Balancing Act: How Unaffiliated Analysts Navigate Private Information Disadvantages

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Abstract: Using analyst-lender affiliation in syndicated loans as a proxy for differential access to private information, we examine how unaffiliated analysts respond to this disadvantage. We find that unaffiliated analysts are more likely to herd toward affiliated analysts following loan origination, leading to improved forecast accuracy but weaker market reactions, consistent with reduced information content. Interestingly, herding analysts improve their forecast accuracy for other firms in their portfolios relative to non-herding analysts, suggesting a reallocation of effort. To capture information acquisition directly, we analyze IP address data from SEC EDGAR log files and find that unaffiliated analysts increase search activity, driven primarily by those not designated as herding. While herding behavior wanes after the first year post loan, elevated EDGAR searches persist for three years consistent with analysts focusing their efforts on information acquisition. Overall, our study provides novel evidence on how selective access to private information influences analysts' competitive behavior.

JEL Classification: G24, G14, G29

Key words: Analyst herding, Private information, Information asymmetry, Forecast accuracy, Syndicated loans

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I. INTRODUCTION

In a competitive market for analysts' services, access to new, non-public information gives analysts an edge over their peers in contributing to price discovery and extracting information rents. Although previous research has documented benefits to analysts with access to private information (Chen and Martin 2011), there is limited research on how analysts lacking such access compete, primarily because it is inherently difficult for analysts to identify who among them has access to private information (Emery and Li 2009; Bagnoli et al. 2008).[1]

We fill this gap in the literature by exploiting a setting where a known subset of analysts has access to private information, allowing us to examine information acquisition and forecasting behavior of other analysts who lack such access. Specifically, we use syndicated loan originations to clearly identify *affiliated* analysts (those associated with the syndicate) with access to private information and *unaffiliated* analysts (those not involved in the syndicate) and examine how the unaffiliated analysts deal with their informational disadvantage.

In a syndicated loan, borrowers are required to provide a consortium of financial institutions (lenders) with private financial information, accompanied by a high degree of monitoring (Gustafson et al. 2021). It is well accepted that sell-side analysts associated with these financial institutions gain an information advantage (Chen and Martin 2011), despite the "Chinese Wall" regulation prohibiting information flow from their investment divisions to research divisions. Indeed, prior research has shown that syndicated loans serve as a source of information for financial markets (Ivashina and Sun 2011; Massoud et al. 2011; Nandy, Saunders, and Song 2011; Peyravan 2020), contributing to price discovery (Bushman, Smith, Wittenberg-Moerman

[1] Despite Regulation Fair Disclosure (Reg FD), which aimed to curb private access to management information, there is considerable evidence suggesting that analysts still have access to firm-specific private information in the post-Reg FD era (Chen and Martin 2011; Green et al. 2014; Han et al. 2018; Cheng et al. 2016).

2010) and improved analyst forecast accuracy (Chen and Martin 2011). Thus, this setting provides a rare opportunity to examine how unaffiliated (uninformed) analysts respond by facilitating a clear identification of affiliated (informed) analysts.

Ex-ante, it is not clear whether unaffiliated analysts will increase, decrease, or maintain costly research efforts following syndicated loan originations. Competing against analysts with private information could create incentives to either reduce information gathering effort by "herding" or increase effort to overcome the informational disadvantage (Altschuler et al. 2015; Mohanram and Sunder 2006). While herding with informed analysts will ostensibly improve unaffiliated analysts' forecast accuracy, such forecasts do not bring new information to the market and thus are unlikely to spur trading activity, which is an important determinant of analysts' compensation (Brown et al. 2015). Moreover, herding may result in reputational damage over time (Jegadeesh and Kim 2010). As a result, some unaffiliated analysts may instead choose to intensify their information search effort. Consequently, the effect of differential access to private information on analyst behavior is an open empirical question.

We find that herding behavior enhances the forecast accuracy of unaffiliated analysts. However, as expected, we also find that herding reduces the informational content of forecasts, as reflected by weaker market reactions to these forecasts. Thus, herding can be a costly strategy for unaffiliated analysts, potentially leading to lower compensation by diminishing brokerage trading profits, as well as causing long-term reputational damage. We test the hypothesis that, to reduce the reputational and trading volume impacts of herding, analysts who herd will redirect their attention and information-gathering efforts toward other firms within their coverage portfolios. The herding literature has not examined this effort-reallocation issue, largely because of the difficulty in systematically identifying when and for which firms analysts are at a disadvantage---

a challenge we are able to overcome because of our clear identification of affiliated and unaffiliated analysts in the syndicated loan setting. Indeed, our evidence shows that unaffiliated analysts who herd for a syndicated loan-borrower improve their forecast accuracy for other firms in their portfolios post-loan origination, relative to those unaffiliated analysts who choose not to herd.

Given the competitive environment in which analysts operate, a natural question is whether some unaffiliated analysts intensify their information-gathering efforts after loan origination to narrow the information gap with affiliated analysts. We follow the novel approach of Gibbons et al. (2021) and use SEC EDGAR log files as a more direct measure. The results reveal that unaffiliated analysts who choose not to herd increase their search activity significantly more than their herding counterparts. These results reinforce our earlier evidence based on forecast accuracy, indicating that unaffiliated analysts who herd reduce their efforts on firms where they face a private information disadvantage and instead reallocate attention to other firms in their coverage.

We next examine how long the information asymmetry arising from syndicated loan originations endures and how herding and information search behaviors change over time. Our results indicate that affiliated analysts maintain an informational edge, demonstrated by their superior forecast accuracy, for at least three years after loan origination. By contrast, unaffiliated analysts' tendency to herd diminishes more quickly, while their information search efforts remain higher than the pre-loan period. These patterns suggest that in a competitive information market, herding is ultimately a costly strategy for disadvantaged analysts since it prevents them from bringing new information to the market. Instead, in the long run analysts invest more in information search to close the information gap.

To strengthen our evidence on the causal relationship between access to private information through syndicated loans by affiliated analysts and herding by unaffiliated analysts, we employ placebo loan origination dates set two years prior to the actual syndicated loan origination dates. We then examine the herding behavior and information search activity of unaffiliated analysts following this alternative date. Our analysis reveals no significant differences in unaffiliated analysts' herding or search activity, lending further support to the narrative that syndicated loan origination drives the shift in analysts' access to private information, which in turn influences the responses of unaffiliated analysts.

Next, we perform several cross-sectional tests to better understand the dynamics of analysts decisions. First, we examine analyst reputation and find that unaffiliated analysts are more likely to herd to affiliated analysts with higher reputation (i.e., greater accuracy in the prior year). Furthermore, we find that unaffiliated analysts with higher reputation are more inclined to herd. These results, combined with our evidence on unaffiliated analysts' increased accuracy for other portfolio firms, demonstrate that high-reputation unaffiliated analysts reallocate their efforts toward firms where they can have a larger impact (Harford et al. 2019). Next, we examine the effect of firm opacity (i.e., higher analyst information processing cost) on analyst herding. We find that herding is stronger for firms with greater information asymmetry, as proxied by high market-to-book ratios and low accrual quality. Overall, our cross-sectional analyses illustrate that the competitive landscape alters analysts' behavior in different ways depending on firm characteristics and analyst expertise.

Our study makes three key contributions to the literature on analyst behavior and information acquisition. To the best of our knowledge, our study is the first to assess information acquisition dynamics in the analyst marketplace using a unique setting wherein analysts are *aware* which peers have access to superior non-public information. Other studies, such as Clement and Tse (2005), investigate whether analysts herd toward the prevailing analyst *consensus*, but do not examine *informed* herding as we do. Incentives to herd may also apply more broadly, such as herding with "Star" analysts. However, evidence suggests that analyst stardom is highly transitory, with over 80% annual turnover in Wall Street Journal rankings (e.g., Emery and Li 2009; Bagnoli et al. 2008). As a result, it is difficult even for an analyst to consistently identify the next "Star Analyst." In contrast, the observability of analysts with private information in the syndicated loan setting makes it far easier for other analysts to engage in informed herding behavior.

Second, we provide the first evidence that unaffiliated analysts differ in the way they respond when confronted with known informational disadvantages. Using analyst-level EDGAR search activity as a direct proxy for effort, we demonstrate that herding analysts decrease their information-gathering activities in response to such information disadvantages. These results suggest that, while some analysts choose to herd with affiliated analysts and decrease their search activity, others intensify their independent research efforts.[2]

Third, our analysis reveals an important positive spillover effect: when analysts face a private information disadvantage for certain firms, they reallocate their attention toward other companies in their portfolios. Prior work (e.g., Clement 1999; Driskill et al. 2020) emphasizes that analysts are subject to limited attention when covering multiple firms and tend to focus on firms that are more important for their careers (Harford et al. 2019). In the context of syndicated loans, we show that unaffiliated analysts who choose to herd strategically reallocate their efforts to improve forecast accuracy for other firms in their portfolios. Similarly, Ru et al. (2025) finds that Chinese analysts often drop coverage of firms for which they find out other analysts have visited resulting in improved accuracy for the remaining firms in their portfolios. Together, these findings

[2] These results support Brown et al. (2015), which argues that an analyst's deep understanding of firms and industries (and not just forecast accuracy or timeliness) is central to their compensation.

are consistent with analysts dynamically shifting attention within their portfolios when facing an information disadvantage.

Overall, our study offers a unique opportunity to peer into what Brown et al. (2015) refers to as the "Black Box" of analyst forecasting. By observing information search behavior rather than relying solely on outcome variables like forecast accuracy or trading profitability, we directly capture analysts' responses to information asymmetries. We document behavioral shifts not only for the focal (borrower) firms, but also for analysts' broader coverage portfolios, shedding light on how analysts navigate the market for information in the presence of selective access.

II. RELATED LITERATURE AND HYPOTHESIS DEVELOPMENT

The literature on analysts' private information often extends from the seminal work of Barron et al. (1998), which develops theoretical predictions about the amount and precision of private information in analysts' forecasts by inferring information from several distributional characteristics of forecasts. Barron et al. (1998) capitalizes on the idea that "forecast dispersion and error relate in different ways to the common and idiosyncratic components of error in analysts' forecasts," with the common (idiosyncratic) component of the error being related to public (private) information (Barron et al. 1998, p 422).

However, one cannot infer which analysts have higher-quality private information using the Barron et al. (1998) measure. Prior studies have frequently used analysts' forecast accuracy and recommendation/target price profitability as the measure of analysts' private information. For example, Chen and Matsumoto (2006) finds that analysts issuing more favorable recommendations experience a greater increase in their relative forecast accuracy compared with analysts with less favorable recommendations. The authors conclude that managers provide analysts with favorable additional information in the pre-Reg-FD period. Similarly, Mayew et al. (2013) finds that forecasts issued immediately after an earnings conference call by analysts who participated in the call are more accurate relative to the forecasts issued by those who did not participate. Critically, both Chen and Matsumoto (2006) and Mayew et al. (2013) infer differential access to private information via tests of forecast accuracy.

Several studies also use Reg FD as a shock to private information access because the communication of material private information was prohibited after the regulation. In a literature survey, Koch et al. (2013) concludes that Reg FD has largely eliminated access to private information from management.[3] However, several later studies document various mechanisms that have emerged to circumvent private communication restrictions imposed by regulation. Green et al. (2014) finds that analysts working for brokers that host investor conferences end up issuing more informative, accurate, and timely earnings forecasts, consistent with these analysts having a private information advantage. Bushee et al. (2018) uses corporate jet flight information as a potential source of private meetings and finds that analysts' activity is higher during these days, which is consistent with the exchange of private information. The authors also find evidence consistent with these private meetings providing an information advantage to participating investors. Han et al. (2018) and Cheng et al. (2016) find that analysts' site visits result in improved forecast accuracy, consistent with private information being helpful to analysts. Based on this stream of research, it appears reasonable to conclude that at least a subset of the analysts continues to have access to private information even post-Reg FD, which raises the question of how other analysts adjust their behavior to stay competitive.

[3] Jiang et al. (2019) find that a decline in the incorporation of firm-specific information into stock prices following the introduction of Directive 40, China's counterpart to Regulation Fair Disclosure (Reg FD), consistent with the notion that restrictions on private communications reduced the flow of non-public information from corporate managers to financial analysts

One paper that sheds light on this question is Lee and Lee (2015). This study focuses on Korean analysts who are part of business groups called Chaebols, which are large, closely held South Korean business conglomerates. Chaebol analysts not only have access to private information about their businesses but also have an incentive to favorably shape market expectations about the Chaebol. Accordingly, Lee and Lee (2015) finds that analysts *outside* of the Chaebol tend to herd toward the Chaebol analysts when it comes to forecasting Chaebol-related businesses. Remarkably, however, Song et al. (2012) provides evidence that forecasts issued by Chaebol analysts are *less* accurate and *more* biased, which is in contrast to the findings of Chen and Martin (2011). As such, it is unclear the extent to which behaviors associated with Chaebol analysts extend to competitive information markets such as in the U.S. Importantly, neither Lee and Lee (2015) nor Song et al. (2012) investigate the allocation of effort by unaffiliated analysts, nor do these studies investigate exogenous shocks resulting in differential access to private information.

Our main goal is to investigate the effects of a shift in information on analysts who now find themselves at a relative disadvantage. As previously noted, syndicated loans provide a unique setting for testing the effects of *known* differential access to private information. Given that informed analysts become more accurate following loan origination, an uninformed analyst (unaffiliated analyst) has two choices: Herd with the informed analyst or increase effort to close the information gap. *Ex-ante*, this choice is not clear. Xue (2017) provides a theoretical model where an unaffiliated analyst follows a conditional herding strategy by choosing to herd if information acquisition is too costly but increasing effort otherwise. However, while herding with informed analysts will help improve forecast accuracy, it contributes little to new trading activity, which is an important determinant of analysts' compensation (Brown et al. 2015; Bernhardt et al.

2006). In addition, herding forecasts are less timely since choosing to herd entails waiting for affiliated analysts to issue a forecast first, which will jeopardize the reputation of the unaffiliated analyst over time (Jegadeesh and Kim 2010). Consequently, less informed analysts may instead choose to intensify their costly information acquisition efforts to close the information gap for these firms. Thus, herding and increased research effort can coexist in equilibrium, making the effect of differential access to private information on analyst behavior an empirical question.

Analysts covering multiple firms face ongoing trade-offs in allocating their limited time and resources across the firms they follow (Harford et al. 2019). Accordingly, we next examine whether analysts who choose to herd shift their focus to other companies within their coverage portfolios in order to remain competitive in the market for information (Effinger and Polborn 2001). However, a central empirical challenge is how to measure analyst effort. Most studies rely on forecast characteristics such as timeliness and accuracy, which, while informative, are outcome-based and may not fully capture the underlying effort. To complement these traditional measures, we draw on the growing literature that uses EDGAR search activity as a direct proxy for information gathering by market participants (e.g., Drake et al. 2015; Drake et al. 2020; Chen et al. 2020; Crane et al. 2023). For example, Gibbons et al. (2021) link EDGAR search activity to analysts' brokerage houses and show that search behavior reflects both informational demand (e.g., for larger firms or during M&A events) and analysts' career incentives. They further demonstrate that greater search activity is associated with more accurate forecasts, more informative recommendations, and higher profitability relative to peers. The tradeoff between herding versus increasing search activities is the focus of our analysis in this study.[4]

III. SAMPLE AND DESCRIPTIVE STATISTICS

[4] In contrast, Ru et al. (2025) finds that Chinese analysts often drop coverage of firms that report being visited by peer analysts, which is an alternative to herding.

Sample

We construct our sample using all analysts' forecasts available from FactSet between 2000 and 2020, which include analyst and brokerage identifiers not provided by I/B/E/S.[5] We limit our sample to earnings (EPS) forecasts issued by analysts associated U.S.-based brokerages, resulting in 7,025 analysts from 359 brokerages. We further restrict our sample to EPS forecasts issued within one year of the forecast period end-date to mitigate the effect of forecast horizon on analyst forecast accuracy. We merge this sample with the I/B/E/S dataset to retrieve earnings announcement dates, resulting in 1,169,622 forecasts for 3,985 firms, issued by 4,215 analysts from 322 brokerages.

Next, we access data on all loans, including single lender loans, made to publicly traded U.S. firm from 1996 to 2023 from DealScan. We use FINRA and Bloomberg to establish whether a lender in our DealScan sample has a brokerage firm in our FactSet sample either directly or through their parent company. We identify 307 brokerages that are associated with lenders in syndicated loans during our sample period. We consider analysts who belong to brokerages that cover the borrower during the two years centered around the loan origination date (i.e., one year before and one year after loan origination) as *affiliated* analysts.[6] We impose an additional requirement that the analyst cover the borrower both before and after loan origination. If multiple loans are issued by the same lender to a borrower during our sample period, we only include the earliest loan origination in our sample.[7] Analysts from other brokerages issuing forecasts for the same

[5] Chen and Martin (2011) uses the IBES Broker ID file to construct their sample. I/B/E/S no longer provides information about broker/analyst identifications therefore we use data provided by FactSet.
[6] Ivashina and Sun (2011) notes that data on loan holdings within the syndicate is generally not available outside of loan originations and renegotiations. As such, we use the two-year window surrounding loan origination to identify the affiliation status of analysts noting that it is likely measured with some error thus limiting the power of our tests.
[7] Using this approach, we attempt to avoid the confounding influence of overlapping loans on analysts' behavior.

borrowers during the same two-year period comprise our *unaffiliated* analyst sample. We require that unaffiliated analysts cover the borrower both before and after the loan origination date.

We obtain information about borrowing firms from COMPUSTAT following the procedure outlined in Chava and Roberts (2008), and drop observations with missing information. Our final affiliated analyst sample consists of 17,745 forecasts by 439 analysts from 26 brokerages for 885 borrowers. The unaffiliated analyst sample consists of 45,831 forecasts issued by 1,110 affiliated analysts from 159 brokerages for the same borrowers during the same period. Table 1 presents a summary of our sample selection process.

[Table 1 Here]

Given our objective of examining herding and information-search behaviors of unaffiliated analysts following syndicated loan origination, we next discuss the measures of herding and information search we use in our empirical analysis.

Herding Measure

Conceptually, a herding measure should reflect an analyst's proclivity to conform to prevailing market opinion (recommendation or forecast) rather than issue an opinion justified by their own information (Stickel 1990; Graham 1999). Welch (2000) shows analysts are more likely to revise their recommendations toward prior consensus recommendations than away from them, and interprets this evidence as consistent with herding (see also Jegadeesh and Kim 2010). Clement and Tse (2005) defines an analyst's forecast as a herding forecast if it is between the most recent consensus forecast and the analyst's own prior forecast. Trueman (1994) defines herding behavior as when analysts issue forecasts that are similar to those previously announced by other analysts.

The definition offered by Trueman (1994) is particularly suited to our context because the information advantage of affiliated analysts is public knowledge. Thus, a natural measure of herding is how *close* a forecast is to an *immediately* previously issued forecast, particularly to a forecast issued by an affiliated analyst. Accordingly, we define *Herd* as equal to one if an analyst issues a forecast after but within six days of a forecast issued by any other analyst and within 1% of the other analyst's estimate. We exclude any estimates made on earnings announcement days to prevent the natural clustering of analyst forecasts around earnings announcements from affecting our herding measure (Gleason and Lee 2003).[8] Thus, this strict definition of herding requires "closeness" of the herding forecast to a prior forecast in terms of *both* time and value. To the extent that we mischaracterize a herding forecast as a non-herding forecast because of the strictness of this definition, we bias against finding results.

Following Welch (2000), Clement and Tse (2005), and Gleason and Lee (2005) we also construct another measure of herding, $Herd_{Consensus}$, which is based on a forecast's proximity (within 1%) to the *consensus* of prior forecasts issued within 6 days. This measure captures the notion that an analyst is herding with a *group* of analysts while at the same time retaining the timing element that is particularly relevant in our setting. Importantly, this consensus includes forecasts issued by both affiliated and unaffiliated analysts, which is necessary to conduct a pre- vs post-syndicated loan analysis since herding toward affiliated analysts in the pre-period, when they are not likely to have private information, only serves to induce measurement error.

[8] Prior studies often use forecasts issued outside of earnings announcement periods to avoid confounding effects related to earnings announcements or management forecasts (e.g., Gleason and Lee 2003; Drake et al. 2020). In addition, Driskill et al. (2020) shows that that the clustering of earnings announcements imposes time constraints on analysts and negatively impacts the timeliness of analysts' forecasts. Consequently, using analyst forecasts issued outside of earnings announcement periods mitigates these concerns and is a cleaner test of our hypothesis.

In addition to our pre- versus post-loan analysis, we conduct supplementary tests focusing exclusively on the post-loan period to examine whether unaffiliated analysts who herd toward affiliated analysts issue more accurate forecasts, and whether these forecasts exhibit lower price impact, consistent with the notion that herding is less likely to convey new information. For this purpose, we construct a third herding measure, $Herd_{Affiliated}$, which equals one if an unaffiliated analyst's forecast falls within 1% the consensus of forecasts issued by *affiliated* analysts over the prior six-day window.[9] Incorporating multiple herding measures enhances the robustness of our findings.

Information Search Activity

To measure the information search activity of an analyst, we turn to SEC EDGAR search-related variables. We follow Gibbons et al. (2021) and match all brokerages in our sample to the SEC server log files available through EDGAR. Pursuant to the Freedom of Information Act (FOIA), the SEC has made the server log files containing all views of companies' primary filings on EDGAR available to the public for the years 2003-2016.[10] These log files include users' IP addresses and the date and time a file was accessed. While the last three digits of IP addresses are masked by the SEC, the mask remains unchanged for any subsequent access by the same user, which ensures the consistency of identification in the dataset. We use the ARIN database to identify IP address blocks registered to each organization. One caveat in using EDGAR log files is that we cannot identify smaller firms that use generic IP addresses through an internet provider (e.g., Verizon, AT&T), and thus we exclude such addresses. In addition, we exclude IP addresses

[9] We thank an anonymous reviewer for suggesting this measure of herding. Note, this measure cannot be used in a pre- vs post-loan origination analysis since there are no "affiliated" analysts in the pre-period thus construction of a consensus is not meaningful.
[10] According to SEC's website, EDGAR log file data for July 1, 2017 to May 18, 2020 are no longer available.

that do not belong to brokerages, such as those registered to the parent company's commercial banking subsidiary.[11]

As in Gibbons et al. (2021), we limit the sample to log views within five days of an analyst issuing a forecast for a firm. The log files are only available on EDGAR through 2016. We begin our sample in 2007 due to a lapse of coverage in EDGAR log files from September 24, 2005, to May 11, 2006. Our main variable of interest is total log views, *ΣViews*. We also use the classification scheme from Gibbons et al. (2021) to separate total views into the most commonly viewed filing types, namely, 10K/Qs, 8Ks, and changes in ownership (forms 3, 4, and SC 13G). After matching our initial sample of forecasts with these log files, we have 47,169 forecasts remaining. This sample consists of 13,397 (33,772) forecasts by affiliated (unaffiliated) analysts, corresponding to 24 (138) brokerages. It is not surprising that many observations in our sample have no SEC EDGAR log views. This sample attrition should not be interpreted as analysts lacking access to SEC EDGAR, but rather as a reflection of the limited data available to capture this activity.[12] We also recognize that some analysts may access financial data through systems other than EDGAR (e.g., Bloomberg, FactSet, and Capital IQ). Consequently, our EDGAR-based search measures should be viewed as *underestimating* analysts' information search activities.

Our descriptive statistics are entirely consistent with those reported in Gibbons et al. (2021), providing some reassurance regarding the validity of our measure. Specifically, we find that the median total log views in the five days surrounding the issuance of an analyst forecast is four, while the median number of 10K/Q filing views is three, followed by four views for 8K

[11] We are also unable to identify specific individuals, namely specific analysts who access a filing. However, we include brokerage, year, and firm-fixed effects in all our analyses which provides greater assurance that the results are related to the change in analyst activity. Nevertheless, the caveat remains that we are not specifically identifying individual analysts' use of EDGAR.
[12] We have no reason to believe our matches are systematically biased in any way, so any misidentifications only serve to weaken the power of our tests.

filings. The median number of changes in ownership filing views is also four. These statistics indicate that analysts rely on financial data sources such as EDGAR, especially when forming a forecast. We find almost no SEC EDGAR search activity by analysts outside the five-day window surrounding the issuance of a forecast, which further validates that analysts use EDGAR to access the information rather than representing random downloads.

Summary Statistics

Table 2 presents the descriptive statistics for the variables we use in our analysis. Detailed variable definitions are in Appendix A. *Unaffiliated* is an indicator variable that equals one if the analyst works at a brokerage that is not part of a particular syndicated loan and zero otherwise. Unaffiliated analysts make up 72 percent of the observations in our sample, with affiliated analysts representing the remaining 28 percent.[13] In our sample, analysts issue herding forecasts to any other analyst (*Herd*) approximately 7 percent of the time.

Using the consensus measure of herding, $Herd_{Consensus}$, we characterize 11 percent of forecasts as herding. The higher frequency for $Herd_{Consensus}$ is consistent with the assumption in the prior literature that analysts are more likely to herd toward a consensus estimate than individual analysts. Nonetheless, *Herd* and $Herd_{Consensus}$ are highly correlated (69 percent untabulated), suggesting both capture similar dynamics. Our third metric, $Herd_{Affiliated}$, isolates herding toward the consensus of affiliated analysts, but is only measured in the post-loan period when affiliated analysts may possess private information.

[13] Chen and Martin (2011) focuses on lead arrangers in their analyses, whereas we designate all brokerages that are part of a syndicated loan as affiliated. Many syndicated loan studies illustrate that syndicate participants (other than lead arrangers) take advantage of the private information that is gathered during the syndication process (see Ivashina and Sun 2011; Massoud et al. 2011). To the extent that affiliated analysts associated with non-lead arrangers do not access private information, we mischaracterize the differential access to private information and thereby bias against finding results. In robustness tests, we separately identify lead arrangers and other affiliated analysts with no change in our inferences. Given that our focus is on unaffiliated analysts, we maintain the broader definition of affiliation.

The remaining variables in Table 2 are in line with prior research. For instance, the average brokerage employs approximately 15 analysts, with the average analyst covering 12 firms, having 11 years of experience, and covering a particular firm for seven years.[14] Following a long line of research, we define forecast accuracy, *Price Adj Error*, as the absolute value of the difference between forecasted and actual EPS values, scaled by the share price at market close at the end of the previous month all multiplied by 100 for display purposes (Larocque 2012). The descriptive statistics for *Price Adj. Error* (before multiplying by 100) are in line with those from Chen and Martin (2011), which reports a mean *Price Adj. Error* of 0.014 versus our 0.008, and a median of 0.004 versus our 0.003.[15]

[Table 2 Here]

IV. UNAFFILIATED ANALYSTS AND PRIVATE INFORMATION

Herding and Private Information Disadvantage

We begin our analysis by investigating whether unaffiliated analysts are more likely to herd following loan origination. We analyze the unaffiliated analyst sample over a two-year window surrounding the syndicated loan origination, one year before and one year after. We focus on this two-year window to maximize the power of our tests in isolating the effect of loan origination as a shock to the analysts' information environment. We estimate the following model using OLS.[16]

[14] All figures are based on the calculation $e^{(Variable)}$ since reported figures in Table 2 are natural logarithms.

[15] In untabulated analysis, we also use *Percent Error* as an additional measure of forecast accuracy, defined as the absolute value of the difference between forecasted and actual EPS values, scaled by forecasted EPS, all multiplied by 100. *Percent Error* has the advantage of being intuitive, but it can suffer from small denominator problems resulting in outliers. For instance, while the mean *Price Adj. Error* is 0.75 percent, the mean *Percent Error* is 14.18 percent because of the scalar differences. Nevertheless, inferences remain unchanged using this alternative definition of forecast accuracy.

[16] We use OLS regressions to estimate the probabilities because of the flexibility of OLS in terms of the inclusion of more than two fixed effects which avoids the incidental parameter problem in the conditional logit model using fixed -effects. Inferences remain unchanged if we limit fixed effects to broker and year and estimate the regression using a conditional logit model.

$$P(Herd = 1) = \alpha_0 + \alpha_1 Post + \alpha_2 Controls + Broker\ FE + Firm\ FE + Year\ FE + \varepsilon, \quad (1)$$

where *Post* is an indicator variable that equals one for the period following loan origination. In all analyses, we control for brokerage, firm, and year fixed effects. Including analyst fixed effects would help us ensure any shifts in analyst behavior are attributable to the exogenous shock to the information environment created by the syndicated loan origination. Unfortunately, we do not have analyst identities in our dataset, but the presence of firm and broker fixed effects, combined with the requirement that brokers have forecasts in both the pre- and post-loan origination periods, is tantamount to including analyst fixed effects.

In addition, we follow prior research to control for variables known to affect analyst behavior (e.g., Chen and Martin 2011; Gibbons et al. 2021), such as firm size, number of analysts who issue forecasts for the firm, broker size, analyst's workload measured by the number of firms the analyst covers, analyst's experience measured by the number of years the analyst has been active in the FactSet database, and the number of years the analyst has covered the firm. We also include firm leverage as a control to account for the differences in information environments across firms related to monitoring effect of debt contracting.

Table 3, Panel A, displays the results for the two measures of herding, *Herd* and $Herd_{Consensus}$, which meaningfully span both the pre- and post-loan periods.[17] In Table 3, we focus our analysis on unaffiliated analysts because our primary objective is to characterize their herding versus information search behaviors following syndicated loan origination. Moreover, the use of a differences-in-differences design that compares the behaviors of both affiliated and unaffiliated analysts pre- and post-origination is not appropriate in this setting, given the common private information available to affiliated analysts in the post-loan period.

[17] Recall that $Herd_{Affiliated}$ can only be measured in the post-loan period because there is no incentive to herd toward affiliated analysts until they have access to private information.

Column 1 reports the results for herding toward any analyst (*Herd*), while Column 2 presents the results for herding toward the prior six-day consensus estimate ($Herd_{Consensus}$). Consistent with our expectations, we find positive and significant coefficients on *Post* in both columns, indicating increased herding by unaffiliated analysts after the loan origination when affiliated analysts have a clear private information advantage. Compared with the unconditional means of *Herd* (0.07) and $Herd_{Consensus}$ (0.11) in Table 2, the coefficient estimates in both Columns 1 and 2 indicate that unaffiliated analysts *increase* their herding behavior by 14%, representing large relative shifts in herding.

In untabulated analysis, we conduct a battery of tests to confirm robustness of our results. First, we use alternate thresholds to define proximity in terms of time and magnitude (i.e., within three days of the forecast, or within 0.5% of the forecast). Our inferences remain unchanged using these alternative thresholds. We also construct a measure of herding based on the *number* of forecasts issued by unaffiliated analysts within six days of an affiliated analyst's forecast. We find that unaffiliated analysts tend to issue forecasts more "clustered" in time around affiliated analysts' forecasts, indicating temporal coordination in response to information shocks. Finally, we also use a continuous measure of herding where we calculate the absolute percentage difference between unaffiliated and affiliated analysts' forecasts. We find that following loan origination, unaffiliated analysts issue forecasts that are closer in magnitude to those of affiliated analysts, reinforcing the narrative that unaffiliated analysts increase herding behavior in response to the affiliated analysts' information advantage.[18] Taken together, these results indicate that our main findings are robust to how we define herding.

[18] In addition, we examine how unaffiliated analyst forecast dispersion evolves following loan origination. If unaffiliated analysts herd to affiliated forecasts, we expect the cross-sectional dispersion among their forecasts to decline. Indeed, we find that unaffiliated analysts' forecast dispersion declines following loan origination. These findings are consistent with the notion that increased herding behavior among unaffiliated analysts reduces the overall variance in earnings expectations. We thank a reviewer for suggesting these analyses.

It is important to stress that we obtain these results after controlling for broker and firm fixed effects, along with a myriad of control variables meant to capture analyst experience and access to resources via broker size. This research design helps reduce the likelihood that correlated omitted variables are responsible for the shift in behavior within analysts for the same set of firms. We further corroborate this interpretation of the results by performing the same analysis using placebo loan origination dates, with no results (as we discuss subsequently). Overall, these findings provide strong evidence concerning an increase in herding behavior when an exogenous shock to the information environment puts certain analysts at an informational disadvantage.

[Table 3 Here]

In Table 3, Panel B, we examine the determinants of what drives unaffiliated analysts to herd when they are at an information disadvantage following loan originations. To allow firm-and broker-level characteristics to explain cross-sectional differences in herding behavior, we exclude firm and broker fixed effects in this test. We find that unaffiliated analysts are more likely to herd when covering larger firms (*Size*), firms with more growth opportunities (*MB*), lower leverage (*Leverage*), and greater analyst coverage (*#Analysts*). This last result suggests that increased competition among analysts contributes to herding. Analysts affiliated with larger brokerage houses also show greater herding propensity, again consistent with competitive pressure being a key driver (Clement 1999; Clement and Tse 2005). Other covariates are not robust across herding measures and are therefore not interpreted. Overall, the determinants model of post-loan herding for unaffiliated analysts in Table 3, Panel B, is consistent with the notion that heightened competition for information increases the likelihood that unaffiliated analysts herd when confronted with an informational disadvantage.

As previously noted, in Table 3, we analyze the sample of unaffiliated analysts' forecasts corresponding to the two-year window surrounding the syndicated loan origination to maximize the statistical power of the tests. Ivashina and Sun (2011) highlights that syndicate membership is disclosed only at the time of loan origination or during major renegotiations. Because syndicate participants can trade their positions in the secondary loan market, changes in membership are not systematically available. This creates potential misclassification of institutional affiliation, thereby biasing our tests against finding evidence in support of herding. Despite this limitation, we still observe strong evidence of increased herding post-origination, suggesting that our findings are robust.

Unaffiliated Analysts' Forecast Accuracy Following Loan Origination

Chen and Martin (2011) finds improvements in forecast accuracy for analysts affiliated with lead arrangers of syndicated loans after the loan origination, consistent with these analysts having access to private information. Given our results on herding, a natural question is, how does this differential private information influence the accuracy of unaffiliated analysts? We first confirm that affiliated analysts improve their forecast accuracy post loan origination, consistent with analysts affiliated with syndicate participants using their private information to improve their forecasts. In a later section, we address the issue of how long this informational advantage persists.

Given our focus is on the response of unaffiliated analysts, in Table 3, we adapt the analyst forecast error model in Chen and Martin (2011), and use the following baseline regression to investigate shifts in unaffiliated analysts during the post-loan period:

$$Analyst\ error_{ijt} = \alpha_0 + \alpha_1 Unaffiliated \times Post + \alpha_2 Post + \alpha_3 controls + Firm\ FE + Broker\ FE + Year\ FE + \varepsilon, \tag{2}$$

where $Analyst\ error_{ijt}$ is the forecast error for analyst i, issued for firm j on day t. We use the absolute value of the differences between forecasted and actual EPS, scaled by the price at the end of the prior month, as the measure of analysts' absolute forecast errors. $Post$ is an indicator variable that equals one for the loan origination quarter and the following four quarters, and zero otherwise. We employ the same controls and fixed effects as before.

[Table 4 Here]

We display the results of this analysis in Table 4. In Column 1, the coefficient on our variable of interest *Unaffilated×Post* is positive and statistically significant at 1% or better. This result suggests that unaffiliated analysts become less accurate, on average, compared to affiliated analysts after loan initiation. The negative and significant coefficient on *Post*, is consistent with affiliated analysts having access to private information and becoming more accurate following loan origination, consistent with results in Chen and Martin (2011).

The coefficients on the control variables are generally consistent with those found in Gibbons et al. (2021), with forecast accuracy in Column 1 increasing in *Size* and *#Analysts*, and decreasing with *AnalystExperience*. Forecast accuracy is decreasing in the number of firms an analyst covers in Column 1. One result that appears puzzling at first glance is the negative and significant coefficient on *MB* in Column 1, indicating that the higher the market-to-book ratio, the better the forecast accuracy. Although this result is also consistent with the findings in Table 4 of Chen and Martin (2011), it is counterintuitive because high-growth firms are often difficult to forecast. One potential explanation is that the result is somewhat mechanical because the market-to-book ratio includes price in the numerator, while *Price Adj. Error* includes price in the denominator.

Having established these baseline results, we focus next on the effect of herding behavior of *unaffiliated* analysts on their forecast accuracy following loan origination. In column 2 we use the indicator variable, $Herd_{Affilated}$, as our independent variable of interest, which reflects an unaffiliated analyst herding with the consensus forecast of *affiliated analysts*. The negative and statistically significant coefficient on this variable indicates that, following syndicated loan origination, unaffiliated analysts who herd with affiliated analysts achieve higher forecast accuracy.[19] Importantly, we obtain this result regardless of the likelihood that some non-herding unaffiliated analysts may intensify their information search activities to offset their informational disadvantage, which we examine later.

Next, we focus on the effort reallocation decision of herding analysts by examining the accuracy of their forecasts of other firms they follow. If unaffiliated analysts opt to herd following loan origination, then presumably they can reallocate their efforts to the other firms they cover, potentially leading to improved forecast accuracy for those firms. Unaffiliated analysts who do not herd need to maintain or even increase their information search efforts related to the syndicated loan firm, and thus, we would not expect similar improvements in forecast accuracy for the other companies that they cover.

We construct the sample for these tests by focusing on forecasts issued by *unaffiliated* analysts, both herding and non-herding, that pertain to other firms in their coverage portfolios during the post-loan period. It is possible that an analyst follows more than one borrower in our sample. In such cases, we exclude all firms with syndicated loans from the set of "other" firms comprising that analyst's coverage portfolio. Our final sample consists of 8,479 forecasts for 1,058 firms, issued by 515 analysts from 125 brokerage firms. Column 3 of Table 4 reports the results.

[19] Our inferences remain unchanged if we use the other two herd measures, *Herd* and $Herd_{Consensus}$, as well.

The coefficient on the herd variable is negative and significant, indicating that unaffiliated analysts who herd post-loan origination improve their accuracy for their other portfolio firms relative to unaffiliated analysts who do not herd. This is consistent with unaffiliated analysts who choose to herd in their forecast for a borrower reallocating their attention and effort toward *other* firms in their coverage portfolio. To our knowledge, this "effort" spillover effect from herding has not been previously empirically documented in the literature.

Overall, our results in Table 4 are consistent with unaffiliated analysts placing less weight on their own personal information when a subset of analysts has access to additional private information. Although the findings indicate a significant shift in herding by unaffiliated analysts after syndicated loan originations, they do not rule out the possibility that some unaffiliated analysts choose not to herd and instead increase their information search effort as a way of compensating for their information disadvantage.

Market Reaction to Herding Forecasts

Given the increase in herding by unaffiliated analysts following loan origination, we next investigate the price discovery effects of herding. Because herding forecasts convey less informational value, we expect unaffiliated analysts' herding forecasts to contribute less to price discovery, leading to weaker market reactions to their revisions. In Table 5, we isolate days that only contain a forecast designated as herding by unaffiliated analysts to examine the market reaction to herding forecast revisions. In Column 1, we use the general tendency to herd (the *Herd* measure); in Column 2, we focus on forecasts designated as herding toward the prior consensus ($Herd_{Consensus}$); in Column 3, we focus on forecasts designated as herding toward affiliated analysts' forecasts ($Herd_{Affiliated}$). Regardless of the definition of herding, the market reaction to unaffiliated analysts herding forecasts is smaller, as evidenced by the negative and significant coefficients on the herding forecast measures. These results confirm that herding forecasts contribute less to price discovery, which supports the notion that unaffiliated analysts who choose to herd are concerned more about their forecast accuracy than informing the market.[20]

[Table 5 Here]

SEC Edgar Usage and Private Information

The lower information content of herding forecasts is likely to negatively impact analysts' reputations and trade generation. As a result, instead of choosing to herd, some analysts may choose to offset their informational disadvantage by increasing their information search efforts. However, given our earlier finding that unaffiliated analysts, on average, increase their herding following loan originations, it is not clear whether and to what extent they will also systematically change their information search behavior. To shed light on this matter, we examine and compare the SEC Edgar filing usage of unaffiliated and affiliated analysts both before and after loan origination.

We expect unaffiliated analysts who want to remain competitive with affiliated analysts to increase their usage (views) of SEC filings, such as 10K/Qs, 8Ks, and ownership filings (forms 4, 13D, 13G), in the period following loan origination to glean information that will offset the private information advantage of affiliated analysts. We adopt a standard differences-in-difference research design for EDGAR search activity and estimate the following Poisson regression:

$$EDGAR\ Search = \alpha_0 + \alpha_1 Unaffiliated \times Post + \alpha_2 Post + \alpha_3 controls + Broker\ FE + Firm\ FE + Year\ FE + \varepsilon, \qquad (3)$$

[20] We do not examine pre versus post differences in the market reaction to herding related forecasts since herding is always expected to lead to lower market impacts. Instead, the market-based tests help to validate the identification of herding forecasts since we expect them to have lower price effects.

where *EDGAR Search* is equal to the total number of times an analyst accesses files on EDGAR. We use Poisson regression to estimate Eq. (3) because our dependent variable (search count) is discrete. We use four measures of EDGAR search based on the most common types of files viewed. Our first measure is the total number of file views across all firm filings. Our other measures narrow down the search variables to specific filing types. We display the results of our analysis in Table 6, Panel A.

[Table 6 Here]

Column 1 of Panel A uses the total number of views, Column 2 examines only 10K/Q views, Column 3 examines only 8K views, and Column 4 looks at only ownership-related form views as the dependent variable. The coefficients on *Post* are not statistically significant in Columns 1 to 4. Thus, we cannot reject the null hypothesis that affiliated analysts do not alter their viewing of SEC EDGAR files after loan origination. In contrast, our results reveal a significant increase in the number of SEC EDGAR filing views by unaffiliated analysts after syndicated loan initiation, as indicated by the positive and significant coefficients on *Unaffiliated×Post* in all columns except Column 2 (10K filings). In terms of economic magnitude, the coefficient on *Unaffiliated×Post* in Column 1 indicates that unaffiliated analysts increase the number of filings viewed by 62% ($e^{0.483} - 1$).[21]

Overall, our findings in Table 6 suggest that unaffiliated analysts respond to their information disadvantage by increasing their views of most types of EDGAR filings. Thus, in the

[21] Although the magnitude of the effect is large, it is important to caveat that the nature of the distribution of views is skewed, with a high degree of zero-filing views.

face of inferior information, unaffiliated analysts, on average, appear to expend greater efforts on information searches to remain competitive.[22]

An important caveat to the findings related to EDGAR filing views is that, following Gibbons et al. (2021), we also assume that the IP address associated with an analyst's institution is indicative of analysts accessing the files as opposed to some other employee of the institution. However, given that we restrict the search views to five days leading up to the issuance of a forecast, it is reasonable to assume that files are mostly being accessed by analysts. Indeed, Gibbons et al. (2021) finds that the EDGAR searches at individual analysts' institutions are heavily tilted toward the portfolio of their analysts. Overall, we believe it is reasonable to assume that our IP address matching has been effective in identifying analyst search behaviors but maintain the caveat that our IP matching procedure is likely imperfect.

Herding versus Searching

Thus far, we have documented an increase in both herding and information search behaviors on the part of unaffiliated analysts after the origination of syndicated loans. At first glance, this seems paradoxical because analysts who herd are unlikely to increase their search activity. Building on these results, we next examine differences in EDGAR search activity between unaffiliated analysts classified as herding and those who are not. We hypothesize that unaffiliated analysts who chose to herd following loan originations are more likely to decrease their EDGAR search activity post-syndicated loan originations. We test this prediction by focusing on the forecasting behavior of unaffiliated analysts following loan originations.

[22] The coefficients on our control variables in Table 6 are generally consistent with those in Gibbons et al. (2021) in terms of their signs, but not in terms of significance levels. This is likely because we have a smaller sample (496,521 observations in Gibbons et al. (2021) versus 47,169 observations in our study).

We present the result of this test in Column 5 of Panel A in Table 6. The dependent variable is the total number of views similar to that in Column 1. We include an indicator variable, *New herding analyst*, that takes on a value of one for unaffiliated analysts that do not herd in the year prior to loan origination but change their behavior by choosing to herd to affiliated analysts following loan origination (as indicated by the $Herd_{Affliated}$ measure).[23] The control variables are as in Column 1. Referring to Column 5, the coefficient on *New herding analyst* is reliably negative, which is consistent with our expectation that unaffiliated analysts who change their behavior by choosing to herd following loan origination decrease their information search relative to other unaffiliated analysts.

Placebo Loan Origination Dates

To test the robustness of our finding, we conduct "placebo" tests by replacing the actual loan origination date with a pseudo loan origination date to ascertain that the syndicated loan origination is indeed a material economic shock to the analysts' information environment. We designate a new loan origination date as two years before the actual loan origination date used in our main analysis and repeat our tests. Our results are displayed in Table 7. For these tests, we only focus on the behavior of unaffiliated analysts post-origination for ease of interpretation, but inferences remain unchanged if we estimate placebo regressions by including both affiliated and unaffiliated analysts.[24] In Table 7, Column 1, we report the corollary to the herding results related

[23] With this design, the indicator variable equals zero for unaffiliated analysts who either maintain the same behavior before and after loan origination or shift from herding prior to origination to non-herding afterward. Although the latter shift may seem unusual—since loan origination increases the informational disadvantage of unaffiliated analysts—we retain these observations for completeness. Nevertheless, we also re-run the analysis excluding them. Our inferences remain unchanged

[24] The placebo event date tests can be viewed as a validation of parallel trends since we select event dates prior to loan origination and find no differences between affiliated and unaffiliated analysts when there are no systematic differences in access to private information.

to unaffiliated analysts in Table 4, Column 2.[25] The key variable of interest is *Post*, our placebo loan origination date, which we do not expect to have a significant coefficient. The findings in Column 1 confirm our expectations.

[Table 7 Here]

Table 7, Columns 2 to 5 report the results related to total EDGAR views and the same placebo loan origination dates. The findings, again, reveal no significant shift in unaffiliated analysts' total views with insignificant coefficients on *Post*, which helps bolster our inferences regarding a causal shift in EDGAR views for unaffiliated analysts documented in Table 6. Overall, these results lend a degree of confidence to our conclusions that differential private information from syndicated loan originations results in shifts in unaffiliated analysts' herding and information search behaviors.

V. Additional Analysis

Persistence of Information and Temporal Effects on Herding vs. Searching

We next investigate how long the informational advantage of affiliated analysts persists after loan origination, how the herding tendencies and information-seeking behaviors of unaffiliated analysts evolve over time, and whether the information gap between the two groups diminishes with time. Exploring these issues offers deeper insight into analysts' information acquisition dynamics.[26]

To assess how long affiliated analysts retain their informational advantage, we extend the sample window to cover one year before and three years after the loan origination. We then evaluate their forecast accuracy over this period to determine the persistence of the increase in

[25] As in Table 4, Column 2, we use the $Herd_{Consensus}$ measure for this placebo test. The results using our other herd measures are similar.

[26] We thank an anonymous reviewer for suggesting the analysis we present in this section.

accuracy following loan origination. We report the results in Panel A of Table 8. The variable *Affiliated* takes on a value of one for an affiliated analyst, zero otherwise. The coefficient on the interaction term *Affiliated*×*Post* is reliably negative in Column 1, and for each of the three years following loan origination in Column 2. These results indicate that affiliated analysts consistently produce more accurate forecasts relative to unaffiliated analysts over this period, and that the informational advantage of affiliated analysts appears to endure at least for a three-year period.[27]

[Table 8 here]

In Panel B, we examine how long the herding tendencies of some unaffiliated analysts last using the same two herding measures as in Table 3. Results indicate that herding is most pronounced in the first-year post-loan, with only the *Herd* variable showing evidence of persistence into year two and neither measure is significant in year three. These results align with the notion that herding is a costly strategy for unaffiliated analysts in the long run as it contributes less to price discovery (as our earlier findings indicate), potentially leading to lower compensation by diminishing brokerage trading profits, as well as causing long-term reputational damage. The results also provide further support for concentrating our analyses on a shorter period surrounding loan originations to detect herding behavior.

Given the result that the herding behavior dissipates over time, it is natural to ask whether analysts substitute herding with increased information acquisition. To answer this question, we re-estimate Eq. (3) using an extended sample of one year pre- and three years post-loan origination,

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[27] We also investigate whether the information advantage that affiliated analysts enjoy with respect to focal firms frees up their capacity to improve forecast accuracy for other firms in their coverage portfolio after the origination of a syndicated loan. Using the loan origination date as the event date, we compare forecast accuracy for all non-focal firms covered by the affiliated analyst in the four quarters before and after loan origination. Untabulated results indicate no significant change in affiliated analysts' forecast accuracy for their non-focal portfolio firms in the post-loan period. Given our primary focus is the forecasting behavior of unaffiliated forecasts, we do not further explore this issue.

and use separate *Post* indicators for each of the three years following loan originations. Table 8, Panel C reports the results corresponding to the four different types of SEC filings. Referring to Column 1, the coefficient on *Unaffiliated* × *Post* is positive and significant in all three years, which suggests that, on average, the increased search activities of unaffiliated analysts (relative to affiliated analysts) last for three years following loan origination. We get similar results for 8K and ownership filings in Columns 2 and 4 (two years), but similar to Table 6, we do not detect increased search activity with respect to 10K filings. Moreover, the variable *Post* does not load significantly in all columns, suggesting that there is no evidence of affiliated analysts increasing their information search activities over the three-year horizon following loan originations.

Overall, results in panel C suggest that unaffiliated analysts intensify their research efforts in the years following the loan event. This pattern supports our earlier findings that herding behavior among unaffiliated analysts is concentrated in the short run and is not a persistent or long-term strategy. Instead, unaffiliated analysts appear to prefer increasing their information-gathering efforts over time, rather than mechanically herding with affiliated analysts. [28]

In light of these findings, a question that arises is whether unaffiliated analysts who increase their information search activities are able to *overcome* their information disadvantage. Gibbons et al. (2021) find a positive relationship between EDGAR usage and forecast accuracy across a broad cross-section of firms. However, given our smaller sample size, we are unable to detect statistically significant improvements in relative forecast accuracy for unaffiliated analysts who increase their EDGAR views following syndicated loan originations (untabulated). This

[28] We note that analysts have access to a firm's financial information via other channels such as Bloomberg, FactSet and Capital IQ, which in turn causes our tests to potentially suffer from low power. Consequently, we view our findings, in spite of the above issues, as strong evidence in support of the notion that some unaffiliated analysts increase their search activities to compete with affiliated analysts.

finding is not necessarily surprising, as our tests focus on *relative* accuracy improvements within analyst subgroups, comparing affiliated versus unaffiliated analysts and herding versus non-herding analysts. Overall, our findings reveal important insights into the different choices unaffiliated analysts make when competing with affiliated analysts with access to private information.

Collectively, the results in this section support the narrative that the informational advantage of affiliated analysts appears to endure over time, but the herding behavior of unaffiliated analysts dissipates over a shorter horizon while their information search intensifies.

Analyst Reputation

Prior research highlights the importance of reputation in the competitive environment in which financial analysts operate. Both markets and the analyst community are likely to place considerable weight on the forecasts and recommendations of well-regarded, established analysts (Jackson 2005; Park and Stice 2000; Gleason and Lee 2003). In our setting, the reputations of both affiliated and unaffiliated analysts could play significant roles in determining whether to herd or increase information search activity.

The reputation of affiliated analysts could potentially shape unaffiliated analysts' herding behavior (Gleason and Lee 2003). It is plausible for unaffiliated analysts to be more likely to mimic forecasts of affiliated analysts with stronger reputations. However, such an argument may not be valid to the extent that *all* affiliated analysts are privy to the same information following loan origination in our syndicated loan context, thus reputation may not be as important a factor. To gain some insight into how affiliated analysts' reputation shapes herding behavior, we classify affiliated analysts into reputation quintiles based on their prior-year forecast accuracy. We then construct two new variables: $Reputation_{High}$ and $Reputation_{Quintile}$. $Reputation_{High}$ is an indicator variable which equals one if an unaffiliated analyst is herding toward an affiliated analyst in the top reputation quintile, and zero otherwise. $\textit{Reputation}_{\textit{Quintile}}$ is an ordinal variable reflecting the quintile rank of affiliated analyst forecast accuracy over the prior-year. [29]

[Table 9 here]

Using these measures, we re-estimate the effect of loan origination on unaffiliated analysts' herding with affiliated analysts post-loan origination. The results are presented in Table 9, Panel A. Column 1 reveals that unaffiliated analysts exhibit a stronger tendency to herd with affiliated analysts with high reputation (i.e., with affiliated analysts in the top reputation quintile). Turning to the $\textit{Reputation}_{\textit{Quintile}}$ the coefficient on this variable is significantly positive, pointing again to the unaffiliated analysts' propensity to herd with more reputable affiliated analysts. In sum, these results suggest that affiliated analysts' reputation plays an important role in shaping herding behavior.

We next examine how the reputation of *unaffiliated* analysts influences their own herding behavior. On the one hand, well-established and highly reputable analysts may be reluctant to jeopardize their standing and thus may be less likely to herd. On the other hand, given the difficulty of outperforming affiliated analysts who possess superior information, they may instead choose to herd and allocate their efforts toward other firms in their coverage portfolio to capture informational rents. To address this issue, we use a similar design as in Panel A of Table 9, and construct two variables: $\textit{Reputation}_{\textit{Unaffiliated-High}}$ and $Q_{\textit{Reputation}}$. $\textit{Reputation}_{\textit{Unaffiliated-High}}$ is an indicator variable that equals one if the unaffiliated analyst issuing the forecast is in the top quintile of prior-year forecast accuracy, and zero otherwise. $Q_{\textit{Reputation}}$ is an ordinal variable reflecting the quintile rank of the unaffiliated analyst forecast accuracy in the prior-year.

[29] We use the ordinal quintile rank measure instead of a more continuous prior forecast accuracy measure to abstract away from magnitude-related non-linearity issues.

The results are presented in Table 9, Panel B. Column 1 of this panel reveals that unaffiliated analysts with a high reputation level are significantly more inclined to herd. Similarly, Column 2 indicates that the coefficient on $Q_{Reputation}$ is reliably positive. These results support the narrative that established unaffiliated analysts seem to acknowledge affiliated analysts' informational advantage and prefer to herd with respect to focal firms, and invest instead in other firms they cover, consistent with our earlier results in Table 6.

Cross-Sectional Tests

The results on herding and EDGAR searches indicate a shift in both behaviors for unaffiliated analysts after the origination of a syndicated loan, because of the private information advantage of affiliated analysts. A natural question is, when are these effects most significant? Intuitively, we expect the private information advantage of affiliated analysts to be a more severe issue for unaffiliated analysts when forecasting is an inherently difficult task. We use two proxies for forecast difficulty: 1) firm growth as captured by the market-to-book ratio, and 2) the firm's accounting quality as measured by its accruals quality using the measure from (Dechow and Dichev 2002). Following the literature, we expect high-growth firms and low-accruals quality firms to present greater difficulty in forecasting (Bhattacharya et al. 2012; Lobo et al. 2012) and, thus, induce greater shifts in herding behavior and EDGAR search activities on the part of unaffiliated analysts. Table 10 reports the results. High and Low refer to the top and bottom quintiles of each variable, respectively.

The positive and statistically significant coefficients in columns 2 and 3 suggest that unaffiliated analysts are more likely to herd when the borrower has a high market-to-book ratio or lower accounting quality. Our cross-sectional results confirm that when a firm's future earnings are more difficult to forecast, differential access to private information becomes more crucial for analysts' forecast accuracy.

[Table 10 here]

Participation in conference calls

To seek additional corroborative evidence on the information search behavior of analysts who prefer not to herd, we explore whether these analysts increase their participation in conference calls post-loan origination. we use the Q&A portion of company conference call transcripts from StreetEvents. In untabulated analysis, we do not find systematic evidence of a significant change in unaffiliated analysts' call participation following loan origination.[30] One explanation is the limitation posed by our data, since we observe only those analysts who actively ask questions during the calls, but we do not observe the full set of attendees. It is possible that unaffiliated analysts decrease their attendance following loan origination; however, we cannot capture this change if they did not actively participate in the call prior to the loan origination. Addressing these measurement issues is an avenue for future research,

V. CONCLUSION

Capitalizing on the private information available following participating in a syndicated loan, this study provides evidence of shifts in analysts' behaviors in response to differential access to private information. Specifically, we find that since affiliated analysts enjoy a significant private information advantage and improve their forecast accuracy, unaffiliated analysts display increased levels of herding activity after the loan initiation, helping them improve accuracy but at the cost of contributing less to price discovery. Additionally, we find that some unaffiliated analysts who herd reallocate their efforts away from syndicated loan firms to other portfolio companies (that do

[30] These results are available upon request. We thank a reviewer for suggesting this analysis.

not pose private information disadvantages), thus improving their forecast accuracy with respect to these companies relative to unaffiliated analysts not designated as herding.

We also find that unaffiliated analysts increase their EDGAR information searches, which is consistent with a subset of unaffiliated analysts attempting to offset their private information disadvantage by conducting more research. In combined analyses, we illustrate that increases in information searches are concentrated in the group of unaffiliated analysts who do not herd.

Our evidence is consistent with syndicated loans providing a rich source of private information that fundamentally alters the competitive landscape of analysts. Those without access to private information are forced to work harder to compete and, at the same time, are often less likely to rely on their own information searches, given they know they are at an information disadvantage. In contrast, affiliated analysts exploit their private information to improve forecast accuracy. We believe this dynamic adjustment to the competitive forces facing analysts is of interest to investors, regulators, and academics as it helps explain the nature of analysts' behaviors in the face of differential access to private information.

Finally, the syndicated loan setting offers a particularly suitable context for examining information acquisition and forecasting behavior among analysts who lack the private access available to a known subset of their peers. An equally compelling setting is broker-hosted conferences: observable events that provide affiliated analysts with a clear and well-recognized informational advantage over others. The findings of Ru et al. (2019), which examine the disclosure of Chinese analysts' site visits, provide evidence consistent with the reallocation of analyst efforts documented in our study. Exploring whether our results extend to U.S.-based, shorter-term information disadvantages, such as site visits and broker-hosted conferences, presents a promising avenue for future research.

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Appendix A: Variable descriptions

Variable	Description
% InstOwnership	Percentage of total shares outstanding held by institutional investors
Herd	An indicator variable that is set to one if a forecast is considered a herding forecast. Herding forecasts are those that are issued within 6 days of another forecast for the same forecast end-date by a different analyst where the estimate value differs at most by 1% from the previous forecast.
$Herd_{Affiliated}$	An indicator variable equal to one if an analyst issues a forecast within 1% of the average of all affiliated analysts' forecasts issued within the past six days.
$Herd_{Consensus}$	An indicator variable equal to one if an analyst issues a forecast within 1% of the average of all other analysts' forecasts issued within the past six days.
Leverage	Total value of the firm's debt as a percentage of its total assets.
Log(AnalystExperience)	Natural log of the total number of years an analyst appears in the IBES dataset starting from 2000.
Log(Analysts)	Natural log of total number of unique analysts who issue forecasts for a firm in each quarter.
Log(BrokerSize)	Natural log of total number of analysts at the brokerage firm.
Log(MB)	Natural log of market-to-book ratio of the firm, calculated as the total floating share market value divided by the book value of the firm's equity, winsorized at 1%.
Log(NumFirmsAnalystCovers)	Natural log of the total number of unique firms an analyst covers.
Log(TimeCompanyCovered)	Natural log of the total number of years that an analyst has issued forecasts for a specific firm.
New herding analyst	An indicator variable that is set to one if an analyst does not herd in its forecast for a covered firm in the year prior to loan origination but chooses to herd to affiliated analysts following the loan origination.
Post	Indicator variable that is set to one for forecasts issued within one year following loan origination date.
Price Adj. Error	Forecast error, scaled by the per share price at the beginning of the month in which the forecast is issued.
$Q_{Reputation}$	An ordinal variable reflecting the quintile rank of the unaffiliated analyst forecast accuracy in the prior-year.
$Reputation_{High}$	An indicator variable which equals one if an unaffiliated analyst is herding toward an affiliated analyst in the top reputation quintile, and zero otherwise.
$Reputation_{Quintile}$	An ordinal variable reflecting the quintile rank of affiliated analyst forecast accuracy over the prior-year.
$Reputation_{Unaffiliated\text{-}High}$	An indicator variable that equals one if the unaffiliated analyst issuing the forecast is in the top quintile of prior-year forecast accuracy, and zero otherwise.
Σ10Ks	Total number of 10 K/Q, 11K, 20F, and 40F filings viewed by an analyst.
Σ10Ks minutes	Total minutes viewing 10 K/Q, 11K, 20F, and 40F filings.
Σ8Ks	Total number of 8 K and 6K filings viewed by an analyst.
Size	Natural log of a firm's total assets.
ΣOwnership	Total number of 3, 4, and SC 13G filings viewed by an analyst.
ΣViews	Total number of files viewed by an analyst.

Table 1: Sample selection

This table presents details of the sample selection process for our main analysis retrieved from FactSet, DealScan, and EDGAR.

Description	Forecasts	Analysts	Brokerages	Firms
1. All analysts from US brokerages from 2000 to 2020 from FactSet		7,025	359	
2. Keep annual EPS estimates issued within one year of the forecast period end date	1,331,450	4,243	322	4,056
3. Drop estimates with missing announcement dates	1,169,622	4,215	322	3,985
4. Manually match all brokerage names to lender names			307	
5. Limit the sample to those forecasts that are issued within one year of each borrower's first loan within the sample	65,490	1,561	185	898
6. Drop observations with missing COMPUSTAT data	63,576	1,549	185	885
• Affiliated analysts: estimates from analysts affiliated with the lender	17,745	439	26	885
• Unaffiliated analysts: estimates from all other analysts covering the firm	45,831	1,110	159	885
7. Match forecasts with log files from EDGAR from 2007 to 2016	47,169		162	684
• Total log views by affiliated analysts	13,397		24	684
• Total log views by unaffiliated analysts	33,772		138	684

Table 2: Summary statistics

This table presents descriptive analyses for affiliated and unaffiliated analysts issuing forecasts for a borrower during the two years surrounding the loan origination date. All variables are defined in Appendix A. The sample size for $Herd_{Affiliated}$ is smaller since this variable is only defined in the post loan origination period.

VARIABLES	(1) N	(2) Mean	(3) p50	(4) p25	(5) p75	(6) SD
Unaffiliated	63,576	0.7209	1.0000	0.0000	1.0000	0.4485
Price Adj. Error	63,576	0.7509	0.2653	0.0870	0.7423	1.3243
Herd	63,576	0.0720	0.0000	0.0000	0.0000	0.2385
$Herd_{Consensus}$	63,576	0.1134	0.0000	0.0000	0.0000	0.3171
$Herd_{Affiliated}$	38,592	0.0829	0.0000	0.0000	0.0000	0.2757
Size	63,576	8.7844	8.7279	7.6310	9.7842	1.5513
Log(MB)	63,576	3.9215	2.6195	1.6982	4.1271	4.5100
Leverage	63,576	0.2739	0.2674	0.1567	0.3771	0.1685
Log(Analysts)	63,576	2.4451	2.7726	2.1972	3.1355	1.0512
Log(BrokerSize)	63,576	2.6964	2.7081	2.0794	3.4012	0.9292
Log(NumFirmsAnalystCovers)	63,576	2.5081	2.5649	2.3026	2.8332	0.5265
Log(Analyst Experience)	63,576	2.4953	2.5649	1.7918	3.2581	0.9682
Log(Time Company Covered)	63,576	1.9791	2.0794	1.3863	2.7081	0.9673
∑Views	47,169	0.3432	0.0000	0.0000	0.0000	3.4130
∑10KQs	47,169	0.1858	0.0000	0.0000	0.0000	1.8665
∑8K	47,169	0.0982	0.0000	0.0000	0.0000	1.6085
∑Ownership	47,169	0.0381	0.0000	0.0000	0.0000	1.0619

*The number of observations for log file variables is different because the observations are at the firm-brokerage level instead of the analysts-firm level, and data is further limited to the 2003 to 2016 time period.

Table 3: Change in analyst herding following loan initiation

This table presents determinants of analyst herding. In panel A we present the change in analysts' likelihood of herding following loan origination. In panel B, we examine which firm and broker characteristics influence analyst herding in the post loan origination period by removing firm and broker fixed effects. We define herding forecasts (Herd) as forecasts that are issued within six days of another forecast for the same forecast end-date by a different analyst where the estimate value differs at most by 1% from the previous forecast. $Herd_{Consensus}$ is an indicator variable which equals one if an analyst issues a forecast within 1% of the average of all other analyst forecasts issued in the past six days. *Post* is an indicator variable that refers to forecasts issued in the one year following the loan origination date. T-statistics in parentheses are based on standard errors clustered at the firm level. ***, **, and * indicate significance at the 0.01, 0.05, and 0.10 levels, respectively. All variables are defined in Appendix A.

Panel A: Likelihood of unaffiliated analysts herding following loan origination

	(1)	(2)
VARIABLES	P(Herd =1)	P($Herd_{Consensus}$ =1)
Post	0.0100***	0.0161***
	(3.61)	(4.92)
Size	0.0057	-0.0001
	(1.01)	(-0.02)
Log (MB)	0.0006	0.0017**
	(0.92)	(1.99)
Leverage	-0.0136	-0.0912***
	(-0.55)	(-3.14)
Log (#Analysts)	-0.0015	0.0111**
	(-0.39)	(2.57)
Log (BrokerSize)	-0.0036	-0.0013
	(-0.67)	(-0.20)
Log (NumFirmsAnalystCovers)	-0.0052	-0.0037
	(-1.44)	(-0.85)
Log (AnalystExperience)	0.0046*	-0.0004
	(1.65)	(-0.11)
Log (TimeCompanyCovered)	-0.0028	0.0005
	(-1.08)	(0.16)
Sample	Unaffiliated	Unaffiliated
Model	OLS	OLS
Broker fixed effects	Yes	Yes
Firm fixed effects	Yes	Yes
Year fixed effects	Yes	Yes
Observations	45,831	45,831
Adjusted R^2	0.0846	0.1255

Panel B: Other determinants of unaffiliated analyst herding following loan origination

VARIABLES	(1) P(Herd =1)	(3) P($Herd_{Consensus}$ =1)
Size	0.0101***	0.0158***
	(9.01)	(11.76)
Log (MB)	0.0029***	0.0044***
	(6.78)	(8.43)
Leverage	-0.0580***	-0.0876***
	(-6.20)	(-7.67)
Log (#Analysts)	0.0079***	0.0150***
	(4.96)	(7.93)
Log (BrokerSize)	0.0118***	0.0070***
	(6.30)	(3.03)
Log (NumFirmsAnalystCovers)	0.0053*	0.0060
	(1.68)	(1.55)
Log (AnalystExperience)	0.0050*	-0.0009
	(1.71)	(-0.27)
Log (TimeCompanyCovered)	0.0010	0.0043
	(0.35)	(1.29)
Sample	Unaffiliated, Post	Unaffiliated, Post
Model	OLS	OLS
Broker fixed effects	No	No
Firm fixed effects	No	No
Year fixed effects	Yes	Yes
Observations	26,846	26,846
Adjusted R^2	0.0161	0.0249

Table 4: Change in analyst forecast error following loan initiation

This table presents changes in analyst forecast error following loan origination. Price Adj. Error is the absolute value of the difference between the analyst forecast and the actual EPS, scaled by the per share price at the beginning of the month in which the forecast is issued. The sample in column 1 corresponds to all forecasts issued by both affiliated and unaffiliated analysts for the borrower. The variable for unaffiliated analysts is absorbed by broker fixed-effects. In column 2 the sample is restricted to the subsample of unaffiliated analysts in the post loan period to examine the forecast accuracy of those analysts who chose to herd to affiliated analysts' forecasts. $Herd_{Affiliated}$ is an indicator variable that equals one if an unaffiliated analyst forecast is within 1% of the average forecasts of affiliated analysts issued within the past six days. In column 3, the sample corresponds to all forecasts issued by unaffiliated analysts for their *other* covered firms excluding the borrower during the same time-period. T-statistics in parentheses are based on standard errors clustered at the firm level. ***, **, and * indicate significance at the 0.01, 0.05, and 0.10 levels, respectively. All variables are defined in Appendix A.

VARIABLES	(1) Price Adj. Error	(2) Price Adj. Error	(3) Price Adj. $Error_{Other}$
$Herd_{Affiliated}$		-0.0944***	-0.1266**
		(-5.41)	(-2.07)
Unaffiliated×Post	0.0807***		
	(4.36)		
Post	-0.0303*		
	(-1.82)		
Size	-0.1717***	-0.1628***	0.1939*
	(-6.71)	(-3.60)	(1.84)
Log (MB)	-0.0160***	-0.0111***	-0.0338***
	(-6.82)	(-2.80)	(-3.30)
Leverage	1.2523***	0.9557***	1.3617***
	(13.85)	(5.77)	(3.33)
Log (#Analysts)	-0.0967***	-0.2110***	-0.0647
	(-5.53)	(-7.71)	(-0.98)
Log (BrokerSize)	-0.0915***	-0.0922***	-0.1065
	(-4.85)	(-3.15)	(-0.71)
Log (NumFirmsAnalystCovers)	0.0269**	0.0155	0.4742***
	(2.27)	(0.89)	(4.10)
Log (AnalystExperience)	-0.0152**	0.0044	-0.6646***
	(-2.09)	(0.37)	(-7.28)
Log (TimeCompanyCovered)	-0.0034	0.0154	0.1157**
	(-0.50)	(1.43)	(2.12)
Sample	All	Unaffiliated, Post	Unaffiliated, post
Model	OLS	OLS	OLS
Broker fixed effects	Yes	Yes	Yes
Firm fixed effects	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes
Observations	63,576	26,846	8,479
Adjusted R^2	0.5456	0.6403	0.7150

Table 5: Market reaction to herding versus non-herding forecasts of unaffiliated analysts

This table examines the market reaction, as measured by cumulative two-day risk adjusted abnormal returns, to herding vs. non-herding forecasts. Herd forecasts ($Herd_{Consensus,}$ Forecast, $Herd_{Affiliated}$ Forecast) is an indicator variable that is set to one if there are only forecasts categorized as herding forecasts (herding forecasts to analysts' consensus within the past six days, herding forecasts to affiliated analyst consensus within the past six days) issued on that day, and zero otherwise. |CAR0-1| is the absolute value of the cumulative risk-adjusted return estimated using the Fama–French three-factor model on the firm's stock over the day the forecast is issued and the subsequent trading day. The sample in all three columns is limited to the affiliated analysts' estimates during the post-loan origination period. T-statistics in parentheses are based on standard errors clustered at the firm level ***, **, and * indicate significance at the 0.01, 0.05, and 0.10 levels, respectively. All variables are defined in Appendix A.

VARIABLES	(1) $\lvert CAR_{0-1} \rvert$	(2) $\lvert CAR_{0-1} \rvert$	(3) $\lvert CAR_{0-1} \rvert$
Herd Forecast	-0.0043***		
	(-7.68)		
$Herd_{Consensus}$ Forecast		-0.0027***	
		(-4.94)	
$Herd_{Affiliated}$ Forecast			-0.0045***
			(-5.30)
Size	-0.0024	-0.0024	-0.0023
	(-1.47)	(-1.48)	(-1.44)
Log (MB)	-0.0000	-0.0000	-0.0001
	(-0.25)	(-0.25)	(-0.27)
Leverage	0.0131**	0.0127*	0.0128*
	(1.97)	(1.91)	(1.92)
Log (#Analysts)	0.0021	0.0021	0.0021
	(1.46)	(1.49)	(1.46)
% InstOwnership	-0.0031	-0.0030	-0.0031
	(-0.53)	(-0.50)	(-0.52)
Sample	Unaffiliated, Post	Unaffiliated, Post	Unaffiliated, Post
Model	OLS	OLS	OLS
Firm fixed effects	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes
Observations	18,852	18,852	18,852
Adjusted R^2	0.1836	0.1829	0.1829

Table 6: Number of EDGAR filings views during the five days prior to analyst forecast issue

This table examines the change in the total number of EDGAR filing views by unaffiliated analysts during the five days leading up to the analyst forecast issuance. In Panel A, we present the results for two years surrounding the loan origination quarter. In Panel B, we extend the sample to one year pre- and three years post-loan origination to further examine analysts' long-term behavior. In columns 1 to 4 of Panels A and B, we present the results for the entire sample using a Poisson model. In column 5 of Panel A, we examine the likelihood of accessing company filings by unaffiliated analysts that have not herd in the pre-loan period but choose to herd to affiliated analysts following loan origination. Z-statistics in parentheses are based on standard errors clustered at the firm level. ***, **, and * indicate significance at the 0.01, 0.05, and 0.10 levels, respectively. All variables are defined in Appendix A.

Panel A: Change in the number of filing views post loan origination for unaffiliated analysts

	(1)	(2)	(3)	(4)	(5)
VARIABLES	ΣViews	Σ10KQs	Σ8Ks	ΣOwnership	ΣViews
New herding analyst					-2.7024*
					(-1.95)
Unaffiliated × Post	0.4834**	0.1822	0.9162***	0.9706**	
	(2.56)	(1.01)	(2.60)	(2.35)	
Post	-0.1859	-0.1312	-0.2755	-0.1611	
	(-1.05)	(-0.86)	(-0.77)	(-0.46)	
Size	0.3449	0.5635*	-0.2068	0.3331	5.7031**
	(1.18)	(1.69)	(-0.50)	(0.45)	(2.12)
Log (MB)	-0.0220	0.0180	-0.0870**	0.1350*	0.0674
	(-0.75)	(0.62)	(-2.50)	(1.79)	(0.33)
Leverage	0.0483	-0.5568	1.4570	1.1621	11.2441*
	(0.06)	(-0.61)	(0.98)	(0.53)	(1.76)
Log (#Analysts)	-0.3102**	0.0590	-0.5546**	-0.7353*	-2.3881***
	(-2.05)	(0.32)	(-2.35)	(-1.77)	(-2.58)
Log (BrokerSize)	0.3187	0.1401	0.7957	-0.1082	1.8253
	(1.06)	(0.46)	(1.59)	(-0.13)	(1.28)
Log (NumFirmsAnalystCovers)	0.0488	-0.2875*	0.1577	1.8399**	0.3548
	(0.32)	(-1.93)	(0.59)	(2.28)	(0.29)
Log (AnalystExperience)	0.0060	0.1758**	-0.2675*	-0.6334**	-1.5362**
	(0.07)	(2.21)	(-1.91)	(-1.99)	(-2.45)
Log (TimeCompanyCovered)	-0.0012	-0.0677	0.2173	0.2819	1.0581
	(-0.02)	(-0.92)	(1.51)	(1.40)	(1.40)
Sample	All	All	All	All	Unaffiliated, post
Model	Poisson	Poisson	Poisson	Poisson	Poisson
Broker/firm/year fixed effects	Yes	Yes	Yes	Yes	Yes
Observations	47,169	47,169	47,169	47,169	19,054
Pseudo (adjusted) R^2	0.5718	0.5383	0.5562	0.5716	0.6026

Table 7: Placebo loan start date

This table presents the placebo analysis using a placebo loan start date that is set two years before the start date of the actual loan. Column 1 presents the results for the likelihood of herding for unaffiliated analysts. Columns 2-4 examine the number of file views for unaffiliated analysts during the five days leading up to the forecast issue using an OLS model. $Herd_{Consensus}$ is an indicator variable which equals one if an analyst issues a forecast within 1% of the average other analyst forecasts within the previous six days. *Post* is an indicator variable that is set to one for forecasts issued within one year following loan origination date. T-statistics in parentheses are based on standard errors clustered at the firm level. ***, **, and * indicate significance at the 0.01, 0.05, and 0.10 levels, respectively. All variables are defined in Appendix A.

	(1)	(2)	(3)	(4)	(5)
VARIABLES	P($Herd_{Consensus}$ =1)	ΣViews	Σ10KQs	Σ8Ks	ΣOwnership
Post	0.0066	-0.0111	-0.0034	0.0011	0.0020
	(1.41)	(-0.28)	(-0.13)	(0.06)	(0.29)
Size	0.0196	-0.1501	0.0669	-0.1679	-0.0197
	(1.49)	(-0.80)	(1.02)	(-1.10)	(-1.08)
Log (MB)	0.0011	0.0546	0.0505	0.0037	-0.0006
	(1.07)	(1.26)	(1.18)	(1.15)	(-0.45)
Leverage	-0.0412	-0.7615	-0.9190*	-0.0217	0.0825
	(-0.85)	(-1.19)	(-1.74)	(-0.08)	(0.96)
Log (#Analysts)	0.0096*	0.1103	-0.0048	0.1129	-0.0072
	(1.80)	(0.90)	(-0.17)	(1.14)	(-0.30)
Log (BrokerSize)	0.0071	0.1559**	0.0761*	0.0589*	0.0077
	(0.79)	(2.31)	(1.72)	(1.78)	(0.63)
Log (NumFirmsAnalystCovers)	-0.0116*	-0.0105	-0.0357	0.0280**	0.0033
	(-1.89)	(-0.21)	(-0.89)	(2.06)	(0.57)
Log (AnalystExperience)	0.0122**	0.0880**	0.0415*	0.0411	-0.0072
	(2.52)	(1.98)	(1.87)	(1.31)	(-1.08)
Log (TimeCompanyCovered)	-0.0088**	-0.1087***	-0.0503***	-0.0399	0.0000
	(-2.31)	(-2.72)	(-2.94)	(-1.41)	(0.00)
Sample	Unaffiliated	Unaffiliated	Unaffiliated	Unaffiliated	Unaffiliated
Model	OLS	OLS	OLS	OLS	OLS
Broker fixed effects	Yes	Yes	Yes	Yes	Yes
Firm fixed effects	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes
Observations	26,999	21,113	21,113	21,113	21,113
Adjusted R^2	0.0812	0.0491	0.0288	0.0238	0.0803

Table 8-Forecasting behavior following loan origination—Duration analysis

This table examines the long-term forecasting behavior of analysts. Panel A examines affiliated analysts' forecast accuracy over one year pre and three years post-loan origination to further examine analysts' long-term behavior. The variable *Affiliated* is an indicator variable which equals one for an affiliated analyst, zero otherwise. *Post* ($Post_{Year=i}$) is an indicator variable that equals one for the years (for the i^{th} year) following origination. Panel B presents unaffiliated analysts' long-term behavior following loan origination by examining one year pre- and three-year post-loan origination. *Herd* is an indicator variable that is set to one if an analyst issues a forecast within six days and 1% of another analyst's forecast. $Herd_{Consensus}$ is an indicator variable which equals one if an analyst issues a forecast within 1% of the average of analyst forecasts issued within the previous six days. *Post* is an indicator variable that equals one for the first, second, or third year following loan origination as indicated by the subscript. Panel C examines the change in the total number of EDGAR filing views by unaffiliated analysts during the five days leading up to the analyst forecast issuance by extending the sample to one year pre- and three years post-loan origination to further examine analysts' long-term behavior. As in Columns 1 to 4 of Table 6, we present the results for the entire sample using a Poisson model. Z-statistics (T-statistics) in parentheses are based on standard errors clustered at the firm level. ***, **, and * indicate significance at the 0.01, 0.05, and 0.10 levels, respectively. All variables are defined in Appendix A.

Panel A: Affiliated analyst forecast accuracy for focal firms following loan origination

	(1)	(2)
VARIABLES	Price Adj. Error	Price Adj. Error
Affiliated×Post	-0.0807***	
	(-4.36)	
Post	0.0505***	
	(5.09)	
Affiliated × $Post_{Year=1}$		-0.0991***
		(-5.13)
Affiliated × $Post_{Year=2}$		-0.0874***
		(-3.96)
Affiliated × $Post_{Year=3}$		-0.0965***
		(-4.04)
$Post_{Year=1}$		0.0606***
		(6.11)
$Post_{Year=2}$		0.1166***
		(8.97)
$Post_{Year=3}$		0.0878***
		(5.71)
Controls	Yes	Yes
Sample	All	All
Model	OLS	OLS
Broker fixed effects	Yes	Yes
Firm fixed effects	Yes	Yes
Year fixed effects	Yes	Yes
Observations	63,576	106,704
Adjusted R^2	0.5456	0.4905

Panel B: Unaffiliated analyst herding following loan origination.

	(1)	(2)
VARIABLES	P(Herd =1)	P($Herd_{Consensus}$ =1)
$Post_{Year=1}$	0.0057**	0.0086***
	(2.12)	(2.70)
$Post_{Year=2}$	0.0070**	0.0025
	(1.99)	(0.63)
$Post_{Year=3}$	0.0042	-0.0034
	(1.02)	(-0.71)
Size	0.0103**	0.0136***
	(2.47)	(2.73)
Log (MB)	0.0011**	0.0029***
	(2.13)	(4.77)
Leverage	-0.0192	-0.0869***
	(-1.09)	(-4.17)
Log (#Analysts)	-0.0027	0.0059*
	(-0.96)	(1.83)
Log (BrokerSize)	-0.0076*	-0.0057
	(-1.80)	(-1.12)
Log (NumFirmsAnalystCovers)	-0.0032	-0.0051
	(-1.10)	(-1.43)
Log (AnalystExperience)	-0.0001	-0.0037
	(-0.06)	(-1.33)
Log (TimeCompanyCovered)	-0.0001	0.0022
	(-0.04)	(0.88)
Sample	Unaffiliated	Unaffiliated
Model	OLS	OLS
Broker fixed effects	Yes	Yes
Firm fixed effects	Yes	Yes
Year fixed effects	Yes	Yes
Observations	71,453	71,453
Pseudo R^2	0.0784	0.1105

Panel C: Change in EDGAR filing views in the three years following loan origination

VARIABLES	(1) ΣViews	(2) Σ10KQs	(3) Σ8Ks	(4) ΣOwnership
Unaffiliated× $Post_{Year=1}$	0.4984***	0.2280	0.6649**	1.3867***
	(2.80)	(1.19)	(2.37)	(2.93)
Unaffiliated × $Post_{Year=2}$	0.5244**	0.0991	0.9060**	1.4531**
	(2.30)	(0.44)	(2.37)	(2.47)
Unaffiliated × $Post_{Year=3}$	0.4467*	0.1724	0.7680*	0.6578
	(1.83)	(0.64)	(1.93)	(1.00)
$Post_{Year=1}$	-0.2069	-0.1839	-0.1718	-0.0169
	(-1.56)	(-1.25)	(-0.83)	(-0.05)
$Post_{Year=2}$	-0.1069	-0.0374	-0.0226	-0.1486
	(-0.68)	(-0.21)	(-0.09)	(-0.35)
$Post_{Year=3}$	-0.0108	0.0791	0.0597	-0.6440
	(-0.06)	(0.38)	(0.18)	(-1.44)
Size	0.5200***	0.4442**	0.4869*	1.0088**
	(2.68)	(2.01)	(1.69)	(2.10)
Log (MB)	0.0057	0.0328	-0.0463*	0.0541
	(0.25)	(1.45)	(-1.68)	(0.78)
Leverage	0.5934	0.6224	0.9797	0.1764
	(1.04)	(0.96)	(1.10)	(0.11)
Log (#Analysts)	0.1267	0.1381	0.3694*	-0.0192
	(0.98)	(1.07)	(1.69)	(-0.04)
Log (BrokerSize)	0.3652	0.4952*	0.5981	-0.5854
	(1.57)	(1.95)	(1.52)	(-0.77)
Log (NumFirmsAnalystCovers)	0.0347	-0.2449*	0.3505*	0.4647
	(0.32)	(-1.90)	(1.78)	(1.64)
Log (AnalystExperience)	0.0623	0.1919***	-0.1738	-0.1091
	(0.96)	(2.77)	(-1.52)	(-0.64)
Log (TimeCompanyCovered)	-0.0810	-0.1232*	0.1128	-0.0581
	(-1.20)	(-1.66)	(0.91)	(-0.38)
Model	Poisson	Poisson	Poisson	Poisson
Broker fixed effects	Yes	Yes	Yes	Yes
Firm fixed effects	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
Observations	73,995	73,995	73,995	73,995
Pseudo R^2	0.4895	0.4471	0.4753	0.5376

Table 9-Herding and analyst reputation

This table examines the relation between herding and analyst behavior. Panel A displays the difference in unaffiliated analysts' herding to high vs. low reputation analysts. Analyst reputation is based on their quintile ranking (one to five, with five being most accurate) on all their forecasts issued in the previous year. $Herd_{Affiliated}$ is an indicator variable that equals one if an analyst issues a forecast that is within 1% of average forecasts of affiliated analysts issued during the past six days. $Reputation_{Quintile}$ corresponds to the quintile ranking of the affiliated analyst issuing forecast within six days prior to unaffiliated analysts' forecast. Reputation quintile ranking is calculated using analyst forecast accuracy within the prior year, with five (one) representing higher (lower) analyst reputation. $Reputation_{High}$ is the ranking of the affiliated analyst issuing forecast within six days *prior* to unaffiliated analysts' forecast. Panel B displays unaffiliated analysts' herding to reputable analysts. Analyst reputation is based on their quintile ranking (one to five, with five being most accurate) on all their forecasts issued in the previous year. $Herd_{Consensus}$ is an indicator variable that equals one if an analyst issues a forecast that is within 1% of average forecasts of other analysts issued during the past six days. $Q_{Reputation}$ refers to the quintile reputation of the unaffiliated analyst, calculated as the quintile ranking of the analyst's forecast accuracy in the prior year, with a higher quintile corresponding to higher reputation. $Reputation_{Unaffiliated\text{-}High}$ to the top (fifth) quintile of the unaffiliated analyst forecast accuracy within the prior year.

Panel A- Difference in unaffiliated analysts' herding to high vs. low reputation analysts.

	(1)	(2)
VARIABLES	P($Herd_{Affiliated}$ =1)	P($Herd_{Affiliated}$ =1)
$Reputation_{High}$	0.2900***	
	(12.57)	
$Reputation_{Quintile}$		0.0569***
		(18.22)
Size	0.0087	0.0032
	(0.83)	(0.33)
Log (MB)	0.0030*	0.0026
	(1.92)	(1.60)
Leverage	-0.0662	-0.0653
	(-1.38)	(-1.40)
Log (#Analysts)	0.0075	0.0083
	(1.50)	(1.62)
Log (BrokerSize)	0.0055	0.0078
	(0.88)	(1.26)
Log (NumFirmsAnalystCovers)	-0.0008	-0.0034
	(-0.20)	(-0.86)
Log (AnalystExperience)	0.0065*	0.0072**
	(1.92)	(2.14)
Log (TimeCompanyCovered)	-0.0036	-0.0044
	(-1.21)	(-1.47)
Sample	Unaffiliated, post	Unaffiliated, post
Model	OLS	OLS
Broker fixed effects	Yes	Yes
Firm fixed effects	Yes	Yes
Year fixed effects	Yes	Yes
Observations	26,846	26,846
Adjusted R^2	0.1131	0.1506

Panel B-Change in Unaffiliated analyst herding based on their reputation

VARIABLES	(1) $P(Herd_{Consensus}=1)$	(2) $P(Herd_{Consensus}=1)$
$Reputation_{Unaffiliated-High}$	0.0191**	
	(2.27)	
$Q_{Reputation}$		0.0060**
		(2.33)
Size	-0.0042	-0.0044
	(-0.34)	(-0.36)
Log (MB)	0.0037**	0.0038**
	(2.23)	(2.29)
Leverage	-0.1226**	-0.1290**
	(-2.34)	(-2.46)
Log (#Analysts)	0.0146**	0.0151**
	(2.08)	(2.15)
Log (BrokerSize)	0.0057	0.0057
	(0.60)	(0.59)
Log (NumFirmsAnalystCovers)	-0.0066	-0.0066
	(-0.95)	(-0.96)
Log (AnalystExperience)	-0.0030	-0.0026
	(-0.55)	(-0.47)
Log (TimeCompanyCovered)	-0.0078*	-0.0079*
	(-1.65)	(-1.67)
Sample	Unaffiliated, post	Unaffiliated, post
Model	OLS	OLS
Broker fixed effects	Yes	Yes
Firm fixed effects	Yes	Yes
Year fixed effects	Yes	Yes
Observations	24,723	24,723
Adjusted R^2	0.1450	0.1449

Table 10: Information environment influence on herding and of unaffiliated analysts

This table examines the cross-sectional variability of analyst herding and filing views based on the firm's information environment using the firm's market-to-book and accruals quality (AQ). Low (high) refers to the first (fifth) quintiles of sample values. $Herd_{Consensus}$ is an indicator variable which equals one if an analyst issues a forecast within 1% of the average other analyst forecasts within the previous six days. *Post* is an indicator variable that is set to one for forecasts issued within one year following the loan origination date. T-statistics in parentheses are based on standard errors clustered at the firm level in Columns 1 and 2 (3 and 4***, **, and * indicate significance at the 0.01, 0.05, and 0.10 levels, respectively. All variables are defined in Appendix A.

	(1)	(2)	(3)	(4)
	Low MB	High MB	Low AQ	High AQ
VARIABLES	$P(Herd_{Consensus}=1)$	$P(Herd_{Consensus}=1)$	$P(Herd_{Consensus}=1)$	$P(Herd_{Consensus}=1)$
Post	0.0100	0.0203**	0.0674***	-0.0012
	(1.55)	(2.31)	(6.95)	(-0.14)
Size	-0.0234	-0.0755***	0.0292	0.0045
	(-0.96)	(-2.77)	(1.11)	(0.31)
Log(MB)	0.0518**	-0.0007	0.0064**	0.0037*
	(2.38)	(-0.46)	(1.96)	(1.96)
Leverage	-0.0909	-0.0752	-0.1523	-0.0943
	(-1.11)	(-0.93)	(-1.04)	(-1.59)
Log (#Analysts)	-0.0057	0.0348**	0.0056	0.0272*
	(-0.53)	(2.53)	(0.31)	(1.96)
Log (BrokerSize)	0.0133	0.0016	-0.0201	0.0291*
	(0.97)	(0.09)	(-1.01)	(1.74)
Log (NumFirmsAnalystCovers)	-0.0057	-0.0234**	-0.0213*	0.0158
	(-0.67)	(-2.01)	(-1.77)	(1.35)
Log (AnalystExperience)	-0.0043	-0.0025	-0.0013	-0.0008
	(-0.64)	(-0.32)	(-0.14)	(-0.10)
Log (TimeCompanyCovered)	0.0013	0.0045	0.0001	-0.0001
	(0.22)	(0.62)	(0.01)	(-0.01)
Sample	Unaffiliated	Unaffiliated	Unaffiliated	Unaffiliated
Model	OLS	OLS	OLS	OLS
Broker fixed effects	Yes	Yes	Yes	Yes
Firm fixed effects	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
Observations	8,200	9,546	8,079	8,339
Adjusted R^2	0.0545	0.1059	0.1490	0.0853