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Working Paper

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CFR Working Paper, No. 17-04

Provided in Cooperation with:

Centre for Financial Research (CFR), University of Cologne

Suggested Citation: Cici, Gjergji; Shane, Philip B.; Yang, Yanhua Sunny (2017) : Do connections with buy-side analysts inform sell-side analyst research?, CFR Working Paper, No. 17-04, University of Cologne, Centre for Financial Research (CFR), Cologne

This Version is available at:

<https://hdl.handle.net/10419/171277>

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centre for financial research
Look deeper

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

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Abstract: We hypothesize that connections with buy-side analysts provide a sell-side analyst with private information generated by the buy-side that enhances the quality of sell-side research. We proxy for these connections with the 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 the relative accuracy of her earnings forecasts. We find that such connections enhance the accuracy of earnings forecasts, but up to a point of diminishing returns. Additional tests rule out that the observed association is due to reverse causality.

First Draft: 3 August 2017

This Draft: 11 October 2017

* Cici is also a research fellow at the Centre for Financial Research at the University of Cologne. We appreciate comments from participants at workshops at Monash University and the University of Queensland. Shane gratefully acknowledges support from the Frank Wood Accounting Research Fund at the College of William and Mary.

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

1. Introduction

This paper investigates whether, through connections with buy-side analysts, sell-side analysts glean information that enhances the quality of their research reports. A vast literature studies the characteristics of the research produced by sell-side analysts and its impact on stock prices, arguably through its impact on institutional investor decisions.¹ This research generally assumes—and indeed some studies show—that the flow of information between sell-side and buy-side analysts is one-directional; i.e., information supplied by the sell-side flows to institutional investors, 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 outputs from sell-side analyst research reports?

We hypothesize that interactions with buy-side analysts provide sell-side analysts with private information generated by the buy-side that enhances the quality of sell-side research. Although buy-side analysts' research is proprietary and therefore not publicly available to other market participants, there are two factors that make sell-side analysts privy to at least part of this information.

First, learning what other buy-side analysts think and sharing that with institutional clients is an implicit service expected of sell-side analysts. Brown, Call, Clement, & Sharp (2016) surveyed and interviewed buy-side analysts who indicated that their demand for sell-side

¹ Recent papers of this ilk include Bradley, Gokkaya, & Liu (2017), Merkley, Michaely, & Pacelli (2017), Horton, Serafeim, & Wu (2017), Bernhardt, Wan, & Zhao (2016), and Franck & Kerl (2013). Earlier papers providing thorough reviews of research with that perspective include Ramnath, Rock, & Shane (2008a, 2008b) and Bradshaw (2011).

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 whose securities represent important components of fund manager portfolios;² (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 investment firms.

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.

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, and broker votes are in turn driven by personalized services that sell-side analysts provide for institutional clients such as high-touch meetings, phone calls, whitepapers, and concierge services that put buy-side analysts in touch with management of the firms of interest to them (Maber, Groysberg, & Healy 2015). Thus, analysts have a strong incentive to meet their institutional clients' needs by providing high-touch services, which necessitate regular communication with current or potential institutional investor clients. These communications provide a window through which sell-side analysts can infer buy-side private information about covered firms. For example, some clients might follow up with a sell-side analyst to ask for more color following her recently issued research report, updated earnings' estimates, or change in a stock recommendation, while other clients might want to ask questions related to company-specific or industry-specific

² A recent survey indicates that one-third of the portion of commission payments used to compensate brokerage firms rewards sell-side analysts for corporate access, including facilitation of meetings between buy-side analysts and company management ... (Greenwich Associates, 2010). Another survey finds that CEOs, CFOs, and investor relation professionals consider facilitating meetings with the buy-side as the most critical aspect of the investor relations function (Thomson Reuters 2009 IR Best Practices).

developments, all of which provide a sell-side analyst with opportunities to uncover and put together various pieces of information produced by various institutional investors.

As rational economic agents, sell-side analysts have strong incentives to use the private information they acquire from their interactions with buy-side analysts to their advantage. Information gleaned from communications with buy-side analysts can provide important input to sell-side analyst research and, ultimately, enhance the quality of the sell-side analyst research report. 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).” By employing the private information gleaned from buy-side analysts and using it to enhance the quality of their whitepapers and research reports, sell-side analysts can do a better job articulating a deep understanding of the value-relevant affairs of the firms s/he covers.³ This in turn would generate more interest among institutional clients and consequently more brokerage votes and higher compensation for the sell-side analysts.

The most salient component of the sell-side analyst research report is the analyst’s forecast of the followed firm’s earnings for the remaining quarters of the current fiscal year. We use these earnings forecasts to proxy for the quality of the sell-side analyst’s research report, and their accuracy determines the dependent variable in our study.⁴ We measure accuracy at the analyst-firm-year level and refer to this dependent variable as *ACCURACY*. In measuring this

³According to Maber, et al. (2015), “whitepapers, despite being non-timely and vulnerable to significant public-goods problems, are an important vehicle through which analysts signal their industry knowledge and build and sustain their franchise.” Maber et al. find that publication of whitepapers explains more variation in broker votes than any other aspect of sell-side analyst output.

⁴ Earnings forecasts represent the most prevalent form of research output, and information in earnings forecasts affects the quality of other research outputs: i.e., analysts’ stock recommendations (e.g., Ertimur, Sunder, & Sunder 2007) and target price forecasts (e.g., Gleason, Johnson, and Li 2013). Thus, we believe earnings forecast accuracy is a reasonable proxy for the overall quality of the sell-side analyst research report. Second, evaluating the ability to forecast earnings is straightforward since the forecast is always compared against a deterministic benchmark, i.e., actual earnings. The same cannot be said for stock recommendations where one has to choose a performance evaluation model and horizon, or for the target price forecasts where the benchmark, the actual price at the end of the 12-month period, might not correctly reflect the fair value of the stock due to volatile market conditions.

variable, we hold constant the firm and year and measure analyst a 's accuracy relative to all other analysts following firm f 's stock in year t . Our multivariate regressions control for other factors known from prior literature to affect analyst earnings forecast accuracy.

Key to our identification approach is an independent variable, which measures the strength of holdings-based connections between sell-side analysts and institutional investors. Given that higher institutional ownership gives rise to more accurate earnings forecasts by sell-side analysts due to a higher demand for more accurate research (see e.g., Frankel, Kothari, and Weber, 2006; Ljungqvist, Marston, Starks, Wei, and Yan (2007); and Wong (2016)), we construct our connections measure to bypass the confounding effect of institutional ownership on forecast accuracy. Specifically, for each stock, f , covered by sell-side analyst a , our measure of connections does not rely on the number of institutions that hold f . Instead, if f is held in the portfolio of institutional investor, i during year t , the number of *other* stocks followed by a and held by i is our proxy for the strength of the connection between a and i during year t .⁵ The average of this number, across all institutions holding f , is our key independent variable, $CONNECTIONS_{aft}$. We expect that the more connections an analyst has with institutional investors, the greater the likelihood of communications with these investors and the greater the opportunity for the sell-side analyst to decipher the private information possessed by institutional investors. A significantly positive relation between $ACCURACY_{aft}$ and $CONNECTIONS_{aft}$ supports the hypothesis that sell-side analysts learn from their interactions with their buy-side clients and that learning process enhances the quality of the sell-side analyst's research reports.

As explained in Section 2 below, we hypothesize and find that the relation between $ACCURACY_{aft}$ and $CONNECTIONS_{aft}$ weakens as $CONNECTIONS_{aft}$ reaches a point of

⁵ Throughout this paper we refer to the issuing firm and the firm's stock with the same subscript, f . We use the subscript, i , to refer to the institutional investors that employ buy-side analysts. The subscript, a , refers to the sell-side analyst, the subscript, t , refers to the year, and our analysis is based on analyst-firm-years, aft .

diminishing returns. This result 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 increased interactions with institutional clients associated with high-touch services come with opportunity costs from not being able to spend time on other aspects of their sell-side analyst jobs.

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 discussion above suggests an endogenous relation between *ACCURACY* and *CONNECTIONS*, whereby buy-side analysts select sell-side analysts who can provide insights that inform the buy-side analysts' research reports to their fund managers, and that selection probably favors sell-side analysts who have already proven themselves in ways that might include forecast accuracy. To support our inferences, we need to address this endogeneity issue.

We address the endogeneity issue in four ways. First, we examine whether the strength of the relation between *ACCURACY* and *CONNECTIONS* depends on the amount of private information that buy-side analysts possess. A stronger positive relation between *ACCURACY* and *CONNECTIONS* for buy-side analysts with more private information validates the inference that sell-side analysts obtain forecast accuracy-enhancing information from buy-side analysts. On the other hand, stronger relation with *CONNECTIONS* for buy-side analysts with less private information would support the inference that buy-side analyst selection of already-informed and accurate sell-side analysts drives the effect we document. Our proxy for the degree to which buy-side analysts possess private information measures the degree to which institutional investors rely on private versus public information to support their trading decisions (Kacperczyk & Seru,

2007). Our results support our hypotheses that the relation between *ACCURACY* and *CONNECTIONS* strengthens with increased reliance on private information by connected institutional investors.

Second, we examine the implications of an exogenous shock hypothesized to increase sell-side analyst demand for information from buy-side analysts. The shock we exploit appears during 2001-2003 when: (i) Regulation Fair Disclosure (Reg FD) came into effect constraining both sell-side and buy-side analyst ability to obtain private information from management of the firms they follow; and (ii) the Global Analyst Research Settlement (GARS) further constrained sell-side analysts' ability to obtain private information from investment bankers in their own firms. If buy-side selection of accurate sell-side analysts drives the relation between *ACCURACY* and *CONNECTIONS*, we see no reason for the relation to change in the wake of the 2001-2003 regulatory period. In fact, the regulation potentially eliminates sell-side ability to provide buy-side analysts with access to private information held by management of the covered firm, and this is a key reason for buy-side interest in connecting with sell-side analysts (Brown et al. 2016). In addition, GARS eliminates communications between sell-side (not buy-side) analysts and investment bankers within their own firms. This increases the relative importance of buy-side analysts as a source of private information for sell-side analysts. Consistent with our main hypothesis that connections with buy-side analysts enhance sell-side analyst earnings forecast accuracy, we find an insignificant relation between *ACCURACY* and *CONNECTIONS* in the pre-2001 period and a significantly positive relation in the post-2003 period when sell-side analysts have more reason to seek private information from buy-side analysts.

Third, we examine factors hypothesized to increase buy-side analyst demand for connections with sell-side analysts (i.e., past sell-side forecast accuracy and sell-side analyst

prior experience following the covered firm), and we find no evidence to support the inference that increased buy-side analyst demand strengthens the relation between *ACCURACY* and *CONNECTIONS* documented in our primary hypothesis tests.

Finally, in additional analysis, we find that our main finding is robust in an analysis that restricts the sample to 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. Also in additional analyses our inferences remain unchanged when we use two alternative proxies for our *CONNECTIONS* variable, thus strengthening our confidence in the construct validity of our measure of connectedness.

This paper contributes to the literature in two important ways. First, we contribute to the stream of research investigating the factors affecting sell-side analyst earnings forecast accuracy. Prior research essentially identifies three factors: (i) incentives (e.g., Michail, Walther, & Willis 1999), (ii) ability (e.g., Jacob, Lys, & Neale 1999; Clement 1999), and (iii) resources (e.g., Jacob, Rock, & Weber 2008). We introduce a fourth factor; i.e., accuracy-enhancing information obtained through interactions with buy-side analysts. Second, and more importantly, 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.

The rest of this paper is organized as follows. The next section reviews the literature and presents our hypotheses. We discuss our research design in Section 3 and in Section 4 present our sample selection procedure. Section 5 discusses the results of our hypotheses tests. Section 6 presents additional analyses, and Section 7 concludes.

2. Hypotheses and Literature Review

Main hypothesis

The Brown et al. (2016) survey suggests that buy-side analysts rely on sell-side analysts, primarily, for industry-related information, access to the management of the firms the sell-side analysts cover, and insight into the perspectives of buy-side analysts working for competing institutional investor firms. Thus, it appears that what buy-side analysts gain from their interactions with sell-side analysts informs a thorough buy-side analyst research process that finds little use for the stock recommendations produced by sell-side analysts. In spite of the fact that they appear to rely primarily on their own research, buy-side analysts regularly interact with sell-side analysts. When Brown et al. asked buy-side analysts how often they have private communication with sell-side analysts, they found that only 4% of their respondents said “never,” and 55% said more than 23 times per year. Maber, Groysberg, & Healy 2015 analysis of sell-side analysts at a mid-size investment banking firm suggest that these interactions could be even more substantial when viewed from the perspective of the sell-side analysts: 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. We expect that, in the course of these interactions, sell-side analysts glean information useful for their own stock recommendations and earnings forecasts.

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, which in turn improves the quality of sell-side research. Given the results of the Brown et al. (2016) survey indicating that buy-side analysts have little, if any, interest in the stock recommendations of sell-side analysts, we expect institutional investors to

have information that does not overlap with information sell-side analysts possess. Bushee, et al. (2016) 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 their 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 investors' private information and does not violate "Reg FD" (Solomon & Soltes, 2015).

Sell-side analysts could acquire information from their institutional clients informally. 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. 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."

As described in Section 1, we develop a novel approach to measure the quantity of private information that sell-side analysts acquire from the interactions with their current or

potential buy-side clients. Our measure is specific to each sell-side analyst, a , and each stock, f , that analyst a follows in year t . For each stock, f , followed by sell-side analyst, a , and held in the portfolio of institutional investor, i during year t , the number of other stocks followed by a and held by i is our proxy for the strength of the connection between a and i during year t . The average of this number, across all institutions holding f , is our key independent variable, $CONNECTIONS_{aft}$. The premise of our analysis is that the more connections an analyst has with institutional investors, the greater the likelihood of communications with these investors and the greater the opportunity for the sell-side analyst to learn and decipher the private information possessed by institutional investors.

While sell-side analysts potentially learn more by talking more with buy-side analysts, it's 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, Lys, & Neale 1999; Myring & Wrege 2011; Pelletier 2015). We expect that for each sell-side analyst there is an optimal allocation of her efforts between conducting research and providing services for her institutional clients. Beyond that point, extra 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 each sell-side analyst to have an optimal number of buy-side analysts from which s/he can glean incremental private information about any given stock. Beyond that number, we expect

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

H1: $ACCURACY_{aft}$ increases with $CONNECTIONS_{aft}$ up to some point where the rate of increase subsides.

Additional hypotheses

Our $CONNECTIONS$ variable proxies for the flow of useful information from buy-side to sell-side analysts, where more information increases the quality of the sell-side analyst research proxied by greater forecast accuracy. Given evidence of the relation hypothesized in H1, we test additional hypotheses that identify factors expected to strengthen the relation between $ACCURACY$ to $CONNECTIONS$. We develop these additional hypotheses to provide more confidence in the validity of the relation we observe in tests of H1 and to address the endogeneity issue discussed in Section 1. 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. 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 $ACCURACY_{aft}$ to $CONNECTIONS_{aft}$ increases with the opportunity for sell-side analysts to learn from buy-side analysts.

To identify institutional investors that produce more versus less private information, we draw on previous research. In particular, we rely on Kacperczyk & Seru (2007), who document that institutions less reliant on public information produce more private information, which results in superior investment performance relative to institutions that rely more on public information.

Since October 2000, Reg. FD has prohibited transmission of private information to sell-side analysts from management of the firms they follow, and since April 2003, the Global Analyst Research Settlement (GARS) between the SEC and the 10 largest investment banks, presumably employing the largest number of sell-side analysts, has prohibited sell-side analysts from discussing the prospects of the firms they cover with the investment bankers within their own firms. We expect that these exogenous shocks considerably strengthened sell-side analyst incentives to obtain private information through discussions with buy-side analysts. These incentives emerged in a new environment where on one hand sell-side analysts were cut off from private information previously obtained from management of the firms they followed and investment bankers within their own firms, and on the other hand sell-side analysts came under increased pressure to generate commission revenue for their firms. If the relation we observe in tests of H1 above emanates from buy-side demand for connections with already-accurate sell-side analysts, then we do not expect the relation to strengthen during the years after GARS. Neither Reg FD nor GARS affected buy-side analyst discussions with fund managers within their own firms, but these regulations did affect discussions between sell-side analysts and

investment bankers within their firms. Furthermore, Reg FD removed one of the buy side's benefits from interacting with sell-side analysts; i.e., obtaining firm-specific private information from the firm's management. This leads us to our third hypothesis:

H3: The sensitivity of *ACCURACY* to *CONNECTIONS* increases in the wake of Reg FD and GARS.

On the other hand, if buy-side analysts' demand for information from already-accurate sell-side analysts drives the relation between *ACCURACY* and *CONNECTIONS*, then we expect the relation to vary with factors hypothesized to reflect future forecast accuracy. This leads us to our fourth hypothesis:

H4: The sensitivity of *ACCURACY* to *CONNECTIONS* increases with increases in buy-side analyst demand for connections with sell-side analysts.

We test H4 with reference to two factors hypothesized to predict sell-side analyst forecast accuracy, which in turn could drive buy-side analyst demand for connections. Prior research finds strong relations between sell-side analyst forecast accuracy and: (i) past accuracy (Brown 2001); and (2) firm-specific experience (Clement 1999). 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. Thus, if buy-side demand drives the relation between *ACCURACY* and *CONNECTIONS*, then we expect to find evidence supporting H4; i.e., we expect the relation to strengthen with sell-side analyst past accuracy and firm-specific experience.

3. Research design

3.1 Models for testing H1

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 a certain optimal 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:

$$ACCURACY_{aft} = \frac{\max(|FE_{ft}|) - |FE_{aft}|}{\max(|FE_{ft}|) - \min(|FE_{ft}|)}$$

$\max(|FE_{ft}|)$ = the maximum absolute forecast error among all analysts issuing forecasts of firm f 's year t earnings during the first 90 days following the firm's year $t-1$ earnings announcement.⁶

$\min(|FE_{ft}|)$ = the minimum absolute forecast error from the distribution generating $\max(|FE_{ft}|)$.

$FE_{aft} = F_{aft} - A_{ft}$ = the error in analyst a 's most recent I/B/E/S-provided forecast, F_{aft} , of firm f 's year t earnings during the first 90 days of the firm's fiscal year t .

A_{ft} is firm f 's I/B/E/S-provided actual year t earnings.

$CONNECTIONS_{aft} = \frac{\sum_i CONNECTIONS_{aft}^i}{INST_OWNER\#_{ft}}$ = the average number of connections between analyst a and the institutions holding stock f , prior to analyst a 's forecast of f 's year t earnings.

$CONNECTIONS_{aft}^i$ = the number of stocks, excluding stock f , covered by analyst a and held by institution i , which invests in stock f , calculated using data prior to the time of F_{aft} .⁷

$INST_OWNER\#_{ft}$ = the number of institutional investors holding stock f .

⁶ If an analyst issues more than one forecast during the 90-day period, we retain only the earliest forecast. The absolute forecast error is scaled by actual earnings.

⁷ Institutional holdings used to construct $CONNECTIONS_{aft}$ are from the calendar quarter preceding analyst a 's forecast of firm f 's year t earnings and analyst coverage of other companies is from the one-year period preceding the calendar quarter end used to measure institutional holdings.

Variables which control for factors that could affect accuracy of earnings forecasts generated by analysts include:

$ACCURACY_{af,t-1}$ = lagged value of the forecast accuracy measure defined above.

$FIRM\#_t^a$ = 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 analyst a .

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 .

All control variables are scaled to fall between 0 and 1 based on the equation below:

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

To test H1, we also employ a piecewise regression in model (2) below, which allows us to calculate the sensitivity of $ACCURACY$ to $CONNECTIONS$ in each $CONNECTIONS$ tercile.⁸

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

where $D_k^{Tercile}$ is a (1/0) indicator variable equaling one for the k^{th} $CONNECTIONS$ tercile

(1=lowest and 3=highest) and zero otherwise. Under H1, we expect $\beta_1^{Tercile} > \beta_3^{Tercile}$.

⁸ Tercile cut-off points are derived from the distribution of $CONNECTIONS_{aft}$.

3.2 Model for testing H2

If the sensitivity of *ACCURACY* to *CONNECTIONS* increases when buy-side analysts produce greater amounts of private information, we expect $\beta_1 > \beta_5$ in the regression model (3) below. On the other hand, if buy-side analyst selection of already-accurate sell-side analysts drives the relation between *ACCURACY* and *CONNECTIONS* then we expect the sensitivity of *ACCURACY* to *CONNECTIONS* to decrease when buy-side analysts produce more of their own private information, and we expect $\beta_1 < \beta_5$ in the regression model (3) below.

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

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

$$CONNECTIONS_{aft}^{High\ Opp} = \frac{\sum_i CONNECTIONS_{aft}^i \times D_{High\ Opp}^i}{INST_OWNER\#_{ft}}$$

where $D_{High\ Opp}^i$ denotes an institutional investor from which sell-side analysts have more opportunities to acquire useful information. $INST_OWNER\#_{ft}$ denotes the number of institutional investors holding stock f at time t . $CONNECTIONS_{aft}^{Med\ Opp}$ and $CONNECTIONS_{aft}^{Low\ Opp}$ are constructed in a similar fashion for medium and low opportunity institutional investors. Note that normalizing the high/medium/low opportunity connections variables by $INST_OWNER\#_{ft}$ ensures that they add up to $CONNECTIONS_{aft}$.

As described when we introduced H3, our approach to identifying high, medium, and low opportunity institutional investors depends on an institution's reliance on public information (RPI). Following Kacperczyk & Seru (2007), we construct RPI for each institution within each

firm-year, as the R^2 from an institution-level regression of changes in the number of shares held in a given stock by a given institution on lagged changes in mean analyst recommendations. All institutional investors are ranked each quarter by their RPI into terciles. Institutions in the lowest (highest) RPI tercile are considered as relying the least (most) on public information and classified as high- (low-) opportunity institutions.

3.3 Model for testing H3 and H4

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.

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

where *DEMAND* is a variable reflecting demand by sell-side (buy-side) analysts for information from the buy-side (sell-side) analysts with whom they are connected. The indicator variable, *POST_GS_t*, proxies for demand from the sell-side. *POST_GS_t* equals 1 for forecasts issued after 2003, and 0 for forecasts issued before 2001.⁹ The variables, *FIRM_EXP_{aft}* and *ACCURACY_{af,t-1}*, proxy for demand from the buy-side. *FIRM_EXP_{aft}* equals the number of years in which analyst *a* issued one-year ahead earnings forecasts for stock *f* up to the current year. *ACCURACY_{af,t-1}* equals the lagged value of the forecast accuracy measure defined above.

⁹ We exclude the regulatory period years, 2001-2003, from this analysis. Regulation Fair Disclosure was promulgated in October of 2000, the Sarbanes Oxley Act took effect in July of 2002, and the Global Analyst Research Settlement occurred in April of 2003.

If sell-side analyst demand drives the relation between *ACCURACY* and *CONNECTIONS* in model (4) above, then we expect $\beta_4 > 0$, when the demand proxy is $POST_GS_t$. Similarly, if buy-side demand drives the relation between *ACCURACY* and *CONNECTIONS*, then we expect $\beta_4 > 0$ when the demand proxy is either $FIRM_EXP_{aft}$ or $ACCURACY_{af,t-1}$.

4 Sample selection

Our sample contains 137,835 analyst-firm-year observations from 1995 to 2012, including 3,980 unique firms and 7,615 unique analysts. We employ the following sample construction steps. We require each observation to have (from I/B/E/S): a one-year ahead EPS forecast issued between 1985 and 2012 and during the first 90 days following the prior year's earnings announcement, and an identifier that allows linkage to the CRSP database. If more than one analyst-firm-year observation exists in the same 90-day period, we keep only the earliest one. We also eliminate all firm-year observations with zero or missing institutional holdings data in the Thomson Reuters 13F database. We impose additional filters associated with data requirements needed to measure analyst characteristic control variables, such as the lagged forecast error. Finally, we require that each firm-year observation has coverage by more than one analyst. Our sample period begins in 1995, the first year when we can construct the RPI measure of Kacperczyk & Seru (2007) and ends in 2012 due to a warning from WRDS documenting severe coverage problems with Thomson Reuters 13F database after 2012.¹⁰ Nonetheless, in unreported supplemental tests, we extended the sample period to 2015 and our results and inferences remain robust.

¹⁰ The RPI measure is constructed for each institutions by regressing changes in the number of shares held in a given stock on lagged changes in mean analyst recommendations. The mean analyst recommendations data in IBES starts in the last quarter of 1993, but because four lags of changes in mean recommendations are needed, 1995 is the first year for which RPI can be constructed for each institutional investor.

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. Panel A shows that the distribution of absolute analyst-firm-year forecast error has a mean (median) of 0.795 (0.146). The *ACCURACY* variable used in our hypotheses tests scales $|FE_{aft}|$ to fall in a range from 0 to 1. The mean (median) of *ACCURACY* is 0.528 (0.550). Scaling all independent variables in this manner maintains the relative values of the variable, while allowing comparison across regression coefficients (Clement & Tse, 2005).

The *CONNECTIONS* variable indicates that, on average, analysts have 6.7 connections per institution holding a given stock followed by the analyst. This means that, on average, an institution holding a given stock followed by an analyst also holds, on average, 6.7 other stocks followed by that analyst, while the average analyst follows 16.7 firms. We attribute this seemingly high overlap between analyst coverage and institutional holding to the relatively broad based and diversified portfolios of stocks held by the average institutional investor. In fact, the mean (median) number of institutional investors holding a particular stock is 293 (213).

Panel A also shows that, in an average analyst-firm-year, a given analyst follows stocks in 3.8 different industries, has about 5 years of experience forecasting the earnings of each stock that she covers, works for a brokerage house or research firm employing 67 analysts, issues forecasts 4.6 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 time of F_{aft} for the same firm, and has a forecast horizon until the end of the fiscal year averaging 310 days. Panel A also shows the averages of the number of connections that the average analyst has with institutions in the

three RPI categories proxying for the opportunity to glean useful information from institutional investors.

Table 1 Panel B shows the univariate correlations among the variables used to test our hypotheses. Consistent with prior literature, our measure of relative within firm-year *ACCURACY* is significantly positively correlated with the prior year's *ACCURACY*, the analyst's firm-specific experience, and brokerage house size; 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 not significantly correlated with *CONNECTIONS*, which is consistent with a non-linear relation requiring a quadratic term in our multiple regression analysis. Both *CONNECTIONS* and analyst forecast *ACCURACY* are significantly greater after the global settlement.

5.2 Test of H1

Table 2 displays the results of our test of H1, which predicts that the accuracy of analyst a 's forecast of firm f 's earnings improves, to a point of diminishing returns, with the degree of connectedness between the analyst and institutional investors who hold stock f in their portfolios. For ease of presentation, the dependent variable (and, thus, each coefficient) is multiplied by 100. The significantly positive coefficient on the *CONNECTIONS* variable and the significantly negative coefficient on the square of the *CONNECTIONS* variable confirm H1's prediction. The p-values being less than 0.01 and the magnitudes of the coefficients suggest that they are statistically, as well as economically, significant. The economic significance is, perhaps, more apparent in column (4) where we perform a piecewise estimation of *CONNECTIONS* terciles.

The coefficient on *CONNECTIONS* in the lowest tercile of the variable is 9.464, which means that a one-standard deviation change in *CONNECTIONS* (untabulated, at 0.345) is associated with a 3.265% (0.345×9.464) change in the *ACCURACY* dependent variable. That represents 6.2% of mean *ACCURACY* ($0.0327/0.528$). The less significant coefficient on *CONNECTIONS* in the second tercile and the insignificant coefficient in the highest tercile indicate that, once the analyst's average amount of connections per institution reaches an optimum level, diminishing returns to additional connections become apparent. The coefficient on *CONNECTIONS* in the lowest terciles is significantly larger than that in the highest terciles, with a p-value (untabulated) of less than 0.001.

With reference to the control variables in model (1), the results in Table 2 indicate that *ACCURACY* significantly improves with the number of firms the analyst covers during the year prior to the forecast date and with the prior year's *ACCURACY* (i.e., the *ACCURACY* variable is relatively stable from one year to the next). The coefficient on the number of firms covered is opposite to results in prior research but should be interpreted with caution because of the mechanically very high univariate correlation between *CONNECTIONS* and coverage.¹¹ *ACCURACY* significantly declines with the number of industries the analyst follows, the number of days between the forecast date and the date of the most recent prior forecast, and the number of days between the forecast date and the end of the firm's fiscal year. These results are consistent with prior literature.

5.3 Test of H2

¹¹ When excluding *CONNECTIONS* and its squared term, the coefficient on the number of firms covered becomes insignificant.

Panel A of Table 3 displays the results of our tests of H2, which predicts that the benefits to sell-side analysts of connections with buy-side analysts intensify when the buy-side analysts' institutional investment firms have more private information; i.e., when greater opportunities for sell-side analysts to learn from buy-side analysts exist. As described above, our proxy for opportunity is the institutional investor's RPI, measured in the manner described in Kacperczyk & Seru, (2007). We divide the observations into three terciles (high, medium, and low opportunity) and estimate the coefficients of *CONNECTIONS* and its quadratic terms within each tercile. We predict that connections with high opportunity institutions reap greater rewards in terms of improved forecast accuracy than connections with medium and low opportunity institutions.

The results in Panel A of Table 3 are consistent with our prediction; i.e., the strength of the relation between *ACCURACY* and *CONNECTIONS* increases when analysts are connected with high opportunity institutions. The difference between the coefficient on connections with highest opportunity institutions and that on connections with lowest opportunity institutions is significant at a p-value of 0.052 (untabulated). The results also support our primary hypothesis that connections with buy-side analysts inform sell-side analyst research and improve sell-side analyst forecast accuracy. Furthermore, these results relieve the endogeneity concern that institutions choose to connect more with already-accurate analysts. If this was happening, *low opportunity* institutions would be more likely to have such a preference given that they produce less of their own information and instead rely on public sources of information such as the research output produced by analysts. Such a preference suggests a stronger relation between connections with *low opportunity* institutions and *ACCURACY*, which is opposite to what we find.

In Panel B of Table 3, we provide an assessment of economic significance for our main effect by estimating Models (1) and (2) for the subsample of observations whose connections with low *RPI* institutions are in the bottom tercile of each firm-year group. Because Panel A of Table 3 indicates that the results concentrate in low *RPI* institutions and the relation between connections and accuracy is nonlinear, we expect larger than average economic significance for this subsample. For this subsample, the untabulated mean, median and standard deviation of *CONNECTIONS* with low *RPI* institutions ($CONNECTIONS^{High\ Opp}$) are 0.517, 0.559, and 0.423, respectively. From Column 2, the coefficient on $CONNECTIONS^{High\ Opp}$ in the lowest tercile of the variable is 38.567, which means that a one-standard deviation change in $CONNECTIONS^{High\ Opp}$ is associated with a 16.31% (0.423×38.567) change in the *ACCURACY* dependent variable, representing 30.9% of mean *ACCURACY* ($0.1631/0.528$).

5.4 Test of H3

Table 4 displays the results of our test of H3, which predicts that variables proxying for the demand for information by sell-side analysts increases the impact of *CONNECTIONS* on *ACCURACY*.¹² The sell-side demand proxy is a dummy variable indicating whether the analyst-firm-year observation occurs after 2003; i.e., after Reg. FD and GARS constrained sell-side analysts' private communications with investment bankers in their own investment firms and with management of the firms the analysts follow. H3 predicts that after these changes in the information environment, sell-side analysts' connections with buy-side analysts are more accuracy-enhancing. Observations during the years of the changing regulatory environment (2001-2003) are omitted from this analysis.

¹² In tables 4 and 5, in the interest of brevity we report results only based on the quadratic specification.

Table 4 shows that the interaction *POST_GS* and *CONNECTIONS* is positive and significant. This supports the prediction from H3 that the regulatory shocks increased the impact of connections with buy-side analysts on sell-side analysts' forecast accuracy. In fact, the coefficients suggest that the *POST_GS* observations drive the results discussed in relation to Table 2 above. Overall, this result suggests that sell-side demand for information from buy-side analysts intensifies the importance of connections that inform sell-side analyst research and improve forecast accuracy.

5.5 Test of H4

Table 5 displays results from tests of H4, which predicts that variables proxying for the demand for information by buy-side analysts strengthens the relation between *CONNECTIONS* and *ACCURACY*. We proxy for this demand with (1) sell-side analyst experience in forecasting earnings of the subject firm and (2) lagged sell-side analyst forecast accuracy for the same firm.

In Table 5 we find no evidence that our proxies for buy-side interest in connecting with already-accurate sell-side analysts strengthen the relation between *ACCURACY* and *CONNECTIONS*. 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.

Overall, we believe that our tests of H2, H3, and H4 provide strong 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 Analyses

6.1 Another Test of Reverse Causality

As described in Section 1, a concern is that rather than sell-side analyst forecast accuracy improving due to connections with information-laden buy-side analysts, less information-laden buy-side analysts may choose to work with sell-side analysts with the best earnings forecast accuracy track records. In other words, the best sell-side analysts may learn nothing from connections with buy-side analysts. Instead, buy-side analysts may connect with the sell-side analysts from whom they can acquire the most information, and the flow of information may be one-directional; i.e., from the sell-side to the buy-side, with accuracy driving connections.

Results described in Sections 5.3 through 5.5 mitigate this concern. 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, which would then drive connections. In this sample, we expect that our firm-specific experience variable is not significant, while all of the other results still hold. Table 6 displays the results, which 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. This suggests that our main result is consistent with connections with buy-side analysts enhancing sell-side analyst forecast accuracy (not the other way around).

6.2 Alternative Measures of CONNECTIONS

Table 7 replicates our test of H1 using models (1) and (2) and two alternative proxies for the degree of connectedness between sell-side and buy-side analysts. The first alternative considers analyst a to have a connection with institution i that informs the analyst's forecasts of

firm f 's year t earnings if i holds f and at least one other stock followed by a . We then divide the total number of a 's connections by the number of institutions that hold f . Unlike our original *CONNECTIONS* variable, this proxy treats all institutions with whom analyst a is connected equally. The estimation results using this alternative measure of *CONNECTIONS* are presented in columns (1) and (2) of Table 7. The results are essentially the same as those presented in Table 2.

The second alternative is the same as our original method of estimating *CONNECTIONS* but with additional stringency. Recall that our original approach measures *CONNECTIONS* as the number of stocks other than f that a holds in common with each institution holding f , averaged across all institutions holding f . The additional stringency is that a stock other than f is only counted as a stock held in common with an institution, if all of the stocks covered by a account for at least 5% of the market value of the institution's market value. Essentially, this measure views an analyst as being connected with an institution only when the stocks commonly covered by the analyst and held by the institution account for a significant portion of the institutions' portfolio. The estimation results using this alternative measure of *CONNECTIONS* are presented in columns (3) and (4) of Table 7. Again, the results are essentially the same as those presented in Table 2. Overall, the results in Table 7 increase our confidence in the construct validity of our *CONNECTIONS* variable.

7 Conclusion

A plethora of research papers examine the impact of sell-side financial analyst research on the investment community (Ramnath et al. 2008b), 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). Ours is the first large-sample study to examine the impact of private buy-side analyst information on the quality of publicly available sell-side analyst research.

Sell-side analysts have substantial incentives to impress buy-side analysts working for various institutional investors, because buy-side votes for Institutional Investor's all-American team of sell-side analysts largely determine sell-side analyst compensation (Groysberg et al. 2011). Buy-side analysts have substantial incentives to enlist the services of sell-side analysts who add value to the information contained in buy-side analyst reports to their fund managers. The value added comes from industry expertise (Bradley, et al. 2017), connections with firm management (Green, Jame, Markov, & Subasi, 2014), and information gleaned from sell-side analysts' connections with other buy-side analysts (Brown et al. 2016).

Most prior academic research regarding the interactions between these two sophisticated groups of market participants focuses on the flow of information from sell-side analyst research into stock prices. Some studies focus on the flow of information from stock price changes into sell-side analyst research (e.g., Clement, Hales, & Xue 2011). Our study focuses directly on what sell-side analysts learn from connections with institutional investors. 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.

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 focus on the flow of information from the buy-side to the sell-side. 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.

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Table 1—Descriptive Statistics and Correlations**Panel A. Descriptive Statistics (137,835 analyst-firm-year observations)**

Variables	mean	p25	p50	p75	Standard Deviation
FE	0.795	0.053	0.146	0.408	5.571
FE	0.476	-0.107	0.000	0.231	5.608
ACCURACY	0.528	0.208	0.550	0.864	0.357
CONNECTIONS	6.680	3.908	5.852	8.267	4.615
INST_OWNER#	292.827	130.000	213.000	363.000	251.839
FIRM#	16.665	11.000	15.000	20.000	9.525
INDUSTRY#	3.825	2.000	3.000	5.000	2.663
FIRM_EXP	4.953	2.000	4.000	7.000	4.137
BSIZE	67.109	22.000	52.000	101.000	58.847
DAYS	4.589	0.000	0.000	3.000	12.525
EPS_FREQ	6.125	4.000	6.000	7.000	2.701
HORIZON	310.102	295.000	320.000	334.000	31.639
CONNECTIONS with high RPI institutions	0.092	0.019	0.049	0.106	0.150
CONNECTIONS with medium RPI institutions	0.453	0.174	0.325	0.565	0.485
CONNECTIONS with low RPI institutions	5.882	3.333	5.144	7.398	4.101

Panel B. Correlations

		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
CONNECTIONS	(1)	1.000											
ACCURACY	(2)	0.001 <i>0.811</i>	1.000										
Lag year ACCURACY	(3)	-0.010 <i>0.000</i>	0.049 <i>0.000</i>	1.000									
FIRM#	(4)	0.822 <i>0.000</i>	0.004 0.192	-0.016 0.000	1.000								
INDUSTRY#	(5)	0.410 <i>0.000</i>	-0.012 0.000	-0.015 0.000	0.474 0.000	1.000							
FIRM_EXP	(6)	0.136 0.000	0.007 0.008	-0.004 0.135	0.135 0.000	0.072 0.000	1.000						
BSIZE	(7)	0.123 <i>0.000</i>	0.006 <i>0.042</i>	0.007 <i>0.006</i>	0.055 <i>0.000</i>	-0.060 <i>0.000</i>	0.033 <i>0.000</i>	1.000					
DAYS	(8)	0.077 <i>0.000</i>	-0.012 <i>0.000</i>	-0.007 <i>0.011</i>	0.056 <i>0.000</i>	0.055 <i>0.000</i>	0.094 <i>0.000</i>	0.032 <i>0.000</i>	1.000				
EPS_FREQ	(9)	-0.032 <i>0.000</i>	-0.022 <i>0.000</i>	-0.070 <i>0.000</i>	-0.039 <i>0.000</i>	-0.055 <i>0.000</i>	-0.014 <i>0.000</i>	0.080 <i>0.000</i>	-0.014 <i>0.000</i>	1.000			
HORIZON	(10)	-0.062 <i>0.000</i>	-0.123 <i>0.000</i>	-0.007 <i>0.016</i>	-0.063 <i>0.000</i>	-0.056 <i>0.000</i>	-0.039 <i>0.000</i>	-0.024 <i>0.000</i>	-0.235 <i>0.000</i>	0.140 <i>0.000</i>	1.000		
CONNECTIONS with low RPI institutions	(11)	0.994 <i>0.000</i>	0.002 <i>0.500</i>	-0.010 <i>0.000</i>	0.835 <i>0.000</i>	0.413 <i>0.000</i>	0.136 <i>0.000</i>	0.124 <i>0.000</i>	0.075 <i>0.000</i>	-0.033 <i>0.000</i>	-0.065 <i>0.000</i>	1.000	
POST_GS	(12)	0.060 <i>0.000</i>	0.025 <i>0.000</i>	0.021 <i>0.000</i>	0.067 <i>0.000</i>	0.014 <i>0.000</i>	-0.069 <i>0.000</i>	-0.010 <i>0.001</i>	-0.089 <i>0.000</i>	-0.019 <i>0.000</i>	0.064 <i>0.000</i>	0.061 <i>0.000</i>	1.00

Panel A reports summary statistics for our sample of 137,835 analyst-firm-year observations from 1995 to 2012, including 3,980 unique firms and 7,615 analysts. Panel B reports correlation coefficients (and associated p-values) among the main variables used in the analysis, where the variables are scaled among analysts for the same firm-year. For ease of interpretation, with the exception of *ACCURACY*, no variable in Panel A is scaled among analysts for the same firm-year.

We choose the absolute forecast errors for the earliest forecasts of all analysts forecasting firm f 's year t earnings, where the forecasts occur during the 90 days post the announcement of firm f 's year $t-1$ annual earnings. Based on these forecast errors, we compute *ACCURACY* as the difference between the maximum and analyst a 's absolute forecast error, scaled by the range between the maximum and minimum. *ACCURACY* falls on a scale between zero (least accurate) and one (most accurate).

$|FE_{aft}|$ = 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, scaled by the absolute value of actual earnings.

CONNECTIONS $_{aft}$ = analyst a 's average number of connections with institutional investors holding f as of the date of F_{aft} , defined as the 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 . Institutional holdings used to construct this measure 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.

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. To classify institutions into high-, medium-, and low-opportunity institutions, we measure an institution's reliance on public information (RPI). We construct RPI of an institution as the R^2 from an institution-level regression of changes in the number of shares held by that institution in a given stock on lagged changes in mean analyst recommendations. All institutional investors are ranked each quarter by their RPI into terciles. Institutions in the lowest RPI tercile are viewed as having the least reliance on public information and classified as high-opportunity institutions.

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	5.679*** (1.176)	5.166*** (1.266)		
CONNECTIONS ²	-5.723*** (1.217)	-5.911*** (1.188)		
Break down of CONNECTIONS				
Bottom CONNECTIONS Tercile			9.430*** (2.430)	9.464*** (2.458)
Middle CONNECTIONS Tercile			2.558*** (0.738)	2.097** (0.867)
Top CONNECTIONS Tercile			0.484 (0.407)	-0.137 (0.577)
Lagged ACCURACY		4.554*** (0.314)		4.565*** (0.315)
FIRM#		0.942* (0.568)		0.920 (0.568)
INDUSTRY#		-1.648*** (0.348)		-1.699*** (0.350)
FIRM_EXP		0.688** (0.286)		0.704** (0.286)
BSIZE		0.251 (0.345)		0.269 (0.347)
DAYS		-3.895*** (0.298)		-3.947*** (0.297)
EPS_FREQ		-0.010 (0.302)		0.001 (0.302)
HORIZON		-11.796*** (0.274)		-11.789*** (0.275)
Constant	52.910*** (1.012)	58.341*** (1.031)	52.878*** (1.016)	58.282*** (1.035)
Year Fixed Effects	YES	YES	YES	YES
N	137,835	137,835	137,835	137,835
Adjusted R-squared	0.21%	2.18%	0.20%	2.17%

Table 2 examines the relation between sell side analysts' forecast accuracy and their connections with institutional investors. This table reports coefficient estimates from the following regressions:

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

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

$D_k^{Tercile}$ is a (1/0) indicator variable equaling one for the k^{th} CONNECTIONS tercile (1=lowest and 3=highest) and zero otherwise. All other variables are defined as in Table 1. In this table, all continuous variables are scaled to fall between 0 and 1 for the same firm-year. 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

Panel A. All observations

Variables	coeff (std. err.)
CONNECTIONS ^{High Opp}	5.719*** (1.709)
CONNECTIONS ^{High Opp2}	-3.888*** (1.462)
CONNECTIONS ^{Med Opp}	0.053 (1.587)
CONNECTIONS ^{Med Opp2}	-1.640 (1.459)
CONNECTIONS ^{Low Opp}	1.470 (1.202)
CONNECTIONS ^{Low Opp2}	-2.667** (1.176)
Lagged ACCURACY	4.533*** (0.313)
FIRM#	0.345 (0.596)
INDUSTRY#	-1.550*** (0.345)
FIRM_EXP	0.729** (0.286)
BSIZE	0.237 (0.345)
DAYS	-3.812*** (0.298)
EPS_FREQ	-0.019 (0.302)
HORIZON	-11.803*** (0.275)
Constant	58.473*** (1.033)
N	137,835
Year Fixed Effects	YES
Adjusted R-squared	2.20%

Panel B. Observations where analysts' connections with institutions are in the High Opportunity tercile

Variables	(1) coeff (std. err.)	(2) coeff (std. err.)
CONNECTIONS ^{High Opp}	9.576*** (1.950)	
CONNECTIONS ^{High Opp2}	-8.754*** (1.896)	
Break down of CONNECTIONS ^{High Opp}		
Bottom CONNECTIONS ^{High Opp} Tercile		38.567*** (11.676)
Middle CONNECTIONS ^{High Opp} Tercile		3.371*** (0.754)
Top CONNECTIONS ^{High Opp} Tercile		0.784 (0.525)
Lagged ACCURACY	3.598*** (0.440)	3.614*** (0.440)
FIRM#	1.056** (0.529)	1.043** (0.529)
INDUSTRY#	-1.074** (0.468)	-1.077** (0.468)
FIRM_EXP	1.618*** (0.437)	1.622*** (0.438)
BSIZE	1.280*** (0.452)	1.272*** (0.452)
DAYS	-2.616*** (0.457)	-2.628*** (0.457)
EPS_FREQ	-0.241 (0.452)	-0.239 (0.453)
HORIZON	-7.033*** (0.407)	-7.028*** (0.407)
Constant	52.104*** (1.850)	52.211*** (1.846)
N	37,563	37,563
Year Fixed Effects	YES	YES
Adjusted R-squared	1.41%	1.41%

Table 3 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. Panel A reports results from the following regression model.

$$\begin{aligned}
 ACCURACY_{aft} = & \beta_0 + \beta_1 CONNECTIONS_{aft}^{High\ Opp} + \beta_2 CONNECTIONS_{aft}^{High\ Opp\ 2} \\
 & + \beta_3 CONNECTIONS_{aft}^{Med\ Opp} + \beta_4 CONNECTIONS_{aft}^{Med\ Opp\ 2} \\
 & + \beta_5 CONNECTIONS_{aft}^{Low\ Opp} + \beta_6 CONNECTIONS_{aft}^{Low\ Opp\ 2} \\
 & + \sum_m \beta_m Control_m + \varepsilon_{aft}
 \end{aligned} \tag{3}$$

where $CONNECTIONS_{aft}^{High\ Opp}$ is measured the same way as the original $CONNECTIONS$ variable except that it is constructed only based on connections with high-opportunity institutions. $CONNECTIONS_{aft}^{Med\ Opp}$ and $CONNECTIONS_{aft}^{Low\ Opp}$ are constructed in a similar fashion based on connections with medium and low-opportunity institutions, respectively. To classify institutions into high-, medium-, and low-opportunity institutions, we measure an institution's reliance on public information (RPI). We construct RPI of an institution as the R^2 from an institution-level regression of changes in the number of shares held in a given stock by a given institution on lagged changes in mean analyst recommendations. All institutional investors are ranked each quarter by their RPI into terciles. Institutions in the lowest RPI tercile are classified as high-opportunity institutions. All other variables are defined as in Table 1. In this table, all continuous variables are scaled to fall between 0 and 1 for the same firm-year. Panel B reports results from estimation of Models 1 and 2 from Table 2 on a subset of our sample including only the observations where analyst connections with High Opportunity institutions, i.e., those in the low RPI group, are in the bottom tercile of the same firm-year group. 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 Pre- and Post-Exogenous Regulatory Changes

Variables	coeff (std. err.)
CONNECTIONS	-0.462 (2.504)
CONNECTIONS ²	-2.358 (2.463)
CONNECTIONS× POST_GS	7.378*** (2.845)
CONNECTIONS ² × POST_GS	-5.106* (2.866)
POST_GS	1.079 (1.119)
Lagged ACCURACY	5.029*** (0.337)
FIRM#	1.159* (0.616)
INDUSTRY#	-1.474*** (0.371)
FIRM_EXP	0.809*** (0.306)
BSIZE	-0.063 (0.366)
DAYS	-3.959*** (0.317)
Constant	59.092*** (1.092)
N	120,983
Year Fixed Effects	YES
Adjusted R-squared	0.0209

Table 4 examines whether the sensitivity of forecast accuracy to connections increases with sell-side analyst demand for information following the regulatory period that includes Reg. FD and GARS. This table reports coefficient estimates from the following regression.

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

$POST_GS_t = 1$ for analyst forecasts issued after 2003, and 0 for forecasts issued before 2001.

$FIRM_EXP_{aft}$ = number of years since the first year analyst a issued one-year ahead earnings forecasts for firm f up to current year.

$LAGGED_ACCURACY_{aft}$ = one year lagged value of the $ACCURACY$ variable.

All other variables are defined as in Table 1. Observations during the years of the changing regulatory environment (2001-2003) are omitted. In this table, all continuous variables are scaled to fall between 0 and 1 for the same firm-year. 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— 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		5.919*** (1.679)	5.950*** (2.183)
CONNECTIONS ²		-6.287*** (1.642)	-6.122*** (2.231)
CONNECTIONS× DEMAND		-2.137 (2.826)	-1.476 (3.183)
CONNECTIONS ² × DEMAND		1.234 (2.723)	0.374 (3.243)
Lagged ACCURACY		4.553*** (0.314)	5.076*** (0.593)
FIRM#		0.941* (0.568)	0.942* (0.568)
INDUSTRY#		-1.651*** (0.347)	-1.650*** (0.348)
FIRM_EXP		1.234** (0.566)	0.688** (0.286)
BSIZE		0.255 (0.345)	0.251 (0.345)
DAYS		-3.895*** (0.298)	-3.894*** (0.298)
Constant		58.147*** (1.045)	58.070*** (1.065)
N		137,835	137,835
Year Fixed Effects		YES	YES
Adjusted R-squared		0.0218	0.0218

Table 5 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.

$$ACCURACY_{aft} = \beta_0 + \beta_1 CONNECTIONS_{aft} + \beta_2 CONNECTIONS_{aft}^2 + \beta_3 DEMAND + \beta_4 DEMAND \times CONNECTIONS_{aft} + \beta_5 DEMAND \times CONNECTIONS_{aft}^2 + \sum_m \beta_m Control_m + \varepsilon_{aft} \quad (4)$$

We employ the following variables as proxies for buy-side analyst *DEMAND*:

*FIRM_EXP*_{aft} = number of years since the first year analyst *a* issued one-year ahead earnings forecasts for firm *f* up to current year.

*LAGGED_ACCURACY*_{aft} = one year lagged value of the *ACCURACY* variable.

All other variables are defined as in Table 1. In this table, all continuous variables are scaled to fall between 0 and 1 for the same firm-year. 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—Another Test for Reverse Causality

Variables	(1) Coeff (std. err.)	(2) Coeff (std. err.)
CONNECTIONS	4.665*** (1.744)	
CONNECTIONS ²	-5.204*** (1.666)	
Break down of CONNECTIONS		
Bottom CONNECTIONS Tercile		7.336** (3.428)
Middle CONNECTIONS Tercile		1.853 (1.201)
Top CONNECTIONS Tercile		-0.046 (0.799)
Lagged ACCURACY	4.660*** (0.436)	4.672*** (0.437)
FIRM#	1.298 (0.796)	1.275 (0.797)
INDUSTRY#	-1.888*** (0.472)	-1.926*** (0.473)
FIRM_EXP	-0.158 (0.516)	-0.147 (0.516)
BSIZE	0.259 (0.462)	0.262 (0.463)
DAYS	-4.357*** (0.433)	-4.399*** (0.432)
EPS_FREQ	-0.131 (0.415)	-0.124 (0.416)
HORIZON	-11.482*** (0.382)	-11.472*** (0.383)
Constant	57.533*** (1.526)	57.515*** (1.531)
Year Fixed Effects	YES	YES
N	67,650	67,650
Adjusted R-squared	2.04%	2.03%

This table replicates the analysis from specifications (2) and (4) of Table 2 on the subset of our sample observations that include only the first three years since an analyst covered the same firm in the IBES database. 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 for Connections

Variables	(1) Measure 1 Coeff (std. err.)	(2)	(3) Measure 2 Coeff (std. err.)	(4)
CONNECTIONS	5.535*** (1.182)		3.757*** (1.127)	
CONNECTIONS ²	-4.370*** (1.145)		-4.929*** (1.176)	
Break down of CONNECTIONS				
Bottom CONNECTIONS Tercile		2.421** (0.969)		131.865*** (43.737)
Middle CONNECTIONS Tercile		2.127*** (0.428)		3.107*** (1.010)
Top CONNECTIONS Tercile		1.007*** (0.362)		-0.752** (0.341)
Lagged ACCURACY	4.558*** (0.315)	4.558*** (0.315)	4.550*** (0.314)	4.555*** (0.315)
FIRM#	-0.002 (0.419)	-0.009 (0.420)	0.820** (0.402)	0.795** (0.403)
INDUSTRY#	-1.694*** (0.348)	-1.706*** (0.348)	-1.606*** (0.346)	-1.632*** (0.348)
FIRM_EXP	0.668** (0.286)	0.676** (0.286)	0.762*** (0.286)	0.770*** (0.286)
BSIZE	0.145 (0.345)	0.137 (0.345)	0.238 (0.344)	0.259 (0.344)
DAYS	-3.944*** (0.297)	-3.966*** (0.297)	-3.906*** (0.298)	-3.923*** (0.297)
EPS_FREQ	0.004 (0.302)	0.005 (0.302)	-0.010 (0.302)	-0.009 (0.302)
HORIZON	-11.807*** (0.275)	-11.799*** (0.275)	-11.791*** (0.274)	-11.792*** (0.275)
Constant	57.987*** (1.042)	58.220*** (1.041)	58.735*** (1.028)	58.672*** (1.029)
N	137,835	137,835	137,835	137,835
Year Fixed Effects	YES	YES	YES	YES
Adjusted R-squared	0.0217	0.0217	0.0217	0.0217

This table replicates the analysis from specifications (2) and (4) of Table 2 with two alternative measures of the *CONNECTIONS* variable. The first alternative version of the *CONNECTIONS* variable is measured as the number of institutions that invest in both firm *j* and at least one other company followed by analyst *i*, divided by the number of all institutions holding firm *j*. The second alternative version of the *CONNECTIONS* variable is measured the same way as the original *CONNECTIONS* variable except that it considers only connections with institutions where the value of all stocks covered by an analyst as a percentage of an institution's portfolio value is above 5 percent of the institution's portfolio value. In other words, *CONNECTIONS* is calculated only for analyst-institution pairs where the aforementioned percentage is above 5 percent. Standard errors are clustered by analyst and are presented in parentheses. ***, **, * denote statistical significance at the 1%, 5%, and 10% significance level, respectively.

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2011

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2010

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2005

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