

Do Managers Learn from Institutional Investors Through Direct Interactions?

Rachel Xi Zhang
xi1@wharton.upenn.edu

The Wharton School
University of Pennsylvania

1 November 2020

Abstract:

Prior evidence suggests that managers learn indirectly from stock prices, which contain private information impounded by informed investors' trades. However, stock price is an indirect aggregate signal, which is likely to be insufficient for managerial learning. I propose that managers seek out direct interactions with institutional investors as a further mechanism to learn relevant information about their firms. Using investor conferences and investor days as the medium for direct learning, I find that managers seek more direct interactions when they have a high demand for information concerning industry trends and supply chain dynamics, and when they expect their current base of institutional investors to be knowledgeable. I also predict that information learned through direct interactions will be reflected in the manager's subsequent corporate and personal decisions. I find that the frequency and accuracy of management forecasts increase after direct learning. Comparing insider trades in the same firm-month, trades executed by participating insiders within seven days after a conference earn greater positive abnormal returns, consistent with managers' information set expanding as a result of their direct learning.

I am very grateful to the members of my dissertation committee for their support, guidance, and insight: Chris Armstrong, Brian Bushee (Chair), Luzi Hail, and Bob Holthausen. I thank multiple anonymous investment professionals and a CEO of a public U.S. corporation for providing helpful institutional insight. I thank Paul Fischer, Yanju Liu (discussant), Cathy Schrand, Frank Zhou, Christina Zhu and participants at the 2020 Deloitte Doctoral Consortium, the 2020 AAA Annual Meeting, and the Wharton School for helpful discussions and comments. I gratefully acknowledge the generous financial support from the Wharton School. All remaining errors are my own. The Internet Appendix is available [at this link](#).

1. Introduction

Extant literature recognizes that managers learn from external parties about different prospects of their own firms. The feedback effects literature also suggests that managers can glean useful information from stock prices about investment opportunities (e.g., Chen et al., 2007; Dessaint et al., 2019; Foucault and Fresard, 2014; Jayaraman and Wu, 2019), cash flows (Bai et al., 2016; Subrahmanyam and Titman, 2001; Zuo, 2016), and M&A synergies (e.g., Luo 2005). However, price as an aggregate signal is likely to be insufficient for managerial learning.

In this study, I propose that institutional investors are the source of relevant information and examine whether direct manager-investor interactions serve as a mechanism for managerial learning. Institutional investors are important external capital providers for the firm. They are often knowledgeable about industry trends, product-market peers, and supply chain dynamics, especially when they are invested in these sectors.¹ All of this information can be relevant for the manager, who might not have perfect knowledge about every decision-relevant aspect of the firm (e.g., Ben-David et al., 2013; Hutton et al., 2012).

The notion that external capital suppliers can provide useful information to managers has been documented in several specific settings: namely between venture capitalists and early entrepreneurial firms (see Da Rin et al., 2013 for useful reviews) and during extreme forms of shareholder intervention initiated by hedge fund activists (e.g., Brav et al., 2008). Yet beyond these specific settings that involve either a subset of firms or an infrequent form of intervention, there is little evidence on institutional investors as a source of relevant information for managerial learning, despite the fact that they regularly interact with managers of public U.S. firms (Brown et al., 2016).

¹ Prior work on institutional cross-holdings recognize that the scale of information gathering and production allows institutions holding shares in multiple firms in the same industry to enjoy an information advantage (He and Huang, 2017; Kang et al., 2018).

I examine *direct* managerial learning from institutional investors, using public and private meetings at investor conferences and investor days as the medium for interactions. Investor conferences bring together informed participants with potentially complementary information to a well-defined physical setting and facilitate two-way information exchange.² Managerial learning from investors can occur in two ways. First, while managers usually do not ask questions during conference presentations, they can learn about investors' opinions by seeking feedback and soliciting questions from investors. By presenting different aspects of the firm during public management discussions and by providing detailed answers during public questions-and-answers sessions, managers can gather relevant feedback from investors. Second, managers can make themselves available for private breakouts and one-on-one meetings, which allows for in-depth discussions around more proprietary topics. Such interactions enable information exchange, and the potential complementarities between managers and institutional investors' information facilitate direct managerial learning.

The empirical challenge to provide evidence of learning is that it is inherently unobservable and thus cannot be measured directly. Researchers can, however, observe the entire content of discussions during public meetings and the occurrence of private meetings at investor conferences. Utilizing 56,924 transcripts gathered for Russell 3000 companies, I develop six empirical proxies to measure the extent of interactions and to estimate the degree of information flow between investors and managers. This is because interaction and information flow are the necessary conditions for learning to occur. I conduct two sets of empirical analyses to provide evidence of learning from direct interactions. First, I examine whether managers seek more direct interactions when they have a higher demand for information that institutional investors are likely to possess.

² For the rest of the document, I use the phrase "investor conferences" to refer to both investor conferences and investor days broadly.

Second, I examine whether information learned through direct interactions is reflected in two subsequent managerial decisions: management forecasts and insider trades.

To test my first prediction, I start by examining specific types of information demand, namely demand for information concerning product-market peers and demand for information about suppliers and customers. Managers often need to pay attention to the actions of their peers in formulating product-market strategy, as well as monitor supply chain conditions (Bernard et al., 2019; Dessaint et al., 2019; Foucault and Fresard, 2014). As a result, they are likely to have a higher information demand when there is an increase in product-market activities among either peer firms and connected firms on the supply chain. Therefore, I capture a manager's demand for peer (supply chain) information using the frequency and the magnitude of product-market announcements made by peer firms (suppliers and customers). In a panel of 73,262 firm-quarter observations constructed using firms covered in transcripts sample, I use a within-firm research design and find that the six proxies of direct interactions are positively associated with measures of managers' information demand. This relation is robust to controlling for investors' demand for information and other capital market incentives for managers to provide investor access. Next, I develop a measure that captures managers' revealed overall uncertainty about the firm's operations, utilizing earnings conference calls whereby managers need to respond in real-time questions about the firm's recent performances and future outlooks. Consistent with my prediction, I find that managers are more likely to seek direct interactions when they face higher uncertainty.

While these results are suggestive of managerial learning, concerns over omitted correlated variables exist. To mitigate such concerns, I develop cross-sectional hypotheses that would be expected under learning but are difficult to be explained by alternative theories. Specifically, managers should have higher incentives to seek direct learning when they expect that their

institutional investors are knowledgeable, and specifically with regard to the types of information that the manager demands. Therefore, I partition the sample based on managers' expectations of the amount of product-market and supply chain knowledge their institutional investor base is likely to possess, whereby investor knowledge is measured using their portfolio holdings and trading activities in the respective industries. Consistent with direct learning, I document a stronger positive relation between demand for product-market (supply chain) information and proxies of direct interactions when institutional investors are knowledgeable about the product-market (supply chain industries) and find no relation when institutional investors are not.

In my second set of analyses, I investigate whether information learned through direct interactions is reflected in subsequent managerial decisions. Because a manager's private information set is inherently unobservable, I focus on two decisions that can serve as a window to the manager's information set: the frequency and accuracy of management forecasts, as well as the timing and profitability of insider trades. I chose these decisions because they are sensitive to the acquisition of investors' sector knowledge, have information content, and are *ex-post* verifiable (Brochet, 2010; Hoskin et al., 1986; Lakonishok and Lee, 2001; Rogers and Stocken, 2005).

I predict that direct learning helps managers to better project future operations and, therefore, to issue more management forecasts and more accurate forecasts. Managers are unable to guide when they do not have enough information to forecast future operations with a sufficient degree of accuracy (Waymire, 1985). Institutional investors' information can be relevant because management forecasts incorporate firm-specific, macroeconomic, and sector information (Bonsall et al., 2013). Using a similar within-firm design, I find that, following direct interactions, managers issue more management forecasts and more accurate earnings-per-share (EPS) forecasts. These results suggest that information acquired from such interactions helps to improve the manager's

private information about the firm's future cashflow, and therefore, the precision of his forecasts. The increase in management forecasts is robust to using only forecast revisions, which are unlikely to be driven by investors demanding new information at the conference, as well as controlling for the need to avoid Regulation Fair Disclosure (Reg FD) violations.

Moreover, trades by corporate insiders often reflect their private information about the firm's future cash flow (Ke et al., 2003; Piotroski and Roulstone, 2005; Seyhun, 1992). Therefore, I predict that information learned through direct information should be reflected in the timing and profitability of that manager's insider trades. In a sample of 28,632 open-market insider transactions within two months before or after a conference, I find that executives who participated in an investor conference (i.e., participating insider) are more likely to utilize their information advantage and trade in the seven-day post-conference window. Next, I examine insider trading profits, which reflect the trading manager's private information, and compare trades made with the benefit of direct learning against those without. I focus on the narrow window of trades made in the same month for a given firm, which controls for all possible omitted correlated variables that do not vary within a given firm-month. I find that trades made by participating insider within the seven-day post-conference window earn more positive abnormal returns. This comparison is made against trades executed by (i) non-participating insiders of the same firm or (ii) participating insiders outside of the conference window. Overall, my evidence suggests that direct learning has expanded the private information set of participating insiders.³

My study contributes to several streams of literature. First, I contribute to the literature on management-investor interactions. Prior studies focus almost exclusively on the transfer of

³ A potential alternative explanation is that managers can anticipate investors' trades to information disclosed during direct interactions, and therefore sell (buy) before negative (positive) investor reactions. I conduct two analyses, described in more detail in section 4.3.2, to distinguish from this alternative explanation.

information *from managers to investors* during these interactions and the associated benefits to brokers, investors, managers and the firm (Bushee et al., 2020, 2017, 2011; Green et al., 2014a, 2014b; Solomon and Soltes, 2015). However, the literature has largely neglected the potential for information transfers in the other direction: *from investors to managers*. Also, my study documents another benefit of disclosure: that voluntary disclosure of information during direct investor interactions (e.g., by presenting different aspects of the firm and by providing longer answers to questions) helps managers to elicit valuable feedback. A related study is Jayaraman and Wu (2019), which examines the use of voluntary disclosure in a different setting where managers use capital expenditure forecasts to solicit market-feedback.

Second, my study complements the learning from price literature (e.g., Chen et al., 2007; Edmans et al., 2017). While price serves to aggregate information in the financial market, it is likely insufficient for managers to learn about multiple dimensions of their firms because price contains noise, and the process of aggregation results in a loss of dimensionality (Bond et al., 2010; Dessaint et al., 2019). Edmans et al. (2017) show that what matters for learning is information in prices that managers do not already know, suggesting a role for informed investors' private information. My study complements such evidence by documenting institutional investors as a source of relevant information for managerial learning.

Third, my study provides large-scale evidence on how institutional investors can provide useful information to managers. Prior literature recognizes that venture capitalists and hedge fund activists offer value-add advice to their portfolio firms (see Brav et al., 2015a; Da Rin et al., 2013 for useful reviews). However, both venture capitalists and activists are only involved with (and therefore can only influence) a limited subset of firms. On the other hand, most public U.S. firms regularly interact with institutional investors, and learning can happen without costly intervention.

As a result, managerial learning from institutional investors may be a more prevalent and widespread phenomenon, despite very little empirical evidence so far. Moreover, my findings contribute to the institutional cross-holding literature by documenting an associated benefit: that institutional investors' industry expertise and sector knowledge, arising from holding shares in multiple firms, can be a valuable source of information for the manager.

2. Relevant Literature and Institutional Background

2.1. Managerial learning from external sources

Prior literature recognizes the notion that managers can and do learn from information possessed by external parties about the prospects of their firms, and the sufficient condition for managerial learning to take place is that the manager does not have perfect information about every decision-relevant aspect. For example, Hutton et al. (2012) suggest that managers have less accurate macroeconomic information than sell-side analysts. Ben-David et al. (2013) show that managers are often miscalibrated in predicting stock market returns.

The feedback effects literature suggests that managers might learn from stock prices, which aggregate information impounded by informed traders, about their own firms (e.g., Chen et al., 2007; Jayaraman and Wu, 2019; Luo, 2005; Zuo, 2016) or about their peers (Dessaint et al., 2019; Foucault and Fresard, 2014). However, even if one assumes that the market is strong-form efficient and price serves as an aggregate signal of all dispersed sources of information, learning from price alone is likely to be insufficient for managers to make corporate decisions. First, price is a noisy signal about the firm's prospects, and managers have limited abilities to distinguish information from noise when using price as a signal (Dessaint et al., 2019; Morck et al., 1990). Second, managers might require granular information that cannot necessarily be extracted from prices as the process of aggregation results in a loss of dimensionality. Third, prices can reflect multiple

equilibria such that there is no one-to-one mapping between managers' decisions and prices (Bond et al., 2010). Last, institutional investors might not trade on some information that they possess (Edmans et al., 2015).⁴ Therefore, the information contained in price alone is likely to be insufficient and needs to be supplemented with other sources of information, and this paper seeks to examine direct interactions with institutional investors as a further mechanism of learning.⁵

2.2. Institutional investors as a source of useful information for managerial learning

The notion that external capital suppliers can offer useful information and advice to their portfolio companies has been documented in two specific settings, which either involve early-stage entrepreneurial firms or is via an extreme form of shareholder intervention.

The first setting involves venture capitalists (VC). VCs are often involved in the operations of the early-stage startups that they invest in by sitting on the board of directors, assisting with talent recruitment and future funding raising, and offering advice to management (see Da Rin et al. (2013) for a review). The second setting involves an infrequent and costly form of intervention -- hedge fund activism. For instance, Brav et al. (2008) document that activist hedge funds can propose strategic, operational, and financial remedies to their target firms.

Yet beyond these specific settings that either involves a subset of firms or an infrequent form of intervention, institutional investors regularly interact with managers of public U.S. corporations. I focus on institutional investors because they have superior information gathering and processing abilities and often possess knowledge that is useful to the manager, including industry trends, product-market knowledge, and supply chain dynamics. Prior work on

⁴ Edmans et al. (2015) show that when firm values are endogenous to trading, feedback effects serve as a limit to arbitrage -- speculators profit less from selling on negative information when decision-makers can increase the value of the underlying assets by using the information revealed through informed trading.

⁵ Prices might be a sufficient confirmatory signal for some decisions that require a simple "good" or "bad" signal, for instance, whether to proceed with an acquisition (Zuo, 2005) and whether to adjust up or down capital expenditures (Jayaraman and Wu, 2019).

institutional cross-holdings recognizes that institutions holding shares in multiple firms often achieve scale in information gathering and production (e.g., He and Huang, 2017; Kang et al., 2018). In a survey of 344 buy-side analysts, Brown et al. (2016) show that industry knowledge and primary research are the two most important sources of information in generating stock recommendations. Their results suggest that part of institutional investors' information advantage comes from gathering and analyzing information beyond company disclosure.

2.3. Manager-investor interactions at investor conferences

Manager-investor interactions can happen through (i) public meetings at investor conferences, (ii) private meetings following public meetings at investor conferences, and (iii) private non-deal roadshows and in-house meetings (Solomon and Soltes, 2015). In this paper, I focus on public and private meetings at investor conferences as the medium for manager-investor interaction for several reasons. First, compared to in-house meetings and non-deal roadshows, investor conferences bring together many investors with diverse backgrounds and expertise, which in turn facilitates managerial learning. Bushee et al. (2011) examine investor conference as a “disclosure milieu” and find that cross-sectional variations in its information content depend on the composition of its audience. Their study highlights the role of the audience's private information in determining the extent of information flow during conferences. Second, the entire content of discussion during public meetings at investor conferences is observable from conference transcripts, which allow researchers to develop multiple empirical proxies to estimate the extent of information flow between investors and managers. Moreover, while the occurrence of in-house meetings or non-deal roadshows is generally unobservable for companies in the United States, researchers can identify the occurrence of private meetings at investor conferences using conference transcripts.

Public meetings at investor conferences usually start with managers making prepared remarks on the firm's overall strategy in the Management Discussions sessions, followed by Questions-and-Answers (Q&A) sessions for managers to respond to questions raised by investors. Managers are careful not to release details on recent information events because of concerns over Reg FD (Bushee et al., 2011). Outside of public meetings, some conference organizers give attending firms the option to meet with investors privately, through either one-to-one meetings throughout the day or breakout sessions after the public presentation (Bushee et al., 2017).

There are a number of ways the managers can learn from investors during investor conferences. First, investors often express their views during Q&A sessions, and managers can encourage such discussions when they are more willing to entertain questions. Second, while public meetings generally do not allow managers to ask a question, managers can present relevant aspects of the firm and learn from investors' reactions and feedback. Moreover, such management presentations can attract investor attention, encourage participation at Q&As, and encourage attendance at breakout sessions, all of which will, in turn, facilitate managerial learning. Finally, private breakouts and one-on-ones sessions allow managers to ask explicit questions, and the closed-door environment facilitates discussions around proprietary investment thesis that investors might not be willing to share otherwise (Park and Soltes, 2018).

While investor conferences are viewed as a predominant venue for manager-investor interaction, prior studies primarily focus on the transfer of information *from managers to investors* at conferences and the associated benefits. Brokers, analysts, and investors benefit from selective (and possibly private) access to management. Specifically, brokers and analysts that have access to management are able to issue more informative research (Green et al., 2014b), earn higher commission revenue (Green et al., 2014a), while equity investors can make profitable trades

(Bushee et al., 2018, 2017; Solomon and Soltes, 2015). At the same time, participating firms derive capital-market benefits, including increased analyst following, institutional ownership, and improved liquidity (Bushee et al., 2018, 2011; Green et al., 2014a). My study differs from prior literature because I document information flowing from *investors to managers* at conferences.

3. Sample Construction

I collect investor conference transcripts for firms that are included in the Russell 3000 index from Factset CallStreet and Thomson StreetEvents.⁶ My sample period starts in 2004 because the coverage of both datasets becomes much more comprehensive after the passage of Reg FD and ends in 2017, the last year with valid data from various data sources. Using Russell 3000 firms allows me to select a sample of firms that are medium to large in size, included in a major index, relatively liquid, and have good visibility among investors. Such firms, therefore, can choose when and how often to attend conferences. This procedure yields 56,924 transcripts.

The unit of analysis in most of my empirical tests is at the firm-quarter level (except for the insider trading analysis, which is conducted at the insider trades level).⁷ I construct the firm-quarter panel by gathering quarterly financial and market information from Compustat/CRSP from 2004 to 2017 for all firms that appear in the transcript sample. For firm-quarters during which no transcripts are available (in other words, without any conferences), I only retain an observation if it occurs within two years before or after a conference to avoid any bias in the data providers' coverage that might be correlated with product-market activities or properties of management forecasts. This approach also serves to mitigate concerns that any results are driven by systematic

⁶ Factset CallStreet covers more firms than Thomson StreetEvents. Therefore, I start the data-collection process with Factset and for firms that are not covered in Factset CallStreet, I obtain transcripts from Thomson StreetEvents. To eliminate bias introduced by Russell index re-constitution, if a firm is ever included in the Russell 3000 index, I include it for the entire sample period (to the extent that data is available).

⁷ Section 4.3.2 provides details of the sampled used in the insider trading analysis.

changes in a firm's policy towards attending investor conferences. This procedure results in 73,262 firm-quarter observations from the sample of 56,924 transcripts.⁸ I obtain data on analyst coverage and management forecasts from I/B/E/S, institutional investors' holdings and trades data from Thomson-Reuters 13F, supply chain information from Factset Revere, earnings conference call transcripts from S&P Capital IQ, and insider trading data from Thomson Insiders. Requiring data coverage from these additional databases results in a smaller sample in some analyses.

Table 1 presents the descriptive statistics of the transcript sample. Panel A (B) shows the frequency of transcripts by year (quarter). The number of transcripts increases gradually over time. It is more concentrated in 2010 to 2013 and during the second quarter, suggesting the importance of controlling for common time trends across years and quarters throughout my empirical analyses.

4. **Research Design**

To provide evidence of managers learning, I develop two sets of analyses. First, I examine whether managers seek more direct interactions when they have a high demand for certain types of information that they expect their current base of institutional investors to possess. Second, I examine whether information learned through direct interactions is reflected in subsequent decisions made by the manager, namely, the frequency and accuracy of management forecasts and the timing and profitability of insider trades. Next, I describe my empirical analyses in detail.

4.1. Measures for managers–investors interaction

Utilizing conference transcripts, I develop six empirical proxies to measure the frequency of interactions and to estimate the degree of information flow between investors and managers, building on the premise that interactions and information flow are the necessary conditions for

⁸ For firm-quarters without any conference attendance, all proxies of direct interactions will take a value of 0. In robustness analysis presented in the Internet Appendix, I repeat my analyses by only retaining firm-quarters with at least one conference occurrence. My results and inferences remain unchanged.

learning to occur. First, I measure the frequency of interactions using the number of investor conferences that a firm has attended during a fiscal quarter (*NumInteract*). Second, the degree of information flow is a function of who is present at such meetings, and firms have control over how much resources, in terms of managerial time, to put in a conference. I measure the number of total corporate participants (*NumExecs*) and the number of times that the CEO has attended an investor conference during a fiscal quarter (*CEO*). Next, as managers can attract investor attention, gather feedback, and solicit questions by presenting different aspects of the firm, I measure the total number of words in the management discussion session(s) of all conferences that a firm has attended during a fiscal quarter (*MDWords*). Investors often express their views during Q&As, and managers' willingness to entertain questions can, in turn, facilitate a more active discussion. Therefore, I calculate the average number of words in answers provided per question during the Q&A session(s) of conferences that a firm has attended during a fiscal quarter (*AnsPerQ*). In addition, firms that invest more managerial time to meet with different investors privately are more likely to benefit from such closed-door discussions. I compute *PrivateMtg*, which is the number of conferences whereby the firm offers private meetings during a fiscal quarter. To identify private meetings, I follow the procedure described in Bushee, Jung, and Miller (2017) and search through transcripts that mention "one-on-one" or "breakout" (and all common variants), or an indication in the last few lines of the transcript that mentions "moving to another room" (or other wording that would indicate the presence of a breakout session). Finally, I extract the first principal component of the above-mentioned six measures (*Direct Interaction*). Principal component analysis reduces the individual variables into a common factor that accounts for most of the variance in the observed measures of direct interactions. It helps to reduce data dimensionality while preserving the most important information from the data sources (Abdi and Williams, 2010).

Table 2 Panel A presents the descriptive statistics for the above-mentioned proxies. The full sample consists of 73,262 firm-quarter observations. For firm-quarters without any conference occurrence, all proxies of interactions take the value of zero. Descriptive evidence suggests that managers interact with investors regularly, through public or private meetings at investor conferences. The average number of manager-investor interactions is 0.678 per quarter, with 18% of quarters have more than one interaction (*NumInteract*). The number of times that a CEO attends a conference is 0.412 per quarter (*CEO*), and the average number of times that a firm offers private meetings is 0.187 per quarter (*PrivateMtg*). On average, 1.041 corporate executives interact with investors at conferences in a quarter (*NumExecs*). In the full sample (including quarters without any interactions), the mean value of *AnsPerQ* (*MDWords*) is 66 words (2,480 words). Conditioning on attending a conference, managers, on average, answer 144 words per question asked, and the median is 136 words per question asked (un-tabulated). The management discussion session usually runs slightly longer, and the mean (median) number of words per conference is 3,729 (3,228) words (un-tabulated). Table 2 Panel B presents the respective factor loadings of the six proxies in the first principal component, *Direct Interaction*, and all six proxies load positively. *Direct Interaction* has an eigenvalue of 4.31 and explains 72% of the variance.

4.2. Incentives for learning

Providing investor access is costly for the firm, as it occupies the managers' time and the firm's resources (Kirk and Markov 2016). As a result, managers are willing to incur such costs when they have a high demand for types of information that they expect external parties to possess, such that the perceived net benefit of direct learning is high. In this section, I develop three distinct and complementary empirical proxies to capture a manager's information demand. I first examine two specific situations whereby the manager is likely to be at an information disadvantage because

of changes in the firms' external competitive and operating environment. The advantage of these two proxies is that they focus on specific sources of information uncertainty, allowing me to develop corresponding measures that capture investors' supply of the relevant information in subsequent cross-sectional analyses. However, these proxies capture a manager's uncertainty indirectly and rely on the assumption that the manager is indeed put into an information disadvantage when there are changes to the firm's external environment. Therefore, to complement these two proxies, I develop a direct measure that captures the overall realization of a manager's uncertainty about the firm's future operating prospects

4.2.1. Demand for product-market information

Managers often need to pay attention to the actions of their peers in formulating product-market strategy (Bernard et al., 2019; Dessaint et al., 2019; Foucault and Fresard, 2014). For example, Bernard et al. (2019) document that firms search for public disclosure of peer firms who operate in a similar product-market space and when there are investment opportunities, suggesting the relevance of peer information in making investment and product decisions. Consequently, managers are likely to have higher information demand when there is an increased amount of product-market activities among their peer firms. The intuition is that when a peer firm makes a product-market announcement, managers want to know about the circumstances surrounding that decision. Institutional investors can possess relevant information because they have superior information processing abilities and enjoy scale economies in acquiring sector-related information.

Therefore, I measure the frequency and the impact of product-market announcements made by the focal firm's peers to capture the focal firm manager's demand for product-market information. For each focal firm, *Demand for Prd Mkt Info* is the sum of absolute announcement-day adjusted stock returns of product-market announcements made by its peer firms during a fiscal

quarter, scaled by the total number of peers.⁹ Using adjusted returns allows me to capture variations in the significance of these announcements and essentially place higher weights on announcements that are more important, thus generating greater stock market reactions. I use Hoberg-Phillips text-based network industry classifications to define peer firms (Hoberg and Phillips, 2016, 2010).

4.2.2. Demand for supply chain information

A production network is an important form of inter-firm linkages that can transmit production shocks from suppliers and demand shocks from customers (Acemoglu et al., 2012; Barrot and Sauvagnat, 2016). Therefore, a firm's suppliers and customers are important and economically connected firms. When there is an increased level of product-market activities from such connected firms, managers are likely to demand more information about their upstream and downstream industries. Therefore, similar to *Demand for Prd Mkt Info*, I capture managers' demand for supply chain information using the sum of the absolute adjusted announcement-day returns of product-market announcements made by the focal firm's direct suppliers and customers, scaled by the total number of suppliers and customers (*Demand for Supply Chain Info*). I obtain information on a firm's suppliers and customers from Factset Revere.

4.2.3. Managerial uncertainty

Next, I develop a proxy that directly measures a manager's revealed uncertainty with respect to the firm's future operating prospects, exploiting a situation whereby the manager has to respond on-the-spot to questions raised by investors during the Q&A sessions of an earnings conference call. Unlike the previous two measures (which focus on specific scenarios that are likely to give rise to higher managerial uncertainty), this measure directly captures the ex-post realization of a manager's overall uncertainty, encompassing all potential sources.

⁹ The purpose of scaling is to make sure this measure captures the frequency and the magnitude of peer activities on a per-peer-firm basis, and does not merely reflect a firm having more product-market peers.

An earnings conference call is an important disclosure event that often involves real-time information exchange between investors and managers (Gow et al., 2019). Compared to other forms of written disclosure that are carefully prepared and reviewed beforehand, the Q&A sessions represent a situation of real-time and dynamic information exchange that is more likely to reveal a manager's uncertainty about the firm's future operations. Therefore, I calculate *Managerial Uncertainty*, which is the proportion of answers that contains at least one uncertain word during the Q&A sessions of the earnings conference call for a given fiscal quarter. An uncertain word is defined using the Loughran and McDonald sentiment wordlist (Loughran and McDonald, 2011).

4.2.4. Empirical specification

I estimate the following OLS model to investigate the relation between managers' information demand and direct interactions:

$$Direct\ Interactions_{it} = \alpha_0 + \alpha_1 Manager\ Information\ Demand_{it-1} + \Gamma X_{it-1} + \eta_i + \phi_t + \nu_q + e_{it} \quad (IC1)$$

where i denotes firm, t denotes quarter, η_i denotes firm dummies, ϕ_t denotes calendar-year-quarter dummies and ν_q denotes fiscal quarter dummies. *Manager Information Demand* is either *Demand for Prd Mkt Info*, *Demand for Supply Chain Info*, or *Managerial Uncertainty*. *Direct Interactions* measure the frequency of manager-investor interactions, as well as the degrees of information exchange between investors and managers using the six empirical proxies described in section (4.1): *NumInteract*, *CEO*, *NumExecs*, *MDWords*, *AnsPerQ*, *PrivateMtg*, and the first principal component, *Direct Interaction*.

One concern is that managers might attend more conferences (i.e., provide more investor access) when investors are demanding information. Therefore, in the vector of control variables (X), I include proxies for investors' demand for information and previously identified capital-market incentives that motivate a manager to increase investor access (i.e., these are incentives for

a manager to “teach,” instead of to learn). Larger firms (*Size*), firms with more institutional investors (*Inst. Ownership*), and analyst following (*Analyst*) are likely to have greater visibility among equity investors. I control for the firm’s financing (*Financing*) and M&A activities (*M&A*), as managers have strong disclosure incentives around these activities (Lang and Lundholm, 2000). I control for profitability, growth, and potential uncertainty over the firm’s undervaluation, including firm age (*Firm Age*), the book-to-price ratio (*BM Ratio*), leverage ratio (*Leverage*), an indicator for loss-reporting firms (*Loss*), whether the firm operates in a high-technology industry (*High Tech*), adjusted returns (*Ret*), return volatility (*Ret Vol*), R&D expenditure (*R&D*) and intangible assets (*Intangibles*) (Bushee et al., 2011; Green et al., 2014a; Kirk and Markov, 2016; Koh and Reeb, 2015). Investors might demand more information when the firm has a complex business model or is undergoing changes to its operations; I control for the number of segments (*Segments*) and an indicator for restructuring (*Restructuring*). To mitigate concerns that activities of firms operating within the same product-markets are correlated, and therefore an increase in direct interactions is driven by investor demanding for more information, I control for the firm’s own product-market activities using the number of product-market announcements (*AnnFreq*) and the sum of absolute market-adjusted announcement-day returns (*AnnAR*).

I estimate equation (IC1) with individual firm dummies to rule out concerns that certain types of firms are more likely to attend investor conferences. I include a separate dummy for each calendar-year-quarter combination to control for time-variant macroeconomic trends that could both affect general product-market activities and the occurrence of investor conferences. I include separate dummies for each of the four fiscal quarters to address concerns that seasonality in the product market might be correlated with firms’ propensity to attend conferences over different fiscal periods of the year.

4.2.5. Results and discussions

Table 2 presents descriptive statistics for the variables used in the subsequent empirical analysis using a firm-quarter as the unit of analysis. The full sample consists of 73,262 firm-quarter observations. Further requiring data coverage from various databases result in a reduction in sample size for some of the variables. The firms in my sample are relatively large, with an average (median) asset size of \$5,630 million (\$1,313 million), and have eight covering analysts on average.

Table 3 presents the results of this analysis. Panel A investigates the association between managers' demand for product-market information and direct interactions, controlling for the firm's own product-market activities. The coefficient on *Demand for Prd Mkt Info* is positive across all six proxies of direct interactions, as well as their first principal component, *Direct Interaction*. It is significant under 1% (10%) significance level for three (four) out of the six proxies, as well as for the principal component, *Direct Interaction*, consistent with my hypothesis that managers seek more direct interactions with investors when there is greater need to gather information about their peer firms. In column (7), the point estimate on *Demand for Prd Mkt Info* is 1.216, which suggests that one standard deviation increase in *Demand for Prd Mkt Info* is associated with a 0.029 ($1.216 \times 0.024 / 1.009$) standard deviation increase in *Direct Interaction*, ceteris paribus. The coefficients on the control variables have the expected signs: larger and more mature firms, firms with more institutional investors, higher analyst coverage, and more product-market activities are more likely to provide investor access.

Panel B examines the association between managers' demand for supply chain information and direct interactions. The reduction in sample size in Panel B (and subsequently in Panel C) is because of requiring coverage from Factset Revere (Capital IQ transcripts) for the computation of *Demand for Supply Chain Info (Managerial Uncertainty)*. The coefficients on *Demand for Supply*

Chain Info are positive across all proxies and are significant under 5% under four out of six, as well as for the first principal component, *Direct Interaction*. Compared to *Demand for Prd Mkt Info*, the economic significance of *Demand for Supply Chain Info* is smaller. The point estimate of 0.665 in column (7) translates to one standard deviation increase in *Demand for Supply Chain Info* is associated with a 0.018 ($0.665 \times 0.027 / 1.009$) standard deviation increase in *Direct Interaction*, ceteris paribus. Consistently, the results suggest that managers seek more direct interactions when they have a higher demand for information regarding their supply chain industries.

Panel C presents the analysis from investigating the association between the managers' overall uncertainty and direct interactions. The coefficients on *Managerial Uncertainty* are consistently positive and significant under 10% across five out of the six empirical proxies of direct interactions, consistent with the notion that managers seek more direct interactions when they face higher uncertainty. The economic magnitude is comparable to that of *Connected Firm Activities*, with one standard deviation increase in *Managerial Uncertainty* is associated with 0.013 ($0.068 \times 0.202 / 1.009$) standard deviation increase in *Direct Interaction*, ceteris paribus.

In the Internet Appendix, I present alternative specifications that address concerns raised by (i) the decline in the number of conferences during the financial crisis in 2007 and 2008 and (ii) implications from inter-firm information transfer. My results and inferences remain unchanged.

4.2.6. *Cross-sectional analyses*

The previous two sections focus on the manager's information demand when it is driven by a specific source of uncertainty, either related to (i) the product market that the firm operates in or (ii) the firm's upstream and downstream industries. Consequently, we would expect that the extent of the manager's propensity to resolve their information uncertainty through direct learning from institutional investors depends on their expectation of how knowledgeable their investors are

in these specific areas. Therefore, in the section, I develop explicit proxies to capture investors' supply of information about the firm's product market as well as its supply chain industries.

First, when the source of information uncertainty arises from product-market peers, I partition the sample based on managers' expectations of the amount of product-market knowledge that their current institutional investor base is likely to possess.¹⁰ I estimate institutional investors' product-market knowledge using their dollar investments (*Prd Mkt Hldgs*) and dollar trading activities (*Prd Mkt Trades*) in the focal firm's product-market peer firms:

$$Prd\ Mkt\ Hldgs_{it} = \sum_{j \in J} \sum_{p \in P}^n \frac{Dollar\ Holdings_{jp}}{n}$$

$$Prd\ Mkt\ Trades_{it} = \sum_{j \in J} \sum_{p \in P}^n \frac{Dollar\ Trades_{jp}}{n}$$

where J is the set of all institutional investors that hold at least 1% of the total common shares outstanding in the focal firm i , P is the set of all product-market peer firms of the focal firm i . Product-market peer groups are defined using Hoberg-Phillips text-based industry classification.¹¹ n is the total number of product-market peer firms. *Dollar Holdings* (*Dollar Trades*) is investor j 's dollar holdings (quarterly dollar trades) in firm p , averaged over all 13F reports made over the trailing 12 months ending before the start of the fiscal quarter, t .

Correspondingly, when managers demand more sector-related information about upstream and downstream industries, I develop measures to capture the investors' knowledge for supply chain industries using the following formulae:

$$Supply\ Chain\ Hldgs_{it} = \sum_{k \in K} \sum_{j \in J} \frac{Industry\ Dollar\ Holdings_{jk}}{n_k}$$

¹⁰ Because managers do not know which investors will attend a conference beforehand, using the current investor base captures the manager's expectation of investor attendance.

¹¹ I focus on institutional investors that hold more than 1% the firm's shares because these investors are more likely to interact with managers during an investor conference. I do not restrict holding size in peer firms.

$$Supply\ Chain\ Trades_{it} = \sum_{k \in K} \sum_{j \in J} \frac{Industry\ Dollar\ Trades_{jk}}{n_k}$$

where K is the set of all SIC 4-digit industries whereby the focal firm i has at least one direct supplier or one customer. J is the set of all institutional investors that hold at least 1% of the total common shares outstanding in the focal firm i . *Industry Dollar Holdings (Industry Dollar Trades)* is the dollar holdings (quarterly dollar trades) in industry k by investor j , averaged over all 13 F reports made over the trailing 12 months ending before fiscal quarter t . n_k is the number of direct suppliers and customers in industry k .

I hypothesize that the positive association between managers' demand for product-market (supply chain) information and direct interactions is stronger when managers expect their institutional investors to be knowledgeable about the product market (supply chain industries). Table 4 panel A (Panel B) examines the relation between *Demand for Prd Mkt Info (Demand for Supply Chain Info)* and direct interactions, dividing the sample in Table 3 Panel A (Panel B) based on the median value of investors' product-market knowledge (supply chain industry knowledge).¹² Requiring coverage in Thomson-Reuters 13F to compute investors' portfolio holdings and trades results in a reduction in the size of the respective sample (see Table 2 for descriptive statistics). Consistent with my predictions, I find that the relation between *Demand for Prd Mkt Info (Demand for Supply Chain Info)* and direct interactions is positive and significant only when investors are more knowledgeable about product-market firms (supply chain industries). Further, the economic magnitude of *Demand for Prd Mkt Info* in the high sub-sample is about two times larger than that in the full sample in Table 3, with one standard deviation increase in *Demand for Prd Mkt Info* is

¹² For parsimony purposes, I only present the results using the component score, *Direct Interaction*, as the dependent variable. However, my inferences remain unchanged if using individual proxies (*NumInteract*, *CEO*, *NumExecs*, *AnsPerQ*, *MDWords*, *PrivateMtg*).

associated with around 0.05 standard deviation increase in *Direct Interaction*.¹³ The F-statistics comparing the coefficients on *Demand for Prd Mkt Info* across the two subsamples is 3.878 (p-value: 0.049) when using *Prd Mkt Trades* as the proxy for investors' product-market knowledge and 4.531 (p-value: 0.033) when using *Prd Mkt Hldgs*. For *Demand for Supply Chain Info*, the F-statistics between the two sub-sample is 2.473 (p-value: 0.116) when using *Supply Chain Trades* to capture investors' supply chain information, and 2.885 (p-value: 0.090) for *Supply Chain Hldgs*.

4.2.7. *Alternative specifications using conference-quarter only*

The sample in my main analyses includes any firm-quarters as long as they occur within two years of a conference for a given firm. This design choice captures variations in a manager's decision to attend an investor conference, which is an important element of a manager's decision set because conference attendance is costly in terms of firm resources and managerial time. However, one possible concern is that broker-hosted conferences are primarily by-invitation. While big firms are invited to most conferences (and therefore, their managers have the choice to attend or decline), smaller firms might not have control over when and to which conference they are invited. While I restrict my sample to a group of relatively liquid firms with good visibility among investors (i.e., the Russell 3000 universe), this might remain a concern among the smaller firms in my sample. Therefore, in the Internet Appendix, I repeat the analyses in Table 3 to Table 5 using the smaller sample of firm-quarters with at least one conference and focus on variations in the amount of managerial time invested and the degrees of information exchange between investors and managers, conditioning on attendance. My results and inferences remain unchanged.

4.3. *Consequences of learning*

¹³ The calculation of standardized coefficient is based on the respective standard deviation of *Demand for Prd Mkt Info* and *Direct Interaction* in the sub-sample.

In the following sections, I investigate whether and how information learned through direct interactions is reflected in the manager's subsequent decisions. While I cannot directly observe how a manager's private information set has changed after direct learning, I instead focus on two managerial decisions that are likely to be sensitive to the acquisition of investors' information and therefore serve as a window into the manager's information set. Specifically, I examine managers' ability to issue more and more accurate management forecasts, as well as their insider trading profits. I focus on these two decisions because (i) they both rely on the manager's private information about the firm's future operating prospects, which could benefit from institutional investors' macroeconomic and sector knowledge, (ii) both decisions have an information content, as suggested by the respective market reactions to the issuance of management forecasts and the disclosure of insider trades (Brochet, 2010; Hoskin et al., 1986; Lakonishok and Lee, 2001; Rogers and Stocken, 2005), (iii) managers' private information reflected in these decisions can be verified *ex-post*, using the accuracy of management forecasts and the abnormal returns associated with insider trades, (iv) managers make both decisions regularly throughout the year, even in the absence of direct learning, which facilitates the design of empirical tests to examine the effect of learning, and (v) prior evidence suggests that managers' personal and corporate decisions are coordinated when the source of underlying information is common (Jenter, 2005).

4.3.1. *Frequency and accuracy of management forecasts*

Managers' ability to issue accurate earnings guidance depends on whether they can accurately forecast firms' future operations (Waymire, 1985). As management forecasts incorporate both firm-specific and sector information (Bonsall et al., 2013), institutional investors' information can be relevant to managers. Institutional investors' information can complement the manager's knowledge about macroeconomic and sector trends, fill in the "mosaic" around his

private information set, and help him to make more accurate predictions about the firm's future operating environment. Therefore, I investigate the effect of direct learning on the frequency and accuracy of management forecasts.¹⁴ The OLS empirical specification is:

$$Disclosure\ Outcome_{it+1} = \beta_0 + \beta_1 Direct\ Interactions_{it} + \Gamma X_{it} + \eta_i + \phi_t + \nu_q + e_{it} \quad (MG1)$$

where i denotes firm, t denotes quarter, η_i denotes firm dummies, ϕ_t denotes calendar-year-quarter dummies and ν_q denotes fiscal quarter dummies. *Direct Interactions* measures the frequency of manager-investor interactions and the degrees of information exchange using empirical proxies discussed in section (4.1): *NumInteract*, *CEO*, *NumExecs*, *MDWords*, *AnsPerQ*, *PrivateMtg*, and their first principal component, *Direct Interaction*.

I examine the following disclosure outcomes. First, I investigate whether managers can issue more forecasts after learning, using the number of management forecasts (*Forecasts*). Because an increase in management forecasts can be driven by investors demanding the manager to release more information about the firm at the conference, I subsequently examine management forecasts that are revisions to an earlier forecast (*Revisions*). This is because if the increase in forecasts is driven by investors demanding new information about previously un-guided periods, it will manifest in the issuance of new forecasts instead of forecast revisions. Last, I examine forecast accuracy using the absolute error for EPS guidance, scaled by one-quarter lagged share price, and averaged across all EPS forecasts in a given fiscal quarter (*FcastError*).

¹⁴ The maintained assumption here is that managers are, on average, motivated to produce accurate earnings forecasts because accurate earnings forecasts are perceived positively by investors, analysts and the board of directors (Lee et al., 2012; Williams, 1996; Yang, 2012; Zhang, 2012). However, managers may be incentivized to provide biased earnings forecasts under certain circumstances. In an alternative theory, managers provide more pessimistic forecasts to avoid negative earnings surprises after direct interactions, and to the extent that lower forecasts are more accurate, one would observe both an increase in the number of forecast revisions and a decline in forecast errors. In the Internet Appendix, I rule out this alternative explanation by showing that the (more accurate) EPS forecasts issued by managers following direct learning are not associated with a higher likelihood of eventual meeting or beating analyst consensus.

The vector of control variables, X , includes time-varying firm characteristics identified in prior studies to be associated with forecast properties. I control for firm size ($Size$) as larger firms tend to issue more and more accurate forecasts (Ajinkya et al., 2005). Firms that report losses may have more difficulty forecasting future earnings, so I include an indicator for whether the firm reported a loss ($Loss$) and returns on assets (ROA). I control for the extent of external monitoring ($Inst. Ownership$), the external information environment ($Analyst$), and liquidity ($Bid-ask Spread$, $Turnover$). Higher earnings volatility ($Earnings Vol$) and changes in the firm's business operations ($Restructuring, M\&A$) decrease managers' ability to predict the firm's future operations (Waymire, 1985). I include growth opportunities ($BM Ratio$), whether the firm operates in a high-technology industry ($High Tech$), and research and development expenses ($R\&D$) to control for the fact that growth and high-tech firms might face more difficulty in forecasting future earnings, following Bamber et al. (2010) and Yang (2012). To mitigate concerns that new forecasts are issued because the manager has (intentionally or inadvertently) disclosed new information during a conference, I include the number of 8k filings that pertain to Reg FD (i.e., item 7.01) ($RegFDDiscl.$). Because I include both annual and quarterly forecasts in my sample, I control for the percentage of annual forecasts ($PctAnnFcast$). I control for forecast horizon ($Horizon$), calculated as the number of days between the forecast date and the actual date, when using $FcastError$ as the outcome variable because earlier forecasts tend to be less accurate (Baginski and Hassell, 1997). Last, I include all other determinants of managers' incentives to seek direct learning in equation (IC1).

Table 5 presents the results of this analysis.¹⁵ Panel A investigates the relation between direct learning and the frequency of management forecasts ($Forecasts$). The coefficients on *Direct Interactions* are positive and statistically significant under 5% across all seven proxies of direct

¹⁵ Compared to the full sample in Table 3, requiring data coverage from I/B/E/S to compute various disclosure variables results in a reduction in the sample size.

interactions, consistent with my predictions that information acquired through direct learning manifest in managers' ability to issue future guidance. The point estimate on column (7) is 0.009, which translates to one standard deviation increase in *Direct Interaction* is associated with a 0.9% ($e^{0.009*1.009} - 1$) increase in the number of management forecasts, ceteris paribus. Panel B restricts to management forecasts that are revisions to an earlier forecast (*Revisions*). The coefficients on the proxies of direct learning remain positive and statistically significant under 1%, and the economic magnitude is larger. One standard deviation increase in *Direct Interaction* is associated with a 1.9% ($e^{0.019*1.009} - 1$) increase in the number of forecast revisions. Panel C presents the result using management forecast error (*FcastError*) as the dependent variable. This analysis essentially restricts to firm-quarters with an EPS forecast, and therefore result in a reduction in the size of the sample. The coefficients on *Direct Interactions* are negative across all six proxies and are significant under 5% (10%) in two (five) out of six, and are also negative and significant under 5% for *Direct Interaction*. The point estimate for *Direct Interaction* is -3.017, which translates to one standard deviation increase in *Direct Interaction* is associated with 0.01 (-3.017*1.009/322.7) standard deviation decrease in EPS forecasts errors (*FcastError*), ceteris paribus. The results are consistent with my prediction that direct learning expands managers' private information set about the firm's future performance, and is in turn, reflected in the lower error of their EPS forecasts.

4.3.2. *Timing and profitability of insider trades*

Prior literature recognizes that trades by insiders both reflect their superior information on the firm's future operation as well as their contrarian belief that the security of their firms differs from its fundamental value (Ke et al., 2003; Piotroski and Roulstone, 2005; Seyhun, 1992, 1986;

Sias and Whidbee, 2010).¹⁶ Direct learning improves managers' information set in both aspects. Institutional investors' knowledge can complement the manager's information set or fill in the "mosaic" around his private information, which in turn helps him to forecast the firm's future operations. Moreover, institutional investors have first-hand knowledge about their trades, general investor sentiments, and the market's perception of the firm's performance, all of which can help managers assess whether their firms' stocks are over- or under-valued.

To investigate whether and how information through direct interactions is reflected in the timing and the profitability of managers' insider trades, I collect insider transactions made by corporate officers using Form 4 data from the Thomson Reuters Insider Filing database. Thomson Reuters collects corporate insider transaction information that is subject to the disclosure requirements under Section 16 of the Securities Exchange Act of 1934. My empirical analysis focuses on the close window around an investor conference and examines how a manager's private information changes after direct learning at the conference. My regression sample includes 28,632 reported open-market stock purchases and sales made by corporate officers within two months before or after the date of a conference that a firm has attended. Following prior literature, I require non-missing data on the trade price, the number of shares traded, and the transaction date. I restrict the sample to only opportunistic trades using Cohen et al. (2012)'s trade-level classification.¹⁷

¹⁶ For instance, Piotroski and Roulstone (2005) document that insider trades are positively associated with future earnings performance (which reflects their superior information), BM ratio and inversely related to recent returns (which reflects trading against potential mis valuation). Ke et al. (2003) show that insiders possess and trade upon knowledge of economically significant forthcoming disclosures. Sias and Whidbee (2010) show insider trades are partly motivated by their perception that their securities are overvalued (undervalued) following a period of institutional net buys (sells). Insider trades predict future stock returns, as insider trading activity is positively correlated with changes in future real activities, and insiders are more likely to buy (sell) follows periods of stock depreciation (appreciation) (Seyhun, 1992, 1986).

¹⁷ A routine trade is one for which the insider has made three trades in the same month in each of the three previous years. All other trades are opportunistic. A trade-level classification is more appropriate because I focus on the narrow window around a conference. However, my results remain unchanged using the person-level classification.

I examine both the timing and the profitability of insider trades made by executives who participated in a conference (i.e., participating insiders) as the information acquired through direct learning, if any, will likely result in participating insiders having an information advantage over non-participating insiders from the same firm.

First, if a manager who participated in the conference was able to acquire information from institutional investors that is relevant for him in predicting the firm's future performance, we should expect that manager to utilize this information advantage in a short-window after the conference. Specifically, I examine if participating insiders are more likely to trade in the seven-day window after a conference, using the following equation:

$$1(Trade_{POST})_{ijk} = \beta_0 + \beta_1 ParticipatingInsider_{ijk} + \Gamma X_{ijk} + Fixed\ Effects + e_{ijk} \quad (IT1)$$

where i denotes firm, j denotes executive and k denotes trade. $1(Trade_{POST})$ is an indicator variable that takes the value of one if the trade is placed within seven days after an investor conference, and zero otherwise. *Participating insider* is an indicator that takes the value of one if the trade is placed by an insider j who has participated in an investor conference prior to the transaction date of the trade on behalf of firm i , and zero otherwise.

Next, information acquired through direct interactions should reflect in the profitability of participating insider trades when compared to other trades executed at the same firm and during the same narrowly-defined window, but without direct learning. Specifically, I examine if trades placed by participating insiders in the seven-day window after a conference (i.e., participating insider trades) generate higher abnormal positive returns when compared to (i) trades made by insiders of the same firm but who did not participate in a conference and (ii) trades made by

participating insiders but outside of the conference window (collectively, non-participating insider trades).¹⁸ The empirical specification is as follows:

$$Profits_{ijk} = \beta_0 + \beta_1 ParInsiderTrade_{POST_{ijk}} + \Gamma X_{ijk} + Fixed\ Effects + e_{ijk} \quad (IT2)$$

where i denotes firm, j denotes executive, and k denotes trade. $ParInsiderTrade_{POST}$ takes the value of one if executive j placed a trade k within the seven-day window after attending an investor conference on behalf of firm i , and zero otherwise. Consistent with prior literature (Bowen et al., 2018; Ravina and Sapienza, 2009), I measure the profitability of insider trades as the (unrealized) capital gains after purchases and losses avoided after sales. The dependent variable is either $Alpha30$ or $BHAR30$. $Alpha30$ measures the average risk-adjusted returns for each insider transaction calculated over the 30 days following a transaction and relative to the Fama and French (1993) three-factor models, multiplied by -1 for sales. $BHAR30$ measures the market-adjusted buy and hold return over 30 days following a transaction, multiplied by -1 for sales.

I estimate both equation (IT1) and (IT2) using only within-firm variations by including either firm-quarter or firm-month fixed effects. This specification focuses exclusively on variations within a firm- quarter (e.g., a fixed effect for 3M Co. in Q1 2012) or a firm-month (e.g., a fixed effect for 3M Co. in January 2012) and subsumes all time-varying firm characteristics that do not vary during a given firm-quarter or firm-month (e.g., the number of product-market announcements made by Abbott Laboratories). To the extent that there is a potential omitted variable that does not vary within a firm-quarter or firm-month, then this specification controls for that variable. This design choice is important because it essentially restricts the comparison to trades made by executives from the same firm and within the same short window (quarter or month). It controls for many time-varying factors that might be associated with conference

¹⁸ In the Internet Appendix, I separately examine these two groups of non-participating insider trades and find participating insider trades have a significant information advantage over both groups.

attendance (e.g., firm performance, operating and financing changes, product-market decisions, and growth opportunities, etc.) and the timing and profitability of insider transactions. While the firm-month specification is the most robust in ruling out omitted firm-level characteristics, its limitation is that it relies on having meaningful variations in *ParInsiderTrade*_{POST} for a given firm-month, which is less of a concern in the firm-quarter specification. In the vector of controls, X , I include a dummy variable for whether the executive is a CEO to mitigate concerns that the CEO is both more likely to attend an investor conference and has more precise firm-specific information. I control for the information content of the conference (from investors' perspective) using conference-window abnormal returns (*Conf Abn Ret*) and abnormal trading volumes (*Conf Abn Turnover*), following Bushee et al. (2011). The coefficient of interest is β_1 , which measures whether participating insiders' trades generate higher abnormal returns, thus reflecting superior private information, when compared to non-participating insider trades.

Panel A of Table 6 provides descriptive statistics of the sample. On average, 13.3% (14.6%) of the trades are executed in the seven-day window after (before) the conference, and the percentage of participating insider trades is around 3% (3%) after (before) a conference. The mean (median) size of transaction is \$1,696,843 (\$143,610). Panel B of Table 6 presents the results from equation (IT1). The coefficient β_1 is positive and significant across all columns. The results suggest that in the same firm-month and compared to executives who did not attend a conference, participating insiders are 6.7% more likely to utilize their information advantage after direct learning and trade in the seven-day post-conference window.

Table 7 Panel A presents the results for equation (IT2). Columns (1) and (2) present the results using 30-day trading alpha, and columns (3) and (4) use 30-day buy-and-hold returns. The coefficients on *ParInsiderTrade*_{POST} are significantly positive across all specifications. Compared

to non-participating insider trades, participating insider trades in the same firm-month generate an incremental alpha of 2.8 basis point per month. The results are consistent with managers' information set expanding as a result of their direct learning. The coefficients on the information content of the conference (from investors' perspective) are positive, and it is significant for *Conf Abn Turnover*, suggesting that information flow between investors and managers is reciprocal in nature. The coefficients on *CEO* are generally negative and significant in some specifications. This is consistent with prior findings that CEOs do not earn higher trading profits than other top executives (Wang et al., 2012).

4.3.2.1. *Distinguish between anticipated disclosure versus direct learning*

An alternative explanation that managers can trade profitably around direct interactions with investors is that managers can anticipate investors' reaction to information that is disclosed by the manager during such meetings (i.e., anticipated disclosure). Managers can sell (buy) before direct interactions if they anticipate investors to react negatively (positively) to what they are planning to talk about, especially when managers are responding to questions raised during Q&As or during private meetings as these responses are less likely to be scripted. For instance, Bowen et al. (2018) examine private meetings between managers and outside investors and analysts for firms listed on China's Shenzhen Stock Exchange. They find that insiders are able to trade profitably in the twenty-day window before or after a private meeting, consistent with both anticipated disclosure and learning (and they do not distinguish between these two explanations). Bushee et al. (2020) show that managers opportunistically issue voluntary disclosure to hype up stock prices and sell their shares at inflated prices *prior to* a conference

While I acknowledge that anticipated disclosure is a possible mechanism for managers to trade profitably around direct interactions, my analyses attempt to isolate the effect of learning by

examining the differential information advantage by participating insiders over non-participating insiders and focusing on trades *after* a conference. Moreover, I conduct two additional analyses to provide more comfort that my results are not driven by anticipated disclosure. First, I restrict the sample to a subset of conferences for which at least two executives from the sample firm have attended. It is less likely that a single participating executive can anticipate investors' overall reactions when multiple executives have interacted with investors during an investor conference. Moreover, strategic disclosure (i.e., managers disclose information to investors that would move stock prices in a certain way) becomes costlier because it would require coordination among top executives to disclose material information, which is a violation of Reg FD. Table 7 presents the results of this analysis. The coefficients on *ParInsiderTrade*_{POST} remain positive and significant.

Next, anticipated disclosure would predict that participating insiders can make profitable trades via front-running (i.e., trading *before* the conference), while direct learning would only predict that participating insiders' information advantage occurs *after* the conference. To distinguish between these two theories, I carry out a falsification test by examining (i) whether participating insiders are more likely to trade in the seven-day window before a conference and (ii) whether trades that are executed in the seven-day pre-conference window earn more positive abnormal returns. I modify equation (IT1) and (IT2) accordingly. Table 8 Panel A modifies equation (IT1) by using $I(Trade_{PRE})$ as the outcome variable, which is an indicator variable that takes the value of one if a trade is placed within the seven-day pre-conference window, and zero otherwise. The coefficients on *Participating Insider* are significantly negative. This result, combined with the results in Table 7, suggest that participating insiders are less likely to trade in the pre-conference window, but rather, wait after they have acquired relevant information from investors after a conference. Table 8 Panel B modifies equation (IT2) using *ParInsiderTrade*_{PRE},

which is an indicator variable that takes the value of one if a trade is placed by an executive in the seven-window before attending an investor conference, and zero otherwise. The coefficients on *ParInsiderTrade_{PRE}* are positive but are not significant. This result suggests that participating insiders do not have an information advantage over non-participating insiders before the conference, which does not support the alternative explanation of anticipated disclosure.

4.3.2.2. *Cross-sectional analysis: nature of information learned*

The above analyses focus on whether managers can learn something useful from direct interactions with investors. However, it is not clear what is the nature of the information learned. On the one hand, investors can pass along sector- and industry-related knowledge that helps managers to better predict their firms' future competitive landscape and operating environment. On the other hand, managers can infer how investors might trade on their firms' stocks after the conference.¹⁹ To shed light on the types of information learned, I develop cross-sectional predictions based on the manager's demand for specific sources of information. If participating insiders' information advantage comes from the fact that they have obtained industry or sector-related information, then we would expect their trades to be more profitable when they, in fact, have a higher demand for such information. Thus, I partition the sample based on various proxies for managers' information demand, namely *Demand for Prd Mkt Info* and *Demand for Supply Chain Info*.

Table 9 presents the results of this analysis. For parsimony purposes, I report the specification using firm-month fixed effects, which is the most robust in terms of ruling out possible confounders. For information related to the product market, I find the coefficients on *ParInsiderTrade_{POST}* are consistently positive and significant (under 5%) when managers' demand

¹⁹ It is well recognized that institutional investors trade on information obtained during conferences (e.g., Bushee et al., 2011; Bushee et al., 2017).

for such information is high, i.e., in the high sub-sample for *Demand for Prd Mkt Info* is high, but are negative and insignificant in the low sub-sample. The F-statistics comparing the coefficient on *ParInsiderTrade*_{POST} across the two subsamples are significantly different under 5%. For information related to supply chain industries, the evidence is mixed. While the coefficients on *ParInsiderTrade*_{POST} are positive and significant (insignificant) in the high (low) sub-sample when using *Alpha30* as the outcome variable, the F-statistics is not significant. Overall, the evidence is suggestive that one source of participating insiders' information advantage comes from learning about the product-market sector from institutional investors at conferences.

4.3.2.3. *Alternative specifications*

In the Internet Appendix, I present various alternative specifications of insider trading profitability, including (i) restricting to non-CEO trades to mitigate concerns that CEOs are more likely to attend conferences and have superior private information, (ii) restricting to trades within the seven-day window around a conference to limit the comparison to a much tighter window, (iii) controlling for whether an executive has ever attended a conference to mitigate concerns that executives who are able to attend conferences tend to have better private information, and (iv) separately compare participating insider trades with (1) trades made by insiders who did not participate in a conference and (2) trades made by participating insiders outside of the seven-day post-conference window. My results are robust to these alternative specifications, and my inferences remain unchanged.

5. **Conclusion**

In this paper, I investigate whether managers learn from institutional investors through direct interactions. Prior evidence on learning from prices suggests that information contained in stock prices is relevant for managerial decisions, although price as an aggregate signal is likely to

be insufficient for learning. I propose that managers seek out direct interactions with institutional investors as a further mechanism to learn relevant information about their firms and examine direct manager-investor interactions at investor conferences as the mechanism of learning.

My empirical analyses examine both the incentives and the consequences of direct learning. I hypothesize that managers are more likely to seek direct interactions when they have a high demand for specific types of information that they expect their current base of institutional investors to possess. Focusing on industry and supply chain information, I find that managers seek out more direct interactions when they have an information demand and when their current base of institutional investors is knowledgeable. Moreover, managers seek out more direct interactions when they face higher overall uncertainty. Information learned through direct interactions is subsequently reflected in managers' corporate and personal decisions. I find that the frequency and accuracy of management forecasts increase after direct learning. Comparing insider trades in the same firm-month, trades executed by participating insiders within seven days after a conference earn greater positive abnormal returns, consistent with managers' information set expanding as a result of their direct learning.

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APPENDIX A. Variable Definitions

Measures of Management-Investor Interaction

<i>NumInteract</i> (number)	The number of investor conferences (including investor days) that firm <i>i</i> has attended or hosted in the fiscal quarter <i>t</i> .
<i>CEO</i> (number)	The number of times that the CEO of firm <i>i</i> has attended an investor conference during the fiscal quarter <i>t</i> .
<i>NumExecs</i> (number)	The total number of executives from firm <i>i</i> who have attended an investor conference during the fiscal quarter <i>t</i> . If an executive attended more than one conference, each attendance is counted as 1.
<i>AnsPerQ</i> (thousands of words)	The average number of words (in thousands) that managers of firm <i>i</i> provided in response to a question in the Questions and Answers (Q&A) session(s) of investor conferences during the fiscal quarter <i>t</i> .
<i>MDWords</i> (thousands of words)	The total number of words (in thousands) in the Management Discussion (MD) session(s) of the transcript for all investor conferences that firm <i>i</i> has attended during the fiscal quarter <i>t</i> .
<i>PrivateMtg</i> (number)	The total number of times that firm <i>i</i> offers private breakout sessions or one-on-one meetings at investor conferences during the fiscal quarter <i>t</i> . Private meetings are identified by searching through transcripts for mentions of “one-on-one,” “breakout,” or an indication towards the end of the transcript for “moving to another room” (and all common variants), following the procedure described in Bushee, Jung, and Miller (2017).
<i>Direct Interaction</i> (component score)	The first principal component of <i>NumInteract</i> , <i>CEO</i> , <i>NumExecs</i> , <i>AnsPerQ</i> , <i>MDWords</i> , <i>PrivateMtg</i> .

Data Source: Thomson StreetEvents and Factset CallStreet.

Measures of Managers’ Information Demand

<i>Demand for Prd Mkt Info</i> (percentage)	The sum of absolute market-adjusted announcement-day returns of product-market announcements made by firm <i>i</i> ’s peer firms during the fiscal quarter <i>t</i> , scaled by the total number of peers. Peer groups are defined using Hoberg-Phillips text-based industry classification.
<i>Demand for Supply Chain Info</i> (percentage)	The sum of absolute market-adjusted announcement-day returns of product-market announcements made by direct suppliers and customers of the firm <i>i</i> during the fiscal quarter <i>t</i> , scaled by the total number of direct suppliers and customers.
<i>Managerial Uncertainty</i> (percentage)	The proportion of answers given by corporate participants that contain at least one uncertain word during the Q&A sessions of firm <i>i</i> ’s earnings conference call for fiscal quarter <i>t</i> ’s performance. Uncertain word is defined using the Loughran and McDonald sentiment wordlist (Loughran and McDonald, 2011). Corporate participants are defined as any of the C-suite executives of a firm to exclude answers provided by conference call operators or investor-relation officers.

Data Source: S&P Capital IQ, Factset Revere, CRSP, Hoberg-Phillips Data library (<http://hobergphillips.tuck.dartmouth.edu/>).

Measures of Institutional Investors’ Industry Knowledge

<i>Prd Mkt Hldgs</i> (\$ Billion)	The average dollar holdings in all firm <i>i</i> ’s peer firms, summed over all institutional investors holding at least 1% of the shares in firm <i>i</i> , computed as: $\sum_{j \in J} \sum_{p \in P} \frac{\text{Dollar Holdings}_{jp}}{n}$, where <i>J</i> is the set of all investors that hold at least 1% of the total common shares outstanding in firm <i>i</i> , <i>P</i> is the set of all product-market peer firms of firm <i>i</i> (Hoberg-Phillips text-based industry classification). <i>n</i> is the total number of product-market peer firms. <i>Dollar Holdings</i> is the dollar holdings in firm <i>p</i> by investor <i>j</i> , averaged over all 13F reports made during the trailing 12 months ending before the start of fiscal quarter <i>t</i> .
<i>Prd Mkt Trades</i> (\$ Billion)	The average absolute dollar trades in all firm <i>i</i> ’s peer firms, summed over all institutional investors holdings at least 1% of the shares in firm <i>i</i> , computed as: $\sum_{j \in J} \sum_{p \in P} \frac{\text{Dollar Trades}_{jp}}{n}$, where <i>J</i> is the set of investors that hold at least 1% of the total common shares outstanding in firm <i>i</i> , <i>P</i> is the set of all product-market peer firms of firm <i>i</i> (Hoberg-Phillips text-based industry classification). <i>n</i> is the total number of product-market peer firms. <i>Dollar Trades</i> is the quarterly dollar trades in firm <i>p</i> by investor <i>j</i> , averaged over all 13F reports made during the trailing 12 months ending before the start of fiscal quarter <i>t</i> .
<i>Supply Chain Hldgs</i> (\$ Billion)	The dollar holdings in firm <i>i</i> ’s supply chain industries, held by all institutional investors holdings at least 1% of the shares in firm <i>i</i> , computed as: $\sum_{k \in K} \sum_{j \in J} \frac{\text{Industry Dollar Holdings}_{jk}}{n_k}$, where <i>K</i> is the set of all SIC

	4-digit industries whereby firm i has at least one direct supplier or one customer. J is the set of all investors that hold at least 1% of the total common shares outstanding in firm i . <i>Industry Dollar Holdings</i> is the dollar holdings in industry k held by investor j , averaged over all 13F reports made during the trailing 12 months ending before the start of fiscal quarter t . n_k is the number of firm i 's direct suppliers and customers in industry k .
<i>Supply Chain Trades</i> (\$ Billion)	The dollar trades in firm i 's supply chain industries, made by all institutional investors holdings at least 1% of the shares in firm i , computed as: $\sum_{k \in K} \sum_{j \in J} \frac{\text{Industry Dollar Trades}_{jk}}{n_k}$, where K is the set of all SIC 4-digit industries whereby firm i has at least one direct supplier or one customer. J is the set of all investors that hold at least 1% of the total common shares outstanding in firm i . <i>Industry Dollar Trades</i> is the quarterly dollar trades in industry k made by investor j averaged over all 13F reports made during the trailing 12 months ending before the start of fiscal quarter t . n_k is the number of firm i 's direct suppliers and customers in industry k .

Data Source: Hoberg-Phillips Data library(<http://hobergphillips.tuck.dartmouth.edu/>), Factset Revere, Thomson-Reuters 13F.

Measures of Management Forecast Frequency and Accuracy

<i>Forecasts</i> (number)	The number of management forecasts made by firm i in fiscal quarter t . In the analysis, log transformation is taken to reduce skewness and the addition by one to avoid taken log over zero (Huang et al., 2017).
<i>Revisions</i> (number)	The number of management forecasts that are a revision to a previously issued forecast made by firm i in fiscal quarter t . Log transformation is taken in the analysis.
<i>FcastError</i> (percentage)	The absolute forecast error, calculated as forecasted value minus actual value and scaled by one-quarter-lagged stock price and times 100, averaged over all EPS forecasts issued by firm i in fiscal quarter t .

Data Source: I/B/E/S, CRSP.

Measures of Insider Trading and Related Controls

<i>Alpha30</i> (percentage)	The risk-adjusted returns for an insider transaction (multiply by 100) calculated over the 30 days following the transaction date and relative to the Fama and French (1993) three-factor models, multiplied by -1 for sales.
<i>BHAR30</i> (percentage)	The market-adjusted buy-and-hold returns for an insider transaction (multiply by 100) calculated over the 30 days following the transaction date, multiplied by -1 for sales. Market-adjustment is computed by subtracting the buy-and-hold returns of CRSP value-weighted index.
$I(\text{Trade}_{POST}) / I(\text{Trade})$ (indicator)	An indicator variable that takes the value of one if a trade k is placed within the 7-day window after (subscript POST) or before (subscript PRE) an investor conference that firm i has attended, and zero otherwise.
<i>Participating Insider</i> (indicator)	An indicator variable that takes the value of one if a trade k is placed by an insider j from firm i who has participated in an investor conference prior to the transaction date of the trade, and zero otherwise.
$\text{ParInsiderTrade}_{POST} / \text{ParInsiderTrade}_{PRE}$ (indicator)	An indicator variable that takes the value of one if an insider trade k is executed by an insider j within 7 days after (subscript POST) or before (subscript PRE) participating in an investor conference on behalf of firm i , and zero otherwise.
<i>CEO</i> (indicator)	An indicator variable that takes the value of 1 if executive j is the CEO of the firm i , and 0 otherwise.
<i>Conf Abn Ret</i> (percentage)	Three-day (-1, +1) absolute market-adjusted returns around the conference date, subtracted by the mean absolute value of three-day market-adjusted returns during the estimation period, and then divided by the standard deviation of the absolute values during the estimation period (Bushee et al., 2011). The estimation period begins 120 days prior to the investor conference and ends 30 days prior to the conference. Market-adjustment is computed by subtracting the buy-and-hold returns of CRSP value-weighted index.
<i>Conf Abn Turnover</i> (percentage)	Three-day (-1, +1) volume divided by shares outstanding around the conference date, subtracted by the average three-day turnover in the estimation period, times 100 (Bushee et al., 2011). The estimation period begins 120 days prior to the investor conference and ends 30 days prior to the investor conference.

Data Source: Thomson Insiders, CRSP, Thomson StreetEvents, Factset CallStreet.

Control Variables: Firm-Quarter Panel

<i>Size</i> (\$ million)	Natural logarithm of total asset (<i>ATQ</i>).
<i>Inst. Ownership</i> (number)	Natural logarithm of one plus number of institutional owners reporting holdings of firm <i>i</i> 's common stock based on the most recent 13-F report issued before the end of fiscal quarter <i>t</i> . Assumed to be 0 for any period in which the company is listed on an exchange, but has no data available in the 13-F filings.
<i>Analyst</i> (number)	Natural logarithm of one plus the number of analysts issued earnings forecasts for firm <i>i</i> during fiscal quarter <i>t</i> . Assumed to be 0 for any period in which the company is listed on an exchange, but has no data available on I/B/E/S.
<i>Financing</i> (indicator)	An indicator variable that takes the value of 1 if firm <i>i</i> issues debt or equity in the prior, current, or subsequent fiscal year as reported in the SDC database.
<i>M&A</i> (indicator)	An indicator variable that takes the value of 1 if firm <i>i</i> has made an acquisition in the prior, current, or subsequent fiscal year as reported in the SDC database, and 0 otherwise.
<i>Restructuring</i> (indicator)	Indicator variable that takes the value of 1 if firm <i>i</i> has a non-zero restructuring charge (<i>RCPQ</i>) to earnings in fiscal quarter <i>t</i> and 0 otherwise.
<i>Firm Age</i> (years)	Natural logarithm of the number of years since firm <i>i</i> first appeared in Compustat.
<i>Segments</i> (number)	The number of unique business segments reported in firm <i>i</i> 's annual filings according to Compustat Segment database.
<i>High Tech</i> (indicator)	Indicator variable that takes the value of 1 for firm <i>i</i> is in SIC codes: 2833–2836 (drugs), 8731–8734 (R&D services), 7371–7379 (programming), 3570–3577 (computers), 3600–3674 (electronics), or 3810–3845 (precise measurement instruments), and 0 otherwise (Kirk and Markov, 2016).
<i>Intangibles</i> (ratio)	Sum of recognized intangibles (<i>INTAN</i>) and goodwill (<i>GDWL</i>) at the end of the fiscal year, scaled by total assets (<i>AT</i>).
<i>Loss</i> (indicator)	An indicator variable that takes the value of 1 if a firm reported negative income before extraordinary items (<i>IBQ</i>) in the fiscal quarter, and 0 otherwise.
<i>R&D</i> (indicator)	R&D expenses (<i>RD</i>) during the fiscal year scaled by total assets (<i>AT</i>). Following Kirk and Markov (2016) and Koh and Reeb (2015), I replace missing values with the two-digit SIC industry median of R&D for the same year; if the latter is also missing, when I set R&D to 0.
<i>BM Ratio</i> (ratio)	Book value of equity (<i>ATQ - LTQ</i>) scaled by the market value of equity (<i>PRCCQ*CSHOQ</i>).
<i>Leverage</i> (ratio)	Book value of debt (<i>DLTTQ + DLCQ</i>) scaled by total assets (<i>ATQ</i>).
<i>Ret</i> (percentage)	Cumulative buy-and-hold returns over the fiscal quarter <i>t</i> , less the cumulative buy-and-hold return of CRSP value-weighted index over the corresponding period.
<i>Ret Vol</i> (percentage)	The standard deviation of daily returns over the fiscal quarter <i>t</i> .
<i>Earnings Vol</i> (\$ million)	The standard deviation of quarterly net income (<i>IBQ</i>) over the previous 16 quarters before fiscal quarter <i>t</i> .
<i>Bid-ask Spread</i> (percentage)	Daily (ask–bid)/price using data on closing prices and quotes from CRSP, multiplied by 100, and averaged over the fiscal quarter <i>t</i> .
<i>Turnover</i> (percentage)	Daily volume traded over share outstanding, averaged over the fiscal quarter <i>t</i> .
<i>AnnFreq</i> (number)	The number of product-market announcements made by firm <i>i</i> during the fiscal quarter <i>t</i> .
<i>AnnAR</i> (percentage)	The sum of absolute market-adjusted one-day returns of product-market announcements made by firm <i>i</i> during the fiscal quarter.
<i>RegFDDiscl.</i> (number)	The number of 8k filings made by firm <i>i</i> that contains item 7.01 (Regulation Fair Disclosure) during the fiscal quarter <i>t</i> .
<i>PctAnnFcast</i> (percentage)	The percentage of annual management forecasts made by firm <i>i</i> during fiscal quarter <i>t</i> .
<i>Horizon</i> (days)	The average number of days between the forecast date and the actual date for all EPS forecasts made by firm <i>i</i> during fiscal quarter <i>t</i> .

Data Source: Compustat, I/B/E/S, S&P Capital IQ, CRSP, WRDS SEC Analytics. Compustat data items are indicated in parenthesis, where applicable.

All continuous variables presented in this appendix are winsorized 1% and 99% to remove the effect of outliers.

Table 1: Descriptive Statistics of Investor Conference Transcripts

This table presents the distribution of conference transcripts by year (panel A) and by calendar quarter (panel B) and between the two sources: Factset CallStreet and Thomson StreetEvents. For the universe of Russell 3000 firms, transcripts are collected from Factset Callstreet from 2004 to 2017. For firms with no transcripts available in Factset, transcripts are collected from Thomson StreetEvents.

Panel A: Distribution of Transcripts by Year

Year	Factset Only		Thomson Only		Both Factset and Thomson		Total	
	Count	Percent	Count	Percent	Count	Percent	Count	Percent
2004	693	2.46	149	2.07	118	0.55	960	1.69
2005	1858	6.60	214	2.97	619	2.87	2691	4.73
2006	1558	5.53	343	4.76	744	3.45	2645	4.65
2007	607	2.16	502	6.97	686	3.18	1795	3.15
2008	349	1.24	590	8.19	752	3.49	1691	2.97
2009	1224	4.35	687	9.54	1646	7.63	3557	6.25
2010	2643	9.39	648	9.00	2634	12.21	5925	10.41
2011	2663	9.46	771	10.71	2892	13.41	6326	11.11
2012	2915	10.35	685	9.51	2375	11.01	5975	10.50
2013	2861	10.16	599	8.32	2057	9.54	5517	9.69
2014	2880	10.23	532	7.39	1868	8.66	5280	9.28
2015	2770	9.84	512	7.11	1890	8.76	5172	9.09
2016	2604	9.25	466	6.47	1640	7.60	4710	8.27
2017	2534	9.00	502	6.97	1644	7.62	4680	8.22
Total	28159	100.00	7200	100.00	21565	100.00	56924	100.00

Panel B: Distribution of Transcripts by Calendar Quarter

Year	Factset Only		Thomson Only		Both Factset and Thomson		Total	
	Count	Percent	Count	Percent	Count	Percent	Count	Percent
Q1	7790	27.66	1860	25.83	5584	25.89	15234	26.76
Q2	8072	28.67	1993	27.68	6868	31.85	16933	29.75
Q3	5927	21.05	1722	23.92	4755	22.05	12404	21.79
Q4	6370	22.62	1625	22.57	4358	20.21	12353	21.70
Total	28159	100.00	7200	100.00	21565	100.00	56924	100.00

Table 2: Summary Statistics and Principal Factor Analysis**Panel A: Summary Statistics (Firm-Quarter Panel)**

This table presents descriptive statistics for the variables used in the subsequent empirical analyses using firm-quarter as the unit of analysis. The sample includes all Russell 3000 firm-year observations with coverage in the intersection of Compustat and CRSP and occurs within two years of an investor conference that a firm has attended. All variables are defined in Appendix A.

Variables	Count	Mean	Std	P25	P50	P75
<i><u>Measures of Manager-Investor Interaction</u></i>						
<i>NumInteract</i>	73262	0.678	1.029	0.000	0.000	1.000
<i>CEO</i>	73262	0.412	0.726	0.000	0.000	1.000
<i>NumExecs</i>	73262	1.041	1.785	0.000	0.000	2.000
<i>AnsPerQ</i>	73262	0.066	0.106	0.000	0.000	0.130
<i>MDWords</i>	73262	2.480	4.919	0.000	0.000	3.502
<i>PrivateMtg</i>	73262	0.187	0.464	0.000	0.000	0.000
<i>Direct Interaction</i>	73262	0.015	1.009	-0.654	-0.654	0.497
<i><u>Measures of Managers' Information Demand</u></i>						
<i>Demand for Prd Mkt Info</i>	73262	0.021	0.024	0.002	0.011	0.036
<i>Demand for Supply Chain Info</i>	54192	0.018	0.027	0.000	0.007	0.023
<i>Managerial Uncertainty</i>	40188	0.441	0.202	0.313	0.429	0.563
<i><u>Measures of Investor Knowledge</u></i>						
<i>Prd Mkt Trades (\$ Bn)</i>	66834	0.279	0.264	0.090	0.208	0.383
<i>Prd Mkt Hldgs (\$ Bn)</i>	66917	1.814	2.168	0.469	1.109	2.234
<i>Supply Chain Trades (\$ Bn)</i>	53282	10.145	12.872	0.434	4.949	15.299
<i>Supply Chain Hldgs (\$ Bn)</i>	53289	111.191	146.991	3.439	52.607	163.611
<i><u>Measures of Disclosure Outcomes</u></i>						
<i>Forecasts</i>	70384	2.177	2.207	0.000	2.000	3.000
<i>Revisions</i>	70384	1.217	1.601	0.000	1.000	2.000
<i>FcastError</i>	31794	120.097	322.789	10.727	29.465	89.747
<i><u>Firm-Level Controls</u></i>						
<i>Size</i>	73262	7.194	1.764	5.899	7.180	8.411
<i>Inst. Ownership</i>	73262	4.814	1.421	4.477	5.043	5.602
<i>Analyst</i>	73262	1.976	0.858	1.540	2.120	2.590
<i>Financing</i>	73262	0.272	0.445	0.000	0.000	1.000
<i>M&A</i>	73262	0.188	0.391	0.000	0.000	0.000
<i>Restructuring</i>	73262	0.025	0.155	0.000	0.000	0.000
<i>Firm Age</i>	73262	2.826	0.738	2.303	2.833	3.401
<i>Segments</i>	73262	2.036	1.509	1.000	1.000	3.000
<i>High Tech</i>	73262	0.349	0.477	0.000	0.000	1.000
<i>Intangibles</i>	73262	0.363	0.360	0.036	0.260	0.611
<i>R&D</i>	73262	0.068	0.107	0.003	0.024	0.087
<i>BM Ratio</i>	73262	0.499	0.411	0.238	0.393	0.634
<i>Returns</i>	73262	0.007	0.205	-0.108	-0.003	0.103
<i>Ret Vol</i>	73262	0.027	0.015	0.017	0.023	0.033
<i>Leverage</i>	73262	0.207	0.185	0.017	0.186	0.330
<i>Loss</i>	73262	0.284	0.451	0.000	0.000	1.000
<i>AnnFreq</i>	73262	1.083	2.151	0.000	0.000	1.000
<i>AnnAR</i>	73262	0.020	0.046	0.000	0.000	0.017
<i>Earnings Volatility</i>	70384	0.027	0.042	0.006	0.013	0.028
<i>Bid-ask Spread</i>	70384	0.197	0.399	0.044	0.088	0.173

<i>Turnover</i>	70384	0.012	0.009	0.006	0.009	0.014
<i>RegFDDiscl.</i>	70384	0.624	1.098	0.000	0.000	1.000
<i>PctAnnFcast</i>	70384	47.797	43.690	0.000	50.000	100.000
<i>Horizon (days)</i>	31794	141.406	90.336	64.000	128.333	195.500

Panel B: Factor Loadings, Eigenvalue and Cumulative Variance

This table reports factor loadings from the principal factor analysis of the six proxies of direct interactions: *NumInteract*, *CEO*, *NumExecs*, *AnsPerQ*, *MDWords*, *PrivateMtg*.

Factor	<i>Eigenvalue</i>	<i>Proportion of the variance explained</i>	<i>Cumulative proportion of the variance explained</i>
1 st	4.31	0.72	0.72
2 nd	0.66	0.11	0.83
3 rd	0.46	0.08	0.90

Variables	<i>Loadings on the first factor (Direct Interaction)</i>
<i>NumInteract</i>	0.946
<i>CEO</i>	0.863
<i>NumExecs</i>	0.932
<i>AnsPerQ</i>	0.807
<i>MDWords</i>	0.847
<i>PrivateMtg</i>	0.656

Table 3: Determinants of Learning-Incentivized Manager-Investor Interaction

This table investigates the hypothesis that managers seek more direct interactions with institutional investors when they have higher information demand. The unit of analysis is a firm-quarter observation. The OLS empirical specification is:

$$Direct\ Interactions_{it} = \alpha_0 + \alpha_1 Manager\ Information\ Demand_{it-1} + \Gamma X_{it-1} + \eta_i + \phi_t + \nu_q + e_{it} \quad (IC1)$$

where i denotes firm, t denotes quarter, η_i denotes firm dummies, ϕ_t denotes calendar-year-quarter dummies and ν_q denotes fiscal quarter dummies. The dependent variable, *Direct Interactions*, measures the frequency and the degrees of information exchange of manager-investor interactions using the following empirical proxies: *NumInteract*, *CEO*, *NumExecs*, *AnsPerQ*, *MDWords*, *PrivateMtg*, as well as their first principal component *Direct Interaction*. *Manager Information Demand* captures a manager's incentives to seek direct interactions and learning as a result of higher information demand, which is driven by (i) heightened activities among product-market peers (Panel A), (ii) heightened activities among connected firms on the supply chain (Panel B), and (iii) higher managerial uncertainty (Panel C). It is one of the following proxies. *Demand for Prd Mkt Info* is the sum of the absolute market-adjusted announcement-day returns of product-market announcements made by firm i 's peers in quarter t , scaled by the total number of peers. *Demand for Supply Chain Info* is the sum of the absolute market-adjusted announcement-day returns of product-market announcements made by firm i 's direct suppliers and customers in quarter t , scaled by the total number of direct suppliers and customers. *Managerial Uncertainty* is the percentage of answers with at least one uncertain word during the Q&A sessions of firm i 's earnings conference call for quarter t . All variables are defined in Appendix A. Control variables in Panel B and Panel C follow those presented in Panel A. Requiring data coverage from Factset Revere (Capital IQ Transcripts) results in a reduction of sample size in Panel B (Panel C). The coefficients on the intercept, firm (Firm), calendar-year-quarter (YQ), and fiscal quarter (FQ) fixed effects are not reported. T-statistics based on robust standard errors clustered by firm are indicated in parenthesis below coefficient estimates. ***, **, and * indicate significance level at 1%, 5%, and 10% respectively (two-tailed).

Panel A: Demand for Product Market Peer Information

Dependent Variable	<i>NumInteract</i>	<i>CEO</i>	<i>NumExecs</i>	<i>AnsPerQ</i>	<i>MDWords</i>	<i>PrivateMtg</i>	<i>Direct Interaction</i>
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
<i>Demand for Prd Mkt Info</i>	1.218*** (3.17)	0.888*** (3.15)	1.177* (1.80)	0.037 (0.97)	1.601 (0.99)	1.295*** (6.78)	1.216*** (3.28)
<i>Size</i>	0.287*** (13.18)	0.166*** (10.45)	0.459*** (13.61)	0.026*** (13.11)	1.021*** (11.34)	0.082*** (9.70)	0.279*** (13.66)
<i>Inst. Ownership</i>	0.042*** (3.89)	0.021*** (2.92)	0.067*** (4.38)	0.005*** (4.96)	0.156*** (3.54)	0.009* (1.89)	0.041*** (4.05)
<i>Analyst</i>	0.127*** (8.38)	0.068*** (6.52)	0.196*** (8.70)	0.010*** (6.95)	0.495*** (8.06)	0.046*** (7.70)	0.123*** (8.79)
<i>Financing</i>	0.004 (0.36)	-0.002 (-0.26)	0.019 (0.98)	0.001 (0.97)	0.086 (1.57)	-0.008 (-1.46)	0.005 (0.49)
<i>M&A</i>	0.012 (0.98)	0.019** (2.15)	0.018 (0.90)	0.002 (1.57)	0.049 (0.87)	0.007 (1.32)	0.018 (1.52)
<i>Restructuring</i>	0.017 (0.73)	-0.011 (-0.68)	0.039 (0.98)	0.001 (0.39)	0.041 (0.33)	0.009 (0.78)	0.012 (0.53)
<i>Firm Age</i>	0.225*** (4.22)	0.153*** (4.29)	0.162* (1.89)	0.016*** (3.10)	0.663*** (3.10)	0.103*** (5.44)	0.201*** (4.05)
<i>Segments</i>	-0.017** (-2.06)	-0.013** (-2.27)	-0.015 (-1.09)	-0.002*** (-2.84)	-0.044 (-1.21)	-0.006* (-1.82)	-0.017** (-2.15)
<i>High Tech</i>	0.031 (0.50)	-0.001 (-0.02)	0.026 (0.24)	-0.002 (-0.25)	-0.051 (-0.19)	0.035 (1.42)	0.017 (0.28)
<i>Intangibles</i>	0.044 (0.94)	0.063* (1.85)	0.157** (2.15)	0.008* (1.85)	0.390** (2.03)	-0.024 (-1.19)	0.069 (1.55)
<i>R&D</i>	0.056 (0.40)	0.019 (0.19)	0.216 (1.07)	0.014 (1.22)	0.420 (0.76)	-0.018 (-0.32)	0.079 (0.60)
<i>BM Ratio</i>	-0.128*** (-7.31)	-0.080*** (-6.50)	-0.195*** (-7.30)	-0.015*** (-8.29)	-0.451*** (-6.19)	-0.032*** (-4.41)	-0.129*** (-7.79)

<i>Ret</i>	0.035** (2.34)	0.031*** (2.72)	0.113*** (4.33)	0.003** (1.97)	0.376*** (5.10)	-0.003 (-0.40)	0.050*** (3.33)
<i>Ret Vol</i>	0.241 (0.60)	0.277 (0.94)	0.671 (1.03)	-0.028 (-0.70)	2.437 (1.35)	0.247 (1.36)	0.343 (0.87)
<i>Leverage</i>	-0.214*** (-2.96)	-0.092* (-1.87)	-0.312*** (-2.84)	-0.021*** (-3.16)	-0.981*** (-3.50)	-0.050* (-1.72)	-0.203*** (-3.03)
<i>Loss</i>	-0.022* (-1.88)	-0.012 (-1.35)	-0.046** (-2.35)	-0.001 (-1.02)	-0.063 (-1.12)	-0.007 (-1.35)	-0.021* (-1.80)
<i>AnnFreq</i>	0.015*** (3.17)	0.005* (1.69)	0.020** (2.37)	0.001* (1.66)	0.005 (0.24)	0.010*** (4.32)	0.012*** (2.74)
<i>AnnAR</i>	-0.109 (-0.78)	-0.010 (-0.10)	-0.231 (-0.99)	0.001 (0.10)	0.077 (0.12)	-0.129* (-1.94)	-0.092 (-0.70)
Fixed Effects	Firm, YQ, FQ	Firm, YQ, FQ	Firm, YQ, FQ	Firm, YQ, FQ	Firm, YQ, FQ	Firm, YQ, FQ	Firm, YQ, FQ
N	73262	73262	73262	73262	73262	73262	73262
Adj. RSQ	0.38	0.26	0.31	0.31	0.22	0.17	0.34

Panel B: Demand for Supply Chain Information

Dependent Variable	<i>NumInteract</i>	<i>CEO</i>	<i>NumExecs</i>	<i>AnsPerQ</i>	<i>MDWords</i>	<i>PrivateMtg</i>	<i>Direct Interaction</i>
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
<i>Demand for Supply Chain Info</i>	0.653** (2.46)	0.503*** (2.58)	1.079** (2.48)	0.036 (1.44)	1.297 (1.11)	0.476*** (3.82)	0.665*** (2.66)
Fixed Effects	Firm, YQ, FQ	Firm, YQ, FQ	Firm, YQ, FQ	Firm, YQ, FQ	Firm, YQ, FQ	Firm, YQ, FQ	Firm, YQ, FQ
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	54192	54192	54192	54192	54192	54192	54192
Adj. RSQ	0.39	0.26	0.31	0.31	0.21	0.18	0.35

Panel C: Managers' Overall Revealed Uncertainty

Dependent Variable	<i>NumInteract</i>	<i>CEO</i>	<i>NumExecs</i>	<i>AnsPerQ</i>	<i>MDWords</i>	<i>PrivateMtg</i>	<i>Direct Interaction</i>
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
<i>Managerial Uncertainty</i>	0.049** (2.14)	0.035* (1.90)	0.078* (1.79)	0.012*** (4.44)	0.247* (1.92)	0.019 (1.60)	0.068*** (2.85)
Fixed Effects	Firm, YQ, FQ	Firm, YQ, FQ	Firm, YQ, FQ	Firm, YQ, FQ	Firm, YQ, FQ	Firm, YQ, FQ	Firm, YQ, FQ
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	40188	40188	40188	40188	40188	40188	40188
Adj. RSQ	0.43	0.28	0.32	0.31	0.21	0.2	0.36

Table 4: Cross-Sectional Analysis Based on Institutional Investors' Supply of Information

This table partitions the sample in Table 3 Panel A (Panel B) based on the median value of institutional investors' knowledge related to product-market peer firms (supply-chain industries). In Panel A, institutional investors' product-market market knowledge is measured by *Prd Mkt Trades* (*Prd Mkt Hldgs*), which is the sum of firm *i*'s >1% institutional investors' average absolute dollar trades (dollar holdings) in product-market peer firms of firm *i*, scaled by the total number of peers. In Panel B, supply chain industry knowledge is measured by *Supply Chain Trades* (*Supply Chain Hldgs*), which is the sum of firm *i*'s >1% institutional investors' absolute dollar trades (dollar holdings) in 4-digit SIC industries whereby firm *i* has at least one direct supplier or customer, scaled by the number of suppliers and customers. All variables are defined in Appendix A. Requiring data coverage from Thomson-Reuters 13F results in a reduction in the size of the sample. Control variables follow those presented in Table 3. F-statistics compares the coefficient on *Demand for Prd Mkt Info* across the two sub-samples. The coefficients on the intercept, firm (Firm), calendar-year-quarter (YQ), and fiscal quarter (FQ) fixed effects are not reported. T-statistics based on robust standard errors clustered by firm are indicated in parenthesis below coefficient estimates. ***, **, and * indicate significance level at 1%, 5%, and 10% respectively (two-tailed).

Panel A: Institutional Investors' Knowledge of the Product Market

Dependent Variable	Direct Interaction		Direct Interaction	
Product Market Knowledge Measured By	<i>Prd Mkt Trades</i>	<i>Prd Mkt Trades</i>	<i>Prd Mkt Hldgs</i>	<i>Prd Mkt Hldgs</i>
Sub-Samples	High Prd Mkt Knowledge	Low Prd Mkt Knowledge	High Prd Mkt Knowledge	Low Prd Mkt Knowledge
	(1)	(2)	(3)	(4)
<i>Demand for Prd Mkt Info</i>	2.207*** (3.35)	0.629 (1.35)	2.288*** (3.46)	0.586 (1.24)
F-stat	3.878		4.531	
P-value	0.049		0.033	
Fixed Effects	Firm, YQ, FQ		Firm, YQ, FQ	
Controls	Yes		Yes	
N	33411	33423	33471	33446
Adj. RSQ	0.37	0.28	0.37	0.29

Panel B: Institutional Investors' Knowledge of Supply Chain Industries

Dependent Variable	Direct Interaction		Direct Interaction	
Supply Chain Knowledge Measured by	<i>Supply Chain Trades</i>	<i>Supply Chain Trades</i>	<i>Supply Chain Hldgs</i>	<i>Supply Chain Hldgs</i>
Sub-Samples	High Supply Chain Knowledge	Low Supply Chain Knowledge	High Supply Chain Knowledge	Low Supply Chain Knowledge
	(1)	(2)	(3)	(4)
<i>Demand for Supply Chain Info</i>	1.241*** (3.22)	0.478 (1.56)	1.322*** (3.38)	0.504* (1.70)
F-stat	2.473		2.885	
P-value	0.116		0.090	
Fixed Effects	Firm, YQ, FQ		Firm, YQ, FQ	
Controls	Yes		Yes	
N	26659	26623	26665	26624
Adj. RSQ	0.36	0.32	0.36	0.33

Table 5: Consequences of Direct Learning from Investors - Management Forecast Frequency and Accuracy

This table investigates the hypothesis that information learned from direct interactions with investors allow managers to issue more forecasts and more accurate forecasts. The unit of analysis is a firm-quarter observation. The OLS specification is:

$$Disclosure\ Outcome_{it+1} = \beta_0 + \beta_1 Direct\ Interactions_{it} + \Gamma X_{it} + \eta_i + \phi_t + \nu_q + e_{it} \quad (MG1)$$

where i denotes firm, t denotes quarter, η_i denotes firm dummies, ϕ_t denotes calendar-year-quarter dummies and ν_q denotes fiscal quarter dummies. The independent variable, *Direct Interactions*, measures the frequency and the degrees of information exchange of manager-investor interactions using: *NumInteract*, *CEO*, *NumExecs*, *AnsPerQ*, *MDWords*, *PrivateMtg*, as well as their first principal component *Direct Interaction*. The dependent variable is the number of management forecasts (*Forecasts*) in Panel A, the number of forecasts that are revisions (*Revisions*) in Panel B, as well as the average absolute error in EPS forecasts (*FcastError*) in Panel C. All variables are defined in Appendix A. Control variables in Panel B and C follow Panel A. Panel C additionally controls for forecast horizon (*Horizon*). The coefficients on the intercept, firm (Firm), calendar-year-quarter (YQ), and fiscal quarter (FQ) fixed effects are not reported. T-statistics based on robust standard errors clustered by firm are indicated in parenthesis below coefficient estimates. ***, **, and * indicate significance level at 1%, 5%, and 10% respectively (two-tailed).

Panel A: Number of Management Forecasts

Dependent Variable	Ln(I+ Forecasts)	Ln(I+ Forecasts)	Ln(I+ Forecasts)	Ln(I+ Forecasts)	Ln(I+ Forecasts)	Ln(I+ Forecasts)	Ln(I+ Forecasts)
	<i>NumInteract</i>	<i>CEO</i>	<i>NumExecs</i>	<i>AnsPerQ</i>	<i>MDWords</i>	<i>PrivateMtg</i>	<i>Direct Interaction</i>
Direct Interactions Measured by	(1)	(2)	(3)	(4)	(5)	(6)	(7)
<i>Direct Interactions</i>	0.011*** (4.55)	0.010*** (3.34)	0.004*** (3.12)	0.075*** (3.88)	0.001** (1.97)	0.015*** (4.10)	0.009*** (4.06)
<i>Size</i>	0.053*** (3.39)	0.055*** (3.49)	0.054*** (3.48)	0.054*** (3.46)	0.055*** (3.55)	0.055*** (3.52)	0.054*** (3.42)
<i>Inst. Ownership</i>	0.010** (2.04)	0.010** (2.08)	0.010** (2.06)	0.010** (2.05)	0.010** (2.09)	0.010** (2.11)	0.010** (2.05)
<i>Analyst</i>	0.087*** (9.46)	0.088*** (9.52)	0.088*** (9.51)	0.088*** (9.51)	0.089*** (9.55)	0.088*** (9.51)	0.088*** (9.48)
<i>Financing</i>	0.006 (1.01)	0.006 (1.00)	0.006 (0.98)	0.006 (0.98)	0.006 (0.97)	0.006 (1.01)	0.006 (1.00)
<i>M&A</i>	0.010* (1.66)	0.010* (1.65)	0.010* (1.65)	0.010* (1.66)	0.010* (1.66)	0.010 (1.63)	0.010* (1.65)
<i>Restructuring</i>	-0.004 (-0.36)	-0.004 (-0.37)	-0.004 (-0.36)	-0.004 (-0.37)	-0.004 (-0.36)	-0.004 (-0.35)	-0.004 (-0.36)
<i>Firm Age</i>	0.074** (2.20)	0.075** (2.23)	0.076** (2.26)	0.075** (2.24)	0.076** (2.27)	0.075** (2.23)	0.075** (2.22)
<i>Segments</i>	-0.003 (-0.76)	-0.003 (-0.77)	-0.003 (-0.79)	-0.003 (-0.76)	-0.003 (-0.80)	-0.003 (-0.79)	-0.003 (-0.77)
<i>High Tech</i>	0.039 (1.30)	0.040 (1.31)	0.040 (1.30)	0.040 (1.31)	0.040 (1.31)	0.039 (1.29)	0.040 (1.30)
<i>Intangibles</i>	0.057** (2.06)	0.057** (2.06)	0.057** (2.06)	0.057** (2.06)	0.057** (2.07)	0.058** (2.09)	0.057** (2.06)
<i>R&D</i>	0.060 (1.04)	0.060 (1.06)	0.060 (1.05)	0.060 (1.04)	0.061 (1.06)	0.061 (1.07)	0.060 (1.04)
<i>BM Ratio</i>	-0.017 (-1.50)	-0.017 (-1.55)	-0.017 (-1.55)	-0.017 (-1.53)	-0.018 (-1.58)	-0.017 (-1.56)	-0.017 (-1.51)
<i>Ret</i>	0.005 (0.73)	0.005 (0.72)	0.005 (0.70)	0.005 (0.73)	0.005 (0.71)	0.005 (0.71)	0.005 (0.73)
<i>Ret Vol</i>	-0.331 (-1.38)	-0.326 (-1.36)	-0.330 (-1.37)	-0.329 (-1.37)	-0.328 (-1.36)	-0.326 (-1.35)	-0.331 (-1.38)
<i>Leverage</i>	-0.067* (-1.85)	-0.068* (-1.88)	-0.068* (-1.88)	-0.068* (-1.87)	-0.069* (-1.89)	-0.068* (-1.88)	-0.067* (-1.86)

<i>Loss</i>	-0.024*** (-3.99)	-0.024*** (-4.00)	-0.024*** (-3.98)	-0.024*** (-3.98)	-0.024*** (-3.98)	-0.025*** (-4.01)	-0.024*** (-3.99)
<i>LitRisk</i>	-0.005 (-0.81)	-0.005 (-0.81)	-0.005 (-0.81)	-0.005 (-0.82)	-0.005 (-0.80)	-0.005 (-0.78)	-0.005 (-0.80)
<i>AnnFreq</i>	-0.003 (-1.39)	-0.003 (-1.32)	-0.003 (-1.33)	-0.003 (-1.31)	-0.003 (-1.30)	-0.003 (-1.35)	-0.003 (-1.36)
<i>AnnAR</i>	0.120** (2.02)	0.118** (1.98)	0.119** (2.00)	0.117** (1.98)	0.117** (1.98)	0.118** (1.99)	0.119** (2.01)
<i>Earnings Vol</i>	-0.037 (-0.35)	-0.037 (-0.34)	-0.036 (-0.34)	-0.036 (-0.34)	-0.036 (-0.34)	-0.038 (-0.36)	-0.037 (-0.35)
<i>Bid-ask Spread</i>	0.004 (0.42)	0.005 (0.49)	0.005 (0.47)	0.005 (0.46)	0.005 (0.51)	0.005 (0.49)	0.004 (0.43)
<i>Turnover</i>	1.595*** (2.93)	1.607*** (2.96)	1.613*** (2.97)	1.618*** (2.97)	1.616*** (2.97)	1.596*** (2.94)	1.601*** (2.94)
<i>RegFDDiscl.</i>	0.030*** (9.55)	0.030*** (9.54)	0.030*** (9.54)	0.030*** (9.53)	0.030*** (9.53)	0.030*** (9.53)	0.030*** (9.55)
<i>PctAnnFcast</i>	0.007*** (60.82)	0.007*** (60.80)	0.007*** (60.79)	0.007*** (60.77)	0.007*** (60.76)	0.007*** (60.75)	0.007*** (60.81)
Fixed Effects	Firm, YQ, FQ	Firm, YQ, FQ	Firm, YQ, FQ	Firm, YQ, FQ	Firm, YQ, FQ	Firm, YQ, FQ	Firm, YQ, FQ
N	70384	70384	70384	70384	70384	70384	70384
Adj. RSQ	0.75	0.75	0.75	0.75	0.75	0.75	0.75

Panel B: Number of Management Forecasts (Revisions Only)

Dependent Variable	<i>Ln(I+ Revisions)</i>	<i>Ln(I+ Revisions)</i>	<i>Ln(I+ Revisions)</i>	<i>Ln(I+ Revisions)</i>	<i>Ln(I+ Revisions)</i>	<i>Ln(I+ Revisions)</i>	<i>Ln(I+ Revisions)</i>
Direct Interactions Measured by	<i>NumInteract</i>	<i>CEO</i>	<i>NumExecs</i>	<i>AnsPerQ</i>	<i>MDWords</i>	<i>PrivateMtg</i>	<i>Direct Interaction</i>
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
<i>Direct Interactions</i>	0.021*** (7.90)	0.018*** (5.53)	0.010*** (7.19)	0.131*** (6.16)	0.003*** (6.27)	0.022*** (5.43)	0.019*** (7.59)
Fixed Effects	Firm, YQ, FQ	Firm, YQ, FQ	Firm, YQ, FQ	Firm, YQ, FQ	Firm, YQ, FQ	Firm, YQ, FQ	Firm, YQ, FQ
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	70384	70384	70384	70384	70384	70384	70384
Adj. RSQ	0.62	0.62	0.62	0.62	0.62	0.62	0.62

Panel C: Absolute Errors in EPS Forecasts

Dependent Variable	<i>FcastError</i>	<i>FcastError</i>	<i>FcastError</i>	<i>FcastError</i>	<i>FcastError</i>	<i>FcastError</i>	<i>FcastError</i>
Direct Interactions Measured by	<i>NumInteract</i>	<i>CEO</i>	<i>NumExecs</i>	<i>AnsPerQ</i>	<i>MDWords</i>	<i>PrivateMtg</i>	<i>Direct Interaction</i>
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
<i>Direct Interactions</i>	-2.954* (-1.83)	-0.721 (-0.40)	-1.363* (-1.90)	-33.621** (-2.42)	-0.530** (-2.29)	-3.251* (-1.71)	-3.017** (-1.98)
<i>Horizon</i>	0.338*** (11.00)	0.338*** (11.01)	0.338*** (11.00)	0.337*** (10.98)	0.338*** (11.01)	0.338*** (11.01)	0.338*** (11.00)
Fixed Effects	Firm, YQ, FQ	Firm, YQ, FQ	Firm, YQ, FQ	Firm, YQ, FQ	Firm, YQ, FQ	Firm, YQ, FQ	Firm, YQ, FQ
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	31794	31794	31794	31794	31794	31794	31794
Adj. RSQ	0.68	0.68	0.68	0.68	0.68	0.68	0.68

Table 6: Consequences of Direct Learning from Investors - Summary Statistics and Insider Trading Timing

Panel A: Summary Statistics - Trades Level Analysis

This table presents descriptive statistics for the variables used in the insider trading analyses. The sample includes all trades by corporate officers that occur within two months before or after an investor conference that the officer's firm has attended. All variables are defined in Appendix A.

Variables	Count	Mean	Std	P50
<i>ParInsiderTrade_{POST}</i>	28632	0.029	0.168	0
<i>ParInsiderTrade_{PRE}</i>	28632	0.029	0.169	0
<i>I(Trade_{POST})</i>	28632	0.133	0.34	0
<i>I(Trade_{PRE})</i>	28632	0.146	0.353	0
<i>Participating Insider</i>	28632	0.159	0.366	0
<i>Alpha30</i>	28632	0.004	0.394	-0.205
<i>BHAR30</i>	28632	-0.166	7.713	-4.342
<i>Unsigned Trading Volume (\$)</i>	28632	1,696,834	32,219,911	143,610
<i>Conf Abn Ret</i>	28632	0.096	1.003	-0.55
<i>Conf Abn Turnover</i>	28632	0.256	1.797	-0.579
<i>CEO</i>	28632	0.241	0.428	0

Panel B: Timing of Participating Insider Trades

This table investigates whether participating insiders are more likely to trade in the seven-day window after a conference. The sample includes all trades by corporate officers that occur within two months before or after an investor conference that the officer's firm has attended. The unit of analysis is at the individual trades level.

$$1(\text{Trade}_{POST})_{ijk} = \beta_0 + \beta_1 \text{ParticipatingInsider}_{ijk} + \Gamma X_{ijk} + \text{Fixed Effects} + e_{ijk} \quad (\text{IT1})$$

where *i* denotes firm, *j* denotes executives and *k* denotes trades. *I(Trade_{POST})* is an indicator variable that takes the value of one if a trade is placed within seven days after an investor conference, and zero otherwise. *Participating Insider* is an indicator that takes the value of one if a trade *k* is placed by an insider *j* who has participated in an investor conference on behalf of firm *i* prior to the trade, and zero otherwise. Column (1) and (3) use firm-quarter fixed effects. Column (2) and (4) use firm-month fixed effects. All variables are defined in Appendix A. The coefficients on the intercept, firm-quarter, firm-month fixed effects are not reported. T-statistics based on robust standard errors clustered by firm are indicated in

parenthesis below coefficient estimates. ***, **, and * indicate significance level at 1%, 5%, and 10% respectively (two-tailed).

Dependent Variable	<i>I(Trade_{POST})</i> (1)	<i>I(Trade_{POST})</i> (2)
<i>Participating Insider</i>	0.092*** (9.48)	0.067*** (6.17)
<i>Conf Abn Ret</i>	-0.001 (-0.13)	0.011 (0.82)
<i>Conf Abn Turnover</i>	0.002 (0.53)	0.003 (0.50)
<i>CEO</i>	-0.024*** (-3.15)	-0.009 (-1.19)
Fixed Effects	Firm-Quarter	Firm-Month
N	28632	24739
Adj. RSQ	0.18	0.37

Table 7: Consequences of Direct Learning from Investors – Insider Trading Profits

This table investigates the association between direct learning and subsequent insider trading profits. The sample includes all trades by corporate officers that occur within two months before or after an investor conference that the officer’s firm has attended. The unit of analysis is at the individual trades level. The OLS specification is:

$$Profits_{ijk} = \beta_0 + \beta_1 ParInsiderTrade_{POSTijk} + \Gamma X_{ijk} + Fixed\ Effects + e_{ijk} \text{ (IT2)}$$

where i denotes firm, j denotes executives and k denotes trades. $ParInsiderTrade_{POST}$ takes the value of one if executive j placed a trade k in the seven-day window after attending an investor conference on behalf of firm i , and zero otherwise. The dependent variable is either $Alpha30$ or $BHAR30$. $Alpha30$ measures the average risk-adjusted returns for each insider transaction (expressed as a percentage) calculated over the 30 days following an insider transaction and relative to the Fama and French (1993) three-factor models, multiplied by -1 for sales. $BHAR30$ measures the market-adjusted buy and hold returns (expressed as a percentage) over 30 days following an insider transaction, multiplied by -1 for sales. All trades are opportunistic, defined following the trade-level classification scheme in Cohen et al., (2012). Panel A (B) presents results using all conferences (conferences with multiple corporate participants). Column (1) and (3) use firm-quarter fixed effects. Column (2) and (4) use firm-month fixed effects. All variables are defined in Appendix A. The coefficients on the intercept, firm-quarter, firm-month fixed effects are not reported. T-statistics based on robust standard errors clustered by firm are indicated in parenthesis below coefficient estimates. ***, **, and * indicate significance level at 1%, 5%, and 10% respectively (two-tailed).

Panel A: All Conferences

Dependent Variable	<i>Alpha30</i>	<i>Alpha30</i>	<i>BHAR30</i>	<i>BHAR30</i>
	(1)	(2)	(3)	(4)
<i>ParInsiderTrade_{POST}</i>	0.064*** (3.16)	0.028** (1.98)	1.482*** (3.70)	0.493* (1.95)
<i>Conf Abn Ret</i>	0.005 (0.56)	0.006 (0.55)	0.243 (1.40)	0.070 (0.34)
<i>Conf Abn Turnover</i>	0.016** (2.48)	0.017** (2.23)	0.308** (2.38)	0.305** (2.16)
<i>CEO</i>	-0.002 (-0.18)	-0.013 (-1.50)	-0.010 (-0.07)	-0.216 (-1.44)
Fixed Effects	Firm-Quarter	Firm-Month	Firm-Quarter	Firm-Month
N	28632	24739	28632	24739
Adj. RSQ	0.390	0.651	0.410	0.692

Panel B: Multiple-Participants Conferences

Dependent Variable	<i>Alpha30</i>	<i>Alpha30</i>	<i>BHAR30</i>	<i>BHAR30</i>
	(1)	(2)	(3)	(4)
<i>ParInsiderTrade_{POST}</i>	0.055** (1.97)	0.026 (1.21)	1.504*** (2.77)	0.697* (1.70)
<i>Conf Abn Ret</i>	0.004 (0.30)	0.006 (0.32)	-0.080 (-0.27)	-0.014 (-0.03)
<i>Conf Abn Turnover</i>	0.012 (1.01)	0.016 (0.67)	0.465*** (2.59)	0.357 (0.89)
<i>CEO</i>	-0.016 (-1.32)	-0.029*** (-2.62)	-0.285 (-1.31)	-0.486*** (-2.58)
Fixed Effects	Firm-Quarter	Firm-Month	Firm-Quarter	Firm-Month
N	14293	12347	14293	12347
Adj. RSQ	0.404	0.663	0.431	0.704

Table 8: Consequences of Direct Learning from Investors –Insider Trading Falsification Tests

Panel A: Timing of Insider Trades

This falsification analysis examines whether participating insiders are more likely to trade in the seven-day window before a conference. It replicates the analysis in Table 6, Panel B, but replace the dependent variable with $I(Trade_{PRE})$, which is an indicator variable that takes the value of one if a trade is placed within the seven-day window before an investor conference, and zero otherwise. All variables are defined in Appendix A. The coefficients on the intercept, firm-quarter, firm-month fixed effects are not reported. Control variables follow those presented in Table 6 Panel B. T-statistics based on robust standard errors clustered by firm are indicated in parenthesis below coefficient estimates. ***, **, and * indicate significance level at 1%, 5%, and 10% respectively (two-tailed).

Dependent Variable	$I(Trade_{PRE})$	$I(Trade_{PRE})$
	(1)	(2)
<i>Participating Insider</i>	-0.115*** (-10.65)	-0.097*** (-7.79)
Fixed Effects	Firm-Quarter	Firm-Month
Controls	Yes	Yes
N	28632	24739
Adj. RSQ	0.19	0.38

Panel B: Insider Trading Profits

This falsification analysis examines if participating insiders' trades made in the seven-day prior to an investor conference earns more positive abnormal returns. It replicates the analysis in Table 7, Panel A, but replace $PTTrade_{POST}$ with $ParInsiderTrade_{PRE}$, which takes the value of 1 if executive j placed a trade k in the seven-day window before attending an investor conference on behalf of firm i . All variables are defined in Appendix A. The coefficients on the intercept, firm-quarter, firm-month fixed effects are not reported. Control variables follow those presented in Table 7 Panel A. T-statistics based on robust standard errors clustered by firm are indicated in parenthesis below coefficient estimates. ***, **, and * indicate significance level at 1%, 5%, and 10% respectively (two-tailed).

Dependent Variable	$Alpha_{30}$	$Alpha_{30}$	$BHAR_{30}$	$BHAR_{30}$
	(1)	(2)	(3)	(4)
<i>ParInsiderTrade_{PRE}</i>	0.043** (1.97)	0.015 (0.77)	0.467 (1.16)	0.170 (0.51)
Fixed Effects	Firm-Quarter	Firm-Month	Firm-Quarter	Firm-Month
Controls	Yes	Yes	Yes	Yes
N	28632	24739	28632	24739
Adj. RSQ	0.390	0.651	0.410	0.692

Table 9: Consequences of Direct Learning from Investors – Insider Trading Profits (Cross-Sectional Analysis)

This table investigates whether the relation between direct learning and subsequent insider trading profits depends on the manager’s demand for information. The sample includes all trades by corporate officers that occur within two months before or after an investor conference and is partitioned based on the median value of *Demand for Prd Mkt Info* (Column 1 to 4) and *Demand for Supply Chain Info* (Column 5 to 8). The unit of analysis is at the individual trades level. The OLS specification is:

$$Profits_{ijk} = \beta_0 + \beta_1 ParInsiderTrade_{POST_{ijk}} + \Gamma X_{ijk} + Fixed\ Effects + e_{ijk} \text{ (IT2)}$$

where i denotes firm, j denotes executives and k denotes trades. $ParInsiderTrade_{POST}$ takes the value of one if executive j placed a trade k in the seven-day window after attending an investor conference on behalf of firm i , and zero otherwise. The dependent variable is either $Alpha30$ or $BHAR30$. $Alpha30$ measures the average risk-adjusted returns for each insider transaction (expressed as a percentage) calculated over the 30 days following an insider transaction and relative to the Fama and French (1993) three-factor models, multiplied by -1 for sales. $BHAR30$ measures the market-adjusted buy and hold returns (expressed as a percentage) over 30 days following an insider transaction. All trades are opportunistic, defined following the trade-level classification scheme in Cohen et al., (2012). All variables are defined in Appendix A. The coefficients on the intercept, and firm-month fixed effects are not reported. Control variables follow Table 7. T-statistics based on robust standard errors clustered by firm are indicated in parenthesis below coefficient estimates. ***, **, and * indicate significance level at 1%, 5%, and 10% respectively (two-tailed).

Dependent Variable	<i>Alpha30</i>		<i>BHAR30</i>		<i>Alpha30</i>		<i>BHAR30</i>	
	<i>Demand for Prd Mkt Info</i>				<i>Demand for Supply Chain Info</i>			
Sub-Sample	High	Low	High	Low	High	Low	High	Low
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
<i>ParInsiderTrade_{POST}</i>	0.060*** (3.12)	-0.005 (-0.25)	1.070*** (3.09)	-0.111 (-0.35)	0.038** (2.11)	0.030 (1.43)	0.478 (1.36)	0.508 (1.40)
F-Stat	6.067		6.593		0.102		0.004	
P-value	0.014		0.010		0.750		0.951	
Fixed Effects	Firm-Month	Firm-Month	Firm-Month	Firm-Month	Firm-Month	Firm-Month	Firm-Month	Firm-Month
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	12316	11211	12316	11211	10794	10147	10794	10147
Adj. RSQ	0.629	0.700	0.669	0.737	0.638	0.694	0.672	0.733