Do Connections with Buy-Side Analysts Inform Sell-Side Analyst Research?

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Abstract: Prior research suggests that private information developed by an institutional investor's buy-side analysts becomes public only through observation of fund manager trading decisions. We identify another pathway. Specifically, we hypothesize that buy-side analyst connections with sell-side analysts offer the sell-side a view of the buy-side's private information, thus enhancing the quality of sell-side research output. We proxy for these connections with the weighted number of stocks at the intersection of stocks held in the portfolios of institutional investors and followed by the sell-side analyst. The larger this intersection, the more opportunities the sell-side analyst has to interact with institutional investors. We proxy for the research quality of the sell-side analyst with her earnings forecast accuracy. We find that such connections enhance the accuracy of earnings forecasts, but up to a point of diminishing returns. Additional tests rule out reverse causality as an explanation for the association and strengthen the inference that connections between sell- and buy-side analysts increase the flow of information and improve the quality of sell-side research output.

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1. Introduction

Buy-side analysts play an important role in the stock market by producing information that supports the trading decisions of their affiliated portfolio managers. Unlike their sell-side counterparts, buy-side analysts have strong incentives to protect their private information, and thus do not publicize their research output (Cheng, Liu, & Qian 2006). Prior research suggests that institutional investors disseminate this information beyond the confines of their own firms only through their trading decisions (e.g., Chan & Lakonishok 1995; Chiyachantana, Jain, Jaing, & Wood 2004; Bushee & Goodman 2007, Foster, Gallahger, & Looi 2011, Guo & Qiu 2016). We investigate an alternative mechanism through which this private information finds its way into the public domain. Specifically, we posit that connections with institutional investors' buy-side analysts provide sell-side analysts with private information generated by the buy-side that enhances the quality of sell-side research reports.

Connections can arise from buy-side analyst demand for information independently developed by sell-side analysts or for concierge services, such as access to company management. Interactions between the two analyst types create opportunities for the exchange of information about firms of mutual interest. Discussions about a particular firm might include topics such as the firm's strategy, growth and value drivers, risks, management quality, and of course, earnings prospects. This paper investigates the following empirical question: through their connections with sell-side analysts, do buy-side analysts, perhaps unknowingly, leak information that enhances the quality of sell-side analyst research reports?

A vast literature describes characteristics of sell-side analyst research and its impact on stock prices, arguably through the impact on institutional investor decisions. The research literature generally assumes that the flow of information between sell-side and buy-side analysts is one-directional; i.e., information flows from sell-side analysts through buy-side analysts to portfolio managers, whose trades move stock prices (e.g., Gu, Li, Li, & Yang 2016; Irvine, Lipson, & Puckett, 2007; Mikhail, Walther, & Willis, 2007). Our paper looks at the flow of information in the other direction; i.e., do insights from the research of buy-side analysts, in support of institutional investor decisions, flow to sell-side analysts and improve the quality of sell-side analyst research reports?

Our primary measure of connections assumes that a sell-side analyst has opportunity to learn about a given firm's prospects from an institution when the analyst also follows *other stocks* held in the institution's portfolio. We expect the opportunity to increase in both the number of institutions the analyst is connected with and in the number of the overlapped *other stocks*. We further weight the number of other stocks by the value of each stock as a percentage of the institution's total portfolio. The idea is that the larger this weighted number, the more important these *other* stocks are for the institution, the more discussions the sell-side analyst likely has with the institutional investor's buy-side analysts, and thus, the more opportunities the sell-side analyst has to discern and process the private information possessed by this institutional investor. This weighted number of *other stocks* averaged across all institutional investors holding the given firm's stock represents our primary unscaled *CONNECTIONS* variable.

For three reasons, we use the sell-side analyst's earnings forecast accuracy relative to other analysts covering the same firm as our primary proxy for the quality of that analyst's research report. First, prior research shows that information in earnings forecasts affects analysts' stock recommendations (e.g., Ertimur, Sunder, & Sunder 2007) and target price forecasts (e.g., Gleason, Johnson, & Li 2013), making earnings forecast accuracy a reasonable proxy for overall sell-side analyst research quality. 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. For these reasons, our primary summary measure of the quality of a research report for a given analyst and a given firm is the absolute difference between the firm's actual earnings and the analyst's forecast of those earnings. We label this measure *ACCURACY*.

For both *ACCURACY* and *CONNECTIONS*, as well as control variables, we hold constant the firm and year and measure the respective variable for a particular analyst relative to all other analysts following the same stock in the same year. This effectively avoids confounding effects of firm characteristics and time-variant macro effects likely to affect both *ACCURACY* and *CONNECTIONS*. For example, both *ACCURACY* and *CONNECTIONS* might be higher for firms of larger size or with higher institutional ownership (see e.g., Frankel, Kothari, & Weber 2006; Ljungqvist et al. 2007). Using the extent of connections and accuracy relative to other analysts covering the same firm-year abstracts away the confounding effect of size or institutional ownership on forecast accuracy. We hypothesize and find that *ACCURACY* improves with *CONNECTIONS* until *CONNECTIONS* reaches a point of diminishing returns. This concave pattern is analogous to prior research that finds lower levels of earnings forecast accuracy among sell-side analysts who cover large numbers of firms. It is also consistent with Maber, Groysberg, & Healy 2015, who show that increasing high-touch services with institutional clients comes with opportunity costs limiting the time sell-side analysts spend on other accuracy-enhancing aspects of their research.

From evidence consistent with the hypothesized non-linear relation between *ACCURACY* and *CONNECTIONS*, we infer that information from connections with buy-side analysts informs sell-side analyst research. However, the relation between *ACCURACY* and *CONNECTIONS* could be endogenous in that buy-side analysts select sell-side analysts who can provide insights that inform the buy-side analysts' research reports, and that selection probably favors sell-side analysts who have already proven themselves in ways that might include forecast accuracy. We implement a number of analyses to mitigate the endogeneity concerns.

In the first and second analyses, we examine the variation in the relation between *ACCURACY* and *CONNECTIONS* with private information of buy-side analysts or demand for such information from sell-side analysts. We generally find a stronger (weaker) relation when buy-side analysts have relatively more (less) private information. In addition, we find no evidence of a relation between sell-side analyst characteristics valued by buy-side analysts and the association between *ACCURACY* and *CONNECTIONS.* This supports the inference that sell-side analysts obtain forecast accuracy-enhancing information from buy-side analysts, as opposed to buy-side analysts seeking guidance from already-accurate sell-side analysts. Third, we find that our main finding is robust in a subsample of analysts with less than four years of firm-specific experience. In those cases, the buy-side analyst has very little basis for judging the accuracy track record of the sell-side analyst with whom s/he chooses to work.

Fourth, to further address endogeneoity and provide additional support for the caual interpretation of our results, we employ exogenous shocks to connections caused by acquisitions or bankruptcies of institutions with which the sell-side analysts are connected and examine changes in earnings forecast accuracy of these sell-side analysts. Using forecasts by analysts not connected with the affected institutions as a control group, we show that accuracy of forecasts by analysts with relatively low connections prior to the shocks, but not by those with high connections, declines subsequent to the shocks. These results strengthen the casual interpretation of our results and support the inference of the curvilinear relation from the main results.

Finally, we conduct a number of tests to check the robustness of our main results to alternative measures of connections and forecast accuracy, and the use of market reaction to recommendation revisions as an alternative proxy for analyst research report quality. Our results are robust to these alternative measures.

This paper contributes to the literature in two important ways. First, we open the door to a new avenue of research that can investigate the role of the bilateral flow of information between sell- and buy-side analysts in increasing the quality of information impounded in capital asset prices. Second, by furthering our understanding of the role that buy-side analysts play in financial markets, our paper contributes to the nascent literature that studies buy-side analysts (e.g., Jung, Wong, and Zhang 2017, Brown, et al. 2016, Cici & Rosenfeld 2016, Rebello & Wei 2014). We identify a channel 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. Section 3 reviews the literature and presents our hypotheses. Section 4 discusses our research design and sample selecton. Sections 5 and 6 present the results of our hypotheses tests and additional tests to address endogeneity, respectively. Section 7 presents robustness tests, and Section 8 concludes.

2. Institutional Setting

Buy-side analysts provide advice to portfolio managers working for entities that pool resources of individual investors and invest on their behalf. These entities house investment vehicles such as mutual funds, pension funds, insurance companies, and hedge funds; e.g., Fidelity Investments, General Motors, Progressive Auto Insurance, and Bridgewater Associates. We refer to each of these entities as an institutional investor and each institutional investor employs buy-side analysts who interacts with one or more sell-side analysts. The majority of sell-side analysts work for full-service investment banks, such as Goldman Sachs, JP Morgan Chase, and Bank of America Merrill Lynch (Cowen, Groysberg, & Healy 2006).

The literature has extensively documented that sell-side analysts provide information to the buy-side (Ramnath, Rock, & Shane 2008a, 2008b; Bradshaw et al. 2017). For example, Brown, Call, Clement, & Sharp (2017) surveyed investment relations professionals and discovered "that some buy-side analysts privately send questions or comments to sell-side analysts during the Q&A portion of the public earnings conference call (p. 36)." Nonetheless, 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 & 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, & Miller (2017) document that trade sizes around investor-management meeting times increase and abnormal net buys around the meetings are profitable during thirty days subsequent to the private access day. They conclude that the private access to management provides information that changes institutional investors' beliefs and trading. Such beliefs-changing 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 & Soltes, 2015).

Supporting anecdotal evidence suggests that buy-side analysts often get preferential access to the management of public companies and this provides an advantage in efforts to generate precise information. 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. 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 & Gryta 2017).[1]

Although buy-side analysts keep their research private and restrict access to the private information developed from their research to only their firm's portfolio managers (Cheng, et al. 2006; Groysberg, Healy, and Chapman 2008), at least two factors make sell-side analysts privy to some part of this information. First, learning what other buy-side analysts think and sharing that with institutional clients is implicitly expected of sell-side analysts. Brown, et al. (2016) surveyed and interviewed buy-side analysts who indicated that their demand for sell-side analyst services depends, primarily, on: (i) the ability of sell-side analysts to facilitate meaningful one-on-one interaction with CFOs and other knowledgeable executives working for the firms with

[1] Holding constant the effects of their interaction with each other, 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 & Herbst (2014); Jung, et al. (2017); and Groysberg, Healy, Serafeim & Shanthikumar (2013).

significant representation in their institution's portfolios; (ii) the quality of sell-side analysts' industry-related research; and (iii) insights sell-side analysts provide into the perspective of buy-side analysts working for other institutional investors. Institutional investors could, and increasingly do, internalize the first two services, but they must outsource the third service, which incentivizes sell-side analysts to discover their buy-side analyst clients' perspectives on the firms the sell-side analysts follow.[2]

Second, sell-side analysts have many opportunities to learn from buy-side analysts. The lion share of a typical sell-side analyst's compensation is driven by broker votes, which are in turn driven by personalized services that sell-side analysts provide for institutional clients including high-touch meetings, phone calls, whitepapers, and concierge services that put buy-side analysts in touch with the management of firms of interest (Maber, et al. 2015). Thus, sell-side analysts have a strong incentive to provide high-touch services, which necessitate regular communication with current or potential institutional investor clients.

Based on a sample of sell-side analysts at a mid-size investment bank, Maber et al. (2015) 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. From the perspective of the buy-side, when Brown et al. (2016) asked buy-side analysts how often they have private communication with sell-side analysts, 55% of their respondents said more than 23 times per year and only 4% said "never." These communications provide sell-side analysts with opportunities to uncover and put together various pieces of information produced by institutional

[2] This differs from information spillovers documented in other studies. For example, Hameed, Morck, Shen, & Yeung (2015) find that sell-side analysts follow stocks whose fundamentals have the greatest correlation with those of other firms in the industry. The information developed about these "bellweather" firm stocks benefits investors in less closely followed stocks. In another study, Muslu, Rebello, & Xu (2014) find that analysts contribute to stock comovement by developing value-relevant information common to the firms in their portfolio of followed firms.

investors. For example, Stephen Byrd, a managing director of research at Morgan Stanley told us "when I speak to a variety of institutional clients, I get a strong sense for the investor debates that really matter for a stock. That helps me to understand what catalysts are likely to move a stock. We all have access to the same information, though sometimes our clients track certain catalysts more closely than we do (whereas sometimes we are closer to a particular catalyst)."[3]

We argue that the regular communications with their institutional clients provide sell-side analysts with a window into the private information generated by their institutional clients about companies of common interest. Specifically, as both parties engage in conversations, the questions raised and the requests for clarifications made by the institutional clients tip off sell-side analysts about the private information of their institutional clients. In this regard, Groysberg, Healy, & Chapman (2008) speculate that "sell-side analysts may develop an information advantage through feedback on their ideas from their own institutional clients (p. 33)." That sell-side analysts discern the private information of their institutional clients in the course of such communications is supported by the fact that many buy-side analysts view the knowledge that sell-side analysts have of other buy-side analysts' opinions as a valuable service provided by the sell-side (Brown et al. 2016). Furthermore, the results of the Brown et al. interviews suggest 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. Quoting one of their interviewees, "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."

[3] Also, Greg Melich, a partner and senior analyst at MoffettNathanson told us that in the course of a typical interaction with an institutional client he might be alerted of a new piece of public information of which he was not aware. For example, the institutional client might have just learned that a certain company became a supplier of Target Corporation and pass that information along.

Given the information environment described above, the next section develops hypotheses concerning the relation between the quality of a sell-side analyst research report and the degree of connectedness between the sell-side analyst and the buy-side analysts she serves.

3. Hypotheses and Literature Review

Main hypothesis

Section 2 suggests that sell-side analysts have strong incentives to interact with buy-side analysts and refers to previous research and anecdotal evidence that those interactions occur frequently. Presumably, more connections with institutional investors' buy-side analysts provide more opportunities for sell-side analysts to discern the institutional investors' private information which, in turn, informs sell-side analysts' earnings forecasts and improves their forecast accuracy. Thus, we expect sell-side analyst forecast *ACCURACY* to be positively correlated with *CONNECTIONS* with institutional investors.

On the other hand, it is costly for analysts to spread themselves too thinly. For example, there appears to be a cost associated with following too many firms (Clement 1999; Jacob, et al. 1999; Myring & Wrege 2011; Pelletier 2015). We expect that for each sell-side analyst there is a cost associated with providing the services associated with too many connections. Too many connections with buy-side analysts are likely to come with an opportunity cost that outweighs the benefit of other sell-side analyst activities, such as independent research, nurturing relationships with the buy-side analysts who matter most, connecting with management of the firms they follow, and writing whitepapers and research reports. This is consistent with Maber, et al. (2015) who show that increases in analysts' time-consuming services for their institutional clients result in less published research output. Thus, we expect the positive impact of *CONNECTIONS* on

ACCURACY to exhibit diminishing returns as the number of interactions with different buy-side analysts increases. In light of this reasoning, we hypothesize the following relation:

> **H1:** *ACCURACY* increases with *CONNECTIONS* up to some point where the increasing rate subsides.

On the other hand, 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 relation between *ACCURACY* and *CONNECTIONS*.

Additional hypotheses

Given evidence of the relation hypothesized in H1, we test additional hypotheses that identify factors expected to strengthen the relation between *ACCURACY* and *CONNECTIONS*. We develop these additional hypotheses to provide more confidence in the validity of H1 and to address the endogeneity issue discussed in Section 1.[4] That is, the tests are designed to sort out whether the relation observed in tests of H1 emerges from sell-side analysts obtaining accuracy-enhancing information from buy-side analysts, or from buy-side analysts seeking connections with already-accurate sell-side analysts.

We predict greater sensitivity of *ACCURACY* to *CONNECTIONS* in situations where sell-side analysts have more opportunities to learn from their buy-side analyst counterparts, which would arise when sell-side analysts are connected with certain buy-side analysts who produce relatively large amounts of private information. If, on the other hand, *ACCURACY* drives *CONNECTIONS* because buy-side analysts have more need for information from sell-side analysts, then we expect greater sensitivity of *ACCURACY* to *CONNECTIONS* in situations where sell-side analysts have *less* opportunities to learn from their buy-side analyst counterparts.

[4] Note that endogenous selection of more accurate sell-side analysts cannot explain a weakened relation between *ACCURACY* and *CONNECTIONS* beyond a certain level of *CONNECTIONS*.

Such situations arise when sell-side analysts are connected with certain buy-side analysts who produce relatively *small* amounts of private information. This discussion leads to our second hypothesis:

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

We next examine the possibility that buy-side analysts' demand for information from sell-side analysts drives the relation between *ACCURACY* and *CONNECTIONS*. In that respect, we hypothesize that:

> **H3:** The sensitivity of *ACCURACY* to *CONNECTIONS* increases with buy-side analyst demand for connections with sell-side analysts.

We expect greater buy-side analyst demand for connections with sell-side analysts predicted to produce more informative research output, proxied by earnings forecast accuracy. Strong predictors of sell-side analyst forecast accuracy include past accuracy (Brown 2001) and firm-specific experience (Clement 1999; Brown, et. al. 2016).[5] Thus, if buy-side demand drives the relation between *ACCURACY* and *CONNECTIONS*, then we expect to find evidence supporting H3; i.e., we expect the relation to strengthen with sell-side analyst firm-specific experience and past earnings forecast accuracy.

4. Research design

4.1 Measurement of CONNECTIONS

Our primary connection variable assumes that analyst *a* learns more about firm *f* as the analyst is connected with more institutions and follows more *other stocks* held by an institution. We let each of these *other stocks* proxy for a connection around *f* between *a* and *i* during year *t*

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[5] 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.

($CONNECTIONS\#^{i}_{aft}$), and we weight each connection with the value of the stock as a percentage of *i*'s total portfolio to incorporate the importance of the stock to *i* and thus, likely more interactions between *a* and *i*. The average weighted number of connections, across all institutions holding *f*, is our primary proxy for how much *a* learns about *f* from interactions with buy-side analysts in period *t*,

$$CONNECTIONS_{aft} = \frac{\sum_i Weighted\ CONNECTIONS\#^{i}_{aft}}{INST\_OWNER\#_{ft}},$$

where $INST\_OWNER\#_{ft}$ is the number of institutions holding *f*. Hence, our primary measure considers both the breadth (as reflected in the number of connected institutions) and depth (as reflected in the weighted number of other overlapping stocks) of connection. We expect that, the greater $CONNECTIONS_{aft}$, the greater the breadth and depth of dialogue between *a* and institutional investors holding *f*, and the greater the opportunity for the sell-side analyst to discern and process the private information possessed by these institutional investors.

To further illustrate the construction of our *CONNECTIONS* measure, consider the example in figure 1. There we see that the stock of interest, *f1,* is held by three institutional investors. Analyst *a1* is strongly connected, having connections (beyond *f1*) with each of the three institutional investors holding *f1* through stocks other than *f1* that account for 95%, 80%, and 90%, respectively, of the corresponding institution's portfolio. Hence *a1*'s *CONNECTIONS* measure is 0.883 [(0.95+0.80+0.90)/3]. On the other hand, analyst *a2* has no connections (beyond *f1*) with the institutional investors holding *f1*. Hence *a2*'s *CONNECTIONS* measure is 0 [(0+0+0)/3].

Our approach to measuring *CONNECTIONS* avoids the confounding effect of institutional ownership on forecast accuracy (Frankel, et al. 2006; Ljungqvist, et al. 2007). Our measure does not relate to institutional ownership of a firm. Specifically, for analysts following the same company *f*, differences in our *CONNECTIONS* measure depends on differences across analysts in their following of stocks other than *f* (and not on the number of *f*'s shares owned by institutions). As we describe in detail in Section 4.2, we further scale *CONNECTIONS* within the same firm-year to control for both time-variant and firm-invariant characteristics.

4.2 Models for testing H1

To examine the hypothesized diminishing impact of *CONNECTIONS* on *ACCURACY*, we use the quadratic form below (see Wooldridge 2016, p636; and Aghion et al. 2005). If analysts produce more accurate forecasts due to the private information they collect from their connections with institutional investors, we expect $\beta_1 > 0$ in model (1) below. In addition, if analysts face diminished returns beyond some level of connections with institutional investors, we expect $\beta_2 < 0$.

$$ACCURACY_{aft} = \beta_0 + \beta_1 CONNECTIONS_{aft} + \beta_2 CONNECTIONS_{aft}^2 + \sum_m \beta_m Control_m + \varepsilon_{aft} \quad (1),$$

where, $ACCURACY_{aft}$ is measured as $\frac{\max(|FE_{ft}|)-|FE_{aft}|}{\max(|FE_{ft}|)-\min(|FE_{ft}|)}$, i.e., absolute error 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*.

We include the following variables to control for factors that could affect forecast accuracy: analyst *a*'s forecast accuracy for the lagged year ($ACCURACY_{af,t-1}$), the number of firms *a* follows ($FIRM\#_{at}$), the number of industries *a* follows ($INDUSTRY\#_{at}$), the number of years *a* has been forecasting firm *f*'s earnings ($FIRM\_EXP_{aft}$), brokerage size ($BSIZE_{at}$), the number of days between *a*'s forecast and the most recent one-year ahead forecast for the same firm-year by any analyst ($DAYS_{aft}$), *a*'s earnings forecast frequency (EPS_FREQ_{aft}), the number of days between the date of *a*'s forecast and the end of fiscal year *t* ($HORIZON_{aft}$). *INDUSTRY#*, *FIRM#*, *BSIZE*, and *EPS_FREQ* are measured for the year ending with the date of F_{aft}. We define all these variables in detail in the Appendix.

$CONNECTIONS_{aft}$ and all control variables except $ACCURACY_{af,t-1}$ are scaled to fall between 0 and 1 based on the equation below:

$$Scaled\ Variable_{aft} = \frac{Variable_{aft} - \min(Variable_{ft})}{\max(Variable_{ft}) - \min(Variable_{ft})}$$

By scaling all dependent and independent variables among analysts following the same firm and year, we control for all firm-invariant characteristics and time-variant macro factors that affect forecast accuracy (e.g., forecast difficulty as described in Hong and Kubik 2003). Scaling all variables in this manner maintains the relative values of each variable, while allowing comparison across regression coefficients (Clement & Tse, 2005).

We also employ a piecewise regression (2) below, which allows us to calculate the sensitivity of *ACCURACY* to *CONNECTIONS* in each *CONNECTIONS* tercile.

$$ACCURACY_{aft} = \beta_0 + \sum_{k=1}^{3} \beta_k^{Tercile} D_k^{Tercile} CONNECTIONS_{aft} + \sum_m \beta_m Control_m + \varepsilon_{aft} \quad (2)$$

where $D_k^{Tercile}$ is an indicator variable equaling one for the k^th^ $CONNECTIONS$ tercile (1=lowest, 2=middle, and 3=highest), where tercile cut-off points are derived from the distribution of scaled CONNECTIONS. Under H1, we expect $\beta_1^{Tercile} > \beta_3^{Tercile}$.

4.3 Model for testing H2

If the sensitivity of *ACCURACY* to *CONNECTIONS* increases when buy-side analysts produce greater amounts of private information creating greater opportunity for sell-side analysts to learn from connections with buy-side analysts, then, in support of H2, we expect $\beta_1 > \beta_5$ in model (3) below. Alternatively, if the sensitivity of *ACCURACY* to *CONNECTIONS* increases because buy-side analysts with less private information seek connection with already-accurate sell-side analysts, then we expect $\beta_1 < \beta_5$.

$$ACCURACY_{aft} = \beta_0 + \beta_1 CONNECTIONS_{aft}^{High\ Opp} + \beta_2 (CONNECTIONS_{aft}^{High\ Opp})^2 + \beta_3 CONNECTIONS_{aft}^{Med\ Opp} + \beta_4 (CONNECTIONS_{aft}^{Med\ Opp})^2 + \beta_5 CONNECTIONS_{aft}^{Low\ Opp} + \beta_6 (CONNECTIONS_{aft}^{Low\ Opp})^2 + \sum_m \beta_m Control_m + \varepsilon_{aft} \quad (3)$$

where $CONNECTIONS_{aft}^{High\ Opp}$ is constructed by:

$$CONNECTIONS_{aft}^{High\ Opp} = \frac{\sum_i weighted\ CONNECTIONS\#_{aft}^{i} \times D_{High\ Opp}^{i}}{INST\_OWNER\#_{ft}}, \text{ and}$$

$D_{High\ OPP}^{i}$ denotes an institutional investor from which sell-side analysts have high (=1) or lower (=0) opportunities to acquire useful information. $INST\_OWNER\#_{ft}$ denotes the number of institutional investors holding stock *f* at time *t*. Similar to *CONNECTIONS*, we scale $CONNECTIONS^{High\ Opp}$ to fall between 0 and 1 among analysts following the same firm and year. $CONNECTIONS_{aft}^{Med\ Opp}$ and $CONNECTIONS_{aft}^{Low\ Opp}$ are constructed similarly. Note that normalizing the high/lower opportunity connections variables by $INST\_OWNER\#_{ft}$ ensures that they add up to $CONNECTIONS_{aft}$.

We apply three approaches to identifying institutional investors that provide high versus low 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.[6] 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.

[6] We thank Brian Bushee for sharing the classification of institutional investors. We group the institutions unclassified by Bushee into one group and include analyst connections with them and its squared term in the regressions. The coefficicents on connections with these institutions are generally insignificant.

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. Along these lines, Chen, Jegadeesh, and Wermers (2000) argue that managers who generate superior information "... trade frequently, while managers with more limited skills may be much more cautious in their trades." Consistent with this, Chen et al. (2000) and Massa, Qian, and Zhang (2015) find that institutions with higher portfolio turnover exhibit superior investment performance. Building on these findings, we view institutions with higher (lower) turnover as providing higher (lower) learning opportunities for sell-side analysts.

The third approach builds on Petajisto (2013) by classifying institutions from his five investment categories − stock pickers, concentrated stock pickers, moderately active stock pickers, closet indexers, and factor bettors − into active stock selectors and passive stock selectors. Specifically, we classify the first three categories of institutions as active stock selectors, and classify the last two categories as passive stock selectors, and view the former group as higher-opportunity institutions relative to the latter group. The rationale is that active stock selectors focus on analyzing individual stocks and potentially have more private information about individual stocks while passive stock selectors focus on replicating an index or placing factor bets without as much attention to individual stock analysis. Petajisto (2013, p82) uses a two-way stratification approach by first ranking all institutions by Active Share and then by Tracking Error to create a five by five grid and assign institutions in each cell to one of the five investment categories.

Similar to Cremers and Petajisto (2009), we compute Active Share as the sum of the absolute differences between the weight of an institution's portfolio and the weight of each stock in the market portfolio, i.e., the CRSP stock universe. Tracking Error is computed as the standard deviation of residuals from regressing monthly excess portfolio returns on the excess returns on the CRSP market index over the last three years. Monthly excess portfolio returns are computed by subtracting the monthly risk-free return from the portfolio return.[7] In essence, Tracking Error captures the variation in the returns of the portfolio not explained by the market portfolio benchmark.

4.4 Model for testing H3

To test whether the sensitivity of forecast accuracy to connections increases with sell-side analyst demand for information from the buy side or with buy-side analyst demand for information from the sell-side, we employ the following regression model.

$$\begin{aligned} ACCURACY_{aft} &= \beta_0 + \beta_1 CONNECTIONS_{aft} + \beta_2 CONNECTIONS^2_{aft} \\ &+ \beta_3 DEMAND + \beta_4 DEMAND \times CONNECTIONS_{aft} \\ &+ \beta_5 DEMAND \times CONNECTIONS^2_{aft} + \sum_m \beta_m Control_m + \varepsilon_{aft} \qquad (4), \end{aligned}$$

where *DEMAND* represents firm-specific experience (*FIRM_EXP*) or forecast accuracy measure for the prior year (lagged *ACCURACY*), both of which are as defined in model (1). If buy-side demand drives the relation between *ACCURACY* and *CONNECTIONS*, we expect $\beta_4 > 0$.

4.5 Sample selection

We employ the following sample construction steps. For fiscal years from 1995 to 2016, the latest full year with available data at the time of our analysis, from I/B/E/S we collect one-year ahead EPS forecasts issued during the first 90 days following the prior year's earnings announcement, and consensus analyst recommendations issued during the year. If an analyst issues more than one forecast for the same firm-year during the 90-day window, we keep only the earliest one. In the latest calendar quarter prior to the 90-day window for each firm-year

[7] Risk-free returns are from Ken French's website http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/.

described above, we collect the number of institutional investors and their holdings for the construction of *CONNECTIONS* and other measures using institutional holdings from the Thomson Reuters 13F database. We collect institution classifications that label institutions as transient, dedicated, and quasi-index types from Bushee's website, and stock returns used for computing institution portfolio returns from CRSP. 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

Table 1 Panel A presents descriptive statistics for variables in our models, along with some variable components. With the exception of *ACCURACY*, no variable is scaled among analysts for the same firm-year. Panel A shows that the distribution of absolute analyst-firm-year forecast error divided by the absolute value of actual earnings, |*FE*|, has a mean (median) of 0.768 (0.132). The *ACCURACY* variable used in our hypotheses tests scales |*FE*| to fall in a range from 0 to 1. The mean (median) of *ACCURACY* is 0.535 (0.561). The *CONNECTIONS* variable indicates that, on average, analysts have connections through stocks that account for 1.3% of an institution's portfolio. On average, 6.8 *other* stocks ($CONNECTIONS_{stock\#}$) overlap between stocks an analyst follows and stocks an institution holds (untabulated).

Panel A also shows that, in an average analyst-firm-year, a given analyst follows stocks in 3.9 different industries, has about 5 years of experience forecasting earnings of the followed firm, works for a brokerage house or research firm employing 66 analysts, issues forecasts 4.3

days after the most recent forecast by any analyst following the same firm, has issued 6 one-year ahead earnings forecasts in the year prior to the current forecast for the same firm, and has a 309-day forecast horizon until the end of the fiscal year.

Table 1 Panel B presents the univariate correlations among the variables used to test our hypotheses, where all variables are scaled among analysts following the same firm-year. Mostly consistent with prior literature, our measure of relative within firm-year *ACCURACY* has a statistically significantly positive correlation with the prior year's *ACCURACY*, the analyst's firm-specific experience, and number of firms followed; and *ACCURACY* is negatively correlated with the number of days since the most recent preceding analyst forecast, forecast frequency, number of industries followed, and the horizon between the forecast and the upcoming annual earnings announcement date. *ACCURACY* is negatively correlated with *CONNECTIONS*, before considering the impact and importance of modeling the hypothesized non-linear (concave) relation between these variables.

Table 1 Panel C offers an explanation for the negative univariate correlation between *ACCURACY* and *CONNECTIONS* observed in Panel B. Consistent with the hypothesized concave relation between *ACCURACY* and *CONNECTIONS*, Panel C shows that for the above-median (at or below-median) ranges of *CONNECTIONS*, the correlation is significantly negative (positive) at -0.020 (0.017). The higher absolute value of the correlation in the higher range of CONNECTIONS arguably provides a reason for a negative overall relation in Panel B. Visually corroborating this pattern, Figure 2 depicts *ACCURACY* across the quintiles of *CONNECTIONS* and shows an overall increasing (decreasing) pattern in both the mean and median of *ACCURACY* when *CONNECTIONS* is in the lower (higher) range. The concave pattern holds both when we use the scaled measure, *ACCURACY*, and when we use an unscaled measure,

−1*mean deflated |FE|. These results support the hypothesized non-linear concave relation between *ACCURACY* and *CONNECTIONS* and confirm our design choices in models (1) and (2) that explicitly account for the nonlinearity.

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, to a point of diminishing returns, with the degree of connectedness between the analyst and institutional investors who hold the firm's stock in their portfolios. For ease of presentation, we multiply the dependent variable in all regressions by 100. This has the effect of multiplying each coefficient by 100, as well. Results estimated from both the quadratic forms in columns (1) and (2) and the piecewise regressions in columns (3) and (4) with or without control variables support H1.

In columns (1) and (2), the coefficient on *CONNECTIONS* is significantly positive and the coefficient on the square of *CONNECTIONS* is significantly negative (with p-values less than 0.01). These results support the curvilinear concave relation predicted by H1. The results suggest that *ACCURACY* reaches its highest level when *CONNECTIONS* is at 0.419 [=4.818/(5.751×2)], or the 61st percentile of the its distribution. Consistent with the evidence portrayed in Figure 2, the significant coefficient on $CONNECTIONS^2$ provides justification for including the squared term in the regression specification. Not doing so would result in a biased coefficient on *CONNECTIONS* since the omitted variable, $CONNECTIONS^2$, is correlated with both *CONNECTIONS* and *ACCURACY* (Greene 2008, p134).[8]

[8] As shown in Table 1, *CONNECTIONS* and $CONNECTIONS^2$ are highly correlated. However, as Aiken and West (1991, p.35) and Jaccard, Turrisi, and Wan (1990, p31) point out, a high correlation between the independent variable and its quadratic term does not result in biased estimation of the coefficients, although it does increase the standard error for the coefficient estimate of the independent variable. See Greene (2008, p136) for a technical proof of this in the context of including an irrelevant variable. We document statistical significance for the coefficient of *CONNECTIONS* despite its standard error being inflated. We also use two ways suggested by the above econometricians to address the high correlation. The first way uses the centered measure that subtracts from

The economic significance, perhaps becomes more apparent in column (4) where we perform a piecewise estimation of *CONNECTIONS* by terciles. The coefficient on *CONNECTIONS* in the lowest tercile of the variable is 13.740, which means that a one-standard deviation change in *CONNECTIONS* for the lowest tercile (0.356, untabulated) is associated with a 4.891% (0.356×13.740) change in *ACCURACY*, which is 9.1% of the variable's mean (0.0489/0.535). The lower coefficient on *CONNECTIONS* in the second tercile and the insignificant coefficient in the highest tercile further support the nonlinear relation documented in Panel C of Table 1 and predicted by H1; i.e., once the analyst's average amount of connections per institution becomes too large, diminishing returns to additional connections become apparent. The coefficient on *CONNECTIONS* in the lowest tercile is significantly larger than that in the higher terciles, with a p-value (untabulated) less than 0.01. Relations between *ACCURACY* and control variables are consistent with the correlations in Panel B of Table 1 and prior literature.

5.3 Tests of H2

Results in Table 2 (discussed above) confirm H1 in that the strongest relation between *CONNECTIONS* and *ACCURACY* occurs among low-connections analysts and, as *CONNECTIONS* increases, the relation reaches a point of diminishing returns. We examine H2 to sort out whether the curvilinear relation between *CONNECTIONS* and *ACCURACY* derives from opportunities for lower-accuracy sell-side analysts to learn from *CONNECTIONS* with private information-laden buy-side analysts (i.e., the high-opportunity ones), or from

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CONNECTIONS its mean. The centered measure and its square have a correlation at 0.608. The other way replaces *CONNECTIONS* and $CONNECTIONS^2$ with a single term ($CONNECTIONS - CONNECTIONS^2$) to remove the multicollinearity in the estimation. The second way builds on the assumption that there is a curvilinear relation between *CONNECTIONS* and *ACCURACY* and the turning point is when *CONNECTIONS* takes the value of 0.5. Both sets of results support a curvilinear relation between *CONNECTIONS* and *ACCURACY*. These results again indicate that the high correlation between *CONNECTIONS* and $CONNECTIONS^2$ does not drive our results.

opportunities for private information-lacking buy-side analysts (i.e., the low-opportunity ones) to learn from *CONNECTIONS* with already-accurate sell-side analysts.

As discussed in Section 4.3, we rely on three variables − used in prior literature to characterize institutional investor trading strategies − to proxy for the degree to which buy-side analysts produce private information. Results in Table 3 for both the quadratic and piecewise regressions shows that the relation between *CONNECTIONS* and *ACCURACY* is generally only significant for connections with institutions having transient, high-turnover, or active trading strategies. We assume that institutions with these trading strategies tend to produce more private information, along with high levels of sell-side analyst learning opportunities. These results support H2, which predicts that the sensitivity of *ACCURACY* to *CONNECTIONS* increases with sell-side analyst learning opportunities.[9] The results also help alleviate the endogeneity concern that institutions choose to connect with already-accurate analysts. Such a preference suggests a stronger relation between sell-side analyst *ACCURACY* and *CONNECTIONS* with *low opportunity* institutions, which is opposite to what we find.

5.4 Test of H3

Table 4 displays results from tests of H3, which predicts that more demand for information by buy-side analysts strengthens the relation between *CONNECTIONS* and *ACCURACY*. We find that neither the firm-specific experience proxy in column (1) nor the past-accuracy proxy in column (2) has a statistically significant interactive effect with the connections variable. Untabulated results based on piecewise regressions are consistent with Table 4.

[9] In terms of economic significance, untabulated results (available upon request) indicate that when sell-side analysts connect with buy-side analysts working for institutions with, respectively, transient, high-turnover, or active trading strategies, we find that a one-standard deviation increase in *CONNECTIONS* with these high-opportunity institutions corresponds to an 8.8%, 7.6%, or 10.0% increase, respectively, in *ACCURACY*.

Overall, we believe that our tests of H2 and H3 provide supporting evidence that sell-side interest in connecting with buy-side analysts in order to glean information that improves the quality of sell-side research reports drives the relation we find between *ACCURACY* and *CONNECTIONS*. The next section describes the results of additional robustness tests.

6. Additional Tests to Address Endogeneity

6.1 Another Look at Reverse Causality

Results described in Sections 5.3 and 5.4 mitigate the concern that rather than connections with information-laden buy-side analysts improving sell-side analyst forecast accuracy, less information-laden buy-side analysts may choose to work with sell-side analysts with the best earnings forecast accuracy track records. To further address this concern, we constrain the sample to sell-side analysts with less than four years of firm-specific experience. We argue that these analysts do not have enough of an accuracy track record to attract the interest of buy-side analysts in the companies they cover. In this subsample, we expect that our firm-specific experience variable is not significant, while all of the other results still hold. Untabulated results mirror the results testing H1 in Table 2, except that, as expected, the firm-specific experience variable is no longer significantly related to forecast accuracy. Thus, our inferences remain unchanged in that connections with buy-side analysts enhance sell-side analyst forecast accuracy (not the other way around).

6.2 Exogenous shocks to connections

In this section, we identify events that likely exogenously diminish the connections between analysts and institutional investors and examine subsequent changes in analyst forecast accuracy. In particular, we collect institutions being acquired or liquidated from the following three sources. From Thomson Reuters we identify all institutions that stopped filing 13F reports between 1995 and 2016 and held more than 100 stocks on average. We then retain those that were either acquired (per Thomson One Banker) or liquidated (per bankruptcy announcements from Capital IQ). This procedure results in a subsample that includes 146 institutions.

We retain all firms held by the aforementioned institutions in the portfolios they reported on their last 13F filing (hereafter, the event). For each stock *f* 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.

We employ a difference-in-differences design and compare changes in accuracy of forecast 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 connection and information flow do not abruptly stop. For 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. If a forecast is in the pre- or post-event period for multiple events, we use the forecast only once. This process results in 52,369 forecasts, with a mean (median) of 3.8 (3.0) forecasts for each firm-year and event.

Based on evidence of the non-linear relation between accuracy and connections we document in the prior tests, for analysts with lower pre-event connections we expect higher decline in accuracy due to the exogenous termination of connections with certain institutions. Another reason for this empirical prediction is that, for such analysts, previous connections with the affected institutions represented a higher fraction of total connections with institutions.

Therefore, subsequent to the acquisitions of liquidation of the affected institution, the flow of information from institutions to sell-side analysts is more severely reduced. We classify an analyst as being in the lower (higher) connections group, if her scaled connection among all analysts covering the same firm-year is at or below (above) the median of the total sample at 0.2775 (untabualted).[10, 11]

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 5 report results for the total sample, lower connections subsample, and higher connections subsample, respectively, for the analysis that relies on use the scaled measure of forecast accuracy (*ACCURACY*). The interaction term is insignificant for the total sample, but more importantly, it is significantly negative for the lower connections subsample, which suggests that the analysts with lower connections experienced a drop in accuracy following the negative shock to their connections. For the higher connections subsample, the coefficient on the interaction term is positive, although insignificant.

Columns (4) to (6) of Table 5 use the unscaled measure of forecast accuracy (-mean deflated |*FE*|). The results show that our inference is insensitive to whether forecast accuracy is scaled. Overall, this analysis provides further support for a causal interpretation of our finding that additional connections for analysts benefit them in the form of higher accuracy up to a certain level of connections, beyond which the rate of increase subsides.

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[10] Results are similar when we use an analyst-firm's standing within the main sample to classify lower or higher connections group.
[11] The small number of forecasts for each firm-year-event renders the ranking infeasible for about 52% observations. The analyses in Table 5 omit the 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 for the subsample.

7. Robustness Tests

7.1 Alternative Measures of CONNECTIONS

We replicate our test of H1 using three alternative proxies for connections between sell-side and buy-side analysts by varying the emphasis and measures of breadth and depth of the connectedness. The first alternative, $CONNECTIONS_{time}$, is the same as our primary measure except that, instead of summing up position size of all *other stocks* in the portfolio of each connected institution, we sum the number of months each connected institution has held the stock. Here the holding period captures a stock's importance to an institution's portfolio. The second alternative, $CONNECTIONS_{stock\#}$, modifies our primary CONNECTIONS measure by taking the straight average number of connections without weighting them. The third alternative, $CONNECTIONS_{inst\#}$, measures the number of institutions that invest in both the stock of interest and at least one *other stock* followed by the same analyst. This alternative treats all institutions with whom an analyst is connected equally, thus emphasizing breadth over depth of connections. Like our primary measure, all alternative measures are divided by the number of institutions holding the firm of interest and scaled among analysts following the same firm-year.

The results in Table 6 using all three alternative proxies for *CONNECTIONS* are consistent with the results of tests of H1 reported in Table 2. These results increase our confidence in the construct validity of our primary *CONNECTIONS* variable as a measure of both breadth and depth of connections between sell-side analysts and institutions holding stocks that the analyst follows. Moreover, statistical and economic significance of the results using the alternative proxies suggest that all of these dimensions of connectivity benefit the accuracy of the corresponding connected analysts.

7.2 Sensitivity of results to alternative measures of forecast accuracy and additional controls

As described in Section 4.2, our main analyses scale the dependent and independent variables among observations of the same firm-year to abstract away from across-firm and across-year differences. In Table 7, we estimate regression models (1) and (2) (used to test H1) after replacing the scaled forecast accuracy with the raw measure of absolute forecast error multiplied by (−1). For comparability across firms, following Clement (1999), Jacob, Lys, and Neale (1999), and Bae, Stulz, and Tan (2008), we divide the raw measure by the mean absolute forecast error for the same firm-year. The results support the validity of inferences based on tests of H1 by showing a similarly significant non-linear relation between *CONNECTIONS* and this alternative measure of forecast accuracy.

7.3 Market reaction to recommendation revisions and connections with institutions

To proxy for the quality of sell-side analyst research output, as an alternative to earnings forecast accuracy, we use the market reaction to recommendation revisions, which reflects the informativenss of sell-side recommendations. 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, with a positive value indicating an upgrade. We regress cumulative abnormal stock returns, measured during three days around the recommendation revision date, on recommendation revisions (ΔREC), the connection variables, and their interactions.

As presented in the first column of Table 8, we document a stronger market reaction to recommendation revisions by analysts with higher institutional investor connections, as suggested by the positive coefficient on $\Delta REC \cdot CONNECTIONS$, but up to a certain level of connections, as suggested by the negative coefficient on $\Delta REC \cdot CONNECTIONS^2$. The last column of Table 8 presents results from interacting ΔREC with the terciles of connections. Market reaction becomes stronger with connections only in the bottom tercile. These results are consistent with our findings regarding earnings forecast accuracy and enhance our inference that sell-side analysts' connections with institutional investors influence the quality of their research output.[12]

8. Conclusion

A plethora of research papers examine the impact of sell-side financial analyst research on the investment community (Ramnath et al. 2008b; Bradshaw et al. 2017), while relatively few papers examine the role of buy-side analysts, working for institutional investors, the most important clients of the investment and boutique research firms that employ sell-side analysts (Brown et al. 2016). Most prior academic research regarding the interactions between these two sophisticated groups of market participants adopts the view that information flows from sell-side to buy-side analysts. We add to this research by considering the bilateral information flow and by specifically examining the impact of private buy-side analyst information on the quality of publicly available sell-side analyst research. Our evidence of a non-linear relation between connections with institutional investors and sell-side analyst earnings forecast accuracy is consistent with these connections enhancing the quality of sell-side analyst research output and, hence, the quality of information impounded in capital asset prices, although up to a point of diminishing returns.

[12] 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.

We recognize that buy-side analysts may invest effort in choosing the sell-side analysts whom they wish to engage, and this choice may depend on the accuracy of sell-side analyst earnings forecasts. At the same time, we hypothesize that the accuracy of sell-side analyst earnings forecasts depends on the intensity of their connections with buy-side analysts. Our tests effectively untangle this endogeneity and reinforce our inference that information flow from the buy-side to the sell-side enhances the quality of sell-side analyst research reports. To the best of our knowledge, ours is the first study to show that sell-side analysts learn about the stocks they follow from connections with their buy-side counterparts.

The idea of a well-connected sell-side analyst goes beyond connections with the buy-side. For example, the analyst has connections with industry contacts that enable interactions with suppliers and customers; with management of public and private companies to develop a pipeline of future coverage; with venture capitalists and private equity firms to help her build a pipeline of investment banking deals and future research coverage; and with the business press for general visibility. Our paper only examines connections with buy-side clients, thus leaving room for future research.

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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 $\frac{Variable_{aft}-\min(Variable_{ft})}{\max(Variable_{ft})-\min(Variable_{ft})}$)

$|FE_{aft}|$= absolute error in analyst *a*'s earliest forecast, F_{aft}, for firm *f*'s year *t* earnings issued during the 90 days post the announcement of firm *f*'s year *t-1* annual earnings, divided by the absolute value of actual earnings.

$ACCURACY_{aft}$ = the difference between the maximum absolute forecast error among all forecasts of firm *f*'s year *t* earnings during the 90 days post the announcement of firm *f*'s year *t*-1 annual earnings and analyst *a*'s absolute forecast error $|FE_{aft}|$, scaled by the range between the maximum and minimum, i.e., $\frac{\max(|FE_{ft}|)-|FE_{aft}|}{\max(|FE_{ft}|)-\min(|FE_{ft}|)}$. *ACCURACY* falls on a scale between zero (least accurate) and one (most accurate).

−Mean deflated $|FE_{aft}|$ = absolute forecasts error for analyst *a*, firm *f*, and year *t*, divided by the mean absolute forecast error among analysts forecasting annual earnings for the same firm-year, and multiplied by −1.

$CONNECTIONS_{aft}$ = analyst *a*'s weighted average number of connections with institutional investors holding *f* as of the date of F_{aft}. It is computed as the weighted number of stocks, other than *f*, covered by analyst *a* and held by institutions that invest in firm *f*, divided by the number of all institutions holding firm *f*, where the weight equals the value of the corresponding stock as a percentage of the value of the corresponding institution's total portfolio. Institutional holdings are from the calendar quarter preceding the date of F_{aft}, and analyst coverage of other companies is from the one year period that precedes the calendar quarter end used for institutional holding measurement.

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

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

$INDUSTRY\#_{at}$ = number of industries 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}.

$BSIZE_{at}$ = number of analysts employed by analyst *a*'s brokerage house or research firm in the year ending with the date of F_{aft}.

$DAYS_{aft}$ = 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}.

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

$CONNECTIONS_{aft}^{High\ Opp}$, $CONNECTIONS_{aft}^{Med\ Opp}$, and $CONNECTIONS_{aft}^{Low\ Opp}$ are measured the same way as the original *CONNECTIONS* variable except that they are constructed based on connections with subsets of institutions, i.e., high-, medium-, and low-opportunity institutions.

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

Opportunity based on portfolio turnover (Chen, Jegadeesh, and Wermers 2000): institutions with high (medium or low) turnover are classified as having high- (medium- or low-) opportunities.

Opportunity based on Petajisto's (2013): We start from Petajisto's five investment categories − stock pickers, concentrated stock pickers, moderately active stock pickers, closet indexers, and factor bettors − and classify the first three types of institutions as active stock selectors, and the rest as passive stock selectors. To create the five investment categories, we follow Petajisto's (2013, p82) two-way stratification approach whereby we rank all institutions first by Active Share and then by Tracking Error to create his five by five grid and follow his cell assignment to come with the five investment categories. Active Share measure is computed as in Cremers and Petajisto (2009). We use the CRSP stock universe as the benchmark market portfolio and measure active share for the portfolio of an institution as the sum of the absolute differences between the institution's portfolio weight and market portfolio weight in each stock. Tracking error is computed for each institution and each year as the standard deviation of residuals from a regression of monthly excess portfolio returns over the last 3 years on the excess returns on the CRSP market index. The monthly excess return is computed by subtracting the monthly risk-free return from the monthly portfolio return.

Variables in additional analyses

$CONNECTIONS_{time}$ = the first alternative measure of connections is defined the same way as our main *CONNECTIONS* variable except that, for each *a*,*i* connection around *f*, the weight is determined by the number of months *i* has held the corresponding stock of mutual interest (other than *f*) between *a* and *i*.

$CONNECTIONS_{stock\#}$ = the second alternative measure of connections modifies our primary CONNECTIONS measure by taking the straight average number of connections across institutional investors based on the number of *other stocks* held by each institutional investor.

$CONNECTIONS_{inst\#}$ = the third alternative measure, 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.

Mean deflated |*FE*| = absolute forecasts error for each analyst-firm-year divided by the mean absolute forecast error among analysts forecasting annual earnings for the same firm-year.

CONNECTIONS_resid = residual from regressing scaled *CONNECTIONS* on scaled *FIRM#*.

$CONNECTIONS^2$*_resid* = residual from regressing scaled $CONNECTIONS^2$ on scaled *FIRM#*.

Bottom *CONNECTIONS* Tercile residual = residual from regressing scaled *CONNECTIONS* in the bottom tercile on scaled *FIRM#*. Middle and Top *CONNECTIONS* Tercile residuals are defined analogously..

CONNECTED = 1 if an analyst has connections with an acquired or liquidated institution over the four quarters prior to the last form 13F filing date, and 0 otherwise. For each stock held by the aforementioned institution and followed by the analyst, we view an analyst as connected with this institution if she followed other stocks the institution held in the quarter the institution filed the last form 13F and in at least one of the previous three quarters. We consider an analyst as unconnected with the institution if she has not followed any other stock held by the institution over the last four quarters.

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.

CAR = cumulative abnormal return during the three days around the recommendation changes, where abnormal return equals the difference between stock return (RET) and value-weighted market return (VWRETD) per CRSP.

Figure 1 − Connections Variable for Analysts *a1* and *a2* regarding Firm-Year *f1,t*, where only Institutions *i1*, *i*2, and *i*3 Hold *f1*

Analysts following ***f1***

*a*1 follows ***f1***, *f*2, *f*3, *f*4, *f*5, *f*6, *f*7, *f*8, *f*9, *f10*

*a*2 follows ***f1***, *f12*, *f13*, *f14*, *f15*, *f16*, *f17*, *f18*, *f19*, *f20*

Portfolios of all institutions that invest in ***f1*** with portfolio weights for each security in parentheses

i1 holds ***f1***(*5%*), *f2*(*20%*), *f7*(*40%*), *f8*(*35%*)

i2 holds ***f1***(*20%*), *f3*(*45%*), *f5*(*15%*), *f6*(*20%*)

i3 holds ***f1***(*10%*), *f4*(*30%*), *f9*(*25%*), *f10*(*35%*)

Connections through firms beyond *f*1:

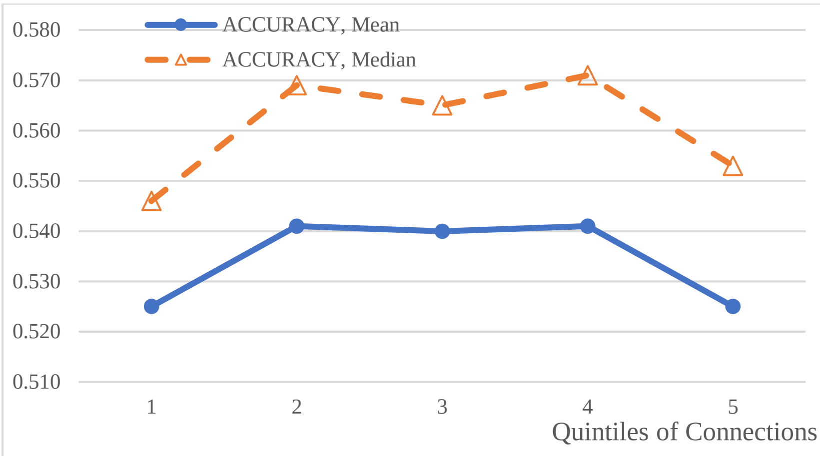
- Analyst *a1* is strongly connected with the three institutions holding *f1* during year *t*. *a1* is connected with *i1* through *f2*, *f7*, and *f8*, which constitute 95% of *i1*'s portfolio; with *i2* through *f3*, *f5*, and *f6*, which constitute 80% of *i2*'s portfolio; with *i3* through *f4*, *f9*, and *f10*, which constitute 90% of *i3*'s portfolio. The unscaled $\mathit{CONNECTIONS}_{f1,t}$ variable takes on a value of (0.95+0.80+0.90)/3 = 0.8833 for analyst *a1*.
- Analyst *a2* is not connected with the three institutions holding *f1* during year *t*. The $\mathit{CONNECTIONS}_{f1,t}$ variable takes on a value of (0+0+0)/3 = 0 for analyst *a2*, the minimum among both analysts.

Scaled $\mathit{CONNECTIONS}_{f1,t}$ variable = (unscaled CONNECTIONS – minimum Connections) / (maximum CONNECTIONS – minimum Connections):

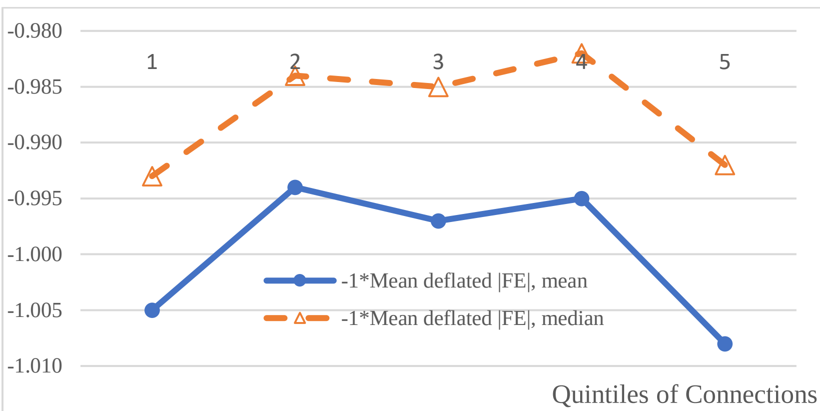
- For analyst *a1*: (0.8833 – 0) / (0.8833 – 0) = 1
- For analyst *a2*: (0 – 0) / (0.8833 – 0) = 0

Figure 2 − Earnings Forecast Accuracy by Quintiles of Connections

Panel A: Scaled forecast accuracy



Panel B: Unscaled forecast accuracy



Note:

Panel A depicts the average and median values of accuracy measured as *ACCURACY* by quintiles of connections measured as CONNECTIONS, both measrues are scaled to fall between 0 and 1 for the same firm-year.

Panel B depicts the average and median values of accuracy measured as −Mean deflated $|FE_{aft}|$ (unscaled) by quintiles of connections measured as CONNECTIONS (scaled to fall between 0 and 1 for the same firm-year).

All variables are defined in the Appendix.

Table 1 – Descriptive Statistics and Correlations

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

Variables	Mean	p25	p50	p75	Standard Deviation
|FE|	0.768	0.048	0.132	0.378	6.708
FE	0.421	-0.098	0.000	0.201	6.739
ACCURACY	0.535	0.226	0.561	0.862	0.353
CONNECTIONS (Unscaled)	0.013	0.004	0.008	0.016	0.015
$\text{CONNECTION}_{\text{Stock\#}}$ (Unscaled)	6.780	3.989	5997	8.466	4.540
CONNECTIONS	0.390	0.070	0.278	0.688	0.356
INST_OWNER#	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)	(11)
CONNECTIONS	(1)	1.000										
CONNECTIONS[2]	(2)	0.966	1.000									
		0.000										
ACCURACY	(3)	-0.005	-0.010	1.000								
		0.040	*0.000*									
Lagged ACCURACY	(4)	-0.010	-0.015	0.056	1.000							
		0.000	*0.000*	*0.000*								
FIRM#	(5)	0.510	0.487	0.006	-0.011	1.000						
		0.000	*0.000*	*0.011*	*0.000*							
INDUSTRY#	(6)	0.281	0.283	-0.009	-0.013	0.465	1.000					
		0.000	*0.000*	*0.000*	*0.000*	*0.000*						
FIRM_EXP	(7)	0.117	0.109	0.006	-0.002	0.134	0.066	1.000				
		0.000	*0.000*	*0.012*	*0.296*	*0.000*	*0.000*					
BSIZE	(8)	0.132	0.119	0.003	0.005	0.082	-0.040	0.029	1.000			
		0.000	*0.000*	*0.256*	*0.034*	*0.000*	*0.000*	*0.000*				
DAYS	(9)	0.089	0.105	-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*	*0.000*			
EPS_FREQ	(10)	-0.021	-0.023	-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*	*0.000*		
HORIZON	*(11)*	-0.049	-0.056	-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*	*0.000*	

Panel C. Correlation between connections and forecast accuracy by the range of connections and p-values

Range of connections	Correlation with *ACCURACY*
CONNECTIONS <= median	0.017 *0.000*
CONNECTIONS > median	-0.020 *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 by 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 *CONNECTIONS*, 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. Subscripts *a*, *f*, and *t* are suppressed for brevity.

Panel C reports correlation coefficients between *CONNECTIONS* and *ACCURACY* for the two ranges of *CONNECTIONS* (those below or at the median and those above the median). Both *CONNECTIONS* and *ACCURACY* are scaled among analysts making forecasts for the same firm-year

All variables are defined in the Appendix.

Table 2 – Earnings Forecast Accuracy and Connections

Variables	(1) Coeff (std. err.)	(2) Coeff (std. err.)	(3) Coeff (std. err.)	(4) Coeff (std. err.)
CONNECTIONS	5.516***	4.818***		
	(0.962)	(0.960)		
CONNECTIONS^2	-6.127***	-5.751***		
	(0.988)	(0.961)		
Break down of *CONNECTIONS*				
Bottom *CONNECTIONS* Tercile			13.908***	13.740***
			(3.338)	(3.283)
Middle *CONNECTIONS* Tercile			3.113***	2.557***
			(0.701)	(0.708)
Top *CONNECTIONS* Tercile			0.032	-0.246
			(0.329)	(0.337)
Lagged *ACCURACY*		5.210***		5.217***
		(0.263)		(0.264)
FIRM#		0.945***		0.851**
		(0.350)		(0.350)
INDUSTRY#		-1.409***		-1.461***
		(0.293)		(0.294)
FIRM_EXP		0.595**		0.604**
		(0.248)		(0.248)
BSIZE		-0.177		-0.138
		(0.291)		(0.292)
DAYS		-3.901***		-3.942***
		(0.257)		(0.257)
EPS_FREQ		0.033		0.044
		(0.259)		(0.259)
HORIZON		-11.000***		-11.000***
		(0.236)		(0.236)
Constant	53.249***	57.895***	53.151***	57.810***
	(1.005)	(1.017)	(1.005)	(1.017)
Year Fixed Effects	YES	YES	YES	YES
N	189,452	189,452	189,452	189,452
Adjusted R^2	0.25%	2.07%	0.25%	2.06%

This table examines the relation between sell-side analysts' forecast accuracy and their connections with institutional investors based on the following regressions:

$$ACCURACY_{aft} = \beta_0 + \beta_1 CONNECTIONS_{aft} + \beta_2 CONNECTIONS_{aft}^2 + \sum_m \beta_m Control_m + \varepsilon_{aft} \quad (1)$$

$$ACCURACY_{aft} = \beta_0 + \sum_{k=1}^{3} \beta_k^{Tercile} D_k^{Tercile} CONNECTIONS_{aft} + \sum_m \beta_m Control_m + \varepsilon_{aft} \quad (2)$$

$D_k^{Tercile}$ is an indicator variable equaling one for the kth $CONNECTIONS$ tercile (1=lowest and 3=highest) and zero otherwise.

All other 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 the 1%, 5%, and 10% significance level, respectively.

Table 3 – Earnings Forecast Accuracy and Connections Stratified by Opportunities for Analysts to Learn

Variables	(1)	(2)	(3)	(4)	(5)	(6)
	Based on transient, quasi-indexers, and dedicated investors Coeff (std. err.)		Based on turnover Coeff (std. err.)		Based on active/passive investors Coeff (std. err.)	
CONNECTIONS $^{High\ Opp}$	5.151***		4.041***		5.003***	
	(1.706)		(1.396)		(1.533)	
(*CONNECTIONS* $^{High\ Opp}$)^2	-4.414***		-4.776***		-4.687***	
	(1.605)		(1.306)		(1.431)	
CONNECTIONS $^{Med\ Opp}$	2.124*		0.553			
	(1.151)		(1.846)			
(*CONNECTIONS* $^{Med\ Opp}$)^2	-2.855**		-1.113			
	(1.143)		(1.680)			
CONNECTIONS $^{Low\ Opp}$	-2.036		1.436		0.396	
	(1.766)		(1.694)		(1.542)	
(*CONNECTIONS* $^{Low\ Opp}$)^2	1.536		-1.333		-1.601	
	(1.657)		(1.584)		(1.469)	
Break down of CONNECTIONS						
Bottom *CONNECTIONS* $^{High\ Opp}$ tercile		6.423**		7.113***		9.574***
		(3.210)		(2.760)		(2.946)
Middle *CONNECTIONS* $^{High\ Opp}$ tercile		2.596**		1.766**		1.914**
		(1.029)		(0.866)		(0.918)
Top *CONNECTIONS* $^{High\ Opp}$ tercile		1.081		-0.277		0.776
		(0.681)		(0.536)		(0.595)
Bottom *CONNECTIONS* $^{Med\ Opp}$ tercile		3.334		3.813		
		(10.292)		(3.891)		
Middle *CONNECTIONS* $^{Med\ Opp}$ tercile		0.339		0.247		
		(0.883)		(1.128)		
Top *CONNECTIONS* $^{Med\ Opp}$ tercile		-0.575		-0.363		
		(0.366)		(0.726)		
Bottom *CONNECTIONS* $^{Low\ Opp}$ tercile		7.338		6.839		7.499*
		(4.503)		(4.870)		(4.455)
Middle *CONNECTIONS* $^{Low\ Opp}$ tercile		-0.518		0.837		0.606
		(1.151)		(1.109)		(1.007)
Top *CONNECTIONS* $^{Low\ Opp}$ tercile		-0.336		0.291		-0.908
		(0.679)		(0.653)		(0.575)
Controls from Table 2	YES	YES	YES	YES	YES	YES
N	149,796	149,796	189,452	189,452	189,452	189,452
Year Fixed Effects	YES	YES	YES	YES	YES	YES
Adjusted R^2	2.20%	2.18%	2.08%	2.06%	2.07%	2.06%

This table examines whether the sensitivity of forecast accuracy to connections increases when sell-side analysts have greater opportunities to learn private information from their connections with institutional investors.

Results are from estimating the following regression model:

$ACCURACY_{aft} = \beta_0 + \beta_1 CONNECTIONS_{aft}^{High\ Opp} + \beta_2 (CONNECTIONS_{aft}^{High\ Opp})^2 + \beta_3 CONNECTIONS_{aft}^{Med\ Opp} + \beta_4 (CONNECTIONS_{aft}^{Med\ Opp})^2 + \beta_5 CONNECTIONS_{aft}^{Low\ Opp} + \beta_6 (CONNECTIONS_{aft}^{Low\ Opp})^2 + \sum_m \beta_m Control_m + \varepsilon_{aft}$ and a piecewise regressions where the terciles of $CONNECTIONS_{aft}^{High\ Opp}$, $CONNECTIONS_{aft}^{Med\ Opp}$ and $CONNECTIONS_{aft}^{Low\ Opp}$ are the main variables of interest.

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

In columns (1) and (2), 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 columns (3) and (4), we classify institutions with high (medium or low) turnover as high- (medium- or low-) opportunity ones.

In columns (5) and (6), we combine Petajisto's (2013) five investment categories to classify institutions as active stock selectors and passive stock selectors.

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 the 1%, 5%, and 10% significance level, respectively.

Table 4 – The Relation between Earnings Forecast Accuracy and Connections by Buy-side Analyst Demand

Variables	DEMAND =	(1) Coeff (std. err.) FIRM_EXP	(2) Coeff (std. err.) Lagged_*ACCURACY*
CONNECTIONS		6.108***	5.970***
		(1.369)	(1.792)
CONNECTIONS^2		-6.888***	-6.997***
		(1.385)	(1.871)
CONNECTIONS× DEMAND		-3.200	-2.170
		(2.456)	(2.711)
CONNECTIONS^2× DEMAND		2.798	2.352
		(2.388)	(2.791)
Lagged_*ACCURACY*		5.211***	5.382***
		(0.263)	(0.459)
FIRM#		0.941***	0.946***
		(0.350)	(0.349)
INDUSTRY#		-1.412***	-1.408***
		(0.293)	(0.293)
FIRM_EXP		1.057**	0.595**
		(0.449)	(0.248)
BSIZE		-0.174	-0.177
		(0.291)	(0.291)
DAYS		-3.902***	-3.901***
		(0.257)	(0.257)
EPS_FREQ		0.033	0.033
		(0.259)	(0.259)
HORIZON		-10.999***	-11.001***
		(0.236)	(0.236)
Constant		57.722***	57.803***
		(1.026)	(1.039)
N		189,452	189,452
Year Fixed Effects		YES	YES
Adjusted R^2		2.07%	2.07%

This table examines whether the sensitivity of forecast accuracy to connections increases with buy-side analyst demand for information. This table reports coefficient estimates from the following regressions.

$ACCURACY_{aft} = \beta_0 + \beta_1 CONNECTIONS_{aft} + \beta_2 CONNECTIONS^2_{aft} + \beta_3 DEMAND + \beta_4 DEMAND \times CONNECTIONS_{aft}$
$\beta_5 DEMAND \times CONNECTIONS^2_{aft} + \sum_m \beta_m Control_m + \varepsilon_{aft}$

We employ *FIRM_EXP* and Lagged_*ACCURACY* as proxies for buy-side analyst *DEMAND*.

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 the 1%, 5%, and 10% significance level, respectively.

Table 5 – Analysis of Exogenous Shocks to Connections

	(1)	(2)	(3)	(4)	(5)	(6)
	Dependent variable = ACCURACY			Dependent variable = −mean deflated |*FE*|		
Variables	Total sample	Lower connections subsample	Higher connections subsample	Total sample	Lower connections subsample	Higher connections subsample
	coeff (std. err.)	coeff (std. err.)	coeff (std. err.)	coeff (std. err.)	coeff (std. err.)	coeff (std. err.)
POST_EVENT	1.195	2.329**	-1.240	0.879	1.937**	-1.496
	(0.836)	(0.989)	(1.548)	(0.681)	(0.786)	(1.289)
CONNECTED	1.116	1.901**	-0.115	1.314**	1.766**	0.408
	(0.684)	(0.891)	(1.205)	(0.560)	(0.720)	(0.997)
CONNECTED×POST_EVENT	-1.310	-3.502***	1.922	-1.303	-2.747***	1.295
	(0.952)	(1.245)	(1.647)	(0.799)	(1.043)	(1.377)
Constant	50.327***	50.413***	50.165***	-101.277***	-102.007***	-99.915***
	(2.278)	(2.757)	(3.834)	(1.503)	(2.182)	(1.860)
N	40,372	20,773	19,599	52,369	26,954	25,415
Year Fixed Effects	YES	YES	YES	YES	YES	YES
Adjusted R^2	0.00%	0.00%	0.02%	-0.03%	-0.04%	-0.05%

This table presents analyses of changes in analyst forecast accuracy for the connected analysts relative to the unconnected analysts from pre to post the events. Events refer to the last dates when form 13Fs were filed by acquired or bankrupt institutions. Forecasts are those issued within two years of the events. The lower (higher) connection subsample includes forecasts by analysts whose scaled *CONNECTIONS* among all analysts following the same firm-year is at or below (above) the sample median of 0.2775.

Columns (1) to (3) estimate the regression below with scaled *ACCURACY* that falls between 0 and 1:

ACCURACY = *CONNECTED* + *POST_EVENT* + *CONNECTED* × *POST_EVENT* + ε_{aft}

Columns (4) to (6) estimate the regression below with unscaled −mean deflated |*FE*|:

−mean deflated |*FE*| = *CONNECTED* + *POST_EVENT* + *CONNECTED* × *POST_EVENT* + ε_{aft}

Mean deflated |*FE*| is measured the same as in the Appendix except the mean is for the same firm-year in the pre-event or post-event period.

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 the 1%, 5%, and 10% significance level, respectively.

Table 6 – Alternative Measures of Connections

Variables	(1)	(2)	(3)	(4)	(5)	(6)
	Measure 1 *$CONNECTIONS_{time}$* Coeff (std. err.)		Measure 2 *$CONNECTIONS_{stock\#}$* Coeff (std. err.)		Measure 3 *$CONNECTIONS_{inst\#}$* Coeff (std. err.)	
CONNECTIONS	6.547***		6.423***		5.932***	
	(0.949)		(1.047)		(0.984)	
CONNECTIONS2	-6.585***		-6.797***		-4.429***	
	(0.931)		-0.969		-0.947	
Break down of CONNECTIONS						
Bottom CONNECTIONS Tercile		4.367***		11.774***		2.611***
		(1.379)		(1.993)		(0.786)
Middle CONNECTIONS Tercile		1.737***		3.184***		2.299***
		(0.467)		(0.729)		(0.356)
Top CONNECTIONS Tercile		0.219		0.409		1.367***
		(0.301)		(0.485)		(0.304)
Control variables in Table 2	YES	YES	YES	YES	YES	YES
Year Fixed Effects	YES	YES	YES	YES	YES	YES
N	189,452	189,452	189,452	189,452	189,452	189,452
Adjusted R2	2.07%	2.05%	2.08%	2.07%	2.07%	2.07%

This table replicates the analyses from specifications (2) and (4) of Table 2 with three alternative measures of the *CONNECTIONS* variable: *$CONNECTIONS_{time}$*, *$CONNECTIONS_{stock\#}$*, and *$CONNECTIONS_{INST\#}$*. All variables are defined as in the Appendix. All variables are scaled to fall between 0 and 1 for the same firm-year and 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 the 1%, 5%, and 10% significance level, respectively.

Table 7 – Alternative Measures of Accuracy

Variables	(1)	(2)
	−Mean deflated |FE| as dependent variable	
	Coeff (std. err.)	
CONNECTIONS	3.428**	
	(1.659)	
CONNECTIONS^2	-4.916***	
	(1.714)	
Break down of *CONNECTIONS*		
Bottom *CONNECTIONS* Tercile		9.503*
		(4.936)
Middle *CONNECTIONS* Tercile		1.284
		(1.099)
Top *CONNECTIONS* Tercile		-0.958*
		(0.547)
Lagged *ACCURACY*	7.000***	7.007***
	(0.503)	(0.505)
FIRM#	1.360**	1.293**
	(0.554)	(0.552)
INDUSTRY#	-1.060**	-1.107**
	(0.466)	(0.472)
FIRM_EXP	1.623***	1.632***
	(0.369)	(0.369)
BSIZE	-0.176	-0.143
	(0.502)	(0.502)
DAYS	-4.189***	-4.228***
	(0.380)	(0.376)
EPS_FREQ	0.317	0.326
	(0.394)	(0.394)
HORIZON	-11.279***	-11.278***
	(0.338)	(0.339)
Constant	-94.806***	-94.829***
	(1.280)	(1.288)
Year Fixed Effects	YES	YES
N	189,452	189,452
Adjusted R^2	0.92%	0.92%
Dependent variable	−Mean deflated |FE|	

This table presents results when forecast accuracy is measured as (−1)×mean deflated |FE|.
All variables are defined in the Appendix. All independent variables are scaled to fall between 0 and 1 for the same firm-year and 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 the 1%, 5%, and 10% significance level, respectively.

Table 8 – Cumulative Abnormal Returns around Recommendation Changes by Connections

Variable	Quadratic form	Piecewise version
ΔREC	0.955***	0.948***
	(0.044)	(0.044)
ΔREC · CONNECTIONS	0.984***	
	(0.374)	
ΔREC · CONNECTIONS^2	-1.038***	
	(0.362)	
ΔREC · Bottom CONNECTIONS Tercile		1.463**
		(0.607)
ΔREC · Middle CONNECTIONS Tercile		0.220
		(0.143)
ΔREC · Top CONNECTIONS Tercile		-0.054
		(0.061)
CONNECTIONS	-0.693	
	(0.458)	
CONNECTIONS^2	0.749*	
	(0.448)	
Bottom CONNECTIONS Tercile		-0.984
		(0.712)
Middle CONNECTIONS Tercile		-0.234
		(0.168)
Top CONNECTIONS Tercile		0.061
		(0.071)
Constant	0.180	0.179
	(0.212)	(0.210)
N	11,550	11,550
Year Fixed Effects	YES	YES
Adjusted R^2	13.2%	13.2%

This table examines the impact that *CONNECTIONS* has on the relation between recommendation changes and the three-day cumulative abnormal returns around recommendation changes. The results are from estimating the regressions below:

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

$$CAR_{[-1,+1]} = \beta_0 + \beta_1 \Delta REC + \Delta REC \cdot \sum_{k=1}^{3} \beta_k^{Tercile} D_k^{Tercile} CONNECTIONS_{aft} + \sum_{k=1}^{3} \gamma_k^{Tercile} D_k^{Tercile} CONNECTIONS_{aft} + \varepsilon$$

$D_k^{Tercile}$ is an indicator variable equaling one for the kth $CONNECTIONS$ tercile (1=bottom, 2=middle, and 3=top) and zero otherwise.

All other variables are defined in the Appendix.

CONNECTIONS is scaled to fall between 0 and 1 for the same firm-year and 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 the 1%, 5%, and 10% significance level, respectively.