Published in Management Science (2023). DOI: 10.1287/mnsc.2023.4809

Intra-Firm Knowledge Sharing in the Investment Research Industry

Artur Hugon*
Arizona State University

An-Ping Lin
Singapore Management University

Stanimir Markov
University of Texas at Dallas

October 10, 2022

Abstract:
We study inter-department knowledge sharing in an investment research setting where the benefits are potentially significant for the brokerage and the capital market, but so are the frictions impeding it. Using hand-collected data on equity analyst access to in-house debt research expertise, we find significant benefits to equity analysts in the form of improved ability to forecast cash flows and to anticipate credit rating downgrades. Moreover, we find evidence that access to management and research expertise underlie in-house debt analysts' capacity to generate information beneficial to equity analysts. Finally, these benefits exist only in the presence of a collaborative brokerage culture or debt-equity analyst collocation, consistent with these factors promoting knowledge sharing in the investment research industry.

Keywords: Knowledge sharing, equity analysts, debt analysts, cash flow forecasts, credit ratings.

JEL Classification: D53, G12, G14, G24.

We would like to thank Neil Bhattacharya, Mark Bradshaw, Andy Call, Kun-Chih Chen, Qiang Cheng, Steve Crawford (AAA discussant), Ricky Johnston, Jae Bum Kim, Yen-Jung Lee, Hai Lu, and seminar participants at National Taiwan University, Singapore Management University, Southern Methodist University, Temple University, and UTS-SMU-UNSW Joint Accounting Conference. Special thanks to Allen Huang for providing the Institutional Investor all-star ranking data. *Corresponding author: artur.hugon@asu.edu

1. Introduction

A large body of work has identified organizational knowledge sharing as a key factor in achieving sustainable competitive advantage (Kogut and Zander, 1992; Grant, 1996; Spender and Grant, 1996; Teece, Pisano, and Shuen, 1997; among many others). However, establishing successful interrelationships between business units is "extraordinarily difficult for many firms," even in the presence of a clear competitive advantage (Porter, 1985: p. 382), with inter-unit competition and silo mentality identified as key impediments (Tsai, 2002; Hansen, Mors, and Lovas, 2005; Gargiulo, Ertug, and Galunic, 2009).

In this study, we examine inter-department knowledge sharing in the investment research industry, a setting where the benefits of knowledge sharing are potentially large, but so are the frictions impeding it. Specifically, we investigate whether information flows from the debt research department to the equity research department; whether a debt analyst's capacity to generate such flows is explained by her access to management and research expertise; and whether organizational culture and geographic proximity facilitate these information flows.[2]

The debt research department is a potentially rich source of information for equity analysts with respect to cash flow analysis and credit quality assessment (Gurun, Johnston, and Markov, 2016). However, the debt research department competes with the equity research department not only internally for resources and senior management attention, but also externally for institutional clients, as many of them trade in both debt and equity. This impedes knowledge sharing, even in the presence of benefits at the organizational level (Porter, 1985; De Long and Fahey, 2000; Schepers and Van den Berg, 2007), and, therefore, makes the existence of informational benefits an empirical question.

Our primary empirical challenge in testing for knowledge transfer is to identify debt analysts who have the capacity to produce valuable information and draw equity analyst attention to it (Arrow, 1974;

[2] Research on knowledge networks focuses on three levels of analysis: individual units, pairs of units, and the network (Gupta and Govindarajan, 2000). Due to the complexity of the analysis and lack of prior work in the brokerage research setting, we focus on the flow of knowledge from the debt research department to the equity research department.

Gupta and Govindrajan, 2000). We rely on *Institutional Investor*'s all-star debt analyst rankings to identify such analysts. We reason that an all-star debt analyst employed by the same brokerage firm to cover companies in the same industry is a potentially valuable information source for the equity analyst.

As an integral part of credit research, analysis and prediction of cash flows constitute a core debt analyst activity. In addition, as financial distress increases, more resources are devoted to the production of debt research (Johnston, Markov, and Ramnath, 2009) since higher financial distress means greater sensitivity of debt prices to information (Merton, 1974). Our expectation is that an equity analyst's motivation to acquire knowledge from a debt analyst colleague is greater for financially distressed companies where credit analysis is more important and debt analysts have greater expertise. Consistent with this expectation, we find that equity analysts who cover financially distressed companies and have access to high-quality debt research are more likely to provide cash flow forecasts than analysts who lack access.[3] Specifically, analysts with access are 4.6% more likely to issue a cash flow forecast than analysts without access when distress is defined at the industry level, and 1.2% more likely to do so when distress is defined at the company level.[4] Analysts who have access to high-quality debt research and cover distressed companies also issue more accurate cash flow forecasts. In terms of economic significance, cash flow forecasts issued by equity analysts with access are 7.2% (7.9 cents) more accurate than those of analysts without access when following companies in distressed industries and 3.9% (4.3 cents) more accurate when covering distressed companies.

A second important setting for knowledge transfer from a debt to an equity analyst is credit research. Credit rating changes are major economic events that normally attract more attention from debt analysts

---

[3] A standard measure of financial distress in the academic literature is the Altman (1968) z-score (DeFond and Hung, 2003). We define a company as financially distressed if its z-score is below the standard threshold of 1.81, or if it resides in a financially distressed industry, defined as an industry with the top quintile percentage of companies that are financially distressed.

[4] These figures are calculated as the probability that an equity analyst with access issues a cash flow forecast for a distressed company minus the probability that an equity analyst without access issues a cash flow forecast for a distressed company, with distress defined at the industry or company level. We hold all other variables constant at their sample means.

than equity analysts. In fact, assessing credit risk in a timely manner and forecasting changes in credit ratings, especially downgrades, are key debt analyst objectives (Johnston et al., 2009; Gurun et al., 2016). If knowledge transfer is successful, we expect that equity analysts with access to high-quality debt research are more likely to revise down their research in the period prior to a covered company's credit rating downgrade; moreover, these revisions are likely to be larger than those by other analysts. We consider revisions in earnings forecasts and stock recommendations, in addition to revisions in cash flow forecasts, because earnings forecasts and stock recommendations are universally provided and rating downgrades have economically important equity market implications (Griffin and Sanvicente, 1982; Holthausen and Leftwich, 1986; Hand, Holthausen, and Leftwich, 1992).

We find evidence that in the 90-day period leading to a covered company's credit rating downgrade, equity analysts with access to high-quality debt research are more likely to revise down their research estimates for the company than other analysts are, and that their revisions have larger magnitudes than other analysts' revisions. These findings are economically significant. For example, the differences in the probabilities of issuing downward earnings forecasts, stock recommendations, and cash flow forecasts between analysts with access to high-quality debt research and other analysts are 3.2%, 1.6%, and 1.4%, respectively. In addition, analysts with access to high-quality debt research provide downward revisions for earnings forecasts and cash flow forecasts that are larger in magnitude by an extra 4 and 6 cents, respectively.[5]

An alternative interpretation of our findings is that the superior performance of equity analysts with access to high-quality debt research is due to equity analysts themselves generating more information and sharing this information with the debt analyst. To examine this explanation, we hand collect a sample of debt reports published in the 90 days prior to credit rating downgrades and test whether all-star debt analyst reports are more likely to precede equity analyst revisions – predicted by our hypothesis – or lag

[5] The economic magnitudes are higher by about 1 cent when we use the IBES unadjusted file to assess economic significance.

equity analyst revisions – predicted by the alternative explanation. We find *only* evidence that all-star debt analyst reports precede equity analyst revisions, suggesting information flows from all-star debt analysts to equity analysts.[6]

Two non-mutually exclusive explanations for why high-quality debt research enhances the informational properties of equity research are that all-star debt analysts obtain private information from management or are better at processing public debt-related information than equity analysts are. We thus examine whether the benefits of high-quality debt research are greater when in-house star debt analysts have better access to management or when they have more research expertise. To measure management access, we set an indicator to one if the all-star debt analyst is employed by a broker that hosted the company at a debt conference or underwrote the company's debt offering in the prior year. To measure research expertise, we set an indicator to one when the all-star analyst is ranked by *Institutional Investor* in multiple sectors in the current year or has a CFA. Both explanations are borne out in the data. In particular, we find equity analysts tend to issue higher quality equity research when their star debt analyst colleagues have more management access and greater expertise.

Drawing on prior work in organizational science (De Long and Fahey, 2000; Kankanhalli, Tan, and Wei, 2005; Schepers and Van den Berg, 2007), we examine whether our baseline results are stronger when brokerage culture is collaborative, and when the debt and equity analysts are geographically proximate. Our measure of collaborative culture is an indicator equal to one when Sull, Sull, and Chamberlain's (2019) collaboration sentiment score is above the industry mean, and zero otherwise. Our measure of geographic proximity is a collocation indicator, equal to one when the equity and debt analysts are located in the same city, and zero otherwise. As expected, we find that our baseline findings are stronger when culture is collaborative, and when the debt and equity analysts are located in the same city. In fact, equity analysts with access to all-star debt analysts issue cash forecasts for distressed companies with higher frequency and accuracy only in the presence of either a collaborative culture or when the

[6] See Table 6 of the Internet Appendix for results.

equity and debt analysts are geographically proximate. Similarly, we find that a collaborative culture and geographic proximity are largely necessary conditions for access to all-star debt analysts to lead to more and better forecasts in advance of credit rating downgrades.

We conduct several analyses to address endogeneity concerns. First, we re-define our primary variable of interest to be access to an all-star debt analyst who covers industries or company types *different* from those followed by the equity analyst. We find no evidence such access benefits the equity analyst, which alleviates the concern that our results reflect differences in resources between all-star employing brokers and other brokers. Second, to address concerns that unobservable time-invariant analyst characteristics or common time effects explain our results, we estimate a model in which access is determined by star debt analyst arrivals/departures and equity analyst and year fixed effects are included; following Do and Zhong (2020), we use the prime moving age of star debt analysts and prior broker connections as an instrument for star debt analyst arrivals/departures. Our results remain inferentially consistent with those of the original design, albeit weaker.

This study extends the literature on inter-unit knowledge sharing by documenting its existence, benefits, sources, and contributing factors in the investment research industry. Specifically, debt and equity analysts are not only capital markets participants—the perspective adopted in prior work—but they are also members of different units within a single organization—the perspective adopted in our study. Our focus on inter-departmental research collaboration complements prior studies which examine intra-departmental collaboration (Brown and Hugon, 2009; Bradley, Gokkaya, and Liu, 2019; Hwang, Liberti, and Sturgess, 2019; Do and Zhang, 2020; Fang and Hope, 2021; Hope and Su, 2021; Huang, Lin, and Zang, 2022) in two ways. First, inter-departmental collaboration is arguably more difficult to achieve than intra-departmental collaboration due to competition internally for resources and externally for clients. Second, our findings of information transfer from debt to equity analysts have implications for how information flows from the debt to equity markets, whereas prior evidence of information transfer among equity analysts has implications only for how information flows within the equity market.

Our study is also related to prior research that documents information transfer between a financial institution's lending arm and investment arm (e.g., Ivashina and Sun, 2011; Massoud, Nandy, Saunders, and Song, 2011). In these studies, the lending arm acquires material non-public information from borrowers legally, but it shares this information with the investment arm in contravention of securities laws and Regulation FD. In our study, debt analysts produce and share material non-public information with equity analysts legally.[7] Hence, the frictions impeding the information transfer are institutional or behavioral rather than legal or ethical. Furthermore, information sharing within the research departments of a sell-side institution has arguably greater market efficiency implications than information sharing within a buy-side institution. Sell-side equity research reports, and earnings forecasts and stock recommendations, in particular, are widely distributed and shown to enhance capital market efficiency (e.g., Brennan, Jegadeesh, and Swaminathan, 1993; Womack, 1996). Buy-side research, on the other hand, benefits only the trading decisions of the fund managers and clients of the research-producing institution.

2. Background and empirical predictions

2.1. Intra-firm knowledge sharing in the investment research industry

Although knowledge sharing is widely viewed as an important factor in achieving a competitive advantage (Kogut and Zander, 1992; Grant, 1996; Spender and Grant, 1996; Teece et al., 1997), many organizations find knowledge sharing difficult to implement in practice (Porter, 1985). One of the key impediments is inter-unit competition: units competing internally for resources and senior management attention (Tsai, 2002; Hansen et al., 2005; Gargiulo et al., 2009) and externally for customers.

Specific to the brokerage industry, there is anecdotal evidence that suggests economic benefits to brokers and analysts from knowledge sharing between departments (Ronan, 2006; Groysberg and Vargas, 2007; Abramowitz, 2008). For example, coordinating research across asset classes allows equity and debt

[7] Regulation FD bans sell-side debt analysts from acquiring material non-public information from managers, but it explicitly allows the acquisition of non-material non-public information which, according to the mosaic theory, can be used to produce material non-public information.

analysts to share model inputs, which helps both groups of analysts reduce costs and cover more companies and subsectors (Abramowitz, 2008). As another example, meeting the rising demand from institutional investors for capital-structure reports, which examine the relative pricing of debt and equity claims, requires the collaboration of equity and debt analysts. Brokers benefit in terms of increased institutional trading, and both the equity and debt analysts benefit from an increased understanding of the alternative asset class (Groysberg and Vargas, 2007). As one final example, credit derivatives trading has been a major revenue stream for brokers in recent years but requires coordinated expertise in debt and equity to provide a "holistic" view of companies (Ronan, 2006).

However, whether these benefits accruing to the broker and analysts result in knowledge transfer is an open question. Knowledge sharing is positively related to organizational commitment to collaboration and a culture of trust (De Long and Fahey, 2000; Kankanhalli et al., 2005), which may be non-existent or too weak to overcome the hyper-competitive nature of Wall Street brokers. In addition, debt and equity analysts frequently work in different locations, and geographic dispersion is known to impede sharing through communication frictions (Gibson and Gibbs, 2006), variation in practices and norms across locations (Curtis, Krasner, and Iscoe, 1988), and weakened social ties (Finholt, Sproull, and Kiesler, 2002; Boh, Ren, Kiesler, and Bussjaeger, 2007).

2.2. Empirical predictions

Ideally, one would identify the specific information flows from a debt to an equity analyst in order to make empirical predictions regarding equity research properties. However, since these information flows are unobservable, we rely on institutional evidence about differences in focus between debt and equity research to identify specific types of relevant information that are more likely to be collected by a debt analyst than an equity analyst: information useful in forecasting cash flows of financially distressed companies (section 2.2.1) and in anticipating credit rating downgrades (section 2.2.2). We suggest that these particular types of information may flow to the equity analyst and, consequently, be reflected in her research.[8]

2.2.1. High-quality in-house debt research and the quality of equity analyst's cash flow forecasts

Cash flow analysis is mandatory for a debt analyst and discretionary for an equity analyst. The reason is that a debt analyst is mainly concerned with assessing a company's ability to pay its debt, which can only be paid with cash, whereas an equity analyst is mainly concerned with assessing a company's performance and equity value, favoring earnings over cash flows in the process. Analyzing a large sample of debt analyst reports, Kim, Kross, and Suk (2015) find that debt analysts are more likely to issue cash flow forecasts and issue more accurate cash forecasts than are equity analysts. Thus, while both types of analysts gather information relevant to assessing a company's capacity to generate cash flows, an equity analyst, whose primary focus is on forecasting earnings, devotes less time to cash flow analysis and prediction than a debt analyst.

We suggest that an equity analyst employed by the same firm and covering the same sector as a high-quality debt analyst potentially has access to more cash flow relevant information than another equity analyst; furthermore, this differential is especially pronounced for distressed companies, which in the aggregate, debt analysts focus on (Johnston et al., 2009). We, therefore, predict access to high-quality in-house debt research leads to increased incidence and accuracy of cash flow forecasts by equity analysts, especially for distressed companies.

[8] Institutionally, brokers distribute their research reports in real time only to their own clients to maximize clients' trading profits, and as result, broker trading revenues. Some brokers sell their research reports to third-party, subscription services like *Mergent Investext* but with a delay. Overall, we believe there are substantial institutional frictions that prevent the equity analysts from one broker from deriving informational benefits from another broker's debt research. In Tables 2 and 3 of the Internet Appendix, we find little evidence of benefits from external debt research.

2.2.2. High-quality in-house debt research and equity research in advance of credit rating downgrades

Credit rating agencies are information intermediaries at the very heart of public debt markets (White, 2010). Accordingly, sell-side debt reports normally discuss a company's credit rating and often include explicit credit rating predictions; sell-side equity reports, on the other hand, discuss credit ratings less often and in less detail, and seldom predict credit ratings (see Appendix B in Gurun et al., 2016). As an illustration of the difference in focus, the same information event—a company's earnings announcement—caused a Credit Suisse First Boston debt analyst to reduce her own debt and financial strength ratings by one notch and forecast a S&P credit rating downgrade, and her colleague in equities to reduce her earnings per share estimates and equity price target (see Appendix I in Johnston et al., 2009).

Debt investors cannot receive more than the amount invested plus interest but can lose 100% of the amount invested, creating stronger demand for information predictive of credit rating downgrades than upgrades. Consistent with debt analysts expending more resources to predict credit rating downgrades than upgrades, Johnston et al. (2009) find that debt report frequency increases in the period prior to a downgrade but not in the period prior to an upgrade.

In sum, debt research is distinguished by greater focus on assessing credit risk and predicting credit rating downgrades than equity research. Given that information pertinent to predicting credit rating changes overlaps with information pertinent to predicting payoffs forecasted by equity analysts, we predict that equity analysts who have access to high-quality debt research are more likely to revise their estimates of earnings, cash flows, and stock recommendations in the period prior to a credit rating downgrade than other analysts, and that these revisions are likely to be larger than those by other analysts. We include revisions in earnings forecasts and stock recommendations as leading indicators of credit rating downgrades because they are universally provided and most credit rating downgrades reflect a decline in a company's prospective cash flows (Goh and Ederington, 1993).

A related question is whether equity analysts can learn from debt analysts employed by other brokers. In our view, such learning is much less beneficial than learning from in-house debt analysts.

Equity analysts can only obtain other brokers' published debt reports from Investext or another third-party provider with a delay, which limits the value of external debt reports as an information resource; and we are not aware of any anecdotal evidence that equity analysts actually do so. In addition, learning through collaboration, communication, and interactions with debt analysts is much more likely to occur within a brokerage. In Tables 2 and 3 of Internet Appendix, we find little evidence of learning from external debt reports, even when these reports are authored by all-star analysts.

3. Sample formation and description

3.1. All-star debt analyst data and matching procedure

The *Institutional Investor* magazine (hereafter, II) ranks top sell-side debt analysts in three broad research categories, Investment Grade, High-Yield, and Economics/Strategy, based on a comprehensive survey of money managers and buy-side analysts. For example, in 2014, the magazine received responses from more than 1,970 individuals employed at 500 institutions overseeing $9.4 trillion in U.S. fixed income assets. The investment grade and high-yield categories represent the majority of ranked debt analysts, and these analysts are the focus of our study because their activities and industry sectors closely mirror those of equity analysts.

Because the all-star debt analysts in our study are ranked by II according to industry sector and investment category, either investment grade or high-yield, we merge the II debt analysts into the IBES equity analyst data along these same two dimensions. To match on industry, we use the IBES three-part Sector-Industry-Group (SIG) codes with the closest match to each of the II industry sectors. For matching on investment category, a company is considered investment grade if its S&P long-term rating is BBB- or above or high-yield if its rating is BB+ or below. We assume that an equity analyst covering a company in a particular year has access to high-quality debt research if the all-star debt analyst and the equity analyst are employed by the same sell-side firm during the year, and the debt analyst is ranked in the industry sector and investment category that matches those of the equity analyst's followed company.[9]

[9] Table 1 of the Internet Appendix reports on matching II-ranked debt analysts to IBES sell-side equity analysts employed at the same broker. There are 1,888 II all-star debt awards during this period, representing 443 unique debt

3.2. Sample selection: Forecasting cash flows

Our first empirical prediction asserts differences in cash flow forecast incidence and accuracy between two groups of equity analysts. We discuss how we construct the samples used to test this prediction, with details provided in Panel A of Appendix 1. We obtain cash flow forecasts from the Thomson Reuters' IBES US Detail file, financial information from the Compustat Annual database, and underwriter affiliations from the Thomson Reuters' Security Data Company (SDC) Platinum database.

To construct the cash flow forecast incidence sample, we first identify a sample of analysts who actively cover a company and face the choice to issue a cash flow forecast or not. Following DeFond and Hung (2003), we equate active company coverage with the practice of issuing one-year ahead earnings forecasts. We require IBES industry codes and S&P credit ratings to merge IBES equity analyst data with II debt analyst data, and Compustat and IBES data to measure financial distress and control variables, resulting in a sample of 165,268 analyst-company-year observations.

To construct the cash flow forecast accuracy sample, we require cash flow actuals to calculate forecast errors, and that the company be followed by at least one analyst with access to an all-star debt analyst and one without such access to allow the calculation of a relative cash flow forecast error. The resulting sample is 24,511 analyst-company-year observations.

3.3. Sample selection: Forecasting in advance of credit rating downgrades

Our second main empirical prediction asserts differences in whether and how equity analysts revise their earnings forecasts, stock recommendations, and cash flow forecasts in the period preceding credit rating downgrades. We explain how we construct the samples used to test this prediction, with details provided in Panel B of Appendix 1.

---

analysts, 24 brokers, and 36 industry sectors. The II industry sectors are matched to 102 IBES industry codes, resulting in 20 unique IBES brokers and 2,363 IBES equity analysts (prior to the Compustat data requirements). This represents an 80% success rate in matching II debt award observations to at least one IBES equity analyst in the same industry category.

There are 12,622 S&P long-term credit rating downgrades for 5,009 companies in our sample period on Compustat. We require that consecutive credit rating changes for the same company be at least four months apart to ensure a clean pre-event window of 120 days.[10] After merging the credit rating changes data with IBES US Detail file, there are 22,552 analyst-company-rating-years, corresponding to 1,835 credit rating downgrades for 960 companies. We further require Compustat and IBES data to measure control variables. The final sample for equity research issuance tests consists of 21,573 analyst-company-rating-year observations (1,725 credit rating downgrades for 907 companies). For tests related to stock recommendations, we exclude observations where the pre-window consensus is equal to 'strong sell' prior to the credit rating downgrade since analysts cannot revise further.

For the equity research revision tests, we require the availability of a prevailing consensus for an earnings forecast, stock recommendation, or cash flow forecast, respectively, in the window [-120, -91] days of a credit rating downgrade.[11] The final samples for the equity research revision tests consist of 9,846 earnings forecasts, 2,222 stock recommendations, and 1,150 cash flow forecasts. If an equity analyst issues multiple estimates in the window [-90, -1] days of a credit rating downgrade, we take the average of their estimates.

4. Empirical framework and results

4.1. High-quality in-house debt research and forecasting cash flows

4.1.1. Research design

Our first prediction asserts a positive relation between access to high-quality debt research and the likelihood of issuing a cash flow forecast, especially for distressed companies. To test this prediction, we estimate the following probit model:

[10] We benchmark analyst revision activities measured over the window [-90, -1] against a trailing consensus measured over the window [-120, -91].

[11] The inferences are similar if the prevailing consensus is measured during the [-30, -1] days of a forecast or stock recommendation or if the pre-window consensus is measured during the [-150, -91] or [-180, -91] days of the credit rating downgrade.

$$P\,(CF\_I_{i,j,t} = 1|\boldsymbol{x}) = \Phi\,(\alpha_0 + \alpha_1\, Access_{i,j,t} + \alpha_2\, Distress_{j,t} + \alpha_3\, Access_{i,j,t} \times Distress_{j,t} + \boldsymbol{\alpha}\, \boldsymbol{z}), \quad (1)$$

where *CF_I* is equal to one if equity analyst *i* issues at least one cash flow forecast for company *j* in year *t* and zero otherwise; *Access* is equal to one if the equity analyst has access to an all-star debt analyst following the same industry and investment category in year *t*, and zero otherwise; *Distress* indicates financial distress at the company level (*F_Distress*), which is equal to one if Altman (1968) z-score is less than 1.81 and zero otherwise, or at the industry level (*I_Distress*), which is equal to one if company *j*'s industry is in the top quintile based on the percentage of financially distressed companies and zero otherwise; and **z** is a vector of control variables including company, analyst, and broker characteristics, a time trend variable to capture the increase in cash flow forecasts over time, and industry effects.

Company characteristics identified in prior literature as determinants of cash flow forecasts include total accruals (*TAcc*), earnings volatility (*Earn_Vol*), capital intensity (*Cap_Intensity*), Altman (1968) z-score (*Z-Score*), company size (*Size*), market-to-book ratio (*MTB*), loss company (*Loss*), and financial leverage (*Leverage*) (DeFond and Hung, 2003). Based on prior literature, we also control for measures of equity analysts' resources and skill: broker size (*Bsize*), an analyst's company-specific experience (*Exp*), the number of industries covered (*NInd*), the number of companies covered (*Nfirm*) (e.g., Clement, 1999; Jacob, Lys, and Neale, 1999), as well as the underwriting relationship with the covered company (*Affiliate*), and the equity analyst's all-star award status (*AA_Equity*) (Lin and McNichols, 1998; Bilinski, 2014).[12] Complete variable definitions appear in Appendix 2. We winsorize continuous variables at the top and bottom 1% in all analyses.

Our first prediction further states that access to high-quality debt research is positively associated with analysts' cash flow forecast accuracy for distressed companies. To address company and time period effects, we subtract company-year means from both the dependent and independent variables (Clement,

[12] Holding total resources constant, an analyst covering more companies or industries has fewer resources available for the purpose of issuing a cash flow forecast for a given company. An underwriting relation may signify greater information flow from the investment banking division (Haushalter and Lowry, 2011).

1999; Lim, 2001). For instance, the dependent variable *R_CF_ACC* is equal to analyst *i*'s absolute forecast error for company *j* in year *t* minus the mean absolute forecast error of all analysts following company *j* in year *t*, scaled by the mean absolute forecast error of all analysts for company *j* in year *t*, and multiplied by -1. Since company, industry, and year variables are common to all analysts in a company-year, they drop out of the model specification. The OLS regression model is:

$$R\_CF\_ACC_{i,j,t} = \beta_0 + \beta_1\, Access_{i,j,t} + \beta_2\, Distress_{j,t} + \beta_3\, Access_{i,j,t} \times Distress_{j,t} + \boldsymbol{\beta}\, \boldsymbol{z} + \varepsilon_{1\,i,j,t}, \tag{2}$$

where **z** includes the analyst and broker-level controls from the issuance model, as well as forecast frequency (*Freq*) and forecast horizon (*Horizon*) (Pae and Yoon, 2012).

4.1.2. Empirical results

Table 1 contrasts the incidence of cash flow forecasts by equity analysts with access to high-quality debt research to those by other analysts, as well as the analyst, broker, and research portfolio characteristics of the two groups of analysts. We observe that *Access* is associated with greater likelihood that cash flow forecasts are provided, 29% vs. 24%, and with greater likelihood of covering companies that are distressed or in a distressed industry. The latter suggests *Access* reduces equity analysts' costs in covering such companies. *Access* is also positively associated with greater overall broker resources and reputation, as measured by the number of equity analysts employed, the likelihood of employing all-star equity analysts, average analyst experience, and the presence of an underwriting relation with the company.

Panel A of Table 2 reports the results from estimating Eq. (1). For all regressions in this study, the test statistics are reported in parentheses, and standard errors are clustered by broker and year to address time-series and cross-sectional dependence (Gow, Ormazabal, and Taylor, 2010). In specifications 1 and 2, we find positive and significant coefficients on *Access* × *F_Distress* and *Access* × *I_Distress*, respectively. In terms of economic significance, analysts with *Access* are 1.2% more likely to issue a cash flow forecast when distress is measured at the company level and 4.6% more likely to do so when distress is measured at the industry level. When both financial distress measures are included, in specification 3, only the coefficient on *Access* × *I_Distress* is statistically significant. Overall, the evidence is consistent with analysts who have access to high-quality debt research being more likely to issue cash flow forecasts for distressed companies than are other analysts.

In the interest of brevity, the control variables are untabulated. However, we note the results are consistent with DeFond and Hung (2003) and reveal that analysts are more likely to provide cash flow forecasts when a company's total accruals are larger, asset liquidity matters more, or financial health is poorer. Furthermore, analysts are less likely to provide cash flow forecasts for loss companies or companies with higher financial leverage (Bilinski, 2014; Ayers, Call, and Schwab, 2018), perhaps due to the greater costs of provision. Finally, analysts are more likely to issue cash flow forecasts when they work for larger investment firms, and less likely to issue forecasts when they follow more industries or companies, consistent with these analysts having increased workload (Clement, 1999).

Panel B of Table 2 reports the results from estimating Eq. (2). In specifications 1 and 2, we find positive and statistically significant coefficients on *Access* × *F_Distress* and *Access* × *I_Distress*, respectively. In specification 3, we find that neither measure of financial distress subsumes the other: both the coefficients on *Access* × *F_Distress* and *Access* × *I_Distress* are statistically significant. In terms of economic significance, in specification 1, cash flow forecasts issued by analysts with access are 3.9% or 4.3 cents more accurate than those of analysts without access when covering distressed companies, and in specification 2, are 7.2% or 7.9 cents more accurate when following companies in distressed industries.[13] These results suggest increased cash flow forecast accuracy for equity analysts who have access to high-quality debt research and cover distressed companies or companies in distressed industries.[14]

---

[13] Specifically, based on the mean absolute forecast error in our sample ($1.098), access to high-quality debt research decreases forecast error by approximately $0.043 (= $1.098 × 3.9%) for distressed companies and by $0.079 (= $1.098 × 7.2%) for companies in distressed industries.

[14] An alternative explanation for these results is that equity analysts employed by firms with all-star debt analysts issue superior cash flow forecasts because they are more skillful forecasters in general. To preclude this explanation, we test whether equity analysts with access to high-quality debt research also issue revenue forecasts with higher frequency and accuracy. A relation between access to high-quality debt research and revenue forecast superiority is predicted by the difference in forecasting skill explanation but not by our prediction. Since forecasting sales revenues is a core equity analyst activity, there is no reason to think availability of high-quality debt research will

4.2. High-quality in-house debt research and forecasting in advance of credit rating downgrades

4.2.1. Research design

Our second empirical prediction asserts a positive relation between access to high-quality debt research and the likelihood of a negative revision in equity research prior to a credit rating downgrade. To test this prediction, we estimate the following probit model for the credit rating downgrade sample:

$$P\,(Down_{i,j,t} = 1|\boldsymbol{x}) \quad = \quad \Phi\,(\alpha_0 + \alpha_1\, Access_{i,j,t} + \boldsymbol{\alpha}\, \boldsymbol{z}), \tag{3}$$

where *Down* denotes a downward earnings forecast (*EF_Down*), stock recommendation (*REC_Down*), or cash flow forecast (*CF_Down*). The variable *EF_Down* is an indicator equal to one when equity analyst *i* issues an earnings forecast in the 90-day period leading to company *j*'s credit rating downgrade in year *t* and the forecast is *lower* than the pre-window consensus, and zero otherwise.[15] The pre-window consensus is calculated by averaging earnings forecasts in the [-120, -91] days preceding the credit rating change.[16] The *REC_Down* and *CF_Down* indicators are defined analogously for stock recommendations and cash flow forecasts. *Access* is equal to one if the equity analyst has access to high-quality debt research in year *t* and zero otherwise; and **z** is a vector of control variables at the company level (*Loss*, *Size*, *MTB*, *Leverage*), analyst level (*AA_Equity*, *Exp*, *NInd*, and *NFirm*), and broker level (*BSize* and *Affiliate*), and a time trend variable. In addition, there are controls for recent company news, including

---

facilitate revenue forecasting. We re-examine the forecasting tests after replacing cash flow forecasts with revenue forecasts and find very limited evidence that the same access improves revenue forecasts.

[15] We rely on a 90-day cutoff for the credit rating downgrade tests but conduct several sensitivity checks to ensure this is a reasonable timeframe. First, we examine the timing of an average analyst's research revision activity in advance of rating downgrades. In particular, we investigate, separately, revision activities related to earnings forecasts, stock recommendations, and cash flow forecasts in each one of the six months, *m*-1 through *m*-6, preceding a credit rating downgrade. In untabulated analyses, we find evidence of significant research revision activities by an average analyst in *m*-1, *m*-2, and *m*-3, but not earlier, providing comfort the 90-day period is a reasonable timeframe to capture revisions prior to credit rating changes. Second, we examine the sensitivity of the results to the following alternative windows: [-100, -1], [-120, -1], and find results consistent with those of the 90-day window. Third, as another alternative window, we examine the period between the last earnings announcement and the rating downgrade, [*EAD*(*t*-1), -1], finding results very similar to those of the 90-day window.

[16] We use the most recent one-year-head cash flow or earnings forecasts by other analysts to calculate the prevailing consensus. In the case where one-year-ahead cash flow or earnings forecasts are not available, we use two-year-ahead cash flow or earnings forecasts by other analysts to calculate the pre-window consensus.

stock return news (*BHAR*), prior year's earnings surprise *(Surprise*), the incidence of earnings announcement in the 90-day period (*EAD*), earnings guidance news (*Guide_News*), the days elapsed since the last research output (*Days_Elapsed*) and industry fixed effects. For the test of *REC_Down*, we further control for the pre-window consensus recommendation level*, Rec_Level,* because it limits the extent to which an equity analyst could revise down from the consensus.[17]

Our second empirical prediction also asserts that access to high-quality debt research is positively associated with the magnitude of equity research revisions prior to a credit rating downgrade. To test this prediction, we estimate the following OLS model:

$$Rev_{i,j,t} \quad = \quad \beta_0 + \beta_1\, Access_{i,j,t} + \boldsymbol{\beta}\, \boldsymbol{z} + \varepsilon_{1i,j,t,} \tag{4}$$

where *Access* is equal to one if the equity analyst has access to high-quality debt research and zero otherwise; and **z** includes the same controls from Eq. (3). In Eq. (4), *Rev* denotes *EF_Rev*, *REC_Rev*, or *CF_Rev*, which is the revision in earnings forecast, stock recommendation, or cash flow forecast, respectively, in the 90-day period leading to a company's credit rating downgrade. Each revision is measured relative to the respective consensus in the [-120, -91] days preceding the credit rating downgrade and scaled by the absolute value of the respective consensus (except for *REC_Rev*). To facilitate interpretation, we multiply revisions preceding a downgrade by -1 so that more positive numbers correspond to larger magnitude revisions. If an equity analyst issues multiple estimates in the window [-90, -1], we take their average in computing the *Rev* variable.

4.2.2. Empirical results

Table 3 contrasts the incidence of equity research revisions by analysts with access to high-quality debt research to those of other analysts in the period leading to a credit rating downgrade. The results show that *Access* is associated with a significantly greater likelihood of downward earnings and cash flow

---

[17] For completeness, in untabulated analyses, we also examine upward revisions in equity research preceding credit rating upgrades. Consistent with the notion that debt analysts prioritize credit deterioration over credit improvement, we do not find a benefit to access prior to credit rating upgrades.

forecast revisions and significantly larger downward earnings forecast revisions prior to credit downgrades.

Panel A of Table 4 reports the results from estimating Eq. (3). In all specifications, we find that the coefficient estimates on *Access* are positive and significant. These results suggest that analysts with access to high-quality debt research are more likely than other analysts to issue negative equity research in advance of a company's rating downgrade. The results are also economically significant: when the control variables are set to their sample means, *Access* is associated with a 3.2%, 1.6%, and 1.4% increase in the probability of revising down the consensus earnings forecast, stock recommendation, and cash flow forecast, respectively. In terms of control variables, we find that analysts are more likely to issue a negative revision following more negative stock return news or earnings guidance news, and that analysts who have not updated their research estimates for a longer period of time are less likely to issue a negative revision in advance of a rating downgrade. Overall, the results suggest that equity analysts with access to high-quality debt research are more informed about deteriorating credit quality and incorporate such information into their equity research in advance of the actual rating downgrades.

Panel B of Table 4 reports the results from estimating Eq. (4). In all specifications, we find that the coefficient estimates on *Access* are consistently positive and significant. These results suggest that prior to a company's rating downgrade, equity analysts with access to high-quality debt research make larger downward revisions in earnings forecasts, stock recommendations, and cash flow forecasts than do other analysts.[18] The results are also economically large: for example, the documented differences between analysts in earnings and cash flow forecast revisions are 4 and 6 cents, respectively.[19] Collectively, the

[18] In an untabulated analysis, we examine one additional aspect of forecast quality, whether access to high-quality debt research is positively associated with the timeliness of equity research. We find that prior to a downgrade, equity analysts with access not only revise down their stock recommendations and cash flow forecasts, but they also do so earlier than other analysts. In economic terms, equity analysts with access revise down their stock recommendations and cash flow forecasts approximately 4 and 6 days earlier than other analysts, respectively.

[19] Specifically, based on the mean absolute pre-window consensus earnings and cash flow forecasts in our sample, access to high-quality debt research is associated with a \$0.04 (= \$2.570 × 1.72%) larger downward revision in earnings forecast and a \$0.06 (= \$7.755 × 0.82%) larger downward revision in cash flow forecast. These revisions are larger by about \$0.01 when we use historical (unadjusted) IBES data.

results suggest that in the three months prior to a credit rating downgrade, analysts with access to high-quality debt research tend to issue more negative equity research than do other analysts.[20]

4.3. Supplementary analyses: Alternative research designs

A potential concern with our results is that equity analysts who have access to all-star debt analysts are different from other analysts in fundamental ways and that our control variables do not adequately account for such differences. Relatedly, there may be fundamental differences between brokers with all-star debt analysts and those without. We offer additional tests to mitigate these concerns.

First, we estimate Eq. (1) to (4) using a staggered difference-in-differences design (DiD).[21] We measure access based on star debt analyst arrivals, and we control for equity analyst and year fixed effects. In this design, *Gain_Access* is equal to one in year *t* and thereafter for analysts who gain access in year *t* due to the arrival of a star debt analyst who follows the same industry and investment category, and zero otherwise. To alleviate the potential concern that the arrival of star debt analysts is endogenous, we adopt an instrumental variable approach suggested by Do and Zhang (2020). The instrumental variable, *Adj_Arrival*, is the number of star debt analysts at other brokerage firms who are in their prime moving age (i.e., between 8 and 10 years since their first job) and who, in their early career (i.e., within 5 years of their first job), were colleagues of the equity analysts currently at the focal analyst's brokerage firm. We collect debt analyst employment data from LinkedIn. Table 5 reports the results from this supplementary analysis. Although weaker than our original results, these results show that equity analysts who gain

---

[20] In untabulated analyses, we explore the potential benefit of having access to "ordinary" debt research. To this end, we identify brokers with debt departments using our II all-star debt analyst data and *Mergent Investext*, a source of full-text debt research reports, as follows. If a broker's first (last) all-star debt research award occurs in year t (τ), we infer the existence of a debt research department over the period [t, τ]. If a broker's first (last) debt report is published in year t (τ), we infer the existence of a debt research department over the period [t, τ]. In an untabulated analysis, we find that access to ordinary debt research helps equity analysts only very modestly.

[21] We note a limitation of this approach is that it prevents us from estimating several of our specifications due to insufficient sample size.

access provide higher quality research in terms of greater likelihood and accuracy of cash flow forecasts, and greater ability to anticipate adverse credit events.[22]

Second, we test whether resources at star debt analyst-employing brokers are responsible for our results. In particular, we replicate the original analyses after redefining our measure of equity analyst access to *Access_Other*, an indicator equal to one if an equity analyst who covers a company has access only to star debt analyst research that does *not* overlap on industry and investment category, and zero otherwise. In other words, the equity analyst is employed at the same broker as the all-star debt analyst but covers a different set of companies. The results are available in Table 5 of Internet Appendix. Based on the *Access_Other* variable, we find just one positive result: increased likelihood of a downward earnings forecast revision prior to a credit rating downgrade. We conclude that unobserved differences in broker characteristics are unlikely to explain our results.

4.4. Debt research properties

In this section, we investigate the properties of star debt analyst reports vis-à-vis those of other analysts to both corroborate our assumption that star debt analyst research is of higher quality and alleviate the reverse causality concern that information flows from the equity analyst to the all-star debt analyst. To minimize data collection costs and as an extension to our credit rating downgrade analysis, we download from Investext all available debt report header data for our sample companies in the credit rating downgrade analysis, and all (747) full debt reports published in the 90 days prior to covered companies' credit rating downgrades.

In Table 6 of the Internet Appendix, we compare debt research reports on three dimensions: prevalence, length, and tone. We find that all-star debt analysts who help equity analyst colleagues to anticipate rating downgrades are more likely to publish a report in the period prior to a downgrade than other debt analysts, and that their reports are lengthier, as well as more negative in tone than those by

[22] In Table 4 of the Internet Appendix, we examine the opposite case of equity analysts who lose access due to the departure of a star debt analyst who follows the same industry and investment category. We find that losing access negatively impacts cash forecast quality. The small sample size prevents us from evaluating the effect of star debt analyst departures on equity research prior to credit rating downgrades.

other debt analysts, consistent with all-star debt analysts providing research of higher quality than other debt analysts. In addition, we find the publication of a star debt analyst report increases the likelihood of a downward equity research revision in the post-publication period by 25% but has no effect on the probability of a downward equity research revision in the pre-publication period, suggesting that information flows from all-star debt analysts to equity analysts and not the other way around.

4.5. The sources of incremental information of high-quality debt research

All-star debt analysts may be helpful to equity analysts because they access different information or analyze the same information differently. To shed light on these non-mutually exclusive explanations, we test whether the informational benefits of debt research are greater when the all-star debt analyst has superior access to management and/or greater research expertise. Echoing studies on management access in the equity analyst literature, we suggest that a debt analyst has superior access to management if she is employed by a broker which has underwritten the company's debt offering (Allen and Faulhaber, 1989) or hosted the company's management at a debt conference in the prior year (Green, Jame, Markov, and Subasi, 2014). Consequently, debt analysts employed by such brokers may acquire extra information pertinent to cash flow and credit risk analyses from management and provide more informational benefits to equity analysts than other debt analysts. We thus proxy for an all-star debt analyst's access to private information with *Debt_Underwriting*, an indicator variable equal to one if the debt and equity analysts' broker acted as a lead manager or co-manager of the debt underwriting team for the equity analyst's covered company in year *t*-1, and *Debt_Conference*, an indicator variable equal to one if the broker invited the company to a debt conference in year *t*-1.

We conjecture that an all-star debt analyst has greater expertise if she is an award winner in multiple sectors or is a CFA (De Franco and Zhou, 2009; Kang, Li, and Su, 2018). Our rationale for the former construct is based on Brown and Mohammad (2010), where the key insight is that breadth of expertise aids analysts in dealing with the dynamic nature of company-specific research. We thus proxy for expertise with *Multi_Award*, an indicator equal to one if the star debt analyst is ranked by *Institutional*

Investor in multiple sectors, and *CFA*, an indicator equal to one if the star debt analyst has a CFA qualification listed on LinkedIn.

The sample for this analysis includes only equity analysts who have access to high-quality debt research.[23] To explore the role of management access and research expertise in explaining the benefit of high-quality debt research for forecasting future cash flows, we modify Eq. (1) and (2) by replacing *Access* with our proxies for management access and research expertise. Panel A of Table 6 reports the results from evaluating cash flow issuance and accuracy; for brevity, we tabulate only the coefficient of interest: Proxy × *Distress*. We find that the interaction terms with management access and research expertise proxies are statistically significant in 5 (of 8) and 4 (of 8) specifications, respectively, suggesting both variables help explain the incremental value of high-quality debt research.

Next, we modify Eq. (3) and (4) by replacing *Access* with our proxies of management access and research expertise. In Panel B of Table 6, we report only the coefficients on each of our proxies. We find that the management access proxies are statistically significant in 6 (of 12) specifications, and that debt analyst expertise proxies are statistically significant in 7 (of 12) specifications. Overall, our findings support both the management access and the research expertise explanations of the incremental value of high-quality debt research.

4.6. Influence of brokerage culture and geographic proximity on the benefits of high-quality in-house debt research

Organizational research suggests that firm culture and geographic proximity among employees can influence intra-firm knowledge sharing and collaboration (Ruggles, 1998; Sveiby and Simons, 2002; Boh et al., 2007; Wang and Noe, 2010). A culture of collaboration increases knowledge sharing through a shared understanding of policies, procedures, and norms, which increases mutual trust and effective communication among organizational members (De Long and Fahey, 2000; Pinjani and Palvia, 2013).

[23] We can only collect these variables for all-star debt analysts due to the need to track debt analysts by broker-year. Hence, inferences are based on cross-sectional variation within high-quality debt research.

Geographic proximity leads to greater knowledge sharing because it reduces communication frictions and coordination costs. For instance, it is easier for employees to interact and form social connections with others (Allen, 1977) and to learn from others (Brandon and Hollingshead, 2004) when they are geographically close. We, therefore, expect that collaborative brokerage culture and geographic proximity will increase the benefits of high-quality in-house debt research.[24]

To measure a broker's collaborative culture, we rely on the Sull et al. (2019) collaboration sentiment measure, which is estimated from a textual analysis of employer reviews on Glassdoor.com.[25] The collaboration sentiment score is calculated as the percentage of employee reviews that discuss a firm's collaboration culture in positive terms. We define *Collaborative_Culture* as an indicator variable equal to one if a sell-side firm's collaboration sentiment score is above the industry mean, and zero otherwise. We measure geographic proximity by using LinkedIn to hand-collect the work locations of 3,380 equity analysts (including both analysts with and without *Access*) and 84 debt analysts. We define *Same_City* as an indicator variable set to one if the equity analyst has access to high-quality debt research and works in the same city as the all-star debt analyst during the year, and zero otherwise.

In Table 7, our findings are consistent with a more collaborative culture strongly impacting the benefit of high-quality debt research to the equity analyst's performance.[26] In Panel A, we observe that equity analysts with access to high-quality debt research issue more frequent and more accurate cash flow forecasts for distressed companies only when brokerage culture is collaborative. In Panel B, we find that in the period prior to a credit rating downgrade, equity analysts in more collaborative cultures are more

---

[24] The organizational culture analysis is based on brokerage firms with culture ratings on Glassdoor.com, and the geographic proximity analysis is based on debt and equity analysts with location information on LinkedIn.

[25] Sull et al. (2019) create a customized machine-learning dictionary to classify unstructured Glassdoor text reviews into topics that can be mapped to specific cultural values such as collaboration. Glassdoor is the largest online resource for employee reviews and allows users to anonymously rate and review various aspects of their companies; for instance, overall rating, company benefits, culture, and senior management.

[26] Results are inferentially similar if we control for the broker's general culture; we do this by taking the average of Glassdoor's overall culture and values ratings for each firm and define *Better_Culture* as an indicator variable set equal to one if the sell-side firm's overall culture is above the sample mean, and zero otherwise.

likely to issue downward earnings and cash flow estimates and provide more negative earnings and stock recommendation revisions.

In Table 8, we find strong evidence that proximity improves knowledge sharing. For instance, in Panel A, collocation benefits equity analysts with access in the form of increased propensity to issue cash flow forecasts and cash flow forecasting accuracy for distressed companies. In Panel B, we observe that in the period prior to a credit rating downgrade, equity analysts collocated with all-star debt analysts are more likely to issue downward equity research and provide more negative earnings forecast revisions than other analysts.[27]

In sum, our evidence points to benefits of high-quality debt research to equity analyst research only in the presence of a collaborative brokerage culture or debt-equity analyst collocation, consistent with these factors being critical to knowledge sharing in the brokerage research environment.

5. Conclusion

We study inter-department knowledge sharing in the investment research industry, a setting where both the economic benefits of sharing and the impediments to sharing are substantial. Using hand-collected data, we examine the role of all-star debt analysts as an in-house resource for equity analysts. We present evidence that sheds light on which aspects of equity research benefit from access to high-quality debt research: forecasting cash flows of distressed companies and anticipating credit rating downgrades; the sources of all-star debt analysts' informational advantage: management access and research expertise; and the organizational factors facilitating the flow of information between the debt and equity research departments: culture of collaboration and collocation of equity and all-star debt analysts.

[27] Our results are qualitatively similar if we use an alternative measure of geographic proximity based on whether the equity analyst and all-star debt analyst work within 50 miles of one another.

References

Abramowitz, P. 2008. Credit to the ones who cover the crisis. *Institutional Investor* 42 (8).

Allen, F., and G. Faulhaber. 1989. Signaling by underpricing in the IPO market. *Journal of Financial Economics* 23: 303-323.

Allen, T. 1977. *Managing the flow of technology*. MIT Press. Cambridge, MA.

Altman, E. 1968. Financial ratios, discriminant analysis and the prediction of corporate bankruptcy. *Journal of Finance* 23: 589-609.

Arrow, K. 1974. *The Limits of Organization*. New York: Norton.

Ayers, B., A. Call, and C. Schwab. 2018. Do analysts' cash flow forecasts encourage managers to enhance real cash flows? Evidence from tax planning. *Contemporary Accounting Research* 35: 767-793.

Bilinski, P. 2014. Do analysts disclose cash flow forecasts with earnings estimates when earnings quality is low? *Journal of Business Finance and Accounting* 41: 401-434.

Boh, W., Y. Ren, S. Kiesler, and R. Bussjaeger. 2007. Expertise and collaboration in the geographically dispersed organization. *Organizational Science* 18: 595-612.

Bradley, D., S. Gokkaya, and X. Liu. 2019. The boss knows best: Directors of research and subordinate analysts. *Journal of Financial and Quantitative Analysis* 54: 1403-1446.

Brandon, D., and A. Hollingshead. 2004. Transactive memory systems in organizations: Matching tasks, expertise and people. *Organization Science* 15: 633-644.

Brennan M., N. Jegadeesh, B. Swaminathan. 1993. Investment analysis and the adjustment of stock prices to common information. *Review of Financial Studies* 6:799-824.

Brown, L., and A. Hugon. 2009. Team earnings forecasting. *Review of Accounting Studies* 14: 587-607.

Brown, L., and E. Mohammad. 2010. Is analyst earnings forecast ability only firm specific? *Contemporary Accounting Research* 27: 727-750.

Clement, M. 1999. Analyst forecast accuracy: Do ability, resources, and portfolio complexity matter? *Journal of Accounting and Economics* 27: 285-303.

Curtis, B., H. Krasner, and N. Iscoe. 1988. A field study of the software design process for large systems. *Communications of the ACM* 31: 1268-1287.

De Franco, G., F. Vasvari, and R. Wittenberg-Moerman. 2009. The informational role of bond analysts. *Journal of Accounting Research* 47: 1201-1248

De Franco, G., and Y. Zhou. 2009. The performance of analysts with a CFA® designation: The role of human-capital and signaling theories. *The Accounting Review* 84: 383-404.

DeFond, M., and M. Hung. 2003. An empirical analysis of analysts' cash flow forecasts. *Journal of Accounting and Economics* 35: 73-100.

De Long, D., and L. Fahey. 2000. Diagnosing cultural barriers to knowledge management. *Academy of Management Executive* 14: 113-127.

Do, T., and H. Zhang. 2020. Peer effects among financial analysts. *Contemporary Accounting Research* 37: 358-391.

Fang, B., and O. K. Hope. 2021. Analyst teams. *Review of Accounting Studies* 26: 425-467.

Finholt, T., L. Sproull, and S. Kiesler. 2002. Outsiders on the inside: Sharing know-how across space and time. In P. Hinds and S. Kiesler, *Distributed Work*. Cambridge: MIT Press.

Gargiulo, M., G. Ertug, and C. Galunic. 2009. The two faces of control: Network closure and individual performance among knowledge workers. *Administrative Science Quarterly* 54: 299-333.

Gibson, C., and J. Gibbs. 2006. Unpacking the concept of virtuality: The effects of geographic dispersion, electronic dependence, dynamic structure, and national diversity on team innovation. *Administrative Science Quarterly* 51: 451-495.

Goh, J., and L. Ederington. 1993. Is a bond rating downgrade bad news, good news, or no news for stockholders? *Journal of Finance* 48: 2001-2008.

Gow, I., G. Ormazabal, and D. Taylor. 2010. Correcting for cross-sectional and time-series dependence in accounting research. *The Accounting Review* 85: 483-512.

Grant, R. 1996. Toward a knowledge-based theory of the firm. *Strategic Management Journal* 17: 109-122.

Green, T., R. Jame, S. Markov, and M. Subasi. 2014. Access to management and the informativeness of analyst research. *Journal of Financial Economics* 114: 239-255.
Griffin, P., and A. Sanvicente. 1982. Common stock returns and rating changes: A methodological comparison. *Journal of Finance* 37: 103-119.
Groysberg, B., and I. Vargas. 2007. Innovation and collaboration at Merrill Lynch. HBS # 9-406-081. Boston: Harvard Business School Publishing.
Gupta, A., and V. Govindarajan. 2000. Knowledge flows within multinational corporations. *Strategic Management Journal* 21: 473-496.
Gurun, U., R. Johnston, and S. Markov. 2016. Sell-side debt analysts and debt market efficiency. *Management Science* 62: 682-703.
Hand, J., R. Holthausen, and R. Leftwich. 1992. The effect of bond rating agency announcements on bond and stock prices. *Journal of Finance* 47: 733-752
Hansen, M., M. Mors, and B. Lovas. 2005. Knowledge sharing in organizations: Multiple networks, multiple phases. *Academy of Management Journal* 48: 776-793.
Haushalter, D., and M. Lowry. 2011. When do banks listen to their analysts? Evidence from mergers and acquisitions. *Review of Financial Studies* 24: 321-357.
Holthausen, R., and R. Leftwich. 1986. The effect of bond rating changes on common stock prices. *Journal of Financial Economics* 17: 57-89.
Hope, O. K. and X. Su. 2021. Peer-level analyst transitions. *Journal of Corporate Finance* 70: 1-21.
Huang, A., A. Lin, and A. Zang. 2022. Cross-industry information sharing among colleagues and analyst research. *Journal of Accounting and Economics*, forthcoming.
Hwang, B., J. Liberti, and J. Sturgess. 2019. Information sharing and spillovers: Evidence from financial analysts. *Management Science* 65: 3624-3636.
Jacob, J., T. Lys, and M. Neale. 1999. Expertise in forecasting performance of security analysts. *Journal of Accounting and Economics* 28: 51-82.
Johnston, R., S. Markov, and S. Ramnath. 2009. Sell-side debt analysts. *Journal of Accounting and Economics* 47: 91-107.
Ivashina, V., and Z. Sun. 2011. Institutional stock trading on loan market information. *Journal of Financial Economics* 100: 284-303.
Kang, Q., X. Li, and T. Su. 2018. Sell-side financial analysts and the CFA® program. *Financial Analysts Journal* 74: 70-83.
Kankanhalli, A., B. Tan, and K. Wei. 2005. Contributing knowledge to electronic knowledge repositories: An empirical investigation. *MIS Quarterly* 29: 113-143.
Kim, R., W. Kross, and I. Suk. 2015. Bond analysts' forecasts on cash flows and earnings. Working paper, University of Massachusetts Boston and State University of New York at Buffalo.
Kogut, B., and U. Zander. 1992. Knowledge of the firm, combinative capabilities, and the replication of technology. *Organization Science* 3: 383-397.
Lim, T. 2001. Rationality and analysts' forecast bias. *Journal of Finance* 56: 369-385.
Lin, H., and M. McNichols. 1998. Underwriting relationships, analysts' earnings forecasts and investment recommendations. *Journal of Accounting and Economics* 25: 101-127.
Massoud, N., D. Nandy, A. Saunders, and K. Song. 2011. Do hedge funds trade on private information? Evidence from syndicated lending and short selling. *Journal of Financial Economics* 99: 477-499.
Merton, R. 1974. On the pricing of corporate debt: The risk structure of interest rates. *Journal of Finance* 29: 449-470.
Pae, J., and S. Yoon. 2012. Determinants of analysts' cash flow forecast accuracy. *Journal of Accounting, Auditing, and Finance* 27: 123-144.
Pinjani, P., and P. Palvia. 2013. Trust and knowledge sharing in diverse global virtual teams. *Information and Management* 50: 144-153.
Porter, M. 1985. *The competitive advantage: Creating and sustaining superior performance*. NY: Free Press.
Ronan, G. 2006. The 2006 All-America Fixed-Income Research Team. *Institutional Investor* (September).

Ruggles, R. 1998. The state of notion: Knowledge management in practice. *California Management Review* 40: 80-89.

Schepers, P., and P. Van den Berg. 2007. Social factors of work-environment creativity. *Journal of Business and Psychology* 21: 407-428.

Spender, J., and R. Grant. 1996. Knowledge and the firm: Overview. *Strategic Management Journal* 17: 5-9.

Sull, D., C. Sull, and A. Chamberlain. 2019. Measuring culture in leading companies. *MIT Sloan Management Review* and Glassdoor.

Sveiby, K., and R. Simons. 2002. Collaborative climate and effectiveness of knowledge work–an empirical study. *Journal of Knowledge Management* 6: 420-433.

Teece, D., G. Pisano, and A. Shuen. 1997. Dynamic capabilities and strategic management. *Strategic Management Journal* 18: 509-533.

Tsai, W. 2002. Social structure of "coopetition" within a multiunit organization: Coordination, competition, and intraorganizational knowledge sharing. *Organizational Science* 13: 179-190.

Wang, S., and R. Noe. 2010. Knowledge sharing: A review and directions for future research. *Human Resource Management Review* 20: 115-131.

White, L. 2010. Markets: The credit rating agencies. *Journal of Economic Perspectives* 24: 211-226.

Womack, K. 1996. Do brokerage analysts' recommendations have investment value? *Journal of Finance* 51(1):137–167.

Appendix 1
Sample Selection

Panel A: Forecasting Cash Flows

	Analyst-Company-Years	Companies
Cash flow forecast issuance test		
Analyst-company-years with IBES research coverage	585,095	12,127
With IBES sector/industry/group code	584,274	12,070
With S&P credit rating	228,066	2,043
With financial data to calculate z-score	183,608	1,579
With financial data to calculate other control variables	165,268	1,371
Relative cash flow forecast accuracy test		
With non-missing cash flow actuals	24,511	852

Panel B: Research Prior to Credit Rating Downgrades

	Analyst-Company-Rating-Years	CR Downgrades (Companies)
Test of likelihood of equity research		
S&P long-term issuer rating downgrades		12,622 (5,009)
With prior rating change being at least four months apart		9,939 (4,891)
Analyst-company-rating-years with IBES research coverage and sector/industry/group code	22,552	1,835 (960)
With financial data to calculate control variables	21,573	1,725 (907)
Earnings forecast test		
With non-missing earnings forecast revision	9,846	1,128 (678)
Stock recommendation test		
With non-missing stock recommendation revision	2,222	622 (440)
Cash flow forecast test		
With non-missing cash flow forecast revision	1,150	367 (277)

Table Notes:

In Panel A, we detail the sample selection for the cash flow forecasting tests. The starting point for the cash flow issuance test is earnings forecast coverage. For the cash flow accuracy test, we require non-missing actuals and coverage by at least one analyst with access to high-quality debt research. In Panel B, we detail the sample selection for the tests of equity research in advance of credit rating downgrades. We require earnings forecast coverage and non-missing consensus forecast in the [-120, -91] days preceding the credit rating downgrade to determine the direction and magnitude of an equity research revision.

Appendix 2
Variable Definitions

Variable	Definition
Dependent variables:	
CF_I	Cash flow forecast issuance, an indicator variable set to one if the equity analyst issues at least one cash flow forecast for company *j* in year *t*, and zero otherwise.
R_CF_ACC	Relative cash flow forecast accuracy, calculated as the equity analyst's absolute cash flow forecast error minus the mean absolute cash flow forecast error of all analysts following company *j* in year *t*, scaled by the mean absolute cash flow forecast error for company *j* in year *t*, and multiplied by -1.
Down	Issuance of a downward equity research revision prior to a credit rating downgrade, an indicator equal to one when the equity analyst issues research in the 90-day period leading to company *j*'s credit rating downgrade in year *t* and the research estimate is lower than the pre-window consensus, and zero otherwise.
Rev	Magnitude of earnings research revision prior to a credit rating downgrade, calculated as the equity analyst's estimate minus the respective consensus, and scaled by the absolute value of the respective consensus (except for stock recommendation revision, which is unscaled). To ease interpretation, we multiply revisions preceding a downgrade by -1 so that more positive numbers correspond to larger magnitude revisions.
Key independent variables:	
Access	Access to high-quality debt research, an indicator variable equal to one if the equity analyst and an all-star debt analyst are employed by the same sell-side firm during the year, and the debt analyst is ranked in the industry sector and investment category that matches those of the equity analyst's followed company *j* in year *t*, and zero otherwise.
F_Distress	Financially distressed company based on Altman (1968) z-score, an indicator variable set to one if company *j* has a z-score below 1.81 at the beginning of year *t*, and zero otherwise.
I_Distress	Financially distressed industry based on Altman (1968) z-score, an indicator variable set to one if the percentage of financially distressed companies (i.e., z-score below 1.81 at the beginning of year *t*) relative to all companies in a given industry-year falls in the top quintile of all industry-years, and zero otherwise.
Debt_Underwriting	Debt underwriter-client relationship, an indicator variable set to one if the sell-side firm acted as the lead manager or co-manager of company *j*'s debt underwriting team in year *t*-1, and zero otherwise.
Debt_Conference	Debt conference participation, an indicator variable equal to one if the sell-side firm invited company *j* to a debt conference in year *t*-1, and zero otherwise.
Multi_Award	Multiple award-winning debt analyst, an indicator equal to one if the debt analyst is ranked by *Institutional Investor* in multiple sectors in year *t*.
CFA	Debt analyst's CFA qualification, an indicator equal to one if the all-star debt analyst has a CFA qualification listed on LinkedIn, and zero otherwise.

Collaborative_Culture	Collaborative culture, an indicator variable set to one if the broker that employs the equity analyst has a collaboration sentiment score that is higher than the industry mean, and zero otherwise.
Same_City	Colocation of equity and debt analysts, an indicator variable set to one if the equity analyst has access to high-quality debt research and works in the same city as the all-star debt analyst in year *t*, and zero otherwise.
Control variables	
AA_Equity	All-star equity analyst, an indicator variable set to one if the equity analyst is ranked in the top three or as a runner-up by *Institutional Investor* in year *t*, and zero otherwise.
Affiliate	Underwriter-client relationship, an indicator variable set to one if the sell-side firm acted as the lead manager or co-manager of company *j*'s debt or equity underwriting team in year *t*-1, and zero otherwise.
BHAR	Stock return news, measured as the buy-and-hold market-adjusted stock return of company *j* during the [-180, -91] days of a credit rating downgrade.
BSize	Brokerage firm size, calculated as the natural logarithm of the number of unique equity analysts employed by the sell-side firm in year *t*.
Cap_Intensity	Capital intensity, measured as gross property, plant, and equipment divided by sales revenue of company *j* in year *t*-1.
Days_Elapsed	Days elapsed since last equity research activity, calculated as the number of days between the equity analyst's most recent research estimate for company *j* prior to the [-90, -1] day window and the beginning of the window.
EAD	Incidence of earnings announcement, an indicator variable set to one if company *j* announces earnings for year *t*-1 during the [-90, -1] days of its credit rating downgrade, and zero otherwise.
Earn_Vol	Earnings volatility, measured as |standard deviation of earnings/mean of earnings| for company *j* between years *t*-4 and *t*-1, where earnings is earnings before extraordinary items scaled by beginning market value of the year.
Exp	Equity analyst's company-specific experience, defined as the number of years that the equity analyst has issued at least one EPS forecast for company *j* prior to year *t*.
Freq	Cash flow forecast frequency, calculated as the number of cash flow forecasts issued by the equity analyst for company *j* in year *t*.
Guide_News	Earnings guidance news, measured as the annual earnings guidance value minus the most recent mean consensus earnings forecast for company *j* in year *t*.
Horizon	Cash flow forecast horizon, defined as the number of days between the equity analyst's cash flow forecast for company *j* and the announcement date of company *j*'s actual cash flow in year *t*.
Leverage	Financial leverage, calculated as the sum of long-term debt and short-term debt divided by total assets of company *j* at the beginning of year *t*.
Loss	Loss company, an indicator variable set to one if company *j* reports negative income before extraordinary items in year *t*-1, and zero otherwise.

MTB	Market-to-book ratio, calculated as market value of common equity divided by book value of common equity of company *j* at the beginning of year *t*.
NFirm	Number of companies that the equity analyst follows in year *t*.
NInd	Number of Fama-French 48 industries that the equity analyst follows in year *t*.
Rec_Level	Mean consensus stock recommendation for company *j* at the beginning of the [-90, -1] day window.
Size	Company size, measured as the natural logarithm of market value of company *j* at the beginning of year *t*.
Surprise	Earnings news, measured as actual earnings minus the most recent mean consensus earnings forecast for company *j* in year *t*-1, and then scaled by the stock price at the beginning of year *t*.
TAcc	Magnitude of total accruals, measured as the absolute value of net income before extraordinary items minus operating cash flows, and then scaled by total assets of company *j* in year *t*-1.
Z_Score	Altman z-score, computed as [1.2 * working capital/total assets - 1.4 * retained earnings/total assets + 3.3 * operating income/total assets + 0.6 * market value of equity/ total liabilities + sales/total assets] of company *j* in year *t*-1.

Table 1
Forecasting Cash Flows:
Analysts with Access to High-Quality Debt Research vs. Analysts without Access

Panel A: Variables Used in Forecast Issuance Test

	Access = 1 (N = 19,776)	*Access* = 0 (N = 145,492)	
Variable	Mean	Mean	*t*-stats
CF_I	0.290	0.242	14.46
F_Distress	0.318	0.301	4.75
I_Distress	0.198	0.187	3.70
Collaborative_Culture	0.592	0.316	66.85
Same_City	0.207	N/A	N/A
BSize	4.943	3.691	150.02
Affiliate	0.073	0.026	35.86
AA_Equity	0.362	0.126	88.13
Exp	4.586	4.405	6.72
NInd	4.161	4.126	1.72
NFirm	14.622	14.248	6.31
Z_Score	3.080	3.289	-9.00
TAcc	0.065	0.066	-1.88
Earn_Vol	1.615	1.564	1.72
Cap_Intensity	1.168	1.211	-3.89
Loss	0.131	0.130	0.62
Leverage	0.285	0.273	9.79
Size	8.816	8.865	-4.31
MTB	3.419	3.490	-2.44

Panel B: Additional Variables in Forecast Accuracy Test

	Access = 1 (N = 4,750)	*Access* = 0 (N = 19,761)	
Variable	Mean	Mean	*t*-stats
R_CF_ACC	0.020	0.018	2.23
Freq	5.041	4.875	3.32
Horizon	295.323	289.084	3.86

Table Notes:
This table compares equity analysts with access to high-quality debt research to those without such access. This table provides univariate test results of whether the incidence and accuracy of cash flow forecasts and relevant broker, analyst and company characteristics depend on access to high-quality debt research. The partitioning variable *Access* is an indicator variable set to one if the equity analyst has access to the research of an all-star debt analyst at the same sell-side firm following the same industry and investment category in year *t*, and zero otherwise. The descriptive samples are reduced for *Collaborative_Culture* and *Same_City* but untabulated for brevity. All remaining variables are defined in Appendix 2.

Table 2
Access to High-Quality Debt Research and Forecasting Cash Flows

Panel A: Likelihood of Issuing Cash Flow Forecasts

	CF_I		
	(1)	(2)	(3)
Access	-0.1087	-0.1178	-0.1276
	(-0.41)	(-0.48)	(-0.50)
F_Distress	-0.0232		0.0013
	(-0.82)		(0.05)
Access × F_Distress	0.1483**		0.0447
	(2.05)		(0.55)
I_Distress		-0.1636***	-0.1616***
		(-2.76)	(-2.68)
Access × I_Distress		0.2817**	0.2571**
		(2.49)	(2.05)
Controls	Included	Included	Included
N	165,268	165,268	165,268
Pseudo R-squared	0.200	0.201	0.201

Panel B: Cash Flow Forecast Accuracy

	R_CF_ACC		
	(1)	(2)	(3)
Access	-0.0112	-0.0053	-0.0143
	(-0.45)	(-0.24)	(-0.56)
F_Distress	0.0028		0.0056
	(0.45)		(0.92)
Access × F_Distress	0.0504**		0.0338*
	(2.33)		(1.86)
I_Distress		-0.0129	-0.0155*
		(-1.37)	(-1.68)
Access × I_Distress		0.0776***	0.0600**
		(2.89)	(2.32)
Controls	Included	Included	Included
N	24,511	24,511	24,511
Adj. R-squared	0.014	0.014	0.014

Table Notes:
This table presents the results from estimating our models of analysts' cash flow forecast issuance (Panel A) and relative cash flow forecast accuracy (Panel B). In Panel A, *CF_I* is an indicator variable set to one if the equity analyst issues at least one cash flow forecast for company *j* in year *t*, and zero otherwise. *Access* is an indicator variable set to one if the equity analyst has access to the research of an all-star debt analyst at the same sell-side firm following the same industry and investment category in year *t*, and zero otherwise. *F_Distress* is an indicator variable set to one if company *j* has a z-score below 1.81 at the beginning of year *t*, and zero otherwise. *I_Distress* is an indicator variable set to one if the percentage of financially distressed companies (i.e., z-score below 1.81 at the beginning of year *t*) relative to all companies in an industry-year falls in the top quintile of all industry-years, and zero otherwise. In Panel B, *R_CF_ACC* is relative cash flow forecast accuracy, measured as the equity analyst's absolute cash flow forecast error minus the mean absolute cash flow forecast error of all equity analysts following company *j* in year *t*, scaled by the mean absolute cash flow forecast error for company *j* in year *t*, and multiplied by -1. *z* and *t*-statistics (in

parenthesis) are calculated using standard errors clustered by broker and year. The notation *, **, and *** indicates significance at the 10%, 5%, and 1% levels, respectively.

Table 3
Research Prior to Credit Rating Downgrades:
Analysts with Access to High-Quality Debt Research vs. Analysts without Access

Panel A: Variables Used in Test of Likelihood of Equity Research Revision

	Access = 1		*Access* = 0		
	n	Mean	n	Mean	*t*-stats
EF_Down	2,852	0.464	18,721	0.422	4.21
REC_Down	2,353	0.063	15,381	0.057	1.09
CF_Down	1,725	0.097	10,177	0.082	2.10
Collaborative_Culture	2,326	0.588	12,091	0.310	26.25
Same_City	1,396	0.386	N/A	N/A	N/A
BHAR	2,852	-0.063	18,721	-0.060	-0.74
Surprise	2,852	0.033	18,721	0.039	-1.41
Loss	2,852	0.273	18,721	0.286	-1.41
EAD	2,852	0.242	18,721	0.233	1.12
Guide_News	2,852	-0.019	18,721	-0.018	-0.22
Size	2,852	8.508	18,721	8.430	2.57
MTB	2,852	3.185	18,721	2.959	2.52
Leverage	2,852	0.311	18,721	0.299	3.43
BSize	2,852	4.947	18,721	3.790	60.75
Affiliate	2,852	0.039	18,721	0.020	6.56
AA_Equity	2,852	0.371	18,721	0.123	35.04
Exp	2,852	4.376	18,721	4.192	2.61
NInd	2,852	3.998	18,721	3.956	0.78
NFirm	2,852	14.018	18,721	13.665	2.31
Days_Elapsed	2,852	3.533	18,721	3.596	-2.80

Panel B: Additional Variables Used in Test of Magnitude of Equity Research Revision

	Access = 1		*Access* = 0		
	n	Mean	n	Mean	*t*-stats
EF_Rev	1,364	0.098	8,482	0.084	1.70
REC_Rev	315	-0.166	1,907	-0.112	-0.86
CF_Rev	194	0.033	956	0.024	0.53

Table Notes:

This table describes the characteristics of equity research provided in the 90-day period prior to credit rating downgrades by equity analysts who have access to high-quality debt research and those who do not. *Access* is an indicator variable equal to one when the equity analyst has access to the research of an all-star debt analyst at the same sell-side firm following the same industry and investment category in year *t*, and zero otherwise. *EF*, *REC*, and *CF* denotes earnings forecast, stock recommendation, and cash flow forecast, respectively. *Down* is an indicator variable equal to one when the equity analyst revises down relative to the consensus in the [-90, -1] window of company *j*'s credit rating downgrade, and zero otherwise. The consensus is calculated by averaging estimates in the [-120, -91] window. *Rev* is the magnitude of equity research revision in the [-90, -1] window of company *j*'s credit rating downgrade, calculated as the equity analyst's estimate minus the consensus, and then scaled by the absolute value of the consensus (except for *REC_Rev*, which is unscaled). To ease interpretation, we multiply revisions preceding a downgrade by -1 so that more positive numbers correspond to larger magnitude revisions.

Table 4
Access to High-Quality Debt Research and Research Prior to Credit Rating Downgrades

Panel A: Likelihood of Equity Research Revision

	(1) *EF_Down*	(2) *REC_Down*	(3) *CF_Down*
Access	0.0819***	0.0162**	0.1327*
	(3.16)	(1.99)	(1.73)
Controls	Included	Included	Included
N	21,573	17,734	11,902
Pseudo R-squared	0.074	0.071	0.178

Panel B: Magnitude of Equity Research Revision

	(1) *EF_Rev*	(2) *REC_Rev*	(3) *CF_Rev*
Access	0.0172**	0.0519***	0.0082***
	(1.96)	(2.70)	(2.90)
Controls	Included	Included	Included
N	9,846	2,222	1,150
Adj. R-squared	0.113	0.310	0.108

Table Notes:
This table explores whether equity analysts with access to high-quality debt research are more likely to revise down their research before upcoming credit rating downgrades (Panel A) and the magnitude of such revisions (Panel B). In Panel A, the dependent variable is one when the equity analyst revises down relative to the consensus earnings forecast (*EF_Down*), stock recommendation (*REC_Down*), and cash flow forecast (*CF_Down*) in the [-90, -1] window of company *j*'s credit rating downgrade, and zero otherwise. The consensus is calculated by averaging all estimates in the [-120, -91] window. *Access* is one when the equity analyst has access to the research of an all-star debt analyst at the same sell-side firm following the same industry and investment category in year *t*, and zero otherwise. In Panel B, the dependent variables are the magnitude of the analyst's earnings forecast revision (*EF_Rev*), stock recommendation revision (*REC_Rev*), and cash flow forecast revision (*CF_Rev*). Each revision is measured relative to the consensus, calculated by averaging all estimates in the [-120, -91] window, and then scaled by the absolute value of the respective consensus (except for *REC_Rev*). To ease interpretation, we multiply revisions preceding a downgrade by -1 so that more positive numbers correspond to larger magnitude revisions. *z* and *t*-statistics (in parenthesis) are calculated using standard errors clustered by broker and year; the notation *, **, and *** indicates significance at the 10%, 5%, and 1% levels, respectively.

Table 5
Instrumental Variable Approach

Panel A: The Effects of Gaining Access on Forecasting Cash Flows

Dep. Var. =	*CF_I*			*R_CF_ACC*		
Distress =	*F_Distress* = 1	*I_Distress* = 1	*Distress* = 0	*F_Distress* = 1	*I_Distress* = 1	*Distress* = 0
	(1)	(2)	(3)	(4)	(5)	(6)
First-stage model:						
Adj_Arrival	0.0010***	0.010***	0.0007***	0.0075**	0.0046**	0.0013**
Adj. R-squared	0.505	0.460	0.482	0.809	0.890	0.735
Rank of partial R-squared of IV	4 of 15	4 of 15	3 of 15	4 of 9	1 of 9	5 of 9
Second-stage model:						
$\widehat{Gain\_Access}$	0.3545**	0.5243*	0.2795	4.9903*	1.8415	0.2084
	(2.00)	(1.65)	(0.59)	(1.73)	(0.97)	(0.19)
Adj. R-squared	0.771	0.744	0.518	0.038	0.095	0.094
Both stages:						
Controls	Included	Included	Included	Included	Included	Included
N	24,442	15,795	50,926	2,681	1,256	4,852

Panel B: The Effects of Gaining Access on Research Prior to Credit Rating Downgrades

	(1)	(2)	(3)	(4)	(5)	(6)
	EF_Down	*REC_Down*	*CF_Down*	*EF_Rev*	*REC_Rev*	*CF_Rev*
First-stage model:						
Adj_Arrival	0.0027***	0.0029***	0.0027**	0.0025***	-0.0007	0.0031*
Adj. R-squared	0.558	0.557	0.557	0.627	0.502	0.344
Rank of partial R-squared of IV	1 of 16	1 of 17	1 of 16	1 of 16	13 of 17	7 of 16
Second-stage model:						
$\widehat{Gain\_Access}$	1.4151**	0.5172*	-0.2279	0.1272***	N/A	4.5237**
	(1.96)	(1.76)	(-0.75)	(2.78)		(2.16)
Adj. R-squared	0.169	0.054	0.376	0.145		0.217
Both stages:						

Controls	Included	Included	Included	Included		Included
N	9,889	8,235	8,812	4,526	415	322

Table Notes:

This table addresses the robustness of our results using a staggered difference-in-differences design (DiD) with an instrumented access to high-quality debt research. In Panels A and B, we estimate the following first-stage model: $Gain\_Access_{i,j,t} = \beta_0 + \beta_1\ Adj\_Arrival_{i,j,t} + \beta\ Controls + \varepsilon_{1i,j,t}$, where *Gain_Access* is equal to one in year *t* and thereafter for analysts who did not previously have access to a star debt analyst prior to year *t* and then gain access in year *t* due to a star debt analyst arrival. *Adj_Arrival* is the number of star debt analysts at other brokerage firms who are in their prime moving age and who, in their early career, were colleagues of the equity analysts currently at analyst *i*'s brokerage firm. *Controls* represent the control variables from the original models plus analyst and year fixed effects. *N/A* denotes the coefficient estimate on the first-stage instrument is not statistically significant. *Rank of partial R-squared of IV* compares the instrumental variable's partial R-squared to those of the other independent variables excluding fixed effects. See Appendix 2 for other variable definitions. *t*-statistics (in parenthesis) are calculated using standard errors clustered by broker and year; the notation *, **, and *** indicates significance at the 10%, 5%, and 1% levels, respectively.

Table 6
Summary of Cross-Sectional Analyses within High-Quality Debt Research

Panel A: Forecasting Cash Flows

Dep. Var. =	*CF_I*		*R_CF_ACC*	
Distress =	*F_Distress*	*I_Distress*	*F_Distress*	*I_Distress*
	(1)	(2)	(3)	(4)
Management access proxies:				
(1) *Debt_Underwriting × Distress*	0.1475*	0.1842**	-0.0671	0.0723*
	(1.65)	(2.06)	(-1.09)	(1.74)
N	19,771	19,771	4,776	4,776
Pseudo/Adj. R-squared	0.337	0.315	0.011	0.010
(2) *Debt_Conference × Distress*	0.7502***	0.0056	-0.1957	0.2269***
	(3.67)	(0.02)	(-1.23)	(3.20)
N	5,062	5,062	1,822	1,822
Pseudo/Adj. R-squared	0.567	0.564	0.011	0.011
Debt analyst expertise proxies:				
(3) *Multi_Award × Distress*	-0.0949	-0.2104	0.1130***	0.1325*
	(-0.49)	(-0.80)	(3.10)	(1.71)
N	19,771	19,771	4,776	4,776
Pseudo/Adj. R-squared	0.322	0.322	0.016	0.017
(4) *CFA × Distress*	-0.0758	0.4673**	-0.0431	0.1115***
	(-0.34)	(2.23)	(-0.74)	(5.10)
N	13,639	13,639	3,238	3,238
Pseudo/Adj. R-squared	0.208	0.212	0.016	0.016

Panel B: Research Prior to Credit Rating Downgrades

	(1) *EF_Down*	(2) *REC_Down*	(3) *CF_Down*	(4) *EF_Rev*	(5) *REC_Rev*	(6) *CF_Rev*
Management access proxies:						
(1) *Debt_Underwritng*	0.1625**	-0.3719	-0.3280	-0.0220	-0.4101	-0.1062
	(2.11)	(-1.28)	(-1.44)	(-0.96)	(-1.14)	(-1.34)
N	2,886	2,206	1,606	1,377	318	180
Pseudo/Adj. R-squared	0.117	0.128	0.327	0.176	0.354	0.254
(2) *Debt_Conference*	0.2162*	0.8066*	0.2123**	-0.1247	0.8093*	0.2975***
	(1.88)	(1.77)	(2.44)	(-1.62)	(1.84)	(4.26)
N	1,282	666	723	644	117	116
Pseudo/Adj. R-squared	0.114	0.213	0.343	0.151	0.273	0.395
Debt analyst expertise proxies:						
(3) *Multi_Award*	0.0883*	-0.0474	-0.0046	-0.0255	0.0891**	0.1104**
	(1.70)	(-0.79)	(-0.03)	(-1.26)	(1.98)	(2.20)
N	2,886	2,206	1,606	1,377	318	180
Pseudo/Adj. R-squared	0.124	0.164	0.361	0.177	0.344	0.269
(4) *CFA*	-0.0583	0.1458**	0.2366*	-0.0113	0.1235**	0.1616**
	(-0.90)	(2.22)	(1.83)	(-0.41)	(2.08)	(2.03)
N	1,743	1,216	802	848	226	108
Pseudo/Adj. R-squared	0.116	0.143	0.334	0.177	0.260	0.368

Table Notes:

This table examines the cash flow forecast issuance and accuracy, and equity research prior to credit rating downgrades, conditional on cross-sectional variation in high-quality debt research. Management access proxies include the following variables: *Debt_Underwriting* is an indicator variable equal to one if the debt analyst's broker acted as a lead manager or co-manager of company *j*'s debt underwriting team in year *t*-1; *Debt_Conference* is an indicator variable equal to one if the debt analyst's broker invited company *j* to a debt conference in year *t*-1. Debt analyst expertise proxies include the following variables: *Multi_Award* is an indicator equal to one if the all-star debt analyst is ranked by II in multiple sectors in year *t*; *CFA* is an indicator equal to one if the all-star debt analyst has a CFA qualification listed on LinkedIn. Remaining variables are defined in Appendix 2. *z* and *t*-statistics (in parenthesis) are calculated using standard errors clustered by broker and year; the notation *, **, and *** indicates significance at the 10%, 5%, and 1% levels, respectively.

Table 7
Cross-Sectional Analysis of Brokerage Firm Factors: Brokerage Culture

Panel A: Forecasting Cash Flows

Dep. Var. =	*CF_I*			*R_CF_ACC*		
	(1)	(2)	(3)	(4)	(5)	(6)
	F_Distress = 1	*I_Distress = 1*	*Distress = 0*	*F_Distress* = 1	*I_Distress = 1*	*Distress = 0*
Access	-0.1857	-0.1993	-0.1216	-0.0449	-0.0935	-0.0624
	(-1.47)	(-1.20)	(-1.12)	(-0.72)	(-1.55)	(-1.10)
Collaborative_Culture	0.4587***	0.4178***	0.6513***	0.0367	0.0663	0.0767***
	(6.32)	(4.20)	(9.23)	(1.44)	(1.50)	(2.82)
Access × *Collaborative_Culture*	0.2708*	0.3916**	-0.1353	0.1025*	0.1331**	0.0186
	(1.70)	(2.07)	(-1.01)	(1.68)	(2.19)	(0.36)
Controls	Included	Included	Included	Included	Included	Included
N	31,132	19,531	65,926	5,820	3,218	9,939
Pseudo/Adj. R-squared	0.535	0.534	0.169	0.024	0.008	0.012

Panel B: Research Prior to Credit Rating Downgrades

	(1)	(2)	(3)	(4)	(5)	(6)
	EF_Down	*REC_Down*	*CF_Down*	*EF_Rev*	*REC_Rev*	*CF_Rev*
Access	-0.0446	0.1272	-0.1372	-0.0235	-0.2126	0.0122
	(-0.84)	(0.94)	(-0.91)	(-0.98)	(-1.07)	(0.77)
Collaborative_Culture	-0.0318	0.1236*	0.0096	-0.0097	-0.1669**	0.0073
	(-0.74)	(1.92)	(0.09)	(-1.03)	(-2.55)	(0.33)
Access × *Collaborative_Culture*	0.1094**	-0.2154	0.2765*	0.0400*	0.3829**	-0.0157
	(2.17)	(-1.47)	(1.74)	(1.81)	(1.98)	(-0.68)
Controls	Included	Included	Included	Included	Included	Included
N	14,417	11,682	8,211	6,923	1,450	820
Pseudo/Adj. R-squared	0.089	0.076	0.163	0.140	0.335	0.071

Table Notes: This table examines the cash flow forecast issuance and accuracy, and equity research prior to credit rating downgrades, conditional on brokerage culture. *Access* is one when the equity analyst has access to the research of an all-star debt analyst at the same sell-side firm following the same industry and investment category in year *t*, and zero otherwise. *Collaborative_Culture* is an indicator variable set to one if the sell-side firm that employs the equity analyst has a collaboration sentiment score that is above the industry mean, and zero otherwise. See Appendix 2 for other variable definitions. *z* and *t*-statistics (in parentheses) are calculated using standard errors clustered by broker and year; the notation *, **, and *** indicates significance at the 10%, 5%, and 1% levels, respectively.

Table 8
Cross-Sectional Analysis of Brokerage Firm Factors: Analyst Colocation

Panel A: Forecasting Cash Flows

Dep. Var. =	*CF_I*			*R_CF_ACC*		
	(1)	(2)	(3)	(1)	(2)	(3)
	F_Distress = 1	*I_Distress = 1*	*Distress = 0*	*F_Distress* = 1	*I_Distress = 1*	*Distress = 0*
Access	-0.0553	-0.1042	-0.0996	-0.0477	-0.0235	-0.1102
	(-0.11)	(-0.18)	(-0.20)	(-0.57)	(-0.45)	(-1.37)
Access × *Same_City*	0.2010*	0.1951**	0.0789	0.0978**	0.0823**	0.0817
	(1.91)	(2.07)	(1.11)	(2.35)	(2.08)	(0.95)
Controls & FE	Included	Included	Included	Included	Included	Included
N	21,867	14,752	41,905	4,217	2,629	6,956
Pseudo/Adj. R-squared	0.207	0.172	0.151	0.008	0.002	0.005

Panel B: Research Prior to Credit Rating Downgrades

	(1)	(2)	(3)	(4)	(5)	(6)
	EF_Down	*REC_Down*	*CF_Down*	*EF_Rev*	*REC_Rev*	*CF_Rev*
Access	0.0880*	-0.0269	0.0953	0.0025	0.1339	-0.0120
	(1.83)	(-0.19)	(0.46)	(0.19)	(0.79)	(-0.64)
Access × *Same_City*	0.1021***	0.2564**	0.3119**	0.0179***	-0.2934	0.0171
	(2.71)	(2.05)	(2.14)	(4.29)	(-1.40)	(0.78)
Controls & FE	Included	Included	Included	Included	Included	Included
N	11,555	9,177	6,309	5,465	1,079	691
Pseudo/Adj. R-squared	0.094	0.084	0.199	0.128	0.360	0.117

Table Notes:
This table examines the cash flow forecast issuance and accuracy, and equity research prior to credit rating downgrades, conditional on colocation of equity and debt analysts. *Access* is one when the equity analyst has access to the research of an all-star debt analyst at the same sell-side firm following the same industry and investment category in year *t*, and zero otherwise. *Same_City* is equal to one if the equity analyst works in the same city as the all-star debt analyst at the same sell-side firm following the same industry and investment category in year *t*, and zero otherwise. See Appendix 2 for other variable definitions. *z* and *t*-statistics (in parentheses) are calculated using standard errors clustered by broker and year; the notation *, **, and *** indicates significance at the 10%, 5%, and 1% levels, respectively.