-0.015*	-1.977*	-0.780*	0.052*	0.032*	1.786*	1.123*
PUBLIC × PRIVATE	0.005*	0.002*	7.801*	4.465*	0.002*	0.001*	1.817*	0.844**	-0.003*	-0.001*	-1.166*	-0.587*
CFO		-14.146*		-12.764*		-4.759*		-4.489*		4.691*		4.450*
ACCRUAL		-10.251*		-9.011*		-2.840*		-2.678*		2.933*		2.699*
V_ROA		-3.424***		-3.777**		1.995		1.779		-1.925***		-1.920***
SIZE		-0.234*		-0.241*		-0.204*		-0.216*		0.381*		0.384*
LEV		3.263*		2.697*		1.267*		1.191*		-2.359*		-2.321*
INTCOV		0.022***		0.015		0.001		-0.000		0.004**		0.004**
BETA		0.921*		0.880*		0.171*		0.174*		-0.287*		-0.289*
MSE		58.073*		54.915*		30.451*		28.747*		-68.423*		-68.019*
MB		0.003		0.011		-0.019		-0.026**		0.021*		0.026*
REG		0.192		0.200		-0.289*		-0.249*		0.166*		0.158*
FIN		-0.472		-0.521		0.070		0.088		0.235*		0.237*
BONDSIZE		0.054***		0.049***		-0.126**		-0.107***				
LNAGE		0.206*		0.194*								
NONSTRT		-2.226*		-2.074*		0.223*		0.229*				
R^2	0.195	0.499	0.281	0.520	0.400	0.646	0.419	0.650	0.207	0.700	0.235	0.704

For variable definitions, see Tables 1 and 2. PUBLIC and PRIVATE are measured according to Barron et al. (1998). OLS regressions are run with pooled observations for the two yield spread samples. For the credit rating sample, ordered-probit regressions are run for each year during 1993-2002. The time-series mean coefficients and statistical significance for the means based on t-statistics are reported. *, ** and *** indicate significance at the 0.01, 0.05 and 0.10 levels.

Income Smoothing and Bond Ratings*

Doctoral Dissertation Chapter 3

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Income Smoothing and Bond Ratings

Abstract: Accounting accruals affect not only the levels but also the volatility of the reported earnings. We show in this paper that the income-smoothing use of accruals plays a useful role in the debt market. More income smoothing is associated with more favorable bond ratings and larger weight on accruals in bond ratings. These results are consistent with the argument that income smoothing signals superior firm performance. They complement the consistent findings from the equity market on the reward to income smoothing and cast doubt on the recent plea to "stop smoothing earnings" (Jensen, 2005).

Keywords: *income smoothing, accruals, cash flows, bond ratings*.

Data Availability: *All data are available from public sources*.

JEL classification: G10, G12, M40, M41

Income Smoothing and Bond Ratings

1. Introduction

Accounting accruals not only affect the levels of earnings but also tend to make earnings less volatile than cash flows. We refer to the use of accruals to offset the volatility of cash flows as income smoothing. While studies on the role of income smoothing in the equity market are voluminous, little empirical research has been done on the role of income smoothing in the debt market. Given the particular importance of performance volatility in assessing firms' default risk, we show in this paper that income smoothing plays a positive role in bond ratings. In particular, more income smoothing is associated with more favorable bond ratings. Accruals that make income smoother also receive larger weight on themselves in bond ratings.

Determination of bond ratings has been extensively researched in the accounting and finance literature. Since bonds must be serviced out of cash flows in the future, the economic determinants examined so far naturally include those that are informative about firms' future cash flows. It has been well established that accruals provide information about future cash flows above and beyond current cash flows (e.g., Dechow et al., 1998; Barth et al., 2001). Thus, bond rating models have long used accrual-based earnings measures such as return-on-asset as economic determinants (e.g., Kaplan and Urwitz, 1979). These studies, however, implicitly utilize only the first-moment effect of accruals on earnings. We differ importantly by focusing on the second-moment effect of accruals.

The use of accruals for reduced volatility of earnings is not without controversy. Regulators and some academics regard such income smoothing as a manifestation of opportunistic earnings management that reduces the representational faithfulness and informativeness of earnings (e.g., Levitt, 1998; Bhattacharya et al., 2003; Leuz et al., 2003). The recent plea by Jensen (2005) to "stop smoothing earnings" highlights the concern. Theories on income smoothing, however, suggest the opposite and positive view: income smoothing is a useful device to signal firms' superior performance (e.g., Chaney and Lewis, 1995; Demski, 1998; Fudenberg and Tirole, 1995; Nan, 2005; Ronen and Sadan, 1981; Kirschenheiter and Melumad, 2002a, 2002b). Empirical results from a fundamentals perspective support the positive view. Firms that smooth income not only have higher level and lower volatility of future cash flows, but also have accruals that are more informative about future cash flows (Gu, 2006).

The implications of income smoothing for future cash flows suggests that income smoothing should help, rather than hurt, bond ratings. Trueman and Titman (1988) similarly argue theoretically that income smoothing would change investors' perception of the volatility of economic income and improve bond ratings. Based on these results, we hypothesize that more income smoothing is associated with more favorable bond ratings. To test the hypothesis, we decompose the volatility of earnings into two components: the volatility of cash flows and a smoothing factor that measures the difference between the volatilities of earnings and cash flows. We find that, after controlling for the volatility of cash flows, the smoothing factor is significantly related to bond ratings in support of our hypothesis. We also hypothesize that income smoothing is associated with larger weight on accruals in bond ratings. This hypothesis is motivated by the Gu (2006) finding that accruals themselves become more informative about future cash flows when they make income smoother. To test this, we interact the smoothing factor with accruals and find the interaction variable highly significant, again supporting the hypothesis.

We conduct a number of additional tests to confirm the above findings. Other than measuring the smoothing factor in absolute terms, we also measure the smoothing factor in relative terms as the ratio of the volatility of earnings to the volatility of cash flows. The effects of income smoothing on bond ratings remain qualitatively the same. The results also do not change qualitatively when the smoothing factor is measured in percentile ranks. We further separate bond ratings into those of investment grade and below investment grade and find that the income-smoothing effect holds for both subsamples. Following Francis et al. (2004), we separate income smoothing into an innate component and a discretionary component. We find that innate income smoothing affects bond ratings by itself, while discretionary income smoothing affects bond ratings indirectly through increased weight on accruals.

Income could be smoother relative to cash flows or to some other income measures. It is up to the researcher to define whether the income-smoothing use of accruals is a normal function or an abnormal function of accruals. We follow two commonly used models to separate accruals into normal and abnormal accruals. In the first Jones (1991) Model, normal accruals are a linear function of change in sales and gross property, plant and equipment. Income smoothing is not explicitly incorporated in this model and is thus regarded as a function of abnormal accruals. When we use cash flow plus normal accruals as the pre-smoothed income, we find that the abnormal accruals serve the income smoothing role in bond ratings as predicted. In the second Dechow and Dichev (2002) Model, normal accruals are a linear function of past, current and future cash flows. Since abnormal accruals are orthogonal to cash flows by construction, income smoothing is achieved by normal accruals. We show that the income-smoothing effect of normal accruals from this model on bond ratings is similar to that of total accruals.

It has been consistently documented that income smoothing is rewarded by the stock market. For example, firms that smooth earnings are found to benefit from lower cost of equity (Francis et al., 2004), higher valuation multipliers of earnings (Barth et al., 1999; Ghosh et al., 2005; Hunt et al., 2000; Bao and Bao, 2004), higher forward price-earnings ratios (Thomas and Zhang, 2003), higher informativeness of earnings (Tucker and Zarowin, 2006), higher Tobin's Q (Allayannis and Weston, 2003), higher abnormal stock returns (Michelson et al., 2000; Myers et al., 2007), and less post-IPO underperformance (Chaney and Lewis, 1998). Our study from the bond market complements these stock market-based studies and provides a more complete picture on the role of income smoothing in the capital markets. While prior studies suggest that the stock market may be fixated on earnings and weighs accruals and cash flows equally (see, e.g., Sloan, 1996), we show that bond rating agencies may have a better understanding of these two components of earnings. They not only put higher weight on cash flows than on accruals, but also put higher weight on the volatility of cash flows than on income smoothing due to accruals.[25]

The rest of the paper proceeds as follows. In the next section we develop our hypotheses and discuss the relevant literature on the role of accruals and the income-smoothing function of accruals. In Secion 3, we describe the sample, research design and summary statistics. Empirical results are reported in Section 4. The final section concludes.

2. Hypotheses Development and Related Literature

Bond rating agencies play a vital informational role in the capital market. They assess firms' likelihood of default or creditworthiness and publish their opinions in the form of bond ratings. Investors rely on these ratings in their investment decisions and the pricing of debt. As a result, bond ratings are closely related to cost of debt and significantly affect firms' financing decisions (Standard and Poor's, 2003). Bond ratings by certain designated rating agencies are also explicitly referenced by regulators in numerous federal and state laws and regulations

[25] Our results from bond ratings do not speak to whether bond prices weigh accruals and cash flows (sufficiently) differently. Bhojraj and Swaminathan (2003) find some evidence of bond market mispricing of accruals.

(Beaver et al., 2006; Covitz and Harrison, 2003). The information contained in bond ratings has become even more pronounced since the enactment of Regulation Fair Disclosure in 2000 as bond rating agencies are exempt from the regulation and continue to receive private information from firms (Jorion, Liu and Shi, 2005).

The importance of bond ratings has led to extensive research on the determination of bond ratings. Using accounting information to determine bond ratings has long been a primary application of financial statement analysis (see e.g., Foster, 1986, Ch. 14). Among the economic determinants examined, reported accounting numbers are perhaps among the most important. On the surface, it is not immediately apparent why bond rating agencies would be concerned with accruals or accrual-based earnings. As Standard & Poor's (S&P) states in its guide to the methodology used to rate bonds, "[I]nterest or principal payments cannot be serviced out of earnings, which is just an accounting concept; payment has to be made with cash" (Standard and Poor's, 2003, p. 26). While this emphasis on cash flows is appropriate, it is important to note that it is *future* cash flows, rather than *current* cash flows, that affect firms' ability to service debt. Bond rating agencies must rely on information available now to assess future cash flows. The key question is, which current performance measure(s) is most informative about future cash flows.

According to the Statement of Financial Accounting Concepts No. 1 (FASB, 1978), the primary objective of accrual-based financial reporting is to "provide information to help present and potential investors, creditors and others assess the amounts, timing, and uncertainty of prospective net cash inflows to the related enterprise." If reported accounting earnings provide information about future cash flows above and beyond current cash flows, we expect bond rating agencies to utilize the information rather than to rely on current cash flows alone.

Accounting accruals mitigate the timing and mismatching problems of current cash flows (Dechow, 1994). Numerous studies have demonstrated that accruals contain significant incremental information about future cash flows and that accruals lead to earnings that are superior to current cash flows in predicting future cash flows (see, e.g., Barth et al., 2001; Bernard and Stober, 1989; Dechow et al., 1998; Finger, 1994; Lorek and Willinger, 1996; Pfeiffer et al., 1998; Rayburn, 1986; Wilson, 1986, 1987). Not surprisingly, many previous bond rating models have used accrual-based earnings measures such as return-on-assets (e.g., Kaplan and Urwitz, 1979). Although these models generally use aggregate earnings without separating accruals from cash flows, the improved usefulness of earnings over cash flows should be a result of the accrual component in earnings.

However, most studies cited above focus only on the first-moment, or the levels, effect of accruals on earnings. Accruals also affect the second moment, or the volatility, of earnings. On average, accruals lead to earnings that are smoother than cash flows. Such income smoothing appears to be a widespread practice by managers (Graham et al., 2005) and has long intrigued academics and practitioners (e.g., Ronen and Sadan, 1981). Although regulators and some academics view income smoothing negatively as a form of opportunistic earnings management that reduces the quality of earnings (e.g., Jensen, 2005; Levitt, 1998; Bhattacharya et al., 2003; Leuz et al., 2003), it is interesting to notice that almost all theories on income smoothing view it positively (e.g., Chaney and Lewis, 1995; Demski, 1998; Fudenberg and Tirole, 1995; Nan, 2005; Ronen and Sadan, 1981; Kirschenheiter and Melumad, 2002a, 2002b). These theories argue that income smoothing is a useful device for signaling firms' superior performance: Compared to firms that do not smooth income, income-smoothers have better performance because of higher managerial effort or expertise, higher endowed firm type, or lower contracting costs.

Drawing upon these theoretical studies, Gu (2006) takes a fundamentals approach and empirically examines how income smoothing affects the prediction of future cash flows. His findings support the signaling role of income smoothing predicted by the theories. After controlling for the volatility of cash flows, firms that use accruals to make income smoother are found to have higher level of future cash flows in the one-year to five-year horizons and lower volatility of future cash flows. Lower volatility of future cash flows associated with income smoothing is particularly relevant to bond ratings since bond investors are unable to benefit from the upside potential but are especially concerned about the downside probability (default risk). Minton and Schrand (1999) show that volatility of current cash flows is negatively related to bond ratings. This is likely because observed cash flow volatility is indicative of the volatility in the future. The incremental ability of income smoothing to predict the volatility of future cash flows makes income smoothing a desirable attribute from bond investors' perspective. Based on the income smoothing theories and the empirical findings of Gu (2006), we hypothesize that

H1: Incremental to the volatility of cash flows, stronger income smoothing effect of accruals is associated with more favorable bond ratings.

Kirschenheiter and Melumad (2002b) theoretically predict that accruals themselves become more informative about permanent cash flows when they serve the income smoothing function. Gu (2006) confirms the prediction and documents that, for a given amount, the accruals that make income smoother are able to predict more future cash flows in the same direction. These results lead us to also hypothesize that

H2: Stronger income smoothing effect of accruals is associated with larger weight on accruals in bond ratings.

While our hypotheses are based on firm fundamentals (future cash flows) associated with income smoothing, Trueman and Titman (1988) provide an alternative perception-based theory on the effect of income smoothing on bond ratings. They argue that claimholders of firms such as debtholders care about the volatility of economic earnings. However, claimholders cannot distinguish income smoothers from firms with truly low volatility of economic earnings. Because only an average volatility can be assessed, income smoothers are able to achieve lower perceived volatility of economic earnings than they actually have. This affects the perceived probability of bankruptcy and leads to lower cost of borrowing. Thus, this theory also predicts H1. However, it is mute on whether the weight on accruals in bond rating should be larger with income smoothing (H2).

The role of income smoothing in the bond market has been largely unexplored in the prior literature. Previous studies have examined the effect of either the volatility of cash flows (Minton and Schrand, 1999) or the volatility of earnings (Ahmed et al., 2002) on bond ratings, but not both. To the best of our knowledge, no study has examined whether and how the difference between the two volatilities, the income-smoothing effect of accruals, would contribute to bond ratings. Although Francis et al. (2005) study a second-moment effect of accruals on cost of debt, their focus is on the volatility of the accrual component that is due to accounting measurement errors. This accrual component from the Dechow and Dichev (2002) Model is, by construction, orthogonal to cash flows. Thus, it only adds to the volatility of cash flows and cannot serve any income smoothing purpose. Thus, the second-moment accrual effect they study is independent of the income smoothing effect we study. Nevertheless, in the specification applying the Dechow and Dichev (2002) Model, we control for the non-income-smoothing related volatility of accruals and thus provide more complete results on the second-moment effect of accruals.

Two other studies focus on the first-moment effect of accruals on bond ratings. Ahmed et al. (2002) use the negative of mean accruals over a period as a measure of accounting conservatism. They find that the higher of this measure (lower accruals) is associated with more favorable bond ratings, *after controlling for mean earnings*. Since higher earnings (sum of cash flows and accruals) are associated with more favorable bond ratings, the net effect of accruals is that higher (rather than lower) accruals are associated with more favorable bond ratings. The weight on accruals, however, is smaller than that on cash flows.[26] The lower weight on accruals than cash flows is consistent with the alternative interpretation that accruals are informative, but less so than cash flows, about future cash flows (Barth et al., 2001; Gu, 2006).[27] We confirm this finding in the paper. Jorion, Shi and Zhang (2006) argue that increased earnings management through abnormal accruals may have caused the over-time downward trend in bond ratings first documented by Blume et al. (1998). As part of our analysis, we also examine the over-time trend in bond ratings but do not find that the trend is attributable to abnormal accruals.

3. Sample Selection, Research Design, and Descriptive Statistics

Sample and variable measurement

Our sample consists of all firm years from Compustat and CRSP files with non-missing values of the required variables for the period 1992 – 2003. Bond ratings (RATING) are the S&P's senior debt ratings from Compustat (item #280). These ratings are coded from 2 to 21, with 2 representing a rating of AAA and 21 representing a rating of CCC-. To facilitate the interpretation, we re-code the bond ratings in reverse order from 19 to 1 so that a higher value

[26] In their regressions, Ahmed et al. (2002) obtain: BOND RATING = -6.320 (-Accruals) – 18.238 Earnings + g(Controls). Econometrically, this is identical to BOND RATING = 6.320 Accruals – 18.238 (Accruals + Cash Flows) + g(Controls) = -11.918 Accruals – 18.238 Cash Flows + g(Controls).

[27] Similarly, Sloan (1996) finds that accruals are not as persistent as cash flows in the prediction of future earnings.

represents a more favorable bond rating.[28] The cash flow measure we use is operating cash flows (CFO) from the cash flow statement reported under SFAS 95 (#308) that are available for the majority of firms from 1988. Following Gu (2006), we require five consecutive years of data up to a particular year to calculate the volatility of a series available to bond raters that year. Therefore, the first year that we examine bond ratings is 1992.

We use income before extraordinary item (#18) as our measure of earnings (INCOME). For comparability across firms, CFO and INCOME are deflated by average total assets (#6, ASSET). To avoid the small deflator problem, we require ASSET to be at least \$10 million. For brevity, the deflators are omitted from notations below (hence INCOME is the usual return on assets). Volatility of earnings and cash flows (V_INC and V_CFO) are calculated as the standard deviations of INCOME and CFO over the 5-year period up to the current year. Standard deviations are used in order to mitigate the skewness in variance measures. However, all of our results are qualitatively the same when we use the variance measures. As in prior studies, accruals (ACCR) are measured as the difference between earnings and cash flows:

ACCR = INCOME – CFO.

We measure the smoothing factor in two ways. The first is an absolute measure calculated as the difference between the volatility of earnings and the volatility of cash flows:

SMTH1 = V_INC – V_CFO.

A negative (positive) value of SMTH1 indicates that earnings are smoother (more volatile) than cash flows. The advantage of SMTH1 is that, as an absolute measure, it is directly comparable in measurement units with the volatility of earnings and the volatility of cash flows. Note that ACCR and SMTH1 can be viewed as the first-moment and second-moment counterpart

[28] Code 3 from Compustat is unassigned, so there are 19 grades in senior debt ratings. We also repeat our analysis by combining ratings at the notch level (e.g., BB+, BB and BB-) into one broader category. The results are very similar.

measures of the accrual component in earnings.

We also use a relative measure for the smoothing factor:

SMTH2 = V_INC/V_CFO.

This measure has been commonly used in prior studies on income smoothing (e.g., Leuz et al., 2003; Francis et al., 2004). For SMTH2, a value smaller (greater) than 1 indicates that earnings are smoother (more volatile) than cash flows. Since the smoothing effects are potentially nonlinear in SMTH1 and SMTH2, we also use percentile ranks of SMTH1 and SMTH2 in our empirical tests for robustness checks.

Other than profitability, prior studies have identified a number of factors that are related to bond ratings such as firm size, risk, leverage and interest coverage (e.g., Kaplan and Urwitz, 1979). We include them as control variables in our study. In particular, we measure firm size (SIZE) as the logarithm of total assets and leverage (LEV) as the long-term debt (#9) divided by average assets.[29] Interest coverage (INTCOV) is calculated as the ratio of the sum of operating income and interest expense (#178+#15) to interest expense (#15). Equity beta (BETA) is estimated from the market model using monthly stock returns and value-weighted market returns in the five years up to the current year obtained from CRSP (requiring a minimum of 24 observations). The market model also yields the variance of the residuals (MSE), that is, return volatility unrelated to market volatility. Following Ahmed et al. (2002), we consider two accounting conservatism proxies. One is the negative of cumulative accounting accruals (CONACCR) measured as the mean of accruals over the five years up to the current year multiplied by -1. The other is the market-to-book ratio (MB) measured as market capitalization

[29] Using market value of capitalization as the size measure does not change the results qualitatively.

(#199 × #25) divided by book value of equity (#60).[30] We also control for two industries with dummy variables, one for regulated firms (REGULATED for 2-digit SIC 40-42, 44-47, 49), and one for financial institutions (FINANCIAL for 2-digit SIC 60-69).

Research Design

Since RATING is a categorical variable, we use ordered-probit models to study the relationship between RATING and economic factors. As a benchmark case, we start from cash flows in first and second moments using the following model,

$$\text{RATING} = b_0 + b_1\,\text{CFO} + b_3\,\text{V\_CFO} + b_3\,\text{Controls} + \varepsilon \qquad (1)$$

To test our first hypothesis, we add the first- and second-moment accrual components of earnings to the above model and examine whether they are incrementally associated with bond ratings. The model that we use is,

$$\text{RATING} = b_0 + b_1\,\text{CFO} + b_2\,\text{ACCR} + b_3\,\text{V\_CFO} + b_4\,\text{SMTH} + b_5\,\text{Controls} + \varepsilon$$

(2)

Hypothesis H1 predicts that $b_4 < 0$, that is, more income smoothing (smaller SMTH) is associated with higher level and lower volatility of future cash flows, hence more favorable bond ratings. Although our focus is on the income-smoothing effect of accruals, we also expect $0 < b_2 < b_1$ because accruals are incrementally informative about future cash flows but less so than current cash flows (Barth et al., 2001; Gu, 2006).

Hypothesis 2 predicts that the weight on accruals is larger as the income smoothing effect of accruals becomes stronger because income smoothing improves the predictive ability of

[30] Ahmed et al. (2002) use a firm-specific component of the market-to-book ratio as the measure of accounting conservatism. We use the overall ratio rather than a component of it in this study, which is common in the accounting literature (e.g., Givoly and Hayn, 2000). In the finance literature, market-to-book ratio is often taken as a measure of a firm's growth potential that should be related to the firm's default risk by itself.

accruals for future cash flows. To test this, we include the interaction of accruals with the smoothing factor. Our third model is,

$$\text{RATING} = b_0 + b_1 \text{ CFO} + b_2 \text{ ACCR} + b_3 \text{ V\_CFO} + b_4 \text{ SMTH} + b_5 \text{ ACCR} \times \text{SMTH} + b_6 \text{ CFO} \times \text{SMTH} + b_7 \text{ ACCR} \times \text{V\_CFO} + b_8 \text{ CFO} \times \text{V\_CFO} + b_9 \text{ Controls} + \varepsilon \quad (3)$$

Hypothesis H2 predicts that $b_5 < 0$. Because coefficient b_2 on ACCR itself is predicted to be positive, negative b_5 implies that smoother income (smaller SMTH) leads to higher (more positive) total coefficient on ACCR. This corresponds to larger weight on accruals. We also include other interaction variables CFO × SMTH, ACCR ×V_CFO, and CFO ×V_CFO in the model both for completeness and because there is some evidence in Gu (2006) that these variables also help predict future cash flows. For example, current cash flows become less informative about future cash flows when they are more volatile. This suggests that $b_8 < 0$. Accruals, on the other hand, are especially informative when current cash flows are volatile and uninformative. This suggests that $b_7 > 0$.

Descriptive statistics

To mitigate the effect of outliers on the regressions, observations with explanatory variables in the top and bottom extreme 1% are deleted. Our final sample consists of 9,985 firm-year observations. Descriptive statistics for the variables are reported in Table 1. Average bond ratings are about 11, which corresponds to a rating of BBB. Consistent with prior findings, mean (median) earnings is 0.037 (0.037), lower than the mean (median) cash flows of 0.090 (0.084) due to negative accruals. On average, earnings are less volatile than cash flows, with mean (median) V_INC of 0.031 (0.021) as opposed to 0.036 (0.029) for V_CFO. Consistent with the income smoothing use of accruals, both the mean and median of SMTH1 are negative. The distribution of SMTH2 is skewed to the right because of small denominators used to calculate SMTH2 for a few observations. The median of SMTH2 is 0.751. The standard deviations of SMTH1 and SMTH2 are 0.028 and 0.824, respectively, indicating wide variations in the degree of income smoothing.[31] Our sample firms tend to be larger than firms in the Compustat population, with mean (median) total assets of $7.7 (2.4) billion. This is consistent with the notion that corporate bonds are usually issued by relatively large firms. About 15.2% of the firms are regulated and 11.4% are in the financial sector.

Correlations among the variables are presented in Table 2, with Pearson (Spearman) correlation coefficients above (below) the diagonal. It can be noted that the correlations between the smoothing factor and INCOME/CFO are generally negative. That is, the smoother earnings are relative to cash flows, the better the performances are. As expected, INCOME and its two components CFO and ACCR are all positively correlated with RATING, consistent with more profitable firms having better bond ratings. In addition, the correlation between ACCR and RATING is smaller than that between CFO and RATING, suggesting that accruals are useful, but less so than cash flows, for bond ratings. As we predict, both smoothing factors SMTH1 and SMTH2 are negatively correlated with RATING, that is, more income smoothing is associated with better bond ratings. The volatilities of earnings and cash flows are also negatively correlated with bond ratings, suggesting the general preference of stable performances by bond rating agencies. The correlations between RATING and other control variables are generally consistent with prior findings that bond ratings are better for larger, lower leveraged, less risky, more solvent, and more conservative (measured by MB) firms. The exception is the accrual-based accounting conservatism measure CONACC. The negative correlation suggests that more conservative firms have worse bond ratings, as similarly found in this setting by Ahmed et al.

[31] For about 34% of the firms, earnings are actually more volatile than cash flows (SMTH1 > 0 or SMTH2 > 1).

(2002, Table 2).

4. Empirical Results

For most results in this section, we run the ordered-probit regressions each year with RATING as the dependent variable for the 12 years in our sample period. We report the mean coefficients and the mean pseudo-R^2s in our tables following the Fama-MacBeth procedures. Statistical significance is based on the t-statistics for the time-series means of the coefficients. Results from pooled regressions are reported in the last subsection.

Basic results

Table 3 provides the regression results for testing hypothesis H1. The benchmark results from model (1) considering only cash flows and volatility of cash flows are reported in columns 1 and 2. With and without the control variables, the coefficient on CFO is positive and the coefficient on V_CFO is negative, suggesting that bond ratings favor higher and less volatile cash flows. The negative relation between bond ratings and the volatility of cash flows is consistent with the findings of Minton and Schrand (1999). In columns 3-6, we report the results from model (2) with accruals and the smoothing factor (SMTH1 and SMTH2) included. In all specifications these two variables are highly significant. For the two components of earnings levels, the coefficients on both CFO and ACCR are significantly positive. The coefficient on CFO is more than double that on ACCR and the difference is significant at the 0.01 level. The lower weight on accruals than cash flows is consistent with the prior finding that accruals provide significant incremental information about future cash flows but are nonetheless not as informative as current cash flows. For the two components of earnings volatility, both V_CFO and SMTH take significantly negative coefficients. Thus, while the volatility of cash flows is important for bond ratings, the ability of accruals to dampen the volatility of cash flows also plays a significant incremental role. In columns 3 and 4 where the smoothing factor (SMTH1) is in comparable measurement units to V_CFO, the coefficients suggests that one unit of the smoothing effect has about half the impact of one unit of the volatility of cash flows on bond ratings. The difference is significant at the 0.01 level. Overall, we find that accruals in both first- and second-moment measures incrementally contribute to bond ratings. Specifically, more income smoothing is associated with more favorable bond ratings, supporting hypothesis H1.

The results from model (3) for testing hypothesis H2 are reported in Table 4. The interactions of the smoothing factor as well as the volatility of cash flows with accruals and cash flows are included to examine if the second-moment components of earnings, especially the smoothing component, affect the weights on accruals and cash flows in bond ratings. The raw smoothing factor measures are used in columns 1 and 3 and their percentile ranks (and percentile ranks of the volatility of cash flows) are used in columns 2 and 4. The coefficients on the four interaction variables are all highly significant in all specifications. Several observations can be made. First, consistent with the prediction of H2, the coefficient on ACCR × SMTH1 is negative, indicating that more income smoothing effect of accruals significantly increases the weight on accruals in bond ratings. In addition, the coefficient on CFO × SMTH1 is also negative. This suggests that income smoothing is also associated with more informative cash flows. Second, the negative coefficient on CFO × V_CFO is as expected since more volatile cash flows are likely to reduce the weight on cash flows. The negative coefficient on ACCR × V_CFO is, however, unexpected. Evidence in Gu (2006) suggests that accruals become more informative about future cash flows when cash flows are more volatile and less informative. Thus, we expect the weight on accruals to be higher with more volatile cash flows (positive coefficient on ACCR × V_CFO).

Third, the coefficient on SMTH remains negative and is significant in all specifications except in column 1 where the smoothing factor is SMTH1 (marginally significant at the 9% level, one-tailed). However, the coefficient on V_CFO becomes insignificant. This indicates that although the total effect of the volatility of cash flows is negative as found in Minton and Schrand (1999) (i.e., higher volatility of cash flow is associated with less favorable bond ratings),[32] the effect is actually achieved indirectly through the varying weight on cash flows. Overall, evidence here supports both hypotheses H1 and H2 that income smoothing improves bond ratings and also increases the weight on accruals in bond ratings.

The results on the control variables are generally consistent with the correlation results in Table 2. Accrual-based accounting conservatism measure CONACC is worth discussion here. Its coefficient is negative though insignificant, opposite to the prediction that more conservatism accounting is associated with better bond ratings. Since CONACC is the negative of average accruals over several years including the current year, it captures the incremental impact of past years' accruals because current year's accruals ACCR are separately included. The insignificance of CONACCR is consistent with the Gu (2006) finding that past accruals have limited incremental predictive power for future cash flows over ACCR. If the effect of accounting conservatism is subsumed, and represented, by ACCR, the positive coefficient on ACCR again suggests that more conservative accounting is associated with *worse* bond ratings. Untabulated results indicate that if total earnings are used in place of cash flows (CFO) in the regression as in Ahmed et al. (2002), the coefficient on ACCR (CONACC) would change to be

[32] For example, in column 1 the total effect of V_CFO is (-0.119 – 142.299 CFO – 85.816 ACCR) × V_CFO. On average, CFO is positive and larger in magnitude than ACCR (see Table 1). Thus, the total coefficient on V_CFO is negative in general.

negative (positive), similar to what Ahmed et al. (2002) find.[33] There is no theory mandating that accounting conservatism should affect bond ratings only jointly with earnings (which contain accruals themselves) but not with cash flows. However, the positive (negative) coefficient on ACCR (CONACC) here is consistent with the alternative interpretation that accruals, especially those in the current year, are informative about future cash flows, though less so than current cash flows.

Additional results

Investment grade vs. non-investment grade bond ratings

If income smoothing improves bond ratings on average due to better fundamentals (future cash flows), it might be enticing for some firms to engage in excessive income smoothing unwarranted by fundamentals. Such behavior, if at all, might occur more among firms with non-investment grade bond ratings since their need for better ratings is stronger. In response, bond rating agencies might rely less on accruals and income smoothing for these firms. This would then reduce the incentive for excessive income smoothing by these firms. Nevertheless, it is worth examining whether income smoothing has similar impacts on investment grade and non-investment grade bond ratings.

Following the standard practice, we use BBB– as the cutoff point and divide the sample into subsamples of investment grade and non-investment grade bond ratings. Regressions are run within each subsample and the results are reported in Table 5. For investment grade firms in columns 1-4, the effects of the smoothing factor are similar to those reported in Table 4 and are as predicted. The coefficients on SMTH and ACCR × SMTH are generally significantly

[33] See footnote 2 earlier for Ahmed et al.'s (2002) results. Note that since they use lower measures of bond ratings to indicate more favorable bond ratings, their positive (negative) coefficients correspond to our negative (positive) coefficients. Change in the sign of coefficient on CONACC can also be seen in our Table 7 where cash flows plus normal accruals are used in place of cash flows.

negative. For non-investment grade firms in columns 5-8, the coefficient on SMTH is negative but not significant. The coefficients on ACCR × SMTH and CFO × SMTH are consistently negative and significant. Thus, it appears that for non-investment grade firms the effects of income smoothing is mostly achieved through the increased informativeness of accruals and cash flows. It is interesting to note that, compared to those for investment grade firms, the coefficients on all accrual-related variables for non-investment grade firms (ACCR, SMTH, ACCR × SMTH and CFO × SMTH) are consistently smaller in magnitude but the coefficients on cash flow-related variables are not consistently larger. This suggests that bond rating agencies use cash flows in similar ways but rely less on accruals for these firms.

A caveat of the analysis here is that partition of the sample is based on the dependent variable, which would bias the coefficient towards zero.[34] The income smoothing effect could be the strongest in differentiating firms between, rather than within, investment grade and non-investment grade groups, as better performing firms in the investment grade group use more income smoothing to signal their performance relative to the poor performing ones in the non-investment grade group. Given that, we still find that income smoothing affects bonding ratings in the predicted directions for each group.

Innate vs. discretionary income smoothing

Francis et al. (2004) suggest that income smoothing may contain two components, one determined by innate factors that reflect firms' business models and operating environment, and the remaining one due to firms' reporting discretion. Econometrically, they include as additional control variables those factors that are presumably innate determinants of income smoothing. Any significance of the smoothing factor in the presence of the control variables captures the

[34] In the extreme case where each individual rating is used to form a subsample, there is no variation in the dependent variable. No coefficient would be significant other than the intercept.

effect of the remaining discretionary income smoothing component. Some of the innate factors they consider are already included in our models (e.g., SIZE and V_CFO). These factors affect not only income smoothing but also bond ratings directly. Thus, our results earlier can be regarded as already capturing partially discretionary income smoothing effect.

To fully account for all the innate factors, we take a different, but econometrically equivalent, approach. If we literally follow Francis et al. (2004), we would include all the innate factors as well as interactions of each of them with ACCR and CFO as we do with the smoothing factor. This will make the presentation of the results unnecessarily complicated. Instead, we take a two-step approach. We first regress the smoothing factor on all the innate factors they identify based on the model:

$$\begin{aligned} SMTH_t = {} & a_0 + a_1\, SIZE_t + a_2\, V\_CFO_t + a_3\, V\_SALES_t + a_4\, OPCYCLE_t + a_5\, NEGEARN_t \\ & + a_6\, INT\_INTENSITY_t + a_7\, INT\_DUM_t + a_8\, CAP\_INTENSITY_t + \varepsilon_t. \end{aligned}$$

where V_SALES_t is the standard deviation of sales deflated by average assets over the five years up to year t, $OPCYCLE_t$ is the log of the sum of days accounts receivable and days inventory, $NEGEARN_t$ is the proportion of loss years over the five years up to year t, $INT\_INTENSITY_t$ is the sum of R&D and advertising expenditures deflated by sales, INT_DUM_t is 1 if INT_INT_t is 0 and zero otherwise, and $CAP\_INTENSITY_t$ is net PPE deflated by total assets. We take the fitted values as the innate component and the residuals as the discretionary component of income smoothing. In the second stage, we separately replace SMTH in model (3) with the innate and the discretionary smoothing factors and run the regressions. Since the two smoothing factors are uncorrelated with each other by construction, considering them separately would not affect the inferences on them.

The regression results are reported in Table 6. For the innate smoothing factor in columns 1-4, the coefficient on the factor itself is significantly negative, but the coefficient on its interaction with ACCR is insignificant. This supports hypothesis H1 but not H2. For the discretionary smoothing factor in columns 5-8, the results are just the opposite. The coefficient on the factor itself is insignificant, but the coefficient on its interaction with ACCR is significantly negative, supporting hypothesis H2 but not H1. It appears that income smoothing driven by firms' business models and operating environment affects bond ratings by the smoothing act itself, and income smoothing due to firms' reporting discretion affects bond ratings indirectly through increased weight on accruals. This result can be easily understood once we consider the fact that the innate smoothing factor is simply a linear combination of other variables. Those other variables individually may affect bond ratings, and thus continue to work when combined into the innate smoothing factor. It is less clear, however, how those variables would affect the informativeness of accruals and thus affect bond ratings indirectly through accruals. On the other hand, reporting discretion is achieved through accruals and is expected to affect the informativeness of accruals. An alternative interpretation is that any effect of the total smoothing factor on the informativeness of accruals not captured by the innate component must be mechanically left over to the residual discretionary component.

Normal vs. abnormal accruals: the Jones (1991) Model

Income could be smoother relative to cash flows or relative to some other income measures. If one believes that there is a normal level of accruals designated by firms' operating activities before any use of other accruals to smooth income, then the appropriate pre-smoothed income would be cash flows plus the normal accruals. To examine whether income smoothing has the same predicted effects when an alternative income benchmark is used, one needs a model to separate normal from abnormal accruals. The widely used Jones (1991) Model provides such a tool:

$$\text{ACCR} = a_0 + a_1\ 1/\text{ASSET} + a_2\ \Delta\text{REV} + a_3\ \text{PPE} + \varepsilon.$$

where ΔREV is change in revenue (#12) and PPE is gross property, plant and equipment (#8), both deflated by ASSET. In this model, the fitted values are taken as normal accruals and the residuals as abnormal accruals. Although normal accruals defined as such have a certain income smoothing element in them,[35] income smoothing is not incorporated as a main use of normal accruals.

We estimate the Jones Model cross-sectionally for each combination of year and 2-digit SIC code with a minimum of 10 observations based on the population of Compustat firms. Normal accruals are estimated as NMACCR = $\hat{a}_0 + \hat{a}_1\ 1/\text{Assets} + \hat{a}_2\ \Delta\text{REV} + \hat{a}_3\ \text{PPE}$, where $\hat{a}_0$, $\hat{a}_1$, $\hat{a}_2$, and $\hat{a}_3$ are the coefficient estimates from the Jones Model. We define pre-smoothed income as PSI = CFO + NMACCR and (income-smoothing) abnormal accruals as ABACCR = ACCR – MNACCR. We then replace CFO with PSI and replace ACCR with ABACCR in all previous measures involving CFO and ACCR and re-calculate the smoothing factors. The (untabulated) means (medians) of the newly calculated SMTH1 and SMTH2 are -0.012 (-0.012) and 0.765 (0.596), respectively, lower than those reported in Table 1. They are consistent with the income-smoothing role of ABACCR in reducing the volatility of PSI (see also Subramanyam, 1996).

The regression results for model (3) based on PSI and ABACCR are reported in Table 7. Compared with those in Table 4, the main results remain qualitatively the same. The coefficient on ABACCR is positive, consistent with the findings in Gu (2006) that abnormal accruals are similar to total accruals in predicting future cash flows.[36] The coefficients on SMTH and PSI × SMTH are negative and significant as predicted. The coefficients of the interaction variables

[35] For example, increased credit sales captured by ΔREV will result in higher cash flows in the future. Recognition of the revenue allows the current income to be higher and possibly smoother than otherwise.
[36] Subramanyam (1996) also finds that abnormal accruals are positively priced by the stock market.

involving the smoothing factors are generally larger than their counterparts in Table 4, suggesting that the smoothing effect of abnormal accruals may increase the weight on earnings components more than the smoothing effect of total accruals.

Overall, the results of Table 7 suggest that abnormal accruals from the Jones Model and their income-smoothing effect affect bond ratings in similar ways to total accruals. This is perhaps not surprising since normal accruals as defined by the Jones Model are not meant to capture the income smoothing function of total accruals. Thus, any income smoothing function of total accruals found earlier should be left over to abnormal accruals.[37]

Normal vs. abnormal accruals: the Dechow and Dichev (2002) Model

Francis et al. (2005) study how the accrual component due to accounting estimation errors affects cost of debt. Their measure is based on the Dechow and Dichev (2002) model relating total accruals to past, current and future cash flows as follows: [38]

$$ACCR_t = a_0 + a_1\, CFO_{t-1} + a_2\, CFO_t + a_3\, CFO_{t+1} + \varepsilon_t.$$

The residuals from this model are regarded as accounting estimation errors and serve as another measure of "abnormal" accruals. Francis et al. (2005) find that higher volatility of such abnormal

[37] Kothari et al. (2005) propose a performance-matched Jones Model by including INCOME as an additional explanatory variable. We do not use this model due to an inherent problem in the smoothing factor calculated with abnormal accruals from this model. This can be illustrated with the volatility and smoothing factor measured in variance terms. Note that as an explanatory variable, INCOME is uncorrelated with the residuals from the regressions: Cov (INCOME, ABACCR) = 0. Since Cov (INCOME, ABACCR) = Cov (CFO +NMACCR + ABACCR, ABACCR) = Cov (CFO, ABACCR) + Var (ABACCR) given Cov (NMACCR, ABACCR) = 0, we have Cov (CFO, ABACCR) = – Var (ABACCR). Then the smoothing factor SMTH1 = Var (INCOME) – Var (PSI) = Var (PSI +ABACCR) – Var (PSI) = Var (ABACCR) + 2 Cov (PSI, ABACCR) = Var (ABACCR) + 2 Cov (CFO+NMACCR, ABACCR) = Var (ABACCR) + 2 Cov (CFO, ABACCR) = Var(ABACCR) – 2 Var (ABACCR) = – Var (ABACCR). Thus, instead of capturing income smoothing, SMTH1 captures the *negative* of the variance of abnormal accruals. That is, regardless of the actual smoothing behavior, abnormal accruals from this model always make income smoother exactly by their own variance. Since higher variance of abnormal accruals is associated with worse bond ratings, this also implies that more income smoothing is associated with worse bond ratings, inconsistent with our predictions. The relative smoothing measure SMTH2 = 1 + SMTH1/Var(PSI) suffers from a similar problem. Empirically, if the Jones Model regressions are run cross-sectionally and SMTH1 is measured firm-specifically, SMTH1 = – Var (ABACCR) may not hold exactly. However, the conceptual problem remains.
[38] When we apply this model to working capital accruals, we obtain qualitatively similar results.

accruals is associated with higher interest expenses. Since, by construction, residuals are orthogonal to the explanatory variables (cash flows), abnormal accruals from this model cannot reduce, but only add to, the volatility of cash flows.[39] Then, income smoothing is performed by the fitted values, or normal accruals. Thus, by this model, mitigating the timing and mismatching problems of cash flows is regarded as a *normal* function of accruals.

Similar to the Jones Model, we estimate the Dechow and Dichev Model cross-sectionally for each combination of year and 2-digit SIC code with a minimum of 10 observations based on the population of Compustat firms. Normal accruals are defined as NMACCR = $\hat{a}_0 + \hat{a}_1 \text{CFO}_{t-1} + \hat{a}_2 \text{CFO}_t + \hat{a}_3 \text{CFO}_{t+1}$ and abnormal accruals are defined as ACCRERR = ACCR – NMACCR, where $\hat{a}_0$, $\hat{a}_1$, $\hat{a}_2$, and $\hat{a}_3$ are the coefficient estimates from the model. Cash flows remain the smoothing target in this case. We replace ACCR with NMACCR and replace INCOME with (CFO+NMACCR) in all previous measures involving ACCR and INCOME and re-calculate the smoothing factors. The (untabulated) means (medians) of the newly calculated SMTH1 and SMTH2 are -0.006 (-0.005) and 0.962 (0.809), comparable to those reported in Table 1. Although we focus on normal accruals for their income smoothing function, we also consider the level and volatility of ACCREER as additional explanatory variables due to their potential effects on bond ratings implied by Francis et al. (2005). Following them, we measure the volatility (V_ACCRERR) as the standard deviation of ACCRERR.

The regression results are reported in Table 8.[40] Compared to the results with total accruals in Table 4, the main results on NMACCR and its smoothing effect remain qualitatively similar, with positive coefficients on NMACCR and negative coefficients on SMTH and SMTH

[39] Empirically, if the model is estimated cross-sectionally and the smoothing factor is measured firm-specifically, the correlation between abnormal accruals and cash flows may not be zero literally.
[40] Because the Dechow and Dichev Model uses lagged and forward cash flows, we lose two years (1992 and 2003) for our bond rating regressions.

× NMACCR. The coefficients on ACCREER are positive but much smaller than those on NMACCR, suggesting that abnormal accruals still contains incremental information relevant for bond ratings. Consistent with the findings of Francis et al. (2005), volatility of abnormal accruals (V_ACCRERR) is negatively related to bond ratings and is highly significant. Overall, normal accruals from the Dechow and Dichev (2002) Model serve similar roles of total accruals in terms of both first- and second-moment effects.

Downward trend in bond ratings

Reporting the mean coefficients from annual regressions implicitly assumes that the coefficients are stable over the years. Blume et al. (1998) show that while this is generally true for the slopes, the relative annual intercepts have decreased gradually over the years.[41] The decrease in intercepts implies that bond ratings would be lower in later years for the same values of explanatory variables. They interpret it as evidence of increasingly stringent credit standards used by bond rating agencies. Jorion, Shi and Zhang (2006) argue that the trend may be due to increasing earnings management measured by abnormal accruals from the Jones (1991) model. Both these studies pool observations across years in the probit regressions and examine the yearly intercepts. To be comparable to their studies, we follow the same research design by pooling observations across years and include yearly dummies using 1992 as the base year.[42]

[41] For an ordered-probit model with n categories and a vector of explanatory variables **x**, there are n-1 estimated cutoff points ($\mu_1, \ldots, \mu_{n-1}$) in addition to the estimated coefficients $\boldsymbol{b}$ on **x**. We did not report these estimated cutoff points earlier for brevity. The probability of $a + \boldsymbol{b}\mathbf{x} + \varepsilon$ falling in between the cutoff points provides the estimates of the likelihood that the observation falls into the particular categories. For example, the probability of $-\infty < a + \boldsymbol{b}\mathbf{x} + \varepsilon < \mu_1$ provides the estimate of the likelihood that the observation falls into the lowest category. Clearly, the intercept a is not identified since, for any a, one can equivalently have $-\infty < \boldsymbol{b}\mathbf{x} + \varepsilon < \mu_1 - a$, that is, a zero intercept and the cutoff point moved downward by a. Thus, for any single year ordered-probit regression, the intercept is normalized to be zero. However, if one pools multiple years together and normalize the intercept for a base year, intercepts for other years can be measured relative to the base year intercept by using dummies for other years. In this way, a time trend can be examined. See more discussion in Blume et al. (1998, p. 1392-1393).

[42] An alternative research design is to include a time trend as an explanatory variable rather than multiple yearly dummies. The results are qualitatively similar and not reported.

The regression results are reported in Table 9. In column 1, we consider the benchmark case where only pre-smoothed/unmanaged earnings PSI (cash flows plus normal accruals from the Jones Model) and its volatility are used. Relative to the base year 1992, the yearly intercepts become increasingly negative over the years, similar to the findings of Blume et al. (1998). In columns 2-5, we include abnormal accruals ABACCR and their smoothing effects. The coefficients on SMTH and SMTH × ABACCR are negative in all specifications, similar to those in Table 7 and in support of hypotheses H1 and H2. Note that the coefficient on ABACCR is significantly positive as before. This is consistent with abnormal accruals being informative about future cash flows and positively weighted in bond ratings, but inconsistent with the argument that more earnings management would lead to worse bond ratings. Since the weight on unmanaged earnings PSI is larger than the weight on ABACCR, bond ratings would be lower if, over time, PSI becomes smaller and abnormal accruals become larger. That is, the over-time variations embedded in PSI and ABACCR might explain the downward trend in bond ratings. However, while we do observe some evidence that ABACCR on average has increased over time,[43] the decreasing time trend in the yearly intercepts is essentially intact in columns 2-5 compared to that in column 1. Thus, abnormal accruals do not appear to be responsible for causing the over-time downward trend in bond ratings.[44] Overall, our main results on the income smoothing effect on bond ratings remain robust in the pooled regressions.

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[43] The median ABACCR for 1992-2003 is0.0006, 0.0012, 0.0007, 0.0040, 0.0018, 0.0030, 0.0043, 0.0059, 0.0013, 0.0163, 0.0104,and 0.0032, respectively.

[44] Jorion, Shi and Zhang (2006) are able to explain away the over-time downward trend in the yearly dummies by using a single value of abnormal accruals (each year's cross-firm median) to represent earnings management of all firms in a year. We find similar results if we follow this approach. Since all firms in each year take a single value for abnormal accruals and another single value for the yearly dummy, one possibility for the observed result is that these variables are easily (spuriously) correlated. To explore this possibility, we use a single value (cross-firm median) of a control variable such as firm size, leverage, and beta to represent that variable of all firms in a year. We find that *any variable* used in this fashion, not just abnormal accruals, can equally explain away the decreasing trend in the yearly dummies (results available upon request). Thus, it appears that Jorion, Shi and Zhang's findings are due to the unique research design they use rather than a fundamental relationship between abnormal accruals and bond ratings. Regardless, our results on the income smoothing effect are not affected by such research design issues.

5. Conclusions

Bond investors and analysts, like their peers in the stock market, are important users of financial statements. They are likely to use accounting variables beyond cash flows in assessing the default risk of firms. We examine the income smoothing effect of accruals on bond ratings in this paper. Accruals mitigate the inherent timing and mismatching problems in cash flows and significantly improve the prediction of future cash flows. The incremental information is conveyed not only through the effects of accruals on the levels but also through the effects on the volatility of reported earnings. Income smoothing theories argue that only those firms with superior performance, more capable or more hardworking managers, or more efficient contracting are able to use accruals to offset the volatility of cash flows (e.g., Chaney and Lewis, 1995; Demski, 1998; Fudenberg and Tirole, 1995; Nan, 2005; Ronen and Sadan, 1981; Kirschenheiter and Melumad, 2002a, 2002b). Empirical evidence suggests that firms reporting smoother income relative to cash flows have higher and less volatile future cash flows and have accruals that are more informative about future cash flows (Gu, 2006). We show that bond rating agencies utilize this information in assessing firms' default risk.

Our results are based on a large sample of firms with S&P senior debt ratings covering the period 1992-2003. We document that, incremental to the volatility of cash flows, the income-smoothing use of accruals significantly improves firms' bond ratings and increases the already positive weight on accruals in bond ratings. These results are rather robust to alternative measures of the income smoothing effect and subsamples of investment grade and non-investment grade bond ratings. We also use alternative definitions of pre-smoothed income and the smoothing component of accruals based on the Jones (1991) and Dechow and Dichev (2002) Models and have similar findings.

Our results from the debt market complement the large body of existing literature on the equity market that has consistently documented the reward to income smoothing by stockholders. Although regulators are concerned that the market may be fooled by the smooth income pattern (Levitt, 1998), income smoothing theories suggest that that the market premium on income smoothing may be warranted. Given that both the debt and equity markets reward income smoothing, one might re-think about whether we should ask firms to "stop smoothing earnings" (Jensen, 2005).

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Table 1. Descriptive Statistics

Variables	mean	std	min	Q1	median	Q3	max
RATING	10.950	3.388	1.000	8.000	11.000	14.000	19.000
INCOME	0.037	0.054	-0.460	0.014	0.037	0.063	0.240
CFO	0.090	0.062	-0.157	0.051	0.084	0.125	0.326
ACCR	-0.053	0.056	-0.466	-0.078	-0.048	-0.023	0.167
V_INC	0.031	0.032	0.001	0.011	0.021	0.040	0.333
V_CFO	0.036	0.025	0.003	0.018	0.029	0.047	0.189
SMTH1	-0.005	0.028	-0.132	-0.017	-0.006	0.005	0.228
SMTH2	0.973	0.824	0.042	0.440	0.751	1.223	7.299
ASSET (in $mil)	7,742	16,317	107	1,001	2,417	6,925	210,488
LEV	0.309	0.183	0.000	0.177	0.287	0.406	1.224
MSE	0.012	0.012	0.001	0.004	0.008	0.015	0.113
BETA	0.881	0.537	-0.328	0.499	0.832	1.192	3.580
INTCOV	6.643	7.237	0.006	2.866	4.382	7.502	82.432
MB	2.539	2.630	-16.958	1.313	1.938	3.029	34.202
CONACC	0.050	0.039	-0.086	0.027	0.047	0.070	0.245
REGULATED	0.152	0.359	0.000	0.000	0.000	0.000	1.000
FINANCIAL	0.114	0.317	0.000	0.000	0.000	0.000	1.000

The sample consists of 9,985 firm-year observations from the Compustat Annual Industrial and CRSP files with non-missing values of the variables, covering the period 1992-2003. RATING is S&P's senior debt rating coded numerically from 1 to 19 (Compustat #280) with a higher number indicating better bond ratings. INCOME is income before extraordinary items (#18) and CFO is cash flow from operations (#308), both deflated by the average total assets (#6) required to be at lest $10 million. ACCR is accounting accruals measured as INCOME – OCF. V_INC and V_CFO are the standard deviations of INCOME and CFO over the five years up to the current year. The smoothing factor SMTH1 is measured as V_INC – V_CFO and SMTH2 measured as V_INC/V_CFO. ASSET is the average of total asset (#6, in millions), the logarithm of which is used as SIZE in later analysis. LEV is leverage measured as long-term debt (#9) divided by ASSET. BETA is the equity beta estimated from the market model beta using monthly stock returns and value-weighted market returns in the five years up to the current year (minimum 24 observations). MSE is the variance of the residuals from the market model. INTCOV is interest coverage measured as the ratio of the sum of operating income after depreciation and interest expense (#178+#15) to interest expense (#15). MB is market capitalization (#199 × #25) divided by book value of equity (#60). CONACC is the negative of average ACCR over the five years up to the current year. REGULATED is a dummy variable for firms with 2-digit SIC 40-42, 44-47, and 49. FINANCIAL is a dummy variable for firms with 2-digit SIC 60-69. Observations with variables (other than RATING) in the extreme top and bottom 1% are removed.

Table 2. Correlation Coefficients

Variables	RATING	INCOME	CFO	ACCR	V_INC	V_CFO	SMTH1	SMTH2	SIZE	LEV	MSE	BETA	INTCOV	MB	CONACC
RATING		0.403	0.278	0.084	-0.364	-0.330	-0.112	-0.154	0.548	-0.515	-0.617	-0.229	0.411	0.252	-0.077
INCOME	0.393		0.532	0.370	-0.201	-0.028	-0.202	-0.179	0.089	-0.288	-0.273	-0.106	0.509	0.359	-0.105
CFO	0.286	0.582		-0.584	0.061	0.076	0.000	-0.011	0.059	-0.181	-0.101	-0.034	0.400	0.314	0.488
ACCR	0.068	0.175	-0.614		-0.257	-0.117	-0.185	-0.156	0.022	-0.078	-0.152	-0.066	0.052	0.001	-0.639
V_INC	-0.392	-0.097	0.082	-0.244		0.534	0.646	0.562	-0.232	0.127	0.452	0.266	-0.041	0.040	0.314
V_CFO	-0.351	0.005	0.071	-0.129	0.569		-0.299	-0.175	-0.282	0.041	0.379	0.247	0.030	0.037	0.114
SMTH1	-0.068	-0.122	-0.002	-0.131	0.448	-0.384		0.792	-0.008	0.107	0.167	0.078	-0.073	0.011	0.251
SMTH2	-0.172	-0.113	0.032	-0.170	0.671	-0.172	0.907		-0.028	0.099	0.179	0.099	-0.068	0.006	0.183
SIZE	0.544	0.052	0.057	0.015	-0.240	-0.304	0.037	-0.030		-0.326	-0.307	-0.062	0.170	0.131	-0.016
LEV	-0.510	-0.292	-0.186	-0.079	0.076	0.009	0.075	0.092	-0.315		0.255	-0.016	-0.455	-0.130	0.117
MSE	-0.683	-0.260	-0.120	-0.143	0.502	0.470	0.055	0.190	-0.337	0.211		0.335	-0.139	-0.099	0.154
BETA	-0.193	-0.066	-0.028	-0.045	0.270	0.245	0.039	0.105	-0.051	-0.065	0.294		0.003	0.034	0.070
INTCOV	0.558	0.736	0.493	0.083	-0.124	-0.023	-0.123	-0.132	0.213	-0.616	-0.263	-0.010		0.306	-0.037
MB	0.338	0.479	0.393	-0.032	0.044	0.024	0.024	0.028	0.171	-0.173	-0.174	0.057	0.461		0.041
CONACC	-0.065	-0.034	0.481	-0.659	0.279	0.140	0.171	0.206	-0.004	0.088	0.127	0.069	-0.056	0.092	

For variable definitions, see Table 1. The upper triangle contains Pearson correlation coefficients; the lower triangle contains Spearman correlation coefficients.

Table 3. The Effect of Income Smoothing on Bond Ratings: Ordered-Probit Regression Results (Dependent Variable is RATING)

Smoothing factor				SMTH1		SMTH2	
Explanatory variables	Predicted signs	(1)	(2)	(3)	(4)	(5)	(6)
CFO	+	6.147*	4.377*	10.810*	5.540*	11.137*	5.907*
ACCR	+			7.667*	2.573*	8.511*	3.212*
V_CFO	–	-13.735*	-5.482*	-20.314*	-7.523*	-17.501*	-6.999*
SMTH	–			-9.036*	-3.507*	-0.260*	-0.126*
SIZE	+		0.403*		0.404*		0.406*
LEV	–		-2.201*		-2.240*		-2.246*
MSE	–		-72.751*		-71.054*		-71.473*
BETA	–		-0.309*		-0.305*		-0.302*
INTCOV	+		0.050*		0.045*		0.044*
MB	+		0.052*		0.045*		0.047*
CONACC	+		-2.540*		-0.652		-0.515
REGULATED	+		0.271*		0.241*		0.234*
FINANCIAL	–		-0.030		-0.024		-0.036
Pseudo-R^2		0.215	0.694	0.323	0.703	0.319	0.703

For variable definitions, see Table 1. Regressions are run for each year in 1992-2003 and the times-series mean coefficients and pseudo-R^2s are reported. *, **, and *** indicate statistical significance at the 1%, 5%, and 10% levels based on the t-statistics for the time-series means.

Table 4. The Effects of Income Smoothing on Bond Ratings and the Weight on Accruals in Bond Ratings: Ordered-Probit Regression Results (Dependent Variable is RATING)

Smoothing factor		SMTH1	Percentile Ranks of SMTH1	SMTH2	Percentile Ranks of SMTH2
Explanatory variables	Predicted signs	(1)	(2)	(3)	(4)
CFO	+	13.043*	17.988*	14.190*	17.815*
ACCR	+	7.458*	12.610*	9.576*	12.790*
V_CFO	–	-0.119	0.000	0.400	0.000
SMTH	–	-1.472	-0.003**	-0.130*	-0.004*
ACCR×SMTH	–	-65.481*	-0.065*	-1.980*	-0.063*
CFO×SMTH	?	-62.927*	-0.046*	-1.130*	-0.039*
ACCR×V_CFO	+	-85.816*	-0.090*	-80.695*	-0.086*
CFO×V_CFO	–	-142.299*	-0.139*	-136.602*	-0.136*
SIZE	+	0.422*	0.420*	0.422*	0.419*
LEV	–	-2.246*	-2.283*	-2.250*	-2.293*
MSE	–	-69.827*	-69.765*	-70.073*	-69.818*
BETA	–	-0.308*	-0.287*	-0.305*	-0.280*
INTCOV	+	0.039*	0.041*	0.040*	0.040*
MB	+	0.034*	0.037*	0.038*	0.040*
CONACC	+	-0.931	-0.671	-0.958	-0.611
REGULATED	+	0.275*	0.246*	0.263*	0.227*
FINANCIAL	–	0.066	0.028	0.045	0.002
Pseudo-R^2		0.713	0.716	0.712	0.715

For variable definitions, see Table 1. Regressions are run for each year in 1992-2003 and the times-series mean coefficients and pseudo-R^2s are reported. *, **, and *** indicate statistical significance at the 1%, 5%, and 10% levels based on the t-statistics for the time-series means.

Table 5. The Effects of Income Smoothing within Investment Grade and Non-Investment Grade Bond Ratings: Ordered-Probit Regression Results (Dependent Variable is RATING)

	Investment Grade				Non-investment Grade			
Smoothing factor	SMTH1	Percentile Ranks of SMTH1	SMTH2	Percentile Ranks of SMTH2	SMTH1	Percentile Ranks of SMTH1	SMTH2	Percentile Ranks of SMTH2
Explanatory variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
CFO	11.132*	15.149*	13.051*	16.307*	11.161*	17.681*	13.567*	18.566*
ACCR	6.538*	13.221*	10.007*	13.373*	4.723*	8.992*	7.154*	9.440*
V_CFO	0.242	0.001	2.978	0.002***	3.865**	0.004**	2.904**	0.004*
SMTH	-3.709	-0.003**	-0.145*	-0.002*	-1.450	-0.003	-0.045	-0.002
ACCR×SMTH	-110.618**	-0.088*	-3.755*	-0.105*	-23.147	-0.054*	-1.638**	-0.058*
CFO×SMTH	-59.616*	-0.039*	-1.641*	-0.057*	-46.524*	-0.069*	-2.388*	-0.082*
ACCR×V_CFO	-114.409**	-0.100*	-91.478*	-0.080*	-10.984	-0.036**	-27.178	-0.039**
CFO×V_CFO	-153.547*	-0.116*	-158.112*	-0.116*	-89.871*	-0.129*	-87.403*	-0.129*
SIZE	0.333*	0.335*	0.330*	0.332*	0.406*	0.410*	0.400*	0.406*
LEV	-3.227*	-3.253*	-3.222*	-3.233*	-0.683*	-0.726*	-0.652*	-0.687*
MSE	-116.638*	-118.523*	-116.157*	-116.664*	-29.842*	-28.279*	-29.727*	-28.005*
BETA	-0.247*	-0.237*	-0.254*	-0.247*	-0.112*	-0.096*	-0.122*	-0.106*
INTCOV	0.027*	0.027*	0.026*	0.027*	0.047*	0.047*	0.051*	0.049*
MB	0.075*	0.075*	0.076*	0.075*	0.014	0.015	0.011	0.012
CONACC	-0.698	-0.679	-0.290	-0.371	-0.041	0.153	-0.315	0.040
REGULATED	0.238*	0.240*	0.229*	0.228*	0.153***	0.150***	0.150	0.146
FINANCIAL	-0.040	-0.047	-0.028	-0.024	-0.265***	-0.285**	-0.179	-0.216
Pseudo-R^2	0.507	0.505	0.506	0.503	0.441	0.451	0.441	0.454

For variable definitions, see Table 1. Investment (non-investment) grade firms are those with RATING ≤ 12 (> 12). Regressions are run for each year in 1992-2003 and the times-series mean coefficients and pseudo-R^2s are reported. *, **, and *** indicate statistical significance at the 1%, 5%, and 10% levels based on the t-statistics for the time-series means.

Table 6. The Effects of Innate and Discretionary Income Smoothing: Ordered-Probit Regression Results (Dependent Variable is RATING)

	Innate Income Smoothing				Discretionary Income Smoothing			
Smoothing factor	SMTH1	Percentile Ranks of SMTH1	SMTH2	Percentile Ranks of SMTH2	SMTH1	Percentile Ranks of SMTH1	SMTH2	Percentile Ranks of SMTH2
Explanatory variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
CFO	11.193*	11.031*	9.968*	11.090*	14.613*	18.791*	13.692*	18.110*
ACCR	5.900*	6.733*	6.091*	6.509*	7.304*	10.842*	7.005*	11.546*
V_CFO	-9.388**	-0.004**	-5.899***	-0.002	3.061	0.003**	2.572	0.003**
SMTH	-23.341*	-0.012*	-0.834*	-0.011*	1.154	0.002	-0.033	0.001
ACCR×SMTH	-48.870	-0.008	-1.331	-0.004	-76.582**	-0.059*	-2.471**	-0.069*
CFO×SMTH	6.908	0.037**	-0.354	0.032**	-52.166**	-0.053*	-1.163***	-0.049*
ACCR×V_CFO	-95.206*	-0.070*	-57.913**	-0.067*	-73.780**	-0.061*	-61.282***	-0.060**
CFO×V_CFO	-143.825*	-0.111*	-117.720*	-0.116*	-160.781*	-0.131*	-143.121*	-0.128*
SIZE	0.385*	0.380*	0.400*	0.395*	0.393*	0.391*	0.392*	0.392*
LEV	-2.724*	-2.735*	-2.685*	-2.704*	-2.647*	-2.645*	-2.595*	-2.584*
MSE	-73.126*	-76.267*	-71.120*	-74.101*	-79.185*	-79.601*	-76.374*	-77.268*
BETA	-0.296*	-0.290*	-0.292*	-0.285*	-0.326*	-0.311*	-0.335*	-0.318*
INTCOV	0.037*	0.036*	0.038*	0.038*	0.031*	0.031*	0.034*	0.034*
MB	0.061*	0.057*	0.063*	0.059*	0.037*	0.039*	0.040*	0.041*
CONACC	-0.597	-1.084	-0.491	-0.904	-2.409***	-2.354***	-2.037**	-1.959***
REGULATED	0.164*	0.154*	0.099**	0.074	0.249*	0.246*	0.237*	0.232*
FINANCIAL	-0.318*	-0.316*	-0.295*	-0.293*	-0.103	-0.097	-0.088	-0.077
Pseudo-R^2	0.724	0.724	0.719	0.718	0.715	0.716	0.707	0.709

Innate and discretionary income smoothing factors are used in place of SMTH and are measured as the fitted values and residuals from the model: SMTH $= a_0 + a_1$ SIZE + a_2 V_CFO + a_3 V_SALES + a_4 OPCYCLE + a_5 NEGEARN+ a_6 INT_INTENSITY + a_7 INT_DUM + a_8 CAP_INTENSITY + ε, where V_SALES is the standard deviations of sales (#12) deflated by average assets over the five years up to the current year, OPCYCLE is operating cycle calculated as LOG(365*average receivables (#2)/sales + 365*average inventory (#3)/COGS(#41)), NEGEARN is the proportion of loss years (#18 < 0) during the past five years, INT_INTENSITY is the intangibles intensity measured as (R&D expense (#46) + advertising expense (#45))/ sales), INT_DUM equals to 1 if INT_INTENSITY = 0 and zero otherwise, and CAP_INTENSITY is the capital intensity measured as net PPE (#8) divided by average assets. For other variable definitions, see Table 1. Regressions are run for each year in 1992-2003 and the times-series mean coefficients and pseudo-R^2s are reported. *, **, and *** indicate statistical significance at the 1%, 5%, and 10% levels based on the t-statistics for the time-series means.

Table 7. The Effects of Income Smoothing through Abnormal Accruals from the Jones (1991) Model: Ordered-Probit Regression Results (Dependent Variable is RATING)

Smoothing factor		SMTH1	Percentile Ranks of SMTH1	SMTH2	Percentile Ranks of SMTH2
Explanatory variables	Predicted signs	(1)	(2)	(3)	(4)
PSI	+	12.058*	17.707*	14.435*	17.271*
ABACCR	+	8.759*	15.124*	11.859*	15.173*
V_PSI	–	-3.976*	-0.004*	-2.316**	-0.003*
SMTH	–	-2.406**	-0.003**	-0.081***	-0.002**
ABACCR×SMTH	–	-81.772*	-0.082*	-3.258*	-0.086*
PSI×SMTH	?	-60.687*	-0.064*	-2.401*	-0.058*
ABACCR×V_PSI	+	-90.604*	-0.096*	-78.950*	-0.086*
PSI×V_PSI	–	-123.961*	-0.132*	-118.378*	-0.124*
SIZE	+	0.424*	0.420*	0.428*	0.423*
LEV	–	-2.216*	-2.249*	-2.236*	-2.251*
MSE	–	-67.691*	-67.276*	-67.608*	-66.598*
BETA	–	-0.314*	-0.295*	-0.312*	-0.289*
INTCOV	+	0.037*	0.037*	0.038*	0.038*
MB	+	0.041*	0.041*	0.042*	0.043*
CONACC	+	1.351*	1.510*	1.134*	1.445*
REGULATED	+	0.194*	0.151*	0.202*	0.143*
FIANCIAL	–	-0.055	-0.085***	-0.073	-0.108**
Pseudo-R^2		0.711	0.714	0.710	0.713

The Jones Model (ACCR = $a_0 + a_1$ 1/ASEETS + a_2 ΔREV + a_3 PPE + ε) is estimated cross-sectionally for each combination of year and 2-digit SIC codes with a minimum 10 observations based on the population of Compustat firms. Abnormal accruals ABACCR are the residuals from the model. Pre-smoothed income PSI is the sum of CFO and normal accruals (fitted values of the model). V_PSI is the standard deviation of PSI over the five years up to the current year. The smoothing factors are measured as SMTH1 = V_INC – V_PSI and SMTH2 = V_INC/V_PSI. For other variable definitions, see Table 1. Regressions are run for each year in 1992-2003 and the times-series mean coefficients and pseudo-R^2s are reported. *, **, and *** indicate statistical significance at the 1%, 5%, and 10% levels based on the t-statistics for the time-series means.

Table 8. The Effects of Income Smoothing through Normal Accruals from the Dechow and Dichev (2002) Model: Ordered-Probit Regression Results (Dependent Variable is RATING)

Smoothing factor		SMTH1	Percentile Ranks of SMTH1	SMTH2	Percentile Ranks of SMTH2
Explanatory variables	Predicted sign	(1)	(2)	(3)	(4)
CFO	+	13.600*	15.167*	14.758*	16.767*
NMACC	+	9.939*	11.383*	11.801*	13.017*
ACCRERR	+	2.247*	2.142*	1.543**	1.475**
V_CFO	–	-0.117	0.000	2.098	0.001
SMTH	–	-2.913	-0.003**	-0.091	-0.003**
V_ACCRERR	–	-2.000**	-1.911**	-2.338**	-1.988**
NMACC× SMTH	–	-100.321**	-0.042	-2.358*	-0.057**
CFO× SMTH	?	-69.751*	-0.015***	-1.362**	-0.027**
NMACC×V_CFO	+	-134.883*	-0.074*	-123.460*	-0.091
CFO×V_CFO	–	-172.225*	-0.120*	-166.039*	-0.136*
SIZE	+	0.418*	0.413*	0.422*	0.419*
LEV	–	-2.174*	-2.214*	-2.119*	-2.161*
MSE	–	-70.539*	-71.123*	-72.537*	-72.366*
BETA	–	-0.340*	-0.323*	-0.331*	-0.312*
INTCOV	+	0.038*	0.038*	0.038*	0.038*
MB	+	0.048*	0.050*	0.049*	0.049*
CONACC	+	-1.413	-1.175	-1.649**	-1.506**
REGULATED	+	0.197*	0.163*	0.198*	0.168*
FINANCIAL	–	-0.049	-0.069	-0.003	-0.043
Pseudo-R^2		0.706	0.707	0.706	0.708

The Dechow and Dichev Model ($ACCR_t = a_0 + a_1\, CFO_{t-1} + a_2\, CFO_t + a_3\, CFO_{t+1} + \varepsilon_t$) is estimated cross-sectionally for each combination of year and 2-digit SIC codes with a minimum of 10 observations based on the population of Compustat firms. Normal accruals (NMACCR) are the fitted values and abnormal accruals (ACCRERR) are the residuals from the model. Smoothed income is the sum of CFO and NMACCR. The smoothing factors are measured as SMTH1 = V_INC1 – V_CFO and SMTH2 = V_INC1/V_CFO, where V_INC1 is the standard deviation of smoothed income over the five years up to the current year. V_ACCRERR is the standard deviation of ACCRERR over the same five years. For other variable definitions, see Table 1. Regressions are run for each year in 1993-2002 and the times-series mean coefficients and pseudo-R^2s are reported. *, **, and *** indicate statistical significance at the 1%, 5%, and 10% levels based on the t-statistics for the time-series means.

Table 9. The Effects of Income Smoothing and Over-time Trend in Bond Ratings: Ordered-Probit Regression Results with Pooled Observations (Dependent Variable is RATING)

Smoothing factor			SMTH1	Percentile Ranks of SMTH1	SMTH2	Percentile Ranks of SMTH2
Explanatory Variables	Predicted signs	(1)	(2)	(3)	(4)	(5)
Year1992		0.000	0.000	0.000	0.000	0.000
Year1993	?	-0.100	-0.074	-0.076	-0.070	-0.075
Year1994	?	-0.236*	-0.241*	-0.231*	-0.235*	-0.228*
Year1995	?	-0.312*	-0.310*	-0.293*	-0.309*	-0.292*
Year1996	?	-0.410*	-0.421*	-0.422*	-0.421*	-0.420*
Year1997	?	-0.491*	-0.489*	-0.504*	-0.485*	-0.503*
Year1998	?	-0.413*	-0.406*	-0.435*	-0.406*	-0.438*
Year1999	?	-0.396*	-0.408*	-0.449*	-0.402*	-0.452*
Year2000	?	-0.380*	-0.426*	-0.491*	-0.425*	-0.494*
Year2001	?	-0.390*	-0.423*	-0.488*	-0.419*	-0.493*
Year2002	?	-0.511*	-0.544*	-0.617*	-0.542*	-0.621*
Year2003	?	-0.806*	-0.814*	-0.889*	-0.811*	-0.891*
PSI	+	2.366*	12.295*	17.763*	14.999*	17.198*
ABACCR	+		8.312*	14.025*	11.653*	14.064*
V_PSI	–	-4.115*	-2.635*	-0.005*	-1.825*	-0.004*
SMTH1	–		-1.295**	-0.003*	-0.070*	-0.003*
ABACCR×SMTH1	–		-53.735*	-0.070*	-3.167*	-0.080*
PSI× SMTH1	?		-60.052*	-0.062*	-2.802*	-0.064*
ABACCR×V_PSI	+		-62.433*	-0.085*	-61.082*	-0.070*
PSI×V_PSI	–		-121.145*	-0.137*	-112.282*	-0.120*
SIZE	+	0.415*	0.436*	0.429*	0.439*	0.431*
LEV	–	-2.192*	-2.131*	-2.202*	-2.130*	-2.198*
MSE	–	-51.909*	-48.599*	-47.381*	-48.629*	-47.205*
BETA	–	-0.292*	-0.278*	-0.247*	-0.277*	-0.244*
INTCOV	+	0.043*	0.030*	0.031*	0.029*	0.030*
MB	+	0.059*	0.043*	0.044*	0.042*	0.044*
CONACC	+	0.285	1.555*	1.872*	1.551*	1.894*
REGULATED	+	0.231*	0.246*	0.178*	0.235*	0.160*
FINANCIAL	–	-0.160*	-0.024	-0.080***	-0.028	-0.094**
Pseudo-R^2		0.675	0.694	0.699	0.695	0.700

Year1992, Year1993, … are yearly dummies. For other variable definitions, see Tables 1 and 7. Regressions are run with observations pooled across years. *, **, and *** indicate statistical significance at the 1%, 5%, and 10% levels.

Summary and Future Research

Doctoral Dissertation Chapter 4

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Summary and Future Research

"Information and the bond market" has been a burgeoning research area in both finance and accounting. The bond market has some unique features to distinguish it from the equity market. First of all, the bond market is an OTC market where dealers act as local monopolies. Dealers have considerable market power to extract economic rents. Second, the bond market has little price transparency until recently. Before the implementation of the TRACE system in July 2002, information on past bond transactions was not publicly disclosed. Investors have to contact dealers directly for their exact quotes. Third, the bond market features a few credit rating agencies who publicly disclose ratings on the creditworthiness of a large number of firms. These rating agencies charge the issuers rather than the rating users for fees. Last but not least, bond securities are by nature different from equity securities. The bondholders hold a combination of the firm's assets and a short position on a call option written on those assets, while the stockholders hold the call option. Therefore, for bondholders upside potential is limited whereas downside risk is significant. These features suggest that the bond market may use information differently from the equity market.

This dissertation comprises three essays on "information and the bond market". The first essay examines certified credit agencies' incentives to issue credit watches before credit rating changes. Credit watches serve as early warnings of possible future rating changes. There are more downgrade watches than upgrade watches. Firms with investment-grade ratings, rating-based contracts, and high litigation risk are more likely to be watched for downgrades but not upgrades. The results hold after controlling for the sample selection bias. This essay shows that regulation/contracting and litigation risk may be the driving forces behind the asymmetric credit watch decisions before downgrades vs. upgrades.

The second essay studies how quality of investors' private information affects bond yield spreads. Private information could reduce dealer market power and assessed default probability while having limited effect on creating information asymmetry among mostly institutional investors. Precision of both private and public information is *negatively* related to bond yield spreads. There is also a substitution effect between the two sources of information. In addition, the information effect is especially large when bond maturity is relatively short, consistent with the theory of Duffie and Lando (2001). The results show that private information plays a different role in the bond market than in the equity market. In the equity market, quality of private information is *positively* related with expected returns.

The third essay studies accrual-based income smoothing from a bond market perspective. More income smoothing is associated with more favorable bond ratings and larger weight on accruals in bond ratings. These results are consistent with the argument that income smoothing signals superior firm performance. The results echoes the positive role of accrual-based income smoothing played in the equity market.

A lot of questions remain unanswered in this area. For example, why are bonds traded in the OTC market with the dealers as the main intermediaries, but not traded on exchanges? Why are bonds traded so infrequently? Why are the transaction costs of bonds so much higher than those of equities? Would high quality of accounting information reduce the transaction costs of bonds? Does high quality of accounting information increase trading frequencies? How does the implementation of the TRACE system affect the relationship between information quality and trading frequencies/costs?

Next, I will discuss two questions related with credit watches and credit rating changes. The first one is on the stock market consequence of credit watches and credit rating changes.

Dichev and Piotroski (1998) find abnormal stock returns in the year after credit rating changes. Stock market doesn't seem to fully incorporate the information conveyed by the credit rating changes at the change dates. We can study whether credit watches help the stock market better understand the information in rating changes. If this is the case, we should observe smaller abnormal returns after rating changes that have been watched first, and larger abnormal returns after rating changes that have not been watched first.

The second question is on the bond market consequence of credit watches and credit rating changes. We can study the question using the transaction data of insurance companies. Insurance companies are required to report their bond purchases and sales and the data is available from 1994 to now. Regulators use certified ratings to monitor insurance companies' bond holdings. Therefore we expect insurance companies to sell after the bonds are downgraded. It is also interesting to know whether credit watches serve as early warnings to insurance companies. If so, we should observe insurance companies start to sell bonds after the downgrade watch announcements. If insurance companies tend to sell bonds after rating downgrades, do they have to sell at a "discount"? Is the round-trip transaction cost higher after a downgrade than at other time? If credit watches serve as early warnings, do they give the insurance companies a longer period of time to rebalance their portfolios and therefore reduce the "discount"? Can insurance companies sell bonds at a better price after watched downgrades than after non-watched downgrades? If the ratings are watched but not changed eventually, will the sales occurring after watches be reversed? What are the transaction costs? Answers to these questions will help us better understand the economic role of credit watches and credit rating changes.