DO MANAGERS LEARN FROM INSTITUTIONAL INVESTORS THROUGH DIRECT INTERACTIONS?

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ABSTRACT

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Xi Zhang

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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.

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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.,

[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).

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).

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

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

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. 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., 2020; 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 the participating 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 information *from managers to investors* during these interactions and the associated benefits to brokers, investors, managers and the firm (Bushee et al., 2011, 2017, 2020; 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

[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.

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.

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.

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[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).

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 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.

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 changes in a firm's policy towards attending investor conferences. This procedure results

[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 evered 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.

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.

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

Research Design and Results

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 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., 2020; 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

[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.

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.

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:

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

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 market 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*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*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*0.202/1.009) standard deviation increase in *Direct Interaction*, ceteris paribus.

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:

[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.

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

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

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:

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

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

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

[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.

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 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-

[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*).

[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.

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

First, 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 Appendix B, I repeat the analyses in section 4.2 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.

Second, I re-estimate equation (IC1) by removing all observations in the year of 2007 and 2008 in Appendix C. This is to address concerns that the financial crisis might be associated with both a decrease in the availability of conference as a medium for direct interaction as well as an overall decline in product-market activities. My results and inferences remain unchanged.

Third, I control for the extent of information transfer between product-market peer firms as well as firms connected on the supply chain to mitigate concerns that an increase in peer activities (or connected firms activities) are correlated with investors' information demand. Appendix C presents the results of this analysis, and my inferences remain unchanged.

Finally, to address concerns that the various proxies for *Manager Information Demand* could have positive serial correlation, I modify equation (IC1) using a lead-lag model. Specifically, I re-estimate equation (IC1) by including one-quarter lagged *Manager Information Demand (t-1)* (the regressor of interest), contemporaneous *Manager Information Demand (t)*, and one- and two-quarter lead *Manager Information Demand (t+1, t+2).* The results of this analysis are presented in Appendix C. Consistent with managerial learning, only the coefficients on the quarter-lagged measure of *Manager Information Demand (t-1)* are positive and significant. The coefficients on the contemporaneous and the quarter-lead measures of *Manager Information Demand* are insignificant.

4.3. Consequences of learning

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:

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

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

[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 Appendix D, 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.

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*).

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 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

[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.

(-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 as 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.

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

[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).

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]

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. Specifically, I make two predictions.

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:

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

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

[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.

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

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

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 3M Co.). 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 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 C of Table 2 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, 15.9% of executives have participated in a conference prior to trading, and 3% (3%) trades are executed by participating insiders in the seven-day window after (before) a conference. The mean (median) size of transaction is $1,696,843 ($143,610).

Panel A of Table 6 presents the results from equation (IT1). The coefficient β_1 is positive and significant across all columns. The result in column (2), for example, suggests 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 6 Panel B 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. In column (2), compared to non-participating insider trades, participating insider trades in the same firm-month generate an incremental 30-day alpha of 2.8 basis point. 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 are 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 falsification tests to provide more comfort that my results are not driven by anticipated disclosure. 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, my falsification tests examine (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 7 Panel A modifies equation (IT1) by using $1(Trade_{PRE})$ 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 6, 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 7 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 8 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 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 coefficients on $ParInsiderTrade_{POST}$ across the two subsamples are significantly different under 5%. For information related to supply

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

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. Subsequent revelation of the manager's private information

Next, I investigate one source of subsequent revelation of the information learned by managers through direct interactions with investors. Specifically, if managers can acquire useful information that helps them to make more accurate forecasts of the firm's future flow, it is plausible that the information will be eventually made public through the issuance of a management forecast. To investigate whether subsequent management forecast is a source of information revelation, I conduct two additional analyses.

First, I examine if the subsequent issuance of a management forecast is associated with greater abnormal trading gains by participating insiders documented above. I expect a positive association if such management forecast is indeed reveals, at least partially, the information in participating managers' insider trades after a conference. To examine this hypothesis, I modify equation (IT2) by interacting $ParInsiderTrade_{POST}$ with *IssueForecast. IssueForecast* is an indicator variable that takes the value of one if a management forecast is issued within 30 days from the date of an insider transaction. If the private information impounded in participating insiders' trades is revealed by the subsequent management forecast, then the interaction between $ParInsiderTrade_{POST}$ and *IssueForecast* should be positive. Table 9 Panel A presents the results from this analysis.

It shows that the coefficient on *ParInsiderTrade*$_{POST}$× *IssueForecast* is positive across different specifications. It is significant under the firm-month specification.

Next, I examine whether the direction of insider trades predicts the nature of news in the subsequent forecast among the subsets of trades that are followed by a management forecast. From the sample of participating insider trades (i.e., trades made by participating insiders in the seven-day post-conference window), I collect all management forecasts that are made within 30 days of the trade. This results in a sample of 145 pairs of management forecasts and insider trades.[20] The empirical specification is as follows:

$$MGNews = \alpha_0 + \alpha_1 TradeDirection + (\eta_i) + (\phi_t) + \varepsilon$$

MGNews captures the nature of the news revealed by a management forecast. It is calculated as the market-adjusted cumulative abnormal returns in the (-1 to +1) 3-day window around the management forecast. *Trade Direction* captures the direction of insider trades. It is measured by either *Buy* or *BSI*. *Buy* is an indicator variable that takes the value of one for net buy trades, and zero otherwise. *BSI* is calculated as the number of shares bought by insiders minus the number of shares sold by insiders scaled by insider trading volume. Both *Buy* and *BSI* are aggregated to an executive-date level. η_i are firm dummies and ϕ_t are year dummies. Because imposing fixed effects result in a further reduction of the sample size, I estimate the above regression using both cross-sectional variations (i.e., without any fixed effects) and within-firm variations (i.e., with firm and year dummies).

[20] If there are multiple forecasts within the 30-day window, I take the closest forecast.

Table 9 Panel B presents the results of this analysis. The coefficients on *Buy* and *BSI* are positive and significant across different specifications, suggesting a positive association between the direction of the insider trade and the nature of news in the subsequent forecast. In other words, insider purchases (sales) predict positive (negative) news in the subsequent forecast. Together with the results from Panel A, these results are consistent with the notion that managers who participated in a conference acquire useful information from investors that help them to make more accurate forecasts of the firm's future operations. This information is first reflected in their insider trades, and is eventually made public by the issuance of a revised management forecast.

4.3.2.4. *Alternative specifications*

In Appendix E, 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) controlling for whether an executive has ever attended a conference to mitigate concerns that executives who are able to attend conferences tend to hold more important roles in the firm, and therefore have better private information, (iii) 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 but are outside of the seven-day post-conference window, and (iv) restricting to trades within the seven-day window around a conference to limit the comparison to a much tighter window. My results are robust to these alternative specifications, and my inferences remain unchanged.

4.4. Future directions and long-term effect of learning

While this paper is a first step at providing evidence of managerial learning, interesting future directions include analyzing the real long-term effects of managerial learning on the firm. In Appendix F, I present a number of exploratory analyses investigating such long-term effects.

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.

Tables

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

	Factset Only		Thomson Only		Both Factset and Thomson		Total	
Year	**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

	Factset Only		Thomson Only		Both Factset and Thomson		Total	
Year	**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 (section 4.2 and 4.3.1). 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
Measures of Manager-Investor Interaction						
NumInteract	73262	0.678	1.029	0.000	0.000	1.000
CEO	73262	0.412	0.726	0.000	0.000	1.000
NumExecs	73262	1.041	1.785	0.000	0.000	2.000
AnsPerQ	73262	0.066	0.106	0.000	0.000	0.130
MDWords	73262	2.480	4.919	0.000	0.000	3.502
PrivateMtg	73262	0.187	0.464	0.000	0.000	0.000
Direct Interaction	73262	0.015	1.009	-0.654	-0.654	0.497
Measures of Managers' Information Demand						
Demand for Prd Mkt Info	73262	0.021	0.024	0.002	0.011	0.036
Demand for Supply Chain Info	54192	0.018	0.027	0.000	0.007	0.023
Managerial Uncertainty	40188	0.441	0.202	0.313	0.429	0.563
Measures of Investor Knowledge						
Prd Mkt Trades ($ Bn)	66834	0.279	0.264	0.090	0.208	0.383
Prd Mkt Hldgs ($ Bn)	66917	1.814	2.168	0.469	1.109	2.234
Supply Chain Trades ($ Bn)	53282	10.145	12.872	0.434	4.949	15.299
Supply Chain Hldgs ($ Bn)	53289	111.191	146.991	3.439	52.607	163.611
Measures of Disclosure Outcomes						
Forecasts	70384	2.177	2.207	0.000	2.000	3.000
Revisions	70384	1.217	1.601	0.000	1.000	2.000
FcastError	31794	120.097	322.789	10.727	29.465	89.747
Firm-Level Controls						
Size	73262	7.194	1.764	5.899	7.180	8.411
Inst. Ownership	73262	4.814	1.421	4.477	5.043	5.602
Analyst	73262	1.976	0.858	1.540	2.120	2.590
Financing	73262	0.272	0.445	0.000	0.000	1.000
M&A	73262	0.188	0.391	0.000	0.000	0.000
Restructuring	73262	0.025	0.155	0.000	0.000	0.000
Firm Age	73262	2.826	0.738	2.303	2.833	3.401
Segments	73262	2.036	1.509	1.000	1.000	3.000
High Tech	73262	0.349	0.477	0.000	0.000	1.000
Intangibles	73262	0.363	0.360	0.036	0.260	0.611
R&D	73262	0.068	0.107	0.003	0.024	0.087
BM Ratio	73262	0.499	0.411	0.238	0.393	0.634
Returns	73262	0.007	0.205	-0.108	-0.003	0.103
Ret Vol	73262	0.027	0.015	0.017	0.023	0.033
Leverage	73262	0.207	0.185	0.017	0.186	0.330
Loss	73262	0.284	0.451	0.000	0.000	1.000
AnnFreq	73262	1.083	2.151	0.000	0.000	1.000
AnnAR	73262	0.020	0.046	0.000	0.000	0.017

Earnings Volatility	70384	0.027	0.042	0.006	0.013	0.028
Bid-ask Spread	70384	0.197	0.399	0.044	0.088	0.173
Turnover	70384	0.012	0.009	0.006	0.009	0.014
RegFDDiscl.	70384	0.624	1.098	0.000	0.000	1.000
PctAnnFcast	70384	47.797	43.690	0.000	50.000	100.000
Horizon (days)	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	***Eigenvalue***	***Proportion of the variance explained***	***Cumulative proportion of the variance explained***
1st	4.31	0.72	0.72
2nd	0.66	0.11	0.83
3rd	0.46	0.08	0.90

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

Panel C: Summary Statistics (Insider Trades Level)

This table presents descriptive statistics for the variables used in the insider trading analyses in section 4.3.2. 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**
$ParInsiderTrade_{POST}$	28632	0.029	0.168	0
$ParInsiderTrade_{PRE}$	28632	0.029	0.169	0
$1(Trade_{POST})$	28632	0.133	0.34	0
$1(Trade_{PRE})$	28632	0.146	0.353	0
Participating Insider	28632	0.159	0.366	0
Alpha30	28632	0.004	0.394	-0.205
BHAR30	28632	-0.166	7.713	-4.342
Unsigned Trading Volume ($)	28632	1,696,834	32,219,911	143,610
Conf Abn Ret	28632	0.096	1.003	-0.55
Conf Abn Turnover	28632	0.256	1.797	-0.579
CEO	28632	0.241	0.428	0

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:

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

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 managers' 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	***NumInteract***	***CEO***	***NumExecs***	***AnsPerQ***	***MDWords***	***PrivateMtg***	***Direct Interaction***
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Demand for Prd Mkt Info	1.218***	0.888***	1.177*	0.037	1.601	1.295***	1.216***
	(3.17)	(3.15)	(1.80)	(0.97)	(0.99)	(6.78)	(3.28)
Size	0.287***	0.166***	0.459***	0.026***	1.021***	0.082***	0.279***
	(13.18)	(10.45)	(13.61)	(13.11)	(11.34)	(9.70)	(13.66)
Inst. Ownership	0.042***	0.021***	0.067***	0.005***	0.156***	0.009*	0.041***
	(3.89)	(2.92)	(4.38)	(4.96)	(3.54)	(1.89)	(4.05)
Analyst	0.127***	0.068***	0.196***	0.010***	0.495***	0.046***	0.123***
	(8.38)	(6.52)	(8.70)	(6.95)	(8.06)	(7.70)	(8.79)
Financing	0.004	-0.002	0.019	0.001	0.086	-0.008	0.005
	(0.36)	(-0.26)	(0.98)	(0.97)	(1.57)	(-1.46)	(0.49)
M&A	0.012	0.019**	0.018	0.002	0.049	0.007	0.018
	(0.98)	(2.15)	(0.90)	(1.57)	(0.87)	(1.32)	(1.52)
Restructuring	0.017	-0.011	0.039	0.001	0.041	0.009	0.012
	(0.73)	(-0.68)	(0.98)	(0.39)	(0.33)	(0.78)	(0.53)
Firm Age	0.225***	0.153***	0.162*	0.016***	0.663***	0.103***	0.201***
	(4.22)	(4.29)	(1.89)	(3.10)	(3.10)	(5.44)	(4.05)
Segments	-0.017**	-0.013**	-0.015	-0.002***	-0.044	-0.006*	-0.017**

	(-2.06)	(-2.27)	(-1.09)	(-2.84)	(-1.21)	(-1.82)	(-2.15)
High Tech	0.031	-0.001	0.026	-0.002	-0.051	0.035	0.017
	(0.50)	(-0.02)	(0.24)	(-0.25)	(-0.19)	(1.42)	(0.28)
Intangibles	0.044	0.063*	0.157**	0.008*	0.390**	-0.024	0.069
	(0.94)	(1.85)	(2.15)	(1.85)	(2.03)	(-1.19)	(1.55)
R&D	0.056	0.019	0.216	0.014	0.420	-0.018	0.079
	(0.40)	(0.19)	(1.07)	(1.22)	(0.76)	(-0.32)	(0.60)
BM Ratio	-0.128***	-0.080***	-0.195***	-0.015***	-0.451***	-0.032***	-0.129***
	(-7.31)	(-6.50)	(-7.30)	(-8.29)	(-6.19)	(-4.41)	(-7.79)
Ret	0.035**	0.031***	0.113***	0.003**	0.376***	-0.003	0.050***
	(2.34)	(2.72)	(4.33)	(1.97)	(5.10)	(-0.40)	(3.33)
Ret Vol	0.241	0.277	0.671	-0.028	2.437	0.247	0.343
	(0.60)	(0.94)	(1.03)	(-0.70)	(1.35)	(1.36)	(0.87)
Leverage	-0.214***	-0.092*	-0.312***	-0.021***	-0.981***	-0.050*	-0.203***
	(-2.96)	(-1.87)	(-2.84)	(-3.16)	(-3.50)	(-1.72)	(-3.03)
Loss	-0.022*	-0.012	-0.046**	-0.001	-0.063	-0.007	-0.021*
	(-1.88)	(-1.35)	(-2.35)	(-1.02)	(-1.12)	(-1.35)	(-1.80)
AnnFreq	0.015***	0.005*	0.020**	0.001*	0.005	0.010***	0.012***
	(3.17)	(1.69)	(2.37)	(1.66)	(0.24)	(4.32)	(2.74)
AnnAR	-0.109	-0.010	-0.231	0.001	0.077	-0.129*	-0.092
	(-0.78)	(-0.10)	(-0.99)	(0.10)	(0.12)	(-1.94)	(-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	***NumInteract***	***CEO***	***NumExecs***	***AnsPerQ***	***MDWords***	***PrivateMtg***	***Direct Interaction***
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Demand for Supply Chain Info	0.653**	0.503***	1.079**	0.036	1.297	0.476***	0.665***
	(2.46)	(2.58)	(2.48)	(1.44)	(1.11)	(3.82)	(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	***NumInteract***	***CEO***	***NumExecs***	***AnsPerQ***	***MDWords***	***PrivateMtg***	***Direct Interaction***
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Managerial Uncertainty	0.049**	0.035*	0.078*	0.012***	0.247*	0.019	0.068***
	(2.14)	(1.90)	(1.79)	(4.44)	(1.92)	(1.60)	(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' 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 compared to that in Table 3. Control variables follow those presented in Table 3. The F-statistics compares the coefficients on *Demand for Prd Mkt Info* and *Demand for Supply Chain 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 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***	***Direct Interaction***	***Direct Interaction***
Product-Market Knowledge Measured By	*Prd Mkt Trades*	*Prd Mkt Trades*	*Prd Mkt Hldgs*	*Prd Mkt Hldgs*
Sub-Samples	High Prd Mkt Knowledge	Low Prd Mkt Knowledge	High Prd Mkt Knowledge	Low Prd Mkt Knowledge
	(1)	(2)	(3)	(4)
Demand for Prd Mkt Info	2.207***	0.629	2.288***	0.586
	(3.35)	(1.35)	(3.46)	(1.24)
F-stat	3.878		4.531	
P-value	0.049		0.033	
Fixed Effects	Firm, YQ, FQ	Firm, YQ, FQ	Firm, YQ, FQ	Firm, YQ, FQ
Controls	Yes	Yes	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***	***Direct Interaction***	***Direct Interaction***
Supply Chain Knowledge Measured by	*Supply Chain Trades*	*Supply Chain Trades*	*Supply Chain Hldgs*	*Supply Chain Hldgs*
Sub-Samples	High Supply Chain Knowledge	Low Supply Chain Knowledge	High Supply Chain Knowledge	Low Supply Chain Knowledge
	(1)	(2)	(3)	(4)
Demand for Supply Chain Info	1.241***	0.478	1.322***	0.504*

	(3.22)	(1.56)	(3.38)	(1.70)
F-stat	2.473		2.885	
P-value	0.116		0.090	
Fixed Effects	Firm, YQ, FQ	Firm, YQ, FQ	Firm, YQ, FQ	Firm, YQ, FQ
Controls	Yes	Yes	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 managers are able to issue more forecasts and more accurate forecasts after direct learning from institutional investors. The unit of analysis is a firm-quarter observation. The OLS specification is:

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

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(1+ Forecasts)***	***Ln(1+ Forecasts)***	***Ln(1+ Forecasts)***	***Ln(1+ Forecasts)***	***Ln(1+ Forecasts)***	***Ln(1+ Forecasts)***	***Ln(1+ Forecasts)***
Direct Interactions Measured by	***NumInteract***	***CEO***	***NumExecs***	***AnsPerQ***	***MDWords***	***PrivateMtg***	***Direct Interaction***
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Direct Interactions	0.011***	0.010***	0.004***	0.075***	0.001**	0.015***	0.009***
	(4.55)	(3.34)	(3.12)	(3.88)	(1.97)	(4.10)	(4.06)
Size	0.053***	0.055***	0.054***	0.054***	0.055***	0.055***	0.054***
	(3.39)	(3.49)	(3.48)	(3.46)	(3.55)	(3.52)	(3.42)
Inst. Ownership	0.010**	0.010**	0.010**	0.010**	0.010**	0.010**	0.010**
	(2.04)	(2.08)	(2.06)	(2.05)	(2.09)	(2.11)	(2.05)
Analyst	0.087***	0.088***	0.088***	0.088***	0.089***	0.088***	0.088***
	(9.46)	(9.52)	(9.51)	(9.51)	(9.55)	(9.51)	(9.48)
Financing	0.006	0.006	0.006	0.006	0.006	0.006	0.006
	(1.01)	(1.00)	(0.98)	(0.98)	(0.97)	(1.01)	(1.00)
M&A	0.010*	0.010*	0.010*	0.010*	0.010*	0.010	0.010*
	(1.66)	(1.65)	(1.65)	(1.66)	(1.66)	(1.63)	(1.65)
Restructuring	-0.004	-0.004	-0.004	-0.004	-0.004	-0.004	-0.004
	(-0.36)	(-0.37)	(-0.36)	(-0.37)	(-0.36)	(-0.35)	(-0.36)
Firm Age	0.074**	0.075**	0.076**	0.075**	0.076**	0.075**	0.075**
	(2.20)	(2.23)	(2.26)	(2.24)	(2.27)	(2.23)	(2.22)
Segments	-0.003	-0.003	-0.003	-0.003	-0.003	-0.003	-0.003
	(-0.76)	(-0.77)	(-0.79)	(-0.76)	(-0.80)	(-0.79)	(-0.77)
High Tech	0.039	0.040	0.040	0.040	0.040	0.039	0.040
	(1.30)	(1.31)	(1.30)	(1.31)	(1.31)	(1.29)	(1.30)
Intangibles	0.057**	0.057**	0.057**	0.057**	0.057**	0.058**	0.057**
	(2.06)	(2.06)	(2.06)	(2.06)	(2.07)	(2.09)	(2.06)

R&D	0.060	0.060	0.060	0.060	0.061	0.061	0.060
	(1.04)	(1.06)	(1.05)	(1.04)	(1.06)	(1.07)	(1.04)
BM Ratio	-0.017	-0.017	-0.017	-0.017	-0.018	-0.017	-0.017
	(-1.50)	(-1.55)	(-1.55)	(-1.53)	(-1.58)	(-1.56)	(-1.51)
Ret	0.005	0.005	0.005	0.005	0.005	0.005	0.005
	(0.73)	(0.72)	(0.70)	(0.73)	(0.71)	(0.71)	(0.73)
Ret Vol	-0.331	-0.326	-0.330	-0.329	-0.328	-0.326	-0.331
	(-1.38)	(-1.36)	(-1.37)	(-1.37)	(-1.36)	(-1.35)	(-1.38)
Leverage	-0.067*	-0.068*	-0.068*	-0.068*	-0.069*	-0.068*	-0.067*
	(-1.85)	(-1.88)	(-1.88)	(-1.87)	(-1.89)	(-1.88)	(-1.86)
Loss	-0.024***	-0.024***	-0.024***	-0.024***	-0.024***	-0.025***	-0.024***
	(-3.99)	(-4.00)	(-3.98)	(-3.98)	(-3.98)	(-4.01)	(-3.99)
LitRisk	-0.005	-0.005	-0.005	-0.005	-0.005	-0.005	-0.005
	(-0.81)	(-0.81)	(-0.81)	(-0.82)	(-0.80)	(-0.78)	(-0.80)
AnnFreq	-0.003	-0.003	-0.003	-0.003	-0.003	-0.003	-0.003
	(-1.39)	(-1.32)	(-1.33)	(-1.31)	(-1.30)	(-1.35)	(-1.36)
AnnAR	0.120**	0.118**	0.119**	0.117**	0.117**	0.118**	0.119**
	(2.02)	(1.98)	(2.00)	(1.98)	(1.98)	(1.99)	(2.01)
Earnings Vol	-0.037	-0.037	-0.036	-0.036	-0.036	-0.038	-0.037
	(-0.35)	(-0.34)	(-0.34)	(-0.34)	(-0.34)	(-0.36)	(-0.35)
Bid-ask Spread	0.004	0.005	0.005	0.005	0.005	0.005	0.004
	(0.42)	(0.49)	(0.47)	(0.46)	(0.51)	(0.49)	(0.43)
Turnover	1.595***	1.607***	1.613***	1.618***	1.616***	1.596***	1.601***
	(2.93)	(2.96)	(2.97)	(2.97)	(2.97)	(2.94)	(2.94)
RegFDDiscl.	0.030***	0.030***	0.030***	0.030***	0.030***	0.030***	0.030***
	(9.55)	(9.54)	(9.54)	(9.53)	(9.53)	(9.53)	(9.55)
PctAnnFcast	0.007***	0.007***	0.007***	0.007***	0.007***	0.007***	0.007***
	(60.82)	(60.80)	(60.79)	(60.77)	(60.76)	(60.75)	(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	***Ln(1+ Revisions)***	***Ln(1+ Revisions)***	***Ln(1+ Revisions)***	***Ln(1+ Revisions)***	***Ln(1+ Revisions)***	***Ln(1+ Revisions)***	***Ln(1+ Revisions)***
Direct Interactions Measured by	***NumInteract***	***CEO***	***NumExecs***	***AnsPerQ***	***MDWords***	***PrivateMtg***	***Direct Interaction***
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Direct Interactions	0.021***	0.018***	0.010***	0.131***	0.003***	0.022***	0.019***
	(7.90)	(5.53)	(7.19)	(6.16)	(6.27)	(5.43)	(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	*FcastError*	*FcastError*	*FcastError*	*FcastError*	*FcastError*	*FcastError*	*FcastError*
Direct Interactions Measured by	***NumInteract***	***CEO***	***NumExecs***	***AnsPerQ***	***MDWords***	***PrivateMtg***	***Direct Interaction***
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Direct Interactions	-2.954*	-0.721	-1.363*	-33.621**	-0.530**	-3.251*	-3.017**
	(-1.83)	(-0.40)	(-1.90)	(-2.42)	(-2.29)	(-1.71)	(-1.98)
Horizon	0.338***	0.338***	0.338***	0.337***	0.338***	0.338***	0.338***
	(11.00)	(11.01)	(11.00)	(10.98)	(11.01)	(11.01)	(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 - Insider Trading

Panel A: 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. The OLS specification is:

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

where i denotes firm, j denotes executives and k denotes trades. *1(Trade$_{POST}$)* is an indicator variable that takes the value of one if a trade k is placed in the seven-day window 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	***1(Trade$_{POST}$)***	***1(Trade$_{POST}$)***
	(1)	(2)
Participating Insider	0.092***	0.067***
	(9.48)	(6.17)
Conf Abn Ret	-0.001	0.011
	(-0.13)	(0.82)
Conf Abn Turnover	0.002	0.003
	(0.53)	(0.50)
CEO	-0.024***	-0.009
	(-3.15)	(-1.19)
Fixed Effects	Firm-Quarter	Firm-Month
N	28632	24739
Adj. RSQ	0.18	0.37

Panel B: Insider Trading Profits

This table investigates whether participating insiders' trades in the seven-day post-conference window earns greater abnormal profits. The sample follows that presented in Panel A. The OLS specification is:

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

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 (Cohen et al., 2012). 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	***Alpha30***	***Alpha30***	***BHAR30***	***BHAR30***
	(1)	(2)	(3)	(4)
ParInsiderTrade$_{POST}$	0.064***	0.028**	1.482***	0.493*
	(3.16)	(1.98)	(3.70)	(1.95)
Conf Abn Ret	0.005	0.006	0.243	0.070
	(0.56)	(0.55)	(1.40)	(0.34)
Conf Abn Turnover	0.016**	0.017**	0.308**	0.305**
	(2.48)	(2.23)	(2.38)	(2.16)
CEO	-0.002	-0.013	-0.010	-0.216
	(-0.18)	(-1.50)	(-0.07)	(-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

Table 7: 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 A, but replaces the dependent variable with *1(Trade$_{PRE}$)*, which is an indicator variable that takes the value of one if a trade k is placed in 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 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	***1(Trade$_{PRE}$)***	***1(Trade$_{PRE}$)***
	(1)	(2)
Participating Insider	-0.115***	-0.097***
	(-10.65)	(-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 window prior to an investor conference earn greater abnormal profits. It replicates the analysis in Table 6, Panel B, but replaces *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 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	***Alpha30***	***Alpha30***	***BHAR30***	***BHAR30***
	(1)	(2)	(3)	(4)
ParInsiderTrade$_{PRE}$	0.043**	0.015	0.467	0.170
	(1.97)	(0.77)	(1.16)	(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 8: Consequences of Direct Learning from Investors – Insider Trading 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 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) (to the extent data is available). 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, multiplied by -1 for sales. 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 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	***Alpha30***	***Alpha30***	***BHAR30***	***BHAR30***	***Alpha30***	***Alpha30***	***BHAR30***	***BHAR30***
	Demand for Prd Mkt Info				*Demand for Supply Chain Info*			
Sub-Sample	High	Low	High	Low	High	Low	High	Low
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
ParInsiderTrade$_{POST}$	0.060***	-0.005	1.070***	-0.111	0.038**	0.030	0.478	0.508
	(3.12)	(-0.25)	(3.09)	(-0.35)	(2.11)	(1.43)	(1.36)	(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

Table 9: Consequences of Direct Learning from Investors – Subsequent Information Revelation

Panel A: Insider Trades Profitability and Subsequent Management Forecasts

This table investigates the issuance of management the relation and insider trading profitability. The sample includes all trades by corporate officers that occur within two months before or after an investor conference. The unit of analysis is at the individual trades level.

$$\begin{aligned} Profits_{ijk} = \beta_0 &+ \beta_1 ParInsiderTrade_{POST\,ijk} + \beta_2 IssueForecast_{ijk} \\ &+ \beta_3 ParInsiderTrade_{POST\,ijk} \times IssueForecast_{ijk} + \Gamma X_{ijk} + Fixed\ Effects \\ &+ e_{ijk} \text{ (IT2)} \end{aligned}$$

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. *IssueForecast* is an indicator variable that takes the value of one if a management forecast is issued within 30-day after the transaction date, 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). 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	***Alpha30***	***Alpha30***	***BHAR30***	***BHAR30***
	(1)	(2)	(3)	(4)
ParInsiderTrade$_{POST}$	0.048***	0.004	1.150***	0.027
	(2.76)	(0.30)	(3.48)	(0.11)
IssueForecast	-0.087***	-0.091***	-1.783***	-2.206***
	(-3.74)	(-3.12)	(-3.44)	(-3.27)
ParInsiderTrade$_{POST}$ × *IssueForecast*	0.016	0.089**	0.238	1.551**
	(0.36)	(2.23)	(0.30)	(2.10)
Conf Abn Ret	0.005	0.005	0.259	0.055
	(0.64)	(0.49)	(1.47)	(0.26)
Conf Abn Turnover	0.016**	0.018**	0.295**	0.311**
	(2.33)	(2.24)	(2.24)	(2.18)
CEO	0.000	-0.011	0.031	-0.171
	(0.04)	(-1.37)	(0.24)	(-1.26)
Fixed Effects	Firm-Quarter	Firm-Month	Firm-Quarter	Firm-Month
N	28632	24739	28632	24739
Adj. RSQ	0.396	0.655	0.417	0.698

Panel B: Directions of Insider Trades and News in the Subsequent Management Forecast

This table investigates the relation between the direction of participating insider trades (i.e., trades made by insiders who have participated in a conference within the seven-day window after a conference) and the nature of news in subsequent management forecasts issued within 30 days of the transaction date. The sample includes 145 participating insider trades that are following by a management forecast within 30-day of the transaction date. The OLS specification is:

$$MGNews = \alpha_0 + \alpha_1 TradeDirection + (\eta_i) + (\phi_t) + \varepsilon$$

MGNews is the market-adjusted cumulative abnormal returns in the (-1 to +1) 3-day window around the management forecast. *Trade Direction* is either *Buy* or *BSI*. *Buy* is an indicator variable that takes the value of one for net buy trades and zero otherwise. *BSI* is calculated as the number of shares bought by insiders minus the number of shares sold by insiders scaled by insider trading volume. η_i are firm dummies and ϕ_t are year dummies. 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	***MGNews***	***MGNews***	***MGNews***	***MGNews***
	(1)	(2)	(3)	(4)
Buy	0.008**		0.136**	
	(2.06)		(2.61)	
BSI		0.004**		0.068**
		(2.06)		(2.61)
FE	NO	NO	Firm, Year	Firm, Year
N	145	145	97	97
RSQ / Adj. RSQ	0.00022	0.00022	0.19	0.19

APPENDIX

APPENDIX A. Variable Definitions

Measures of Management-Investor Interaction

NumInteract (number)	The number of investor conferences (including investor days) that firm i has attended or hosted in the fiscal quarter t.
CEO (number)	The number of times that the CEO of firm i has attended an investor conference during the fiscal quarter t.
NumExecs (number)	The total number of executives from firm i who have attended an investor conference during the fiscal quarter t. If an executive attended more than one conference, each attendance is counted as 1.
AnsPerQ (thousands of words)	The average number of words (in thousands) that managers of firm i provided in response to a question in the Questions and Answers (Q&A) session(s) of investor conferences during the fiscal quarter t.
MDWords (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 has attended during the fiscal quarter t.
PrivateMtg (number)	The total number of times that firm i offers private breakout sessions or one-on-one meetings at investor conferences during the fiscal quarter t. 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).
Direct Interaction (component score)	The first principal component of *NumInteract, CEO, NumExecs, AnsPerQ, MDWords, PrivateMtg*.

Data Source: Thomson StreetEvents and Factset CallStreet.

Measures of Managers' Information Demand

Demand for Prd Mkt Info (percentage)	The sum of absolute market-adjusted announcement-day returns of product-market announcements made by firm i's peer firms during the fiscal quarter t, scaled by the total number of peers. Peer groups are defined using Hoberg-Phillips text-based industry classification.
Demand for Supply Chain Info (percentage)	The sum of absolute market-adjusted announcement-day returns of product-market announcements made by direct suppliers and customers of the firm i during the fiscal quarter t, scaled by the total number of direct suppliers and customers.
Managerial Uncertainty (percentage)	The proportion of answers given by corporate participants that contain at least one uncertain word during the Q&A sessions of firm i's earnings conference call for fiscal quarter t'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

Prd Mkt Hldgs ($ Billion)	The average dollar holdings in all firm i's peer firms, summed over all institutional investors holding at least 1% of the shares in firm i, computed as: $\sum_{j\in J}\sum_{p\in P}^{n}\frac{Dollar\ Holdings_{jp}}{n}$, where J is the set of all investors that hold at least 1% of

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

Forecasts (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).
Revisions (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.
FcastError (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

Alpha30 (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.

BHAR30 (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.
1(Trade$_{POST}$) / *1(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.
Participating Insider (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.
ParInsiderTrade$_{POST}$ / *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.
CEO (indicator)	An indicator variable that takes the value of 1 if executive j is the CEO of the firm i, and 0 otherwise.
Conf Abn Ret (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.
Conf Abn Turnover (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.
Unsigned Trading Volume (dollar)	The dollar value of an insider trading transaction, calculated as the transaction price multiplied by the number of shares purchased or sold.
IssueForecast	An indicator variable that takes the value of one if a management forecast is issued within 30-day after the transaction date of an insider trade, and zero otherwise.
MGNews	The market-adjusted cumulative abnormal returns in the (-1 to +1) 3-day window around management forecasts that are issued within 30-day after the transaction date of an insider trade.
BSI	The number of shares bought by insiders minus the number of shares sold by insiders scaled by insider trading volume. This variable is measured on a firm-executive-day level.
Buy	An indicator variable that takes the value of one for net buy trades and zero otherwise. This variable is measured on a firm-executive-day level.

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

Control Variables: Firm-Quarter Panel

Size ($ million)	Natural logarithm of total asset (*ATQ*).
Inst. Ownership (number)	Natural logarithm of one plus number of institutional owners reporting holdings of firm i's common stock based on the most recent 13-F report issued before the end of fiscal quarter t. 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.
Analyst (number)	Natural logarithm of one plus the number of analysts issued earnings forecasts for firm i during fiscal quarter t. 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.
Financing (indicator)	An indicator variable that takes the value of 1 if firm i issues debt or equity in the prior, current, or subsequent fiscal year as reported in the SDC database.

M&A (indicator)	An indicator variable that takes the value of 1 if firm i has made an acquisition in the prior, current, or subsequent fiscal year as reported in the SDC database, and 0 otherwise.
Restructuring (indicator)	Indicator variable that takes the value of 1 if firm i has a non-zero restructuring charge (*RCPQ*) to earnings in fiscal quarter t and 0 otherwise.
Firm Age (years)	Natural logarithm of the number of years since firm i first appeared in Compustat.
Segments (number)	The number of unique business segments reported in firm i's annual filings according to Computsat Segment database.
High Tech (indicator)	Indicator variable that takes the value of 1 for firm 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).
Intangibles (ratio)	Sum of recognized intangibles (*INTAN*) and goodwill (*GDWL*) at the end of the fiscal year, scaled by total assets (*AT*).
Loss (indicator)	An indicator variable that takes the value of 1 if a firm reported negative income before extraordinary items (*IBQ*) in the fiscal quarter, and 0 otherwise.
R&D (indicator)	R&D expenses (*RD*) during the fiscal year scaled by total assets (*AT*). 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.
BM Ratio (ratio)	Book value of equity (*ATQ* - *LTQ*) scaled by the market value of equity (*PRCCQ*CSHOQ*).
Leverage (ratio)	Book value of debt (*DLTTQ* + *DLCQ*) scaled by total assets (*ATQ*).
Ret (percentage)	Cumulative buy-and-hold returns over the fiscal quarter t, less the cumulative buy-and-hold return of CRSP value-weighted index over the corresponding period.
Ret Vol (percentage)	The standard deviation of daily returns over the fiscal quarter t.
Earnings Vol ($ million)	The standard deviation of quarterly net income (*IBQ*) over the previous 16 quarters before fiscal quarter t.
Bid-ask Spread (percentage)	Daily (ask–bid)/price using data on closing prices and quotes from CRSP, multiplied by 100, and averaged over the fiscal quarter t.
Turnover (percentage)	Daily volume traded over share outstanding, averaged over the fiscal quarter t.
AnnFreq (number)	The number of product-market announcements made by firm i during the fiscal quarter t.
AnnAR (percentage)	The sum of absolute market-adjusted one-day returns of product-market announcements made by firm i during the fiscal quarter.
RegFDDiscl. (number)	The number of 8k filings made by firm i that contains item 7.01 (Regulation Fair Disclosure) during the fiscal quarter t.
PctAnnFcast (percentage)	The percentage of annual management forecasts made by firm i during fiscal quarter t.
Horizon (days)	The average number of days between the forecast date and the actual date for all EPS forecasts made by firm i during fiscal quarter t.

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.

APPENDIX B. Robustness Analysis using Conference Quarters Only

The main analyses include 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 still be a concern among the smaller firms in my sample.

In robustness analyses reported below, I restrict the sample to firm-quarters with at least one conference. This alternative design only uses variations in the amount of managerial time invested and the degrees of information exchange between managers and investors, conditioning on attendance. I re-estimate equation (IC1) using this reduced sample for *Demand for Prd Mkt Info* (Panel A), *Connected Firm Activities* (Panel B) and *Managerial Uncertainty* (Panel C). The results remain unchanged, although slightly weaker, given the smaller sample. The α_1 coefficients remain positive across the different proxies for direct interactions and are significant under 0.05 for most of them.

Table A1: Determinants of Learning-Incentivized Manager-Investor Interaction: Conference Quarters Only

This table investigates the hypothesis that managers seek more direct interactions with institutional investors when they have higher demand for information on the reduced sample of firm-quarters with at least one conference occurrence. The unit of analysis is a firm-quarter observation. The OLS empirical specification is:

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

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 follow those presented in Table 2. 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	***NumInteract***	***CEO***	***NumExecs***	***AnsPerQ***	***MDWords***	***PrivateMtg***	***Direct Interaction***
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Demand for Prd Mkt Info	1.996***	1.156**	1.795	0.077	2.145	2.491***	2.026***
	(3.53)	(2.17)	(1.55)	(1.17)	(0.66)	(6.07)	(3.66)
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	28229	28229	28229	28229	28229	28229	28229
Adj. RSQ	0.3	0.21	0.21	0.22	0.16	0.18	0.22

Panel B: Demand for Supply Chain Information

Dependent Variable	***NumInteract***	***CEO***	***NumExecs***	***AnsPerQ***	***MDWords***	***PrivateMtg***	***Direct Interaction***
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Demand for	1.012***	0.831***	1.603**	0.087**	0.265	0.991***	1.103***

Supply Chain Info							
	(3.22)	(2.60)	(2.37)	(2.16)	(0.12)	(3.75)	(3.52)
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	22681	22681	22681	22681	22681	22681	22681
Adj. RSQ	0.3	0.21	0.21	0.21	0.16	0.17	0.21

Panel C: Managers' Overall Revealed Uncertainty

Dependent Variable	***NumInteract***	***CEO***	***NumExecs***	***AnsPerQ***	***MDWords***	***PrivateMtg***	***Direct Interaction***
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Managerial Uncertainty	0.016	0.028	0.001	0.018***	0.059	0.019	0.052
	(0.46)	(0.89)	(0.01)	(4.49)	(0.24)	(0.78)	(1.49)
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	19385	19385	19385	19385	19385	19385	19385
Adj. RSQ	0.32	0.22	0.22	0.23	0.17	0.19	0.23

APPENDIX C.Determinants of Learning-Incentivized Manager-Investor Interaction: Alternative Specifications

This section presents alternative specifications of the incentive analyses. For parsimony purposes, I report the coefficient estimates for various regressors of interest when during *Direct Interaction* as the outcome variable. The inclusion of control variables and fixed effects dummies follow those presented in equation (IC1) and in Table 3.

First, the drop in the number of conferences in 2007 and 2008 may raise concerns that the financial crisis might be associated with both a decrease in the availability of conference as a medium for direct interaction as well as an overall decline in product-market activities. The mitigate this concern, I re-estimate equation (IC1) by removing all observations in the year of 2007 and 2008. Panel A Column (1) presents the results of this analysis. The coefficient estimates on *Demand for Prd Mkt Info, Demand for Supply Chain Info,* and *Managerial Uncertainty* remain positive and significant, and my results and inferences remain unchanged.

Second, extant literature recognizes that one firm's announcement can contain value-relevant information about another firm that has economic links to it. Examples of such information events include earnings announcements (Firth, 1976; Foster, 1981; Freeman and Tse, 1992; Ramnath, 2002; Thomas and Zhang, 2008) and management forecasts (Baginski, 1987; Han et al., 1989; Kim et al., 2008; Pyo and Lustgarten, 1990). In the main analyses in section 4.2.1 and 4.2.2, I use product-market announcements among peer firms and among suppliers and customers as a proxy for the manager's demand for external information. However, to the extent that peer firms' or supply chain firms' announcements contain value-relevant information about the focal firm, which in turn could result in investor *demanding for more information* about the focal firm. Therefore, any subsequent changes in managers' propensity to seek direct interactions with investors could be driven by the manager's incentives to disclose (instead of to learn).

To address this concern, I re-estimate equation (IC1) for $Peer\ Activities$ and $Connected\ Firms\ Activities$ by controlling for the extent to which such announcements contain value-relevant information for the focal firm (*Focal Firm Abs Ret*). *Focal Firm Abs Ret* is calculated as the sum of the focal firm's absolute market-adjusted returns on the day of the peer firms' (supply chain connected firms') announcements, scaled by the number of peer firms (connected firms) respectively. The purpose of the scaling is to make sure that this measure does not merely capture a firm having more product-market peers or suppliers and customers. Panel A Column (2) presents the results of this analysis. The coefficient estimates on *Demand for Prd Mkt Info* and *Demand for Supply Chain Info* remains positive and significant, and my results and inferences remain unchanged.

Third, to address concerns that the various proxies for *Manager Information Demand* could have positive serial correlation, I modify equation (IC1) using a lead-lag model. Specifically, I re-estimate equation (IC1) by including one-quarter lagged *Manager Information Demand (t-1)* (the regressor of interest), contemporaneous *Manager Information Demand (t)*, and one- and two-quarter lead *Manager Information Demand (t+1, t+2).* Consistent with managerial learning, only the coefficients on the quarter-lagged measure of *Manager Information Demand (t-1)* are positive and significant. The coefficients on contemporaneous and lead measure of *Manager Information Demand* are insignificant.

Table A2: Alternative Specifications for Determinants of Learning-Incentivized Manager-Investor Interaction

Panel A: Exclude 07 and 08 as well as Control for the Extent of Information Transfer

This table reports the coefficient estimate (t-statistics based on robust standard errors clustered by firm in parenthesis) on *Demand for Prd Mkt Info, Demand for Supply Chain Info,* and *Managerial Uncertainty* under two alternative specifications of equation (IC1):

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

The fixed effect structure and the inclusion of control variables follow that in Table 3. For parsimony purposes, the dependent variable is *Direct Interaction*, which is the first principal component of the six empirical proxies of direct interaction. It corresponds to Column (7) of Table 3. The various specifications are:

- Column (1): the sample modifies that in Table 3 by removing all observations in the year 2007 and 2008

- Column (2): this empirical specification includes the additional control of *Focal Firm Abs Ret. Focal Firm Abs Ret* is calculated as the sum of the focal firm's absolute market-adjusted returns on the day of the peer firms' (supply chain connected firms') announcements, scaled by the number of peer firms (connected firms), respectively.

Dependent Variable	***Direct Interaction***	***Direct Interaction***
Alternative Specifications	**Exclude 07 and 08**	**Information Transfer among Connected Firms**
	(1)	**(2)**
Independent Variable:		
Demand for Prd Mkt Info	1.370***	1.062**
	(3.40)	(2.42)
Demand for Supply Chain Info	0.707***	0.977***
	(2.72)	(3.40)
Managerial Uncertainty	0.065***	--
	(2.73)	--

Panel B: Lead-Lag Model
This table modifies the analysis in Table 3 into a lead-lag model. It replaces *Mgr Info Demand (t-1)* with *Mgr Info Demand* measured at quarter t-1, t, t+1 and t+2, respectively. Control variables and the fixed effect structure follow that in Table 3. For parsimony purposes, the dependent variable is *Direct Interaction*, which is the first principal component of the six empirical proxies of direct interaction. It corresponds to Column (7) of Table 3.

Dependent Variable	***Direct Interaction (t)***	***Direct Interaction (t)***	***Direct Interaction (t)***
Mgr Info Demand measured by	*Demand for Prd Mkt Info*	*Demand for Supply Chain Info*	*Managerial Uncertainty*
	(1)	(2)	(3)
Mgr Info Demand (t-1)	1.185***	0.537**	0.052*
	3.168	2.354	1.759
Mgr Info Demand (t)	0.275	0.282	0.023
	0.828	1.281	0.793
Mgr Info Demand (t+1)	0.045	0.193	0.027
	0.133	0.918	0.916
Mgr Info Demand (t+2)	-0.364	0.049	0.047
	-1.035	0.213	1.622
FE	Firm, Year-Qtr, Fiscal Qtr	Firm, Year-Qtr, Fiscal Qtr	Firm, Year-Qtr, Fiscal Qtr
Controls	Yes	Yes	Yes
N	66609	48242	29642
Adj. RSQ	0.35	0.36	0.37

APPENDIX D.Managers' Incentives to Issue Biased EPS Forecasts

An underlying assumption in the analyses is that managers are, on average, motivated to produce accurate earnings forecasts. Prior literature suggests that accurate earnings forecasts are perceived positively by investors, analysts, and the board of directors. Higher forecast accuracy is associated with a lower likelihood of CEO turnover (Lee et al., 2012). Establishing a track record of producing accurate forecasts allows managers to issue future forecasts that have a greater influence on equity investors (Yang, 2012; Zhang, 2012) and analysts (Williams, 1996). In addition, survey evidence finds that over 90% of managers agree (or strongly agree that) promoting a reputation for transparent and accurate reporting is a key motivation in their voluntary disclosure decision (Graham et al., 2005).

Under some circumstances, however, managers may be incentivized to provide biased earnings forecasts. Managers may provide more pessimistic forecasts to avoid negative earnings surprises (Matsumoto, 2002), to reduce the risk of litigation (Rogers and Stocken, 2005), to purchase their own stocks at a lower price (Rogers and Stocken, 2005) and to deter entry (Rogers and Stocken, 2005). In particular, one might argue that a manager's incentive to meet or beat might change after such direct interactions with investors and analysts during a conference.

Therefore, in this analysis, I examine whether managers are revising their management forecasts after direct interactions to manage analysts' expectations. In this alternative explanation, managers might realize that analysts have high expectations for the firm's future performance that are difficult to achieve during the conference. They then issue a revised management forecast in order to walk down analysts' expectations. Under this hypothesis, one would observe both an increase in the number of forecast revisions after a conference (such that the increase in management forecasts is not driven by managers having better information after learning, but is by managers wanting to manage expectations), and might observe a decrease in forecast errors if a lower forecast also happens to be more accurate. To investigate this alternative theory, I calculate the corresponding earnings surprise with respect to the forecasted period for each EPS forecast issued during the quarter - if a manager attends a conference at quarter t, issues an EPS forecast at quarter t+1 with respect to the quarter t+3, I look at the likelihood that earnings in quarter t+3 meet or beat prevailing analyst consensus. I compute *FutureMeet/Beat,* which is the percentage of EPS forecasts for which the actual earning of the forecasted period exceeds analyst consensus, computed using the most recent forecast issued by each analyst during the 90 days window prior to the actual date. I modify equation (MG1) using *FutureMeet/Beat* as the outcome variable.

I find that the coefficients on *Direct Learning* have mixed signs and are not significant. Therefore, 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 results are not consistent with the alternative theory that managers issue revised forecasts (which also happen to be more accurate) to manage analysts' expectations.

Table A3: Managers' Incentives to Issue Biased EPS Forecasts

The table investigates whether managers have incentives to bias their EPS forecast after direct learning in order to manage analysts' expectations, which in turn increases the propensity to meet or beat. The unit of analysis is a firm-quarter observation. The empirical specification is

$$FutureMeet/Beat_{it+1} = \beta_0 + \beta_1 Direct\ Interactions_{it} + \Gamma X_{it} + \eta_i + \phi_t + \nu_q + e_{it}$$

where i denotes firm, t denotes quarter, η_i denotes firm dummies, ϕ_t denotes year-quarter dummies and ν_q denotes fiscal quarter dummies. The independent variable, *Direct Learning*, 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, *FutureMeet/Beat,* is the percentage of EPS forecasts for which the actual earning of the forecasted period exceeds analyst consensus, computed using the most recent forecast issued by each analyst during the 90 days window prior to the actual date. All variables are defined in Appendix A. Control variables follow those presented in Table 5.The coefficients on the intercept, firm (Firm), 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).

Dependent Variable	***Future Meet/Beat***	***Future Meet/Beat***	***Future Meet/Beat***	***Future Meet/Beat***	***Future Meet/Beat***	***Future Meet/Beat***	***Future Meet/Beat***
Direct Interactions Measured by	***NumInteract***	***CEO***	***NumExecs***	***AnsPerQ***	***MDWords***	***PrivateMtg***	***Direct Interaction***
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Direct Interactions	-0.002	0.000	-0.001	-0.004	-0.000	0.001	-0.001
	(-0.74)	(0.09)	(-0.76)	(-0.16)	(-0.34)	(0.24)	(-0.38)
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	29547	29547	29547	29547	29547	29547	29547
Adj. RSQ	0.18	0.18	0.18	0.18	0.18	0.18	0.18

APPENDIX E. Alternative Specifications of Insider Trading Profits Analyses

This section presents alternative specifications of the insider trading tests. First, to further address the concerns that CEOs are more likely to attend investor conferences, and at the same have superior private information than non-CEO executives in the same firm, I re-estimate equation (IT2) using only trades made by non-CEO executives. Specification A presents the results of this analysis. The coefficient on $ParInsiderTrade_{POST}$ remains positive consistently and is significant in most of the specifications under 1%. My inferences remain unchanged.

Second, in the main analyses, I compare trades placed by participating insiders in the seven-day window after a conference with 1) trades made by insiders of the same firm but did not participate in a conference and 2) trades made by participating insiders but outside of the conference window during the same period (collectively, non-participating insider trades). To address concerns that there could be systematic differences between insiders who can participate in a conference and those who do not (for instance, some of these insiders are not involved in the daily operations of the firm, and therefore do not usually attend a conference), I include a dummy variable that takes the value of 1 if the trade is executed at any point in time by an insider who has participated in a conference, and 0 otherwise (*participateEVER*). Specification B presents the results of this analysis. The coefficient on $ParInsiderTrade_{POST}$ remains positive consistently and is significant in most of the specifications under 1%. My inferences remain unchanged.

Third, I restrict the sample to separately compare trades made by participating insiders within the seven-day after a conference (i.e., participating insider trades) with 1) trades made by insiders from the same firm but have not participated in a conference in the same month (quarter) in specification C, and 2) trades made by participating insiders in the same month (quarter) but outside of the seven-day post-conference window in specification D. The coefficient on $ParInsiderTrade_{POST}$ remains positive and significant across both specifications, suggesting that the participating insider trades have an information advantage over both 1) trades by insiders who have participated in a conference but are placed outside of the conference window and 2) trades by non-participating insiders.

Finally, the main analyses restrict the insider trades sample to those within the two-month window around the conference. This design choice captures a counterfactual group of trades that are made without information acquired through direct learning but are in close proximity to participating insider trades, which in turn allows the comparison between participating and non-participating insider trades. In the robustness analysis, I impose a much smaller window, i.e., trades during the 7-day around a conference. This sample restriction results in a substantial reduction in the size of the sample because non-participating insiders are less likely to trade around the conference window. However, it offers the benefit of comparing trades executed within a tighter window and, therefore, can control for firm characteristics and time trends that do not vary in the 14-day period. Specification E presents the results of this analysis. The coefficient on

ParInsiderTrade$_{POST}$ remains positive and significant, and my inferences remain unchanged.

Table A4: Insider Trading Profits: Alternative Specifications

This table reports the coefficient estimate (t-statistics based on robust standard errors clustered by firm in parenthesis) on *ParInsiderTrade*$_{POST}$ under various alternative specifications of equation (IT2):

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

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, multiplied by -1 for sales. All trades are opportunistic, defined following the trade-level classification scheme in Cohen et al., (2012). The various specifications are

- Specification A: The sample includes all transactions by ***non-CEO*** corporate officers within two months before or after an investor conference that the officer's firm has attended.
- Specification B: The sample is the same as that in Table 6 Panel A (i.e., all transactions by corporate officers within two months of an investor conference that the officer's firm has attended). I modify equation (IT2) by including an additional control, *ParticipateEVER*, which is an indicator variable that takes the value of 1 if a trade k is executed at any point in time by an insider j who has participated in a conference
- Specification C: Starting from the sample in Table 6 Panel A (i.e., all transactions by corporate officers within two months before or after an investor conference), this specification removes all trades made by insiders who have participated in a conference but are outside of the seven-day window after a conference.
- Specification D: Starting from the sample in Table 6 Panel A (i.e., all transactions by corporate officers within two months before or after an investor conference), this specification further requires a trade to be made by an insider who has ever participated in a conference.
- Specification E: The sample include all transactions by corporate officers within the ***seven-day window*** before or after an investor conference that the officer's firm has attended.

Dependent Variable	***Alpha30***	***Alpha30***	***BHAR30***	***BHAR30***
	(1)	(2)	(3)	(4)
Specifications:	The coefficient estimates on *ParInsiderTrade*$_{POST}$:			
A. Non-CEO trades only	0.045*	0.023	1.062**	0.539*
	(1.94)	(1.30)	(2.49)	(1.68)
B. Controlling for insider types	0.065***	0.031**	1.450***	0.518*
	(2.92)	(2.06)	(3.28)	(1.92)
C. Participating vs non-participating insider	0.059***	0.017	1.678***	0.518**
	(2.68)	(1.22)	(3.89)	(2.06)

D. Within participating insiders	0.090***	0.060***	1.710***	0.866**
	(3.29)	(3.02)	(2.95)	(2.45)
E. (-7, +7 days) around the conference	0.018	0.024**	0.837***	0.752***
	(1.30)	(2.02)	(3.28)	(3.75)
Fixed Effects	Firm-Quarter	Firm-Month	Firm-Quarter	Firm-Month

APPENDIX F. Real Effects of Direct Learning

1. Investment efficiency

Capital allocation and investment is an important aspect of corporate decision making. Managers need to make accurate predictions about expected future cash flows from various investment opportunities to make such investment decisions (Goodman et al., 2014). Institutional investors' knowledge about sector trends and product-market dynamics can help managers to project payoffs from capital expenditures, and their knowledge about other sectors and industries can help managers to evaluate potential acquisitions.

In this analysis, I investigate the relationship between direct learning and the efficiency of managers' investment decisions. To measure investment efficiency, I follow Biddle et al. (2009) to estimate a firm-specific model of investment as a function of growth opportunities (as proxied using sales growth). The residual from this estimation is a firm-specific proxy for deviations from expected investment.

$$Investment_{it+1} = \beta_0 + \beta_1 Sales\ Growth_{it} + \varepsilon_{it+1}$$

where *Investment* is the sum of research and development expenditure (*XRD*), capital expenditure (*CAPX*), acquisition expenditure (*ACQ*) less cash receipts from sales of property, plant, and equipment (*SPPE*), scaled by lagged total asset (*AT*) and multiply by 100. *Sales Growth* is the percentage change in sales (*SALE*). I estimate the above equation for each industry-year based on Fama-French 48 industry classification for all industries with at least 20 observations in a given year. The absolute residual from this equation, *Investment Deviation*, is the proxy for the inverse of investment efficiency.

Follow prior literature on investment efficiency (Biddle et al., 2009; Goodman et al., 2014), and because capital allocation and investment decisions are usually made on an annual basis, I perform this analysis at a firm-year level. The OLS empirical specification is as follows:

$$Investment\ Deviation_{it+1} = \alpha_0 + \alpha_1 Direct\ Learning_{it} + \Gamma controls_{it+1} + \varepsilon_{it+1}$$

whereby *Direct Learning* is the six empirical proxies discussed in section (4.1) and aggregated to a firm-year level: *NumInteract*, *NumCEO*, *NumCP*, *MDWords*, *AnsPerQ*, *PrivateMtg*, and their first principal component, *Direct Interaction*.

The results of this analysis are presented below. The coefficients across all proxies of direct learning are negative, and is also significant for the first principal component, *Direct Interaction*. The results are consistent with direct learning help managers to make more accurate forecast of potential investment opportunities, thereby reducing deviations from efficient investment levels.

Table A5: Investment Efficiency

Panel A: Summary Statistics

Variables	**Count**	**Mean**	**Std**	**P25**	**P50**	**P75**
Measures of Investment Efficiency						
Inv. Dev.	17147	9.931	12.059	2.997	6.333	11.766

Panel B: Regression Analysis

This table investigates the relation between direct learning and subsequent investment efficiency. The unit of analysis is a firm-year observation. The OLS specification is

$$Investment\ Deviation_{it+1} = \alpha_0 + \alpha_1 Direct\ Learning_{it} + \Gamma controls_{it+1} + \varepsilon_{it+1}$$

where i denotes firm and t denotes fiscal year. The independent variable, *Direct Learning*, measures the occurrence, frequency, and the degrees of information exchange of manager-investor interactions using: *NumInteract*, *NumCEO*, *NumCP*, *MDWords*, *AnsPerQ*, *PrivateMtg* (all variables are aggregated to a firm-year level), as well as their first principal component *DI*. The dependent variable, *Investment Deviation*, is the absolute value of the residual from an estimation of investment on growth opportunities for each Fama-French 48 industry and year. The coefficients on the intercept, firm dummies, fiscal year dummies, and control variables are not reported for parsimony purposes. 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	***Inv. Dev.***	***Inv. Dev.***	***Inv. Dev.***	***Inv. Dev.***	***Inv. Dev.***	***Inv. Dev.***	***Inv. Dev.***
Direct Interactions Measured by	***NumInteract***	***NumCEO***	***NumCP***	***AnsPerQ***	***MDWords***	***PrivateMtg***	***Direct Interaction***
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Direct Interactions	-0.107**	-0.132*	-0.0647**	-0.828	-0.0199**	-0.226**	-0.352**
	-2.222	-1.876	-2.284	-1.032	-2.147	-2.204	-2.284
Fixed Effects	Firm, Year	Firm, Year	Firm, Year	Firm, Year	Firm, Year	Firm, Year	Firm, Year
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	17147	17147	17147	17147	17147	17147	17147
Adj. RSQ	0.33	0.33	0.33	0.33	0.33	0.33	0.33

2. External acquisitions

Another aspect that managers can from investors is investors' opinions about a pending acquisition. Institutional investors may have knowledge about the target firm or industry, the estimated synergies from the transaction, or possess expertise from evaluating past business combinations. While investors can impound their information about a pending acquisition by trading on the acquirer's stock (Luo, 2005), they can also voice their concerns directly to managers during the Q&A sessions of an investor conference, or through private one-on-ones and breakouts. As a result, such face-to-face interactions with investors allow managers to elicit firsthand sfeedback from investors about a pending acquisition. While I do not observe the content of discussion during private meetings, I make use of observed public Q&A portion of conference transcripts to document another consequence of direct learning – how do investors' expressed opinions at investor conferences affect the probability of completion of the pending acquisition.

In order to form the sample of corporate acquisitions, I gather M&A transactions from SDC Domestic M&A Database (SDC) from 2004 to 2018. Following prior literature (Luo, 2005; Masulis et al., 2007; Schmidt and Fahlenbrach, 2017), I restrict the sample to only friendly transactions and exclude recapitalization, related transactions, repurchases, and rumored transactions. I require that the deal value has to be greater than $ 1 million and represents at least 1% of the acquirer's market capitalization. Because I investigate the probability of deal completion, I include both completed and incomplete deals. This results in 8,116 transactions.

Next, I merge the M&A sample with the sample of conferences based pm the acquirer firms. In order to identify acquisitions whereby direct learning could have an impact on their eventual outcomes, I require the conference to take place before the transaction closes such that the effect of direct learning can be reflect in, and therefore be tested from, the eventual outcome of the transaction. To be clear, it is possible that investors can still express their opinions about an acquisition, and managers can learn, even after the completion of a deal. However, it is difficult to provide empirical evidence of such learning. I require the conference to take place within 90 days of the deal announcement date. Requiring the conference to take place in a relatively short window after the deal announcement date allows me to focus on conferences that represent a timely opportunity for investors to express their opinion. The final sample consists of 981 transactions. The OLS empirical specification is as follows

$$1(Complete) \quad = \alpha + \beta_1 Question + \beta_2 Tone + (\beta_3 Question \times Tone) + controls$$

1(Complete) is an indicator variable if the deal is completed eventually. *Question* is the total number of questions asked by investors that are about the pending transaction. This variable is computed by searching through all questions in the Q&A session of conference transcripts that mentions the name of the target company. If the acquirer has attended more than one conference, the total number of acquisition-related questions across all conferences is computed. *Tone* is the number of acquisition-related questions that have a positive tone. A positive-tone sentence is defined as a sentence that contains more positive words than negative words. The list of positive and negative words is defined using the Loughran-McDonald dictionary. The list of control variables serves the following purpose. I control for the extent to which investors express their opinions by trading on the acquirer's stock and managers learning from prices (Luo, 2005), using the cumulative market-adjusted buy-and-hold returns in the (-2, +2) window around the announcement date (*CAR*). I control for the size of the acquirer using the natural logarithm of the market value of equity (*MVE*), the size of the transaction (*DealSize*), and the importance of the transaction using transaction size scaled by the market value of the acquirer (*DealPct*). I include separate year dummies and separate dummies of the acquirer's 2-digit SIC industry.

I estimate two specifications. In the first specification, I estimate the main effect of *Question* and *Tone*. Column (1) presents the result. The coefficient on *Question* is significantly negative, suggesting that when investors raise more questions about the acquisition during an investor conference, the probability of subsequent deal completion is lower. The coefficient on *Tone* is significantly positive, suggesting that the number of positive questions asked by investors is associated with a higher probability of deal completion. This suggests an interactive effect between *Question* and *Tone*. While more questions raised signal investors expressing concerns, positive questions suggest more favorable investor opinions towards the pending transaction. Column (2) presents the results. Consistent with my prediction, the coefficient of the interaction term is positive and significant. These results are consistent with managers learning about investors' opinions about a pending acquisition during investor conferences, which subsequently affect the managers' decisions toward that acquisition.

Table A6: Corporate Acquisitions

Panel A: Summary Statistics

Variables	**Count**	**Mean**	**Std**	**P25**	**P50**	**P75**
Measures of Investor Opinions						
Complete	972	0.933	0.250	1.000	1.000	1.000
Question	972	0.750	2.060	0.000	0.000	0.000
Tone	972	0.233	0.861	0.000	0.000	0.000
Controls						
CAR	972	0.002	0.070	-0.027	0.001	0.032
MVE	972	8.790	1.556	7.812	8.751	9.781
DealSize	972	6.333	1.573	5.199	6.214	7.507
DealPct	972	22.382	38.964	2.817	7.480	21.090

Panel B: Regression Analysis

This table investigates direct learning and subsequent acquisition outcomes. The sample consists of 981 corporate acquisitions that were announced within 90-day prior to the acquirer attends an investor conference and are pending at the date of the conference. The OLS specification is

$$1(Complete) \quad = \alpha + \beta_1 Question + \beta_2 Tone + (\beta_3 Question \times Tone) + controls$$

1(Complete) is an indicator variable if the deal is completed eventually. *Question* is the total number of questions asked by investors that are about the pending transaction. *Tone* is the number of acquisition-related questions that have a positive tone. A positive-tone sentence is defined as a sentence that contains more positive words than negative words. Controls include the cumulative market-adjusted buy-and-hold returns in the (-2, +2) window around the announcement date (*CAR*), the size of the acquirer using the natural logarithm of the market value of equity (*MVE*), the size of the transaction (*DealSize*), and transaction size scaled by the market value of the acquirer (*DealPct*). The coefficients on the intercept, industry dummies, year dummies are not reported for parsimony purposes. T-statistics based on robust standard errors clustered by industry are indicated in parenthesis below coefficient estimates. ***, **, and * indicate significance level at 1%, 5%, and 10% respectively (two-tailed).

Dependent Variable	**1(Complete)**	**1(Complete)**
	(1)	(2)
Question × *Tone*		0.00188*
		1.659
Question	-0.0159**	-0.0177**
	-2.408	-2.489
Tone	0.0447***	0.0343***
	3.446	2.962
CAR	0.139	0.144
	1.179	1.227
MVE	0.00225	0.00214
	0.232	0.221
DealSize	0.00849	0.00866
	0.762	0.776
DealPct	-0.0003	-0.0003

	-0.817	-0.806
FE	Acquirer Ind, Year	Acquirer Ind, Year
N	981	981
Adj. RSQ	0.24	0.24

3. Direct learning and indirect learning

Chen et al., (2007) argue and find that corporate investment becomes more sensitive to stock price when stock price provides more information that managers can use to make decisions. They document that investment-to-price sensitivity increases with proxies for price informativeness.

It is ex-ante unclear whether direct learning from interactions and indirect learning from prices are substitute or complement mechanisms. On the one hand, managers might turn to direct learning when it is difficult to learn from prices. For instance, price movement can be driven by transitory non-fundamental related shocks, and managers are not able to distinguish between information and noise (Dessaint et al., 2019). Under this scenario, direct learning from institutional investors and learning from prices are substitute mechanisms, and one would expect investment-to-price sensitivity to decrease following direct learning. On the other hand, direct learning could complement learning from prices. Direct learning help managers to make better assessments about whether fundamentals or noise drive movements in prices or to disaggregate various signals in prices. For instance, one source of non-fundamental-driven movements in prices is mutual fund capital redemption-induced sales (i.e., fire sales) (Coval and Stafford, 2007). Institutional investors are more informed about funds' capital flows and portfolio re-balancing policies, which can, in turn, help managers to distinguish signals from noises. Direct learning serves as a complementary mechanism for learning from prices.

To examine how direct learning affects learning from prices, I aggregate my regression sample into a firm-year frequency, following Chen, Goldstein, and Jiang (2007) (CGJ). I estimate the following equation, modified from equation (5) of CGJ, and partition the sample based on the median value of DI.

$$Inv_{it} = \beta_0 + \beta_1 Q_{it-1} + \beta_2 Info_{it-1} \times Q_{it-1} + \Gamma controls + \eta_i + \phi_t + e_{it} \quad (4)$$

where η_i denotes firm dummies and ϕ_t denotes year dummies. Price informativeness, *Info*, is measured by the probability of informed trades (*PIN*). The dependent variable, corporate investments (*Inv*), is measured using capital and R&D expenditure (*CapxRD*) as well as changes in total assets (*DeltaAT)*. Control variables include cash flow, the inverse of total assets, and the next three-year future returns.

CGJ finds that investment-to-price sensitivity increases with price informativeness. In the table below, I find that this positive relation only exists when the extent of direct learning is high. The T-statistics comparing the coefficients on *PIN*×Q across the two sub-samples are significant 5%. This result suggests a complementary relationship between direct learning and indirect learning from prices.

Table A7: Direct Learning and Indirect Learning from Prices

Panel A: Summary Statistics

Variables	**Count**	**Mean**	**Std**	**P25**	**P50**	**P75**
Measures of Corporate Investment						
Capx	14063	11.736	11.697	4.273	8.122	14.788
DeltaAT	14063	10.404	28.282	-2.442	5.169	15.495
Q	14063	2.093	1.447	1.259	1.67	2.402
PIN	14063	0.115	0.08	0.057	0.107	0.151

Panel B: Regression Analysis

This table investigates the interplay between learning from direct interactions and indirect learning from prices. It examines how price informativeness affects the sensitivity of investment to stock prices in two subsamples: high learning and low learning. The unit of analysis is a firm-year observation.
The OLS empirical specification is

$$Inv_{it} = \beta_0 + \beta_1 Q_{it-1} + \beta_2 Info_{it-1} \times Q_{it-1} + \Gamma controls + \eta_i + \phi_t + e_{it}$$

Where η_i denotes firm dummies and ϕ_t denotes year dummies. This specification is modified from equation (5) of Chen, Goldstein, and Jiang (2007). The samples are partitioned based on the median value of *Direct Interaction*. Price informativeness, *Info*, is measured by the probability of informed trades (PIN). The dependent variable, corporate investments (Inv_{it}), is measured using capital expenditure (*Capx*) and changes in total assets (*DeltaAT)*. The coefficients on the intercept, firm dummies, fiscal year dummies, and control variables are not reported for parsimony purposes. 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	***CapxRD***	***CapxRD***	***DeltaAT***	***DeltaAT***
Sample	High *Direct Interaction*	Low *Direct Interaction*	High *Direct Interaction*	Low *Direct Interaction*
	(1)	(2)	(3)	(4)
$PIN \times Q$	2.614**	-0.811	15.758**	-15.603***
	(1.97)	(-0.59)	(2.50)	(-2.73)
PIN	-2.173	1.472	-7.689	33.284***
	(-0.89)	(0.62)	(-0.82)	(3.26)
Q	1.762***	1.951**	9.721***	16.791***
	(3.58)	(2.56)	(3.77)	(5.42)
F-stat	3.417		13.446	
P-value	0.065		0.000	
Controls	Yes	Yes	Yes	Yes
FE	Firm, Year	Firm, Year	Firm, Year	Firm, Year
N	7484	6579	7484	6579
Adj. RSQ	0.84	0.79	0.26	0.36

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