Learning from Complexity: Private Managerial Communication and the Transfer of Analyst Expertise

Feng Chen[a], Yaohua Qin[b], and He Xiao[b]

[a] *Rotman School of Management, University of Toronto*
[b] *Faculty of Business and Management, Beijing Normal-Hong Kong Baptist University*

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ABSTRACT

Analysts learn from interacting with management, but managers vary in how clearly they communicate. We examine how the quality of managerial communication during analyst site visits shapes analyst learning and the transfer of expertise across covered firms and colleagues. Using mandatory site-visit disclosures from Chinese-listed firms, we follow Bushee et al. (2018) and identify both informative complexity (INFO) and obfuscatory complexity (OBFU) in managerial linguistic complexity. INFO improves the visiting analyst's forecast accuracy for the visited firm, particularly in informationally challenging settings, whereas OBFU reduces accuracy, especially for junior analysts. INFO (OBFU) generates positive (negative) spillovers to other firms in the analyst's coverage portfolio and to colleagues within the same brokerage. These effects occur through three predicted expertise-transfer channels: industry membership, supply-chain connections, and accounting comparability. Collectively, our findings show that substantive managerial communication produces portable analyst human capital, while obfuscation transmits cognitive frictions through both individual and organizational channels.

Keywords: Linguistic Complexity, Analyst Site Visits, Analyst Learning, Managerial Communication, Analyst Expertise

JEL Classification: D83, G14, G24, M41

I. INTRODUCTION

Sell-side equity analysts produce informed earnings forecasts not merely by transmitting raw information, but by learning from interactions with management and converting that learning into analytical expertise. As face-to-face meetings at company facilities that include extended question-and-answer exchanges, site visits allow analysts to conduct such learning by initiating unscripted dialogue, observing operations firsthand, and probing management about operational and strategic issues (Cheng, Du, Wang, and Wang 2016; Han, Kong, and Liu 2018). Yet the learning value of this channel depends not only on the volume of communication but also on its quality: a lengthy exchange may convey substantive economic content in one case and obscure meaning in another. We therefore ask how the quality of managerial communication during site visits shapes analyst learning and whether the expertise developed from such learning transfers across the visiting analysts' coverage portfolios and brokerage organizations.

The quality of managerial communication is difficult to observe directly. In this study, we focus on a central, measurable dimension of communication quality: linguistic complexity. Complexity is especially relevant in site visits because analysts must process detailed verbal exchanges in real time and translate them into forecasts. However, complexity is theoretically ambiguous. A long-standing debate concerns whether complex disclosure reflects managerial obfuscation (Bloomfield 2002; Li 2008) or the communication of substantive but inherently complex information (Guay, Samuels, and Taylor 2016). Our decomposition addresses this debate by separating these two effects in site-visit transcripts, building on Bushee, Gow, and Taylor (2018) and Bushee and Huang (2024). Bushee et al. (2018) show that complex language in conference calls reflects two latent components with opposite implications for information asymmetry: an information component (INFO), which captures substantive content depth, technical detail, and

business complexity, and an obfuscation component (OBFU), which captures unnecessarily convoluted language that imposes processing costs without commensurate informational benefits. This decomposition is based on the identifying assumption that analysts have no incentive to obfuscate. Accordingly, analyst question complexity helps distinguish managerial response complexity that reflects substantive information demands from complexity that reflects obfuscatory communication.

We extend this framework to analysts' site visits, a setting in which the distinction between informative and obfuscatory complexity is especially consequential. Site visits differ from public conference calls and written filings in several important ways. First, they often contain deeper operational and strategic content, including discussions of production processes, capacity, supply-chain relationships, business-model details, and competitive positioning that may be difficult to convey in standardized public disclosures (Cheng et al. 2016; Solomon and Soltes 2015). Second, their interactive format allows visiting analysts to ask follow-up questions and probe management's responses in real time. Third, because site visits are subject to less public scrutiny than scripted conference calls or regulatory filings, managers may have greater latitude to shape the clarity of their communication and potentially introduce obfuscatory complexity (Hollander, Pronk, and Roelofsen 2010; Hoberg and Lewis 2017). Finally, China's mandatory disclosure of site-visit records provides rare large-scale evidence on the content of semi-private manager-analyst exchanges. These features make site visits a powerful setting for examining whether managerial communication quality affects what analysts learn about the visited firm and whether that learning develops into transferable expertise.

Our central argument is that substantive private communication can generate portable analyst human capital. In high-INFO exchanges, substantive managerial responses and targeted

analyst follow-up questions can reinforce one another, helping visiting analysts acquire a generalizable understanding of business fundamentals, industry dynamics, operational linkages, and financial reporting structures. This learning can then improve their forecasts for the visited firm. Further, if learning leads to the development of analysts' expertise, we expect this expertise to spill over to other firms whose analytical demands overlap with those of the visited firm, thereby enhancing the visiting analysts' forecasts for those firms as well. By contrast, when analysts encounter obfuscatory complexity, their limited cognitive resources are diverted toward parsing unclear language rather than developing a substantive understanding of the firm. This crowding-out effect reduces cognitive resources available for genuine learning and expertise development, thereby weakening forecast performance for the visited firm and potentially imposing spillover costs on related forecasting tasks.

We identify where such spillovers may occur by examining how analysts conduct their research. Analysts often adopt a top-down analytical perspective (Kadan, Madureira, Wang, and Zach 2012; Brown, Call, Clement, and Sharp 2015), using macroeconomic conditions and within- and cross-industry expertise to assess firm-level performance. This approach helps analysts understand common business models, value drivers, and risk factors across firms. As a result, we argue that learning from one firm may spill over to other firms through three distinct channels: firms operating in similar industries, firms linked through supply-chain relationships, and firms with high accounting comparability. Symmetrically, drawing on limited attention theory (e.g., Driskill, Kirk, and Tucker 2020; Bourveau, Garel, Joos, and Petit-Romec 2024) and cognitive load theory (Sweller 1988), we argue that OBFU disrupts the learning process and task-specific cognitive schemas through which substantive learning would otherwise transfer, generating negative spillovers along the same three channels.

We test these predictions using 972,679 question-answer pairs and 24,078 site-visit events from Shenzhen-listed firms over 2012—2023. Following Bushee et al. (2018) and Bushee and Huang (2024), we adapt the INFO-OBFU decomposition to Chinese-language site-visit transcripts and construct firm-visit-level measures of informative and obfuscatory complexity. We then examine how these components affect analyst forecast accuracy for the visited firm, forecast accuracy for other firms in the visiting analyst's portfolio, and forecast accuracy of other analysts within the same brokerage.

We document three sets of findings. First, INFO and OBFU have opposite effects on analyst forecast accuracy for the visited firm. A one-standard-deviation increase in INFO improves forecast accuracy by approximately 10.8% of the sample mean, whereas a one-standard-deviation increase in OBFU reduces forecast accuracy by approximately 6.3%. These effects are stronger in informationally challenging environments, including firms with high R&D intensity, high return volatility, and low institutional ownership. The adverse effect of OBFU is also more severe for junior analysts, consistent with experienced analysts being better able to discount uninformative complexity (Clement 1999; Mikhail, Walther, and Willis 1997, 2003).

Second, INFO generates positive spillovers within the visiting analysts' own coverage portfolios. Analysts who attend high-INFO site visits subsequently issue more accurate forecasts for other covered firms, especially when those firms share the visited firm's industry, are linked through supply-chain relationships, or have high accounting comparability. OBFU exhibits the opposite pattern: it is associated with lower forecast accuracy for related firms in the analyst's portfolio, with negative spillovers concentrated along the same three channels. This symmetric channel structure, positive for INFO and negative for OBFU, supports the interpretation that substantive communication produces transferable expertise, while obfuscation imposes cognitive

costs along the same dimensions where expertise would otherwise have been applied.

Third, we find similar spillovers across analysts within the same brokerage. INFO acquired by a visiting analyst improves the forecast accuracy of her colleagues, while OBFU reduces colleagues' forecast accuracy. The brokerage-level effects are amplified through industry and supply-chain channels, consistent with brokerages organizing research teams around sectors and economically linked firms. In contrast, the accounting-comparability channel is weaker at the brokerage level than at the portfolio level, consistent with financial-measurement expertise being more individualized and less easily diffused through organizational infrastructure. Both INFO and OBFU spillovers are stronger for the visiting analysts with longer brokerage tenure, consistent with internal network embeddedness amplifying knowledge diffusion and communication frictions.

As a market-based validation of the economic significance of our decomposition, we also examine investor responses around site-visit disclosures. INFO is associated with positive abnormal returns, whereas OBFU is associated with negative abnormal returns. This evidence suggests that the distinction between substantive and obfuscatory complexity is not confined to analyst forecasts but is also reflected in investors' pricing of disclosed site-visit content.

Our findings are robust to several identification-oriented and validation tests. Alternative fixed-effect structures, including firm-by-analyst fixed effects and site-visit fixed effects, yield results consistent with our baseline estimates. We also implement a Heckman selection correction using the staggered introduction of high-speed rail between analysts' brokerage cities and firms' headquarters cities as an exclusion restriction for analyst site-visit attendance. The results are also robust to excluding high-tech and pharmaceutical firms and omitting the COVID-19 period, and placebo spillover tests show no comparable effects when visited firms are randomly paired with firms outside the relevant analyst portfolio or brokerage network. Together, these tests suggest that

our findings are not driven by time-invariant unobserved heterogeneity, non-random site-visit selection, sample composition, pandemic-period conditions, or spurious cross-firm correlations.

This study makes three contributions. First, we extend the INFO–OBFU framework (Bushee et al. 2018; Bushee and Huang 2024) from public conference calls to semi-private manager-analyst interactions. Prior work shows that public disclosure complexity contains both informative and obfuscatory components. We show that the same distinction applies to analyst site visits, a richer, less scripted communication setting in which both substantive learning and obfuscatory communication are likely to be especially important. In doing so, we identify private managerial communication as an important source of variation in communication quality and analyst learning.

Second, we provide direct evidence on the content of the learning event that produces analyst expertise. Existing work observes either the inputs to expertise (Clement 1999; Bradley, Gokkaya, and Liu 2017) or its outputs (Mikhail et al. 1997; Kadan et al. 2012); we observe the underlying manager-analyst exchange and decompose it into components that facilitate learning versus those that impede it. Anchoring our predictions in limited attention and cognitive load theory, we show that analyst expertise does not arise simply from access to management but depends on whether managerial communication supports or disrupts the task-specific schema construction through which generalizable understanding is encoded.

Third, we develop and validate a top-down framework of analyst expertise transfer that predicts not only that spillovers occur, but also where they should occur and why their magnitudes should differ across portfolio and brokerage settings. The framework unifies three previously separate literatures on intra-industry information transfer (e.g., Hilary and Shen 2013), supply-chain spillovers (e.g., Guan, Wong, and Zhang 2015; Huang, Lin, and Zang 2022), and accounting

comparability (e.g., Choi, Choi, Myers, and Ziebart 2019), deriving a common structure from what have been treated as distinct phenomena. The existence of symmetric spillover findings (i.e., positive INFO spillovers combined with negative OBFU spillovers) demonstrates that substantive communication generates generalizable expertise rather than merely firm-specific knowledge.

The remainder of the paper proceeds as follows. Section II reviews related literature and develops the hypotheses. Section III describes the data, variable construction, and empirical design. Section IV presents the empirical results and Section V shows robustness test results. Section VI concludes.

II. LITERATURE REVIEW AND HYPOTHESIS DEVELOPMENT

2.1 Linguistic Complexity in Managerial Disclosure

A central insight from the disclosure literature is that managerial linguistic complexity is theoretically ambiguous. Complex language may reflect substantive economic content that is inherently difficult to communicate, or it may reflect obfuscatory presentation that makes disclosure harder to process without providing commensurate informational benefits. Bushee et al. (2018) provide an empirical framework by decomposing conference-call complexity into an information-driven component (INFO) and an obfuscation-driven component (OBFU). INFO captures complexity associated with substantive content depth, technical detail, operational complexity, and strategic specificity. OBFU captures unnecessarily convoluted language that imposes processing costs without corresponding informational benefits. Consistent with this distinction, INFO is associated with lower information asymmetry, whereas OBFU is associated with higher information asymmetry. Bushee and Huang (2024) further show that analysts and investors process these two components differently when forming forecasts and trading decisions.

Two theoretical perspectives motivate the INFO-OBFU distinction. First, strategic-disclosure theory (Verrecchia 2001; Beyer, Cohen, Lys, and Walther 2010) explains why managers may have incentives to vary the clarity of communication independently of its substantive content. Second, the limited-attention perspective (Hirshleifer and Teoh 2003; Blankespoor, deHaan, and Marinovic 2020) holds that processing costly information consumes scarce cognitive resources; under this view, obfuscation imposes processing costs without corresponding informational benefits, whereas informative complexity yields commensurate understanding. These perspectives imply that INFO and OBFU should have opposite effects: INFO may require effort to process but yields useful economic understanding, whereas OBFU incurs cognitive costs without producing productive insight.

Despite the conceptual clarity of the INFO-OBFU distinction, prior research leaves two important questions unresolved. First, the decomposition has been developed and validated primarily in public conference-call settings. It is less clear whether the same distinction operates in semi-private disclosure settings, where analysts are more actively involved, interactions include more spontaneous questioning, and managerial communication is less scripted and subject to less public scrutiny. In such settings, richer and more interactive disclosures may facilitate learning and the accumulation of task-specific knowledge. At the same time, less structured and less scrutinized communication may introduce communication frictions that hinder effective learning. Second, while prior work has focused mainly on how INFO and OBFU affect the focal firm's information environment, it has not examined whether informative communication can generate transferable analyst expertise that improves forecasts for other firms, or whether obfuscatory communication can impose spillover costs beyond the visited firm. These questions motivate the

learning-based framework developed below, which articulates where INFO-driven expertise should transfer and how OBFU disrupts the same pathways.

2.2 Site Visits as a Distinctive Private Managerial Communication Setting

Analyst site visits provide a setting in which the distinction between informative and obfuscatory complexity is especially consequential. Site visits differ from public conference calls and written filings in several ways. They often involve richer operational and strategic content, including discussion of production processes, capacity, supply-chain relationships, competitive positioning, and business-model details that may be difficult to convey in standardized public disclosures (Cheng et al. 2016; Han et al. 2018). They also involve a more interactive format, allowing analysts to ask follow-up questions and probe management's responses in real time. At the same time, site visits occur in a less publicly scrutinized setting than conference calls or regulatory filings, which may give managers greater flexibility in how clearly they communicate and whether they introduce obfuscatory complexity (Hollander et al. 2010; Hoberg and Lewis 2017). In China, mandatory disclosure of site-visit records makes it possible to examine the content of these interactions at scale. These features make site visits a powerful setting for examining whether managerial communication quality affects what analysts learn about the visited firm and whether that learning develops into transferable expertise.

Recent studies on analyst site visits suggest that such interactions can generate spillovers, but they differ in their interpretation of the mechanism. You, Wu, Ying, and Zhou. (2025) document that site visits reduce forecast accuracy for non-visited firms in the analyst's portfolio and attribute the negative spillover to limited attention: analysts may shift cognitive resources toward the visited firm at the expense of other covered firms. Du, Guo, Qi, and Wang (2024), exploiting COVID-19 travel restrictions, identify countervailing effects: a fundamental-

information learning channel that improves forecast accuracy and an earnings-information leakage channel that may transmit firm-specific signals. These studies show that site visits can affect forecasts beyond the visited firm, but they leave unresolved how the content and quality of the site-visit exchange determine whether such spillovers are beneficial or costly.

The INFO-OBFU framework offers a way to reconcile these patterns. If site-visit complexity is informative, analysts may learn from the interaction and develop expertise that improves forecasts for the visited firm and economically related firms. If complexity is obfuscatory, analysts may expend cognitive resources without acquiring transferable understanding, generating the type of attention-related cost emphasized by You et al. (2025). Similarly, the distinction between substantive learning and firm-specific leakage in Du et al. (2024) can be sharpened by examining whether spillovers concentrate along theoretically predicted channels of expertise transfer. In this sense, our framework complements prior work by explaining when site visits produce productive learning and when they instead impose cognitive costs.

2.3 A Top-Down Framework for Analyst Expertise Transfer

We develop a unified framework that explains where analyst learning from site visits should transfer and why the magnitude of that transfer should differ across channels and settings. This framework builds on two types of analyst expertise documented by Kadan et al. (2012): cross-industry expertise, or the ability to rank industries against one another, and within-industry expertise, or the ability to rank firms within an industry. Rather than treating these forms of expertise as separate, we identify the economic and informational dimensions along which analysts compare firms and through which site-visit learning can be redeployed. Specifically, INFO facilitates learning by providing substantive content from which analysts extract economic insights. This learning develops into expertise when analysts encode generalizable understanding rather

than merely firm-specific facts. That expertise can then transfer to other firms whose analytical demands overlap with those of the visited firm. OBFU, by contrast, interrupts this chain at its first link: it consumes processing capacity without producing substantive understanding, limiting both direct learning and subsequent transfer.

We identify where transfer should occur based on the top-down analytical approach commonly used by analysts. Two strands of evidence motivate this framing. First, equity analysts not only issue firm-specific reports but also produce industry-level research (Kadan et al. 2012). Survey evidence on analysts' actual workflows shows that industry analysis is the most important input to their forecasts and recommendations, followed by firm-level operational and financial analysis (Brown et al. 2015). Second, academic research shows that analysts who have industry experience (Bradley et al. 2017), cover more industries (Crane and Crotty 2020), incorporate macroeconomic shocks into their analyses (Hugon, Kumar, and Lin 2016), or use supply-chain information (Huang et al. 2022) tend to outperform their peers. This evidence highlights the value of a top-down analytical approach and suggests that expertise can transfer across firms through industry, operational, and financial-reporting linkages. We therefore organize expertise transfer around three dimensions of analysts' top-down research process: industry environment, operational linkages, and financial measurement.

First, analysts evaluate the industry environment in which a firm operates, including competitive dynamics, regulation, demand conditions, and technological change (e.g., Hilary and Shen 2013). Learning about these factors should be portable across firms that share similar industry conditions, giving rise to the industry channel. Second, analysts translate industry and market conditions into a firm's operational positioning, including input procurement, production processes, capacity decisions, pricing power, and exposure to customers and suppliers (e.g., Cohen

and Frazzini 2008; Pandit, Wasley, and Zach 2011; Guan et al. 2015). Learning about these operational linkages should be portable across firms connected through supply-chain relationships, giving rise to the supply-chain channel. Third, analysts translate operational outcomes and business fundamentals into earnings forecasts and valuation inputs (De Franco, Kothari, and Verdi 2011; Young and Zeng 2015; Choi et al. 2019). Learning about how operations map into accounting earnings should be most transferable across firms with comparable reporting environments and similar accounting structures, giving rise to the accounting-comparability channel.

These three channels are conceptually distinct. Firms may operate in the same industry without being supply-chain partners; supply-chain partners need not belong to the same industry; and neither industry membership nor supply-chain connection necessarily implies high accounting comparability. This non-redundancy helps distinguish expertise-mediated learning from a more generic information-transfer explanation. A generic information-flow account would predict spillovers to decline with economic proximity, without specifying why particular dimensions of relatedness should matter. By contrast, our framework predicts that spillovers should concentrate along the dimensions corresponding to the main stages of analyst learning: industry environment, operational linkages, and financial measurement. The same logic also applies to OBFU. If obfuscatory communication prevents productive learning, its costs should be most visible in the same task-relevant settings where analysts would otherwise apply newly acquired expertise. Thus, INFO and OBFU should operate through the same three channels but in opposite directions: INFO generates transferable expertise, whereas OBFU creates task-specific cognitive frictions.

2.4 Hypothesis Development

Direct Learning Effects. Analyst forecast accuracy should improve when analysts acquire

substantive economic understanding from interactions with management (Brown et al. 2015; Cheng et al. 2016). Site visits with high INFO provide analysts with detailed content about operations, competitive positioning, investment plans, and strategic priorities. Although such communication may be linguistically complex, the complexity reflects economically meaningful information that can help analysts understand the drivers of future profitability and translate qualitative insights into quantitative forecasts (Cheng et al. 2016; Han et al. 2018). In interactive site visits, substantive managerial responses and targeted analyst follow-up questions may reinforce one another, allowing visiting analysts to extract additional value-relevant information from management. Communication with high OBFU should have the opposite effect. When managers use convoluted language that imposes processing demands without substantive insight, visiting analysts face greater difficulty extracting value-relevant information. Prior research shows that less readable disclosures reduce forecast accuracy and increase analyst uncertainty (Lehavy, Li, and Merkley 2011). Under limited attention, processing obfuscatory communication consumes cognitive resources that could otherwise be used for productive analysis (Huang et al. 2022; Driskill et al. 2020). More fundamentally, obfuscation interferes with the schema-building process through which analysts encode site-visit content into usable forecasting inputs. When communication is obfuscated, visiting analysts may struggle to formulate meaningful follow-up questions and therefore rely more heavily on historical extrapolation, consensus forecasts, or other less diagnostic signals. We therefore hypothesize:

H1a: *INFO is positively associated with analyst forecast accuracy for the visited firm.*

H1b: *OBFU is negatively associated with analyst forecast accuracy for the visited firm.*

Portfolio-Level Spillovers. A more stringent test of expertise formation is whether learning from one site visit improves the analyst's forecasts for other firms in the analyst's

coverage portfolio. If site visits provide only firm-specific information, any benefit should be limited primarily to the visited firm. If, however, site visits generate transferable expertise, then learning from the visited firm should improve forecasts for other firms whose analytical demands overlap with those of the visited firm.

Based on the top-down framework, INFO-driven spillovers should be strongest along three channels: (1) industry-environment learning should transfer to firms within the same industry (Bradley et al. 2017; Kadan et al. 2012); (2) operational learning should transfer through supply-chain relationships (Cohen and Frazzini 2008; Pandit et al. 2011); and (3) financial-measurement learning should transfer across firms with high accounting comparability (e.g., De Franco et al. 2011).

OBFU should generate negative spillovers through the same three channels, for three complementary reasons rooted in how cognitive resources are organized around forecasting tasks. First, analyst attention is scarce and substitutable across coverage tasks: time and processing capacity spent decoding obfuscatory site-visit content cannot be reallocated to analyses of other portfolio firms. Prior research shows that analysts subject to attention shocks, including concurrent earnings announcements (Driskill et al. 2020), distracting industry events (Bourveau et al. 2024), and competing career demands across portfolio firms (Harford, Jiang, Wang, and Xie 2019), produce less timely, less accurate, and less informative forecasts for non-focal firms in their coverage. OBFU operates as a comparable cognitive shock because it consumes processing capacity without producing transferable understanding. Second, the cognitive cost is unlikely to be diffused uniformly. Cognitive load theory (Sweller 1988; Paas, Renkl, and Sweller 2003) holds that processing effort is organized around task-specific schemas. When OBFU disrupts schema construction, the resulting loss should be concentrated on tasks that would have drawn on those

schemas, including forecasts for industry peers, supply-chain partners, and comparability-linked firms. Third, obfuscation may leave analysts with miscalibrated rather than simply incomplete priors: convoluted communication may be processed as a noisy signal, leading to incorrect inferences that contaminate forecasts for economically related firms. In summary, OBFU should propagate negatively along the same channels through which INFO propagates positively. We therefore hypothesize:

H2a: *INFO is positively associated with forecast accuracy for other firms in the analyst's portfolio, with effects channeled through industry membership, supply-chain connections, and accounting comparability.*

H2b: *OBFU is negatively associated with forecast accuracy for other firms in the analyst's portfolio, with effects channeled through industry membership, supply-chain connections, and accounting comparability.*

Brokerage-Level Spillovers. Expertise acquired through site visits may also diffuse beyond the individual analyst to colleagues within the same brokerage. Brokerages facilitate knowledge sharing through research teams, internal meetings, shared models, mentoring relationships, and informal communication (Hwang, Liberti, and Sturgess 2019; Hugon, Lin, and Markov 2024). Because brokerage research teams are often organized around industries and economically related firms, they provide infrastructure for transmitting industry- and supply-chain-specific knowledge. If high-INFO site visits generate transferable expertise, that expertise may improve the forecasts of other analysts at the same brokerage who cover economically related firms.

The same organizational channels may also transmit the effects of OBFU. When a site visit fails to yield productive learning, colleagues may receive less useful information, rely on distorted

interpretations, or expend additional effort to resolve ambiguity. Critically, the cognitive cost of OBFU does not rest solely with the attending analyst. When obfuscation disrupts the visiting analyst's schema construction at the site visit, colleagues who receive her summaries, models, and verbal interpretations through internal channels may inherit an incomplete or distorted understanding of the firm's industry conditions, operational linkages, or accounting structures. Thus, we expect INFO and OBFU spillovers at the brokerage level to be channeled through all three dimensions. We therefore hypothesize:

H3a: *INFO is positively associated with forecast accuracy for firms covered by other analysts at the same brokerage, with effects channeled through industry membership, supply-chain connections, and accounting comparability.*

H3b: *OBFU is negatively associated with forecast accuracy for firms covered by other analysts at the same brokerage, with effects channeled through industry membership, supply-chain connections, and accounting comparability.*

III. DATA AND METHODOLOGY

3.1 Sample Construction and Data Sources

Our sample consists of A-share firms listed on the Shenzhen Stock Exchange from 2012 to 2023.[1] We focus on Shenzhen-listed firms because, during our sample period, these firms are subject to mandatory disclosure requirements for analyst site visits. These disclosures provide unusually detailed records of semi-private manager-analyst interactions, including the questions asked by analysts and the responses provided by managers. We obtain site-visit transcripts and analyst forecast data from the Chinese Research Data Services Platform (CNRDS). Stock returns

[1] In untabulated tests, our results are also robust to two sample restrictions. First, we exclude firms in the high-tech and pharmaceutical industries, where linguistic complexity may reflect inherent technical content rather than strategic communication choices. Second, we omit the COVID-19 pandemic period (2020–2022) to rule out the possibility that our findings are driven by abnormal market conditions.

and financial statement data are obtained from the China Stock Market & Accounting Research (CSMAR) database. We exclude financial firms and Special Treatment (ST) firms because their regulatory environments, financial statement structures, and disclosure incentives differ substantially from those of other listed firms.[2] We also require non-missing values for the variables used in our main analyses. To reduce the influence of outliers, we winsorize all continuous variables at the 1st and 99th percentiles.

Our final sample contains 972,679 question-answer pairs, which we use to construct linguistic complexity measures, and 24,078 site-visit events, which we use in the analyst-learning, spillover, and market-response analyses. The large number of question-answer pairs reflects the active use of site visits in the Chinese capital market and allows us to examine variation in communication quality across a broad set of firms, analysts, and time periods.

3.2 Measuring Linguistic Complexity in Chinese Site-Visit Transcripts

We begin by measuring the linguistic complexity of both analysts' questions and managers' responses. Because Chinese differs fundamentally from English in linguistic structure, standard English-language readability measures cannot be applied mechanically. Chinese uses characters as basic written units, with each character integrating form, sound, and meaning (Yang 1971). As a result, syllable-based measures, which are commonly used in English readability formulas, are not well-suited to Chinese financial disclosure.

We therefore construct a complexity measure that reflects features of Chinese-language disclosure.[3] The measure incorporates three dimensions. First, we measure sentence complexity

[2] ST firms are the firms that have reported negative net profits or shareholder equity below registered capital for two consecutive years, or have been identified by regulators as exhibiting abnormal financial conditions.

[3] To validate our complexity measure based on the Chinese language, we examine whether higher complexity in site-visit communication is associated with less favorable announcement-window cumulative abnormal returns (CARs), a relationship documented in prior literature for both analyst reports (De Franco et al. 2015) and annual reports (Ertugrul, Lei, Qiu, and Wan 2017). Consistent with these prior studies, we find that greater complexity is associated with more

using average clause length. We focus on clauses rather than full sentences because Chinese sentences often contain multiple clauses, and clause length better captures the processing burden imposed by syntactic structure.

Second, we measure adverbial and conjunctive density, defined as the proportion of adverbs and conjunctions relative to total word count. Psycholinguistic evidence shows that modifiers and connectors impose substantial working-memory costs by introducing qualifications, transitions, and long-distance dependencies between sentence elements (e.g., Just and Carpenter 1980). They capture a processing-cost dimension closely analogous to the syntactic-complexity component of the BOG Index, which Bonsall, Leone, Miller, and Rennekamp (2017) and Loughran and McDonald (2014) identify as a primary driver of disclosure readability.

Third, we measure character frequency using the proportion of commonly used characters. Less common characters tend to increase processing difficulty because they require greater recognition and interpretation effort. This approach is related to the BOG index's emphasis on word complexity.

Following De Franco, Hope, Vyas, and Zhou (2015), we combine these three dimensions into a composite complexity index. Each component is converted into a decile rank and scaled to the 0-1 interval. We then assign equal weights to the three standardized components. Higher index values indicate lower readability and greater linguistic complexity. This procedure yields two primary measures: *COMPLEXITY_Q*, the complexity of analysts' questions, and *COMPLEXITY_A*, the complexity of managers' responses.

3.3 Decomposing Complexity into Information and Obfuscation

Following Bushee et al. (2018) and Bushee and Huang (2024), we decompose managerial

negative announcement-window CARs, thereby supporting the construct validity of our complexity measure.

response complexity into an information component and an obfuscation component. Specifically, we estimate the following model at the question-answer level during a site visit:

$$COMPLEXITY_A = \beta_0 + \beta_1 COMPLEXITY_Q + CONTROLS + FIXED\ EFFECTS\ (FIRM, TIME) + \varepsilon \quad (2)$$

where *COMPLEXITY_A* is the complexity of managers' responses during the site visit, and *COMPLEXITY_Q* is the complexity of analysts' questions during the same site visit. Including question complexity allows us to account for the fact that more technically demanding analyst questions may naturally elicit more complex managerial responses. The control variables include: *LEV* (leverage ratio, capturing financial complexity); *SIZE* (firm size, measured by the natural log of a firm's market value); *BM* (book-to-market ratio, proxying for growth opportunities); *RETURN* (quarterly stock returns); *ACQUISITION* (acquisition activities indicator); *CAP_INTENSITY* (net property, plant, and equipment scaled by assets); *CAPEX* (capital expenditures scaled by total assets); *RD* (research and development intensity); *FINANCING* (external financing activities indicator); *GOODWILL* (indicator for goodwill impairment charges); *CFO* (standard deviation of cash flows from operations scaled by total assets over the prior five years); and *RESTRUCTURING* (indicator for restructuring charges). Finally, we include firm and time (including year and quarter) fixed effects to control for time-invariant firm characteristics, secular time trends, and seasonal patterns in site-visit activity and communication complexity.

We define INFO as the fitted value from Eq. (1). This component captures the portion of managerial response complexity that reflects substantive business complexity and information richness. We define OBFU as the residual from Eq. (1). This component captures the portion of managerial response complexity that is not explained by these observable fundamentals and is

therefore more consistent with obfuscatory communication or unproductive processing costs.[4]

3.4 Empirical Design

Direct Learning Effects. To test whether INFO and OBFU affect analyst learning about the visited firm, we estimate the following baseline specification at the matched site visit-analyst report level:

$$ACCURACY_{ijt} = \beta_0 + \beta_1 INFO_{ijt} + \beta_2 OBFU_{ijt} + CONTROLS + FIXED\ EFFECTS\ (FIRM, TIME, ANALYST) + \varepsilon \quad (2)$$

where $ACCURACY_{ijt}$ is the forecast accuracy of analyst *j*'s most recent report after a site visit to firm *i* and before the next earnings announcement in time *t*. We measure forecast accuracy as the negative of the absolute forecast error scaled by the stock price, so higher values indicate more accurate forecasts. INFO and OBFU are the estimated information and obfuscation components of linguistic complexity from the most recent site visit attended by analyst *j* prior to the forecast date.[5]

The vector of controls includes firm characteristics, information-environment variables, site-visit characteristics, and analyst characteristics. First, we control for firm characteristics including leverage (*LEV*), firm size (*SIZE*), auditor quality (*BIG4*), earnings management (*DA*, measured as the absolute value of discretionary accruals), loss indicator (*LOSS*), and R&D intensity (*RD*). Second, we include information environment variables: analyst following (*AFN*), institutional ownership (*INST_OWN*), and state ownership indicator (*SOE*). Third, we control for

[4] As a validity check for our decomposition, we examine whether OBFU correlates with established proxies for managerial incentives to obfuscate (*BAD_NEWS*, *LOSS*, *DA*, and *UE*) following Bushee et al. (2018). Our untabulated results confirm that OBFU is significantly higher for firm-quarters with negative news, losses, and larger discretionary accruals, while INFO is unrelated to these proxies but positively associated with firm complexity (*RD*, *CAP_INTENSITY*, and *RESTRUCTURING*). This divergent pattern is consistent with OBFU capturing genuine obfuscation rather than residual noise.

[5] Moreover, the first-stage decomposition regression in Eq. (1) addresses some of the endogeneity concerns: INFO is the predicted value from a structural model that conditions on observable firm fundamentals, purging the portion of *COMPLEXITY_A* driven by firm complexity rather than communication choices.

site-visit characteristics, including question-answer divergence times negative one (*SIMILARITY*), forward-looking content (*FORWARD_LOOKING*), linguistic tone of questions (*QTONE*) and answers (*ATONE*), management guidance indicator (*GUIDANCE*), and the time lag between the site visit and the transcript's disclosure (*DATE_DIFF*). Finally, we include analyst characteristics: gender (*MALE_ANALYST*), forecast frequency (*FORECASTNUMBER*), education level (*ANALYST_EDUCATION*), and experience (*ANALYST_EXPERIENCE*).

We include firm, analyst, and time (including quarter and year) fixed effects to control for time-invariant firm and analyst heterogeneity and common time trends. Standard errors are clustered at the analyst level to account for within-analyst correlation in the error term.

Portfolio-Level Spillovers. To examine whether site-visit learning generates transferable expertise within an analyst's own coverage portfolio, we re-estimate Eq. (2) using the visiting analyst's subsequent forecasts about her other covered firms, as specified in Eq. (3):

$$ACCURACY_{kjt} = \beta_0 + \beta_1 INFO_{ijt} + \beta_2 OBFU_{ijt} + CONTROLS + FIXED\ EFFECTS\ (FIRM, TIME, ANALYST) + \varepsilon \quad (3)$$

where the unit of observation is the forecast issued by the visiting analyst *j* for non-visited firm *k* in her portfolio at time *t*. INFO and OBFU are the components of linguistic complexity from the visiting analyst's site-visit interaction with the visited firm. To ensure that the forecast plausibly reflects the expertise acquired during the site visit, we restrict the sample to the first forecast issued after the site-visit date but before the visited firm's next earnings announcement. A positive coefficient on INFO would indicate that substantive site-visit communication produces expertise that transfers to other covered firms, while a negative coefficient on OBFU would indicate that obfuscatory communication imposes cognitive costs that propagate beyond the visited firm.

To test the predicted channels of portfolio-level transfer, we respectively interact INFO and

OBFU with three measures of inter-firm relatedness between the visited firm and other firms covered by the same visiting analyst: *SAME_INDUSTRY*, *CONNECTED_SUPPLY_CHAIN*, and *COMPARABILITY*. *SAME_INDUSTRY* equals one when the two firms share the same two-digit industry classification. *CONNECTED_SUPPLY_CHAIN* indicates whether the firms are linked through a customer-supplier relationship. *COMPARABILITY* captures accounting comparability following De Franco et al. (2011).

Brokerage-Level Spillovers. We next examine whether site-visit learning diffuses beyond the visiting analyst to colleagues within the same brokerage organization. We test this with the following specification:

$$ACCURACY_{lpmt} = \beta_0 + \beta_1 INFO_{ijmt} + \beta_2 OBFU_{ijmt} + CONTROLS + FIXED\ EFFECTS\ (FIRM, TIME, ANALYST) + \varepsilon \quad (4)$$

where the unit of observation is the first forecast issued by colleague analyst p at the visiting analyst j's brokerage m for firm l in time t. INFO and OBFU are taken from the visiting analyst j's site-visit interaction with the visited firm. As in the portfolio-level analysis, we restrict the sample to the first forecast issued by colleague analyst p after the site-visit date but before the visited firm's next earnings announcement, to align forecast timing with the potential window of intra-firm knowledge diffusion. A positive coefficient on INFO and a negative coefficient on OBFU would indicate that brokerage-level organizational channels diffuse both productive learning and communication frictions. We also examine the three predicted channels by interacting INFO and OBFU with *SAME_INDUSTRY*, *CONNECTED_SUPPLY_CHAIN*, and *COMPARABILITY*, respectively, measured between the visited firm and the firm covered by the colleague. This design allows us to test whether brokerage-level spillovers operate through the same economic linkages

as portfolio-level spillovers and whether their magnitudes differ across channels.[6]

3.5 Descriptive Statistics

Table 1 provides variable definitions, and Table 2 reports descriptive statistics for the two estimation samples. Panel A summarizes the complexity-decomposition sample, which comprises 972,679 question-answer pairs aggregated from 105, 841 site-visit transcripts at Shenzhen Stock Exchange–listed firms over 2012–2023, corresponding to approximately 9.19 question-answer pairs per transcript on average. The mean linguistic complexity of analysts' questions (*COMPLEXITY_Q*) is 0.978, while the mean linguistic complexity of managers' responses (*COMPLEXITY_A*) is 1.340. Managers' responses are therefore more complex than analysts' questions on average, consistent with managers' role as information providers who must explain business operations and strategy in greater detail than the often more pointed questions analysts pose.

Panel B reports descriptive statistics for the baseline sample of 18,144 analyst-firm-year observations. The mean of *ACCURACY* is 0.564, indicating that the average analyst forecast deviates from realized earnings by approximately 0.56% of the share price. The predicted component of complexity, *INFO*, exhibits a relatively narrow distribution (mean 0.495, standard deviation 0.035), whereas *OBFU* shows substantially wider variation (mean 0.007, standard deviation 0.160), reflecting the considerable cross-visit heterogeneity in the unexplained, residual component of managerial response complexity. In addition, site visits occur at an average of 2.41

[6] To address the concern that our spillover findings could reflect spurious correlation or unobservable common shocks rather than causal expertise transfer, we conduct a placebo test by randomly pairing each visited firm with a firm that is not in the visiting analyst's coverage portfolio (or, for brokerage-level tests, not covered by any analyst at the same brokerage) and re-estimate the spillover models (Equations (3) and (4)) using these placebo firm pairs. Because no learning channel exists between the visited firm and the randomly paired firm, INFO and OBFU should exhibit no significant association with the placebo firm's forecast accuracy. Untabulated results show that the INFO and OBFU coefficients in the placebo tests are statistically insignificant and economically negligible across all three channels, confirming that our documented spillovers reflect genuine expertise transfer through visiting analysts' coverage portfolios and brokerage networks rather than spurious correlation.

days from an analyst's subsequent forecast (*DATE_DIFF*).

[Insert Tables 1 and 2 here]

IV. EMPIRICAL RESULTS

4.1 Decomposing Linguistic Complexity into Information and Obfuscation

Table 3 reports the first-stage decomposition of managerial response complexity (Eq. (1)). The coefficient on *COMPLEXITY_Q* is positive and significant, indicating that more complex analyst questions elicit more complex managerial responses. This pattern is consistent with the idea that technically demanding questions naturally require more detailed and linguistically complex answers (Matsumoto, Pronk, and Roelofsen 2011; Brown et al. 2015).

Several firm characteristics are also associated with response complexity. The book-to-market ratio is positively associated with complexity, suggesting that firms with greater uncertainty about future prospects may require more detailed explanation. Capital intensity is also positively associated with complexity, consistent with capital-intensive firms needing to discuss asset deployment, capacity utilization, and operational efficiency in greater detail. Restructuring charges are positively related to complexity, reflecting the fact that restructuring events often involve intricate strategic, operational, and financial issues. By contrast, stock returns are negatively associated with response complexity, suggesting that firms with stronger recent performance communicate more straightforwardly. This pattern is consistent with prior evidence that managers of better-performing firms tend to provide clearer disclosure, whereas firms facing performance challenges may rely on more complex linguistic strategies (Li 2008). The first-stage results support the premise that managerial response complexity contains both a predictable component associated with substantive business complexity and a residual component consistent with obfuscatory communication.

[Insert Table 3 here]

4.2 Direct Analyst Learning from Site Visits

Baseline Results. Table 4 examines whether the information and obfuscation components of site-visit communication affect analyst forecast accuracy for the visited firm. Column (1) reports the baseline results. The coefficient on INFO is positive and highly significant, indicating that information-driven complexity improves forecast accuracy. Economically, a one-standard-deviation increase in INFO (0.035) is associated with a 0.061% improvement in forecast accuracy (1.732 × 0.035), equivalent to approximately 10.8% of the sample mean (0.564%) This finding supports H1a and suggests that substantive managerial communication facilitates analyst learning.

The coefficient on OBFU is negative and significant. A one-standard-deviation increase in OBFU (0.160) reduces forecast accuracy by 0.036% (0.223 × 0.160), or about 6.3% of the sample mean. This finding supports H1b and indicates that obfuscatory complexity impedes analysts' ability to extract value-relevant information from site-visit interactions.

The contrasting signs of INFO and OBFU provide initial evidence for our core theoretical framework. Complexity is not uniformly beneficial or harmful. When complexity reflects substantive information, analysts appear to process it productively and incorporate it into more accurate forecasts. When complexity reflects obfuscation, it imposes processing costs without generating useful understanding.

Cross-Sectional Heterogeneity. Columns (2) through (9) in Table 4 examine cross-sectional variation in these effects. The effects of INFO and OBFU are strongest in informationally challenging environments. For high-R&D firms, the positive effect of INFO is substantially larger than for low-R&D firms, while the negative effect of OBFU is also more pronounced. A similar pattern appears for high-volatility firms, where substantive managerial communication is

especially valuable and obfuscation is especially costly. The effects are also stronger among firms with low institutional ownership, consistent with site visits being more important when alternative information channels are weaker.

Finally, the negative effect of OBFU is more pronounced for junior analysts than for senior analysts. This asymmetry between *INFO* and *OBFU* across experience levels is itself informative about the underlying mechanism. The benefit of *INFO* is statistically indistinguishable between senior and junior analysts ($p = 0.251$ for the cross-group difference), consistent with the notion that substantive economic content is accessible to analysts at all experience levels; once managers convey information-rich content, even less-experienced analysts can incorporate it into their forecasts. By contrast, the cost of *OBFU* is significantly higher for junior analysts ($p = 0.003$), consistent with experienced analysts having developed cognitive heuristics that allow them to recognize and discount uninformative complexity rather than expend processing capacity on it (Clement 1999; Mikhail et al. 1997, 2003). These patterns suggest that experience matters primarily as a filter against unproductive complexity rather than as an amplifier of productive learning.

Overall, the cross-sectional evidence strengthens the interpretation that INFO facilitates learning while OBFU disrupts it, especially in settings characterized by greater underlying uncertainty (high R&D, high volatility) and weaker alternative information sources (low institutional ownership). Consistent with our theoretical framework, these results confirm that when substantive insights are most valuable, and alternative information is most scarce, the quality of managerial communication during site visits becomes particularly consequential for analyst learning and forecast accuracy.

[Insert Table 4 here]

4.3 Analyst Portfolio Spillovers

Having documented that site-visit communication affects forecasts for the visited firm, we next examine whether these effects extend to other firms in the visiting analyst's coverage portfolio. This test distinguishes firm-specific information acquisition from transferable expertise: if analysts learn generalizable lessons from substantive managerial communication, the effects should appear not only for the visited firm but also for other covered firms with overlapping analytical demands. Table 5 presents the portfolio-level spillover results. Column (1) shows that INFO significantly improves forecast accuracy for other firms in the analyst's portfolio, with a coefficient of 0.358 ($p < 0.05$). Although the spillover is modest relative to the direct learning effect, approximately 20.7% of the visited-firm coefficient, it indicates that informative site-visit communication generates learning benefits beyond the visited firm. In contrast, OBFU has a significantly negative spillover effect, with a coefficient of −0.043 ($p < 0.05$), indicating that obfuscation impairs forecast quality for other covered firms. These results support H2a and H2b and are consistent with our framework: INFO generates transferable expertise, whereas OBFU imposes cognitive costs that reduce analysts' ability to apply such expertise across their portfolios.

Columns (2) through (4) examine whether these spillovers are amplified along the three channels predicted by our top-down framework: industry membership, supply-chain connections, and accounting comparability. Specifically, Column (2) shows that *SAME_INDUSTRY* × *INFO* is positive and significant, indicating that substantive site-visit learning transfers more strongly to firms in the same industry. The interaction *SAME_INDUSTRY* × *OBFU* is negative and significant, indicating that the costs of obfuscation are also amplified within industries. Column (3) shows that *CONNECTED_SUPPLY_CHAIN* × *INFO* is positive and significant. This result indicates that learning about a firm's operations, input costs, demand conditions, or pricing power transfers to

customer-supplier partners whose performance is economically linked (e.g., Pandit et al. 2011; Guan et al. 2015). The interaction *CONNECTED_SUPPLY_CHAIN* × *OBFU* is negative and significant, suggesting that obfuscation also propagates through operational linkages.

Column (4) examines accounting comparability. The interaction *INFO* × *COMPARABILITY* is positive and significant, indicating that informative site-visit communication transfers more strongly to firms with comparable accounting systems. (Young and Zeng 2015; Choi et al. 2019). The interaction *OBFU* × *COMPARABILITY* is negative and significant, indicating that obfuscation disrupts the same financial-measurement channel.

In summary, this channel-specific pattern suggests that substantive managerial communication creates transferable expertise, while obfuscation imposes cognitive costs along the same task-relevant dimensions, supporting a learning-based interpretation of analyst spillovers rather than a generic information-transfer account.

To assess which channel most strongly amplifies portfolio-level spillovers, we compute the implied change in *ACCURACY* (as a percentage of its sample mean) associated with a one-standard-deviation increase in the moderator. The industry channel generates the largest amplification: a one-standard-deviation increase in SAME_INDUSTRY amplifies the INFO spillover by approximately 41.1% of the sample mean of ACCURACY, compared with 35.0% for the supply-chain channel. The OBFU amplifications follow the same ordering (−9.6% and −7.0% for industry and supply-chain). This pattern indicates that industry-environment knowledge and operational linkages are the dominant conduits of portfolio-level expertise transfer, while financial-measurement transfer plays a quantitatively minor role. The dominance of the industry channel is consistent with our framework: industry-level economic conditions and competitive dynamics provide the broadest transferable expertise, and operational learning about input

procurement, production processes, and demand conditions further enables analysts to extend their insights to economically linked firms (Pandit et al. 2011; Guan et al. 2015; De Franco et al. 2011)

[Insert Table 5 here]

4.4 Brokerage-Level Spillovers

We next examine whether the effects of INFO and OBFU diffuse across analysts within the same brokerage. Table 6 presents the brokerage-level spillover results. Column (1) shows that INFO from one analyst's site visit is positively and significantly associated with the forecast accuracy of that analyst's colleagues at the same brokerage when they cover economically related firms, supporting H3a. In contrast, OBFU is negatively and significantly associated with colleagues' forecast accuracy, supporting H3b.

Columns (2) through (4) examine whether brokerage-level spillovers operate through the same three channels documented at the portfolio level: industry membership, supply-chain connections, and accounting comparability. Specifically, Column (2) shows that *SAME_INDUSTRY* × *INFO* is positive and significant. This pattern is consistent with brokerages organizing research teams along industry lines, where sector-specific analyst groups facilitate the transmission of industry knowledge through formal meetings and informal exchanges. The interaction *SAME_INDUSTRY* × *OBFU* is negative and significant, indicating that obfuscation also propagates strongly along industry lines. Thus, industry-based research networks appear to transmit both productive learning and communication-related frictions.

Column (3) examines supply-chain linkages. The interaction *CONNECTED_SUPPLY_CHAIN* × *INFO* is positive and significant, indicating that substantive learning from one firm can transfer to colleagues covering customer-supplier partners. The interaction *CONNECTED_SUPPLY_CHAIN* × *OBFU* is negative and highly significant. This

result suggests that when operational understanding is obstructed by obfuscatory communication, the resulting cognitive cost is especially salient for colleagues covering firms economically linked to the visited firm.

In Column (4), the interaction *INFO* × *COMPARABILITY* is positive and significant, indicating that financial-measurement expertise can diffuse to colleagues covering firms with comparable accounting environments. The interaction *OBFU* × *COMPARABILITY* is significantly negative, suggesting that obfuscation disrupts the same accounting-framework channel through which productive expertise would otherwise transfer.

In summary, INFO generates positive brokerage-level spillovers, whereas OBFU generates negative spillovers, and both effects operate through industry membership, supply-chain connections, and accounting comparability.

The magnitude of brokerage-level spillovers should depend on the type of knowledge being transferred. By contrast, financial-measurement expertise, such as valuation assumptions, earnings-quality assessments, and accounting interpretations, may be more individualized and less easily transmitted through organizational channels. Thus, we expect INFO and OBFU spillovers at the brokerage level to be channeled through all three dimensions, although industry and supply-chain spillovers may be more strongly supported by brokerage infrastructure, whereas comparability-based spillovers may be relatively attenuated.

Applying the same standardization to the brokerage-level spillover estimates reveals a different channel ranking. The supply-chain channel generates the largest standardized amplification of INFO spillovers (4.5% of the sample mean of ACCURACY), while the industry channel produces 0.7%. OBFU amplifications follow the same ordering (−0.8% and −0.4% respectively). The absolute magnitudes of all three brokerage-level channels are substantially

smaller than their portfolio-level counterparts, consistent with intra-brokerage diffusion involving inevitable signal attenuation as expertise passes from the visiting analyst to colleagues. First, Second, the relative ranking shifts: whereas industry membership dominates at the portfolio level, the supply-chain channel emerges as the most efficient brokerage-level conduit. A plausible interpretation is that the value of supply-chain knowledge is highest when transferred between analysts covering distinct but economically linked sectors, since neither analyst would naturally observe the upstream or downstream firm's site visit alone; in contrast, industry knowledge, readily available through brokerage sector teams and shared industry reports, offers less marginal value when transmitted across analysts already specialized within the same sector.

[Insert Table 6 here]

V. ADDITIONAL ANALYSES AND ROBUSTNESS TESTS

5.1 Endogeneity Tests

While our baseline specifications already include a rich set of fixed effects and a comprehensive set of control variables, two residual concerns merit further investigation. First, time-invariant unobserved heterogeneity at the site-visit event level is not fully absorbed by our baseline fixed-effect structure, raising the possibility that systematic differences across visits (e.g., the strategic importance of the meeting and the seniority of the management team present) could correlate with both communication complexity and forecast outcomes. Second, the sample of analyst-firm observations on which our baseline regressions are estimated is non-random: analysts strategically choose which firms to cover and which site visits to attend, and these choices may correlate with unobserved factors that also affect forecast accuracy. We address these concerns through two complementary tests, with results reported in Table 7.

Alternative Fixed Effects. Column (1) of Panel A of Table 7 employs firm × analyst fixed

effects together with year fixed effects, which absorb all time-invariant heterogeneity at the analyst-firm pair level. This specification effectively asks whether, holding constant the analyst-firm relationship, *within-pair* variation in INFO and OBFU across different site visits is systematically associated with variation in forecast accuracy. The advantage of this specification is that it rules out any time-invariant confounders specific to the analyst-firm match.

Column (2) of Panel A uses site-visit fixed effects together with analyst and year fixed effects. The site-visit fixed effects absorb all unobserved heterogeneity that is specific to each individual site-visit event, including the strategic context of the meeting, the macroeconomic conditions at the time, and the specific managerial communication style displayed during that visit. This specification investigates, *within the same site-visit event*, how the components of complexity we classify as INFO versus OBFU are differentially associated with subsequent forecast accuracy among the analysts attending that visit.

Overall, the results in Panel A are highly consistent with our baseline findings, suggesting that they are not driven by time-invariant unobserved heterogeneity at the analyst-firm, analyst, or site-visit event level.

Heckman Selection Tests. A second concern is sample selection: the analyst-firm-year observations on which we estimate our baseline regressions are not a random sample of the universe of potential analyst-firm pairings. To address this selection concern, we implement the two-stage Heckman (1979) correction procedure. In the first stage, we model the probability that an analyst attends a site visit at a given firm in a given year using a probit specification, with the staggered introduction of high-speed rail (HSR) connecting the analyst's brokerage city and the visited firm's headquarters city serving as the key exclusion restriction (Chen, Ma, Martin and

Michaely 2022).[7] Following Chen et al. (2022), we construct *HSR_CONNECT*, an indicator equal to one if high-speed rail service exists between the analyst's brokerage city and the firm's headquarters city in year *t*, and zero otherwise.

The first-stage probit also includes standard determinants of analyst coverage and visit attendance, all of which may affect the analyst's probability of visiting the firm but are absorbed in the second-stage outcome equation through our control variables and fixed effects. The results in Panel B of Table 7 confirm that selection does not drive our findings. The coefficient on *HSR_CONNECT* in the first-stage probit is positive and significant, confirming the relevance of HSR connectivity as a driver of analyst visit attendance and validating our identifying variation. More importantly, the coefficients on INFO and OBFU in the second-stage outcome equation remain economically and statistically consistent with our baseline estimates after Heckman correction.

[Insert Table 7 here]

5.2 Market-based Validation of the Economic Significance of Information and Obfuscation Components

INFO and OBFU are the information-driven and obfuscation-driven components of linguistic complexity from the analyst site-visit transcript. A positive INFO coefficient and a negative OBFU coefficient would indicate that market participants efficiently differentiate substantive from obfuscatory complexity around private-communication events.

[7] Three features make HSR connectivity an ideal exclusion restriction in our setting. First, HSR connectivity satisfies the relevance condition. The introduction of HSR significantly increases the frequency of analyst site visits by reducing the time and monetary costs of physical travel. The introduction of HSR therefore acts as a direct shifter of analyst visit attendance probability, providing strong identifying variation for the selection equation (Chen et al. 2022). Second, HSR connectivity plausibly satisfies the exclusion restriction: the timing of HSR rollout was determined by China's central government based on long-term national strategic considerations, population density, regional economic development priorities, and geographical topography, rather than by firm-level information environment characteristics or analyst-specific factors that could directly affect forecast accuracy (Chen et al. 2022). Third, conditional on attendance, HSR connectivity affects forecast accuracy only through its effect on analyst access to substantive managerial communication: once an analyst attends a site visit, the marginal effect of travel mode on forecast accuracy operates through information acquired during the visit, which is precisely what our INFO and OBFU measures capture.

Having documented that analysts respond differently to INFO and OBFU in their forecast accuracy and that these effects spill over across firms and analysts, we now examine whether investors efficiently incorporate these components of site-visit linguistic complexity into stock prices. This market-based test complements the analyst-based tests: if INFO and OBFU capture meaningful variation in information quality, investors should reward INFO and penalize OBFU in announcement-window returns.

As shown in Table 8, INFO is associated with a positive and highly significant cumulative abnormal return, indicating that markets respond favorably when site-visit transcripts convey substantive content that reflects genuine business complexity. In contrast, OBFU elicits a significantly negative market reaction, indicating that markets recognize obfuscatory content and discount firms whose managerial communication impedes rather than facilitates information transmission.

[Insert Table 8 here]

The economic asymmetry between INFO and OBFU market reactions, with positive INFO effects exceeding negative OBFU effects in absolute magnitude, is consistent with the asymmetric pattern documented throughout our analyses: substantive content provides clear positive informational value, while obfuscation produces a more muted negative effect because its primary cost is the consumption of cognitive resources rather than the transmission of explicitly false content. Beyond validating our decomposition, these market reactions also reveal a broader implication for the design of private-disclosure regimes. The fact that markets systematically price INFO and OBFU suggests that the information content of analyst-mediated private disclosure is sufficiently transparent to public market participants to generate measurable price effects. This indicates that mandatory disclosure of site visit records, as implemented on the Shenzhen Stock Exchange, effectively enables broader market participation in the information benefits of these otherwise private interactions, an externality that would not arise under voluntary or undisclosed analyst-management meeting regimes.

5.3 Validating the Spillover Mechanism: The Moderating Role of Analyst Tenure

Our brokerage-level spillover hypothesis (H3) posits that INFO-driven learning at site visits generates transferable expertise that propagates to colleagues at the same brokerage through formal team meetings, internal research presentations, shared analytical frameworks, and informal mentorship (Hwang et al. 2019; Hugon et al. 2024).

A direct empirical implication of this mechanism is that the spillover effect of a site visit should depend on how deeply the visiting analyst is embedded in her brokerage's knowledge-sharing network. A visiting analyst who is more central in the brokerage's internal forums, models, and mentoring relationships has more channels through which to disseminate the substantive insights she acquires at the site visit, and her interpretations exert greater influence on colleagues'

subsequent analyses. Symmetrically, when her own learning is impaired by obfuscatory communication, the resulting distortions in her summaries, models, and verbal interpretations are more likely to propagate to colleagues who rely on her output. In both directions, deeper embeddedness of the visiting analyst should amplify the cross-analyst transmission of site-visit content.

Analyst tenure at the brokerage provides a natural proxy for the visiting analyst's organizational embeddedness: longer-tenured analysts have accumulated more opportunities to participate in internal research forums, develop trust-based information-sharing relationships with colleagues, contribute to shared analytical templates, and assimilate the brokerage's analytical conventions. This organizational-diffusion channel is conceptually distinct from the individual-cognitive-expertise channel documented in Section 4.1, where the visiting analyst's own experience moderates her ability to discount obfuscation in her own forecasts. The present test instead concerns how effectively the visiting analyst's site-visit content, productive or distorted, travels to her colleagues. If brokerage-level spillovers operate through organizational diffusion, we should observe that both the positive spillover effect of *INFO* and the negative spillover effect of *OBFU* on colleagues' forecast accuracy are amplified when the visiting analyst has longer brokerage tenure.

We test this prediction by augmenting the brokerage spillover specification with *TENURE* and its interactions with INFO and OBFU. *TENURE* is defined as the number of years the visiting analyst (i.e., the analyst attending the site visit) has been employed at her current brokerage as of the site-visit date, measured from her first observed forecast under the brokerage's affiliation in our sample.

As shown in Column (1) of Table 9, the interaction *INFO* × *TENURE* is positive and highly

significant, confirming that the spillover benefit from colleagues' substantive site visit communication is substantially amplified for analysts more deeply embedded in the brokerage. Symmetrically, the interaction *OBFU* × *TENURE* is negative and statistically significant, indicating that the negative impact of colleagues' obfuscatory communication is also amplified for longer-tenured analysts. This symmetric amplification is precisely what an organizational diffusion mechanism predicts: deeper embeddedness in the brokerage's knowledge-sharing network exposes the analyst more intensively to colleagues' communication choices, whether those choices facilitate learning or impose cognitive costs.

[Insert Table 9 here]

VI. CONCLUSION

This study examines how the quality of managerial communication during analyst site visits shapes analyst learning and the transfer of analyst expertise. Adapting the Bushee et al. (2018) framework to mandatory site-visit disclosures from Shenzhen-listed firms over 2012–2023, we decompose managerial response complexity into an information-driven component (INFO) and an obfuscation-driven component (OBFU). We then trace their effects from the visited firm to the analyst's coverage portfolio and to colleagues within the same brokerage.

Three findings emerge. First, INFO and OBFU have opposite effects on forecast accuracy for the visited firm, with effects strongest in informationally challenging settings, including firms with high R&D intensity, high return volatility, and low institutional ownership. The cost of OBFU is also concentrated among junior analysts. Second, INFO generates positive spillovers within the analyst's coverage portfolio, while OBFU generates negative spillovers. Both effects are channeled through the three dimensions predicted by our top-down framework: industry membership, supply-chain connections, and accounting comparability. Third, similar spillovers arise across analysts

within the same brokerage, with industry and supply-chain channels amplified by organizational infrastructure and the comparability channel is relatively weaker, consistent with financial-measurement expertise being more individualized. Additional analyses showing stronger spillovers for longer-tenured analysts and significant market reactions of opposite signs around site-visit disclosures reinforce the interpretation that managerial communication produces portable analyst human capital when substantive, and transmits cognitive frictions when obfuscatory.

Our findings have several implications. For regulators, the evidence shifts attention from disclosure quantity to disclosure quality. Mandating the disclosure of manager-analyst interactions, as the Shenzhen Stock Exchange has required since 2012, does not by itself ensure that analysts and investors benefit, because managers retain latitude over how clearly and substantively they communicate within mandated channels. Disclosure rules and enforcement practices that emphasize the completeness, specificity, and clarity of site-visit records may better support regulators' information-environment objectives. For brokerage organizations, the channel-specific spillover pattern, amplified along industry and supply-chain lines but weaker along accounting comparability, supports the importance of organizing research teams around sectors and economically linked firms. At the same time, it suggests that organizational infrastructure can transmit not only productive expertise but also the cognitive costs of obfuscation.

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Table 1 Variable Definitions

VARIABLES	Definitions
Measures of Linguistic Complexity	
COMPLEXITY_Q	The complexity index of analysts' questions during the site visit, by applying equal weights to three standardized components (average words per sentence, adverbial/conjunctive density, and the proportion of uncommon characters per sentence).
COMPLEXITY_A	The complexity index of managers' response during the site visit, by applying equal weights to three standardized components (average words per sentence, adverbial/conjunctive density, and the proportion of uncommon characters per sentence).
INFO	Estimated latent information component of site visit following Bushee et al. (2018) and Bushee and Huang (2024).
OBFU	Estimated latent obfuscation component of site visit following Bushee et al. (2018) and Bushee and Huang (2024).
Firm Characteristics to Estimate Linguistic Complexity	
LEV	Leverage ratio, measured as long-term debt plus short-term debt, scaled by total assets at the beginning of the quarter.
MV	Market value, measured as natural log of market value of equity at the beginning of the fiscal quarter, prior to the site-visit transcript disclosure.
SIZE	Firm Size, measured as natural log of market value of equity at the beginning of the quarter.
BM	Book value of equity, measured as scaled by market value of equity at the beginning of the quarter.
RETURN	Buy-and-hold return over the quarter, in percent.
ACQUISITION	Total acquisitions during the quarter, scaled by total assets at the beginning of the quarter.
CAP_INTENSITY	Capital intensity, measured as net plant, property, and equipment, scaled by total assets at the beginning of the quarter.
CAPEX	Capital expenditure, measured as amount of capital expenditures scaled by total assets at the beginning of the quarter.
RD	Ratio of research and development expense to sales.
FINANCING	Amount raised from stock and debt issuances during the quarter scaled by total assets at the beginning of the quarter.
GOODWILL	Indicator variable for whether the firm had a goodwill impairment charge that quarter.
CFO	Standard deviation of cash flows from operations scaled by total assets over the prior five years.
RESTRUCTURING	Indicator variable for whether the firm had a restructuring charge that quarter.
Key Dependent Variables	
ACCURACY	The absolute value of the difference between actual earnings and the mean earnings forecasts for firm i by analyst j at day t, scaled by the stock price times negative one and times 100.
CAR[-1, 1]	The size-adjusted cumulative daily abnormal return over the three-day [-1, 1]

	window for the site-visit transcript release date.
COMPLEXITY	The complexity index of analyst report.
Independent and Additional Variables of Interest	
RETURN_VOL	Stock return volatility, measured as the standard deviation of daily stock returns over the period [-127, -2] relative to the site-visit transcript release date, following Mayew and Venkatachalam (2012).
RETURN_MOM	The buy-and-hold return over the window [-127, -2] before the site-visit transcript release date.
AFN	The number of analysts following at the end of the fiscal quarter, prior to the site-visit transcript disclosure.
INST_OWN	The percentage of institutional ownership at the beginning of the fiscal year end, prior to the site-visit transcript disclosure.
SOE	An indicator variable that equals 1 if the firm is state-owned enterprise and 0 otherwise.
AFSTD	The standard deviation of analyst forecasts in the fiscal quarter prior to the site-visit transcript disclosure, scaled by price at the beginning of the fiscal quarter.
UE	The difference between actual earnings and the most recent median consensus analyst forecast prior to the site-visit transcript disclosure, scaled by the price at the beginning of the fiscal quarter.
BAD_NEWS	An indicator variable that equals 1 if the unexpected earnings are negative and 0 otherwise.
DEPS	The change in earnings per share at the beginning of the quarter (EPS_q1 – EPS_q5) prior to prior to the site-visit transcript disclosure, scaled by q5 quarter price.
SIMILARITY	Question-Answer similarity, derived from site-visit transcripts, serves as a proxy for non-responsive answers.
QTONE	The frequency difference between the positive and the negative sentences scaled by total sentences in the analyst questions in the site-visit transcript.
ATONE	The frequency difference between the positive and the negative sentences scaled by total sentences in the response in the site-visit transcript.
GUIDANCE	An indicator variable that equals 1 if at least one quantitative guidance is provided on the same day as the site-visit transcript release date.
DATE_DIFF	The number of days between site visit date and site-visit transcript release date.
BIG4	An indicator variable that equals 1 if the firm is audited by a Big 4 auditor (PricewaterhouseCoopers, Deloitte, Ernst & Young, or KPMG) and 0 otherwise.
DA	Discretionary accruals, measured as the absolute value of residuals from the modified Jones model (Dechow et al., 1995), capturing the magnitude of earnings management.
LOSS	An indicator variable that equals 1 if the firm reports negative net income for the fiscal year and 0 otherwise.
TONE	(Positive Sentences-Negative Sentences)/Total sentences within firm i's annual report by analyst j at day t. Positive and negative tone is identified based on Loughran-McDonald Master Dictionary.

FORWARDLOOKING	The ratio of forward-looking sentences versus total sentences of firm i's annual report by analyst j at day t. Forward looking refers to analysts' predictions of various aspects of a company's future, which is determined by machine learning techniques.
Analyst Characteristics	
MALE_ANALYST	An indicator variable that equals 1 if the analyst issuing the forecast is male and 0 otherwise.
FORECASTNUMBER	The total number of earnings forecasts issued by the analyst during the fiscal year, capturing forecast frequency.
ANALYST_EDUCATION	The analyst's highest education level, coded on an ordinal scale (1 = bachelor's, 2 = master's, 3 = MBA, 4 = PhD).
ANALYST_EXPERIENCE	The number of years the analyst has been issuing forecasts since first appearing in the database, measured at the forecast date.
TENURE	The number of years analyst j has been employed at her current brokerage as of the forecast date, measured from her first observed forecast under the brokerage's affiliation in our sample, and proxies for analyst embeddedness in the brokerage's internal knowledge-sharing network
Inter-Firm Linkage Variables (Spillover Channels)	
SAME_INDUSTRY	An indicator variable that equals 1 if the spillover firm shares the same two-digit industry classification as the visited firm, and 0 otherwise.
CONNECTED_SUPPLY_CHAIN	An indicator variable that equals 1 if the spillover firm has an economically meaningful customer-supplier relationship with the visited firm based on the Factset Database, and 0 otherwise.
COMPARABILITY	Accounting comparability between the visited firm and the spillover firm, calculated following De Franco et al. (2011) using the closeness of their earnings-return mappings estimated over the prior 16 quarters. Higher values indicate greater comparability.
HSR_CONNECT	An indicator equal to one if high-speed rail service exists between the analyst's brokerage city and the firm's headquarters city in year *t*, and zero otherwise.

Notes: This table provides detailed definitions of all variables used in the empirical analysis. Variables are grouped by category: (1) dependent variables measuring analyst forecast accuracy at the visited firm, portfolio level, and brokerage level; (2) key independent variables capturing information-driven complexity (INFO) and obfuscation-driven complexity (OBFU), constructed following the decomposition procedure described in Section 3.3; (3) channel-specific moderators including industry membership, supply-chain connections, and accounting comparability; (4) firm-level control variables; (5) site-visit characteristics; and (6) analyst-level control variables. All continuous variables are winsorized at the 1% and 99% levels.

Table 2 Descriptive Statistics

Panel A: Complexity Decomposition Sample (Question-Answer Pairs)

	Questions	Answers
Mean of COMPLEXITY	0.978	1.340
Total No. of Question-Answer Pairs	972,679	972,679
No. of Question-Answer Pairs Per Transcript	9.187	9.187

Panel B: Direct Learning Sample (Matched Site Visit Transcript-Analyst Forecast Report Level)

VARIABLES	Obs	Mean	Std. dev.	Min	Max
ACCURACY	18,144	0.564	1.357	0.002	9.768
INFO	18,144	0.495	0.035	0.418	0.582
OBFU	18,144	0.007	0.160	-0.375	0.402
LEV	18,144	0.403	0.174	0.069	0.818
SIZE	18,144	23.614	1.159	21.241	26.715
BIG4	18,144	0.098	0.297	0.000	1.000
DA	18,144	0.063	0.064	0.001	0.348
LOSS	18,144	0.030	0.171	0.000	1.000
RD	18,144	5.486	6.174	0.000	31.830
AFN	18,144	3.385	0.929	0.000	4.905
INST_OWN	18,144	48.549	24.692	1.529	91.460
SOE	18,144	0.078	0.268	0.000	1.000
SIMILARITY	18,144	0.655	0.118	0.357	0.934
FORWARDLOOKING	18,144	0.116	0.068	0.000	0.301
QTONE	18,144	0.293	0.268	-0.389	1.000
ATONE	18,144	-0.545	0.196	-0.933	0.000
GUIDANCE	18,144	0.054	0.226	0.000	1.000
DATE_DIFF	18,144	2.409	1.386	0.000	4.852
MALE_ANALYST	18,144	0.743	0.437	0.000	1.000
FORECASTNUMBER	18,144	25.415	33.179	1.000	161.000
ANALYST_EDUCATION	18,144	3.079	0.477	1.000	4.000
ANALYST_EXPERIENCE	18,144	8.260	8.949	0.130	43.430

Notes: This table reports summary statistics for the two estimation samples used in the analysis. Panel A presents statistics for the linguistic complexity decomposition sample (Equation 1), comprising 972,679 question-answer pairs from analyst site visits at Shenzhen Stock Exchange-listed firms over 2012–2023, where *COMPLEXITY_Q* and *COMPLEXITY_A* are the linguistic complexity indices for analysts' questions and managers' responses, respectively, constructed by equally weighting three standardized components (average words per sentence, adverbial/conjunctive density, and the proportion of common characters); higher values indicate greater linguistic complexity. The remaining variables in Panel A represent firm characteristics that proxy for the firm's fundamental information environment and strategic disclosure incentives. Panel B presents statistics for the direct learning sample (Equation 2), comprising 18,144 analyst-firm-year observations over the same period, where *ACCURACY* is the absolute forecast error scaled by share price (multiplied by -1, so higher values indicate greater accuracy), and *INFO* and *OBFU* are the estimated information-driven (fitted value) and obfuscation-driven (residual) components of linguistic complexity from the first-stage decomposition in Table 3. The remaining Panel B variables include firm-level controls, information-environment controls, site-visit characteristics, and analyst-level controls. The two samples differ in unit of analysis: Panel A is at the firm-quarter level for all visited firms, whereas Panel B is at the analyst-firm-year level conditional on the analyst issuing a forecast after the site visit. Detailed variable definitions are provided in Table 1. All continuous variables are winsorized at the 1% and 99% levels.

Table 3 Estimating the Information-Driven (INFO) and Obfuscation-Driven (OBFU) Components of Managerial Linguistic Complexity in Site-Visit Communication

VARIABLES	(1) COMPLEXITY_A
COMPLEXITY_Q	0.171***
	(0.008)
LEV	-0.052
	(0.034)
SIZE	0.008
	(0.010)
BM	0.068**
	(0.026)
RETURN	-0.017**
	(0.008)
ACQUISITION	-0.164
	(0.126)
CAP_INTENSITY	0.078*
	(0.042)
CAPEX	0.091
	(0.070)
RD	-0.001
	(0.001)
FINANCING	-0.030
	(0.052)
GOODWILL	0.003
	(0.012)
CFO	-0.022
	(0.089)
RESTRUCTURING	0.125*
	(0.071)
Constant	0.510**
	(0.234)
Firm FE	Yes
Year FE	Yes
Quarter FE	Yes
Observations	972,679
Adjusted R-squared	0.391

Notes: This table reports estimates of Equation (1), which decomposes managerial response complexity (COMPLEXITY_A) into an information-driven component (INFO) and an obfuscation-driven component (OBFU). COMPLEXITY_A is the linguistic complexity index of managers' responses during site visits at the firm-quarter level. COMPLEXITY_Q is the linguistic complexity of analysts' questions during the same site visits. Firm characteristics proxy for the firm's fundamental information environment. Fitted values from this regression define INFO (the component of complexity explained by analyst questions and firm fundamentals); residuals define OBFU (the component orthogonal to these determinants). Firm, year, and quarter fixed effects are included to absorb time-invariant firm heterogeneity, secular time trends, and seasonal patterns. Detailed variable definitions are provided in Table 1. Standard errors clustered at the firm level are reported in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 4 Direct Learning Effects of Site-Visit Communication on Analyst Forecast Accuracy for the Visited Firm

VARIABLES	(1) Full Sample ACCURACY	(2) High RD ACCURACY	(3) Low RD ACCURACY	(4) High Volatility ACCURACY	(5) Low Volatility ACCURACY	(6) High INST_OWN ACCURACY	(7) Low INST_OWN ACCURACY	(8) Senior Analysts ACCURACY	(9) Junior Analysts ACCURACY
INFO	1.541***	3.965***	0.119	1.891***	0.467	1.136**	1.719***	1.492**	1.450***
	(0.351)	(0.827)	(0.354)	(0.644)	(0.571)	(0.456)	(0.598)	(0.610)	(0.457)
OBFU	-0.221***	-0.594***	-0.081	-0.462***	-0.146	-0.069	-0.503***	-0.145	-0.313***
	(0.065)	(0.133)	(0.072)	(0.137)	(0.099)	(0.069)	(0.109)	(0.106)	(0.077)
LEV	0.331*	-0.114	0.523**	0.308	-0.047	-0.361	0.575**	-0.041	0.427*
	(0.189)	(0.330)	(0.222)	(0.288)	(0.403)	(0.220)	(0.239)	(0.326)	(0.233)
SIZE	0.123***	0.126*	0.050	0.150**	0.128	0.128***	0.155**	0.195***	0.092*
	(0.037)	(0.071)	(0.050)	(0.065)	(0.096)	(0.049)	(0.067)	(0.071)	(0.047)
BIG4	0.034	-0.231**	0.040	-0.016	0.014	-0.063	-0.082	0.092	-0.047
	(0.069)	(0.115)	(0.092)	(0.075)	(0.135)	(0.074)	(0.129)	(0.082)	(0.092)
DA	-0.829***	-2.381***	-0.478*	-2.067***	-0.221	0.526*	-2.102***	-1.094**	-0.496*
	(0.236)	(0.510)	(0.271)	(0.417)	(0.445)	(0.307)	(0.373)	(0.434)	(0.288)
LOSS	1.483***	2.464***	0.963***	0.627*	1.751**	1.386***	1.554***	1.264***	1.569***
	(0.166)	(0.388)	(0.156)	(0.343)	(0.585)	(0.234)	(0.269)	(0.262)	(0.194)
RD	0.043***	0.022	-0.045*	0.072***	0.016	0.031*	0.057***	0.059***	0.033***
	(0.011)	(0.017)	(0.026)	(0.027)	(0.012)	(0.018)	(0.015)	(0.022)	(0.012)
AFN	-0.032*	0.043	-0.021	-0.029	-0.032	-0.060**	-0.015	-0.027	-0.027
	(0.018)	(0.031)	(0.021)	(0.043)	(0.032)	(0.025)	(0.027)	(0.035)	(0.023)
INS_OWN	0.002	0.007	0.003**	0.009*	-0.001	-0.003	0.001	0.006**	0.000
	(0.002)	(0.005)	(0.001)	(0.005)	(0.005)	(0.002)	(0.004)	(0.003)	(0.002)
SOE	-0.013	0.119	-0.036	0.362***	-0.147	0.048	-0.659***	-0.075	-0.036
	(0.058)	(0.105)	(0.067)	(0.096)	(0.136)	(0.055)	(0.205)	(0.110)	(0.069)
SIMILARITY	0.098	0.151	0.067	0.120	0.182	0.055	0.244	0.079	0.173
	(0.115)	(0.216)	(0.130)	(0.165)	(0.223)	(0.130)	(0.167)	(0.166)	(0.129)
FORWARDLOOKING	-0.245	-0.901***	0.238*	-0.975***	0.086	0.138	-0.791***	0.154	-0.410**
	(0.151)	(0.304)	(0.143)	(0.272)	(0.380)	(0.161)	(0.266)	(0.278)	(0.171)
QTONE	-0.074*	-0.293***	-0.038	-0.243***	-0.006	-0.092**	-0.052	-0.066	-0.057
	(0.039)	(0.081)	(0.039)	(0.064)	(0.092)	(0.044)	(0.063)	(0.070)	(0.048)
ATONE	0.119**	-0.024	0.174***	0.065	0.135	-0.020	0.238***	0.107	0.112*

	(0.055)	(0.146)	(0.056)	(0.108)	(0.089)	(0.067)	(0.092)	(0.087)	(0.063)
GUIDANCE	-0.085*	-0.251***	0.010	-0.106	-0.002	-0.130	-0.075	-0.136*	-0.120*
	(0.045)	(0.062)	(0.059)	(0.066)	(0.052)	(0.080)	(0.050)	(0.076)	(0.064)
DATE_DIFF	-0.065***	-0.078***	-0.053***	-0.077***	-0.048***	-0.053***	-0.074***	-0.047***	-0.075***
	(0.008)	(0.017)	(0.008)	(0.012)	(0.013)	(0.010)	(0.012)	(0.013)	(0.010)
MALE_ANALYST	-0.030	0.006	-0.017	-0.117	0.005	-0.039	-0.018	-0.056	-0.024
	(0.034)	(0.047)	(0.041)	(0.079)	(0.045)	(0.041)	(0.048)	(0.057)	(0.047)
FORECASTNUMBER	-0.001***	-0.001**	-0.001**	-0.002*	-0.001**	-0.001**	-0.001**	-0.001	-0.000
	(0.000)	(0.001)	(0.000)	(0.001)	(0.000)	(0.000)	(0.001)	(0.001)	(0.001)
ANALYST_EXPERIENCE	-0.015	-0.047	-0.006	-0.010	0.048	0.025	-0.006	-0.011	0.018
	(0.027)	(0.058)	(0.029)	(0.044)	(0.037)	(0.032)	(0.041)	(0.066)	(0.036)
ANALYST_EDUCATION	0.004**	0.006	0.002	0.006	0.003**	0.004*	0.003	0.005	0.019**
	(0.002)	(0.004)	(0.001)	(0.004)	(0.001)	(0.002)	(0.003)	(0.003)	(0.008)
Constant	-3.189***	-4.471**	-0.745	-4.240***	-2.745	-2.748**	-3.978***	-5.133***	-2.504**
	(0.905)	(1.776)	(1.208)	(1.601)	(2.126)	(1.202)	(1.530)	(1.645)	(1.162)
Diff of INFO (P value)			0.000		0.000		0.048		0.251
Diff of OBFU (P value)			0.000		0.000		0.000		0.003
Firm FE	YES	YES	YES	YES	YES	YES	YES	YES	YES
Analyst FE	YES	YES	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES	YES	YES	YES
Observations	18,144	5,728	12,111	7,130	10,517	9,343	8,408	5,890	11,860
Adjusted R-squared	0.346	0.469	0.321	0.437	0.412	0.389	0.406	0.361	0.377

Notes: This table reports the direct learning effects of site-visit linguistic complexity on analyst forecast accuracy for the visited firm, testing Hypotheses H1a and H1b. The dependent variable is ACCURACY, measured as the negative of the absolute forecast error scaled by share price; higher values indicate more accurate forecasts. Column (1) reports the full-sample estimates. Columns (2)-(9) report cross-sectional heterogeneity tests partitioning the sample by R&D intensity (Columns 2-3), return volatility (Columns 4-5), institutional ownership (Columns 6-7), and analyst experience (Columns 8-9), each split at the sample median. INFO and OBFU are the information-driven and obfuscation-driven components of linguistic complexity. All specifications include the full set of firm-level, information-environment, site-visit, and analyst-level control variables. Firm, analyst, and year fixed effects are included in all specifications to absorb time-invariant firm and analyst heterogeneity and common time trends. Detailed variable definitions are provided in Table 1. Standard errors clustered at the analyst level are reported in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 5 Spillover of Site-Visit Communication to Other Firms in the Analyst's Portfolio

VARIABLES	(1) *ACCURACY*	(2) *ACCURACY*	(3) *ACCURACY*	(4) *ACCURACY*
INFO	0.170**	0.486**	0.647	0.587***
	(0.061)	(0.175)	(0.385)	(0.179)
OBFU	-0.045**	-0.059	-0.007	-0.086**
	(0.023)	(0.043)	(0.026)	(0.038)
SAME_INDUSTRY		0.262**		
		(0.107)		
SAME_INDUSTRY × INFO		0.495**		
		(0.213)		
SAME_INDUSTRY × OBFU		-0.093**		
		(0.037)		
CONNECTED_SUPPLY_CHAIN			0.361*	
			(0.184)	
CONNECTED_SUPPLY_CHAIN × INFO			0.713*	
			(0.395)	
CONNECTED_SUPPLY_CHAIN × OBFU			-0.130***	
			(0.021)	
COMPARABILITY				0.084**
				(0.040)
COMPARABILITY × INFO				0.170**
				(0.083)
COMPARABILITY × OBFU				-0.032*
				(0.017
Firm FE	YES	YES	YES	YES
Analyst FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES
Observations	98,362	98,362	35,026	54,582
Adjusted R-squared	0.330	0.350	0.382	0.372

Notes: This table reports portfolio-level spillover effects of site-visit linguistic complexity on analyst forecast accuracy, testing Hypotheses H2a and H2b. Column (1) reports the baseline portfolio-spillover regression; Columns (2)-(4) augment the baseline with channel-specific moderators and their interactions with *INFO* and *OBFU*: *SAME_INDUSTRY* (Column 2), *CONNECTED_SUPPLY_CHAIN* (Column 3), and *COMPARABILITY* (Column 4). All specifications include the full set of control variables from Table 4. Firm, analyst, and year fixed effects are included in all specifications. Detailed variable definitions are provided in Table 1. Standard errors clustered at the analyst level are reported in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 6 Brokerage-Level Spillover Effects of Site-Visit Communication on Forecast Accuracy of Colleagues' Covered Firms

VARIABLES	(1) ACCURACY	(2) ACCURACY	(3) ACCURACY	(4) ACCURACY
INFO	0.110***	0.070***	0.212***	0.182***
	(0.002)	(0.003)	(0.017)	(0.041)
OBFU	-0.035***	-0.010***	-0.035***	-0.041***
	(0.010)	(0.001)	(0.003)	(0.009)
SAME_INDUSTRY		0.010***		
		(0.003)		
SAME_INDUSTRY × INFO		0.012*		
		(0.006)		
SAME_INDUSTRY × OBFU		-0.007***		
		(0.001)		
CONNECTED_SUPPLY_CHAIN			0.153*	
			(0.090)	
CONNECTED _ SUPPLY_CHAIN × INFO			0.179***	
			(0.052)	
CONNECTED _ SUPPLY_CHAIN × OBFU			-0.031**	
			(0.014)	
COMPARABILITY				0.018**
				(0.007)
COMPARABILITY × INFO				0.043***
				(0.015)
COMPARABILITY × OBFU				-0.008**
				(0.003)
Control Variables	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES
Analyst FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES
Observations	4,090,588	4,090,588	1,456,658	1,970,720
Adjusted R-squared	0.307	0.307	0.307	0.364

Notes: This table reports brokerage-level spillover effects of site-visit linguistic complexity, testing Hypotheses H3a and H3b. Column (1) reports the baseline brokerage-spillover regression; Columns (2)-(4) augment the baseline with the three channel-specific moderators (*SAME_INDUSTRY*, *CONNECTED_SUPPLY_CHAIN*, and *COMPARABILITY*) and their interactions with *INFO* and *OBFU*. All specifications include the full set of control variables from Table 4. Firm, analyst, and year fixed effects are included in all specifications. Detailed variable definitions are provided in Table 1. Standard errors clustered at the analyst level are reported in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 7 Identification Tests

Panel A Alternative Fixed-Effect Structures

VARIABLES	(1) ACCURACY	(2) ACCURACY
INFO	1.457***	1.536***
	(0.491)	(0.382)
OBFU	-0.285***	-0.239***
	(0.091)	(0.071)
Control Variables	Yes	Yes
Firm×Analyst FE	Yes	NO
Year FE	Yes	Yes
Firm FE	NO	NO
Site Visit FE	NO	Yes
Analyst FE	NO	Yes
Observations	12,182	17,705
Adjusted R-squared	0.410	0.507

Panel B Heckman Selection Correction Using High-Speed Rail Connectivity as the Exclusion Restriction

VARIABLES	(1) VISIT	(2) ACCURACY
HSR_CONNECT	0.005***	
	(0.001)	
INFO		1.541***
		(0.351)
OBFU		-0.221***
		(0.065)
INVERSE_MILLS		0.247
		(0.286)
Control Variables	YES	YES
Firm FE	YES	YES
Analyst FE	YES	YES
Year FE	YES	YES
Observations	38,127	18,144
Adjusted R-squared	0.494	0.365

Notes: This table reports robustness tests addressing two residual identification concerns: time-invariant unobserved heterogeneity at granular levels (Panel A) and non-random selection of analyst-firm observations into the sample (Panel B). In Panel A, Column (1) includes firm × analyst fixed effects together with year fixed effects, which absorb all time-invariant heterogeneity at the analyst-firm pair level; Column (2) includes site-visit fixed effects together with analyst and year fixed effects, which absorb all unobserved heterogeneity specific to each individual site-visit event. The sample sizes in Panel A differ from the baseline 18,144 observations in Table 4 because these high-dimensional fixed-effect structures absorb singleton groups. Specifically, Column (1) drops analyst-firm pairs observed only once during the sample period, since firm × analyst fixed effects offer no within-pair variation for identification in singleton groups; this restriction reduces the sample to 12,182 observations. Column (2) drops site-visit events attended by only one analyst, since within-event variation across analysts is required to identify the coefficients on *INFO* and *OBFU* when the site-visit fixed effect is included; this restriction reduces the sample from 18,144 to 17,705 observations. In Panel B, we implement the two-stage Heckman (1979) selection correction. Column (1) of Panel B reports the first-

stage probit modeling the probability that an analyst attends a site visit; the exclusion restriction is *HSR_CONNECT*, an indicator equal to one if high-speed rail service exists between the analyst's brokerage city and the firm's headquarters city in year *t*, and zero otherwise (Chen et al., 2022). Column (2) of Panel B reports the second-stage outcome equation with *ACCURACY* as the dependent variable, including the Inverse Mills Ratio (*INVERSE_MILLS*) computed from the first-stage probit. The larger first-stage sample size (38,127) relative to the second-stage sample of 18,144 thus reflects the inclusion of non-attendance observations required for identification of the selection equation. All specifications include the full set of baseline control variables. Detailed variable definitions are provided in Table 1. Standard errors clustered at the firm level are reported in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 8 External Validity Test: Market Reactions to the Information-Driven (INFO) and Obfuscation-Driven (OBFU) Components of Site-Visit Communication

VARIABLES	(1) CAR[-1, 1]
INFO	3.512***
	(1.087)
OBFU	-0.407**
	(0.178)
DA	-1.603*
	(0.965)
LEV	0.938
	(0.812)
SIZE	-1.520***
	(0.209)
RETURN_VOL	0.108***
	(0.003)
RETURN_MOM	0.348
	(0.279)
AFN	-0.065
	(0.086)
INST_OWN	0.016**
	(0.008)
SOE	0.086
	(0.316)
AFSTD	-0.445
	(0.386)
UE	-6.156*
	(3.446)
BAD_NEWS	-0.270
	(0.232)
DEPS	-0.354*
	(0.191)
SIMILARITY	-0.631
	(0.526)
QTONE	0.085
	(0.224)
ATONE	0.091
	(0.318)
GUIDANCE	0.438
	(0.429)
DATE_DIFF	0.083**
	(0.042)
Constant	31.652***
	(4.830)
Firm FE	Yes
Year FE	Yes
Quarter FE	Yes

Observations	24,078
Adjusted R-squared	0.107

Notes: This table reports market reactions to the information-driven and obfuscation-driven components of site-visit linguistic complexity, providing external validity for the INFO-OBFU decomposition. The dependent variable is *CAR[−1, +1]*. INFO and OBFU are the information-driven and obfuscation-driven components of linguistic complexity from the site-visit transcript. Firm, year, and quarter fixed effects are included. Detailed variable definitions are provided in Table 1. Standard errors clustered at the firm level are reported in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 9 Validating the Organizational Diffusion Mechanism: Heterogeneous Brokerage-Level Spillover Effects by Analyst Tenure

VARIABLES	(1) ACCURACY
INFO	2.965***
	(0.150)
INFO × TENURE	0.377***
	(0.047)
OBFU	-0.435***
	(0.031)
OBFU ×TENURE	-0.023**
	(0.010)
TENURE	0.158
	(0.223)
Control Variables	YES
Firm FE	YES
Analyst FE	YES
Year FE	YES
Observations	4,090,588
Adjusted R-squared	0.306

Notes: This table reports tests that validate the organizational diffusion mechanism underlying brokerage-level spillovers (H3) by examining how the site-visit analyst's tenure moderates the transfer of the analyst's expertise gained through a site visit. All specifications include the full set of control variables from our baseline analysis. Firm, analyst, and year fixed effects are included in all specifications. Detailed variable definitions are provided in Table 1. Standard errors clustered at the firm level are reported in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.