Loan Spreads and Unexpected Earnings

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Abstract

This paper explores whether banks have superior information to financial analysts about borrowers' future earnings at the financing decision stage. The results suggest that at the loan initiation banks have "priced-in" borrowers' future earnings news that is unexpected by analysts. The sensitivity of loan spreads to unexpected earnings varies cross-sectionally and over time in the same direction as the predicted changes in banks' relative information advantages. Further tests show that the results are robust to alternative measures of unexpected earnings, and are unlikely to be driven by correlated omitted risk factors.

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1. Introduction

Contemporary theories of financial intermediation highlight the special role of banks in private information production and mitigation of informational asymmetries in an imperfect capital market (see Leland and Pyle, 1977; Campbell and Kracaw, 1980; Allen, 1990). One important implication of these theories is that at the financing decision stage, banks have superior information to other investors about the borrowers' earnings prospects.[1] I label this the "superior information hypothesis".

In contrast, an alternative theoretical view recognizes that there are other solutions to the information problem. Given the information spillover from public signals, private information production by banks can be efficient only when other information sources are noisy (Berlin and Loeys, 1988; Sunder, 2006). In the extreme, Fama (1980) argues that banks can exist as passive portfolio managers.[2]

The tension between these two views is likely to be the highest for publicly-traded U.S. firms with analyst coverage, where both financial reporting and analyst following are well-known solutions to the "lemons" problem (Akerlof, 1970) and both provide valuable information services to the capital market.[3] Frankel, Kothari and Weber (2006) further show that the informativeness of analyst reports complements that of financial statements. Rich public information environment mitigates banks' relative information advantage via two channels: (1) Improved information set of other investors; (2) Reduced incentive of banks to obtain private signals because they have low cost alternatives to assess and control for default risk (substitution effect). For example, banks can use stock performance

[1] James (1987, page 217) summarizes the hypothesis as "[banks] know more about a company's prospects than other investors do."
[2] Campbell and Kracaw (1980, page 864) cite this as "a potentially powerful null hypothesis."
[3] See Healy and Palepu (2001) for a comprehensive review of the related literature.

or credit rating as a screening device (Sunder, 2006), or set tight financial covenant thresholds as "trip wires" (Dichev and Skinner, 2002). Consequently, this paper examines the following research questions: (1) For publicly-traded U.S. firms with analyst following, does the superior information hypothesis still hold? (2) How do banks' economic incentives and disclosure regulation affect banks' relative information advantage?

Two strands of prior empirical research have explored the superior information hypothesis. One strand investigates whether the stock market reacts favorably to bank loan announcements (James, 1987; Lummer and McConnell, 1989; Billet, Flannery and Garfinkel, 2006), while the other examines whether the secondary loan market is more informationally efficient than the equity market (Altman, Gande and Sauders, 2004; Allen, Guo and Weintrop, 2004; Allen and Gottesman, 2005). However, the former approach is confounded by the self-selection bias that firms are more likely to make voluntary announcements when loan terms are favorable. The latter approach, by construction, mainly captures banks' *ex post* information advantage. It also lacks power due to the relative illiquidity of the secondary loan market. As a result, findings of the above studies are largely mixed. What is perhaps more relevant, but remains missing in the literature, is a more direct test of banks' *ex ante* information advantage before loans are granted.

My study fills this void, focusing on the primary bank loan market and banks' information advantage at the financing decision stage. It also avoids the aforementioned self-selection bias by obtaining the loan contracts from mandatory SEC filings. Exploiting detailed loan contract data and a new research design, this study provides a more direct test of the superior information hypothesis by exploring whether at the loan initiation banks have "priced-in" borrowers' future earnings news that is unexpected by other investors.

Focusing on publicly-traded U.S. borrowers with equity analyst coverage, I find robust evidence consistent with the superior information hypothesis.[4] In particular, I document that banks set loan spreads at the loan initiation as if they have anticipated the sign and magnitude of borrowers' future earnings that is unexpected by equity analysts. Unexpected earnings are significantly negatively associated with the loan spreads, after controlling for forecast complexity and bias, earnings volatility, credit rating, and other loan- or firm-specific determinants of credit risk. Consistent with banks' asymmetric payoff function, loan spreads are significantly more sensitive to negative unexpected earnings than to positive ones. Moreover, the results suggest that the sensitivity of loan spreads to unexpected earnings varies cross-sectionally and over time in predictable ways consistent with banks' economic incentives and regulatory environment: (1) loan spreads are significantly less sensitive to unexpected earnings for secured loans and firms with high analyst following, where banks have less incentive to engage in costly private information production; (2) loan spreads are significantly more sensitive to unexpected earnings for firms with high income-increasing abnormal accruals, where more bank scrutiny is required and the lead bank retains larger stake to commit to effective *ex ante* evaluation; (3) the sensitivity is significantly higher after Regulation Fair Disclosure (hereafter Reg FD), when private communications between managers and analysts are prohibited, but banks are exempted from the regulation.

Supplementary analyses exploit the timing difference in information availability to differentiate whether the results above capture information advantage or correlated omitted risk factors. I find that: (1) the results become weaker if unexpected earnings are measured

[4] Leuz and Verrecchia (2000) argue that under current U.S. GAAP the disclosure environment for publicly traded U.S. firms is "already rich" and cross-sectional variation in voluntary disclosure among these firms is unlikely to have discernable economic consequences. Here I focus on this first-order effect of mandatory disclosure.

one quarter forward, when uncertainty gradually resolves and some private information at the loan initiation has been revealed to the public; (2) the results disappear if unexpected earnings are measured two quarters forward, when most firms have filed bank loan contracts with the SEC. These findings lend more support to the information story, since risk factors are unlikely to vanish over a short period of time.

Finally, sensitivity analyses suggest that the results are robust to using abnormal returns around earnings announcement as an instrument for unexpected earnings, and to using analysts' annual forecasts instead of quarterly forecasts. Sub-sample analyses further indicate that the results are not driven by a mechanical association or by post-Reg FD observations.

This paper contributes to the literature in several ways. First, I take a new approach and provide more direct evidence consistent with the superior information hypothesis, which is in contrast to the mixed findings in the prior literature. The new research design and detailed loan contract data enable me to circumvent the common limitations that have contaminated previous studies. Second, Holthausen and Watts (2001, page 52) call for more research on "the nature and strength of the other forces (besides the demand of equity investors) that shape accounting." Since the demand of lenders is an important force (Ball, Robin and Sadka, 2005), this paper answers the call by investigating how lenders' information environment may be different from that of equity investors. Finally, since banks' information environment is not affected by Reg FD, my finding of widened relative information advantage after Reg FD provides cleaner evidence that the information environment for equity analysts has deteriorated after the regulation. This result helps inform the debate on Reg FD and contributes to this growing literature.

The rest of the paper is organized as follows. Section 2 reviews the related literature. Section 3 develops the hypotheses. Section 4 describes the data and research design. Section 5 presents the results. Section 6 concludes the paper.

2. Literature Review

This study is related to two strands of literature. The first strand examines the stock market reactions to firms' voluntary announcements of bank loan agreements. The rationale is as follows. If banks have superior information, they will screen borrowers based on that information. By granting or renewing a loan, banks implicitly provide a certification of the financial condition of the borrower. Therefore, bank loan announcements should convey a favorable signal to the market. Consistent with this prediction, a series of studies (James, 1987; Lummer and McConnell, 1989; Billet, Flannery and Garfinkel, 1995) have reported a significantly positive two-day abnormal return for bank loan announcements.

One limitation of these studies is that firms choose to voluntarily disclose the loan agreements before filing with the SEC. To the extent that firms are more likely to make announcements when the loan terms are favorable, it will bias in favor of finding the positive market reactions to loan announcements during a short-window. In other words, the self-selection problem may generate a biased sample. Without appropriate correction for endogeneity, the results are hard to interpret. In fact, using a long event window, Billet et al. (2006) document that firms announcing bank financing suffer negative abnormal stock returns instead during the three-year post-announcement period, which is no different from the findings for equity offerings or public debt issuances.

In this study, I avoid the self-selection bias by obtaining the loan agreements from mandatory SEC filings. Public firms are required to file all material contracts with the SEC, including bank loan agreements.

The second strand of research compares the informational efficiency of the secondary syndicated loan market with that of the equity or bond market. The argument is that if banks have superior information about borrowers, it should first be incorporated into the loan price on the secondary loan market, before it is released publicly and reflected in the equity or bond price.

Consistent with this argument, Altman et al. (2004) find that the secondary loan market leads the bond market in reacting to bankruptcy and default announcements. Similarly, Allen et al. (2004) report significant price movements in the secondary loan market four weeks prior to the announcement of earnings declines, which coincides with the timing of monthly covenant reports to banks. However, bankruptcy, default and earnings declines are all significant negative events. On a regular day-to-day basis, Allen and Gottesman (2005) find contrary evidence that equity returns lead and "Granger cause" secondary loan returns.

This approach is a joint test of the superior information hypothesis and the implicit assumption that the secondary loan market is otherwise as efficient as the equity or bond market. The latter has yet to be established in order to draw unambiguous inferences. Given the relative illiquidity of the secondary loan market, this assumption is unlikely to hold. More importantly, this approach mainly captures banks' *ex post* information advantage. After loans are granted, banks typically receive monthly covenant reports. So it is not surprising that during the loan period banks learn news about borrowers' forthcoming defaults and earnings declines ahead of equity investors, who only receive quarterly financial reports.

Because banks' *ex ante* information advantage is essential in the theories to derive banks' special role in mitigating information asymmetries, this paper focuses on the primary loan market instead, and examines whether banks have superior information before loans are granted.

3. Hypothesis Development

3.1 Possible sources of superior information

There are good reasons to expect that banks may have superior information to analysts before loans are granted. First, banks may simply have better access to information. For example, some banks maintain deposit or cash management services with borrowers, which grant them a unique "insider" view of borrowers' cash flows. There are also information spillovers if some banks happen to have an existing relationship with a major supplier or customer of the borrower. Further, borrowers could have material proprietary information. It is costly to publicly disclose such information since an undesirable reaction by competitors may be triggered. But firms have incentives to disclose the information to private lenders to obtain favorable terms. Finally, banks can write contracts requiring managers to provide private information as a condition for lending, although such requirements are costly in a competitive primary loan market.

3.2 Null hypothesis

Conversely, Berlin and Loeys (1988) develop a theoretical model where the value of bank investigation depends on the informativeness of other public indicators. It is not efficient for banks to engage in costly private information production when other information sources can substitute. For publicly-traded U.S. firms with analyst coverage, banks are less likely to have superior information relative to equity analysts regarding borrowers' future earnings, to the extent that regulated financial reporting and equity analysts help substantially reduce information asymmetries (Healy and Palepu, 2001), and to the extent that they complement each other in informing the capital market about the firm's future performance (Frankel et al. 2006). In addition, banks now have plenty of low cost substitute goods to assess and control for the default risk. For example, they can use stock performance or credit ratings as a screening device, or set tight covenant thresholds as "trip wires" (Dichev and Skinner, 2002). These alternatives could be relatively more efficient for average borrowers. Hence, on average, banks have less incentive to obtain and analyze private signals regarding borrowers' future earnings, especially when compared to analysts, who specialize in forecasting earnings.

Furthermore, prior to Reg FD, managers could circumvent the proprietary cost by selectively disclosing information to trusted analysts via closed conference calls. In that case, managers have incentives to disclose more earnings relevant information to analysts than to banks. For instance, if managers privately observe a negative signal about future earnings, they may not disclose it to banks worrying about a hike in the interest rate. But they have incentives to disclose it to trusted analysts to guide the earnings forecasts down so that they can meet or beat analysts' consensus forecast when actual earnings are disclosed. Consistent with this argument, Ke and Yu (2005) document that most of the private information analysts received from closed conference calls is bad news.

Taken together, it is an empirical question whether on average banks will have an *ex ante* information advantage over equity analysts regarding borrowers' future earnings.

3.3 The negative association between loan spreads and unexpected earnings

At the loan initiation, banks set the interest rates (measured as loan spreads) as a function of their private signals as well as all available public information. When banks' private signals about future earnings are sufficiently superior to those of analysts, a significant portion of earnings unexpected by analysts will be incorporated into loan spreads and we should observe that unexpected earnings are correlated with loan spreads over and above all public indicators of default risk. The lower the unexpected earnings, that is, the more negative the earnings shocks predicted by banks' private signals, the higher interest rates will be charged on bank loans. In the extreme, when the private information allows banks to perfectly predict unexpected earnings, this negative association will be the strongest. In contrast, if banks do not have an informational advantage over analysts, or analysts have superior information to banks, then unexpected earnings will be merely noise to banks and on average should have no effect on loan spreads. This leads to my first hypothesis:

H1: *Ceteris paribus, loan spreads are negatively associated with unexpected earnings*.

3.4 Cross-sectional Predictions

Private debt claims are different from equity claims in that banks often do not benefit from borrowers' large profits, but may be seriously hurt by large losses (Ball, 2001). Hence, banks inherently care more about downside risk and get more actively involved when borrowers are performing poorly. In addition, expecting that borrowers have incentives to selectively disclose more good news and withhold bad news during the contracting process (Kothari, Shu and Wysocki, 2005; Pae, 2005), banks may price protect themselves by putting more weight on private information signaling bad news when setting loan spreads. This leads to my second hypothesis:

H2: *Ceteris paribus, loan spreads are more sensitive to negative unexpected earnings than to positive unexpected earnings.*

Secured loans are typically very risky in the sense that there is increased uncertainty concerning borrowers' future performance and banks' private signals are relatively noisier (Berger and Udell, 1990). Therefore, banks tend to have less superior information compared to analysts in the case of secured loans. This is reinforced by the fact that once the loan is secured, banks might devote fewer resources in private information production since collateral itself helps reduce credit risk (Manove, Padilla, and Pagano, 2001). These arguments yield the third hypothesis:

H3: *Ceteris paribus, the sensitivity of loan spreads to unexpected earnings is lower for secured loans than non-secured loans.*

Berlin and Loeys (1988) contend that the value of private information production by banks depends on the reliability of other indicators of borrower type. Further investigation of the firm is only valuable when both the prior probability of the firm type and the informativeness of other indicators are quite low. In addition, Best and Zhang (1993) find some empirical support that banks invest in costly private information production only when alternative information sources are noisy.

Firms with high analyst following tend to have more informative disclosure (Lang and Lundholm, 1996), and stock prices of these firms incorporate information on accruals and cash flows more quickly (Barth and Hutton, 2000).

Consequently, for borrowers with high analyst following, banks' relative informational advantage over analysts is likely lower. This leads to my fourth hypothesis:

H4: *Ceteris paribus, the sensitivity of loan spreads to unexpected earnings is lower for borrowers with higher analyst following.*

Sufi (2007) argues that borrowers reporting high positive abnormal accruals operate in a high information asymmetry environment and require more rigorous screening and monitoring by banks. Consistent with this argument, he documents that lead banks retain significantly higher shares of the syndicated loan for these borrowers to commit to effective *ex ante* evaluation and *ex post* monitoring. Moreover, Moerman (2006) finds that firms with income-increasing abnormal accruals tend to violate debt covenants or have financial numbers just above the covenant threshold. Expecting that, banks have incentives to give these firms more scrutiny before loans are granted. These arguments yield the following hypothesis:

H5: *Ceteris paribus, the sensitivity of loan spreads to unexpected earnings is higher for firms with income-increasing abnormal accruals.*

3.5 Time-series Prediction

On October 23, 2000, SEC enacted Reg FD prohibiting selective disclosure of material information to financial analysts. If the information disclosed in closed conference calls before Reg FD is primarily bad news or proprietary information, then after Reg FD firms will have incentives to withhold the information (Kothari et al., 2005; Dye, 1985), now that private communications are not allowed. To the extent that analysts cannot fully recover the information loss by independent research, analysts' information set is likely to be smaller. Consistent with this, Ke and Yu (2005) find that the informativeness of analysts' downgrade recommendation declines significantly after Reg FD for closed conference call firms. Wang (2006) reports that most firms replace private earnings guidance with nondisclosure after Reg FD, resulting in significant deterioration in their information environment.

If the public information environment deteriorates after Reg FD, then private information becomes more valuable and banks will find it efficient to invest more in private information production (Berlin and Loeys, 1988; Best and Zhang, 1993). Meanwhile, since commercial banks are exempted from Reg FD as contractual parties, they also have better access to information than equity analysts. For instance, banks can still have private communications with managers after Reg FD while analysts cannot. As a result, the information gap between the two parties should increase and unexpected earnings should be more strongly associated with loan spreads. My last hypothesis is:

H6: *Ceteris paribus, the sensitivity of loan spreads to unexpected earnings is higher after Reg FD than before Reg FD.*

4. Data and Research Design

4.1 Sample Selection

Bank loan information is obtained from the LPC Dealscan database. I start with 11,356 bank loan facilities from January 1987 to June 2005 that meet the following restrictions: (1) The borrower must be a publicly traded firm, that is, the borrower's ticker is not missing and correctly matches CRSP ticker; (2) The facility active date and the loan spread (AIS drawn) information are not missing; (3) The borrower country must be "the United States" to facilitate comparison and avoid unnecessary complications of different accounting standards; (4) The borrower must be covered by Compustat Industrial Quarterly file, as well as the I/B/E/S Detail History file; (5) The borrower type must be coded as "corporation," excluding banks, insurance companies and utility firms. Utility firms are often heavily regulated with very stable cash flows and predictable earnings. As a result, information asymmetry is rarely a problem for these firms, and their credit risks are unusually low relative to their leverage. As for banks and insurance companies, regulatory monitoring and explicit investor insurance schemes such as deposit insurance may strongly influence the credit decisions for these borrowers. Their debt-like liabilities may not be strictly comparable to the debt issued by non-financial firms. I exclude them in the current analysis to make sure that the results are not driven by these special observations. In future research, it may be interesting to examine banks as a separate sample, given their dual role of borrowers and lenders.

Some firms in the sample have multiple bank loan deals during the same quarter, and the same deal may include multiple facilities. As a result, some firm-quarters are likely over-represented in the sample. This could also cause cross-sectional dependence in the regression error terms. To address this concern, I select the first deal for each firm-quarter and randomly include in the sample one facility for each deal. This further reduces the sample to 8,016 observations. The results are qualitatively the same if I do not impose this restriction.

The final sample size varies depending on the independent variables used. Further requirements of non-missing data for unexpected earnings and all control variables results in a sample of 5,859 observations used in the main regression analyses.

4.2 Variable Definitions

The main objective of the analysis is to explore whether the borrower's future unexpected earnings are incorporated into the interest rate at the loan initiation. Therefore, the dependent variable for all regressions is the interest rate of each bank loan. Following Bharath, Sunder and Sunder (2007), I measure the interest rate using "all-in-spread drawn" (AISD), which is the mark-up over LIBOR paid by the borrower on all drawn lines of credit. LIBOR is a floating rate. Analogous to market return in the equity case, it fluctuates as the macroeconomic conditions change. As a result, by using this loan spread measure, I have adjusted for (at least to a certain extent) economy-wide shifts in the cost of debt.

The main independent variable is unexpected earnings (UE). Following O'Brien (1988), I use analysts' consensus earnings forecast as a proxy for other investors' expectation about firms' future earnings. Brown and Rozeff (1978) and Givoly (1982) have established that analysts' consensus earnings forecast performs better than time-series models of earnings, and that it is a superior surrogate for market expectations in part because analysts are able to incorporate firm and economy news into their forecasts in a timely manner.

For each firm-quarter, I choose the most recent EPS forecast for each analyst. To facilitate comparison and to approximate the lower bound of banks' relative informational advantage over analysts, I restrict all analysts' EPS forecasts for quarter t to be made after the facility active date. The EPS forecasts with estimate dates before or at the facility active date are deleted. To the extent that uncertainty gradually resolves as time goes by and analysts can update their forecasts based on newer information, it will bias against rejecting the null of no superior information. I then obtain the consensus analyst forecast for each firm-quarter by taking the median of the remaining most recent analysts' forecasts.[5] UE is measured at the quarter t earnings announcement date as the difference between the actual EPS and the consensus analyst forecast of EPS, deflated by the absolute value of the consensus analyst forecast of EPS.[6]

This UE measure is similar to the calculation of return and has an intuitive interpretation of percentage forecast error. One limitation is that the treatment of non-positive EPS in the denominator may not be ideal. Alternatively, I use beginning-of-the-quarter price as the deflator and the results are qualitatively the same. The problem with this price deflated measure, however, is that P/E ratios may vary substantially across firms and the measure is often unreliable for firms with small share prices (Durtschi and Easton, 2005). More seriously, since price or P/E ratio is correlated with risk, this alternative measure may confound or bias my results and make them hard to interpret.

In untabulated univariate analysis, I find UE is highly skewed and has large outliers, with the lowest value less than -91 and the highest value more than 37, which can be translated to percentage forecast errors of -9100% and 3700% respectively. I winsorize UE at the top and bottom 1% to mitigate the undue influence of extreme values.[7]

The control variables include loan characteristics such as loan size (FSIZE), loan maturity (MATURITY), secured loan (SECURE) and loan purpose (TAKEOVER), as well

[5] Median measure is less susceptible to outliers. The results are robust to using the mean measure.
[6] Actual EPS is also taken from I/B/E/S Detail History file to ensure comparability.
[7] The results are robust to winsorizing UE based on an alternative cutoff of top and bottom 5%, as well as an intuitive cutoff point of 1 at the top and -1 at the bottom (100% forecast error).

as firm-specific credit risk factors such as leverage (LEVERAGE), total assets (ASSETS), Tobin's Q (TobinQ), prior performance (LAGRET), S&P senior debt credit rating (RATING) and a dichotomous variable that equals 1 for firms that do not have a credit rating, 0 otherwise (D_NR).[8] All of these controls variables have been shown in the prior literature to be important determinants of loan spreads (see for example, Bharath et al., 2007; Asquith, Beatty and Weber, 2005). Variable definitions are detailed in the appendix.

A possible concern is that unexpected earnings also capture the confounding factor of forecast complexity and operational uncertainty. Consider a firm whose business model is so complex and operating environment so volatile that it is simply hard for analysts to accurately forecast its earnings. Absent any private information, banks will also view the firm as very risky. In this case, one could observe that banks charge firms high interest rates when the absolute value of analysts' forecast errors are high, despite the possibility that banks may have no relative information advantage over analysts at all. In other words, although I controlled for many factors that are known to influence loan spreads, the controls are likely to be incomplete. A correlated omitted variable problem might still exist and cause a spurious association in the OLS regression.

To address this concern, I construct three additional control variables. The first variable is complexity (COMPLEX), measured as the mean absolute value of analyst forecast errors (actual EPS minus consensus EPS forecast) over the 4 fiscal quarters prior to the loan quarter deflated by the absolute value of last quarter's consensus EPS forecast. This variable is expected to partly control for business and forecast complexity. Interestingly, to the extent that the incentives in place that cause analysts to bias their forecasts are stable over a short period of time, this variable may also control for analysts'

[8] The results are robust to using ROA (item 8 / item 44) instead of LAGRET to measure prior performance.

systematic forecast bias. The second variable is earnings volatility (EARN_VOL), measured as the standard deviation of quarterly earnings before extraordinary items (item 8) over the 4 fiscal quarters prior to the loan quarter scaled by the standard deviation of quarterly CFO (item 108) over the same window.[9] The third variable is return volatility (RET_VOL), measured as the standard deviation of the monthly return over the 12 months prior to the loan initiation month. I use these two variables to control for operational uncertainty, which may affect banks' perceived default risk as well as the unexpected earnings measure. To the extent that these controls are successful, the correlated omitted variable problem will be mitigated.

4.3 Estimation Models

Using the above measures, I run the following regression to test hypothesis 1:

$$AISD = \alpha + \beta_1{*}UE + \beta_2{*}FSIZE + \beta_3{*}MATURITY + \beta_4{*}SECURE + \beta_5{*}TAKEOVER + \beta_6{*}LEVERAGE + \beta_7{*}RATING + \beta_8{*}D\_NR + \beta_9{*}ASSETS + \beta_{10}{*}TobinQ + \beta_{11}{*}LAGRET + \beta_{12}{*}COMPLEX + \beta_{13}{*}EARN\_VOL + \beta_{14}{*}RET\_VOL + \varepsilon \quad (1)$$

H1 predicts that $\beta_1 < 0$. The greater the relative information advantage, the more negative the β_1. In addition, if β_1 really captures banks' superior information, I expect to see that it varies cross-sectionally and over time in predictable ways, i.e., the absolute magnitude of β_1 will be greater (lower) in cases when banks' relative information advantage is expected to be larger (smaller). To perform these contingency analyses, I construct dichotomous variables for negative unexpected earnings (NUE), secured loans (SECURE), high analyst following (D_AF), and post-Reg FD period (Aft_RFD) to test

[9] The results are qualitatively the same if using the standard deviation of earnings alone or the standard deviation of CFO alone.

hypothesis 2, 3, 4 and 6 respectively. To test hypothesis 5, I calculate signed abnormal accruals (SAA) using the modified Jones model:

$$TA = k_1 + k_2*\Delta REV + k_3* PPE + \varepsilon \quad (*)$$

where TA is the total accruals for firm i in year t, calculated as the earnings before extraordinary items (item 123) minus the operating cash flows (item 308). ΔREV is the annual change in revenues (item 12), and PPE is the gross value of property, plant and equipment (item 7). Regression (*) is estimated for each of the 48 Fama and French (1997) industry groups for each year and the coefficient estimates are used to estimate the firm-specific normal accruals (NA) for my sample firms as follows:

$$NA = \hat{k}_1 + \hat{k}_2(\Delta REV - \Delta AR) + \hat{k}_3\, PPE + \varepsilon \qquad (**)$$

where ΔAR is the annual change in account receivables. To account for possible heteroskadasticity, all variables in (*) and (**), including intercepts, are scaled by lagged total assets (item 6). SAA is calculated as the difference between the deflated total accruals and the fitted normal accruals. Pos_AA (Neg_AA) equals to 1 if SAA>0 (<0), and 0 otherwise. Each firm-quarter in my sample is matched with Pos_AA (Neg_AA) of the past year.

I then estimate the following two regressions:[10]

$$\begin{aligned} AISD = {} & \alpha + \beta_1*UE + \beta_2*NUE + \beta_3*UE*NUE + \beta_4*SECURE + \beta_5*UE*SECURE + \\ & \beta_6*D\_AF + \beta_7*UE*D\_AF + \beta_8* Pos\_AA + \beta_9* UE * Pos\_AA + \beta_{10}* Neg\_AA + \\ & \beta_{11}* UE * Neg\_AA + Controls + \varepsilon \qquad (2) \end{aligned}$$

$$AISD = \alpha + \beta_1*UE + \beta_2* Aft\_FD + \beta_3* UE*Aft\_FD + Controls + \varepsilon \qquad (3)$$

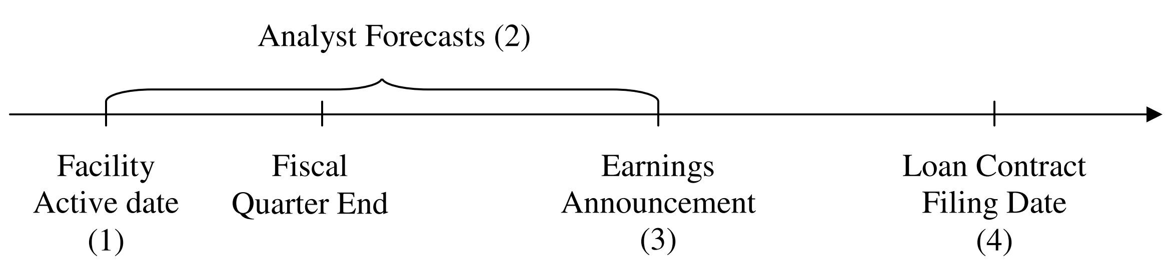
[10] The results are qualitatively the same if estimating each interaction in model (2) in a separate regression.

"Controls" denote all the independent variables in regression (1) except UE. I predict that $\beta_3 < 0$, $\beta_5 > 0$, $\beta_7 > 0$ and $\beta_9 < 0$ in regression (2) and $\beta_2 < 0$ in regression (3).

Since the regressions (1)-(3) are all estimated using pooled panel data, I include year and industry fixed effects in all regressions. Furthermore, I compute t-statistics based on robust standard errors clustered by firm. The estimated variance-covariance matrix is a modified Huber/White/sandwich estimate of variance, which is robust to heteroskedasticity and has been adjusted to account for within-cluster correlation across residuals. Petersen (2005) demonstrates that when the residuals of a given firm are correlated across years, robust standard errors clustered by firm are unbiased and produce correctly sized confidence intervals regardless of whether the firm effect is permanent or temporary.

4.4 The Time Line

The timeline is characterized as follows: (1) banks set interest rates for loan facilities with active dates in fiscal quarter t based on all available public and private information; (2) by construction, all analysts' most recent earnings forecasts for quarter t are made after the facility active date, up to the earnings announcement date; (3) quarter t earnings are announced, usually about 40 days after the fiscal quarter end; (4) quarter t bank loan agreements are filed with the SEC as material contracts, normally several months after the earnings announcement.



All control variables capturing firm-specific characteristics (such as total assets, leverage, etc.) are measured in the fiscal quarter ending at least 2 months before the facility active dates to ensure that the related accounting information is available when banks set the loan spreads. In contrast, unexpected earnings are calculated for the fiscal quarter in which the loan facility is initiated, subject to the restriction that all analysts' forecasts are issued after the facility active date.

The time line above suggests that analysts normally do not observe the loan spread information until well after the earnings announcement, when loan agreements are filed with the SEC as material contracts. To the extent that some firms may voluntarily disclose loan terms before the earnings announcement so that analysts can update their earnings forecasts accordingly, it will bias against rejecting the null.

5. Results

5.1 Descriptive Statistics

Table 1 presents descriptive statistics for the final sample of 5,859 observations used in the main analyses. To assess the extent to which the sample characteristics are comparable to those of the population of interest, Table 1 also provides descriptive statistics for two matched unrestricted samples. Since all variables in Panel A are obtained from the Dealscan database, a natural benchmark for comparison is the original Dealscan sample, which includes 20,153 bank loan facilities borrowed by publicly traded US corporations from January 1987 to June 2005. And because all variables in Panel B are constructed using financial data from Compustat and I/B/E/S, the unrestricted sample in panel B (Compustat & IBES sample) is the universe of 232,479 firm-quarter observations that have financial data on both Compustat and I/B/E/S during the same period.

Panel A compares loan characteristics and credit rating measures. The mean (median) AISD for the final sample is 137 basis points (100 basis points) over LIBOR, which is significantly lower than the counterpart in original Dealscan sample (198 and 175 basis points respectively). Loans in the final sample are also on average significantly larger ($470 million versus $296 million) and less likely to require collaterals (35.3% versus 50.6%), although there is no difference in the median loan maturity (36 months). Finally, borrowers in the final sample on average have slightly better S&P senior debt rating (9.56 versus 10.45)[11], and they are significantly more likely to have a credit rating than firms in original Dealscan sample (94.4% versus 50.2%).

Panel B compares firm characteristics. The reported numbers for UE are after winsorization. The mean (median) value of UE for the final sample is −0.027 (0.024), comparable to −0.033 (0.005) for the unrestricted sample. Compared to average firms covered by both Compustat and I/B/E/S, firms in the final sample are on average significantly larger in terms of total assets and market capitalization ($5,429 million versus $2,502 million) and more profitable in terms of ROA and prior stock performance. They also feature lower percentage of negative earnings surprises (28% versus 37%), on average more analyst following (7.6 versus 4.4), and significantly lower forecast complexity (0.37 versus 0.64), earnings volatility (0.469 versus 0.881) and return volatility. Overall, it seems that banks are less likely to have an informational advantage over analysts for my sample

[11] By construction, lower number indicates better credit rating. For example, 1 denotes “AAA”, 9 denotes “BBB”, 10 denotes “BBB−”, and 11 denotes “BB+”.

firms as compared to the firms in unrestricted samples, which creates another bias against rejecting the null.

One confounding issue is that analysts are less likely to update on a timely basis for poorly performing firms, while banks tend to be more actively scrutinizing borrowers when their performance deteriorates. If poorly performing firms are heavily represented in my sample, then one would expect to derive similar results absent banks' superior information. Table 1 partly refutes this alternative explanation. To the contrary, the borrowers in my final sample are on average larger, more profitable, and have better credit rating than the average firm in the population of interest. Banks also recognize that and offer them larger amount of loans at significantly lower interest rates. In addition, I have controlled for various performance measures such as lagged stock return, Tobin's Q and credit rating in the multivariate regression analyses to mitigate this concern.

Panel C of Table 1 illustrates the distribution of the final sample by year. Over time, more observations enter the sample. On average there is greater analyst following after Reg FD than before Reg FD. No monotonic patterns are observed for AISD over time. Panel D shows that the sample is very evenly distributed across industries. No industry consists of more than 10% of the final sample.

The Pearson correlation coefficients between the variables in regression (1) are tabulated in Table 2. At the univariate level, loan spreads tend to be higher for secured loans and for borrowers with negative unexpected earnings, but lower for firms with high analyst following. The control variables for forecasting complexity and operational uncertainty, COMPLEX, EARN_VOL, and RET_VOL, are significantly positively correlated with loan spreads, as predicted. Consistent with prior literature, larger borrowers with lower leverage are on average charged lower interest rates.

Not surprisingly, some independent variables are highly correlated. For example, large firms are more likely to have high analyst following. Firms with high return volatility are more likely to have secured loans. It is therefore important to control for firm size, return volatility, and other measures to help mitigate the correlated omitted variable problem that may interfere with the interpretation of results.

5.2 Multivariate Analyses

Table 3, 4 and 5 present the main results. Table 3 investigates the impact of unexpected earnings on bank loan spreads in a multivariate regression, controlling for a variety of loan and firm-specific measures that proxy for default risk or earnings forecast complexity. To avoid the undue influence of outliers, all independent variables are winsorized at the top and bottom 1%.

The coefficient on UE is negative and significant at the 1% level, consistent with the prediction of H1. This result indicates that banks exploit their superior information about borrowers' future earnings in assessing potential loans and charge higher interest rates on firms with anticipated worse future earnings news.

Besides the statistical significance, it is also helpful to discuss the economic significance of this result. Since the standard deviation of UE is 0.91 for the whole sample, one standard deviation of decrease in UE is associated with an average increase of six basis points in loan spreads. However, because banks care more about downside risk, it might be misleading to mingle the positive and negative UE together in assessing the economic magnitude. Hence, I also run the same regression (untabulated) on a sub-sample of observations with negative UE only, where UE has a standard deviation of 1.3. As expected, the coefficient on UE is −12, much bigger than the −6.6 reported in Table 3. This evidence suggests that one standard deviation of decrease in negative UE can be associated with an average increase of 15.6 basis points in loan spreads. Since several aspects of the empirical design bias against rejecting the null, this number may approximate the lower bound of the economic magnitude. The actual magnitude is likely to be much larger. In fact, after correcting for possible measurement errors in UE using an instrument variable estimation, the coefficient on predicted UE becomes −20.3 for the whole sample (see Table 7). So, a standard deviation of decrease in UE can be associated with 18.5 basis points in loan spread, which is about 20% of the median loan spread in the sample.

Consistent with the findings in Strahan (1999), smaller loans, loans that are secured and loans with shorter maturity are associated with higher loan spreads, even after controlling for public available measures of default risk.

The coefficients on all borrower specific control variables have the expected sign and are largely significantly associated with loan spreads. The results are robust to adding other firm-specific determinants of default risk in the model, such as interest coverage, current ratio, Altman's Z-score and Ohlson's O-score.

5.3 Cross-sectional Variations

Table 4 examines whether banks' relative information advantage over analysts varies cross-sectionally in predictable ways and whether my empirical design is powerful enough to capture the changes in the relative information advantage. The regression results imply that banks seem to have correctly anticipated the signs of future earnings shocks unexpected by analysts and reflected them in loan spreads asymmetrically. The interaction term is significantly negative, suggesting that negative unexpected earnings news is assigned higher weight in determining loan spreads than positive unexpected earnings news. This evidence provides support for H2.

Consistent with H3, the coefficient on the interaction of the secured loans dummy with UE is significantly positive, indicating that loan spreads are less sensitive to unexpected earnings news in secured loans.[12]

To test H4, I construct a dummy variable (D_AF) that equals 1 when the number of analysts covering the firm is greater than 4, approximately the average number of the analyst following for the merged population of Compustat and I/B/E/S, and 0 otherwise. I then use this variable to proxy for high analyst following. Consistent with H4, the coefficient on the interaction of the high analyst following dummy with UE is significantly positive, implying that banks' relative information advantage is mitigated for firms with high analyst following.

Consistent with H5, the coefficient on the interaction of the positive abnormal accruals with UE is significantly positive, suggesting that banks have more superior information to analysts about borrowers with high income-increasing accruals in the previous year.

5.4 Changes before and after Reg FD

Effective October 23rd, 2000, Reg FD prohibits private communications between managers and analysts. To the extent that before Reg FD analysts are able to cultivate management access to get more accurate signal about earnings, and to the extent that after

[12] One concern is that loan spreads and the requirement for collateral may be simultaneously determined. I also run a two-stage least squares estimation and substitute the predicted value from the first stage for SECURE. The results are weaker but remain qualitatively similar after partially adjusting for endogeneity.

Reg FD firms may withhold proprietary information and bad news that are earnings relevant, Reg FD triggers a structural change that may have consequences on the information environment. Previous empirical studies have produced mixed findings (Heflin, Subramanyam and Zhang, 2003; Bailey, Li, Mao, and Zhong, 2003; Mohanram and Sunder, 2006), partly because there are significant macro-environment changes during the same period, and it is difficult to disentangle the Reg FD treatment effect from simple before-and-after comparisons.[13]

Instead of comparing analyst forecast accuracy before and after Reg FD, Table 5 exploits the fact that if banks' private signals about future earnings become more precise, unexpected earnings will be more strongly associated with loan spreads. In Table 5, the interaction of Aft_RFD dummy with UE is negative and significant at 10% level (two-tailed), suggesting that banks have larger relative information advantage over analysts after Reg FD than before Reg FD.

Because banks are exempted from Reg FD, this analysis essentially performs a "difference in differences" test to filter out the confounding macro-environment changes, which allows me to disentangle the treatment effect of Reg FD on the information environment. The result supports H6 and provides cleaner evidence that the information environment for equity analysts gets worse after the regulation.

One possible concern is that the results in Table 3 and 4 may be driven by the post-FD observations. As a robustness check, I also rerun all regressions in Table 3 and 4 using a sub-sample that contains only the bank loan deals announced before June 2000, well in advance of the effective date of Reg FD. The results are qualitatively the same.

[13] One notable exception is Jorion, Liu and Shi (2005), who exploit the fact that credit rating agencies are also exempted from Reg FD and find that stock price responses to credit rating changes are bigger after Reg FD.

5.5 Risk or Information?

As discussed above, to guard against the possibility that UE could be capturing an omitted default risk factor of the borrower, I explicitly control for a number of measures of default risk used in prior literature, such as credit rating, leverage, earnings volatility, etc. I find UE continues to be a significant predictor of loan spreads.

Despite these efforts, it is impossible to completely control for correlated omitted risk factors. To further mitigate the concern of possible risk explanations, I repeat the analyses for subsequent quarters. If the results disappear for later quarters when the relative information advantage diminishes (after earnings announcements and especially after observing the interest rates in the material contracts that firms file with the SEC, analysts may infer part of the private information and update the forecasts), then it lends more support for the information story, since risk factors are not likely to change a lot within a couple of quarters.

In Table 6 column 1, I repeat the same analysis as Table 3 except that quarter t+1 unexpected earnings (UE_f) are used instead of quarter t unexpected earnings (UE). Specifically, for each firm, UE_f is calculated as the difference between actual EPS of quarter t+1 and the consensus EPS forecast for quarter t+1, deflated by the absolute value of this consensus EPS forecast.[14] As we can see from the table, the results become weaker. The coefficient of UE_f is less than half the size of that of UE in Table 3 (−3.29 versus −6.64), and is only marginally significant.

In Table 6 column 2, similarly measured quarter t+2 unexpected earnings replace UE in the multivariate regression. The coefficient of UE_f becomes even smaller and is

[14] For each analyst, only his or her most recent forecast of EPS_{t+1} issued after the quarter t facility active date is taken. Consensus analyst forecast for quarter t+1 is measured as the median of these most recent forecasts.

statistically insignificant. This finding is consistent with the information story that as uncertainty gradually resolves and the private information at loan initiation eventually becomes public information, banks' relative information advantage also vanishes. If instead what this empirical design captures is a risk factor, it might be difficult to explain why this risk may diminish and disappear over a short period of time.

5.6 Sensitivity Analyses

A plausible critique is that the unexpected earnings measure may capture systematic analyst forecast bias, which is predictable by analysts as well and may be correlated with some omitted risk factors. For example, Klein (1990) documents that analysts issue more optimistic annual earnings forecasts for firms reporting recent losses than for firms reporting recent profits. Bradshaw et al. (2006) also find that optimism in analysts' forecasts is significantly positively associated with net external financing, while net external financing is a negative predictor of future profitability.

I implement several procedures to address this issue. First, to the extent that the systematic forecast bias is persistent over a short period of time, the control variable COMPLEX (measured as the average absolute analyst forecast error over the previous 4 quarters) should partly mitigate this concern. I have controlled for prior performance (ROA and LAGRET) in the regression as well. Second, I have demonstrated above that the association between unexpected earnings and loan spreads gradually disappear in two quarters as information gets revealed. For any risk story to hold, one has to explain why the correlated omitted risk factor will vanish over a short period of time. Finally, I use abnormal returns around earnings announcements as an instrument for UE. It is well documented that abnormal return over event window (−1, +1) is correlated with UE. In addition, in an efficient market it is reasonable to believe that abnormal return is not predictable, that is, CAR(−1, +1) is unlikely to be correlated with the error term. In Table 7, the instrument variable estimation yields qualitatively similar results, which further mitigates the concern and confirms the validity of the main analyses. It is worth noting that the coefficient of UE in the instrument variable estimation is −20.33, much larger than −6.64 in Table 3.

Another possible concern is that banks may care more about long-term performance of the borrowers than a single quarter. Note that this argument will only bias against my finding the result. Despite that, I also examine whether the results are robust to using longer term analysts' forecasts to construct the unexpected earnings measure. Because long-term analysts' forecasts tend to be less frequent, noisier and more susceptible to optimism (Bradshaw et al. 2006), as a compromise, I re-run the main analyses using an unexpected earnings measure constructed based on analysts' *annual* earnings forecasts, with the requirement that the annual forecasts are issued after the loan initiation and before the current quarter's earnings announcement date. Table 7 shows that the results are actually slightly stronger using this alternative measure.

Another alternative interpretation of the results may be that they are driven by a mechanical association. The fact that a firm obtains a bank loan implies that its interest expense for the current quarter is likely to increase, which may lead to negative unexpected earnings if the loan agreement is not voluntarily disclosed before the earnings announcement date. Holding facility size constant, the higher the interest rate, the larger the interest expense, hence the more negative the unexpected earnings. In order to test this alternative interpretation, I conduct the above analyses on two sub-samples respectively:

one consists only of observations whose current quarter interest expense actually decreases (44% of the final sample), and the other includes only facilities whose primary purpose is "debt repay" (24% of the final sample). If the mechanical association story is correct, then I expect to see no results for these two sub-samples. Instead, Table 7 reports qualitatively the same results. An alternative way is to include dummy variables of "interest expense decrease" and "debt repay" respectively, and add interaction terms of these dummies with all independent variables in the regression. In untabulated analyses, I also find that the interactions are not statistically significant for all variables of interest. In sum, the evidence is inconsistent with the mechanical association argument.

6. Conclusions

An important implication of contemporary theories of financial intermediation is that banks have superior information to external investors about borrowers' future prospects. Two strands of research have explored this superior information hypothesis and the results are largely mixed. This paper exploits a new research design and detailed primary loan contract data to provide a cleaner and more direct test of the hypothesis.

Focusing on a sample of publicly-traded US firms that have both bank debt and analyst following, I find evidence suggesting that banks set interest rates at the loan initiation as if they have anticipated the sign and magnitude of future earnings news that are unexpected by analysts. I also find that the sensitivity of loan spreads to unexpected earnings varies cross-sectionally and over time in predictable ways. The results are consistent with the superior information hypothesis, and are difficult to explain using a correlated omitted default risk factor argument.

The findings of this paper are of potential interest to standard setters, regulators and financial analysts. First, the documented differences between the information environments faced by banks and other investors may help us understand the differential demands for financial reporting among external users. Second, the finding that banks' information advantage over analysts widened after Reg FD provides cleaner evidence that analysts' information environment has deteriorated after the regulation. Third, the evidence that banks still have an information advantage over analysts for publicly-traded U.S. borrowers implies that banks continue to play a critical role in mitigating informational asymmetries in the capital market. Although financial reporting regulation and analyst information service together may have substantially improved the public information environment, banks still find it efficient to engage in costly private information production. Finally, the results suggest that bank loan agreements contain valuable information about future earnings that are unexpected by analysts. To the extent that analysts can obtain and decipher the loan information on a timely basis, it may improve market efficiency.

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Appendix: Definition of Variables

AISD	All-in-spread drawn, the loan spread charged by the bank over LIBOR for the drawn portion of the loan facility (obtained from Dealscan).
UE	Unexpected earnings, measured as the difference between actual EPS and the consensus analyst forecast of EPS, deflated by the absolute value of the consensus analyst forecast of EPS
NUE	A dichotomous variable that equals 1 if UE <0, 0 otherwise.
Pos_AA (Neg_AA)	Signed abnormal accruals (SAA), calculated using modified Jones model. The estimation is run for each Fama-French industry and year. Pos_AA (Neg_AA) equals to 1 if SAA>0 (<0), and 0 otherwise.
D_AF	A dichotomous variable that equals 1 if the number of analysts following the firm is greater than 4, 0 otherwise.
Aft_RFD	A dichotomous variable that equals 1 if the loan facility became active in a fiscal quarter ended before Reg FD, 0 otherwise.
FSIZE	Logarithm of the loan facility size.
MATURITY	Loan facility maturity, measured in months.
SECURE	A dichotomous variable that equals 1 if the loan is secured, 0 otherwise.
TAKEOVER	A variable that equals to 1 if the loan purpose is takeover, 0 otherwise.
LEVERAGE	Total Debt (item 51+ item 45) divided by Total Assets (item 44).
RATING	S&P senior debt rating at close, recoded numerically from 1 to 23, with 1 being "AAA' and 23 being 'D', and 0 for 'not rated'.
D_NR	A dichotomous variable that equals 1 for firms that are not rated, 0 otherwise.
ASSETS	Logarithm of Total Assets (item 44).
TobinQ	Tobin's Q, measured as the market value of equity plus the book value of debt (item 14 * item 61+ item 44 – item 59) divided by total assets (item 44).
LAGRET	Cumulative stock return over the 12 months prior to the loan initiation month.
COMPLEX	The average absolute value of analyst forecast error (actual EPS minus consensus EPS forecast) over the 4 fiscal quarters prior to the loan quarter, deflated by the absolute value of last quarter's consensus EPS forecast.
EARN_VOL	Standard deviation of quarterly earnings before extraordinary items (item 8) over the 4 fiscal quarters prior to the loan quarter, deflated by the standard deviation of quarterly CFO (item 108) over the same period.
RET_VOL	Standard deviation of monthly returns over the 12 months prior to the loan initiation month.

Table 1: Descriptive Statistics

Panel A: *Loan Characteristics and Credit Rating*

	Final Sample		Original Dealscan Sample	
	Mean	Median	Mean	Median
AISD	**137**	**100**	198	175
FSIZE ($million)	**470**	**200**	296	92
MATURITY (months)	**36**	36	40.6	36
SECURE	**0.353**	**0**	0.506	1
RATING	**9.56**	**9**	10.45	10
D_NR	**0.056**	0	0.498	0
N		5,859		20,153

Panel B: *Borrower Characteristics*

	Final Sample		Compustat & IBES Sample	
	Mean	Median	Mean	Median
UE	**–0.027**	**0.024**	–0.033	0.005
NUE	**0.279**	0	0.371	0
Analyst Following	**7.63**	**6**	4.45	3
Aft_FD	**0.374**	0	0.224	0
LEVERAGE	**0.241**	**0.225**	0.185	0.135
ASSETS ($million)	**5243**	**1029**	4632	447
Market Value ($million)	**5429**	**912**	2502	368
TobinQ	**1.849**	**1.489**	2.137	1.41
LAGRET	**0.19**	**0.10**	0.147	0.04
ROA	**0.052**	**0.051**	0.041	0.045
COMPLEX	**0.372**	**0.099**	0.636	0.143
EARN_VOL	**0.469**	**0.178**	0.881	0.265
RET_VOL	**0.126**	**0.112**	0.144	0.115
N		5,859		232,479

Notes:
Final Sample is the sample of 5, 859 observations used in the main analyses. Original Dealscan Sample in panel A includes all 20,153 loan facilities borrowed by publicly traded US corporations from January 1987 to June 2005. Compustat & IBES Sample in panel B includes the universe of 232,479 firm-quarter observations that have financial data on both Compustat and I/B/E/S during the same period. The bolded numbers are statistically different from their counterparts in the unrestricted sample at the 5% level (two-tailed) or better according to t-tests for means and Wilcoxon tests for medians. See Appendix for variable definitions.

Table 1: Descriptive Statistics (continued)

Panel C: *Distribution by Year*

Year	Number of Observations	AISD	Analyst Following
1988	5	136	6
1989	52	145	6
1990	116	120	6
1991	104	167	6
1992	140	141	7
1993	143	126	6
1994	254	103	8
1995	242	104	7
1996	280	110	7
1997	335	95	7
1998	278	116	7
1999	305	132	7
2000	366	127	9
2001	397	131	10
2002	354	144	9
2003	467	171	9
2004	342	157	9

Panel D: *Distribution by Industry*

2-digit SIC Code	Industry	# of Observations	Percentage
13	Oil and Gas	351	8.4
20	Food	170	4.1
26	Paper	125	3.0
28	Chemicals	307	7.3
33	Primary Metal	107	2.6
35	Machinery and Computer	271	6.5
36	Electrical Equipment	202	4.8
37	Transportation Equipment	156	3.7
38	Lab and Medical Instruments	161	3.9
50	Wholesale Trade	159	3.8
53	General Merchandise Store	123	2.9
59	Miscellaneous Retail	114	2.7
73	Business Services	192	4.6
80	Health Services	133	3.2

Notes:
Panel C and panel D show descriptive statistics for the final sample. For parsimony, industries with less than 100 observations in the final sample are not tabulated in Panel D.

Table 2
Correlation Analysis

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18
1.AISD	1.00																	
2.UE	**–0.11**	1.00																
3.NUE	**0.10**	**–0.46**	1.00															
4.SECURE	**0.50**	**–0.04**	**0.03**	1.00														
5.D_AF	**–0.36**	**0.08**	**–0.11**	**–0.30**	1.00													
6.PACC	**0.09**	**–0.03**	**0.04**	**0.10**	**–0.12**	1.00												
7.NACC	**–0.14**	**0.04**	–0.02	**–0.09**	**0.05**	**0.30**	1.00											
8.COMPLEX	**0.22**	**–0.07**	**0.09**	**0.12**	**–0.15**	0.02	**–0.09**	1.00										
9.FSIZE	**–0.40**	**0.08**	**–0.11**	**–0.25**	**0.47**	**–0.15**	**0.13**	**–0.16**	1.00									
10.MATURITY	0.02	0.02	0.02	**0.15**	**–0.10**	0.01	0.01	0.02	**0.04**	1.00								
11.LAGRET	0.02	**0.08**	**–0.10**	**0.05**	**–0.05**	–0.01	**–0.07**	**–0.03**	**–0.04**	**0.05**	1.00							
12.LEVERAGE	**0.11**	–0.02	**0.06**	**0.06**	0.00	**–0.07**	**0.07**	**0.07**	**0.22**	**0.12**	–0.01	1.00						
13.ASSETS	**–0.44**	**0.07**	**–0.10**	**–0.39**	**0.59**	**–0.20**	**0.13**	**–0.15**	**0.77**	**–0.12**	**–0.09**	**0.20**	1.00					
14.TobinQ	**–0.09**	**0.04**	**–0.11**	**–0.04**	**0.11**	0.02	**–0.12**	**–0.11**	**–0.08**	**–0.08**	**0.20**	**–0.24**	**–0.11**	1.00				
15.RATING	–0.02	**0.04**	**–0.05**	**–0.01**	**0.23**	**–0.11**	**0.04**	**–0.04**	**0.41**	**0.06**	–0.01	**0.39**	**0.42**	**–0.15**	1.00			
16.D_NR	**0.05**	**–0.09**	**0.16**	**–0.05**	**–0.12**	**0.03**	0.00	**0.16**	**–0.22**	**0.04**	–0.02	0.01	**–0.17**	**–0.07**	**–0.30**	1.00		
17.EARN_VOL	**0.23**	**–0.05**	**0.06**	**0.15**	**–0.09**	**0.03**	**–0.27**	**0.20**	**–0.12**	**–0.02**	**–0.07**	**0.00**	**–0.10**	**–0.03**	0.01	–0.01	1.00	
18.RET_VOL	**0.43**	**–0.05**	0.02	**0.30**	**–0.17**	**0.12**	**–0.22**	**0.15**	**–0.33**	**–0.05**	**0.06**	**–0.08**	**–0.34**	**0.11**	**–0.08**	0.01	**0.27**	1.00
19.TAKEOVER	**0.04**	0.00	0.00	**0.08**	–0.02	0.02	0.02	**–0.05**	**0.15**	0.02	0.02	0.00	**–0.03**	0.01	**0.03**	–0.02	–0.02	**–0.04**

Notes:
Pearson correlations among variables are reported. Bolded numbers are significant at the 1% level (two-tailed). See Appendix for variable definitions.

Table 3

Multivariate Regression of Loan Spread on Unexpected Earnings
(Dependent Variable: AISD)

Variable	Predicted Sign	Coefficient	T-statistic
UE	–	–6.641	(–3.07)***
FSIZE	?	–13.292	(–7.13)***
MATURITY	?	–2.107	(–1.15)
SECURE	?	61.371	(18.66)***
TAKEOVER	+	25.639	(6.34)***
LEVERAGE	+	77.150	(8.97)***
RATING	+	1.871	(5.90)***
D_NR	+	24.902	(2.12)**
ASSETS	–	–13.151	(–7.03)***
TobinQ	–	–6.591	(–5.57)***
LAGRET	–	–2.603	(–1.37)
COMPLEX	+	11.390	(6.67)***
EARN_VOL	+	8.490	(4.39)***
RET_VOL	+	384.992	(11.95)***
Year Fixed Effects		YES	
Industry Fixed Effects		YES	
N		5859	
Adjusted R-squared		0.50	

Notes:
T-statistics are computed based on robust standard errors clustered at the firm level.
See Appendix for variable definitions.

***, **, * denote significance at the 1%, 5%, and 10% level (two-tailed), respectively.

Table 4

Cross-sectional Analysis of Banks' Relative Information Advantage (Dependent Variable: AISD)

Variable	Predicted Sign	Coefficient	T-statistic
UE	–	–0.533	(–0.11)
NUE	+	5.894	(2.02)**
UE * NUE	–	–11.754	(–2.51)**
D_AF	–	–15.259	(–4.66)***
UE * D_AF	+	8.946	(1.96)**
SECURE	?	60.356	(17.13)***
UE * SECURE	+	10.068	(2.57)**
Pos_AA	+	11.859	(0.40)
UE * Pos_AA	–	–77.670	(–3.21)***
Neg_AA	?	–45.891	(–1.74)*
UE * Neg_AA	?	–13.411	(–0.54)
Controls		YES	
Year Fixed Effects		YES	
Industry Fixed Effects		YES	
N		5,097	
Adjusted R-squared		0.51	

Notes:
T-statistics are computed based on robust standard errors clustered at the firm level.
Control variables are the same as in Table 3. See Appendix for variable definitions.

***, **, * denote significance at the 1%, 5%, and 10% level (two-tailed), respectively.

Table 5

Inter-temporal Analysis of Banks' Relative Information Advantage (Dependent Variable: AISD)

Variable	Predicted Sign	Coefficient	T-statistic
UE	–	–1.611	(–2.86)***
Aft_RFD	?	4.767	(0.56)
UE * Aft_RFD	?	–2.880	(–1.94)*
FSIZE	?	–12.574	(–6.22)***
MATURITY	?	1.586	(0.81)
SECURE	?	60.36	(23.71)***
TAKEOVER	+	32.224	(7.46)***
LEVERAGE	+	91.240	(9.74)***
RATING	+	2.266	(6.68)***
D_NR	+	19.278	(1.58)
ASSETS	–	–20.168	(–10.07)***
TobinQ	–	–8.541	(–6.26)***
LAGRET	–	–3.069	(–1.58)
COMPLEX	+	13.071	(6.80)***
EARN_VOL	+	10.258	(5.27)***
RET_VOL	+	462.855	(13.81)***
Year Fixed Effects		YES	
Industry Fixed Effects		YES	
N		5, 859	
Adjusted R-squared		0.45	

Notes:
T-statistics are computed based on robust standard errors clustered at the firm level.
See Appendix for variable definitions.

***, **, * denote significance at the 1%, 5%, and 10% level (two-tailed), respectively.

Table 6

Multivariate Regression of Loan Spread on Unexpected Earnings
One Quarter and Two Quarter Forward
(Dependent Variable: AISD)

Variable	Predicted Sign	Quarter t+1 Coefficient	Quarter t+1 T-statistic	Quarter t+2 Coefficient	Quarter t+2 T-statistic
UE_f	–	–3.286	(–1.73)*	–2.001	(–0.40)
FSIZE	?	–13.607	(–7.23)***	–13.650	(–7.07)***
MATURITY	?	–0.100	(–0.05)	–0.238	(–0.12)
SECURE	?	60.324	(18.44)***	63.190	(18.61)***
TAKEOVER	+	24.667	(6.55)***	24.658	(6.40)***
LEVERAGE	+	78.936	(8.59)***	80.717	(8.33)***
RATING	+	1.915	(5.76)***	1.927	(5.52)***
D_NR	+	31.042	(2.82)***	33.587	(3.02)***
ASSETS	–	–12.420	(–6.67)***	–11.813	(–6.20)***
TobinQ	–	–6.253	(–5.30)***	–5.719	(–4.89)***
LAGRET	–	–1.606	(–0.87)	–0.755	(–0.41)
COMPLEX	+	11.442	(6.50)***	10.738	(5.44)***
EARN_VOL	+	7.465	(3.74)***	6.780	(3.31)***
RET_VOL	+	373.862	(11.25)***	371.174	(11.28)***
Year Fixed Effects		YES		YES	
Industry Fixed Effects		YES		YES	
N		5,581		5,228	
Adjusted R-squared		0.51		0.51	

Notes:
UE_f denotes unexpected earnings measured at quarter t+1 and quarter t+2 earnings announcement date respectively. See Appendix for other variable definitions.
T-statistics are computed based on robust standard errors clustered at the firm level.
***, **, * denote significance at the 1%, 5% and 10% level (two-tailed), respectively.

Table 7

Sensitivity Analyses
(Dependent Variable: AISD)

Variables	Instrument Variable Estimation [a]	"Debt Repay" Sub-sample	"Decreasing Interest Expense" Sub-sample	UE based on Annual Forecasts
UE	−20.327	−11.258	−8.778	−6.896
	(−1.74)*	(−2.16)**	(−1.85)*	(−3.87)**
FSIZE	−13.433	−11.968	−14.132	−14.785
	(−6.80)**	(−2.29)*	(−3.98)**	(−7.18)**
MATURITY	−1.218	−13.930	2.975	−1.105
	(−0.64)	(−2.81)**	(1.05)	(−0.56)
SECURE	67.083	51.061	60.002	58.730
	(19.15)**	(8.68)**	(10.35)**	(16.63)**
TAKEOVER	17.268		35.833	27.204
	(4.03)**		(4.30)**	(6.49)**
LEVERAGE	66.641	74.906	94.088	73.258
	(7.17)**	(5.02)**	(7.73)**	(7.85)**
RATING	2.100	1.361	1.540	2.194
	(6.34)**	(2.13)*	(3.03)**	(6.56)**
D_NR	−6.578	40.601	26.572	11.280
	(−0.91)	(1.77)*	(1.45)	(1.08)
ASSETS	−8.417	−10.441	−8.648	−12.452
	(−4.53)**	(−2.27)*	(−2.49)*	(−6.16)**
TobinQ	−7.093	−12.104	−8.466	−6.066
	(−5.79)**	(−4.41)**	(−4.89)**	(−5.09)**
LAGRET	1.350	−4.433	−3.673	−1.095
	(0.61)	(−1.36)	(−0.97)	(−0.54)
COMPLEX	10.782	6.384	13.657	8.926
	(5.77)**	(2.40)*	(5.33)**	(5.07)**
EARN_VOL	7.606	15.023	5.326	8.865
	(3.61)**	(4.14)**	(1.63)	(4.44)**
RET_VOL	413.846	323.929	439.583	367.446
	(13.82)**	(4.38)**	(9.13)**	(11.34)**
Year Fixed Effects	YES	YES	YES	YES
Industry Fixed Effects	YES	YES	YES	YES
N	5,804	1,277	2,106	4,743
R-squared	0.45	0.48	0.52	0.52

Notes:
[a]: The instrument variable is CAR(-1, +1) around quarter t earnings announcement date. In the first stage estimation, CAR(-1, +1) is significantly positively associated with UE (t-stat = 10.97).
Reported in parentheses are t-statistics computed based on robust standard errors clustered at the firm level.
See Appendix for variable definitions.
***, **, * denote significance at the 1%, 5%, and 10% level (two-tailed) respectively.