Lender-Affiliated Analysts and Syndicated Loans

Yongqiang Chu[*] Tao Ma[†] Cong (Roman) Wang[‡]

September 13, 2022

Abstract

We examine whether coverage by analysts affiliated with lenders affects loan contracting. We find that loans to borrowers covered by affiliated analysts have lower spreads but more financial covenants. Further analyses suggest that the results are driven mostly by affiliated analysts sharing information with, but not demanding information from, the lending side. Exploiting plausibly exogenous variation in affiliated analysts generated by changes in brokerage house affiliation, we find that the result is likely to be causal. The results suggest that analysts could transfer private information to their affiliated lenders.

Keywords: Affiliated Analysts, Monitoring, Loan Contracting
JEL Codes: G23, G32, G34

[*]Department of Finance and the Childress Klein Center for Real Estate, Belk College of Business, University of North Carolina at Charlotte. 9201 University City Blvd, Charlotte, NC 28223. Email: yongqiang.chu@uncc.edu.

[†]Department of Accounting, Rawls College of Business, Texas Tech University. 703 Flint Ave, Lubbock, TX 79409. Email: tao.ma@ttu.edu.

[‡]Department of Finance, Rawls College of Business, Texas Tech University. 703 Flint Ave, Lubbock, TX 79409. Email: roman.wang@ttu.edu.

1 Introduction

Recent studies document that information flows among different divisions of a financial conglomerate despite the Chinese Walls. In particular, private information often flows from the lending arms to asset management, security analysis, and trading divisions (e.g., Ivashina, Nair, Saunders, Massoud, and Stover, 2009; Bushman, Smith, and Wittenberg-Moerman, 2010; Chen and Martin, 2011; Ivashina and Sun, 2011; Addoum and Murfin, 2020; Kumar, Mullally, Ray, and Tang, 2020). Given that lenders have access to private information, it is not surprising that information could flow from the lending arms to other parts of a financial conglomerate. However, the literature has largely ignored the possibility that information could flow from other divisions to the lending arms. Other divisions, especially the security analysis division, could access or produce private information about the firms they cover (e.g., Lys and Sohn, 1990; Womack, 1996; Brav and Lehavy, 2003). Such private information may not perfectly overlap with the private information to which lenders have access. If the lending arms happen to lend to those firms, the information could flow from the security analysis division to the lending division.

It is, however, difficult, if not impossible, to directly observe and measure information flow. In this paper, we rely on syndicated loan contracting terms to infer such information flow. If private information can flow from affiliated analysts to the lending arm of the same financial conglomerate, the lenders can use the additional information to better screen and/or more effectively monitor borrowers. The reduced screening or monitoring costs could thus lead to lower spreads on loans covered by lender-affiliated analysts. On the other hand, lenders with better access to exclusive information could increase their information monopoly power to hold up the borrowers, and loan spreads could increase as a result (e.g., Rajan, 1992; Houston and James, 1996; Santos and Winton, 2008).

We obtain syndicated loans information between 1990 and 2016 and identify loans with lead lenders that have affiliated analysts covering the borrowing firms.[1] We refer to a loan whose borrower is (not) covered by a lender-affiliated analyst as an AA (non-AA) loan. We find that AA loans have lower spreads (14 basis points). The results are robust to controlling for various loan and borrower characteristics. In particular, the results remain robust after controlling for the presence of non-commercial bank lenders who are also dual holders, that is, institutions holding the borrowers' equities simultaneously (Jiang, Li, and Shao, 2010). The results also remain robust after controlling for the number of analyst coverage and analyst forecast accuracy, suggesting that we are not just picking up the impact of analyst coverage.

We next examine whether the private information shared by affiliated analysts reduces loan spreads through the screening or the monitoring channel. On one hand, information from affiliated analysts can help lenders better screen potential borrowers and avoid borrowers with excessive risk. On the other hand, lenders can use the information to better monitor the borrowers. Although not mutually exclusive, we try to disentangle these two channels by examining how affiliated analysts affect loan covenants and loan amendments.

If the effects of affiliated analyst coverage are driven by screening, that is, lenders use the private information to select high-quality borrowers, we should expect less need for covenants. On the other hand, if the private information is used for better monitoring, we should expect a greater demand for financial covenants. Specifically, private information possessed by affiliated analysts can help lenders better detect borrowers' financial performance deterioration, which decreases borrower default risk through timely covenant amendments or transfer

[1]We focus on lead-lender-affiliated analysts because lead lenders, rather than participant lenders, conduct screening and monitoring of syndicated loan borrowers, which affects the loan pricing. Consistently, Chen and Martin (2011) find that private information sharing between lenders and analysts occurs only when the lenders are lead lenders.

of control rights after covenant violations.[2] Furthermore, affiliated analysts can constrain borrowers' misreporting to ensure compliance of financial covenants (Yu 2008). Hence, the private information from affiliated analysts can make financial covenants more effective as a monitoring tool. Consistent with the monitoring channel, we find that AA loans have more financial covenants.

To further show that private information is used to better monitor borrowers, we examine whether affiliated analysts affect loan amendments, a likely consequence of material monitoring through financial covenants (David and Jing 2014). If the financial performance of borrowers deteriorates, the lenders can intervene by amending the loan contracts, requiring more loan collateral or increasing loan spreads, for example. Hence, AA loans can result in more amendments, compared with non-AA loans. Consistently, we find that AA loans are more likely to be amended afterwards.

Our results show that affiliated analysts lower loan spreads, consistent with affiliated analysts sharing information with the lenders. However, the results are also consistent with affiliated analysts demanding information from the lenders. Chen and Martin (2011) show that affiliated analysts can use information from the lending side to improve forecast accuracy. As a result, affiliated analysts could pressure the lending side to obtain more information through financial covenants and compensate the borrower with lower loan spreads. To mitigate this concern, we exploit the heterogeneity in the quality of the affiliated analysts. High-quality affiliated analysts are less likely to demand information from, but more likely to share information with, the lending side. If the results are driven by affiliated analysts sharing information with the lending side, the effect should be stronger for high-quality affiliated analysts, who have better access to private information. In contrast, if the results are

[2]For example, upon receiving warnings from affiliated analysts, lenders can increase their site visits to ensure the value of the loan collateral, require more frequent financial reports and personal meetings with the borrowers' management, hire independent auditors to verify firms' financial information or collateral value.

driven by affiliated analysts demanding information from the lending side, the effect should be weaker for high-quality affiliated analysts.

We first use whether the affiliated analyst is an all-star analyst as a proxy for analyst quality and find that the effect is stronger for all-star affiliated analysts. We also use forecast accuracy to measure analyst quality and find that the effect is stronger for affiliated analysts with more accurate forecast. Both results are consistent with affiliated analysts sharing information with, but not demanding information from, the lending side.

The OLS results could suffer from the omitted variable bias. For example, high-quality borrowers are likely to be covered by more analysts, and hence more likely to be covered by analysts affiliated with the lenders. Besides, lenders affiliated with brokerage houses could be different from other lenders and thus could price risk differently. To mitigate these concerns, we conduct analyses at the facility-lender level and add lender×borrower fixed effects to address time-invariant borrower and lender characteristics, as well as endogenous lender-borrower matching. With the lender×borrower fixed effects, we continue to find the negative effect of affiliated analysts on loan spreads, suggesting that the baseline results are unlikely to be driven by endogenous matching or time-invariant borrower or lender characteristics.

With the lender×borrower fixed effects, the variation in the presence of affiliated analysts can only come from two sources. First, the brokerage house affiliated with the lender initiates or terminates the coverage of the borrower; second, the brokerage house changes its affiliation with the lender. The variation generated by affiliated analysts' initiation or termination of coverage is more likely to be endogenous because the decision to change coverage could be driven by the borrower's performance. On the other hand, the variation generated by the changes in brokerage house affiliation with the lenders is less likely to be endogenous because mergers and acquisitions between financial conglomerates are unlikely to be correlated with changes in individual borrower performance. Exploiting variations generated only by changes in brokerage house affiliation, we still find that the presence of affiliated analysts is negatively associated with loan spreads. The results further suggest that the effect of affiliated analysts on loan spreads is likely to be causal.

Our paper contributes to the literature on private information spillover in loan contracting. Most of the existing literature documents that lenders gain access to private information and some lenders use the information for other purposes. Several studies document that lender-affiliated divisions, including asset management, hedge funds, mutual funds, and prime brokers, benefit from trading on the borrowers' equity (e.g., Ivashina, Nair, Saunders, Massoud, and Stover, 2009; Massa and Rehman, 2008; Bushman, Smith, and Wittenberg-Moerman, 2010; Ivashina and Sun, 2011; Massoud, Nandy, Saunders, and Song, 2011; Addoum and Murfin, 2020; Kumar, Mullally, Ray, and Tang, 2020). In particular, Chen and Martin (2011) and Ergungor, Madureira, Nayar, and Singh (2015) show that analysts affiliated with lenders produce more accurate forecasts of borrowers. While these papers all show that private information on loan borrowers flows to the equity market, we contribute to this strand of literature by showing that information can also flow from security analysis divisions to lending divisions.

Our paper also contributes to the literature on analyst information production. The literature has extensively focused on analysts' informational role in the stock market (e.g., Kross, Ro, and Schroeder, 1990; Lys and Sohn, 1990; Womack, 1996; Brav and Lehavy, 2003; Mayew, Sharp, and Venkatachalam, 2013; Amiram, Owens, and Rozenbaum, 2016). Several recent papers examine the role of analyst information production in the debt market. Cheng and Subramanyam (2008), Derrien, Kecskés, and Mansi (2016), and Hallman, Howe, and Wang (2022) show that firms covered by more analysts have a lower cost of debt. Call, Donovan, and Jennings (2021) show that lenders use analyst earnings forecasts to set covenant thresholds and such covenants are more effective. Coyne and Stice (2018) find that analyst forecast accuracy affects collateral requirement in loan contracts. Our paper contributes to this strand of literature by showing that, in addition to using the public information released by analysts to the market, lenders also use private information generated by affiliated analysts to improve the monitoring of borrowers.

The rest of the paper is organized as follows. Section 2 describes the data and sample construction process, Section 3 provides the main empirical results, Section 4 provides the results of different identification strategies, Section 5 provides some additional empirical results, and Section 6 concludes.

2 Data and Summary Statistics

2.1 Sample Selection

We start our sample with syndicated loans from Thomson Reuters Loan Pricing Corporation's (LPC) DealScan database. Our sample starts in 1990, the first year of comprehensive coverage of loan facilities, and ends in 2016. We follow Jiang, Li, and Shao (2010) and exclude the following loans: 1) loans with missing all-in-drawn spread; 2) loans not benchmarked against LIBOR; and 3) bankers' acceptance, bridge loans, leases, loan style floating rate notes, standby letters of credit, step payment leases, bonds, notes, guidance lines, traded letters of credit, multi-option facilities, or undisclosed loans. We focus on analysts affiliated with lead lenders because lead lenders are responsible for screening and monitoring. A lender is a lead lender if the lead arranger credit is coded "Yes" in DealScan or the lender role is reported as "arranger," "lead bank," "agent," "syndication agent," "admin agent," "bookrunner," "mandated arranger," "lead manager," or "managing agent." The final sample consists of 23,586 loan facilities and 44,484 facility-lenders from 17,104 loan packages.

2.2 Variable Construction

2.2.1 Affiliated Analysts

To identify analysts affiliated with the lenders, we use the following procedures. We first obtain all lead lenders from DealScan. To account for mergers and acquisitions among all the lead lenders during our sample period, we construct a comprehensive list of subsidiaries for each financial conglomerate.[3] We obtain the "Relationship" data file, which describes the ownership relationships between banks, and the "Transformation" data file, which tracks mergers and acquisitions between financial institutions, from the National Information Center (NIC). For each lead lender, we identify its ultimate parent and then obtain all subsidiaries of the ultimate parent. We can thus identify all subsidiaries of a financial conglomerate to which a DealScan lead lender belongs.

We obtain data on financial analysts from the 2017 Institutional Brokers' Estimate System database (I/B/E/S). We first obtain all analysts covering the borrowers. We keep analysts who cover the borrower starting from at least three months before facility origination and issue at least one earnings forecast during the lifetime of the facility. In October 2018, Thomson Reuters reshuffled individual broker and analyst IDs in I/B/E/S, making matching individual analysts with brokerage houses impossible. To overcome this issue, we use the 2017 vintage to establish the historical link between analysts and their brokerage houses. Finally, using name matching and manual checking, we pair brokerage houses with DealScan lenders if they are subsidiaries of the same financial conglomerate. A borrower of a syndicated loan is covered by an analyst affiliated with the lender if the brokerage house and the lender are under the umbrella of the same financial conglomerate.

We measure affiliated analyst coverage at the facility, loan, and facility-lender levels. At

[3] See Chen and Martin (2011) for more discussions.

the facility level, we construct the variable *AA Facility*, which equals one if at least one lead lender has affiliated analyst(s) covering the borrower. We also construct *Ln(# AA Lender)*, the natural logarithm of one plus the number of lead lenders with affiliated analyst(s) covering the borrower. At the loan level, we define *AA Package* as an indicator variable that equals one if there is at least one AA facility in the loan package and *Ln(# AA Lender)* as the natural logarithm of one plus the number of AA lead lenders in the loan package. For a given facility-lender pair, we construct *AA Lender*, an indicator variable equal to one if the lead lender is an AA lender for the facility.

2.2.2 Loan Characteristics

Our main dependent variable is *Spread*, the basis points over LIBOR for each dollar drawn down. Loan characteristics include the natural logarithm of the amount of a loan facility (*Ln(Loan Amount)*), the natural logarithm of the loan maturity in months (*Ln(Maturity)*), an indicator variable equal to one if a loan is secured (*Secured*), an indicator variable equal to one if the secured status of a loan is missing (*Missing Secured*), and the natural logarithm of the total number of lenders in a loan syndicate (*Ln(# Lender)*). Following Jiang, Li, and Shao (2010), we construct *Non-CB*, an indicator variable equal to one if there is at least one non-commercial bank lead lender in the loan syndicate, and *Non-CB DH*, an indicator variable equal to one if at least one of the lead lenders is a non-commercial bank with significant equity holdings in the borrowing firm in the same quarter of loan origination. The position must amount to at least 1% of the borrower's common stock outstanding, or its value must exceed $2 million. We use the Thomson Reuters Institutional (13f) Holdings database to identify lenders' equity holdings. We construct *Amendment Dummy*, an indicator variable that equals one if there is at least one amendment for the loan and *Ln(# Amendment)* as the natural logarithm of one plus the number of amendments.

We follow Christensen and Nikolaev (2012) and Bradley and Roberts (2015) to define financial and non-financial covenants and construct two variables (*Covenant Dummy* and *Ln(# Covenant)*) for each category. Financial and non-financial covenants are measured at the package level. We provide detailed discussions of the variable definitions in Table A1 of the Appendix.

2.2.3 Other Variables

We follow Jiang, Li, and Shao (2010) to choose borrower characteristics. We construct borrower characteristics using CRSP, Compustat, the Thomson Reuters Institutional Holdings (13f) database, and the I/B/E/S database, including *Ln(Market Cap)*, *Leverage*, *BM*, *Sales Growth*, *HHI*, *IOR*, *Ind-adj. Ret*, *Z-score*, *Rating*, *No Rating*, *Ln(# Analyst)*, *SUE Volatility*, *Illiq*, and *S&P 500*.[4] We describe the definitions of these variables in Table A1 of the Appendix.

2.3 Summary Statistics

We report the summary statistics of the variables used in the paper in Table 1, with Panel A for variables related to affiliated analyst coverage, Panel B for loan characteristics, and Panel C for borrower characteristics. About 38% of facilities have lead lenders with affiliated analysts. Some facilities have more than one affiliated analyst, resulting in an average of 0.63 affiliated analysts per facility.

The loan and borrower characteristics are similar to those reported by prior studies. The average loan spread is about 177 basis points, and the average loan amount is about $331 million. About 47% of the facilities have a non-commercial bank lead lender, and about 26% have a non-commercial bank dual holder. On average, a syndicated loan has about eight lenders, 1.27 financial covenants and 0.64 non-financial covenants.

[4] We calculate *Z-score* without the leverage component and include leverage as a separate regressor.

[Insert Table 1 here]

3 Main Results

3.1 Lender-Affiliated Analysts and Loan Spreads

We study private information sharing by affiliated analysts by examining the effects of affiliated analysts on loan spreads. If analysts share private information with their affiliated lenders, the private information can help the lenders better screen and/or monitor borrowers, which would lead to lower loan spreads. On the other hand, lenders with affiliated analysts covering the borrowers could also hold up the borrowers (e.g., Rajan, 1992; Houston and James, 1996; Santos and Winton, 2008). If so, we should observe higher loan spreads on AA loans. We estimate the following specification,

$$Spread_i = \beta AA_i + \Gamma Z_i + \text{Fixed Effects} + \varepsilon_i, \tag{1}$$

where i indexes facility; the dependent variable is *Spread*, the loan spread in basis points; the key independent variable is AA, which is either *AA Facility* or *Ln(# AA Lender)*; and Z_i is a vector of loan and borrower characteristics, as defined above. In particular, we include *Non-CB* and *Non-CB DH* to control for non-bank lenders and non-bank debt-equity dual holders to ensure that the effects are not driven by non-bank lenders or non-bank dual holders. We also include the number of analyst coverage *Ln(# Analyst)* and analyst forecast accuracy (SUE) to ensure that our results are not driven by public information released by analysts to the market. To mitigate the concern that loan characteristics are simultaneously determined, we estimate Eq. (1) both with and without loan characteristics. We also include three-digit SIC industry, year-month, loan-type, and loan-purpose fixed effects in the regressions. We double-cluster the standard errors by borrower and year-month.

The results are presented in Table 2. The coefficient estimates on *AA Facility* in columns (1) and (2) are negative and statistically significant at the 1% level, suggesting that the presence of affiliated analysts is associated with lower loan spreads. Without controlling for other loan characteristics, the coefficient estimate on *AA Facility* is -14.0, which amounts to an average saving of $463,400 in interest payments (the average facility amount is $331 million). The coefficient estimates on *Ln(# AA Lender)* in columns (3) and (4) are also negative and statistically significant. As the number of affiliated analysts covering the borrower increases, the lender charges lower loan spreads. The results are consistent with the hypothesis that affiliated analysts share private information with their lending arms.

The coefficient estimates on the control variables are consistent with Jiang, Li, and Shao (2010). In particular, the coefficient estimates on the non-bank dual-holder loan, *Non-CB DH*, are negative and statistically significant in all equations. We also find that the facility amount is negatively associated with the spreads, and the maturity of the facility is not significantly associated with loan spreads. Loan spreads are negatively associated with the number of lenders in a facility. We also find that low book-to-market borrowers, borrowers with more analyst followings, and less levered borrowers incur lower loan spreads. Furthermore, borrowers with no credit rating or low credit rating, high return volatility, low liquidity, and borrowers not included in the S&P 500 index have to pay higher spreads.

[Insert Table 2 here]

3.2 Uses of Shared Information: Screening vs. Monitoring

In this section, we examine how lenders use private information from affiliated analysts. Lenders can use the shared information to better screen potential borrowers and avoid borrowers with excessive risk. Lenders can also use the information to better monitor borrowers after loan origination. Although not mutually exclusive, we try to disentangle the two different uses by analyzing the effects of affiliated analysts on loan covenants and loan amendments.

3.2.1 Affiliated Analysts and Loan Covenants

If the effects of affiliated analysts are driven by better screening, we should expect fewer financial covenants in AA loans. With the selection of low-risk borrowers, ex-post monitoring of borrowers through financial covenants is less important. Financial covenants are costly for borrowers as they restrict borrowers' business operations and financing flexibility (e.g., Chava and Roberts, 2008; Nini, Smith, and Sufi, 2009). They are costly for lenders as well because lenders have to devote resources to monitor covenant compliance (Carrizosa and Ryan, 2017; Frankel, Kim, Ma, and Martin, 2020). Therefore, if lenders can successfully screen out risky borrowers ex ante, we should see fewer covenants in AA loans.

In contrast, if lenders use private information to monitor the borrowers, we should expect more financial covenants in AA loans. Private information of affiliated analysts can help lenders detect borrowers' financial performance deterioration in a timely fashion and minimize default risk through covenant amendments or take control after covenant violations. Furthermore, financial covenants are effective only if borrowers accurately report their financial information. Affiliated analysts can help monitor and discipline borrowers (e.g., Jensen and Meckling, 1976; Healy and Palepu, 2001) and monitor the accuracy of reported financial information (e.g., Yu, 2008; Dyck, Morse, and Zingales, 2010). Therefore, loan contracts are likely to contain more financial covenants when the borrowers are covered by affiliated analysts.

To test the above conjectures, we estimate the following specification,

$$Covenant_i = \beta AA_i + \Gamma Z_i + \text{Fixed Effects} + \varepsilon_i, \tag{2}$$

where i indexes package; the dependent variable is either a dummy variable of indicating at least one financial covenant (*Covenant Dummy*) or the natural logarithm of one plus the number of financial covenants (*Ln(# Covenant)*); the key independent variable is AA, which is either *AA Package* or *Ln(# AA Lender)*; and Z_i is a list of borrower characteristics, as in Eq. (1), and a list of loan package characteristics, including *Ln(Loan Amount)*, *Ln(Maturity)*, *Non-CB*, *Non-CB DH*, and *Ln(# Facility)*. We follow Christensen and Nikolaev (2012) to define financial covenant (see Table A1 in the Appendix for more details). All loan characteristics are aggregated at the package level. We also include three-digit SIC industry and year-month fixed effects in the regressions. We double-cluster the standard errors by borrower and year-month.

The results are presented in Table 3. In columns (1) and (3), the dependent variables are *Covenant Dummy* and *Ln(# Covenant)*. The coefficient estimates on *AA Package* are positive and statistically significant in both columns, suggesting that loans with affiliated analyst coverage have more financial covenants. The coefficient estimate in column (1) (0.057) suggests that the probability that a loan contains financial covenants increases by 5.7% (9.8% of the mean unconditional probability) if the borrower is covered by affiliated analysts. We find similar results using *Ln(# AA Lender)* as the key independent variable. Overall, we find evidence consistent with lenders using the information from affiliated analysts to better monitor borrowers.

As a placebo test, we also examine whether affiliated analysts affect the use of non-financial covenants. Financial analysts are less likely to have non-financial information that is not available to the lenders and therefore are unlikely to affect non-financial covenants. Following Bradley and Roberts (2015), we use sweeps covenants as non-financial covenants. Sweeps covenants require borrowers to retire the loan early if the borrower violates the covenant by issuing more than allowed debt or equity securities (equity sweeps and debt sweeps) or by selling more than allowed assets (assets sale sweeps). The results for non-financial covenants are presented in columns (5)–(8) of Table 3. Consistent with our conjecture, the coefficient estimates on *AA Package* and *Ln(# AA Lender)* are all small and statistically insignificant.

[Insert Table 3 here]

3.2.2 Affiliated Analysts and Loan Amendment

In this section, we provide further evidence to show that information from affiliated analysts helps lenders monitor their borrowers. Active monitoring by affiliated analysts allows lenders to take timely and necessary actions to mitigate lending risk through loan amendments. For example, when informed by the affiliated analysts that the borrower's performance is deteriorating, the lenders can request additional collateral, require more covenants, increase the strictness of current covenants, reduce the loan amount, or increase the loan spreads. Likewise, if the borrower's performance has improved significantly, the lender will feel more confident increasing the loan amount and/or renegotiating other loan terms if requested by the borrower. Hence, if affiliated analysts indeed improve monitoring, we expect AA loans to be likely to be amended. To test this hypothesis, we estimate the following specification,

$$Amendment_i = \beta AA_i + \Gamma Z_i + \text{Fixed Effects} + \varepsilon_i, \tag{3}$$

where i indexes facility; the dependent variable is the dummy variable that equals to one if the loan experiences at least one amendment (*Amendment Dummy*), or the natural logarithm of one plus the number of amendments (*Ln(# Amendment)*); and the key independent variable is AA, which is either *AA Facility* or *Ln(# AA Lender)*. We also include three-digit SIC industry, year-month, loan-type, and loan-purpose fixed effects in the regressions. We double-cluster the standard errors by borrower and year-month.

The results are reported in Table 4. The coefficients on *AA Facility* and *Ln(# AA Lender)* are all positive and statistically significant for both measures of loan amendment, suggesting that AA loans are more likely to be amended. The results are again consistent with the hypothesis that affiliated analysts' shared information facilitates lender monitoring.

[Insert Table 4 here]

3.3 An Alternative Explanation

Our results show that affiliated analysts lower loan spreads, consistent with affiliated analysts sharing information with lenders. However, the results are also consistent with affiliated analysts demanding information from lenders. Chen and Martin (2011) show that affiliated analysts can use information from the lending side to improve forecast accuracy. Consequently, affiliated analyst could pressure the lending side to obtain more information through financial covenants, and compensate the borrower with lower loan spreads. To mitigate this concern, we exploit the heterogeneity in the quality of the AA analysts. High-quality affiliated analysts, who have better access to private information, are less likely to demand information from, but more likely to share information with, the lending side. If the results are driven by affiliated analysts sharing information with the lending side, the effect should be stronger for high-quality affiliated analysts. In contrast, if the results are driven by affiliated analysts demanding information from the lending side, the effect should be weaker for high-quality affiliated analysts. In this section, we use two measures of analyst quality to distinguish between these two channels.

3.3.1 Affiliated All-Star Analysts

First, we use whether the affiliated analysts are all-star analysts to measure analyst quality. We consider an affiliated analyst to be an affiliated all-star analyst if the analyst is on *Institutional Investor*'s All-America Research Team in the year before loan origination. We then compute our AA measures for affiliated all-star and non-all-star analysts. Specifically, *All-Star* (*Non-AllSstar*) *AA Facility* is an indicator variable equal to one if the borrower is covered by at least one affiliated all-star (non-all-star) analyst. *All-Star* (*Non-All-Star*) *Ln(# AA Lender)* is the natural logarithm of one plus the number of AA lenders who have an affiliated all-star (non-all-star) analyst. We estimate the following equation,

$$Spread_i = \beta_1 All\text{-}Star\ AA_i + \beta_2 Non\text{-}All\text{-}Star\ AA_i + \Gamma \mathrm{Z}_i + \text{Fixed Effects} + \varepsilon_i, \qquad (4)$$

where *All-star AA* and *Non-All-Star AA* is either *AA Facility* or *Ln(# AA Lender)*, calculated separately for affiliated all-star and non-all-star analysts.

Table 5 presents the results. We find that the effect on loan spreads for both affiliated all-star and non-all-star analysts remains negative and statistically significant. More importantly, the effect of affiliated all-star analysts is much stronger, as the coefficient estimates on *All-Star AA* are twice as large as those on *Non-all-star AA*. We also formally test the difference between the coefficient estimates and find it to be statistically significant. These results are consistent with affiliated analysts sharing information with the lending side, but inconsistent with affiliated analysts demanding information from, the lending side.

3.3.2 Affiliated Analysts Forecast Accuracy

We also use forecast accuracy to measure analyst quality or analysts' access to private information. We measure analyst forecast accuracy based on the last forecast made by the analyst closest to the firm's fiscal quarter end. However, there are at least two concerns when computing forecast accuracy: 1) firm-year fixed effects in forecast accuracy, and 2) time-series variation in forecast accuracy for the same affiliated analyst.

To account for the first concern, we compute a scaled rank of forecast accuracy ($RAFE$) for each analyst forecast, similar to Healy and Palepu (2001) and Bradley, Gokkaya, and Liu (2017). Specifically, we rank forecasts from all analysts covering the same firm-quarter by the absolute forecast error in *descending* order and scale the rank by the total number of analysts covering that firm-quarter. A forecast with a high $RAFE$ has high forecast accuracy relative to other forecasts of the same firm during the same time period. To account for the second concern, we compute an analyst-facility-level forecast accuracy ranking, $RAFE_{i,j}$. That is, for an affiliated analyst i covering facility j, we compute the average $RAFE$ across all forecasts made by the affiliated analyst i within one year prior to the origination date of facility j. Therefore, the same analyst may have different levels of forecast accuracy for different facilities. To ensure robustness, we also compute the average $RAFE$ across all forecasts made during the lifetime of the facility.

Finally, we group all $RAFE_{i,j}$ into terciles and compute our AA measures for each tercile. Specifically, *High* (*Mid*, *Low*) *AA Facility* is an indicator variable equal to one if the borrower is covered by at least one affiliated analyst whose $RAFE_{i,j}$ is in the top (middle, bottom) tercile. *High* (*Mid*, *Low*) Ln(# AA Lender) is the natural logarithm of one plus the number of AA lenders who have an affiliated analyst whose $RAFE_{i,j}$ is in the top (middle, bottom) tercile.

To illustrate the measure with an example, consider an affiliated analyst i covering firms A, B, and C, where firm A is an affiliated borrower. For a given fiscal quarter q of firm B (and C), we compute the scaled rank of absolute forecast error, $RAFE_{i,B,q}$. Specifically, $RAFE_{i,B,q}$ is the *descending* rank of i against all other analysts that issued an earnings forecast for fiscal quarter q of firm B, based on absolute forecast errors and scaled by the total number of analysts. For example, if i is the most accurate among five analysts, $RAFE_{i,B,q}$ equals $1/5 = 0.2$. We do the same for firm C. Suppose firm A receives facility j from the lender affiliated with i at time t. We then compute a facility-analyst level $RAFE_{i,j}$. Specifically, $RAFE_{i,j}$ is the average of $RAFE_{i,B,q}$ and $RAFE_{i,C,q}$ over the four quarters before loan origination. We do not include analyst i's forecast of firm A in this calculation because lender affiliation affects analyst forecast accuracy (Chen and Martin 2011). We also compute the average $RAFE_{i,B,q}$ and $RAFE_{i,C,q}$ over the life time of the loan. Further suppose there are two AA facilities in our sample. The first AA facility covered by two affiliated analysts with an $RAFE_{i,j}$ of 0.1 and 0.9, respectively. The second AA facility is covered by one affiliated analyst with an $RAFE_{i,j}$ of 0.5. After grouping all three $RAFE_{i,j}$ into terciles, the first AA facility is covered by an affiliated analyst in the High group and an affiliated analyst in the Low group. The second AA facility is covered by an affiliated analyst in the Mid group. Therefore, *High AA Facility*, *Mid AA Facility*, and *Low AA Facility* take values of 1, 0, and 1 for the first AA facility and values of 0, 1, and 0 for the second AA facility.

We estimate the following equation,

$$Spread_i = \beta_1 High\ AA_i + \beta_2 Mid\ AA_i + \beta_3 Low\ AA_i + \Gamma Z_i + \text{Fixed Effects} + \varepsilon_i, \quad (5)$$

where *High* (*Mid*, *Low*) *AA* is either *AA Facility* or *Ln(# AA Lender)* calculated separately for *High* (*Mid*, *Low*) affiliated analysts. *High*, *Mid*, and *Low* affiliated analysts are defined above.

In columns (1) and (2) of Table 6, we measure the accuracy in the year before loan origination, and in columns (3) and (4), we measure the accuracy after loan origination. In column (1), the coefficient estimate on *High AA Facility* is -5.393 and statistically significant at the 1% level. The coefficient estimate on *Low AA Facility* is 3.139 and statistically insignificant. Furthermore, the difference between the two coefficient estimates is statistically significant at the 1% level. We find similar results for the last three columns. These results suggest that the effect of affiliated analysts on loan spreads is stronger when the affiliated analysts are more accurate in their forecast earnings. They are consistent with our hypothesis that the private information possessed by affiliated analysts helps lenders better monitor the borrowers.

4 Identification

The results above suggest that loans with affiliated analysts have lower spreads, which is consistent with private information flows from affiliated analysts to the lending division. However, the effects on the loan spreads can also be driven by unobservable borrower or lender characteristics that can affect loan contracting. For example, low credit risk borrowers are likely to be covered by more analysts, and hence more likely to be covered by analysts affiliated with the lenders. Besides, lenders affiliated with brokerage houses could be very different from other lenders and thus could price risk or monitor borrowers differently. In this section, we reconstruct the sample at the lender-facility level and conduct additional tests to mitigate the endogeneity concerns.

4.1 Lender-Borrower Fixed Effects

To control for endogeneity concerns driven by time-invariant borrower or lender characteristics and endogenous matching between borrowers and lenders, we conduct our analysis at the lender-facility level and include lender$\times$borrower fixed effects in our baseline regressions. Specifically, we estimate the following equation,

$$Spread_i = \beta AA\ Lender_{i,j} + \Gamma Z_i + \text{Fixed Effects} + \varepsilon_{i,j}, \quad (6)$$

where i indexes facility and j indexes lead lender. $AA\ Lender_{i,j}$ is an indicator variable equal to one if lead lender j has one or more affiliated analysts covering the borrower of facility i. Besides the inclusion of lender×borrower fixed effects, the control variables and fixed effects are the same as those in Eq. (1). To ensure that our results are not driven by the difference in sample selection, we require the observations to have non-missing values for all independent variables, regardless of the inclusion of control variables. Under this specification, we compare loan spread differences between loans issued by the same lender to the same borrower but that differ in affiliated analyst coverage.

The results are presented in columns (1) and (2) of Table 7. The coefficient estimates on *AA Lender* are both negative and statistically significant. For example, in column (2), in which all other loan characteristics are included, the coefficient is -5.724 and statistically significant at the 1% level. Hence, for the same firm borrowing from the same lender, the loan spread is 5.72 basis points lower if the borrower is covered by analysts affiliated with the lender. These results suggest that the negative effect of the affiliated analyst on loan spreads, as documented in Table 2, is unlikely to be driven by time-invariant unobservable borrower or lender characteristics or endogenous matching between borrowers and lenders.

4.2 Changes in Brokerage House Affiliation

With the inclusion of lender×borrower fixed effects, the variation in affiliated analyst coverage within the same lender-borrower pair could come from either (1) the initiation or termination of coverage by an analyst affiliated with the lender, or (2) the change of affiliation of the brokerage house with analysts covering the borrower. The initiation or termination of coverage by analysts affiliated with the lender can still be endogenous. For example, analysts affiliated with the lender could initiate the coverage of the borrower because the borrower is performing better, or terminate the coverage because the borrower is performing worse. On the other hand, the variation driven by the changes in brokerage house affiliation is less likely to suffer from endogeneity concerns. In particular, the decision of a lender to acquire (or to divest from) a brokerage house that has an analyst covering the borrower is unlikely to be driven by the borrower in question (e.g., Hong and Kacperczyk, 2010; Kelly and Ljungqvist, 2012; Chu, 2018). In this subsection, we therefore exploit variations in affiliated analyst coverage generated by changes in brokerage house affiliation.

To this end, we construct a more restrictive affiliated analyst measure, *Conditional AA Lender*, and repeat the analyses in Section 4.1. For a given facility-lender pair, *Conditional AA Lender* equals one if: (1) the lender has at least one affiliated analyst covering the borrower, (2) the borrower has at least one loan from the lender before the analyst becomes affiliated with the lender, and (3) the analyst must cover at least one loan from the borrower before becoming affiliated with the lender. Note that *AA Lender* in Section 4.1 is defined using criterion (1) alone. Criterion (2) ensures that the borrower-lender relationship is not endogenous to change in the brokerage house affiliation. Criterion (3) ensures that the coverage from affiliated analysts is not endogenous to the change in the brokerage house affiliation. Combining all three criteria, we capture the changes in the brokerage house affiliation status (from unaffiliated to affiliated) while maintaining the same brokerage house coverage and the same lending relationship.

Using *Conditional AA Lender*, we estimate the following regression:

$$Spread_i = \beta Conditional\ AA\ Lender_{i,j} + \Gamma Z_i + \text{Fixed Effects} + \varepsilon_{i,j}, \tag{7}$$

where i indexes facility and j indexes lender. To isolate the effect of *Conditional AA Lender*, we exclude AA loans in which none of the AA lenders are conditional AA lenders. All other empirical specifications are the same as in Eq. (6). We report the results in columns (3) and

(4) of Tables 7. The coefficient estimates on *Conditional AA Lender* are both negative and statistically significant. To the extent that changes in brokerage affiliation are exogenous, these results suggest that the effect of affiliated analysts on loan spreads is likely to be causal.

[Insert Table 7 here]

5 Additional Results

5.1 Lender Loan Share

In this section, we provide further evidence that affiliated analysts privately share their information with their affiliated lenders. Ivashina (2009) argues that, due to moral hazard concerns stemming from the information asymmetry between lenders of the syndicated loans, lead lenders have to hold more shares of the loan to commit to monitoring of the borrower. If affiliated analysts privately share information with their affiliated leader lenders, the information asymmetry among the lead lenders should increase. Hence, to minimize the moral hazard problems within the syndication, AA lenders would likely commit to the monitoring by retaining more loan shares. Therefore, we should observe a higher loan share held by AA lenders. To test this conjecture, we estimate the following regression,

$$Allocation_{i,j} = \beta AA\ Lender_{i,j} + \text{Fixed Effects} + \varepsilon_{i,j}, \tag{8}$$

where i indexes facility and j indexes lead lender. The dependent variable is *Allocation*, which is the share of the loans held by lead lender j in facility i. The key independent variable is *AA Lender*, a dummy variable equal to one if lead lender j has an affiliated analyst covering the borrower in facility i. We also control for facility and lender-year fixed effects. We double-cluster the standard errors by borrower and year-month. The results are reported in Table 8. The coefficient estimates on *AA Lender* are positive and statistically significant, suggesting that lead banks with affiliated analysts hold more shares of the loans within the same loan facility. The results are consistent with affiliated analysts privately sharing their information with the lenders.

[Insert Table 8 here]

5.2 Affiliated Analysts and Ex Post Borrower Credit Risk

In this section, we examine whether the lower spreads on AA loans are driven by the reduced borrower credit risk. If the effect of affiliated analysts is through more effective monitoring, we should expect the credit risk of AA borrowers to deteriorate less or improve after receiving the loans relative to a non-AA borrower. To test this conjecture, we use Altman's *Z-score* to measure borrower credit risk. Following Jiang, Li, and Shao (2010), We adopt a differences-in-differences specification to examine how affiliated analysts impact firm risk. In particular, we estimate the following equation at the borrower-year level to compare changes in risk before and after loan origination, with and without affiliated analysts.

$$Z\text{-}score_{i,t} = \sum_{j=-4}^{4} \beta_{t+j}^{AA} d_{t+j}^{AA} + \sum_{j=-4}^{4} \beta_{j}^{non\text{-}AA} d_{t+j}^{non\text{-}AA} + \Gamma Z_{i,t} + \text{Fixed Effects} + \varepsilon_{i,t}, \qquad (9)$$

where i indexes borrowers and t indexes years. The dependent variable is Altman's *Z-score*. *Z-score* is calculated without the leverage component when estimating the score to avoid the mechanical effects due to borrowing a new loan. A higher value of *Z-score* corresponds to lower credit risk. d_{t+j}^{AA} ($d_{t+j}^{non\text{-}AA}$), $j \in [-4, 4]$ are indicator variables for a firm-year where $j =$ years before/after receiving an AA (non-AA) loan. β_{t+j}^{AA} ($\beta_{t+j}^{non\text{-}AA}$) represents the difference in *Z-score* for firms that are j years from the AA (non-AA) loan origination and that of firms without any loan. $Z_{i,t}$ is the same vector of control variables as in Eq. (1), excluding *Z-score*. We also control for borrower and year fixed effects and double-cluster the standard errors by borrower and year.

We plot the estimates of β_{t+j}^{AA} and β_{t+j}^{non-AA} in Figure 1. The top plot shows the coefficient estimates without control variables. The *Z-score* for both AA and non-AA borrowers increases before loan origination. After receiving loans, AA borrowers and non-AA borrowers exhibit different trends. Non-AA borrowers' *Z-score* decreases and becomes indistinguishable from non-borrowers, two years after loan origination. In contrast, AA borrowers' *Z-score* remains significantly higher than non-borrowers, after loan origination. We find similar results when including control variables (the bottom plot in Figure 1).

[Insert Figure 1 here]

5.3 Affiliated Analysts and Information Opacity

We argue that lead lenders benefit from their affiliated analysts' information sharing, which enhances the monitoring of the borrowers after loan origination. It follows that the benefits should be greater if the borrowers are more opaque and, hence more costly to monitor. In this section, we exploit the cross-sectional heterogeneity in borrowers' information opacity to further ascertain whether the effects of affiliated analyst coverage are indeed driven by analysts' sharing of private information in facilitating ex-post monitoring.

To measure information opacity, we follow Dechow, Sloan, and Sweeney (1995) and calculate the absolute value of discretionary accruals ($|DiscAcc|$) (e.g., Francis, LaFond, Olsson, and Schipper, 2005; Bhattacharya, Desai, and Venkataraman, 2013). Companies may hide financial information using discretionary accruals, which lowers the information quality and makes it difficult for lenders to monitor. Analysts, however, are experts in deciphering financial information and could mitigate the information opacity induced by discretionary accruals (e.g., Yu, 2008; Lobo, Song, and Stanford, 2012). We therefore expect that lenders may find affiliated analysts' information more valuable if the borrowers are more opaque. Hence, the effect of affiliated analysts on loan spreads should be stronger for firms with high discretionary accruals. To ensure robustness, We also compute the opacity measure, (*Opacity*), as the three-year rolling sum of $|DiscAcc|$, as in Hutton, Marcus, and Tehranian (2009).

We then estimate the following equation,

$$\begin{aligned} Spread_i =& \beta_1 AA_i \times Information\ Opacity_i + \beta_2 AA_i + \beta_3 Information\ Opacity_i \\ &+ \Gamma Z_i + \text{Fixed Effects} + \varepsilon_i, \end{aligned} \tag{10}$$

where i indexes facility; *Information Opacity* is one of the two information opacity measures, $|DiscAcc|$ or *Opacity*. All other empirical specifications are the same as in Table 2. We report the results in Table 9. The coefficient estimates on AA remain negative and statistically significant. Furthermore, the coefficient estimates on the interaction terms are negative and statistically significant across all specifications. The result is consistent with our conjecture that the negative effect of affiliated analysts on the loan spreads is stronger for the more opaque borrowers.

[Insert Table 9 here]

5.4 Affiliated Analysts and Borrower Distress

In this section, we examine whether affiliated analysts' monitoring effect is more pronounced for financially distressed firms. If the affiliated analysts indeed help lenders monitor borrowers, the benefits of additional information should be greater when the borrowers are close to default. We use *Z-score* and *Leverage* to measure borrower distress and estimate the following equation,

$$\begin{aligned} Spread_i =& \beta_1 AA_i \times Borrower\ Distress_i + \beta_2 AA_i + \beta_3 Borrower\ Distress_i \\ &+ \Gamma Z_i + \text{Fixed Effects} + \varepsilon_i, \end{aligned} \tag{11}$$

where *Borrower Distress* is one of the two distress measures, *Z-score* or *Leverage*. We calculate *Z-score* excluding the leverage component to capture the financial distress caused by factors not related to leverage and examine the leverage component separately. All other empirical specifications are the same as in Table 2. We report the results in Table 10. Consistent with our conjecture, the effect of affiliated analysts is more pronounced for more financially distressed firms, that is, firms with a lower *Z-score* or higher leverage.

[Insert Table 10 here]

6 Conclusion

We examine how the coverage by analysts affiliated with lenders affects loan contracting. We find that affiliated analysts lead to lower loan spreads but more financial covenants. The results suggest that affiliated analysts produce and transmit information to affiliated lenders, who then use the information to more effectively monitor the borrowers. More broadly, the results suggest that information can flow from the equity side to the lending side of financial conglomerates, which helps resolve the information asymmetry problem in loan contracting and improves monitoring ex post. Our study contributes to the literature on private information spillover in loan contracting. Prior studies document that lenders gain access to private information and share the information with other divisions of the same conglomerate. We show that information produced by equity analysts can also flow to affiliated lenders and improve loan contracting.

References

Addoum, Jawad M, and Justin R Murfin, 2020, Equity price discovery with informed private debt, *Review of Financial Studies* 33, 3766–3803.

Altman, Edward I, 1968, Financial ratios, discriminant analysis and the prediction of corporate bankruptcy, *Journal of Finance* 23, 589–609.

Amihud, Yakov, 2002, Illiquidity and stock returns: Cross-section and time-series effects, *Journal of Financial Markets* 5, 31–56.

Amiram, Dan, Edward Owens, and Oded Rozenbaum, 2016, Do information releases increase or decrease information asymmetry? New evidence from analyst forecast announcements, *Journal of Accounting and Economics* 62, 121–138.

Bhattacharya, Nilabhra, Hemang Desai, and Kumar Venkataraman, 2013, Does earnings quality affect information asymmetry? Evidence from trading costs, *Contemporary Accounting Research* 30, 482–516.

Bradley, Daniel, Sinan Gokkaya, and Xi Liu, 2017, Before an analyst becomes an analyst: Does industry experience matter?, *The Journal of Finance* 72, 751–792.

Bradley, Michael, and Michael R Roberts, 2015, The structure and pricing of corporate debt covenants, *Quarterly Journal of Finance* 5, 1550001.

Brav, Alon, and Reuven Lehavy, 2003, An empirical analysis of analysts' target prices: Short-term informativeness and long-term dynamics, *Journal of Finance* 58, 1933–1967.

Bushman, Robert M, Abbie J Smith, and Regina Wittenberg-Moerman, 2010, Price discovery and dissemination of private information by loan syndicate participants, *Journal of Accounting Research* 48, 921–972.

Call, Andrew C, John Donovan, and Jared Jennings, 2021, Private lenders' use of analyst earnings forecasts when establishing debt covenant thresholds, Forthcoming, The Accounting Review.

Carrizosa, Richard, and Stephan Ryan, 2017, Borrower private information covenants and loan contract monitoring, *Journal of Accounting and Economics* 64, 313–339.

Chava, Sudheer, and Michael R Roberts, 2008, How does financing impact investment? The role of debt covenants, *Journal of Finance* 63, 2085–2121.

Chen, Ting, and Xiumin Martin, 2011, Do bank-affiliated analysts benefit from lending relationships? *Journal of Accounting Research* 49, 633–675.

Cheng, Mei, and KR Subramanyam, 2008, Analyst following and credit ratings, *Contemporary Accounting Research* 25, 1007–1044.

Christensen, Hans B, and Valeri V Nikolaev, 2012, Capital versus performance covenants in debt contracts, *Journal of Accounting Research* 50, 75–116.

Chu, Yongqiang, 2018, Shareholder-creditor conflict and payout policy: Evidence from mergers between lenders and shareholders, *Review of Financial Studies* 31, 3098–3121.

Coyne, Joshua, and Derrald Stice, 2018, Do banks care about analysts' forecasts when designing loan contracts?, *Journal of Business Finance & Accounting* 45, 625–650.

David, Denis, and Wang Jing, 2014, Debt covenant renegotiations and credit control rights, *Journal of Financial Economics* 113, 348–367.

Dechow, Patricia M, Richard G Sloan, and Amy P Sweeney, 1995, Detecting earnings management, *The Accounting Review* 70, 193–225.

Derrien, François, Ambrus Kecskés, and Sattar A Mansi, 2016, Information asymmetry, the cost of debt, and credit events: Evidence from quasi-random analyst disappearances, *Journal of Corporate Finance* 39, 295–311.

Dyck, Alexander, Adair Morse, and Luigi Zingales, 2010, Who blows the whistle on corporate fraud? *Journal of Finance* 65, 2213–2253.

Ergungor, Ozgur E, Leonardo Madureira, Nandkumar Nayar, and Ajai K Singh, 2015, Lending relationships and analysts' forecasts, *Journal of Financial Intermediation* 24, 71–88.

Francis, Jennifer, Ryan LaFond, Per Olsson, and Katherine Schipper, 2005, The market pricing of accruals quality, *Journal of Accounting and Economics* 39, 295–327.

Frankel, Richard, Bong H Kim, Tao Ma, and Xiumin Martin, 2020, Bank monitoring and financial reporting quality: The case of accounts receivable-based loans, *Contemporary Accounting Research* 37, 2120–2144.

Hallman, Nicholas, John S Howe, and Wei Wang, 2022, Analyst coverage and syndicated lending, Forthcoming, *Review of Accounting Studies*.

Healy, Paul M, and Krishna G Palepu, 2001, Information asymmetry, corporate disclosure, and the capital markets: A review of the empirical disclosure literature, *Journal of Accounting and Economics* 31, 405–440.

Hong, Harrison, and Marcin Kacperczyk, 2010, Competition and bias, *Quarterly Journal of Economics* 125, 1683–1725.

Houston, Joel, and Christopher James, 1996, Bank information monopolies and the mix of private and public debt claims, *Journal of Finance* 51, 1863–1889.

Hutton, Amy P, Alan J Marcus, and Hassan Tehranian, 2009, Opaque financial reports, R2, and crash risk, *Journal of Financial Economics* 94, 67–86.

Ivashina, V., 2009, Asymmetric information effects on loan spreads, *Journal of Financial Economics* 92, 300 – 319.

Ivashina, Victoria, Vinay B Nair, Anthony Saunders, Nadia Massoud, and Roger Stover, 2009, Bank debt and corporate governance, *Review of Financial Studies* 22, 41–77.

Ivashina, Victoria, and Zheng Sun, 2011, Institutional stock trading on loan market information, *Journal of Financial Economics* 100, 284–303.

Jensen, Michael C, and William H Meckling, 1976, Theory of the firm: Managerial behavior, agency costs and ownership structure, *Journal of Financial Economics* 3, 305–360.

Jiang, Wei, Kai Li, and Pei Shao, 2010, When shareholders are creditors: Effects of the simultaneous holding of equity and debt by non-commercial banking institutions, *Review of Financial Studies* 23, 3595–3637.

Kelly, Bryan, and Alexander Ljungqvist, 2012, Testing asymmetric-information asset pricing models, *Review of Financial Studies* 25, 1366–1413.

Kross, William, Byung Ro, and Douglas Schroeder, 1990, Earnings expectations: The analysts' information advantage, *The Accounting Review* 65, 461–476.

Kumar, Nitish, Kevin Mullally, Sugata Ray, and Yuehua Tang, 2020, Prime (information) brokerage, *Journal of Financial Economics* 37, 371–391.

Lobo, Gerald J, Minsup Song, and Mary Stanford, 2012, Accruals quality and analyst coverage, *Journal of Banking and Finance* 36, 497–508.

Lys, Thomas, and Sungkyu Sohn, 1990, The association between revisions of financial analysts' earnings forecasts and security-price changes, *Journal of Accounting and Economics* 13, 341–363.

Massa, Massimo, and Zahid Rehman, 2008, Information flows within financial conglomerates: Evidence from the banks-mutual funds relation, *Journal of Financial Economics* 89, 288–306.

Massoud, Nadia, Debarshi Nandy, Anthony Saunders, and Keke Song, 2011, Do hedge funds trade on private information? Evidence from syndicated lending and short-selling, *Journal of Financial Economics* 99, 477–499.

Mayew, William J, Nathan Y Sharp, and Mohan Venkatachalam, 2013, Using earnings conference calls to identify analysts with superior private information, *Review of Accounting Studies* 18, 386–413.

Nini, Greg, David C Smith, and Amir Sufi, 2009, Creditor control rights and firm investment policy, *Journal of Financial Economics* 92, 400–420.

Rajan, Raghuram G, 1992, Insiders and outsiders: The choice between informed and arm's-length debt, *Journal of Finance* 47, 1367–1400.

Santos, Joao AC, and Andrew Winton, 2008, Bank loans, bonds, and information monopolies across the business cycle, *Journal of Finance* 63, 1315–1359.

Womack, Kent L, 1996, Do brokerage analysts' recommendations have investment value? *Journal of Finance* 51, 137–167.

Yu, Fang, 2008, Analyst coverage and earnings management, *Journal of Financial Economics* 88, 245–271.

Table A1: Variable Definitions

Panel A: Facility-Level Loan Characteristics	
AA Facility	An indicator variable equal to one if at least one lead lender that have affiliated analyst(s) covering the borrower, or zero otherwise.
Ln(# AA Lender)	Natural logarithm of one plus the number of lead lenders that have affiliated analyst(s) covering the borrower.
Spread	The number of basis points over LIBOR for each dollar drawn.
Ln(Loan Amount)	Natural logarithm of the loan facility amount.
Ln(Maturity)	Natural logarithm of the loan maturity in months.
Non-CB	An indicator variable equal to one if at least one Non-CB lender in the loan syndicate.
Non-CB DH	An indicator variable equal to one if at least one Non-CB lender of the facility has significant equity holdings in the borrowing firm in the same quarter of loan origination. The position must amount to at least 1% of the borrower's common stock outstanding or its value must exceed $2 million.
Secured	An indicator variable equal to one if a loan is secured, and zero otherwise.
Missing Secured	An indicator variable equal to one if the secured status of a loan is missing, and zero otherwise.
Ln(# Lender)	Natural logarithm of the total number of lenders in a loan syndicate.
Amendment Dummy	An indicator variable equal to one if there is at least one amendment.
Ln(# Amendment)	Natural logarithm of the total number of amendments.
Panel B: Package-Level Loan Characteristics	
AA Package	An indicator variable equal to one if there is at least one lead lender that has affiliated analyst(s) covering the borrower, or zero otherwise.
Ln(# AA Lender)	Natural logarithm of one plus the number of lead lenders that have affiliated analyst(s) covering the borrower.
Spread	The loan amount-weighted average spread in a loan package.
Ln(Loan Amount)	Natural logarithm of the total loan amount in a loan package.
Ln(Maturity)	Natural logarithm of the loan amount-weighted average loan maturity in months in a loan package.
Non-CB	An indicator variable equal to one if at least one Non-CB lender in the loan syndicate.
Non-CB DH	An indicator variable equal to one if at least one facility has one or more Non-CB lenders that have significant equity holdings in the borrowing firm in the same quarter of loan origination. The position must amount to at least 1% of the borrower's common stock outstanding or its value must exceed $2 million.
Ln(# Facility)	Natural logarithm of the number of facilities.
Covenant Dummy	An indicator variable equal to one if there is at least one covenant.
Ln(# Covenant)	Natural logarithm of one plus the total number of covenants.
Financial covenant	Following Christensen and Nikolaev (2012), financial covenants include all the debt or interest coverage ratios, level of earnings, quick/current ratios, debt to equity, value, or tangible net worth; leverage ratio, and net worth requirement.
Non-financial covenants	Following Bradley and Roberts (2015), non-financial covenants include debt/equity issuance sweep, insurance proceed sweep, and excess cash flow sweep.

Table A1: Continued

Panel C: Loan-Lender-Level Characteristics	
AA Lender	An indicator variable equal to one if the lead lender has affiliated analyst(s) covering the borrower of the loan, or zero otherwise.
Conditional AA Lender	An indicator equal to one if, (1) the lead lender has at least one affiliated analyst covering the borrower, (2) the borrower has at least one loan from the lender before the analyst become affiliated with the lead lender, and (3) the affiliated analyst must cover at least one loan before the analyst becomes affiliated with the lead lender.
Allocation	The percentage a lender has committed to the given facility.
Panel D: Borrower Characteristics	
Ln(Market Cap)	Natural logarithm of the borrower's market capitalization.
Leverage	The borrower's book value of total debt over book value of total assets.
BM	The borrower's book-to-market ratio from Financial Ratios Suite by WRDS.
Sales Growth	The borrower's sales growth over the past 12 quarters.
HHI	The sum of squares of the fractions of sales contributed by the borrower's different business segments.
IOR	The fraction of total institutional ownership in the borrower.
Ind-adj. Ret	The borrower's stock return in excess of the corresponding three-digit SIC industry return.
Z-score	Altman bankruptcy *Z-score* is calculated as $Z = 1.2X_1 + 1.4X_2 + 3.3X_3 + 0.6X_4 + 1.0X_5$, where X_1 is working capital/total assets, X_2 is retained earnings/total assets, X_3 is earnings before interest and taxes/total assets, X_4 is market value equity/book value of total liabilities, and X_5 is sales/total assets (Altman, 1968). Following Jiang, Li, and Shao (2010), all X variables are winsorized at -4.0 and +8.0. In regressions, we use Altman bankruptcy *Z-score* excluding the term X_4.
Rating	The borrower's S&P long-term domestic issuer credit rating. A higher value corresponds to a lower rating. Missing ratings are assigned to zero.
No Rating	An indicator variable equal to one if the borrower does not have an S&P credit rating, and zero otherwise.
Ln(# Analyst)	Natural logarithm of one plus the total number of analysts who make forecasts for the borrower's stock.
SUE	The absolute forecast errors calculated as the absolute value of the difference between the consensus forecast of the borrower's annual earnings per share (EPS), scaled by the borrower's stock price. Consensus forecast is based on the median forecast of the most recent report for each analysts issued within 90 days of the fiscal year end. For each loan, we average scaled absolute forecast errors three years prior to the loan origination date. If a borrower is not covered by any analyst, SUE is assigned a value of zero.
No Coverage	An indicator variable equal to one if the borrower is not covered by any analyst, and zero otherwise.
Volatility	The borrower's stock return volatility using the most recent years of monthly stock returns.

Table A1: Continued

Panel D: Continued	
Illiq	The Amihud (2002) illiquidity measure is defined as the yearly average of 1,000 times the square root of return/(dollar trading volume), using daily data.
S&P 500	An indicator variable equal to one if the borrower belongs to the S&P 500 index, and zero otherwise.
|DiscAcc|	The absolute value of discretionary annual accrual as a fraction of lagged assets, following Hutton, Marcus, and Tehranian (2009).
Opacity	The three-year moving sum of the absolute value of annual discretionary accruals.

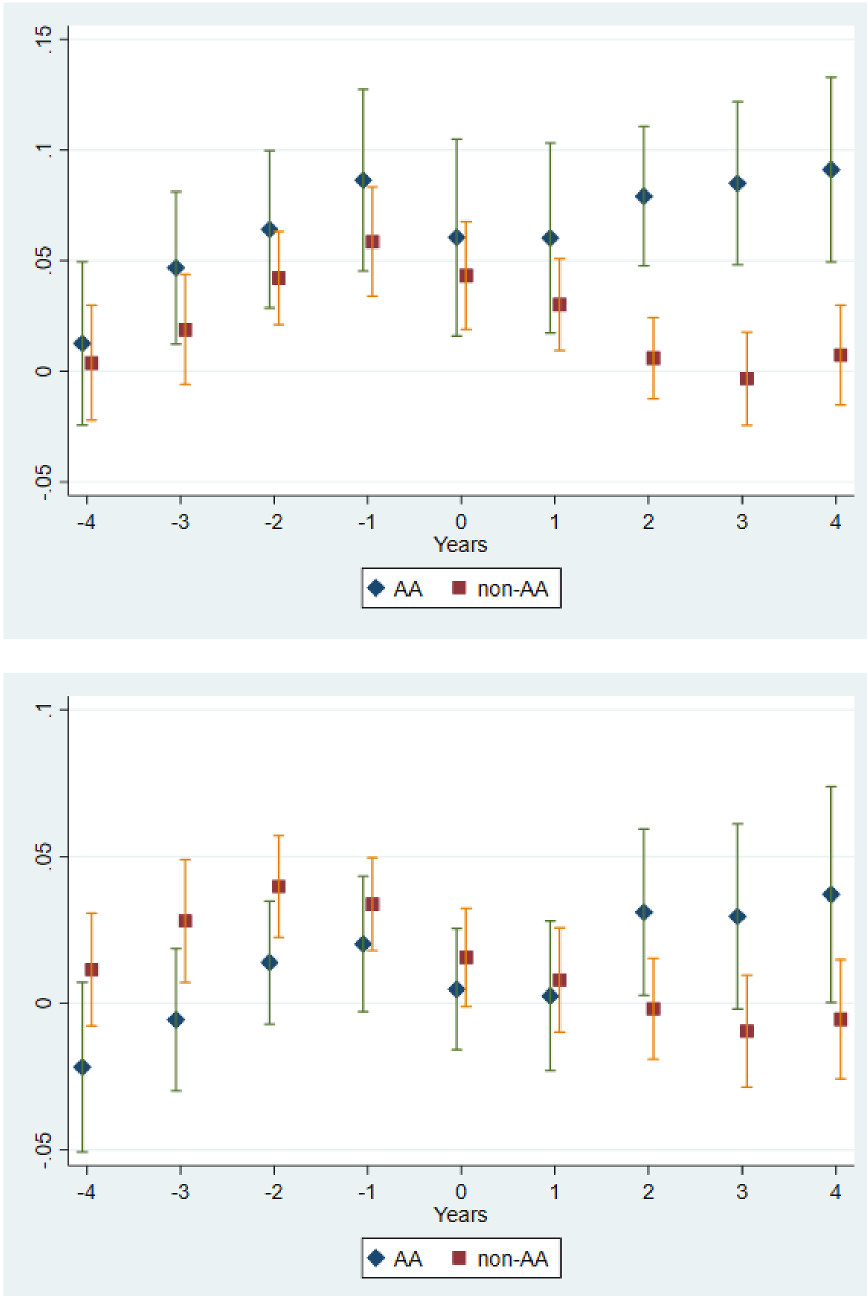

Figure 1: Ex Post Borrower Credit Risk

This figure plots the coefficient estimates of the event year dummy variables from Eq. (9). We plot estimates of β^{AA}_{t+j} and $\beta^{\text{non-AA}}_{t+j}$, $j =\in [+4, -4]$, as well as the 95% confidence band of the estimates (vertical lines). In the top (bottom) figure, we plot the coefficient estimated with (without) control variables.

Table 1: Descriptive Statistics

This table reports summary statistics for the main variables used in the analyses. Affiliated analyst variables and loan characteristics are at the facility level, unless indicated otherwise. Firm characteristics are computed using the most recent data as of one month before loan origination. Variable definitions are in Table A1 of the Appendix.

Panel A: Affiliated Analyst

	Mean	Std. Dev.	25th Percentile	Median	75th Percentile
AA Facility (Facility Level)	0.38	0.49	0.00	0.00	1.00
# AA Lender (Facility Level)	0.63	0.93	0.00	0.00	1.00
AA Package (Loan Level)	0.38	0.48	0.00	0.00	1.00
# AA Lender (Loan Level)	0.63	0.94	0.00	0.00	1.00
AA Lender (Facility-Lender Level)	0.24	0.43	0.00	0.00	0.00

Panel B: Loan Characteristics

	Mean	Std. Dev.	25th Percentile	Median	75th Percentile
Spread	177.30	116.10	87.50	150.00	250.00
Loan Amount	331.00	472.23	50.00	150.00	400.00
Maturity	48.28	21.68	36.00	60.00	60.00
Non-CB	0.47	0.50	0.00	0.00	1.00
Non-CB DH	0.26	0.44	0.00	0.00	1.00
Secured	0.50	0.50	0.00	0.00	1.00
Missing Secured	0.29	0.45	0.00	0.00	1.00
# Lender	8.06	7.34	2.00	6.00	11.00
# Amendment	0.50	1.38	0.00	0.00	0.00
# Facility (Package)	1.38	0.67	1.00	1.00	2.00
Covenant Dummy (Financial)	0.58	0.49	0.00	1.00	1.00
# Covenant (Financial)	1.27	1.31	0.00	1.00	2.00
Covenant Dummy (Non-financial)	0.21	0.41	0.00	0.00	0.00
# Covenant (Non-financial)	0.64	1.36	0.00	0.00	0.00
Allocation	0.13	0.10	0.06	0.10	0.15

Table 1: Continued

Panel C: Firm Characteristics					
	Mean	Std. Dev.	25th Percentile	Median	75th Percentile
Market Cap (millions)	4,680.98	10,159.52	252.69	964.15	3,629.33
Leverage	0.28	0.18	0.15	0.28	0.40
BM	0.62	0.44	0.31	0.50	0.81
Sales Growth	0.06	0.09	0.01	0.04	0.07
HHI	0.34	0.37	0.08	0.11	0.61
IOR	0.61	0.27	0.42	0.65	0.83
Ind-adj. Ret	0.01	0.10	-0.05	0.00	0.06
Z-score	0.75	0.66	0.32	0.74	1.19
S&P Rating	5.53	5.62	0.00	5.00	11.00
No Rating	0.46	0.50	0.00	0.00	1.00
Ln(# Analyst)	5.31	4.76	2.00	4.00	8.00
SUE	0.01	0.01	0.00	0.00	0.00
No Coverage	0.10	0.30	0.00	0.00	0.00
Volatility	0.11	0.06	0.07	0.10	0.14
Illiq	0.47	1.88	0.00	0.00	0.04
S&P 500	0.24	0.43	0.00	0.00	0.00
Opacity	0.21	0.24	0.07	0.13	0.25
DiscAcc	0.00	0.11	-0.04	0.00	0.03

Table 2: Affiliated Analysts and Loan Spread

This table reports the OLS regression results of the effect of affiliated analysts on loan spreads. The dependent variable is *Spread*, the loan spread over LIBOR for each dollar drawn down in basis points. The key independent variables are *AA Facility*, an indicator variable equal to one if there is at least one lender that has affiliated analyst(s) covering the borrower, and *Ln(# AA Lender)*, the natural logarithm of one plus the number of lenders that have affiliated analyst(s) covering the borrower. Variable definitions are in Table A1 of the Appendix. We also include three-digit SIC industry, year-month, loan-type, and loan-purpose fixed effects in the regressions. T-statistics are reported in parentheses and standard errors are double-clustered by borrower and year-month. Significance at 1%, 5%, and 10% levels are indicated by ***, **, and *, respectively.

	(1)	(2)	(3)	(4)
AA Facility	-14.052***	-8.275***		
	(-6.081)	(-4.274)		
Ln(# AA Lender)			-17.166***	-10.123***
			(-7.120)	(-5.071)
Ln(Loan Amount)		-16.376***		-16.269***
		(-14.384)		(-14.437)
Ln(Maturity)		0.332		0.303
		(0.148)		(0.136)
Non-CB		22.625***		22.507***
		(9.872)		(9.844)
Non-CB DH		-4.745**		-3.964*
		(-2.165)		(-1.799)
Secured		48.654***		48.564***
		(23.561)		(23.563)
Missing Secured		14.542***		14.368***
		(9.017)		(8.912)
Ln(# Lender)		-4.967***		-4.857***
		(-4.425)		(-4.337)
Ln(Market Cap)	-13.306***	-2.404*	-12.889***	-2.316*
	(-10.889)	(-1.766)	(-10.453)	(-1.698)
Leverage	41.557***	52.758***	42.474***	53.017***
	(6.776)	(8.729)	(6.921)	(8.771)
BM	10.941***	19.611***	11.315***	19.713***
	(4.625)	(8.004)	(4.763)	(8.030)

Table 2: Continued

	(1)	(2)	(3)	(4)
Sales Growth	42.389***	28.629***	42.506***	28.614***
	(4.227)	(2.953)	(4.252)	(2.957)
HHI	-2.439	-5.272*	-2.194	-5.155*
	(-0.754)	(-1.801)	(-0.680)	(-1.762)
IOR	-9.300**	-5.018	-9.768**	-5.449
	(-2.215)	(-1.285)	(-2.334)	(-1.398)
Ind-adj. Ret	1.694	-9.507	1.391	-9.567
	(0.238)	(-1.336)	(0.197)	(-1.350)
Z-score	-22.236***	-17.955***	-22.275***	-17.984***
	(-13.047)	(-10.841)	(-13.053)	(-10.842)
S&P Rating	6.725***	5.657***	6.725***	5.654***
	(11.242)	(10.307)	(11.281)	(10.311)
No Rating	69.024***	59.363***	69.109***	59.413***
	(9.661)	(9.318)	(9.692)	(9.330)
Ln(# Analyst)	-1.272	-1.808	-1.004	-1.657
	(-0.807)	(-1.242)	(-0.637)	(-1.138)
SUE	305.335***	299.825***	310.317***	302.105***
	(3.860)	(3.875)	(3.926)	(3.908)
Missing SUE	10.668***	8.545***	11.089***	8.755***
	(3.354)	(2.809)	(3.483)	(2.876)
Volatility	257.160***	210.225***	257.191***	210.293***
	(13.541)	(10.926)	(13.513)	(10.917)
Illiq	1.355***	0.809*	1.450***	0.854*
	(2.696)	(1.676)	(2.883)	(1.773)
S&P 500	19.078***	17.359***	20.187***	17.988***
	(6.032)	(5.976)	(6.361)	(6.177)
Industry Fixed Effects	Yes	Yes	Yes	Yes
Year-Month Fixed Effects	Yes	Yes	Yes	Yes
Loan-Type Fixed Effects	Yes	Yes	Yes	Yes
Loan-Purpose Fixed Effects	Yes	Yes	Yes	Yes
Observation	243,53	23,586	243,53	23,586
Adj. R-squared	0.595	0.644	0.596	0.644

Table 3: Affiliated Analysts and Covenants

This table reports the OLS regression results of affiliated analysts on loan covenants. The dependent variables are *Covenant Dummy*, an indicator variable equal to one if there is at least one covenant, and *Ln(# Covenant)*, the natural logarithm of one plus the total number of covenants. We separately examine the financial covenants (*Financial*) and non-financial covenants (*Non-financial*). The key independent variables are *AA Package*, an indicator variable equal to one if there is at least one lender that has affiliated analyst(s) covering the borrower, and *Ln(# AA Lender)*, the natural logarithm of one plus the number of lenders that have affiliated analyst(s) covering the borrower. Variable definitions are in Table A1 of the Appendix. All loan characteristics are aggregated at the loan package level. We also include three-digit SIC industry and year-month fixed effects in the regressions. T-statistics are reported in parentheses and standard errors are double-clustered by borrower and year-month. Significance at 1%, 5%, and 10% levels are indicated by ***, **, and *, respectively.

	Financial				Non-financial			
	Covenant Dummy		Ln(# Covenant)		Covenant Dummy		Ln(# Covenant)	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
AA Package	0.057***		0.039***		-0.011		-0.010	
	(4.600)		(2.791)		(-1.165)		(-0.773)	
Ln(# AA Lender)		0.043***		0.031**		0.000		0.008
		(3.752)		(2.278)		(0.023)		(0.616)
Package Characteristics	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Borrower Characteristics	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year-Month Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observation	17,104	17,104	17,104	17,104	17,104	17,104	17,104	
Adj. R-squared	0.259	0.298	0.250	0.283	0.258	0.298	0.250	0.283

Table 4: Affiliated Analysts and Loan Amendments

This table reports the OLS regression results of the effect of affiliated analysts on loan amendments. The dependent variables are *Amendment Dummy*, an indicator variable equal to one if there is at least one amendment, and *Ln(# Amendment)*, the natural logarithm of one plus the number of amendments. The key independent variables are *AA Facility*, an indicator variable equal to one if there is at least one lender that has affiliated analyst(s) covering the borrower, and *Ln(# AA Lender)*, the natural logarithm of one plus the number of lenders that have affiliated analyst(s) covering the borrower. Variable definitions are in Table A1 of the Appendix. We also include three-digit SIC industry and year-month fixed effects in the regressions. *T*-statistics are reported in parentheses and standard errors are double-clustered by borrower and year-month. Significance at 1%, 5%, and 10% levels are indicated by ***, **, and *, respectively.

	(1)	(2)	(3)	(4)
	Amendment Dummy		Ln(# Amendment)	
AA Facility	0.040***	0.044***		
	(4.081)	(3.845)		
Ln(# AA Lender)			0.022**	0.022**
			(2.426)	(2.048)
Loan Characteristics	Yes	Yes	Yes	Yes
Borrower Characteristics	Yes	Yes	Yes	Yes
Industry Fixed Effects	Yes	Yes	Yes	Yes
Year-Month Fixed Effects	Yes	Yes	Yes	Yes
Loan-Type Fixed Effects	Yes	Yes	Yes	Yes
Loan-Purpose Fixed Effects	Yes	Yes	Yes	Yes
Observation	23,586	23,586	23,586	23,586
Adj. R-squared	0.165	0.169	0.164	0.168

Table 5: All-Star Affiliated Analysts and Loan Spreads

This table reports the OLS regression results on how analyst forecast accuracy impacts the effect of affiliated analysts. The dependent variable is *Spread*, the cost of each dollar drawn down over LIBOR measured in basis points. The key independent variables are *AA Facility*, an indicator variable equal to one if there is at least one lender that has affiliated analyst(s) covering the borrower, and *Ln(# AA Lender)*, the natural logarithm of one plus the number of lenders that have affiliated analyst(s) covering the borrower. Both variables are constructed using all-star and non-all-star affiliated analysts. Variable definitions are in Table A1 of the Appendix. We also include three-digit SIC industry, year-month, loan-type, and loan-purpose fixed effects in the regressions. T-statistics are reported in parentheses and standard errors are double-clustered by borrower and year-month. Significance at 1%, 5%, and 10% levels are indicated by ***, **, and *, respectively.

	(1)	(2)
All-star AA Facility	-11.064***	
	(-4.769)	
Non-all-star AA Facility	-5.027***	
	(-2.933)	
All-star Ln(# AA Lender)		-12.637***
		(-4.9931)
Non-all-star Ln(# AA Lender)		-6.381***
		(-3.237)
Loan Characteristics	Yes	Yes
Borrower Characteristics	Yes	Yes
Industry Fixed Effects	Yes	Yes
Year-Month Fixed Effects	Yes	Yes
Loan-Type Fixed Effects	Yes	Yes
Loan-Purpose Fixed Effects	Yes	Yes
Observation	23,586	23,586
Adj. R-squared	0.626	0.626
All-star−Non-all-star	0.038**	0.043**

Table 6: Affiliated Analysts, Loan Spreads, and Analyst Forecast Accuracy

This table reports the OLS regression results on how analyst forecast accuracy impacts the effect of affiliated analysts. The dependent variable is *Spread*, the cost of each dollar drawn down over LIBOR measured in basis points. The key independent variables are *AA Facility*, an indicator variable equal to one if there is at least one lender that has affiliated analyst(s) covering the borrower, and *Ln(# AA Lender)*, the natural logarithm of one plus the number of lenders that have affiliated analyst(s) covering the borrower. Both variables are constructed using affiliated analysts from the High, Mid and Low tercile, ranked based on their forecast accuracy. We report the difference between the coefficient estimates of *High AA* and *Low AA* in the last row of the table. Forecast accuracy is measured using the average absolute forecast errors from forecasts issued within one-year prior to loan origination (columns (1) and (2)) and during the lifetime of the loan (columns (3) and (4)). Variable definitions are in Table A1 of the Appendix. We also include three-digit SIC industry, year-month, loan-type, and loan-purpose fixed effects in the regressions. T-statistics are reported in parentheses and standard errors are double-clustered by borrower and year-month. Significance at 1%, 5%, and 10% levels are indicated by ***, **, and *, respectively.

	(1)	(2)	(3)	(4)
	Pre-loan		Post-loan	
High AA Facility	-5.393**		-4.628**	
	(-2.533)		(-2.205)	
Mid AA Facility	-2.196		-1.809	
	(-0.990)		(-0.805)	
Low AA Facility	3.139		1.692	
	(1.388)		(0.712)	
High Ln(# AA Lender)		-6.222**		-5.805**
		(-2.433)		(-2.277)
Mid Ln(# AA Lender)		-2.741		-2.335
		(-0.984)		(-0.843)
Low Ln(# AA Lender)		3.386		2.204
		(1.194)		(0.715)
Loan Characteristics	Yes	Yes	Yes	Yes
Borrower Characteristics	Yes	Yes	Yes	Yes
Industry Fixed Effects	Yes	Yes	Yes	Yes
Year-Month Fixed Effects	Yes	Yes	Yes	Yes
Loan-Type Fixed Effects	Yes	Yes	Yes	Yes
Loan-Purpose Fixed Effects	Yes	Yes	Yes	Yes
Observation	23,586	23,586	23,586	23,586
Adj. R-squared	0.603	0.603	0.603	0.603
High−Low	-8.533***	-9.607**	-6.32**	-8.009**

Table 7: Affiliated Analysts, Loan Spread, and Endogeneity

This table reports the identification results of the effect of affiliated analysts on loan spreads. The dependent variable is *Spread*, the loan cost in basis points over LIBOR for each dollar drawn down. In columns (1) and (2), results are based on the full sample. The key independent variables are *AA Lender*, an indicator equal to one if a lead lender has affiliated analyst(s) covering the borrower. In columns (3) and (4), results are based on use a sample that exploits changes in brokerage house affiliation. The key independent variable is *Conditional AA Lender*, an indicator equal to one if: (1) the lender has at least one affiliated analyst covering the borrower, (2) the borrower has at least loan from the lender before the analyst become affiliated with the lender, and (3) the affiliated analyst must cover at least one loan before the analyst becomes affiliated with the lender. Variable definitions are in Table A1 of the Appendix. We also include lender×borrower, year-month, loan-type, and loan-purpose fixed effects in the regressions. T-statistics are reported in parentheses and standard errors are double-clustered by borrower and year-month. Significance at 1%, 5%, and 10% levels are indicated by ***, **, and *, respectively.

	(1)	(2)	(3)	(4)
	Full Sample		Changes in Brokerage House Affiliation	
AA Lender	-10.931***	-5.724***		
	(-4.979)	(-3.183)		
Conditional AA Lender			-12.202***	-8.559**
			(-3.022)	(-2.428)
Loan Characteristics		Yes		Yes
Borrower Characteristics		Yes		Yes
Lender×Borrower Fixed Effects	Yes	Yes	Yes	Yes
Year-Month Fixed Effects	Yes	Yes	Yes	Yes
Loan-Type Fixed Effects	Yes	Yes	Yes	Yes
Loan-Purpose Fixed Effects	Yes	Yes	Yes	Yes
Observation	44,484	44,484	31,461	31,461
Adj. R-squared	0.852	0.874	0.870	0.888

Table 8: Affiliated Analysts and Bank Allocation

This table reports the OLS regression results of the effect of affiliated analysts on loan allocation. The dependent variable is *Allocation*, which is the percentage of the facility taken by a lender. The key independent variables are *AA Lender*, an indicator equal to one if a lead lender has affiliated analyst(s) covering the borrower. Variable definitions are in Table A1 of the Appendix. We include facility and lender fixed effects in the regressions. *T*-statistics are reported in parentheses and standard errors are double-clustered by borrower and year-month. Significance at 1%, 5%, and 10% levels are indicated by ***, **, and *, respectively.

	(1)	(2)	(3)	(4)
AA Lender	0.007***	0.007***	0.006***	0.006***
	(4.283)	(4.276)	(3.775)	(3.786)
Borrower Characteristics		Yes		Yes
Facility Fixed Effects	Yes	Yes	Yes	Yes
Lender Fixed Effects	Yes	Yes		
Lender-Year Fixed Effects			Yes	Yes
Observation	143,85	143,51	135,14	134,82
Adj. R-squared	0.825	0.825	0.849	0.849

Table 9: Affiliated Analysts, Loan Spreads, and Information Opacity

This table reports the OLS regression results on how information opacity impacts the effect of affiliated analysts. The dependent variable is *Spread*, the cost of each dollar drawn down over LIBOR measured in basis points. The key independent variables are *AA Facility*, an indicator variable equal to one if there is at least one lender that has affiliated analyst(s) covering the borrower, and *Ln(# AA Lender)*, the natural logarithm of one plus the number of lenders that have affiliated analyst(s) covering the borrower. We interact *AA Facility* and *Ln(# AA Lender)* with *Information Opacity*. We use $|DiscAcc|$, the absolute value of the discretionary annual accruals, and *Opacity*, the three-year rolling sum of $|DiscAcc|$, as proxies for *Information Opacity*. Variable definitions are in Table A1 of the Appendix. We also include three-digit SIC industry, year-month, loan-type, and loan-purpose fixed effects in the regressions. T-statistics are reported in parentheses and standard errors are double-clustered by borrower and year-month. Significance at 1%, 5%, and 10% levels are indicated by ***, **, and *, respectively.

	(1)	(2)	(3)	(4)
	Opacity		|DiscAcc|	
AA Facility	-12.964**		-2.309***	
× Information Opacity	(-2.467)		(-2.732)	
Ln(# AA Lender)		-13.020***		-3.305***
× Information Opacity		(-2.632)		(-2.734)
AA Facility	-6.249**		-8.966***	
	(-2.510)		(-3.948)	
Ln(# AA Lender)		-8.279***		-10.776***
		(-3.573)		(-4.972)
Information Opacity	10.885**	10.381**	1.828**	1.816**
	(2.582)	(2.589)	(2.330)	(2.322)
Loan Characteristics	Yes	Yes	Yes	Yes
Borrower Characteristics	Yes	Yes	Yes	Yes
Industry Fixed Effects	Yes	Yes	Yes	Yes
Year-Month Fixed Effects	Yes	Yes	Yes	Yes
Loan-Type Fixed Effects	Yes	Yes	Yes	Yes
Loan-Purpose Fixed Effects	Yes	Yes	Yes	Yes
Observation	19,014	19,014	18,855	18,855
Adj. R-squared	0.624	0.624	0.624	0.624

Table 10: Affiliated Analysts, Loan Spreads, and Borrower Distress

This table reports the OLS regression results on how borrower distress impacts the effect of affiliated analysts. The dependent variable is *Spread*, the cost of each dollar drawn down over LIBOR measured in basis points. The key independent variables are *AA Facility*, an indicator variable equal to one if there is at least one lender that has affiliated analyst(s) covering the borrower, and *Ln(# AA Lender)*, the natural logarithm of one plus the number of lenders that have affiliated analyst(s) covering the borrower. We interact *AA Facility* and *Ln(# AA Lender)* with *Borrower Distress*. We use Altman's *Z-score* and *Leverage* as proxies for *Borrower Distress*. Variable definitions are in Table A1 of the Appendix. We also include three-digit SIC industry, year-month, loan-type, and loan-purpose fixed effects in the regressions. T-statistics are reported in parentheses and standard errors are double-clustered by borrower and year-month. Significance at 1%, 5%, and 10% levels are indicated by ***, **, and *, respectively.

	(1)	(2)	(3)	(4)
	Z-score		Leverage	
AA Facility	4.766*		-21.482**	
× Borrower Distress	(1.846)		(-2.143)	
Ln(# AA Lender)		4.782**		-22.451**
× Borrower Distress		(2.016)		(-2.309)
AA Facility	-12.230***		-2.401	
	(-4.247)		(-0.712)	
Ln(# AA Lender)		-13.969***		-3.722
		(-5.236)		(-1.073)
Borrower Distress	-18.157***	-18.101***	62.431***	62.481***
	(-10.121)	(-10.281)	(8.414)	(8.537)
Loan Characteristics	Yes	Yes	Yes	Yes
Borrower Characteristics	Yes	Yes	Yes	Yes
Industry Fixed Effects	Yes	Yes	Yes	Yes
Year-Month Fixed Effects	Yes	Yes	Yes	Yes
Loan-Type Fixed Effects	Yes	Yes	Yes	Yes
Loan-Purpose Fixed Effects	Yes	Yes	Yes	Yes
Observation	23,586	23,586	23,586	23,586
Adj. R-squared	0.626	0.626	0.626	0.626