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Do Buy-side Analysts Inform Sell-side Analyst Research?

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Abstract: This paper examines whether sell-side analysts' interactions with buy-side analysts influence the quality of sell-side research output. We hypothesize that these interactions offer the sell side a view of the buy side's private information, which enhances the quality of sell-side research. Our findings show that analyst earnings forecast accuracy improves with these interactions with diminishing returns. Results are robust to alternative proxies for research quality and information flow from buy-side to sell-side analysts. Additional tests rule out endogeneity concerns, strengthening the inference that feedback from interactions with buy-side analysts improves the quality of sell-side research output.

Key words: buy-side analysts; sell-side analysts; stock intersection; information flow; research quality; forecast accuracy.

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1. Introduction

Both buy-side and sell-side analysts are important market participants, whose interactions enhance the evolution of a firm's information environment in capital markets. Although a vast literature describes sell-side analyst research characteristics and their impact on stock prices, little is known about the flow of information from the buy to the sell side. The research literature generally focuses on information flows from sell-side analysts through buy-side analysts to portfolio managers, whose trades move stock prices (e.g., Irvine, Lipson, and Puckett 2007; Mikhail, Walther, and Willis 2007; Kang, Yoo, and Cha 2018; Gu, Li, Li, and Yang 2019; Kumar, Mullally, Ray, and Tang 2020). This study highlights the flow of information in the other direction and its implications for the quality of outputs from sell-side analyst research.

Interactions between buy- and sell-side analysts create opportunities to exchange information about firms of mutual interest. Discussions about a particular focal firm might include topics such as the firm's position in its industry, management quality, strategy, growth and value drivers, risks, and of course, earnings prospects. In the context of these discussions and spillover from discussions around the prospects of other firms' stocks, we investigate whether sell-side analysts glean information from buy-side analysts that enhances the quality of their research output regarding the focal firm's prospects.

Our main proxy for the sell-side analyst's research output quality (*ACCURACY*) employs the relative accuracy of the analyst's first forecast of a focal firm's current year earnings following the firm's announcement of its prior year earnings. For three reasons, we use *ACCURACY* as our primary proxy for the quality of sell-side analyst research output. First, prior research shows that information in earnings forecasts affects analysts' stock recommendations (e.g., Ertimur, Sunder, and Sunder 2007; Loh and Mian 2006; Brown, Call, Clement, and Sharp 2015) and target price forecasts (e.g., Gleason, Johnson, and Li 2013), making earnings forecast accuracy a reasonable proxy for overall sell-side analyst research quality.[1] Second, earnings forecasts are more prevalent than stock recommendations and target price forecasts. Third, we can measure earnings forecast accuracy more precisely than the accuracy of stock recommendations and target price forecasts.

To proxy for institutional investor interest in the stocks covered by the sell-side analyst, we develop our main test variable (*INTERSECTION*) as follows. First, we identify each institution having a current investment in a focal firm's stock. Next, we derive the market value of the institution's investments in all *non-focal firms* concurrently covered by the sell-side analyst, as a proportion of the total market value of the institution's investment portfolio. The average of these proportions across all institutions holding the focal firm stock measures *INTERSECTION*. We refer to an institution holding the focal firm's stock and at least one non-focal firm's stock as a connected institution. We expect that greater institutional investor interest in the non-focal firm stocks in the sell-side analyst's coverage portfolio creates more opportunities for informative interactions with the buy-side analysts working for connected institutional investors. Thus, we expect a positive relation between *ACCURACY* and *INTERSECTION*.

To focus on the impact of the flow of information from buy-side analysts to the sell-side analyst, we must consider other factors that affect the quality of sell-side analyst research. In light of arguments and findings in Harford, Jiang, Wang, and Xie (2019) and Ljungqvist,

[1] More than 70% of the subjects responding to the Brown et al. (2015) survey of sell-side analysts reported that their own earnings forecasts are the most important input to their stock recommendations, and respondents cited the use of earnings forecasts to support their recommendations as most important in motivating earnings forecast accuracy.

Marston, Starks, Wei, and Yan (2007), one such factor is the likely positive relation between the sell-side analyst's effort to develop earnings forecast accuracy-enhancing information about the focal firm and the importance of the focal firm to institutional investors. We hold this factor constant by measuring *ACCURACY* relative to all other analysts forecasting the focal firm's current year earnings. Thus, the year and the focal firm are the same and the amount of institutional investor interest in the focal firm is the same across all analysts forecasting the focal firm's earnings.

The portfolio of covered *non-focal firms* differs across sell-side analysts covering the focal firm, so institutional investor interest in the focal firm *relative to* institutional investor interest in the non-focal firms covered by the sell-side analyst differs across sell-side analysts covering the focal firm. Thus, one could argue that as *INTERSECTION* increases, the sell-side analyst has less time to spend forecasting the focal firm's earnings because relatively stronger institutional interest in non-focal firm stocks distracts the analyst's attention away from the focal firm. This argument suggests a negative relation between *ACCURACY* and *INTERSECTION*, due to effort capacity constraints.

We thus hypothesize a positive relation between *ACCURACY* and *INTERSECTION* with diminishing returns. Diminishing returns set in when the relative importance of non-focal firm stocks becomes so great that the sell-side analyst must allocate effort away from the task of forecasting the focal firm's earnings and towards the task of forecasting the earnings of non-focal firms having relatively more importance in institutional investors' investment portfolios. Our test design enables us to model these diminishing returns and estimate a point where the distraction due to relatively greater institutional investor interest in non-focal firm stocks becomes great enough to fully offset earnings forecast accuracy-enhancing information spillover effects of covering related firms.

As hypothesized, we find that *ACCURACY* improves with *INTERSECTION* with diminishing returns. We estimate that at approximately the 61st percentile of the distribution of *INTERSECTION*, the sell-side analyst shows no further improvement in forecast accuracy due to interactions with the buy-side analysts following the focal firm. Until that point, we observe a strong positive relation in the bottom tercile of the distribution (lowest values of *INTERSECTION*) and a weakening positive relation in the middle tercile of the distribution. We find an insignificantly negative relation between *ACCURACY* and *INTERSECTION* in the top tercile of the distribution. Confirming diminishing returns, the improvement in forecast accuracy with a one standard deviation change of *INTERSECTION* is 2.5 times greater when *INTERSECTION* is at the 25th percentile of its distribution, as compared to the improvement in forecast accuracy associated with a one standard deviation change in *INTERSECTION* when the variable is at the median of its distribution.[2]

We also consider the possibility of an endogenous relation between *ACCURACY* and *INTERSECTION*, whereby institutional investors select stocks covered by more accurate sell-side analysts. Addressing this concern, we first note that the concave relation we observe between *ACCURACY* and *INTERSECTION* is inconsistent with endogeneity driving the results. If *ACCURACY* correlates with characteristics that inspire buy-side analysts to interact with sell-side analysts, we expect a linear relation (without diminishing returns). We also conduct a number of formal analyses to address endogeneity concerns. First, if the main results are driven by institutional investor selection of high-quality sell-side analysts, the selection would arguably

[2] As described in Section 5.2, improvement in *ACCURACY* is measured along a line tangent to the curve representing the relation between *INTERSECTION* and *ACCURACY*.

be more prevalent when institutional investors produce less private information. Contrary to this, we find a stronger (weaker) relation between *ACCURACY* and *INTERSECTION* when buy-side analysts have relatively more (less) private information. This supports the inference that sell-side analysts obtain forecast accuracy-enhancing information from buy-side analysts with more private information, as opposed to less-informed buy-side analysts seeking guidance from already-accurate sell-side analysts.

Two additional analyses are designed to rule out endogeneity concerns. In the first analysis, we instrument for *INTERSECTION* with institutional investors' unexpected cash flow, a higher value of which likely prompts further interactions with the sell-side analysts. Results are robust to this approach. The second analysis examines changes in a sell-side analyst's earnings forecast accuracy following exogenous shocks that likely disrupt information flows between the sell-side analysts and the connected institution's buy-side analysts due to the institution's acquisition or bankruptcy. We document a decrease in forecast accuracy for analysts who have relatively lower *INTERSECTION*; i.e., for whom the reduction of information flow is relatively large. These results reinforce the causal interpretation of our results.

Our main analyses rely on earnings forecast accuracy as a proxy for the underlying construct of the quality of the sell-side analyst's research output. To alleviate concerns about construct validity, we consider two alternative proxies and obtain robust results. The first (second) alternative proxy is the intensity of the market's reaction to the sell-side analyst's earnings forecast (stock recommendation) revisions. The idea is that the market would not respond if the stock recommendations and earnings forecasts were not reflective of research quality.

This paper contributes to the literature in three important ways. First, prior research generally focuses on information flow from sell-side analysts to buy-side analysts (e.g., Irvine, et al. 2007; Gu, et al. 2019; Kumar, et al. 2020). We add to the literature by examining the information flow in the other direction. In particular, we highlight information flow from the buy side to the sell side, and how it heightens the quality of sell-side analysts' research output, which would in turn enhance the focal firm's information environment. Thus, our study makes an important contribution to the literature in presenting a more complete picture of how interactions between sell- and buy-side analysts enhance the quality of a firm's information environment. Sell-side analysts learn from their interactions with the buy-side and the resulting improved sell-side research output enhances the timeliness with which the stocks of mutual interest reflect their underlying fundamental values.

Second, this paper adds to the literature on sell-side analyst incentives and behaviors in the context of interactions with institutional investors. Our evidence suggests that the process of catering to institutional investors' needs could facilitate information flow from the buy side to the sell side with diminishing returns. By identifying buy-side analysts as a source of sell-side analyst information, our paper "expand(s) our knowledge about how (sell-side) analysts gather information, a relatively underdeveloped (area) in the literature (Bradshaw 2011; Bradshaw, Ertimur, and O'Brien 2017, p. 19)." Furthermore, our paper is the first to explore the effect of the tension associated with a sell-side analyst's interactions with buy-side analysts on the quality of sell-side analyst research output. On one hand, from these interactions, sell-side analysts glean information that improves the quality of their research output. On the other hand, these interactions require effort to respond to institutional investor demand for services, and this effort detracts from the sell-side analyst's limited capacity to engage in other research qualityenhancing activities. This study finds evidence consistent with the inference that interactions between buy- and sell-side analysts significantly improve the quality of the sell-side analyst's research output with diminishing returns.

Third, by furthering our understanding of the role that buy-side analysts play in financial markets, our paper contributes to the literature that studies buy-side analysts (e.g., Jung, Wong, and Zhang 2018, Brown, Call, Clement, and Sharp 2016, Cici and Rosenfeld 2016, Rebello and Wei 2014). By using a large sample and archival data, we complement the current literature relying on survey data or private datasets and, by doing so, deepen the understanding of channels through which buy-side analysts' private information flows to the stock market.

The rest of this paper is organized as follows. The next section describes the institutional setting and related literature. Section 3 presents our hypotheses. Section 4 discusses our research design and sample selection. Sections 5 and 6 present, respectively, the results of our hypotheses tests and additional tests to address endogeneity. Section 7 presents robustness tests, and Section 8 concludes.

2. Institutional Setting and Related Literature

Buy-side analysts provide research support to their firm's portfolio managers (also known as fund managers). We refer to firms employing buy-side analysts and fund managers as institutional investors. Funds managed by institutional investors include hedge funds, mutual funds, pension funds, and endowment funds. Institutional investors include such firms as General Motors Investment Management Corporation and Bridgewater Associates. The firms employing the sell-side analysts in our study are known as brokerage houses or investment banks, and these include such firms as JP Morgan and Goldman Sachs.

The institutional setting encourages information exchange between sell- and buy-side analysts. Sell-side analysts covet interactions with buy-side analysts in hopes that they lead to trading commissions and broker votes in the context of Institutional Investor Magazine's annual survey seeking to identify the best sell-side analysts in each industry.[3] One aspect of the institutional environment that encourages information flow between buy- and sell-side analysts features the relationship between buy-side analysts working for hedge funds and sell-side analysts working for the hedge funds' prime brokers. These prime brokerage agreements have recently attracted the attention of the academic literature, with two papers emphasizing information flowing from the sell-side to the buy-side and one paper emphasizing information flowing in the other direction. Kumar et al. (2020) provide evidence suggesting that hedge funds trade on information garnered from the prime brokerage houses through which they conduct trades when the prime brokerage house is likely to possess inside information about firms of mutual interest. In particular, the study finds that the information advantage enjoyed by an institutional investor with respect to a particular firm's stock strengthens when the investor's prime brokerage house has recently negotiated a loan to the firm, and that information advantage strengthens further when the prime brokerage house employs a sell-side analyst covering the firm.

Other recent studies of interactions between hedge funds and the prime brokerage houses through which they conduct trades include Klein, Saunders, and Wong (2019) and Chung, Kulchania, and Teo (2021). Klein et al. (2019) provide evidence of a correlation between the direction of institutional investor trades and the direction of upcoming changes in the stock

[3] Prior research shows that sell-side analyst compensation and career advancement depend on actions that increase brokerage and investment banking revenues (Groysberg, Healy, and Maber 2011; Brown, et al. 2015), and the buy-side uses broker votes as a mechanism for allocating trading commissions across sell-side analysts' brokerage firms (Maber, Groysberg, and Healy 2014).

recommendations made by sell-side analysts working for the prime brokerage house. The authors interpret this evidence as an indication of a *quid pro quo* relationship whereby sell-side analysts leak information about their upcoming as yet unpublished recommendation revisions in exchange for trading commissions and broker votes. Based on similar evidence, Chung et al. (2021) conclude that sell-side analysts conform their recommendation revisions to the direction of their institutional investor clients' trades. Thus, it's unclear whether sell-side analysts tip their hand regarding upcoming recommendation revisions or whether they support their institutional investor clients by making recommendation revisions consistent with the direction of trades already made.

The Chung, et al. (2021) interpretation of the relation between the direction of prime brokerage sell-side analyst forecast revisions and the direction of hedge fund trades is consistent with the idea that much (if not all) of a hedge fund's trading operations are routed through its prime broker, giving that broker (and their sell-side analysts) regular and timely knowledge of the demand patterns of these presumably well-informed investors.[4] Following Bushee (1998, 2001) we divide the institutional investors in our study into three categories: transient investors; dedicated investors, and quasi-indexers. As the transient group includes frequent traders, they likely overlap with hedge funds. Results for the transient group are thus informative for information flowing between hedge funds' buy-side analysts and sell-side analysts working for the funds' prime brokers.

The literature has extensively documented that sell-side analysts provide information to the buy-side (Ramnath, Rock, and Shane 2008a, 2008b; Bradshaw et al. 2017). In particular, buy-side analysts rely heavily on industry knowledge, largely obtained from interactions with

[4] We are grateful to an anonymous referee for referring us to research investigating prime brokerage relationships with institutional investors and for elucidating its implications for our study.

sell-side analysts who concentrate on covering fewer industries and fewer firms (Brown et al. 2015, 2016). Benefits flowing from sell- to buy-side analysts include access to industry-specific information independently developed by sell-side analysts, arranged meetings with senior management of companies of interest, information that sell-side analysts glean from their own private conversations with senior management, and insight into what other buy-side analysts are thinking about particular stocks or industries (Soltes 2014; Brown et al. 2016; Maber, Groysberg, and Healy 2020). We investigate whether, in the context of interactions around these services, sell-side analysts become privy to forecast accuracy-enhancing information.

Academic and anecdotal evidence suggests that buy-side analysts generate information incremental to the information developed by sell-side analysts. Direct academic evidence comes from Rebello and Wei (2014), who conclude that "…buy-side analysts produce research that is very different from sell-side research…(p. 777)." They find that the opinions of buy-side analysts, as measured by their stock ratings, differ from the opinions of typical sell-side analysts and that trading strategies utilizing information contained in those opinions can generate significant risk-adjusted returns over the next year. Bushee, Jung, and Miller (2017) document that trade sizes around investor-management meetings increase and abnormal net buys around the meetings are profitable during the thirty days subsequent to the private access day. They conclude that private access to management provides information that changes institutional investors' beliefs and trading. Such information, which is unlikely to be in the information set of sell-side analysts, could be "mosaic" but, nonetheless, valuable in combination with institutional investors' private information and does not violate "Reg FD" (Solomon and Soltes, 2015).

Anecdotal evidence suggests that buy-side analysts often get preferential access to management. This potentially provides institutional investors with access to information incremental to that of the sell-side analysts. For example, during a June 22, 2016 conference call announcing the $2.8 billion acquisition of SolarCity, Tesla's CEO, Elon Musk acknowledged that, over the years in private discussions with institutional shareholders, he "bandied about" the idea of combining Tesla Motors with SolarCity (Reuters 2016). The article also suggests that at least one institutional investor, a Fidelity portfolio manager, benefited from trading on foreknowledge of the merger.[5]

From interactions with buy-side analysts, the sell-side analyst has the potential to learn about the private information that the buy-side analysts generate about companies of common interest.[6] Groysberg, Healy, and Chapman (2008) speculate that "sell-side analysts may develop an information advantage through feedback on their ideas from their own institutional clients (p. 33)."[7] That sell-side analysts discern the private information of their institutional clients in the course of their interactions is supported by interviewees who report that buy-side analysts value their relationships with sell-side analysts, because "they are the only portal" into the thinking of buy-side analysts working for other institutions (Brown et al. 2016, p.148). One interviewee from the Brown et al. 2016 study commented: "the buy side is this whole poker game of, 'I don't want to show my cards, but I want to see your cards.' The only people that can actually see everyone's cards is the sell side. When we ask them questions, they can figure out what we're thinking."

[5] In another article, David Strasser, a former sell-side analyst at Janney Montgomery Scott LLC, stated that in the meetings he arranged between institutional investors and the companies he followed, he "was sometimes asked to sit outside the room so investors could ask questions without him" (Ng and Gryta 2017). Further reason to believe buy-side analysts have information incremental to the information developed by sell-side analysts is provided in: Martin (2005); Abramowitz (2006); Retkwa (2009); Frey and Herbst (2014); Jung, et al. (2018); and Groysberg, Healy, Serafeim and Shanthikumar (2013).

[6] Based on a sample of sell-side analysts at a mid-size investment bank, Maber et al. (2020) document that the average sell-side analyst holds approximately 750 private calls and 45 one-on-one meetings with client investors in the course of a typical semiannual period.

[7] In an experimental study, Barradale, Plenborg, and Staehr (2022) find that feedback from investors enhances the quality of forecasts by students posing as sell-side analysts.

The private information sell-side analysts glean from the buy side could aid the sell-side in gaining better insight into the market's expectation of earnings-related measures, such as revenue and growth, which in turn can allow sell-side analysts to more confidently issue or revise earnings forecasts. The view that sell-side analysts have much that they can potentially learn from buy-side analysts was corroborated by Greg Melich, partner and senior analyst at MoffettNathanson, who indicated to us that talking with buy-side analysts gives him a general understanding of what the market is thinking in terms of general expectations or even where active managers are moving their money and why. He told us that in the course of a typical interaction with an institutional client he might be alerted to a new piece of public information of which he was not aware and the information could be very specific.[8]

Our argument for diminishing returns to *INTERSECTION* is consistent with the finding by Maber, et al. (2020) that increasing high-touch services with institutional clients limits the time sell-side analysts spend on other accuracy-enhancing aspects of their research. It's also consistent with Driskill, Kirk, and Tucker (2020) who study the effects of analyst attention constraints on the timeliness of analysts' earnings forecasts. Driskill et al. (2020) find that, when forecasting a firm's earnings, busy analysts compromise the timeliness and thoroughness of their publication of earnings forecasts, where busyness is measured by the number of non-focal firm earnings announcements on the same day as the focal firm's earnings announcement. Driskill et al. (2020) point out that, while busyness compromises timeliness, there is tension due to "information transfers across related firms (which) may help analysts digest each particular

[8] Melich gave us a hypothetical example, whereby the buy-side client has learned that a certain company has become a supplier of Target Corporation, and the buy-side analyst passes that information along. Melich noted that this kind of information could be potentially used to sharpen revenue predictions for either Target or the supplier company.

firm's disclosures more efficiently (p. 169)."[9] Consistent with Maber, et al. (2020) and Driskill, et al. (2020), our models allow for diminishing returns to the sell side's interactions with its buy-side counterpart. The next section formally states our hypotheses.

3. Hypotheses

Section 2 refers to previous research and anecdotal evidence suggesting that buy- and sell-side analysts have strong incentives to interact. Presumably, more interactions between the two parties provide more opportunities for sell-side analysts to discern the institutional investors' private information, which likely informs sell-side analysts' earnings forecasts and improves their accuracy. We expect more interactions when buy- and sell-side analysts have more common interests, which we measure with the intersection between stocks covered by the sell-side analyst and held in the investment portfolio of the institution employing the buy-side analyst. Thus, we predict that a sell-side analyst's focal firm earnings forecast accuracy increases with this intersection, i.e., there is a positive correlation between *ACCURACY* and *INTERSECTION*.

At the same time, we expect that following too many stocks with importance to institutional investors comes with an opportunity cost that offsets the benefit of information flow from the buy-side. Spreading themselves too thinly could compromise the sell-side analyst's ability to engage in other forecast accuracy-enhancing activities, such as independent research, nurturing relationships with the buy-side analysts who matter most, connecting with management

[9] This argument is closely related to Bourveau, Garel, Joos, and Petit-Romec (2022) which finds that analysts following stocks with varying degrees of attention-grabbing news allocate attention away from covered firms with less salient news and this compromises the analysts' accuracy in forecasting the earnings of the less news-worthy firms in their coverage portfolios. Instead of attention-grabbing news, we study relative institutional investor interest in non-focal firm stocks as the construct that distracts analyst attention away from accurately forecasting the focal firm's earnings.

of firms in the analyst's coverage portfolio, and composing whitepapers and research reports. This is consistent with Maber, et al. (2020) who show that increases in analysts' time-consuming services for their institutional clients result in less published research output. Prior literature suggests a similar cost associated with following too many firms (Clement 1999; Jacob, Lys, and Neale 1999; Myring and Wrege 2011; Pelletier 2015), particularly when those firms announce their earnings on the same day (Driskill, et al. 2020). Thus, we expect the positive impact of *INTERSECTION* on *ACCURACY* to exhibit diminishing returns as *INTERSECTION* increases, and we hypothesize the following relation:

> **H1:** *ACCURACY* increases with *INTERSECTION* with diminishing returns.

If buy-side analysts successfully maintain the confidentiality of their private information when communicating with sell-side analysts, then we expect to find no evidence of a positive relation between *ACCURACY* and *INTERSECTION*.

H2 below is conditional on H1 and addresses whether there is a greater sensitivity of *ACCURACY* to *INTERSECTION* with buy-side analysts who produce more private information. If the relation hypothesized in H1 emerges from sell-side analysts obtaining accuracy-enhancing information from buy-side analysts, then there are more opportunities for such information acquisition when the buy-side analysts possess more private information. This leads to our second hypothesis:

> **H2:** The sensitivity of *ACCURACY* to *INTERSECTION* increases with the opportunity for sell-side analysts to learn from buy-side analysts.

If, on the other hand, the relation hypothesized in H1 arises from buy-side analysts choosing stocks followed by already-accurate sell-side analysts, then opposite to H2, we expect greater sensitivity of *ACCURACY* to *INTERSECTION* when buy-side analysts produce less private information and provide fewer opportunities for learning by the sell-side analysts. Thus, evidence consistent with H2 mitigates this particular endogeneity concern. Additional analyses in Section 6 further address endogeneity in a number of ways.

4. Research design

4.1 Measurement of INTERSECTION

INTERSECTION proxies for the amount of institutional investor interest in the set of non-focal firms covered by sell-side analyst *a*. To develop this proxy for each analyst-firm-year, we first identify each institution, *i*, holding stock in the focal firm. Next, we obtain the total market value of *i*'s investments in all non-focal firm stocks covered by *a* as a proportion (can be zero) of the total market value of *i*'s investment portfolio. Then, the average of these proportions across all institutional investors holding *f* in year *t* proxies for institutional investor interest in interacting with *a* and this average becomes $INTERSECTION_{aft}$. The idea is that as $INTERSECTION_{aft}$ increases, the interest buy-side analysts have in interacting with *a* also increases and *a* has more opportunity for informative interactions. While these interactions are stimulated by the strength of institutional investor interest in the non-focal firms covered by *a*, we expect spillover effects to provide earnings forecast accuracy-enhancing insights into *f*'s prospects.

Equation (1) below formally defines *INTERSECTION* for each analyst-firm-year.

$$INTERSECTION_{aft} = \frac{\sum_{i=1}^{N\_INST_{ft}} \sum_{s=1}^{S_{i,a,-f,t}} \frac{\text{Value of } i'\text{s holdings of non-focal firm stock } s \text{ covered by analyst } a}{\text{Total market value of all stocks held by i}}}{N\_INST_{ft}} \quad (1)$$

Non-focal firm stock *s* refers to a stock other than *f* that is held by institution *i* in the calendar quarter preceding the forecast date and covered by analyst *a* in the one-year period preceding that calendar quarter. $S_{i,a,-f,t}$ is the number of overlapping non-focal stocks covered by *a* and held by *i*. N_INST_{ft} is the number of institutions that invest in *f* in the calendar quarter preceding the forecasting date. Among all sell-side analysts covering *f* in year *t*, if any two of those analysts have exactly the same coverage portfolios, then those two analysts will have exactly the same value for *INTERSECTION*. In other words, differences in coverage portfolios drive differences in *INTERSECTION*. Since focal firm *f* is in both analysts' year *t* coverage portfolios, we exclude the focal firm from the computation in (1) above. We then use equation (2) below to scale *INTERSECTION* among all analysts following firm *f* in year *t* to fall between 0 and 1.

$$Scaled\ Variable_{aft} = \frac{Variable_{aft} - \min\left(Variable_{ft}\right)}{\max(Variable_{ft}) - \min(Variable_{ft})} \qquad (2)$$

Conceptually, *INTERSECTION* centers around the focal firm *f* but does not depend on it, i.e., bears no influence from focal firm characteristics.[10] *INTERSECTION* considers both: breadth, as reflected in the number of connected institutions (i.e., those observations with $INTERSECTION_{aft} > 0$); and depth of interactions, as reflected in the market value of each institution, *i*'s, connected non-focal firm stocks as a proportion of the total market value of all stocks held by *i*. We expect that greater *INTERSECTION* corresponds to greater breadth and depth of dialogue between sell- and buy-side analysts and, therefore, greater opportunity for the sell-side analyst to discern and process the buy-side's private information.

To further illustrate the construction of *INTERSECTION*, consider the example in Figure 1. There we see that the focal stock, *f1,* is held by three institutional investors, *i1* to *i3*, and

[10] Ljungqvist, et al (2007) find a positive correlation between the proportion of shares owned by institutional investors and sell-side analyst earnings forecast accuracy, and they interpret this as evidence that "analysts strive for greater accuracy in stocks predominantly held by institutional investors (p. 447)." Driskill, et al. (2020) find that busy analysts allocate their time towards timely forecasting of the economically more important firms in their coverage portfolios, including firms with high institutional investor interest. Our test design holds institutional investor holdings of focal firm stock constant.

followed by two analysts, *a1* and *a2*. Analyst *a1* is connected with *i1* through non-focal stocks *f2* and *f8,* with a weight of 55% (20%+35%); not connected with *i2*; and connected with *i3* through *f9* and *f10,* with a weight of 60% (25% + 35%). Hence, unscaled $INTERSECTION_{a1,f1,t}$ is 0.383 [(0.55+0.0+0.60)/3]. On the other hand, analyst *a2* connects with only *i2* through non-focal stocks *f3* and *f5,* which account for 45% and 15%, respectively, of *i2*'s portfolio. Unscaled $INTERSECTION_{a2,f1,t}$ is 0.2 [(0+0.6+0)/3]. Our scaling procedure results in scores of 1.0 [(0.383 – 0.2)/(0.383 – 0.2)] for *a1* and 0 [(0.2 – 0.2)/(0.383 – 0.2)] for *a2*. Note that including the focal firm *f1* would increase both unscaled $INTERSECTION_{a1,f1,t}$ and unscaled $INTERSECTION_{a2,f1,t}$ by about 0.117 [(0.05+0.20+0.10)/3] and does not affect the scaled measures. As described earlier, using the scaled measures holds the focal firm-year constant, thus controlling for time- and focal firm-variant characteristics.

4.2 Models for testing H1

To examine the hypothesized diminishing impact of *INTERSECTION* on *ACCURACY*, we use the quadratic form below (see Wooldridge 2016, p. 636; and Aghion, Bloom, Blundell, Griffith, and Howitt 2005).

$$ACCURACY_{aft} = \beta_0 + \beta_1 INTERSECTION_{aft} + \beta_2 INTERSECTION_{aft}^2 + \sum_m \beta_m Control_m + \varepsilon_{aft}, \quad (3)$$

where $ACCURACY_{aft}$ is measured as $\frac{\max(|FE_{ft}|)-|FE_{aft}|}{\max(|FE_{ft}|)-\min(|FE_{ft}|)}$, i.e., absolute error ($|FE_{aft}|$) of analyst *a*'s forecast for firm *f* and year *t* (F_{aft}) scaled to fall between 0 (least accurate) and 1 (most accurate), relative to all other analysts following firm *f* in year *t* ($|FE_{ft}|$). If analysts produce more accurate forecasts due to the private information they collect from their interactions with institutional investors, we expect $\beta_1 > 0$ in model (3). In addition, if beyond some level of interactions with institutional investors, the associated opportunity costs outweigh the benefit of information flow from the buy-side, we expect $\beta_2 < 0$.

To increase the power of our tests to detect any earnings forecast accuracy-enhancing effect of information flowing from buy- to sell-side analysts (proxied by institutional investor interest in non-focal firm stocks covered by *a*), our tests include variables that control for differences across analysts in their effort and ability to develop forecast accuracy-enhancing information independent of their interactions with buy-side analysts. Specifically, we control for the following factors known from prior research to affect sell-side analyst earnings forecast accuracy: the frequency of *a*'s prior year forecasts of *f*'s year *t*-1 earnings;[11] *a*'s accuracy relative to other analysts in forecasting *f*'s prior year earnings (lagged *ACCURACY*);[12] the number of firms and industries represented in *a*'s coverage portfolio;[13] *a*'s experience in forecasting *f*'s earnings (Mikhail, Walther, and Willis 1997; Clement 1999; Jacob et al. 1999); the size of *a*'s brokerage firm (Clement 1999; Jacob et al. 1999); the number of days in the forecast horizon (O'Brien 1988; Jacob et al. 1999); and the gap in time between *a*'s forecast and the most recent forecast of *f*'s year *t* earnings by any other analyst (i.e., a negative measure of herding) (Clement and Tse 2003). The appendix provides detailed definitions of all variables.

$INTERSECTION_{aft}$ and all of model (3)'s control variables, except $Lagged\ ACCURACY_{aft}$, are scaled to fall between 0 and 1 based on equation (2). By scaling all dependent

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[11] Jacob, et al. (1999) interpret their evidence that analyst earnings forecast accuracy improves with forecast frequency as follows: "it appears that frequency of forecasting proxies for analyst effort or the incorporation of the latest information into forecasts (p. 66)."

[12] Brown (2001) and Brown and Mohammad (2010) find that past earnings forecast accuracy is the best predictor of current forecast accuracy. We include analyst *a*'s forecast accuracy for the previous year ($Lagged\ ACCURACY_{aft}$) to alleviate concerns that accuracy increases with *INTERSECTION* due to institutional investor interest in connecting with already-accurate sell-side analysts.

[13] Jacob et al. (1999) find that the number of covered firms detracts from analyst forecast accuracy, and Clement (1999) finds that the number of covered firms and industries detracts from analyst forecast accuracy. On the other hand, Dong, Hu, Li, and Liu (2017) find a positive relation between the number of firms covered and earnings forecast accuracy in the post-Reg FD era.

and independent variables among analysts following the same firm and year, we control for all firm-variant characteristics and time-variant macro factors that affect forecast accuracy; e.g., forecast difficulty as described in Hong and Kubik (2003) and institutional ownership as described in Frankel, Kothari, and Weber (2006). Scaling all variables in this manner maintains the relative values of each variable, while allowing comparison across regression coefficients (Clement and Tse, 2005; Franco and Zhao 2009; Yin and Zhang 2014; Cao, Xue, and Zhu 2022).

4.3 Model for testing H2

We test H2 with model (4), which includes separate measures of *INTERSECTION* for institutional investors that provide high, medium, or low accuracy-enhancing learning opportunities for sell-side analysts ($INTERSECTION^{High\ Opp}$, $INTERSECTION^{Med\ Opp}$, and $INTERSECTION^{Low\ Opp}$, respectively).

$$ACCURACY_{aft} = \beta_0 + \beta_1 INTERSECTION_{aft}^{High\ Opp} + \beta_2 (INTERSECTION_{aft}^{High\ Opp})^2 + \beta_3 INTERSECTION_{aft}^{Med\ Opp} + \beta_4 (INTERSECTION_{aft}^{Med\ Opp})^2 + \beta_5 INTERSECTION_{aft}^{Low\ Opp} + \beta_6 (INTERSECTION_{aft}^{Low\ Opp})^2 + \sum_m \beta_m Control_m + \varepsilon_{aft}, \quad (4)$$

where high/medium/low opportunity intersection variables are measured the same way as *INTERSECTION* except that they are constructed based on intersection of stocks with only high-, medium-, and low-opportunity institutions, respectively. We scale each *INTERSECTION* variable to fall between 0 and 1 among analysts following the same firm and year.

If the relation between *ACCURACY* and *INTERSECTION* arises from sell-side analysts learning from buy-side analysts, then we expect the relation to be stronger when the buy-side analysts produce greater amount of private information and from whom the sell-side analysts have more opportunities to learn, i.e., $\beta_1 > \beta_5$. Alternatively, if the relation hypothesized in H1 is driven by buy-side analysts with less private information learning from already-accurate sell-side analysts, we expect $\beta_1 < \beta_5$.

We apply two approaches to identify institutional investors that provide different accuracy-enhancing learning opportunities for sell-side analysts. The first approach follows Bushee (1998, 2001) and classifies institutions into transient, dedicated, and quasi-index institutions.[14] The transient institutions are active traders with high portfolio turnover and diversified portfolios, which are presumably active collectors of information (Ke and Petroni 2004). We thus view them as higher-opportunity institutions relative to the dedicated and quasi-index types, which we classify, respectively, as medium- and low-opportunity institutions.

The second approach relies on an institution's portfolio turnover. The idea is that institutions that are able to generate more private information will likely trade more in order to exploit that information (Chen, Jegadeesh, and Wermers (2000); Massa, Qian, Xu, and Zhang (2015)). Along these lines, Chen et al. (2000) argue that managers who generate superior information "... trade frequently, while managers with more limited skills may be much more cautious in their trades." Building on this insight, we view institutions with higher (lower) turnover as providing higher (lower) learning opportunities for sell-side analysts. We classify each institution based on its average portfolio turnover over the most recent four quarters, where quarterly portfolio turnover is measured as the lower amount of total security purchases or sales that the institution conducted during the quarter divided by the average portfolio value over the course of the quarter.

4.4 Sample selection

[14] We thank Brian Bushee for sharing the classification of institutional investors. In untabled analyses, we include institutions unclassified by Bushee in one group. The coefficients on *INTERSECTION* and *INTERSECTION*^{2} for this group are generally insignificant.

We collect sell-side analyst forecasts from the I/B/E/S database for fiscal years from 1995 to 2016.[15] The sample includes one-year ahead EPS forecasts issued during the first 90 days following the prior year's earnings announcement. If an analyst issues more than one forecast for the same firm-year during the 90-day window, we keep only the earliest one. We select the 90-day window to maximize the number of analysts issuing forecasts and limit the difference in forecast horizon across different analysts, as analysts tend to be active post earnings announcement (Ivković and Jegadeesh 2004), and forecast horizon significantly influences forecast accuracy (Clement and Tse 2005).

In the latest calendar quarter prior to the 90-day window for each firm-year described above, we collect the number of institutional investors and their holdings for the construction of *INTERSECTION* and other measures using the Thomson Reuters 13F database. We collect institution classifications that label institutions as transient, dedicated, and quasi-index types from Bushee's website. We exclude analyst-firm-years missing any of the analyst characteristic control variables, such as the lagged forecast error. Finally, we require each firm-year to be covered by more than one analyst during the 90-day window. These steps result in 189,452 analyst-firm-year observations, including 4,564 unique firms and 8,790 unique analysts.

5. Hypotheses Test Results

5.1 Descriptive statistics

[15] An earlier version of our study used a sample period ending in 2012 because WRDS had at that time issued a data integrity warning about the Thomson 13F holdings data after 2012. We obtained essentially the same results using that sample and the current sample ending in 2016. Given a number of warnings WRDS issued about 13F data issues after 2016 we did not extend the sample beyond the 1995-2016 timeframe. (See, for example, WRDS Research Note of February 2022 available at https://wrds-www.wharton.upenn.edu/documents/1744/s12_s34_data_issues_202203.pdf).

Table 1 Panel A presents descriptive statistics for variables in our models. *ACCURACY*, which is scaled within each firm-year and for which a higher value indicates greater accuracy, has a mean (median) of 0.535 (0.561), a standard deviation of 0.353, and an interquartile range of 0.636.[16] *INTERSECTION* (unscaled) indicates that, on average, the intersected stocks account for 1.3% of an institution's portfolio (median = 0.8%).[17] The mean (median) of the scaled value of *INTERSECTION* is 0.390 (0.278), the standard deviation is 0.356, and the interquartile range is 0.618, where a higher value indicates more intersection.

Panel A also shows that on average an analyst follows 17 stocks in 4 different industries,[18] has about 5 years of firm-specific experience,[19] works for a brokerage house or research firm employing 66 analysts,[20] issues forecasts 4 days after the most recent forecast by any analyst following the same firm,[21] and has issued 6 one-year ahead focal firm earnings forecasts in the one-year period prior to the current forecast.[22] Largely by design, on average, the forecast in our sample is issued 309 days prior to the end of the forecasted fiscal year. Finally, we find that, on average, 326 institutions hold the focal firm's stock.[23]

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[16] The mean (median) of unscaled absolute forecast error is 42.1% (0) of actual earnings.
[17] We also find substantial variation in the number of non-focal stocks in the institutional investor's portfolio that the analyst follows.
[18] Boni and Womack (2006) find that, on average, sell-side analysts cover 9.4 firms and 2.7 industries. More recently, Driskill, et al. (2020) find that, on average, sell-side analysts cover 15 firms and they note that the number has increased in recent years.
[19] Hoitash, Hoitash, and Yezegel (2021) find that analysts have an average of 4.5 years of experience in covering a given firm.
[20] Lehmer, Lourie, and Shanthikumar (2022) find that the average brokerage house in their sample of 18 large brokerages employs 103 sell-side analysts. Our sample includes brokerage houses with a wider range of sizes.
[21] Kim, Lobo, and Song (2011) find that the average analyst takes 6.8 days to revise an earnings forecast after the most recent forecast by any other analyst. This study also finds that the average analyst covers 18 companies and 2 industries, and the average brokerage house employs 70 sell-side analysts.
[22] Analysts generally update their annual earnings forecasts in the wake of each of the firm's quarterly earnings announcements. The analysts in our sample forecast annual earnings more frequently than once per quarter. In our sample analysts issue a second annual forecast in about one-half of the quarters.
[23] The standard deviations of the variables in our sample are consistent with those in other studies. For example, FIRM#, FIRM_EXP, and BSIZE have similar standard deviations (relative to mean values) to those in Driskill, Kirk, and Tucker (2020).

Table 1 Panel B presents the univariate correlations among the scaled variables that are used to test our hypotheses. Mostly consistent with prior literature, *ACCURACY* has a statistically significant positive correlation with the lagged year *ACCURACY*, number of firms followed, [24] and the analyst's firm-specific experience; and *ACCURACY* is negatively correlated with the number of industries followed, the number of days since the most recent preceding analyst forecast, forecast frequency, and the horizon between the forecast and the end of the forecast fiscal year. *ACCURACY* is negatively correlated with *INTERSECTION*. However, this univariate correlation does not consider the hypothesized concave relation between these variables, which we document in the next section.

5.2 Test of H1

Table 2 displays the results of testing H1, which predicts that the accuracy of an analyst's forecast of a firm's earnings improves (with diminishing returns), with the degree of intersection between the non-focal stocks covered by the sell-side analyst and held by the institutional investors who also hold the focal stock. For ease of presentation, we multiply the dependent variable in all regressions by 100, which effectively multiplies each coefficient by 100 as well. Supporting the curvilinear concave relation hypothesized in H1, Columns (1) through (4) show that the coefficient on *INTERSECTION* is significantly positive and the coefficient on the square of *INTERSECTION* is significantly negative (with p-values less than 0.01). Columns (1) and (3) include no control variables and Columns (1) and (2) do not include broker fixed effects. We show broker fixed effects as a sensitivity check. Our main results are in Column (2) with all

[24] Prior studies of determinants of analyst forecast accuracy have mixed results regarding the impact of number of firms followed. For example, Clement (1999) and Jacob et al. (1999) find a negative relation; whereas, like us, Dong, et al. (2017), Drake, Joos, Pacelli, and Twedt (2020) and He, Yin, Zeng, Zhang, and Zhao (2019) find a positive relation.

control variables and without broker fixed effects. Because brokers generally have only one sell-side analyst covering any particular firm, there is little variation in sell-side analyst forecast accuracy within a broker-firm-year. Nonetheless, robustness of our results to the inclusion of broker fixed effects rules out the possibility that unobserved broker characteristics drive the results.

The results in column (2) suggest that *ACCURACY* reaches its highest level when *INTERSECTION* is at 0.419 [=4.818/(5.751×2)], or the 61st percentile of its distribution. The curvilinear relation suggests economic significance that varies with *INTERSECTION*. For example, a one standard deviation change in *INTERSECTION* along a line tangent to the curve at the point where *INTERSECTION* equals 0.070 (the 25th percentile of the *INTERSECTION* distribution) yields an improvement in *ACCURACY* of 1.429 (= $[4.818 - 2 \cdot 5.751 \cdot 0.070] \cdot 0.356$), which is two and a half times the 0.577 improvement in forecast accuracy for a one standard deviation change in *INTERSECTION* along a line tangent to the curve at the point where *INTERSECTION* equals 0.278 (the median of the *INTERSECTION* distribution). Coefficients on the control variables are generally consistent with the correlations in Table 1.[25]

Column (5) of Table 2 demonstrates the curvilinear relation between *ACCURACY* and *INTERSECTION* using a piecewise regression that shows how the relation changes from one tercile of the *INTERSECTION* variable's distribution to the next. *ACCURACY* and *INTERSECTION* have a strong positive relation within the bottom and middle terciles of the *INTERSECTION* distribution, as hypothesized. Also, as hypothesized, the relation diminishes as we move from the bottom to the middle and from the middle to the top terciles. While still

[25] The significant coefficient on $INTERSECTION^2$ provides justification for including the squared term in the regression specification. Not doing so would result in a biased coefficient on *INTERSECTION* since the omitted variable, $INTERSECTION^2$, is correlated with both *INTERSECTION* and *ACCURACY* (Greene 2008, p134).

statistically significant (at the 10% level), the positive relation in the second tercile is significantly weaker than the relation in the bottom tercile of the distribution, and the relation becomes insignificantly negative in the top tercile. These results are consistent with the hypothesized diminishing returns relation between *ACCURACY* and *INTERSECTION.*

5.3 Tests of H2

We examine H2 to sort out whether the concave relation between *INTERSECTION* and *ACCURACY* derives from opportunities for sell-side analysts to learn from private information-laden buy-side analysts, or from opportunities for private information-lacking buy-side analysts to learn from already-accurate sell-side analysts.

As discussed in Section 4.3, we identify institutions engaging in transient or high-turnover trading strategies as those producing more private information, and from whom the sell-side analysts potentially have high opportunities to learn. Results in Table 3 strongly support the evidence of a concave relation between *INTERSECTION* and *ACCURACY*, as the strength of the relation increases with opportunities for the sell-side analyst to learn from the buy-side analysts (due to the buy-side analyst developing information with either a transient or high turnover investment style). These results support H2 and validate our inference from testing H1 that sell-side analysts learning from buy-side analysts drives sell-side analyst forecast accuracy. The results also help alleviate the endogeneity concern that institutions choose to invest in stocks followed by already-accurate analysts. Such a preference suggests a stronger relation between sell-side analyst *ACCURACY* and *INTERSECTION* with low opportunity institutions, which is opposite to what we find.

As discussed in Section 2, transient investors likely overlap with hedge funds, which tend to be frequent traders. Thus, our evidence of a strong relation between *ACCURACY* and

INTERSECTION among observations identified with transient investors is consistent with evidence in Chung et al. (2021), and supports the notion that sell-side analysts working for hedge funds' prime brokers learn from their interactions with the buy-side analysts at such hedge funds. We also find some evidence of diminishing returns in the relation between *ACCURACY* and *INTERSECTION* among dedicated investors, which typically do not include hedge funds. Untabulated tests indicate that differences between the coefficients on "*INTERSECTION* - with transient investors" and "*INTERSECTION* - with dedicated investors" or the corresponding squared terms are not statistically significant. We thus infer that hedge fund observations do not entirely drive our results.

6. *Tests to Address Endogeneity*

6.1 Endogeneity Due to Institutional Preferences for Certain Observable Analyst Characteristics

This section describes two sets of analyses that address the concern that institutional investors prefer to interact with certain sell-side analysts who have traits that are correlated with forecast accuracy. First, it is possible that institutional investors, especially those with less private information, choose to invest in stocks followed by already-accurate sell-side analysts, which as a result produces a higher stock overlap. Our results from testing H2 rule this out as we find stronger results from *INTERSECTION* with private information-laden institutional investors. Nonetheless, we conduct additional tests to mitigate the concern. In column (1) of Table 4 we first examine whether predictors of sell-side analyst forecast accuracy influence *INTERSECTION* by regressing the latter on past accuracy (Brown 2001) and firm-specific experience (Clement

1999; Brown, et. al. 2016; Call, Hewitt, Watkins, and Yohn 2021).[26] The results provide mixed evidence in that the relations between *INTERSECTION* and past accuracy and experience are marginally significantly negative and significantly positive, respectively. We then explicitly control for the two predictors in equation (3) and examine whether the sensitivity of *ACCURACY* to *INTERSECTION* is greater when the sell-side analysts are predicted to be more accurate. In other words, whether the results in Table 2 are driven by analysts who are predicted to be accurate. Columns (2) and (3) of Table 4 show that neither firm-specific experience nor past accuracy has a statistically significant interactive effect with *INTERSECTION*.

From these results, we infer that although predictors of accuracy, particularly firm-specific experience, seem to correlate with *INTERSECTION*, they do not explain the impact of *INTERSECTION* on *ACCURACY*. Furthermore, after including the interaction terms with firm-specific experience or past accuracy, the coefficients on *INTERSECTION* and $INTERSECTION^2$ retain high levels of statistical significance. These results mitigate the concern that institutional investor selection of stocks covered by higher quality sell-side analysts drives our primary results.

Second, institutional investors could choose to interact more with analysts that acquire information from other information sources in order to gain access to that information. Such analysts could also issue more accurate forecasts. We employ analyst participation in corporate information events such as investor conferences, conference calls, analyst/investor days, and non-deal roadshows (Frankel, Johnson, and Skinner, 1999; Bushee, Jung, and Miller 2011; Kirk and Markov, 2016; Bradley, Jame, and Williams, 2020) to proxy for sell-side analyst effort to

[26] In response to the Brown, et al. (2016) survey, buy-side analysts rate the sell-side analyst's firm-specific experience as the most important attribute affecting the decision to use information provided by the sell-side analyst. In fact, this attribute is rated as more important than how often the sell-side analyst speaks with firm management, and whether the sell-side analyst is a member of the Institutional Investor All-American Research Team.

acquire information from sources other than their interactions with buy-side analysts. Cen, Dasgupta, and Ragunathan (2021) and Mayew, Sharp, and Venkatachalam (2013) find that analysts participating in conference calls publish more accurate earnings forecasts than other analysts. We collect company events and participants from Capital IQ for firm-years between 2005 and 2016. Capital IQ covers 234 event types, including the common ones referenced above.[27] We match participants in these events with our main sample based on analyst names and brokerage names. If names of brokerages are missing in Capital IQ, we match only on analyst names. This procedure requires manual checks. We err on the side of caution by only including matches where we are certain of their accuracy. This procedure identifies 73,644 analyst-firm-year forecasts by 7,816 sell-side analysts who participate in 79,051 information events sponsored by 6,531 firms in Capital IQ.

Column (4) of Table 4 indicates that within the same firm-year, the relation between *INTERSECTION* and whether the analyst attended one or more information events (*D_EVENT*) is insignificant.[28] More importantly, as column (5) shows, controlling for attendance at other information events does not change the inference from the main results. The positive and marginally significant coefficient on *D_EVENT* suggests that attending these information events impacts forecast accuracy, but does not detract from our main findings of a positive relation between *INTERSECTION* and *ACCURACY* with diminishing returns.

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[27] Capital IQ data start in 2004 with only sparse coverage that year. We thus collect data since 2005. It does not include non-deal roadshows. Bradley et al. (2020) collect this information from theflyonthewall.com for 2013 and later years, which we do not have access to. To the extent that the tendency of analysts to organize/attend such events correlates with the other events covered by Capital IQ, our results can be generalized to non-deal roadshows.
[28] Sixteen percent of the 73,644 observations are associated with participation of one or more information events. We thus use the binary variable *D_EVENT* in the analyses. Using the number of events attended does not qualitatively change the results in Table 4 except that the number of events is significantly negatively correlated with *INTERSECTION* (p-value at 5%). These results suggest that analysts attending other information events more frequently do not have more opportunities to interact with the buy-side.

Overall, the results from the two sets of analyses mitigate the concern that characteristics that vary across sell-side analysts drive the relation that we find between *INTERSECTION* and *ACCURACY*. They increase our confidence in *INTERSECTION* capturing information exchange with the buy-side analysts rather than analyst traits that correlate with both *INTERSECTION* and *ACCURACY*.

6.2. Instrumental Variable Approach

In this section we use the unexpected cash flows that the institutions receive from investors as an instrumental variable to address endogeneity concerns. Our choice of the instrumental variable is motivated by an institutional feature of our setting, namely, that institutional clients of sell-side analysts typically invest on behalf of investors. These investors can provide additional capital or redeem their investments at any time depending on their needs and are one step removed from the sell-side analysts connected with the institutions. We argue that the unexpected cash flow to an institution is driven largely by investor-specific considerations, such as liquidity shocks, and are highly unlikely to be driven by the forecast accuracy of the sell-side analysts connected with the institutions.

To avoid a drag on performance an institution would invest the unexpected flow, a process that could lead to further consultations with the analyst and increase opportunities for mutual communications. Thus, like *INTERSECTION*, an institutional investor's unexpected flow serves as a plausible proxy for earnings forecast accuracy-enhancing interactions between the two parties. Unlike *INTERSECTION*, we see no reason for unexpected flow to directly influence earnings forecast accuracy. Therefore, unexpected flow potentially serves as a strong instrument for *INTERSECTION*, as we expect it to only indirectly impact earnings forecast accuracy through its association with *INTERSECTION*.

We estimate unexpected flow (*UNEXPECT_FLOW*) for each institution-quarter as the residual from regressing current quarter flow on four quarterly lags of flow and four quarterly lags of the institution's portfolio returns.[29] To be consistent with our main measure of *INTERSECTION*, we weight the unexpected flow using the same weighting scheme as that for the construction of *INTERSECTION*. We first obtain the fitted value of unscaled *INTERSECTION* by regressing it on the weighted *UNEXPECT_FLOW* and all of the unscaled exogenous variables in equation (3), including year fixed effects. We then scale the fitted value across all analysts following the same firm-year to fall between 0 and 1 and use the scaled measure as an instrument for the scaled *INTERSECTION* variable and the square of the scaled measure as an instrument for $INTERSECTION^2$, the latter of which follows Wooldridge (2002, p236).[30]

Table 5 shows that the instrument is strong. The instrument's F-statistic, which refers to the Cragg and Donald (1993) minimum eigenvalue statistic, equals 210.92, way above the critical value of 7.03 for a 10 percent significance level (as constructed by Stock and Yogo 2005). Importantly, results in Table 5 Column 3, based on the two-stage least square procedure, continue to support our hypothesized concave relation between *ACCURACY* and *INTERSECTION* and help mitigate endogeneity concerns.

6.3. Exogenous Shock Analysis

To further support a causal interpretation of our results, this section explores events that are likely to exogenously affect the information flow from buy-side to sell-side analysts. To that end, we identify institutions that went bankrupt or were acquired. These organizational changes

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[29] This is similar to the approach used in Coval & Stafford (2007).

[30] To add confidence in the accuracy of the overall unexpected capital flows, we retain only observations for which unexpected flows are available for more than 75% of the connected institutions.

likely displace or distract employees at the affected institutions. We therefore expect such occurrences to exogenously diminish subsequent sell-side analyst access to information from these institutions' buy-side analysts, which would in turn affect earnings forecast accuracy of sell-side analysts with pre-event connections to these institutions. Utilizing these exogenous events mitigates potential endogeneity concerns.

We collect acquisitions and bankruptcies from three sources. From Thomson Reuters we identify every institution that stopped filing 13F reports between 1995 and 2016 and held more than 100 stocks on average over the period beginning with the year 1995. We then focus on those institutions that were either acquired (137 per Thomson One Banker) or liquidated (9 per bankruptcy announcements from Capital IQ).

The sample for this analysis includes all firms with stocks held by the aforementioned institutions in the portfolios they reported on their last 13F filing (hereafter, the event). For each firm *f* with stock held by affected institution *i* and followed by analyst *a* during the event quarter, we consider *a* and *i* to be unconnected if *a* has followed only *f* and no other stock held by *i* in the four quarters ending with the event quarter. In these cases, the indicator variable, *CONNECTED*, equals 0. *CONNECTED* equals 1 if *a* followed stocks held by *i* other than *f* in the event quarter and in at least one of the previous three quarters.[31]

We employ a difference-in-differences design and compare changes in the accuracy of forecasts issued by connected versus unconnected analysts from pre- to post-event periods. We define whether a forecast is pre- or post-event (*POST_EVENT* = 0 or 1, respectively) based on whether the forecast is issued before or more than three months after the event. We use three months to allow for the possibility that interaction and information flow do not abruptly stop. For

[31] We exclude analysts that followed stocks held by *i* other than *f* in the event quarter but in none of the previous three quarters.

this analysis, we retain only forecasts issued within two years of the events and only analysts that issue one or more annual forecasts for the same firm in both periods. We require that each firm-year is followed by two or more analysts in both the pre- and post-event period. If a forecast is in the pre- or post-event period for multiple events, we use the forecast only once. This process results in 40,372 forecasts issued for 2,038 firms by 3,907 analysts, with a mean (median) of 4.6 (4.0) forecasts for each firm-year and event.

Based on the concave relation between *ACCURACY* and *INTERSECTION* we document in the prior tests, for analysts with lower (higher) *INTERSECTION* we expect a larger (smaller) decline in accuracy due to the exogenous curtailment of sell-side analyst access to information from buy-side analysts working at the affected institutions. Another reason for this empirical prediction is that, at lower *INTERSECTION*, pre-event information flow from the affected institutions represents a higher fraction of total information flow from all institutions. Therefore, subsequent to the acquisition or liquidation of the affected institution, the flow of information from institutions to sell-side analysts with lower *INTERSECTION* is more severely reduced. We classify an analyst as being in the lower (higher) intersection group, if *INTERSECTION* is at or below (above) the median of 0.2775 for the entire sample.[32]

We regress *ACCURACY* on *CONNECTED* and *POST_EVENT* dummies and their interaction. The key variable is the interaction variable, which helps determine whether the decline in accuracy was larger for the connected relative to the unconnected analysts after the event. Columns (1) to (3) of Table 6 report results for the total sample, lower *INTERSECTION* subsample, and higher *INTERSECTION* subsample, respectively. The interaction term is

[32] The analyses in Table 6 omit control variables to preserve the sample. Results are qualitatively similar after including unscaled control variables or scaled control variables for a subset of observations, with albeit weaker statistical significance.

insignificant for the total sample, but more importantly, it is significantly negative for the lower *INTERSECTION* subsample, which suggests that the analysts with lower *INTERSECTION* experienced a drop in accuracy following the negative shock. For the higher *INTERSECTION* subsample, the coefficient on the interaction term is insignificant. These results corroborate the concave relation between *ACCURACY* and *INTERSECTION* documented in Table 2.

7. Alternative Proxies for Informative Interactions between Buy- and Sell-side Analysts and for the Quality of the Sell-side Analyst's Research Output

7.1 Alternative Proxies for Informative Interactions between Buy- and Sell-side Analysts

We replicate our test of H1 using five alternative proxies for informative interactions between sell-side and buy-side analysts. The first four capture the breadth and depth of intersection differentially. The fifth proxy incorporates stocks investors are interested in buying.

The first alternative, $INTERSECTION_{time}$, is the same as our primary measure except that a different weighting is used. Instead of position size of all non-focal stocks in the portfolio of each intersecting institution, we sum up the number of months each institution has held the non-focal stocks and use the thus computed holding period as the weight of those stocks. Here the holding period captures a stock's importance to an institution's portfolio. The second alternative, $INTERSECTION_{stock\#}$, modifies our primary measure by taking the straight average number of non-focal stock intersections without weighting them. The third alternative, $INTERSECTION_{inst\#}$, measures the number of institutions that invest in both the focal stock and at least one non-focal stock followed by the same analyst. This alternative treats all institutions with whom an analyst is connected equally, thus emphasizing intersection breadth over depth. Like our primary measure, all alternative measures are divided by the number of institutions holding the focal stock and scaled among analysts following the same firm-year. The fourth alternative measure, *INTERSECTION*$_{asset}$, builds on *INTERSECTION*$_{inst\#}$ by further including each institution's assets as a weight. The rationale is that a larger institution likely possesses more information and also matters more for a sell-side analyst's career (Harford et al. 2019), both of which motivate sell-side analysts to interact more with the institution. The fifth measure expands the main measure by further counting stocks institutions are interested in buying, which could potentially lead to more interactions between the two sides. We use stocks invested in the quarter subsequent to the forecast date as a proxy for such interest (*INTERSECTION*$_{nextq}$).

Results in Table 7 using all five alternative measures of *INTERSECTION* are consistent with the testing results of H1 reported in Table 2. Forecast accuracy increases with each measure of *INTERSECTION* up to a point (ranging from 0.417 to 0.670), after which the increasing rate subsides. Robustness of these results to various modifications of the primary measure increases our confidence in the construct validity of our primary *INTERSECTION* variable as a measure of information flow from buy-side to sell-side analysts. Moreover, the results suggest that both the breadth and depth of connectivity through existing portfolios or stocks of potential interest to both sides benefit the accuracy of the corresponding connected analysts.

7.2 Market Reaction to Recommendation Revisions and Forecast Revisions as Alternative Measures of Research Output Quality

In this section, we check robustness of our results using two alternative proxies for the quality of sell-side analyst research output, as alternatives to earnings forecast accuracy: market reactions to stock recommendation revisions and to earnings forecast revisions (Francis and Soffer 1997). Regarding recommendation revisions, for each analyst-firm-year observation in our main sample, we further collect the earliest recommendation issued in 90 days subsequent to prior annual earnings announcement. We require each firm-year to have two or more recommendations. For this subsample of 11,550 observations, we calculate recommendation changes relative to the most recent prior recommendation by the same analyst for the same firm (Δ*REC*), with a positive value indicating an upgrade. We regress cumulative abnormal stock returns, measured during three days around the recommendation revision date, on Δ*REC*, *INTERSECTION*, and their interaction. In the left column of Table 8, we document a stronger market reaction to recommendation revisions by sell-side analysts with higher *INTERSECTION*, as suggested by the positive coefficient on $\Delta REC \cdot INTERSECTION$, but up to a certain level, as suggested by the negative coefficient on $\Delta REC \cdot INTERSECTION^2$. These results are consistent with our findings regarding earnings forecast accuracy.[33]

Regarding earnings forecast revisions, for each analyst-firm-year observation in our main sample, we collect the latest prior earnings forecast by the same analyst for the same year. Revision is computed as current forecast minus the prior forecast (Δ*FCST*). We then regress cumulative abnormal stock returns, measured during three days around the forecast revision date, on Δ*FCST*, *INTERSECTION*, and their interaction. The results presented in the right column of Table 8 are consistent with those based on recommendation revisions. We continue to document stronger market reaction to forecast revisions by sell-side analysts with higher *INTERSECTION*, but up to a certain level. Overall, results in Table 8 strengthen our inference that sell-side analysts' interactions with and the resulting information flow from institutional investors enhance the quality of their research output.

[33] In measuring abnormal returns, we use the value-weighted market return as a proxy for expected returns. Results (untabulated) are similar when we use four alternative proxies for expected returns: the equal-weighted market returns, the average stock returns during prior 100 days, expected returns from the market model estimated for the prior 100 days, and expected returns estimated from the Fama-French (1993) three-factor model. In untabulated results, we also use lagged-year *INTERSECTION* and document qualitatively similar results, although with a loss of more than 50% of observations.

8. Conclusion

Sell-side analysts are motivated to foster relationships with both the management of the firms they follow and with institutional investors interested in those firms. In the context of these relationships, management wants to know what institutional investors think about buying and selling the stock in its firm, buy-side analysts at the institutions want to know more about management's strategic plans, and both management and buy-side analysts have an interest in the industry expertise that sell-side analysts have. Thus, by serving as intermediaries, sell-side analysts are in a unique position to learn from both management of the firms they follow and institutional investors investing in those firms. We expect that these interactions create feedback loops, whereby sell-side analysts learn about the results of independent research performed by buy-side analysts on the firms' prospects and the stocks' intrinsic values. Our paper explores these dynamics and documents a concave relation between earnings forecast accuracy and the intersection of stocks between institutional investors' portfolios and sell-side analyst coverage.

This paper's results strongly support our inference that sell-side analysts glean information from their interactions with institutional investors that enhances the quality of sell-side analyst research output with diminishing returns. The concave relation is consistent with our identification of two opposing effects of institutional investor interest in the non-focal firms covered by a particular sell-side analyst. The first effect is *positive*, as more institutional investor interest in non-focal firms covered by the sell-side analyst creates more informative interactions from which the sell-side analyst gleans focal firm earnings forecast accuracy-enhancing information. The second effect is negative, as more institutional investor interest in non-focal firms covered by the sell-side analyst creates pressure to spend relatively more effort forecasting non-focal firm earnings and relatively less effort forecasting focal firm earnings. The observed concave relation between *ACCURACY* and *INTERSECTION* is consistent with the first effect dominating at lower levels of institutional investor interest in non-focal firm stocks covered by the sell-side analyst.

The idea of a well-connected sell-side analyst goes beyond interactions with the buy-side. For example, the analyst has interactions with various potential information providers: suppliers and customers who help the sell-side analyst with his/her "channel checks;" senior management of the firms in the sell-side analyst's coverage portfolio who help the analyst understand catalysts for the firms' earnings; venture capitalists and private equity firms which help the sell-side analyst build a pipeline for investment banking deals and future research coverage; and the business press for general visibility. A limitation of our paper is that it only examines interactions with buy-side clients, thus leaving room for future research into what sell-side analysts learn from interactions with various parties in the circles where they operate. Another limitation is that we treat the actual conversations between buy- and sell-side analysts as a black box and, while we do our best to control for other factors affecting the quality of sell-side analyst research output, like most other archival studies of the behavior of capital market participants, our regressions have low explanatory power. We encourage future research that opens the black box and provides the details and ramifications of actual conversations between buy- and sell-side analysts. Such research might focus more directly on the identity and characteristics of the interacting analysts and the nature of the information they access to justify trades by the buy-side and recommendations by the sell-side.

Appendix

Variables in main analyses (when scaled among the same firm-year to fall between 0 and 1, unless pointed out otherwise, the scaling follows $\frac{Variable_{aft} - \min(Variable_{ft})}{\max(Variable_{ft}) - \min(Variable_{ft})}$)

Dependent variables

$ACCURACY_{aft}$ = analyst a's forecast accuracy, measured as the absolute forecast error of analyst a scaled among all forecasts of firm f's year t earnings, calculated as $\frac{\max(|FE_{ft}|) - |FE_{aft}|}{\max(|FE_{ft}|) - \min(|FE_{ft}|)}$, where the forecasts are the earliest ones issued by each analyst during the 90 days post the announcement of f's year t-1 annual earnings. FE_{aft} is the difference between analyst a's earliest forecast, F_{aft}, and E_{ft}, actual earnings per share from IBES. The maximum and minimum, max($|FE_{ft}|$) and min($|FE_{ft}|$), are among earliest forecasts of firm f's year t earnings issued by all analysts during the 90 days post the announcement of firm f's year t-1 annual earnings. *ACCURACY* falls on a scale between zero (least accurate) and one (most accurate).

Variables of interest

$INTERSECTION_{aft}$ = overlap in non-focal stocks (i.e., other than f) covered by sell-side analyst a that issues F_{aft}, forecast for focal firm f and year t, and held by institutional investors that invest in f, computed as $\frac{\sum_{i=1}^{N\_INST_{ft}} \sum_{s=1}^{S_{i,a,-f,t}} \frac{\text{Value of non-focal stock } s \text{ covered by analyst } a}{\text{Portfolio value of institution } i}}{N\_INST_{ft}}$. $S_{i,a,-f,t}$ refers to the number of overlapping non-focal firm stocks between the coverage of analyst a and portfolio of institution i that invests in focal firm f. N_INST_{ft} refers to the number of institutional investors that invest in focal firm f. The value of the corresponding non-focal firm stock as a percentage of the value of the corresponding institution's total portfolio serves as the weight. Institutional holdings are from the calendar quarter preceding the date of F_{aft}, and analyst coverage of non-focal stocks is from the one year period that precedes the calendar quarter end used for institutional holding measurement.

$INTERSECTION_{aft}^{High\ Opp}$, $INTERSECTION_{aft}^{Med\ Opp}$, and $INTERSECTION_{aft}^{Low\ Opp}$ are measured the same way as *INTERSECTION* except that they are constructed based on intersections of non-focal stocks with subsets of institutions, i.e., high-, medium-, and low-opportunity institutions.

Opportunity based on transient, dedicated, and quasi-index institutions: transient, dedicated, and quasi-index institutions categorized by Bushee's (1998, 2001) are classified as having high, medium, and low private information and thus opportunities, respectively.

Opportunity based on portfolio turnover: institutions with high (medium or low) turnover (see Chen, et al. 2000) are classified as having high- (medium- or low-) opportunities. To classify institutions, we use the average portfolio turnover of each institution over the last four quarters. Portfolio turnover each quarter is measured as the minimum of total security purchases or total security sales that the institution conducted during the quarter divided by the average portfolio value.

Control variables (in alphabetic order)

$BSIZE_{at}$ = number of analysts employed by analyst a's brokerage house or research firm in the year ending with the date of F_{aft}, analyst a's earliest forecast for firm f and year t as defined above under *ACCURACY*.

$DAYS_{aft}$ = number of days between the date of F_{aft} and the most recent one-year ahead forecast of firm f's year t earnings preceding F_{aft} by any analyst.

EPS_FREQ_{aft} = frequency of analyst a's one-year ahead earnings forecasts for firm f in the one-year period prior to the date of F_{aft}.

$FIRM\#_{at}$ = number of firms analyst a followed in the year ending with the date of F_{aft}.

$FIRM\_EXP_{aft}$ = number of years since the first year analyst *a* issued one-year ahead earnings forecasts for firm *f* up to the date of F_{aft}.

$HORIZON_{aft}$ = number of days between the date of F_{aft} and the end of fiscal year *t*.

$INDUSTRY\#_{at}$ = number of industries based on 2-digit SIC codes analyst *a* followed in the year ending with the date of F_{aft}.

Lagged $ACCURACY_{aft}$ =one year lagged value of the *ACCURACY* variable.

Variables in additional analyses (in alphabetic order)

CAR = cumulative abnormal return during the three days around revisions of recommendations or earnings forecasts, where abnormal return equals the difference between stock return (RET) and value-weighted market return (VWRETD) per CRSP.

CONNECTED = 1 if an analyst followed the focal stock and other stocks the acquired or liquidated institution held in the quarter the institution filed the last form 13F and in at least one of the previous three quarters; and 0 if she has followed only the focal stock and no other stocks held by the affected institution over the four quarters ending with the event quarter.

D_EVENT = 1 if an analyst attends one or more firm events, such as earnings calls, conference presentations, and analyst/investor day during the one-year period prior to the forecast date per Capital IQ, and 0 otherwise.

$\Delta FCST$ = current forecast minus the latest prior forecast by the same analyst for the same firm-year, scaled to fall between zero and one.

Instrument for *INTERSECTION* = average unexpected cash flow to the institutions with which an analyst is connected. Each institution-quarter unexpected cash flow is the residual from regressing current quarter flow (divided by institution assets) on four lagged quarterly flows and four lagged quarterly portfolio returns of the institution. Consistent with the weighting scheme used to construct *INTERSECTION*, the unexpected flow to an institution is weighted by the value of all other stocks covered by the analyst and held by the connected institution as a percentage of the institution's total portfolio. Only observations for which unexpected cash flows are available for more than 75% of the connected institutions are retained. We first obtain the fitted value of unscaled *INTERSECTION* by regressing it on unexpected cash flow and all of the unscaled exogenous variables in specification (2) of Table 2, including year fixed effects. We then scale the fitted value within each firm-year to fall between 0 and 1 and use the scaled measure as an instrument for the scaled *INTERSECTION* variable.

Instrument for $INTERSECTION^2$ **=** the square of the scaled fitted value defined above (see Wooldridge (2002, p236)).

$INTERSECTION_{asset}$ = the fourth alternative measure of *INTERSECTION*, computed as the number of institutions that invest in both the firm of interest and at least one other firm followed by the same analyst, weighted by the assets of the institution, and divided by the number of all institutions holding the firm of interest.

$INTERSECTION_{inst\#}$ = the third alternative measure of *INTERSECTION*, computed as the number of institutions that invest in both the firm of interest and at least one other firm followed by the same analyst, divided by the number of all institutions holding the firm of interest.

$INTERSECTION_{nextq}$ = the fifth alternative measure of *INTERSECTION*, defined the same way as our main *INTERSECTION* variable except that it also counts stocks invested by the institutional investors in the quarter subsequent to the analyst's forecast.

$INTERSECTION_{stock\#}$ = the second alternative measure of *INTERSECTION*. It modifies our primary *INTERSECTION* measure by taking the straight average number of other stocks held by each institutional investor.

$INTERSECTION_{time}$ = the first alternative measure of *INTERSECTION*, defined the same way as our main *INTERSECTION* variable except that, in computing the weighted number of stocks, the weight is determined by the number of months an institution has held the corresponding stock of mutual interest other than the focal stock between the institution and the analyst.

POST_EVENT = 1 if a forecast is issued more than three months after the event described below, and 0 otherwise. The event refers to the last date when form 13F was filed by an acquired or bankrupt institution. Forecasts are those issued within two years of the events. Only forecasts by analysts that issue one or more annual forecasts for the same firm both pre and post the events are retained.

ΔREC = prior recommendation level minus current recommendation level, with a positive value indicating an upgrade and a negative value a downgrade.

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Figure 1 − Intersection Variable for Analysts *a1* and *a2* regarding Firm-Year *f1, t*.

Stocks followed by analysts that cover *f*1		Stocks held by institutions that invest in *f*1		
Stocks followed by analyst *a*1	Stocks followed by analyst *a*2	Stocks held by institution *i*1 (% of total portfolio)	Stocks held by institution *i*2 (% of total portfolio)	Stocks held by institution *i*3 (% of total portfolio)
***f*1**	***f*1**	***f*1** (5%)	***f*1** (20%)	***f*1** (10%)
***f*2**		***f*2** (20%)		
	*f*3		*f*3 (45%)	
				*f*4 (30%)
	*f*5		*f*5 (15%)	
			*f*6 (20%)	
		*f*7 (40%)		
***f*8**		***f*8** (35%)		
***f*9**				***f*9** (25%)
***f*10**				***f*10** (35%)
	*f*11			

This figure depicts our measure of *INTERSECTION* between analysts and institutions regarding firm-year *f*1, *t*. Three institutions *i1*, *i2*, and *i3* hold *f1*, and two analysts *a1* and *a2* follow *f1* during year *t*.

Unscaled $INTERSECTION_{f1,t}$ = the weighted number of non-focal firm stocks intersected between analyst coverage and institution portfolio / number of institutions holding *f1*

- Analyst *a1* is connected with *i1* through non-focal firm stocks *f2* and *f8* with a weight of 20% and 35%, respectively, or 55% for *i1*; and connected with *i3* through *f9* and *f10* with a weight of 25% and 35%, respectively, or 60% for *i3*. Unscaled $INTERSECTION_{a1,f1,t}$ takes on a value of (0.55+0+0.60)/3 = 0.3833, the maximum among the two analysts.
- Analyst *a2* is connected with institution *i2* through stocks *f3* and *f5*, with a weight of 45% and 15%, respectively, or 60% for *i2*. Unscaled $INTERSECTION_{a2,f1,t}$ takes on a value of (0+0.60+0)/3 = 0.2, the minimum among the two analysts.

Scaled $INTERSECTION_{f1,t}$ = (unscaled *INTERSECTION* – minimum *INTERSECTION*) / (maximum *INTERSECTION* – minimum *INTERSECTION*):

- For analyst *a1*: (0.3833 – 0.2) / (0.3833 – 0.2) = 1
- For analyst *a2*: (0.2 – 0.2) / (0.3833 – 0.2) = 0

Table 1 – Descriptive Statistics and Correlations

Panel A. Descriptive Statistics (189,452 analyst-firm-year observations)

Variables	Mean	p25	p50	p75	Standard Deviation
ACCURACY	0.535	0.226	0.561	0.862	0.353
INTERSECTION (Unscaled)	0.013	0.004	0.008	0.016	0.015
INTERSECTION	0.390	0.070	0.278	0.688	0.356
N_INST	326.461	139.000	231.000	406.000	296.714
Lagged ACCURACY	0.532	0.222	0.556	0.858	0.353
FIRM#	17.057	12.000	16.000	20.000	9.406
INDUSTRY#	3.855	2.000	3.000	5.000	2.626
FIRM_EXP	5.232	2.000	4.000	7.000	4.385
BSIZE	65.812	22.000	51.000	99.000	55.868
DAYS	4.327	0.000	0.000	3.000	12.208
EPS_FREQ	6.189	4.000	6.000	7.000	2.845
HORIZON	309.463	295.000	319.000	333.000	31.310

Panel B. Correlations and p-values

		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
INTERSECTION	(1)	1.000									
ACCURACY	(2)	-0.005	1.000								
		0.040									
Lagged ACCURACY	(3)	-0.010	0.056	1.000							
		0.000	*0.000*								
FIRM#	(4)	0.510	0.006	-0.011	1.000						
		0.000	*0.011*	*0.000*							
INDUSTRY#	(5)	0.281	-0.009	-0.013	0.465	1.000					
		0.000	*0.000*	*0.000*	*0.000*						
FIRM_EXP	(6)	0.117	0.006	-0.002	0.134	0.066	1.000				
		0.000	*0.012*	*0.296*	*0.000*	*0.000*					
BSIZE	(7)	0.132	0.003	0.005	0.082	-0.040	0.029	1.000			
		0.000	*0.256*	*0.034*	*0.000*	*0.000*	*0.000*				
DAYS	(8)	0.089	-0.014	-0.009	0.054	0.053	0.088	0.031	1.000		
		0.000	*0.000*	*0.000*	*0.000*	*0.000*	*0.000*	*0.000*			
EPS_FREQ	(9)	-0.021	-0.020	-0.065	-0.035	-0.050	-0.015	0.087	-0.013	1.000	
		0.000	*0.000*	*0.000*	*0.000*	*0.000*	*0.000*	*0.000*	*0.000*		
HORIZON	*(10)*	-0.049	-0.114	-0.008	-0.063	-0.054	-0.035	-0.031	-0.244	0.130	1.000
		0.000	*0.000*	*0.000*	*0.000*	*0.000*	*0.000*	*0.000*	*0.000*	*0.000*	

Panel A reports summary statistics for our sample of 189,452 analyst-firm-year forecasts issued from 1995 to 2016, for 4,564 unique firms and 8,790 analysts. The forecasts are the earliest annual earnings forecasts issued by an analyst for a firm-year during the 90 days post the announcement of the firm's prior year annual earnings. For ease of interpretation, with the exception of *ACCURACY* and *INTERSECTION*, no variable in Panel A is scaled among analysts for the same firm-year.

Panel B presents correlation coefficients (with the associated p-values below in *italics*) among the main variables used in the analysis, where all variables are scaled among analysts making forecasts for the same firm-year.

All variables are defined in the Appendix

Table 2 – Earnings Forecast Accuracy and Information Flow to the Sell-Side Analysts

Variables	(1) Coeff (std. err.)	(2) Coeff (std. err.)	(3) Coeff (std. err.)	(4) Coeff (std. err.)	(5) Coeff (std. err.)
INTERSECTION	5.516***	4.818***	3.172***	2.730***	
	(0.962)	(0.960)	(0.994)	(0.996)	
INTERSECTION^2	-6.127***	-5.751***	-4.046***	-3.807***	
	(0.988)	(0.961)	(1.019)	(0.996)	
Bottom *INTERSECTION* Tercile					13.740***
					(3.283)
Middle *INTERSECTION* Tercile					2.557***
					(0.708)
Top *INTERSECTION* Tercile					-0.246
					(0.337)
Lagged ACCURACY		5.210***		4.895***	5.217***
		(0.263)		(0.266)	(0.264)
FIRM#		0.945***		0.777**	0.851**
		(0.350)		(0.360)	(0.350)
INDUSTRY#		-1.409***		-1.071***	-1.461***
		(0.293)		(0.300)	(0.294)
FIRM_EXP		0.595**		0.433*	0.604**
		(0.248)		(0.249)	(0.248)
BSIZE		-0.177		-2.208***	-0.138
		(0.291)		(0.448)	(0.292)
DAYS		-3.901***		-3.587***	-3.942***
		(0.257)		(0.257)	(0.257)
EPS_FREQ		0.033		-0.070	0.044
		(0.259)		(0.261)	(0.259)
HORIZON		-11.000***		-11.092***	-11.000***
		(0.236)		(0.234)	(0.236)
Constant	53.249***	57.895***		59.289***	57.810***
	(1.005)	(1.017)		(1.052)	(1.017)
Fixed Effects	Year	Year	Year, Broker	Year, Broker	Year
N	189,452	189,452	189,379	189,379	189,452
Adjusted R^2	0.25%	2.07%	0.53%	2.32%	2.06%

Columns (1) to (4) examine the relation between sell-side analysts' forecast accuracy and information flow to the sell-side analysts from institutional investors through their interactions based on regression (3). When including the broker fixed effects 73 observations are dropped due to being the only ones by the corresponding brokers.

$$ACCURACY_{aft} = \beta_0 + \beta_1 INTERSECTION_{aft} + \beta_2 INTERSECTION_{aft}^2 + \sum_m \beta_m Control_m + \varepsilon_{aft} \qquad (3)$$

Column (5) estimates the following regression:

ACCURACY = β_0 + β_1Bottom *INTERSECTION* Tercile + β_2Middle *INTERSECTION* Tercile + β_3Top *INTERSECTION* Tercile + $\sum_m \beta_m Control_m$ + ε_{aft}

Bottom (Middle or Top) *INTERSECTION* Tercile equals *INTERSECTION* when it is in the bottom (middle or top) tercile, and 0 otherwise. All variables are defined in the Appendix and scaled to fall between 0 and 1 for the same firm-year.

The dependent variable (and, thus, each coefficient) is multiplied by 100.

Standard errors are clustered by analyst and presented in parentheses.

Table 3 – Earnings Forecast Accuracy Stratified by Opportunities for Sell-side Analysts to Learn

Variables	(1) Based on transient, quasi-indexers, and dedicated investors Coeff (std. err.)	(2) Based on turnover Coeff (std. err.)
$INTERSECTION^{High\ Opp}$	5.151***	4.041***
	(1.706)	(1.396)
$(INTERSECTION^{High\ Opp})^2$	-4.414***	-4.776***
	(1.605)	(1.306)
$INTERSECTION^{Med\ Opp}$	2.124*	0.553
	(1.151)	(1.846)
$(INTERSECTION^{Med\ Opp})^2$	-2.855**	-1.113
	(1.143)	(1.680)
$INTERSECTION^{Low\ Opp}$	-2.036	1.436
	(1.766)	(1.694)
$(INTERSECTION^{Low\ Opp})^2$	1.536	-1.333
	(1.657)	(1.584)
Controls from Table 2	YES	YES
N	149,796	189,452
Year Fixed Effects	YES	YES
Adjusted R^2	2.20%	2.08%

This table examines whether the sensitivity of *ACCURACY* to *INTERSECTION* increases when sell-side analysts have greater opportunities to glean private information from institutional investors.
Results are from estimating the following regression model:

$$ACCURACY_{aft} = \beta_0 + \beta_1 INTERSECTION_{aft}^{High\ Opp} + \beta_2(INTERSECTION_{aft}^{High\ Opp})^2 + \beta_3 INTERSECTION_{aft}^{Med\ Opp} + \beta_4(INTERSECTION_{aft}^{Med\ Opp})^2 + \beta_5 INTERSECTION_{aft}^{Low\ Opp} + \beta_6(INTERSECTION_{aft}^{Low\ Opp})^2 + \sum_m \beta_m Control_m + \varepsilon_{aft}. \quad (4)$$

$INTERSECTION_{aft}^{High\ Opp}$, $INTERSECTION_{aft}^{Med\ Opp}$ and $INTERSECTION_{aft}^{Low\ Opp}$ are measured the same way as the original *INTERSECTION* variable except that they are constructed based on intersections with only high-opportunity, medium-opportunity, and low-opportunity institutions, respectively.

In column (1), we utilize Bushee's (2001) categorization of institutions into transient, dedicated, and quasi-indexers (unclassified ones as other type) to classify institutions into high-, medium-, and low-opportunity institutions.

In column (2), we classify institutions with high (medium or low) turnover as high- (medium- or low-) opportunity ones.

All variables are defined in the Appendix and scaled to fall between 0 and 1 for the same firm-year.
The dependent variable (and, thus, each coefficient) is multiplied by 100.
Standard errors are clustered by analyst and are presented in parentheses.
***, **, * denote statistical significance at 1%, 5%, and 10%, respectively.

Table 4 – Additional Tests to Address Endogeneity

	(1)	(2)	(3)	(4)	(5)
Approach	Impact of lagged accuracy and firm-specific experience on *INTERSECTION*	Interact with firm-specific experience	Interact with lagged accuracy	Impact of event attendance on *INTERSECTION*	Control for event attendance
Dependent variable =	*INTERSECTION*	*ACCURACY*	*ACCURACY*	*INTERSECTION*	*ACCURACY*
Variables	Coeff (std. err.)	Coeff (std. err.)	Coeff (std. err.)	Coeff (std. err.)	Coeff (std. err.)
INTERSECTION		6.108***	5.970***		6.762***
		(1.369)	(1.792)		(1.586)
INTERSECTION^2		-6.888***	-6.997***		-7.660***
		(1.385)	(1.871)		(1.599)
INTERSECTION× *FIRM_EXP*		-3.200			
		(2.456)			
INTERSECTION^2× *FIRM_EXP*		2.798			
		(2.388)			
INTERSECTION× *Lagged ACCURACY*			-2.170		
			(2.711)		
INTERSECTION^2× *Lagged ACCURACY*			2.352		
			(2.791)		
Lagged ACCURACY	-0.404*	5.211***	5.382***		
	(0.243)	(0.263)	(0.459)		
FIRM_EXP	4.118***	1.057**	0.595**		
	(0.494)	(0.449)	(0.248)		
D_EVENT				-0.294	0.667*
				(0.348)	(0.367)
Controls from Table 2	YES	YES	YES	YES	YES
N	189,452	189,452	189,452	73,644	73,644
Year Fixed Effects	YES	YES	YES	YES	YES
Pseudo/Adjusted R^2	27.70%	2.07%	2.07%	25.10%	1.98%

Table 4 – (continued)

Columns (1) to (3) examine the relation between *ACCURACY* and *INTERSECTION* conditional on predictors of analyst forecast accuracy.

Column (1) examines whether *INTERSECTION* is positively correlated with the two predictors of forecast accuracy: *FIRM_EXP* and *Lagged ACCURACY*. The following regression is estimated:

$INTERSECTION_{aft} = \beta_0 + \beta_1 Lagged\_ACCURACY_{aft} + \beta_2 FIRM\_EXP_{aft} + \sum_m \beta_m Control_m + \varepsilon_{aft}$,

where *Control* includes all control variables other than *FIRM_EXP* and *Lagged ACCURACY* from Table 2.

Columns (2) and (3) examine whether the sensitivity of forecast accuracy to *INTERSECTION* increases with predictors of accuracy. The following regression is estimated:

$ACCURACY_{aft} = \beta_0 + \beta_1 INTERSECTION_{aft} + \beta_2 INTERSECTION^2_{aft} + \beta_3 FIRM\_EXP$ (or $Lagged\ ACCURACY$) $\times INTERSECTION_{aft} + \beta_4 FIRM\_EXP$ (or $Lagged\ ACCURACY$) $\times INTERSECTION^2_{aft} + \sum_m \beta_m Control_m + \varepsilon_{aft}$,

where *Control* includes *FIRM_EXP* (or *Lagged_ACCURACY)* and all other control variables from Table 2.

Columns (4) and (5) examine the relation between *ACCURACY* and *INTERSECTION* in the context of other information sources. Estimations are based on the subsample of 73,644 analyst-firm-year forecasts determined by availability of data in Capital IQ between 2005 and 2016.

Column (4) examines whether *INTERSECTION* is positively correlated with analyst event attendance in the year leading to the forecast date (*D_EVENT*). The regression below is estimated:

$INTERSECTION_{aft} = \beta_0 + \beta_1 D\_EVENT_{aft} + \sum_m \beta_m Control_m + \varepsilon_{aft}$,

where *Control* includes all control variables from Table 2.

Column (5) examines the relation between *ACCURACY* and *INTERSECTION* after controlling for analyst attendance of information events. The regression below is estimated:

$ACCURACY_{aft} = \beta_0 + \beta_1 INTERSECTION_{aft} + \beta_2 INTERSECTION^2_{aft} + \beta_3 D\_EVENT_{aft} + \sum_m \beta_m Control_m + \varepsilon_{aft}$,

where *Control* includes all control variables from Table 2. The regression augments equation (3) in Table 2 by further controlling for *D_EVENT*.

All variables are defined in the Appendix. Except *D_EVENT*, all are scaled to fall between 0 and 1 for the same firm-year.

The dependent variable (and, thus, each coefficient) is multiplied by 100.

Standard errors are clustered by analyst and are presented in parentheses.

***, **, * denote statistical significance at 1%, 5%, and 10%, respectively.

Table 5 – Instrumental Variable Analysis

Variables	(1) First stage for *INTERSECTION* coeff (std. err.)	(2) First stage for *INTERSECTION* ^{2} coeff (std. err.)	(3) Second stage for *ACCURACY* coeff (std. err.)
Instrument for *INTERSECTION*	7.175***	-18.875***	
	(2.372)	(2.509)	
Instrument for *INTERSECTION* ^{2}	6.211***	31.989***	
	(2.241)	(2.479)	
INTERSECTION			19.877**
			(8.844)
INTERSECTION ^{2}			-26.629***
			(4.504)
Lagged ACCURACY	-0.329	-0.691**	5.367***
	(0.278)	(0.295)	(0.299)
FIRM#	35.222***	33.284***	3.358
	(1.320)	(1.396)	(2.998)
INDUSTRY#	5.514***	6.836***	-0.823*
	(0.786)	(0.821)	(0.451)
FIRM_EXP	3.353***	3.049***	0.451
	(0.548)	(0.569)	(0.389)
BSIZE	9.898***	9.103***	-0.187
	(0.902)	(0.966)	(0.812)
DAYS	5.705***	6.722***	-3.184***
	(0.413)	(0.437)	(0.432)
EPS_FREQ	-1.585***	-1.630***	0.075
	(0.557)	(0.601)	(0.309)
HORIZON	-0.246	-0.210	-10.856***
	(0.333)	(0.340)	(0.266)
Constant	9.116***	2.572	53.685***
	(1.935)	(2.002)	(2.173)
N	142,814	142,814	142,814
Year Fixed Effects	YES	YES	YES
Adjusted R^2	27.2%	25.6%	N.A.
IV F-stat			210.92

This table presents results based on the instrumental variable approach.
The instrumental variables for *INTERSECTION* and *INTERSECTION* ^{2} are defined in the Appendix.
All other variables are defined in the Appendix and scaled among the same firm-year to fall between 0 and 1.
The dependent variable (and, thus, each coefficient) is multiplied by 100.
Standard errors are clustered by analyst and are presented in parentheses.
***, **, * denote statistical significance at 1%, 5%, and 10%, respectively.

Table 6 – Change in Forecast Accuracy Post Exogenous Shocks to the Information Flow from Buy-side to Sell-side Analysts

Variables	(1) Total sample	(2) Lower *INTERSECTION* subsample	(3) Higher *INTERSECTION* subsample
	coeff (std. err.)	coeff (std. err.)	coeff (std. err.)
POST_EVENT	1.195 (0.836)	2.329** (0.989)	-1.240 (1.548)
CONNECTED	1.116 (0.684)	1.901** (0.891)	-0.115 (1.205)
CONNECTED × *POST_EVENT*	-1.310 (0.952)	-3.502*** (1.245)	1.922 (1.647)
Constant	50.327*** (2.278)	50.413*** (2.757)	50.165*** (3.834)
N	40,372	20,773	19,599
Year Fixed Effects	YES	YES	YES
Adjusted R^2	0.00%	0.00%	0.02%

This table presents analyses of changes in sell-side analyst forecast accuracy from pre to post the dates when the last form 13Fs were filed by acquired or bankrupt institutions. The focus is on the difference between forecasts by analysts connected with those institutions and forecasts by analysts unconnected with the institutions. Forecasts are those issued within two years of the events. The regression below is estimated:

ACCURACY = *CONNECTED* + *POST_EVENT* + *CONNECTED* × *POST_EVENT* + Year fixed effects + ε_{aft}

The lower (higher) *INTERSECTION* subsample includes forecasts by analysts whose scaled *INTERSECTION* among all analysts following the same firm-year is at or below (above) the sample median of 0.2775.

All other variables are defined in the Appendix and scaled values are scaled among the same firm-year.

The dependent variable (and, thus, each coefficient) is multiplied by 100.

Standard errors are clustered by analyst and are presented in parentheses.

***, **, * denote statistical significance at 1%, 5%, and 10%, respectively.

Table 7 – Alternative Measures of *INTERSECTION*

	(1)	(2)	(3)	(4)	(5)
Dependent variable=			*ACCURACY*		
Independent variable=	Measure 1 $INTERSECTION_{time}$	Measure 2 $INTERSECTION_{stock\#}$	Measure 3 $INTERSECTION_{inst\#}$	Measure 4 $INTERSECTION_{Asset}$	Measure 5 $INTERSECTION_{nextq}$
	Coeff (std. err.)	Coeff (std. err.)	Coeff (std. err.)	Coeff (std. err.)	Coeff (std. err.)
INTERSECTION	6.547***	6.423***	5.932***	4.429***	4.870***
	(0.949)	(1.047)	(0.984)	(1.041)	(0.965)
$INTERSECTION^2$	-6.585***	-6.797***	-4.429***	-2.894***	-5.846***
	(0.931)	-0.969	-0.947	(0.978)	(0.967)
Controls in Table 2	YES	YES	YES	YES	YES
Year Fixed Effects	YES	YES	YES	YES	YES
N	189,452	189,452	189,452	189,452	189,452
Adjusted R2	2.07%	2.08%	2.07%	2.07%	2.07%

This table estimates the regression below with five alternative measures of the *INTERSECTION* variable: $INTERSECTION_{time}$, $INTERSECTION_{stock\#}$, $INTERSECTION_{INST\#}$, $INTERSECTION_{Asset}$, and $INTERSECTION_{nextq}$.

$ACCURACY_{aft} = \beta_0 + \beta_1 \cdot$Alternative Measure of $INTERSECTION_{aft} + \beta_2 \cdot$Alternative Measure of $INTERSECTION_{aft}^2 + \sum_m \beta_m Control_m + \varepsilon_{aft}$, where *Control* includes all control variables from Table 2.

All variables are defined as in the Appendix and scaled to fall between 0 and 1 for the same firm-year.

The dependent variable (and, thus, each coefficient) is multiplied by 100.

Standard errors are clustered by analyst and are presented in parentheses.

***, **, * denote statistical significance at 1%, 5%, and 10%, respectively.

Table 8 – Cumulative Abnormal Returns around Recommendation Revisions and Forecast Revisions by *INTERSECTION*

Variable	Around recommendation revisions Coeff (std. err.)	Around forecast revisions Coeff (std. err.)
ΔREC	0.955***	
	(0.044)	
$\Delta REC \cdot INTERSECTION$	0.984***	
	(0.374)	
$\Delta REC \cdot INTERSECTION^2$	-1.038***	
	(0.362)	
$\Delta FCST$		0.400***
		(0.033)
$\Delta FCST \times INTERSECTION$		0.519***
		(0.190)
$\Delta FCST \times INTERSECTION^2$		-0.464**
		(0.186)
INTERSECTION	-0.693	-0.308**
	(0.458)	(0.121)
$INTERSECTION^2$	0.749*	0.276**
	(0.448)	(0.118)
Constant	0.180	-0.395***
	(0.212)	(0.059)
N	11,550	186,712
Year Fixed Effects	YES	YES
Adjusted R^2	13.2%	0.50%

The left column examines the impact of *INTERSECTION* on the relation between recommendation revisions and the three-day cumulative abnormal returns around the revisions. The regression below is estimated:

$CAR_{[-1,+1]} = \beta_0 + \beta_1 \Delta REC + \beta_2 \Delta REC \cdot INTERSECTION + \beta_3 \Delta REC \cdot INTERSECTION^2 + \beta_4 INTERSECTION + \beta_5 INTERSECTION^2 + \varepsilon$.

The right column examines the impact of *INTERSECTION* on the relation between forecast revisions and the three-day cumulative abnormal returns around the revisions. Estimation is based on the same regression as above except that ΔREC is replaced with $\Delta FCST$.

All variables are defined in the Appendix.

INTERSECTION is scaled to fall between 0 and 1 for the same firm-year.

The dependent variable (and, thus, each coefficient) is multiplied by 100.

Standard errors are clustered by analyst and are presented in parentheses.

***, **, * denote statistical significance at 1%, 5%, and 10%, respectively.

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