EQUITY ANALYSTS' EARNINGS FORECASTS AND INFORMATION ASYMMETRY

Joshua G. Coyne

A dissertation submitted to the faculty of the University of North Carolina at Chapel Hill in partial fulfillment of the requirements for the degree of Doctor of Philosophy in the Kenan-Flagler School of Business.

Chapel Hill
2014

Approved by:

John R. M. Hand

Jeffery S. Abarbanell

Robert M. Bushman

Wayne R. Landsman

Theodore E. Christensen

ABSTRACT

Joshua G. Coyne: Equity Analysts' Earnings Forecasts and Information Asymmetry in Private Lending
(Under the direction of John R. M. Hand)

In this study I hypothesize and find that the precision of the private information in sell-side equity analysts' earnings forecasts is associated with price and non-price characteristics of private debt. Using a measure of the precision of analysts' private information following Barron et al. (1998) for a sample of loans issued to US firms between 1994 and 2012, I find that higher precision is associated with lower interest rates and a lower likelihood of collateralization, especially when accruals quality is low or the borrower has low credit quality. I then isolate the two sources of analysts' private information (i.e., information-processing ability and information from management) and find that both are associated with preferable loan terms. I investigate the impact of one regulatory shock (i.e., Regulation Fair Disclosure) and one economic shock (i.e., the recent financial crisis). After Reg FD, the association between precision of analysts' private information and loan terms declines while the association between quality of information from management and loan terms increases. During the financial crisis, analysts' precision ceases to be correlated with loan terms, while the importance of information from management again increases. Overall, I conclude that analysts' forecasts provide a useful input for decreasing information risk in private loans.

ACKNOWLEDGEMENTS

I would like to thank John Hand (dissertation chair), Jeff Abarbanell, Robert Bushman, Wayne Landsman, Ted Christensen, Derrald Stice, Thomas Steffen, Matthew Cobabe, Allen Huang, the participants of the 2013 BYU Accounting Research Symposium, workshop participants at Hong Kong University of Science and Technology, Singapore Management University, Florida International University and the University of Memphis and the PhD students at the University of North Carolina at Chapel Hill for helpful comments.

TABLE OF CONTENTS

LIST OF TABLES

CHAPTER 1: INTRODUCTION

This study examines whether the precision of the private information in analysts' forecasts is associated with the terms of bank loans. Using a sample of loans from Dealscan issued to US firms between 1994 and 2012, I find that borrowers whose analysts release forecasts with higher precision of private information as defined by Barron et al. (1998) have loans with lower interest rate spreads and a lower likelihood of collateralization.

I then extend this main result by investigating the importance of the precision of private information in analyst forecasts relative to three other signals available to banks when making lending decisions (i.e., credit ratings, financial reporting quality and interest coverage). In each of these tests I find that analyst precision is more highly correlated with loan terms when the signal is negative (i.e., no investment-grade credit rating, low accruals quality, insufficient interest coverage).

Because private information available to an analyst has two components—information-processing ability and information communicated privately to the analyst by managers— I use a proxy for the quality of information from management to isolate the association of each component with loan terms, and I find that both parts of analysts' private information precision are associated with preferable loan terms. Because Regulation Fair Disclosure ("Reg FD") represents a shock to the ability of analysts to access private information from management, I investigate whether these associations changed after the introduction of Reg FD. Following Reg FD, the correlation between analysts' private precision and loan terms decreases in significance, while that of the quality of information from management and loan terms increases. In addition to Reg FD, the financial crisis represents a shock to analysts' information environment. I find that during the crisis the precision of analysts' private information is no longer associated with either loan term. Furthermore, the correlation between the quality of information from management and loan terms again increases relative to the pre-crisis period.

This study contributes to the literature on the information content of analysts' forecasts. Prior studies collectively suggest that analysts' reports are relevant for equity investment decisions. Past research has provided evidence that analyst forecasts are superior to time-series models (e.g., Brown and Rozeff 1978, Fried and Givoly 1982, Brown et al. 1987) and that a stronger association exists between market response and analyst forecasts than market response and forecasts using academics' mathematical models (Schipper 1991). Lys and Sohn (1990) find that markets respond to analysts' revisions, and Fried and Givoly (1982) find a stronger price response to more accurate analysts' forecasts, which is consistent with analysts who issue more accurate forecasts providing more profitable recommendations (Loh and Mian 2006).

This study furthers this line of research by being the first to investigate the information content of analysts' reports in a private debt setting by documenting an association between analysts' forecast quality and price (i.e., spread) and non-price (i.e., collateral) terms of private loans. The only other study to investigate such an association is by Mansi et al. (2011), in which the authors investigate the association between analyst forecast quality and bond spreads and conclude that higher forecast quality provides information to institutional investors regarding asset valuation, which is incremental to the information provided by credit scores and which results in lower bond spreads. This study differs from theirs in two important ways. First, Mansi et al. do not attempt to exclude the portion of analyst forecast quality that relies on the precision of public information, which is observable by other market participants. By focusing on the precision of private information, I am able to identify the contribution of analysts' information processing ability. Second, bondholders constitute outsiders, whereas throughout my sample period banks have private access to borrowers. The resulting information sets available to each group of debt holders may have very little overlap, and the conclusion that equity analyst reports are a useful component of the information set of bondholders does not necessarily extend to banks, especially post Reg FD when analysts' private access to management was revoked.

Despite banks having direct access to management, it is not necessary for analysts to have superior information in order to inform the lending process. Because analysts' forecasts and recommendations are the result of generating private information from public, analysts can contribute unique signals that the bank cannot acquire from the borrowing firm. Furthermore, research indicates that management learns from equity prices (Chen et al. 2007), which provides evidence that outsiders can provide information to insiders.

This study also contributes to the streams of literature on the effects of Reg FD and the financial crisis. Heflin et al. (2003) provide early evidence of the effects of Reg FD on analysts' forecast quality and find no change relative to the pre-Reg FD period, but they do document an increase in voluntary firm disclosures. Monhanram and Sunder (2006) follow Barron et al. (1998) and decompose forecast quality into public and private precision and find that, although public precision does not change, private precision increases, and they conclude that information discovery by analysts has increased following Reg FD. Amiram et al. (2012), on the other hand, document a decrease in analysts' ability to reduce information asymmetry following Reg FD. With respect to the financial crisis, Arand and Kerl (2012) and Amiram et al. (2013) conclude that analysts' forecast quality decreased following the start of the crisis but that investor reliance on forecasts simultaneously increased. I add to this body of research by providing evidence of the effect of these two shocks on the association between loan terms and two components of analysts' private precision—precision of information-processing and quality of information from management.

I begin with a sample of loans issued to US firms between 1994 and 2012 from the Dealscan database. For each loan facility, I select two loan terms from Bharath et al. (2008) (i.e., loan spread and an indicator for whether the loan is collateralized) as my proxies for the characteristics of the loan contract.[1]

To conduct my initial test, I calculate the precision of analysts' private information as modeled by Barron et al. (1998) and regress each loan term on this precision measure, as well as several loan and firm controls. In each case I find that higher precision prior to loan issuance is associated with preferable loan terms (i.e., lower spreads and lower likelihood of collateralization).

I then extend this main result by investigating three scenarios to determine when analyst precision has a stronger association with loan terms. In the first scenario, I regress each loan term on analysts' precision separately for firms with and without an investment-grade credit rating prior to the loan issuance. In the second, I split the sample at the median for accruals quality. I construct a measure of accruals quality by combining three measures of abnormal accruals from prior research (i.e., Dechow et al. 1995, Teoh et al. 1998 and Dechow and Dichev 2002) into one principal component according to Bharath et al. (2008). In the third scenario, I separate firms into those with sufficient interest coverage (i.e., interest coverage ratio > 1.5) and those with insufficient interest coverage. In all three tests, two consistent results manifest. First, the

[1] Bharath et al. (2008) also include loan maturity as a loan term. I exclude it because when conducting untabulated factor analysis of the three loan terms used in that study, I find that maturity loads in the same direction as loan spread and collateralization despite preference working in the opposite direction (i.e., higher maturity is more preferable) indicating that it may represent a different construct. I instead include maturity as a control variable.

association between analysts' precision and loan spread remains constant. Second, analysts' precision is only associated with the likelihood of collateral when the firm is of low type with respect to these three characteristics (i.e., no investment-grade credit rating, low accruals quality, insufficient interest coverage).

In the period before Reg FD, analysts had private access to management. Because potential lenders also have private access to management, I isolate private precision attributable to analysts' processing ability from private precision attributable to the quality of information communicated privately by management. I measure the quality of information from management by the number of days between fiscal period end and earnings announcement, which prior research has found to be associated with the quality of the firm's accounting information system (Brazel and Dang 2008, Jennings et al. 2012, Gallemore and Labro 2013). When including private precision and earnings announcement delay in the same regression, both measures are associated with preferable loan terms. This result represents the first evidence of an association between information system quality on loan contracts, and it complements the literature documenting a lower cost of debt for firms with higher disclosure quality ratings (Sengupta 1998).

Because Reg FD changed the information environment for analysts, as well as firms (Heflin et al. 2003), I split my sample into two periods (i.e., 1994-2000 and 2001-2006) and test each period separately. Similar to the prior cross-sectional tests, here again, I find that the association between analysts' private precision and loan spread is robust while the association between analysts' private precision and collateral loses significance following Reg FD. With respect to earnings announcement delay, I find that its association with loan spread is also constant in both periods, whereas both the magnitude and significance of the association between this proxy for quality of information from management and collateral increases following Reg FD.

Finally, I investigate the effect of another shock (i.e., financial crisis). Using all loans issued during 2007-2009, I find that the precision of analysts' private information is not associated with loan terms. This result is consistent with banks changing their loan pricing models, as well as the model inputs, during the financial crisis at a time when analysts' information-processing abilities were affected by the overall increase in uncertainty (Arand and Kerl 2012, Amiram et al. 2013).[2] The association between earnings announcement delay and loan terms again increases in magnitude relative to the pre-crisis period (i.e. the post-Reg FD period), but the difference in coefficients is not significant at conventional levels.

The results of these cross-sectional and longitudinal tests may also have implications for internal validity. Because the regressions are associative in nature, the correlations may be evidence of reverse causality, in which case information generated by the lending process would allow analysts to issue more precise forecasts. However, a decrease in the association between analysts' precision and loan terms after Reg FD and during the financial crisis—times when analysts lost access to information sources—may be more consistent with banks not relying on analysts' forecasts, than analysts no longer learning from loans. Furthermore, a stronger association between analysts' precision and loan terms for firms with insufficient interest coverage also seems more consistent with banks learning from analysts than vice versa.

[2] This inference is also supported by statements from banking executives that erroneous modeling assumptions masked the true level of risk in loan portfolios.

CHAPTER 2. HYPOTHESIS DEVELOPMENT

A large body of literature in accounting, economics and finance investigates the agency issues of debt. Smith and Warner (1979) build on analytical models by Jensen and Meckling (1976) and Myers (1977) and identify three forms of incentive misalignment between managers/shareholders and creditors. First, managers can increase dividends and thereby decrease resources available for repayment. Second, managers can issue additional debt which may subordinate existing claims. Third, managers may risk-shift by investing in assets with more volatile payouts or forego projects with positive net present values when in distress.

Creditors will make lending decisions based on a rational anticipation of these agency conflicts which increase the cost of debt (Jensen and Meckling 1976, Armstrong et al. 2010), but research has shown that accounting information, as well as governance, can mitigate agency concerns in the debt market (Watts 2003).

Sell-side analysts represent a source of accounting information. Although unanimity does not exist in the early literature, research has provided evidence that analysts' forecasts are superior to time-series models of earnings (e.g. Brown and Rozeff 1978, Fried and Givoly 1982, Brown et al. 1987). Schipper (1991) finds this result intuitive because analysts have access to additional information not impounded into mechanical models, as well as the models themselves. Schipper goes on to explain that prior research has found a stronger association between market response and analysts' forecasts than market response and forecasts using mathematical models. Despite this stronger co-movement, analyst forecasts also provide information not already impounded in price (Lys and Sohn 1990, Abarbanell 1991).

With respect to information precision, Fried and Givoly (1982) find a stronger price response to more accurate analysts' forecasts. This evidence is consistent with Loh and Mian (2006), who observe that analysts who issue more accurate forecasts also provide more profitable recommendations because although the stock recommendation itself is the ultimate output of an analyst report, both buy-side and sell-side analysts rely on sell-side analyst earnings forecasts in making recommendations (Schipper 1991, Bradshaw 2004). This evidence leads to my first hypothesis:

H1a: Loans to borrowers with higher private precision of analysts' forecasts have lower interest rate spreads.

H1b: Loans to borrowers with higher private precision of analysts' forecasts have a lower likelihood of collateralization.

In addition to their expertise and information-processing methods, analysts obtain necessary forecast inputs directly from management (Schipper 1991). Prior to the introduction of Reg FD, managers were able to communicate this information privately to analysts. Consequently, during that time period the precision of private information in analysts' forecasts was, in part, a function of the quality of information provided by managers.

Prior research finds evidence consistent with banks using the borrower's private information in lending decisions. Bharath et al. (2008) conclude that the preference of firms with poorer accounting quality to access the private debt market is attributable, in part, to banks' ability to impound private information into the lending contract. Furthermore, firms with low accounting quality have more proximate lenders (Wang 2011) because the ability to access the borrower's private information increases with the proximity of the lender (Hauswald and Marquez 2006).

Mansi et al. (2011) assert that analyst forecast quality is associated with bond spreads because analysts provide outsiders with information. Unlike bondholders, banks are not outsiders, but rather have private access to management. As a result, banks may not need to rely on analyst reports. On the other hand, even after excluding the private information from management, analysts' information processing abilities still represent private information analysts have to offer. This logic leads to my next hypothesis:

H2a: Analysts' forecasts with more precise information-processing are associated with preferable loan terms.

H2b: Analysts' forecasts with more precise information from management are associated with preferable loan terms.

CHAPTER 3: SAMPLE SELECTION AND METHODOLOGY

My sample begins with the set of sole lender and syndicated loans issued in the United States in US$ from the Dealscan database for the years 1994-2013[3]. Syndicated loans are by far the most common form of loan with 80% of all loan facilities in Dealscan. Other than club deals, which involve private equity firms and not banks, sole lender loans are the second most frequent distribution method with 5% of all facilities. I restrict my sample to these two methods because they represent good coverage of the database while excluding bonds and loans issued by non-bank institutions (e.g., private equity, insurance agencies).

I retain loans to non-financial firms, which I can match to Compustat and I/B/E/S via the August 2012 version of the Dealscan-Compustat linking table first introduced by Chava and Roberts (2008).[4] I require all observations to have non-missing values for loan spread, collateral, Compustat and Dealscan control variables and I/B/E/S analyst forecast measures. Finally, I exclude all observations with values more extreme than the 1% and 99% for each of the continuous regression variables. My final sample includes 9,045 loan facilities from 6,703 loan packages issued to 2,279 borrowers. Table 1 Panel A presents the sample selection procedure.

Table 1 Panel B provides descriptive statistics of the regression variables. The loan facilities in my sample have a mean (median) size of $203 million ($215 million) and range between $6 million and $3,000 million with mean (median) spread over LIBOR of 122 (150)

[3] I restrict my sample to loans issued after 1993 because of the I/B/E/S regime change in 1991-1992 (Abarbanell and Lehavy 2007) .

[4] I exclude firms with four-digit SIC codes 6000-6999.

basis points with a range of 17 to 600 basis points. 44% of the loans are secured with collateral. The borrowing firms have a mean (median) of $1,635 million ($1,540 million) of total assets.

3.1 Analyst Precision and Loan Characteristics

I use the following model to test my first hypothesis:

$$Loan\ characteristic_i = \alpha_0 + \alpha_1 Private\ precision_i + \sum_k \alpha_k Loan\ controls_{i,k} + \sum_l \alpha_l Borrower\ controls_{i,l} + \sum_m \alpha_m Fixed\ effects_{i,m} + \varepsilon_i \quad (1)$$

where *Loan characteristic* is *Loan spread* = *ln*(all-in-spread drawn over LIBOR in basis points) or *Collateral* = 1 if the loan is collateralized and 0, otherwise.[5]

Loan controls are *Deal size* = *ln*(facility amount), *Maturity* = *ln*(months to maturity), *Financial covenants* = number of financial covenants, *General covenants* = number of general covenants, *Performance pricing* = 1 if the contract includes a performance-pricing provision and 0, otherwise, *Prior lender* = 1 if the lender has previously issued a loan facility to the borrower and 0, otherwise, as well as a loan type fixed effect.[6]

Borrower controls are *Size* = *ln*(total assets), *Leverage* = (long-term debt / total assets), *BTM* = book-value of equity / (fiscal year-end price * common shares outstanding), *ROA* = (income before extraordinary items / total assets), *Earnings volatility* = *stdev*(past five years of earnings / average total assets) and *Interest coverage* = 1 if the (interest expense + income before extraordinary items) / interest expense is greater than 1.5 and 0, otherwise.[7] I use an indicator to address the upward skewness and to include firms with no interest expense. Multiple sources

[5] Whenever *Collateral* is the dependent variable, I use probit regression. All other specifications use OLS. Greene (2004) finds that fixed-effects in probit models induce bias in the maximum likelihood estimator. As a result, I do not include fixed effects in my probit models. I check the robustness of this exclusion and find, consistent with Greene's tests, that the coefficients generally increase in magnitude when including fixed effects.

[6] The fixed effect for loan type is a more general version of the controls in prior literature for whether the loan is a revolver, term loan, etc.

[7] I calculate independent variables using annual data as of the most recent fiscal year end prior to loan issuance.

identify 1.5 as the threshold of healthy interest coverage. Additional fixed effects for this model beyond those listed under loan controls are year and four-digit SIC industry. Standard errors are clustered at the borrowing-firm level.[8]

Several studies have found that opaque firms experience adverse lending outcomes with respect to loan spreads and collateralization (e.g., Chan and Kanatas 1985, Sengupta 1998, Anderson et al. 2004, Wittenberg-Moerman 2008). However, Sufi (2007) observes that firms become more known as they repeatedly access the debt market, which counteracts opacity. Based on this evidence, I predict that *Prior lender* will be negatively correlated with *Loan spread* and *Collateral*. I include the other loan controls to address the simultaneity of the determination of characteristics on the loan contract. To the extent that individual loan terms play a substitute role in reducing risk, these controls will be negatively correlated with *Loan spread* and *Collateral*.

Risk of default, and thereby, cost of debt (Fisher 1959), is decreasing in firm size and profitability and increasing in leverage (Ohlson 1980). Furthermore, value-stocks have higher probability of default than growth-stocks (Vassalou and Xing 2004). Prior research has also found that the occurrence of collateralization is tied to default risk (Orgler 1970, Berger and Udell 1990). As a result, I predict that *Size*, *ROA* and *Interest coverage* will be negatively correlated with *Loan spread* and *Collateral* and that *Leverage* and *BTM* will be positively correlated with these loan terms.

I also include *Investment* = 1 if the borrower's most recent S&P credit rating prior to the loan issuance is BBB- or higher and 0, otherwise, and *Noninvestment* = 1 if the credit rating is below BBB- and 0, otherwise. Credit analysts represent the primary information intermediary for the debt market, and research has shown that both having a credit rating (Sufi 2007) and the

[8] In untabulated results, I also cluster at the firm-year level. Inferences remain unchanged.

value of that rating affect the cost of debt. I use indicators to combine the effects of having a credit rating with the magnitude of the rating by setting both indicators to 0 for firms without a rating.

Bharath et al. (2008) investigate the effect of accruals quality and loan characteristics and find that firms with low accounting quality are more likely to issue private rather than public debt and that higher accounting quality is associated with more favorable loan characteristics when seeking either public or private debt. Wang (2011) finds that firms with higher accounting quality can obtain loans from less proximate banks. These studies indicate that financial reporting quality may reduce the information risk that banks face when constructing loan packages.

Because of these findings, I include a measure of financial reporting quality as calculated in Bharath et al. (2008) as an additional control variable. Bharath et al. are not the first to investigate the link between financial reporting and the cost of debt (e.g., Ahmed et al. 2002, Francis et al. 2005) nor is their measure of accruals quality widely used, but I adopt their method for two reasons. First, my research question and setting are most similar to theirs, and second, as the authors of the original study observe, a factor of multiple measures is a parsimonious way of capturing commonality among several representations of accruals quality.

Bharath et al. begin with three existing models for calculating abnormal accruals: Dechow and Dichev (2002), Teoh et al. (1998) and a modified Jones model from Dechow et al. (1995). They calculate the residual (i.e., abnormal accruals) from the three regressions for each year by Fama-French 48 industry. After transforming the residual into its absolute value, Bharath et al. condense the three variables into one factor. I follow this same pattern and obtain a factor with the following loadings[9]:

$$AQ = .33 * UAA_{DD} + .68 * UAA_{TWW} + .64 * UAA_{MJ} \tag{2}$$

Private precision is calculated using the log form of the model of precision of analysts' private information from Barron et al. (1998), as follows:

$$Private\ precision = \log \frac{D}{\left[\left(1 - \frac{1}{N}\right) * D + SE\right]^2} \tag{3}$$

where *D* is forecast dispersion (i.e., forecast variance), *SE* is the squared forecast error and *N* is the number of forecasts. The use of the log form addresses skewness in the measure (Botosan et al. 2004).

Little theoretical research exists that derives proxies for analyst uncertainty. Many studies have used analyst forecast dispersion as a proxy for investor uncertainty (e.g., Hughes and Ricks 1987, Daley et al. 1988, Ziebart 1990, Imhoff and Lobo 1992, Atiase and Bamber 1994, Lang and Lundholm 1996), but Abarbanell et al. (1995) observe that forecast dispersion measures the precision of investors' information with error because of the presence of other relevant forecast attributes. They develop a model of analyst forecast precision using forecast dispersion, forecast error and analyst following. Barron et al. (1998) extend this model to measure the precision of analysts' public and private information. By assumption, public information is available to other market participants, and research has already investigated the effects of public information on cost of debt (e.g., Sengupta 1998, Bharath et al. 2008, Zhang 2008). Private information, on the other hand, is unique to the analyst and can allow me to capture information content that is

[9] Although my loadings are not identical to those in the original study, because all three measures load in the same direction and because the first factor is the only factor with an eigenvalue greater than one as in the original study, I am confident that we are capturing similar constructs.

unique to the analysts' reports, which is why I select this model for my measure of the precision of analysts' private information.[10]

It is observable from Equation (3) that *Private precision* is decreasing in squared forecast error and forecast dispersion and increasing in analyst following. As the theory predicts, the correlations between precision and both squared error and dispersion are negative (ρ = -0.09 and -0.11, respectively) and the correlation between precision and following is positive (ρ = 0.11).

To test H1, I regress each of the two loan characteristics individually on *Private precision*. Because higher values of each of the dependent variables are less favorable, I predict that the α_1 coefficient from Equation (1) will be negative for each dependent variable. Table 1 reports descriptive statistics for this measure unscaled, but when including it in any regression I scale the variable by its pooled standard deviation so that the coefficient is interpretable as the change in a loan term with a one standard deviation change in analyst precision.

<u>Cross-sectional Tests</u>

I then extend this main test to investigate cross-sectional changes in the association between analysts' private precision and loan terms using three separate cuts of the data based on credit rating, accruals quality and interest coverage. [11]

In addition to credit rating being a relevant determinant of loan terms, the relation between analyst precision and loan terms may vary as a function of credit rating. To investigate this possibility, I recalculate the coefficients in Equation (1) separately for those firms with an

[10] Analysts' private information comprises information generated by the analysts' information processing abilities, as well as information communicated privately by management. Because I want to measure the first source of private information directly, I address the measurement of the second source in a later section.

[11] As an alternative to splitting the sample it would be possible to interact *Private precision* with indicators for the various levels. Although such interactions would be interpretable in an OLS regression, difficulties arise for a probit regression (Ai and Norton 2003). Furthermore, such an interaction assumes that the coefficients over the control variables are the same for both groups, and I do not have an *ex ante* prediction that this is the case.

investment-grade credit rating prior to loan issuance and those without an investment-grade rating. By grouping firms with a non-investment-grade rating together with firms with no credit rating, this test combines the effect of low credit quality with the effect of a lack of alternative signals on the association between analysts' precision and loan terms.[12] The two subsequent tests attempt to isolate each effect separately.

Because the role of analysts as information intermediaries is ostensibly to reduce information risk—as is the role of financial reporting—the precision of analysts' forecasts and the quality of financial reporting may act as substitutes. Prior research finds some evidence of substitutability between these two information sources in the equity markets. DeFond and Hung (2003) find that analysts are more likely to issue supplementary cash flow forecasts when firms have more opaque financial reporting. Lobo et al. (2012) also look at firm accruals and conclude that analyst coverage increases as accruals quality decreases. Furthermore, Lobo et al. specifically find that analysts' private precision increases as accruals quality decreases.

For this test I split my sample into two groups based on whether the value of *Accruals quality*, as defined previously, is above or below the median value pooled across the entire sample and calculate the α coefficients in Equation (1) separately for each group. Because accruals quality measures the opacity of financial reporting, this test investigates the association between analysts' precision and loan terms when an alternative signal is less informative.

Unlike equity holders whose gains on investment have no upper bound, debt holders do not experience upside benefits, but rather focus on borrowers' ability to pay interest and repay

[12] I choose to group non-investment grade firms with firms with no credit rating because the reasons for belonging to the group without a credit rating are less clear. Firms may have no credit rating because they have never issued public debt, because they have not issued public debt in the recent past, because the dataset is not perfectly populated, etc. Although I do not tabulate them, I also investigate the results of this test using three groups (i.e., investment grade, non-investment grade and no credit rating) and find that the latter two groups have coefficients of similar magnitude and significance.

principal. As a result, banks may be less likely to need additional information when lending to healthy, low-risk firms. I investigate the effect of financial health on my main results by splitting the sample into loans to firms with an interest coverage ratio greater than 1.5 and loans to firms with an interest coverage ratio below 1.5. This test focuses on the implications of credit quality for the association between analysts' precision and loan terms.

For each of these tests, I predict that the high-type firm (i.e., investment-grade credit rating, high accruals quality and good interest coverage) will derive less benefit from forecast precision than the low-type firm.

3.2 Private Information from Management

Equation (1) measures the association between analysts' private precision and loan terms. However, as previously observed, analysts' private information has two sources. The first is the analyst's ability to generate private information by means of proprietary information-processing mechanisms. The second is firm information, which management privately communicates to the analyst. Both inputs contribute to the information content of analysts' reports, but only the former is unique to analysts in a private debt setting because banks also have private access to management. As a result, α_1 from Equation (1) may capture the correlation between quality of information supplied by management and loan terms, as well as the correlation between information-processing precision and loan terms.

To distinguish between these two sources of precision, I include a proxy for the portion attributable to the precision of information from management. Prior research has used the number of days between the fiscal period end and earnings announcement date as a measure of the quality of firm internal information (Brazel and Dang 2008, Jennings et al. 2012, Gallemore and Labro 2013). Jennings et al. (2012) assert that more sophisticated accounting systems allow the firm to release earnings numbers more quickly, in part because of the ability to avoid inefficiencies in data storage and manipulation. Brazel and Dang (2008) find that earnings announcement delay decreases following an ERP implementation, and Gallemore and Labro (2013) find that firms with lower earnings announcement delay have more successful tax outcomes. I prefer this proxy because it is available for the entirety of my sample period and only results in minimal sample size attrition.[13]

To test my second hypothesis, I modify Equation (1) to include earnings announcement delay as a measure of the quality of information from management:

$$\begin{aligned} Loan\ characteristic_i = \ & \beta_0 + \beta_1 Private\ precision_i + \beta_2 EA\ speed_i + \\ & \textstyle\sum_k \beta_k Loan\ controls_{i,k} + \sum_l \beta_l Borrower\ controls_{i,l} + \\ & \textstyle\sum_m \beta_m Fixed\ effects_{i,m} + \varepsilon_i \end{aligned} \quad (4)$$

where *EA speed* = (-1) * *log*(earnings announcement date - fiscal period end date). Because higher values of *Private precision* indicate higher quality, I multiply earnings announcement delay by -1 to obtain a similar interpretation.[14] Jennings et al. (2012) use raw count (in days) for this variable. I follow Jennings et al. but apply a log transformation to address skewness I observe in my sample. As with *Private precision*, Table 1 reports unscaled statistics for *EA speed*, but when including it in this regression, I scale the variable by its standard deviation to bring the interpretation of the coefficient γ_2 in line with the interpretation of γ_1.

In Equation (4), β_1 captures the association between loan terms and analysts' information-processing abilities while β_2 measures the association between loan terms and the

[13] Management forecasts is an alternative proxy, but its inclusion results in a more than 90% reduction in sample size. Furthermore, because almost all of the remaining observations are between 2001 and 2006, I would not be able to investigate the effects of Reg FD and the financial crisis as described later in this study.

[14] Because I scale earnings announcement delay by -1, I adopt the variable name coined by Gallemore and Labro: 'EA speed'.

quality of management's information to include the information which management may privately supply to analysts. Because better internal information leads to lower information asymmetry (Lang and Lundholm 1996), better financial outcomes (Gallemore and Labro 2013) and lower monitoring costs (Armstrong et al. 2010), I predict that β_2 will be negative for each loan characteristic. Consistent with H1, I also predict that β_1 will continue to be negative.

3.3 Shocks

All tests up to this point have included the entire sample period. I extend these main findings by identifying one regulatory shock (i.e., Regulation Fair Disclosure) and one economic shock (i.e., the recent financial crisis) to analysts' information environment and investigating the impact of these shocks on the relation between analysts' precision and loan terms.

Regulation Fair Disclosure

Since Reg FD, in order for management to communicate information to analysts, they have been obliged to disclose that information publicly. Heflin et al. (2003) document an increase in voluntary disclosure and Mohanram and Sunder (2006) find that the precision of public information in analysts' forecasts remains constant following Reg FD. These studies provide evidence that analysts continued to have access to relevant information for forming forecasts and recommendations despite the restriction on private communication, but they do not agree on the consequences of this regulation for the quality of analysts' forecasts. Mohanram and Sunder (2006) find that the precision of private information in analysts' forecasts increases and conclude that increased information discovery enhances analysts' ability to convert public information into private information; Heflin et al. (2003) find no change with respect to analyst forecast quality; and Amiram et al. (2012) assert that the ability of analysts' forecasts to reduce information asymmetry in the equity market decreases following Reg FD.

Additionally, firms with higher disclosure quality have a lower cost of debt (Sengupta 1998). If the benefits of added voluntary disclosure following Reg FD complement the benefits of a reduction in information asymmetry from banks having private access to higher quality information, then the quality of information provided by management may be more important for setting loan terms since the introduction of that regulation.

For this test I split my sample into two groups, and using Equation (4) I measure β_1 and β_2 separately for each group. I identify 1994-2000 as the pre-Reg FD period and 2001-2006 as the post-Reg FD period.[15] I end the post-Reg FD period in 2006 to avoid including the financial crisis. Based on prior literature β_1 may increase, decrease or remain constant, but I predict that β_2 will increase in absolute value in the post-Reg FD period.

Financial Crisis

Unlike Reg FD, because of the universal increase in uncertainty, the financial crisis likely affected analysts' access to relevant information inputs. Because analyst forecasts decreased in quality (Arand and Kerl 2012, Amiram et al. 2013) after the start of the crisis, lenders may have relied on them less. However, these studies also observe that the market's response to analysts' forecasts increased consistent with analysts continuing to be able to provide information because of the lack of alternative sources. Banks, unlike other market participants, do have an alternative source of information through private access to management and may have instead shifted toward increased reliance on information from management.

Because the post-Reg FD period is also the pre-financial-crisis period, in this test I compare the years of the crisis with the post-Reg FD period. Based on information from the St. Louis Fed, I identify 2007 as the start of the crisis, and I include all loans issued through the end

[15] The difference in starting years between this and earlier tests is attributable to sample attrition when adding additional independent variables.

of 2009. I then re-estimate Equation (4) for this sub-sample. Here again, prior literature does not allow for a clear prediction for the change in β_1 following the start of the crisis. Banks' reliance on analysts' forecasts may have decreased because of a drop in precision, or it may have increased because of a drop in the availability of other sources of information. My prediction for β_2 is also consistent with that from the post-Reg FD period. Because of the increase in uncertainty following the start of the crisis, I predict that banks would choose to rely even more on information provided by management. As a result, I predict that β_2 will be negative for each loan term and larger in absolute value than in the period before the crisis.

CHAPTER 4: RESULTS

Table 1 Panel C displays univariate Pearson and Spearman correlations of the regression variables. All firm characteristics are also correlated with the loan terms in the predicted direction (i.e., larger, more profitable, less highly leveraged firms with higher credit ratings have preferable loan terms). *Private precision* and *EA speed* are positively correlated with one another (ρ = 0.09) indicating that the underlying constructs may be related. The low correlation also indicates that these measures do not capture identical constructs. *Loan spread* and *Collateral* are also positively correlated with one another (ρ = 0.53) and negatively correlated with *Private precision* and *EA speed* with correlations between -0.09 and -0.37. The correlations between loan terms and *EA speed* are larger in absolute value than the correlations between loan terms and *Private precision*, which may imply that the quality of information provided by management is a stronger determinant of loan contracts than the precision of analysts' information-processing abilities. Although it is intuitive that private access to the borrowing firm is an important source of information when setting loan terms, analysts may still be able to provide relevant, incremental information.

Table 2 presents the results of the test of H1 using Equation (1). For both dependent variables the coefficient over *Private precision* is negative and significant at higher than the 1% level. A one standard deviation increase in precision corresponds to a 5 basis point decrease in loan spread and a 7% decrease in the likelihood of posting collateral. These results indicate that analyst forecast quality is associated with preferential treatment with respect to both price (i.e., spread) and non-price (i.e., collateral) loan characteristics, which finding is consistent with

Mansi et al. (2011), who conclude that analyst forecast quality is negatively associated with the price of bonds.

Table 3 presents the results of three cross-sectional tests. For parsimony in presentation, I have only included the coefficient over *Private precision* in each case. Panel A shows the results of splitting the sample by whether the borrowing firm had an investment-grade credit rating prior to the loan issuance; Panel B shows the results of splitting the sample on the median value of accruals quality; and Panel C shows the results of splitting sample by whether the borrowing firm has an interest coverage ratio greater than 1.5. In all three tests, two consistent stories manifest. With respect to loan spread, the correlation between *Private precision* and this loan term remains constant across all sub-samples. The only noticeable difference in coefficients is between those firms with sufficient interest coverage (-0.03) and those without (-0.05), but the difference is not significant at conventional levels. This lack of variability may be evidence of high levels of complexity surrounding the decision for an interest rate such that additional reductions in information asymmetry can always benefit the borrower. On the other hand, the relation between analysts' precision and the likelihood of collateralization seems dependent on the availability of other signals and the credit quality of the borrowing firm. In each case, the coefficient over *Private precision* is larger in absolute value for low-type firms and statistically insignificant for high-type firms.[16]

Table 4 reports the results of H2. *Private precision*, which, after controlling for the quality of information from management, captures the precision of analysts' information-processing, remains significantly correlated with both loan terms. *EA speed* is also negatively associated with each loan term, and consistent with the univariate correlations, the coefficients

---

[16] When I split the "Not Investment Grade" group into "Below Investment Grade" and "No Rating", I find coefficients of similar magnitude and significance for each group.

over *EA speed* are larger in absolute value than those for *Private precision*. This reinforces the intuitive inference that private access to the borrowing firm is more relevant for lending decisions than information provided by analysts.

Table 5 reports results for three sub-periods: before Reg FD (columns 1 and 2), after Reg FD (columns 3 and 4) and during the financial crisis (columns 5 and 6). The results in columns 1 and 2 are similar to the results in prior tables and imply that before Reg FD, the precision analysts' information-processing was associated with preferable loan terms. In the periods thereafter, banks seem to have ceased relying on information from management. According to columns 3 and 4 following Reg FD, *Private precision* ceases to be correlated with *Collateral*. Furthermore, as shown in columns 5 and 6 during the financial crisis, *Private precision* ceases to be correlated with either loan term. This loss of significance may indicate that a decrease in analyst forecast quality decreased banks' reliance on analysts' reports or that after the start of the crisis banks changed their loan pricing models, as well as the model inputs.

An opposite result holds for *EA speed*. The association between *EA speed* and *Loan spread* remains constant across all periods, while the correlation between *EA speed* and *Collateral* increases from one period to the next. Prior to Reg FD, *EA speed* is not correlated with *Collateral*, but the coefficient increases in absolute magnitude and gains statistical significance following Reg FD. The coefficient again increases in magnitude during the financial crisis. Although the differences are not statistically significant, the trend indicates that banks may have increased reliance on communication from management when additional sources of information became less reliable and informative.

4.1 Robustness Tests

The evidence up to this point is consistent with analysts' forecast quality being correlated with loan terms, but I include additional untabulated tests to gauge the robustness of these results.

Outliers

Table 1 Panel C displays both parametric and non-parametric correlation coefficients. Although the univariate Pearson and Spearman correlations between loan terms and analyst precision are of similar magnitude, I test for the effects of outliers in two ways. First, I replicate my tests using rank regressions. Second, in addition to truncating all continuous variables at 1% and 99%, I truncate forecast dispersion, which is one dimension of *Private precision*, at 1% and 99%.[17] In both cases inferences remain unchanged.

Analyst Following

Prior literature has found an association between analyst following and credit ratings (Cheng and Subramanyam 2008). Although I control for credit ratings, I also want to verify that the association between analysts' private precision and loan terms captures more than simply the association between analyst following and loan terms. I test this by adding analyst following, as well as the other components of *Private precision* (i.e., forecast dispersion and squared forecast error) as control variables and find that *Private precision* remains correlated with both loan terms.

Omitted Variables

Despite the control variables in the hypothesis tests, the results could be affected by other correlated omitted variables. It is not feasible to identify all such variables, but a changes specification will exclude the effects of any time-invariant omitted variables. In order to be able

[17] This truncation addresses outliers, as well as herding behavior among analysts.

to calculate changes, the firm must have accessed the private debt market at least twice during the sample period. To perform this test, I replace the dependent variables with the change in the dependent variables from one loan to the next, and I do the same for *Private precision*. All controls and fixed effects for this model are calculated as of the fiscal period end prior to the issuance of the more recent of the two loans. *Private precision* remains significantly correlated with *Loan spread* and *Collateral*.[18]

I also test for omitted variables by including each loan term as an independent variable in a regression with the other loan term as the dependent variable. *Private precision* continues to be correlated with each loan term when controlling for the other.

Management Communication

I use earnings announcement delay as an attempt to capture the ability of management to provide analysts with private information. Although prior research has demonstrated a correlation between this proxy and the quality of the firm's information system, earnings announcement delay is a publicly observable measure and instead may capture the effect of public information on loan terms. I attempt to address this issue in my main tests by including *Accruals quality* and *Earnings volatility* as proxies for publicly observable accounting information.

I also perform a robustness test to further address this issue, in which I replace *EA delay* with the change in *EA delay*.[19] To calculate the change I subtract earnings announcement delay for the fiscal year end immediately prior to loan issuance from earnings announcement delay for the first fiscal year end following loan issuance. Because *EA delay* following loan issuance is not

[18] Because *Collateral* is an indicator variable, change in *Collateral* has three levels (i.e., -1, 0, 1). As a result, I use ordered probit for this robustness test.

[19] I also try including both EA delay and change in EA delay in the same regression.

publicly observable I use the change as an attempt to capture the effects of the information system on earnings announcement delay more readily. In both tests inferences are unchanged relative to my main results.

CHAPTER 5: CONCLUSION

This study investigates whether the private precision in analysts' forecasts is correlated with bank loan terms. Using a measure of precision of analysts' private information from Barron et al. (1998), I find that higher precision is associated with lower loan spreads and lower likelihood of collateralization.

I then perform three cross-sectional tests to discover whether this association depends on other firm characteristics. For the first test, I separate firms into those with an investment-grade credit rating prior to the loan issuance and those without; for the second, I split the sample on the median for accruals quality as of the fiscal-year end prior to the loan issuance as measured by Bharath et al. (2008); and for the third, I separate firms into those with an interest coverage ratio greater than 1.5 and those with an interest coverage ratio less than 1.5 prior to the loan issuance. In each case, I find that the association between analysts' precision and loan spread remains constant while the association between analysts' precision and collateral is only significant for low-type firms (i.e., without an investment-grade credit rating, low accruals quality or insufficient interest coverage).

Because analysts' private information contains both private information-processing ability, as well as private information communicated from management, I select a measure of quality of information provided by management (i.e., earnings announcement delay) to separate the two parts and regress loan terms on both parts. I find that both components are associated with preferable loan terms.

I then investigate two shocks. First, Regulation Fair Disclosure affected the ability of management to communicate privately with analysts. I investigate the change in the association between loan terms and these two components of the precision of analysts' private information after the introduction of Reg FD. I find that while the association between analysts' precision and loan spread remains constant, the correlation between analysts' precision and collateral ceases to be significant. Quality of information provided by management, on the other hand, increases in importance in the post period with respect to collateralization.

The second shock is the financial crisis. When observing loans during the years 2007-2009, I find that analysts' forecast quality is no longer correlated with either loan term consistent with overwhelming uncertainty in the market regarding asset values prompting a change in loan pricing models. As with the post-Reg FD period, information from management again increased in importance following the start of the crisis. I conclude that banks may have responded to the increase in uncertainty by increasing reliance on private communications with management.

My study has several limitations. First, all tests are conditional. I can only observe accepted loan terms of approved loans. This limits the external validity of my study because I do not know the nature of firms who did not receive loans. Second, the study is associative in nature. This is a first attempt at understanding the existence of a tie between analysts' forecast quality and the cost of private debt, and I am not able to establish causality.[20] The decision to measure analyst forecast quality before loan issuance, as well as the changes model, are attempts to rule out reverse causality (i.e., that preferable loan terms result in higher analyst forecast

[20] A recent study by Ergungor et al. (2014) states that the accuracy of the forecasts by analysts affiliated with a bank, with which the covered firm has a prior lending relationship, is higher than those of unaffiliated analysts. Because F/I/S/D does not disclose the names of analysts and brokers, I cannot identify which analysts are affiliated with lending banks, but I attempt to address this issue in two ways. First, because I use summary forecasts with a minimum of three estimates, individual analysts should have undue influence on the main findings. Second, I control for the existence of a lending relationship, which according to this prior study, represents a proxy for the higher accuracy of forecasts by affiliated analysts.

quality). The results of the cross-sectional tests and the tests of the effects of Reg FD and the financial crisis also seem consistent with the assertion that banks are learning from analysts. Finally, I am not able to measure the quality of information from management directly and select earnings announcement delay because prior studies have found it to be correlated with firm information system quality. Future investigation into measures of management information quality can allow for more direct identification of the effect of a borrower's private information on loan terms.

TABLES

TABLE 1

Sample selection, descriptive statistics and correlations for sample years 1994-2012.
All sample restrictions apply to the borrowing firm.

Panel A: Sample selection procedure

	Number of observations		
	Facilities	Packages	Borrowers
Sample of loans issued in the United States and in United States Dollars	105,067	72,432	28,268
Sample after requiring Dealscan variables	75,869	51,197	20,611
Sample of loans matched with Compustat	40,691	28,725	8,248
Sample after excluding financial firms	35,515	24,520	7,027
Sample after requiring Compustat variables	18,310	12,888	4,014
Sample after requiring IBES variables	10,783	7,891	2,573
Sample after removing outliers of continuous variables	9,045	6,703	2,279

Panel B: Descriptive statistics of model variables

Variable	**Obs.**	**Mean**	**Std. Dev.**	**Min.**	**25%**	**Median**	**75%**	**Max.**
Loan spread	9,045	4.81	0.80	2.86	4.32	5.01	5.42	6.40
Collateral	9,045	0.44	0.50	0	0	0	1	1
Private precision	9,045	4.11	3.22	-6.93	2.08	4.59	6.52	9.57
EA speed	9,045	-3.64	0.35	-4.52	-3.91	-3.66	-3.37	-2.71
Deal size	9,045	19.13	1.21	15.52	18.42	19.19	20.03	21.82
Maturity	9,045	3.69	0.65	1.79	3.56	4.09	4.09	4.58
Financial covenants	9,045	1.72	1.52	0	0	2	3	8
General covenants	9,045	4.38	3.62	0	0	4	8	10
Performance pricing	9,045	0.56	0.50	0	0	1	1	1
Prior lender	9,045	0.76	0.43	0	1	1	1	1
Size	9,045	7.40	1.50	4.08	6.31	7.34	8.47	10.97
Leverage	9,045	0.26	0.19	0.00	0.12	0.25	0.37	0.93
BTM	9,045	0.50	0.33	-0.38	0.28	0.44	0.65	2.05
ROA	9,045	0.04	0.06	-0.33	0.02	0.04	0.07	0.23
Earnings volatility	9,045	0.04	0.04	0.00	0.02	0.03	0.06	0.31
Accruals quality	9,045	0.12	0.41	-2.72	0.04	0.24	0.36	0.48
Interest coverage	9,045	0.74	0.44	0	0	1	1	1
Investment grade	9,045	0.33	0.47	0	0	0	1	1
Noninvestment grade	9,045	0.44	0.50	0	0	0	1	1

rrelation matrix of model variables (Pearson above/Spearman below)

	Loan spread	*Collateral*	*Private precision*	*EA speed*	*Deal size*	*Maturity*	*Financial covenants*	*General covenants*	*Performance pricing*	*Prior lender*	*Size*	*Leverage*	*BTM*	*ROA*	*Earnings volatility*	*Accruals quality*	*Interest coverage*	*Investment grade*	*Noninvestment grade*
.oan spread		0.53	-0.16	-0.37	-0.29	0.26	0.30	0.30	-0.02	-0.04	-0.34	0.22	0.19	-0.28	0.23	-0.12	-0.27	-0.49	0.35
Collateral	0.53		-0.09	-0.29	-0.22	0.27	0.45	0.55	0.18	-0.06	-0.36	0.14	0.06	-0.18	0.22	-0.13	-0.18	-0.43	0.33
:e precision	-0.15	-0.08		0.09	0.02	0.02	0.02	-0.02	0.05	0.01	-0.01	-0.12	-0.15	0.19	-0.10	0.03	0.17	0.07	-0.08
EA speed	-0.37	-0.29	0.08		0.20	-0.20	-0.19	-0.18	-0.03	0.06	0.33	-0.10	-0.11	0.16	-0.09	0.10	0.15	0.29	-0.14
Deal size	-0.28	-0.23	0.00	0.20		0.03	-0.18	-0.11	0.05	0.26	0.71	0.12	-0.09	0.07	-0.19	0.21	0.10	0.40	-0.02
Maturity	0.22	0.26	0.02	-0.16	0.07		0.20	0.24	0.13	-0.02	-0.16	0.13	-0.05	0.01	0.05	0.02	-0.02	-0.24	0.22
l covenants	0.27	0.45	0.04	-0.18	-0.17	0.16		0.69	0.46	-0.02	-0.34	0.06	0.00	-0.02	0.12	-0.10	-0.06	-0.30	0.19
l covenants	0.30	0.56	-0.01	-0.19	-0.13	0.24	0.72		0.47	-0.03	-0.30	0.13	-0.01	-0.06	0.14	-0.09	-0.09	-0.29	0.26
ınce pricing	-0.04	0.18	0.05	-0.03	0.03	0.08	0.48	0.49		0.03	-0.11	-0.04	-0.03	0.06	0.01	-0.03	0.06	-0.03	-0.01
'rior lender	-0.04	-0.06	0.01	0.05	0.26	-0.01	-0.02	-0.03	0.03		0.27	0.11	0.00	0.00	-0.09	0.09	0.04	0.10	0.03
Size	-0.32	-0.36	-0.03	0.34	0.71	-0.10	-0.33	-0.31	-0.11	0.27		0.16	-0.02	-0.03	-0.26	0.28	0.05	0.56	-0.11
Leverage	0.19	0.11	-0.11	-0.08	0.14	0.14	0.03	0.09	-0.03	0.12	0.19		-0.08	-0.31	-0.09	0.15	-0.21	-0.05	0.31
BTM	0.15	0.04	-0.13	-0.10	-0.07	-0.07	-0.01	-0.03	-0.03	0.00	0.01	-0.02		-0.24	-0.10	0.04	-0.10	-0.04	0.02
ROA	-0.30	-0.18	0.19	0.16	0.02	0.01	-0.02	-0.07	0.06	-0.03	-0.09	-0.37	-0.34		-0.13	0.01	0.58	0.11	-0.14
gs volatility	0.24	0.24	-0.09	-0.12	-0.22	0.05	0.17	0.19	0.04	-0.09	-0.33	-0.17	-0.20	0.08		-0.26	-0.20	-0.23	0.10
uals quality	-0.14	-0.16	0.02	0.13	0.25	0.04	-0.12	-0.12	-0.05	0.10	0.35	0.19	0.07	-0.05	-0.34		0.05	0.19	-0.02
st coverage	-0.28	-0.18	0.16	0.14	0.10	-0.02	-0.06	-0.09	0.06	0.04	0.05	-0.17	-0.06	0.61	-0.21	0.06		0.18	-0.17
ment grade	-0.47	-0.43	0.05	0.29	0.40	-0.19	-0.30	-0.30	-0.03	0.10	0.56	-0.01	-0.02	0.10	-0.29	0.26	0.18		-0.62
ment grade	0.35	0.33	-0.08	-0.13	-0.04	0.24	0.18	0.26	-0.01	0.03	-0.10	0.30	0.01	-0.18	0.14	-0.07	-0.17	-0.62	

All correlations greater than .02 are significant at the 5% level

TABLE 2

This table displays the results of regressing two loan characteristics (i.e., spread and collateralization) on the precision of analysts' private information (Barron et al. 1998), loan- and borrower-specific controls and year, loan type and four-digit SIC industry fixed effects for the years 1994 through 2012. All variables are calculated as of the fiscal-year end prior to loan issuance.Standard errors are clustered at the borrowing firm level. T-statistics (Z-statistics) are reported in parentheses.

Dependent variables

Loan Spread = log(all-in-spread drawn over LIBOR in basis points)

Collateral = 1 if the loan is collateralized and 0, otherwise

Independent variable of interest

Private Precision = f(squared forecast error (SE), forecast dispersion (D) and analyst following (N))

$$\log\left(\frac{D}{\left[\left(1-\frac{1}{N}\right)*D+SE\right]^2}\right)$$

		Dependent Variable	
	Prediction	Loan Spread	Collateral
Intercept		6.15	-0.91
		(32.8)	(-2.1)
Private Precision	-	-0.04	-0.07
		(-4.9)	(-3.0)
Deal Size		-0.07	-0.05
		(-6.8)	(-1.7)
Maturity		-0.05	0.39
		(-2.4)	(10.1)
Financial Covenants		0.02	0.11
		(2.7)	(5.4)
General Covenants		0.03	0.17
		(8.1)	(20.0)
Performance Pricing		-0.10	-0.18
		(-6.0)	(-3.5)
Prior Lender		-0.04	0.00
		(-2.5)	(0.1)
Size		-0.11	-0.11
		(-9.2)	(-3.7)
Leverage		0.52	0.43
		(9.0)	(2.8)
BTM		0.24	0.29
		(9.0)	(4.0)
ROA		-0.99	-2.41
		(-6.2)	(-5.3)
Earnings Volatility		0.46	3.30
		(2.5)	(6.0)
Accruals Quality		-0.07	-0.11
		(-3.1)	(-1.9)
Interest Coverage		-0.07	-0.05
		(-3.3)	(-0.9)
Investment		-0.16	-0.58
		(-4.9)	(-6.5)
Noninvestment		0.20	0.17
		(8.5)	(2.6)
Observations		9,045	9,045
Adjusted R-square		0.69	0.38

TABLE 3

This table displays the results of regressing two loan characteristics (i.e., spread and collateralization) on the precision of analysts' private information (Barron et al. 1998), earnings announcement delay, loan- and borrower-specific controls and year, loan type and four-digit SIC industry fixed effects for the years 1994 through 2012. All variables are calculated as of the fiscal-year end prior to loan issuance. Standard errors are clustered at the borrowing firm level. T-statistics (Z-statistics) are reported in parentheses. Each panel reports only the coefficient for the independent variable of interest. Panel A reports the results of splitting the sample into firms with and without an investment-grade credit rating. Panel B reports the results of splitting the sample into firms with accruals quality (Bharath et al. 2008) above and below the median. Panel C reports the results of splitting the sample into firms with an interest coverage ratio greater than and less than 1.5.

Dependent variables

Loan Spread = log(all-in-spread drawn over LIBOR in basis points)

Collateral = 1 if the loan is collateralized and 0, otherwise

Independent variable of interest

Private Precision = f(squared forecast error (SE), forecast dispersion (D) and analyst following (N))

$$\log\left(\frac{D}{\left[\left(1-\frac{1}{N}\right)*D+SE\right]^{2}}\right)$$

Panel A: Credit rating

	Investment Grade		Not Investment Grade	
	Loan Spread	Collateral	Loan Spread	Collateral
Private Precision	-0.04	-0.02	-0.03	-0.08
	(-2.8)	(-0.5)	(-3.6)	(-3.1)
Observations	3,023		6,022	

Panel B: Accruals quality

	AQ Above the Median		AQ Below the Median	
	Loan Spread	Collateral	Loan Spread	Collateral
Private Precision	-0.04	-0.04	-0.04	-0.09
	(-3.8)	(-1.1)	(-4.1)	(-3.0)
Observations	4,523		4,522	

Panel C: Interest coverage

	Coverage > 1.5		Coverage < 1.5	
	Loan Spread	Collateral	Loan Spread	Collateral
Private Precision	-0.03	-0.03	-0.05	-0.16
	(-2.7)	(-1.0)	(-3.3)	(-4.2)
Observations	6,658		2,387	

TABLE 4

This table displays the results of regressing two loan characteristics (i.e., spread and collateralization) on the precision of analysts' private information (Barron et al. 1998), earnings announcement delay, loan- and borrower-specific controls and year, loan type and four-digit SIC industry fixed effects for the years 1994 through 2012. All variables are calculated as of the fiscal-year end prior to loan issuance. Standard errors are clustered at the borrowing firm level. T-statistics (Z-statistics) are reported in parentheses.

Dependent variables

Loan Spread = log(all-in-spread drawn over LIBOR in basis points)
Collateral = 1 if the loan is collateralized and 0, otherwise

Independent variable of interest

Private Precision = f(squared forecast error (SE), forecast dispersion (D) and analyst following (N))

$$\log\left(\frac{D}{\left[\left(1-\frac{1}{N}\right)*D+SE\right]^2}\right)$$

*EA Speed = (-1) * log(earnings announcement date - fiscal period end date)*

	Prediction	Dependent Variable: Loan Spread	Dependent Variable: Collateral
Intercept		5.46	-2.57
		(22.8)	(-5.0)
Private Precision	-	-0.04	-0.06
		(-4.6)	(-2.6)
EA Speed	-	-0.06	-0.17
		(-5.1)	(-6.5)
Deal Size		-0.07	-0.06
		(-6.8)	(-2.1)
Maturity		-0.05	0.36
		(-2.3)	(9.4)
Financial Covenants		0.02	0.11
		(2.6)	(5.1)
General Covenants		0.03	0.17
		(8.0)	(19.9)
Performance Pricing		-0.10	-0.16
		(-5.9)	(-3.2)
Prior Lender		-0.04	-0.00
		(-2.3)	(-0.0)
Size		-0.10	-0.07
		(-7.9)	(-2.5)
Leverage		0.51	0.35
		(8.8)	(2.3)
BTM		0.23	0.25
		(8.5)	(3.4)
ROA		-0.93	-2.20
		(-5.8)	(-4.9)
Earnings Volatility		0.50	3.37
		(2.7)	(6.0)
Accruals Quality		-0.06	-0.10
		(-2.9)	(-1.8)
Interest Coverage		-0.07	-0.04
		(-3.0)	(-0.7)
Investment		-0.16	-0.56
		(-4.9)	(-6.3)
Noninvestment		0.20	0.18
		(8.3)	(2.8)
Observations		9,045	9,045
Adjusted R-square		0.69	0.39

TABLE 5

This table displays the results of regressing two loan characteristics (i.e., spread and collateralization) on the precision of analysts' private information (Barron et al. 1998), earnings announcement delay, loan- and borrower-specific controls and year, loan type and four-digit SIC industry fixed effects for the years 1994 through 2012. All variables are calculated as of the fiscal-year end prior to loan issuance. Standard errors are clustered at the borrowing firm level. T-statistics (Z-statistics) are reported in parentheses. Columns 1 and 2 report results for loans issued prior to Reg FD (before 2001). Columns 3 and 4 report results for loans issued after Reg FD (2001-2006). Columns 5 and 6 report results for loans issued during the financial crisis (2007-2009).

Dependent variables

Loan Spread = *log(all-in-spread drawn over LIBOR in basis points)*

Collateral = *1 if the loan is collateralized and 0, otherwise*

Independent variable of interest

Private Precision = *f(squared forecast error (SE), forecast dispersion (D) and analyst following (N))*

$$\log\left(\frac{D}{\left[\left(1-\frac{1}{N}\right)*D+SE\right]^2}\right)$$

EA Speed = *(-1) * log(earnings announcement date - fiscal period end date)*

	Before Reg FD		After Reg FD		Financial Crisis	
	Loan Spread	Collateral	Loan Spread	Collateral	Loan Spread	Collateral
Intercept	5.78	0.19	6.22	-1.08	6.05	-2.70
	(16.4)	(0.2)	(14.1)	(-1.3)	(8.6)	(-1.6)
Private Precision	-0.04	-0.08	-0.03	-0.04	-0.02	-0.05
	(-2.8)	(-2.3)	(-2.2)	(-1.1)	(-0.8)	(-0.9)
EA Speed	-0.05	-0.07	-0.05	-0.11	-0.06	-0.15
	(-3.3)	(-1.6)	(-2.8)	(-2.6)	(-2.0)	(-2.2)
Deal Size	-0.07	-0.11	-0.10	-0.11	-0.08	0.08
	(-4.5)	(-2.3)	(-5.5)	(-2.5)	(-2.8)	(0.9)
Maturity	-0.03	0.32	-0.08	0.41	-0.10	0.16
	(-1.1)	(6.0)	(-2.3)	(6.3)	(-1.5)	(1.4)
Financial Covenants	0.02	0.10	0.01	0.11	-0.02	0.00
	(2.3)	(3.7)	(0.9)	(2.8)	(-0.8)	(0.1)
General Covenants	0.02	0.16	0.04	0.23	0.04	0.26
	(4.1)	(12.8)	(6.8)	(12.8)	(3.6)	(9.4)
Performance Pricing	-0.07	-0.21	-0.13	-0.26	-0.17	-0.14
	(-2.6)	(-2.5)	(-4.7)	(-2.7)	(-3.3)	(-0.9)
Prior Lender	-0.01	-0.06	-0.09	-0.19	0.02	-0.47
	(-0.5)	(-0.8)	(-3.0)	(-1.9)	(0.4)	(-2.9)
Size	-0.15	-0.19	-0.08	-0.09	-0.09	-0.27
	(-7.9)	(-3.8)	(-3.9)	(-1.9)	(-2.2)	(-2.8)
Leverage	0.58	1.02	0.60	0.23	0.55	0.33
	(6.5)	(4.3)	(5.5)	(0.8)	(3.6)	(0.9)
BTM	0.22	0.33	0.22	0.26	0.30	0.19
	(4.7)	(2.8)	(4.5)	(1.9)	(3.9)	(1.0)
ROA	-0.78	-1.67	-1.33	-2.67	-0.69	-2.91
	(-3.0)	(-2.2)	(-4.8)	(-2.9)	(-1.5)	(-3.1)
Earnings Volatility	1.29	3.02	0.25	3.34	-0.54	0.73
	(3.5)	(2.8)	(0.7)	(3.3)	(-0.9)	(0.5)
Accruals Quality	-0.05	-0.20	-0.02	-0.03	-0.18	-0.10
	(-1.8)	(-2.5)	(-0.4)	(-0.3)	(-2.2)	(-0.6)
Interest Coverage	-0.14	-0.22	-0.06	0.01	0.06	0.11
	(-3.7)	(-2.2)	(-1.6)	(0.1)	(0.9)	(0.7)
Investment	-0.19	-0.47	-0.27	-0.37	-0.19	-0.04
	(-3.5)	(-3.4)	(-4.8)	(-2.6)	(-2.0)	(-0.2)
Noninvestment	0.11	0.19	0.16	0.26	0.31	0.66
	(2.7)	(1.9)	(3.7)	(2.2)	(4.6)	(4.1)
Observations	3,159	3,159	3,390	3,390	1,154	1,154
Adjusted R-square	0.73	0.40	0.73	0.46	0.74	0.40

WORKS CITED

Abarbanell, J.S. 1991. Do Analysts' Earnings Forecasts Incorporate Information in Prior Stock Price Changes? *Journal of Accounting and Economics* 14 (2): 147-165.

Abarbanell, J.S., W.N. Lanen, and R.E. Verrecchia. 1995. Analysts' Forecasts as Proxies for Investor Beliefs in Empirical Research. *Journal of Accounting and Economics* 20 (1): 31-60.

Abarbanell, J.S., and R. Lehavy. 2007. Letting the "Tail Wag the Dog": The Debate over GAAP versus Street Earnings Revisited. *Contemporary Accounting Research* 24 (3): 675-723.

Ahmed, A.S., B.K. Billings, R.M. Morton, and M. Stanford-Harris. 2002. The Role of Accounting Conservatism in Mitigating Bondholder-Shareholder Conflicts Over Dividend Policy and in Reducing Debt Costs. *The Accounting Review* 77 (4): 867-890.

Amiram, D., E. Owens, and O. Rozenbaum. 2012. Do Information Releases Increase or Decrease Information Asymmetry? New Evidence from Analyst Forecast Announcements. Working Paper. Columbia University.

Amiram, D., W.R. Landsman, E. Owens, and S.R. Stubben. 2013. Analysts' Forecasts During Periods of High Uncertainty. Working Paper. University of North Carolina at Chapel Hill.

Anderson, R.C., S.A. Mansi, and D.M. Reeb. 2004. Board Characteristics, Accounting Report Integrity, and the Cost of Debt. *Journal of Accounting and Economics* 37 (3): 315-342.

Arand, D., and A.G. Kerl. 2012. Analyst Research and Investor Reactions: Evidence From the 2008 Financial Crisis. Working Paper. University of Giessen.

Armstrong, C.S., W.R. Guay and J.P. Weber. 2010. The Role of Information and Financial Reporting in Corporate Governance and Debt Contracting. *Journal of Accounting and Economics* 50 (2): 179-234.

Atiase, R.K., and L.S. Bamber. 1994. Trading Volume Reactions to Annual Accounting Earnings Announcements: The Incremental Role of Predisclosure Information Asymmetry. *Journal of Accounting and Economics* 17 (3): 309-329.

Barron, O.E., O. Kim, S.C. Lim and D.E. Stevens. 1998. Using Analysts' Forecasts to Measure Properties of Analysts' Information Environment. *The Accounting Review* 73 (4): 421-433.

Berger, A.N., and G.F. Udell. 1995. Relationship Lending and Lines of Credit in Small Firm Finance. *The Journal of Business* 68(3): 351-381.

Bharath, S.T., J. Sunder and S.V. Sunder. 2008. Accounting Quality and Debt Contracting. *The Accounting Review* 83 (1): 1-28.

Botosan, C.A., M.A. Plumlee and Y. Xie. 2004. The Role of Information Precision in Determining the Cost of Equity Capital. *Review of Accounting Studies* 9 (2-3): 233-259.

Bradshaw, M. 2004. How Do Analysts Use Their Earnings Forecasts in Generating Stock Recommendations? *The Accounting Review* 79 (1): 25-50.

Brazel, J.F., and L. Dang. 2008. The Effect of ERP System Implementations on the Management of Earnings and Earnings Release Dates. *Journal of Information Systems* 22 (2): 1-21.

Brown, L.D., and M.S. Rozeff. 1978. The Superiority of Analyst Forecasts as Measures of Expectations: Evidence From Earnings. *The Journal of Finance* 33 (1): 1-16.

Brown, L.D., R.L. Hagerman, P.A. Griffin and M.E. Zmijewski. 1987. Security Analyst Superiority Relative to Univariate Time-Series Models in Forecasting Quarterly Earnings. *Journal of Accounting and Economics* 9 (1): 61-87.

Chan, Y.C., and G. Kanatas. 1985. Asymmetric Valuations and the Role of Collateral in Loan Agreements. *Journal of Money, Credit and Banking* 17 (1): 84-95.

Chen, Q., I. Goldstein and W. Jiang. 2007. Price Informativeness and Investment Sensitivity to Stock Price. *Review of Financial Studies* 20 (3): 619-650.

Chava, S., and M.R. Roberts. 2008. How Does Financing Impact Investment? The Role of Debt Covenants. *The Journal of Finance* 63 (5): 2085-2121.

Cheng, M., and K.R. Subramanyam. 2008. Analyst Following and Credit Ratings. *Contemporary Accounting Research* 25 (4): 1007-1043.

Daley, L.A., D.W. Senkow and R.L. Vigeland. 1988. Analysts' Forecasts, Earnings Variability, and Option Pricing: Empirical Evidence. *The Accounting Review* 63 (4): 563-585.

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

Dechow, P.M., and I. Dichev. 2002. The Quality of Accruals and Earnings: The Role of Accrual Estimation Errors. *The Accounting Review* 77 (Supplement): 35–59.

DeFond, M.L., and M. Hung. 2003. An Empirical Analysis of Analysts' Cash Flow Forecasts. *Journal of Accounting and Economics* 35 (1): 73–100.

Ergrungor, O.E., L. Madureira, N. Nayar and A.K. Singh. 2014. Lending Relationships and Analysts' Forecasts. *Journal of Financial Intermediation* (forthcoming).

Francis, J., K. Schipper and L. Vincent. 2005. Earnings and Dividend Informativeness when Cash Flow Rights Are Separated from Voting Rights. *Journal of Accounting and Economics* 39 (2): 329–360.

Fisher, L. 1959. Determinants of Risk Premiums on Corporate Bonds. *The Journal of Political Economy* 67 (3): 217-237.

Fried, D., and D. Givoly. 1982. Financial Analysts' Forecasts of Earnings: A Better Surrogate for Market Expectations. *Journal of Accounting and Economics* 4 (2): 85-107.

Gallemore, J., E. Labro. 2013. The Importance of the Internal Information Environment for Tax Avoidance. Working Paper. University of North Carolina at Chapel Hill.

Greene, W. 2004. The Behaviour of the Maximum Likelihood Estimator of Limited Dependent Variable Models in the Presence of Fixed Effects. *Econometrics Journal* 7 (1): 98-119.

Hauswald, R., R. Marquez. 2006. Competition and Strategic Information Acquisition in Credit Markets. *Review of Financial Studies* 19 (3): 967-1000.

Heflin, F., K.R. Subramanyam and Y. Zhang. 2003. Regulation FD and the Financial Information Environment: Early Evidence. *The Accounting Review* 78 (1): 1-37.

Hughes, J.S., and W.E. Ricks. 1987. Associations Between Forecast Errors and Excess Returns Near to Earnings Announcements. *The Accounting Review* 62 (1): 158-175.

Imhoff Jr, E.A., and G.J. Lobo. 1992. The Effect of Ex Ante Earnings Uncertainty on Earnings Response Coefficients. *The Accounting Review* 67 (2): 427-439.

Jennings, J., R. Stoumbos and L. Tanlu. 2012. The Effect of Organizational Complexity on Earnings Forecasting Behavior. Working Paper. University of Washington.

Jensen, M.C., and W.H. Meckling. 1976. Theory of the Firm: Managerial Behavior, Agency Costs and Ownership Structure. *Journal of Financial Economics* 3 (4): 305-360.

Lang, M.H., and R.J. Lundholm. 1996. Corporate Disclosure Policy and Analyst Behavior. *The Accounting Review* 71 (4): 467-492.

Lobo, G.J., M. Song and M. Stanford. 2012. Accruals Quality and Analyst Coverage. *Journal of Banking and Finance* 36 (2): 497-508.

Loh, R.K., and G.M. Mian. 2006. Do Accurate Earnings Forecasts Facilitate Superior Investment Recommendations? *Journal of Financial Economics* 80 (2): 455-483.

Lys, T., and S. Sohn. 1990. The Association Between Revisions of Financial Analysts' Earnings Forecasts and Security-Price Changes. *Journal of Accounting and Economics* 13 (4): 341-363.

Mansi, S.A., W.F. Maxwell and D.P. Miller. 2011. Analyst Forecast Characteristics and the Cost of Debt. *Review of Accounting Studies* 16 (1): 116-142.

Mohanram, P.S., and S.V. Sunder. 2006. How Has Regulation FD Affected the Operations of Financial Analysts? *Contemporary Accounting Research* 23 (2): 491-525.

Myers, S.C. 1977. Determinants of Corporate Borrowing. *Journal of Financial Economics* 5 (2): 147-175.

Ohlson, J.A. 1980. Financial Ratios and the Probabilistic Prediction of Bankruptcy. *Journal of Accounting Research* 18 (1): 109-131.

Orgler, Y.E. 1970. A Credit Scoring Model for Commercial Loans. *Journal of Money, Credit and Banking* 2 (4): 435-445.

Schipper, K. 1991. Analysts' Forecasts. *Accounting Horizons* 5 (4): 105-121.

Sengupta, P. 1998. Corporate Disclosure Quality and the Cost of Debt. *The Accounting Review* 73 (4): 459-474.

Smith Jr, C.W., and J.B. Warner. 1979. On Financial Contracting: An Analysis of Bond Covenants. *Journal of Financial Economics* 7 (2): 117-161.

Sufi, A. 2007. Information Asymmetry and Financing Arrangements: Evidence From Syndicated Loans. *The Journal of Finance* 62 (2): 629-668.

Teoh, S.H., I. Welch, and T.J. Wong. 1998. Earnings Management and the Underperformance of Seasoned Equity Offerings. *Journal of Financial Economics* 50 (1): 63–99.

Vassalou, M., and Y. Xing. 2004. Default Risk in Equity Returns. *The Journal of Finance* 59 (2): 831-868.

Wang, Q. 2011. The Trade-off Between Hard and Soft Information in Bank Lending. Working Paper. National University of Singapore.

Watts, R.L. 2003. Conservatism in Accounting Part I: Explanations and Implications. *Accounting Horizons* 17 (3): 207-221.

Wittenberg-Moerman, R. 2008. The Role of Information Asymmetry and Financial Reporting Quality in Debt Trading: Evidence From the Secondary Loan Market. *Journal of Accounting and Economics* 46 (2): 240-260.

Zhang, J. 2008. The Contracting Benefits of Accounting Conservatism to Lenders and Borrowers. *Journal of Accounting and Economics* 45 (1): 27-54.

Ziebart, D.A. 1990. The Association Between Consensus of Beliefs and Trading Activity Surrounding Earnings Announcements. *The Accounting Review* 65 (2): 477-488.