

Access versus Accuracy: Reappearance of Supportive Analysts ^{*}

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Abstract

We map IBES analyst price targets to transcripts of S&P 500 earnings-call Q&A sessions, constructing a new dataset of more than 28,000 analyst-firm-quarter observations from 2015 to 2023. We introduce a reappearance score that measures whether analysts regain access to the same firm’s future earnings-call Q&A sessions. We use this measure to examine whether price-target optimism, analyst tone, and question topics predict future access. Panel regressions show that analysts with above-consensus price targets, more positive tone, and certain topic choices are more likely to reappear. However, analysts with greater past reappearance also have larger forecast errors relative to the consensus, suggesting a trade-off between access and accuracy. By using large language models to match anonymized analyst records and measure tone and topics, the paper contributes to the literature on call casting, analyst incentives, price-target optimism, and the use of LLMs in financial text analysis.

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1. Introduction

Firms cannot script analysts’ questions, but they control who speaks during earnings calls. Managers often call on optimistic analysts and avoid those with tough questions. This practice, known as call casting, helps hide bad news and predicts future underperformance (Cohen, Lou, and Malloy, 2020, 2013). Analysts also have their own incentives. Those who ask early questions gain visibility and find better jobs, which encourages them to be polite and upbeat (Cen, Chen, Dasgupta, and Ragunathan (2016); Hilary and Hsu (2013)). Together, these forces shape what investors hear.

This paper studies whether analysts’ future access to earnings-call Q&A sessions is associated with their observable behavior. We ask whether analysts are more likely to reappear when they issue price targets above the consensus, use a more positive tone, or emphasize particular topics, and whether such behavior results in lower forecast accuracy. These questions are motivated by evidence that price targets and recommendations contain information but are also systematically optimistic (Brav and Lehavy, 2003; Asquith, Mikhail, and Au, 2005; Bradshaw, Brown, and Huang, 2013; Lim, 2001) and shaped by analyst incentives (Lin and McNichols, 1998; Michaely and Womack, 1999; Michaely, Womack, et al., 2005).

We build a new dataset of S&P 500 conference calls from 2015–2023. For each analyst, we record how often they speak, their price target relative to the consensus, the tone of their questions, and the topics they raise. Because the Institutional Brokers’ Estimate System (IBES) anonymized analyst and broker names after 2018, we develop with our own approach to link analysts to their price targets. We then compute each analyst’s reappearance score and forecast errors and study what are the drivers for each.

Our results show that analysts with optimistic price targets, positive sentiment and certain topic choices are more likely to reappear. We also find that bullish analysts have larger forecast errors than their peers. These findings suggest that access comes at the cost of accuracy. By quantifying reappearance and connecting it to tone and topics, our paper sheds light on incentives and trade-offs of conference call-casting.

1.1. Literature and Contribution

Research on analysts’ price targets documents both information content and systematic bias. Lim (2001) and Easterwood and Nutt (1999) show that price targets are often overly optimistic and that forecast errors have systematic components. Brav and Lehavy (2003) find that revisions to one-year targets generate significant abnormal returns even after controlling for recommendations, yet targets are on average 20–30% above market prices. Asquith et al. (2005) show that each component of an analyst report—earnings forecast, recommendation and target price—carries incremental information. Bradshaw et al. (2013) find that only about 40% of stocks reach their target within twelve months and that investors do not reward analysts with superior accuracy. Hilary and Hsu (2013) document that analysts with consistent forecast errors, often downward biases, gain recognition and that consistency matters more than accuracy. These findings imply that analysts may trade objectivity for reputation or access.

Cohen et al. (2020) show that managers “cast” conference calls by favoring bullish analysts; firms that call on optimistic analysts experience negative future earnings surprises and underperform peers. Such selective Q&A is more common when managers have bad news or are about to sell shares. Brown, Call, Clement, and Sharp (2019) document that investor-relations teams actively manage the Q&A queue, soliciting questions in advance and rehearsing answers. This practice can operate as a subtle form of selective disclosure. Cohen et al. (2013) argue that restricting skeptical analysts delays negative information and predicts later underperformance. Together, these studies indicate that analysts balance information gathering with appeasing management, shaping their behavior in Q&A sessions.

Analysts have strong incentives to gain access to management. Cen et al. (2016) show that early participation in earnings conference calls predicts analysts’ subsequent career outcomes following brokerage closures. They interpret early call participation as a signal of analyst-specific access to management and show that early participants engage more in strategic distortion between earnings forecasts and recommendations. Our paper builds on this access-based interpretation of conference call participation, but shifts the focus from analyst labor-market outcomes to whether analysts’ behavior inside the call is associated with future access to earnings-call Q&A sessions and if that access is related to forecast accuracy. Hilary and Hsu (2013) show that forecast consistency can matter more for price formation and analyst careers than conventional forecast accuracy.

They further argue that analysts may strategically issue downward-biased forecasts to improve consistency and maintain access to managerial information. They show that analysts strategically low-ball earnings to build a reputation for consistency and are more likely to be named all-star analysts. Malmendier and Shanthikumar (2014) go one step further and argue that analysts strategically communicate different signals across different outputs. Their “two-tongues” metric compares recommendation optimism with forecast optimism and identifies cases in which analysts issue optimistic recommendations while providing less optimistic forecasts. Mayew, Sethuraman, and Venkatachalam (2020) find that bearish analysts who miss forecasts produce more informative conversations; investors react more to their tone and managers’ vocal pitch.

Early research uses textual analysis to quantify economic and political risk. Baker, Bloom, and Davis (2016) develop an economic-policy-uncertainty index and show that high uncertainty predicts lower investment and employment. Hassan, Hollander, Van Lent, and Tahoun (2019) construct firm-level political-risk scores from earnings-call transcripts; firms with high political risk reduce hiring and investment and increase lobbying. Gentzkow, Kelly, and Taddy (2019) survey text-as-data methods and demonstrate how textual measures can forecast macro variables. Later studies move beyond word counts. Brown et al. (2019) show that increases in managerial negativity during calls predict lower future earnings and that investors under-react to tone changes. Recent work measures the specificity of analysts’ questions and finds that analysts ask more specific questions when they lack private information; managers respond defensively, and investors react negatively to such calls (Barcellos, 2025).

The emergence of large language models (LLMs) has expanded the tools available for text analysis. Bai, Boyson, Cao, Liu, and Wan (2023) compare executives’ answers in earnings calls with answers generated by ChatGPT; their “human–AI difference” measure predicts stock-price reactions and forecast revisions. Bybee, Kelly, Manela, and Xiu (2024) apply topic models to millions of Wall Street Journal articles and show that time-varying news attention tracks the business cycle. Katz, Bommarito, Gao, and Arredondo (2024) demonstrate that GPT-4 can pass the U.S. bar exam, illustrating LLMs’ ability to handle complex domain-specific text. Beckmann, Beckmeyer, Filippou, Menze, and Zhou (2024) classify Q&A segments as unusual or typical using ChatGPT and find that unusual communication explains lower returns and higher volatility. Lopez-Lira and Tang (2023) show that GPT-4 can predict immediate market reactions to news headlines. These studies suggest that LLMs can extract latent signals from financial texts and may

outperform traditional techniques.

The literature shows that analysts’ outputs contain both information and systematic bias. Prior work further documents that managers selectively allocate access during conference-call Q&A sessions, and that analysts value this access because it can reflect management connectivity, reputation, and career-relevant information advantages (Cohen et al., 2020; Cen et al., 2016). At the same time, analysts may strategically adjust forecasts, recommendations, and other forms of communication to preserve access and maintain relationships with management (Hilary and Hsu, 2013; Malmendier and Shanthikumar, 2014).

This paper contributes to the literature in three ways. First, we introduce analyst reappearance in earnings-call Q&A sessions as a direct measure of repeated access to management. Prior work shows that managers selectively allocate call access and that early participation reflects analyst connectivity and career-relevant reputation (Cohen et al., 2020; Cen et al., 2016). We extend this literature by studying not only who receives access in a given call, but whether analysts who appear today are more likely to obtain access again in future calls. Second, we link future access to analysts’ observable behavior. The literature documents that analysts face incentives to maintain management relationships and may strategically distort forecasts, recommendations, and other outputs (Hilary and Hsu, 2013; Malmendier and Shanthikumar, 2014). We examine whether similar incentives are visible inside the earnings call itself by relating future reappearance to analysts’ price target deviations from consensus, sentiment, and topic choices. Third, we combine conference-call transcripts with IBES price-target data at the analyst–firm–quarter level. This matched dataset allows us to connect soft communication inside the call to hard forecast outputs and subsequent access. Our evidence shows that analysts with more optimistic price targets and more positive tone are more likely to reappear, while access is also associated with larger forecast errors.

The next section describes our data and methods, detailing how we constructed a unique dataset of analyst (brokerage)–earnings call observations with associated analyst behavior and price targets. The rest of the paper is organized as follows. Section 3 provides summary statistics of our dataset. The subsequent analysis in Section 4 quantifies the relationships between analyst behavior and reappearance. Section 5 concludes.

2. Data and Methodology

2.1. Data Sources and Sample

Our empirical setting focuses on the Q&A sections of earnings conference calls for large U.S. firms. We obtain transcripts of the calls from Refinitiv. We restrict the sample to firms in the S&P 500 index and to calls held between January 2015 and December 2023, yielding several thousand call transcripts. Because the introductory remarks are largely scripted, we analyze only the Q&A sessions where analysts ask questions and managers respond. Accounting data (e.g., total assets, book-to-market, momentum) come from Compustat. Price-target and brokerage information are drawn from the IBES database. The IBES data provide time-stamped price targets but, due to a post-2018 anonymization policy, record only the analyst’s surname and initial together with an anonymized brokerage identifier. This anonymization prevents a direct merge of analyst names from transcripts with price-target data. Our approach overcomes this issue by using a large language model to extract analyst identities and brokerages from the transcripts and then uniquely mapping them to the IBES records. Table 10 in Appendix A reports the 50 most frequently observed brokerages in our sample and their matched IBES broker identifiers. We cross-check the resulting mappings against prior approaches to identifying IBES broker codes, including Law (2023). Several identifiers closely resemble the brokerage name, such as *CANACCOR* for Canaccord Genuity and *GOLDMAN* for Goldman Sachs. Others are less transparent, such as *LAWRENCE* for Deutsche Bank.

2.2. ChatGPT Prompting Strategy

To extract structured information from unstructured call transcripts, we use a multi-layer prompting strategy with ChatGPT. This approach follows recent work that uses large language models to identify topics from text, such as Pham, Hoyle, Sun, Resnik, and Iyyer (2024) and Fieberg, Hesse, Liedtke, and Zaremba (2025). In our setting, each Q&A transcript from S&P 500 earnings calls is submitted to the model with detailed task-specific instructions.

In the first layer, ChatGPT reads the full Q&A section and identifies analyst-level statements. For each statement, the model assigns one or more high-level topics, cites the original statement number, and separates multiple topics. This step produces analyst-

statement-level topic classifications for the full transcript. In the second layer, we provide ChatGPT with the specific topics generated in the first layer and ask the model to group them into a smaller set of high-level categories. The instructions require the categories to be mutually exclusive and assign each specific topic to exactly one high-level topic. This procedure yields 20 high-level topics and one catch-all category, *None of the above*. We then use these 21 categories in a final classification prompt, in which ChatGPT re-reads each transcript and assigns every analyst statement to one topic while citing the original statement number. This step produces topic counts at the analyst-call level. In the third layer, ChatGPT classifies the sentiment of each analyst interaction. In a separate extraction step, the model identifies each analyst’s position, when available, such as junior or senior analyst, and the analyst’s brokerage or employer from the transcript. These fields allow us to link the transcript data to the anonymized IBES data. We first apply the prompts to a random subsample of 1,000 Q&A transcripts to calibrate the topic taxonomy. We then apply the final prompts to the full sample. For each earnings call, the prompt extracts analyst-level identifiers and classifies how often each analyst raises each topic, as well as the sentiment of the analyst’s interaction.

After extracting analyst information from the conference call transcripts, we merge this data with IBES price-target forecasts. Since IBES reports only the analyst surname and first initial, we match analysts using surname, first initial, call date, and brokerage. We construct a lookup table of unique analyst-firm-quarter appearances and corresponding IBES price targets. Using the analyst information from Refinitiv, we map anonymized IBES brokerage identifiers to brokerage names. This procedure yields a unique, quarterly analyst-brokerage-call dataset that links analyst behavior in earnings calls to price target forecasts.

To mitigate look-ahead concerns, we use ChatGPT only to classify analysts’ statements by topic and sentiment. The prompts do not ask the model to assess stock-price implications, forecast future outcomes, or identify links to financial markets. This design limits the scope for the model to exploit ex post information and keeps the classification task close to the text observed at the time of the call. Recent evidence suggests that look-ahead bias in LLM-based financial text applications is limited in practice. Chen, Kelly, and Xiu (2022) show that LLM-based return predictions are not driven by look-ahead bias, while He, Lv, Manela, and Wu (2025) and Kelly, Malamud, Schwab, and Xu (2026) find that chronologically consistent LLMs and point-in-time models produce similar conclusions.

3. Summary Statistics

This section introduces the dataset constructed in Section 2 and provides descriptive evidence on analyst behavior in earnings calls. We first describe what analysts ask about, then examine which analysts and brokerages appear in the calls, how their sentiment and price targets vary across observations, and how often analysts reappear for the same firms.

3.1. Price Targets

Our dataset contains 28,181 individual analyst one-year price targets and 7,791 IBES consensus price targets. The consensus expected return is positive on average, with a mean of 11.60%, a median of 10.55%, and a standard deviation of 9.28%. The distribution ranges from -68.71% to 88.88%. These summary statistics indicate that the IBES consensus is generally optimistic over our sample period, which is consistent with prior literature.

Figure 1 plots the distribution of price target deviations from the IBES consensus for the 28,181 individual targets by those analysts who appear in S&P 500 earnings conference calls.

$$\text{PT Deviation}_{i,k,t} = PT_{i,k,t}^{12m} - \text{ConsensusPT}_{i,t}^{12m}. \quad (1)$$

The deviation is defined as the difference between the analyst’s price target and the consensus price target for the same firm-quarter. Eq. (1) shows the calculation for firm i , analyst k , at time t . We match IBES price targets to earnings call events using the most recent price target issued no more than 90 days before the call. The average and median deviation are both approximately 0.01, with a standard deviation of 0.12. The observed deviations range from -0.90 to 1.67. Thus, analysts who participate in earnings calls issue price targets that are, on average, about one percentage point above the IBES consensus. This suggests a modest upward tilt relative to the broader analyst consensus, while the standard deviation and range indicate substantial cross-sectional variation in relative price target optimism.

Table 5 in Appendix A reports the results from regressing analysts’ price target deviations from the consensus on firm characteristics. As expected, greater analyst dispersion is associated with larger deviations from the consensus. Interestingly, profitability is also

strongly related to price target deviations, suggesting that analysts deviate more from the consensus when covering highly profitable firms.

Taken together, these descriptives suggest that analyst optimism is a meaningful source of variation in the sample. While the average earnings-call participant is only modestly more optimistic than the IBES consensus, the dispersion in price target deviations is substantial.

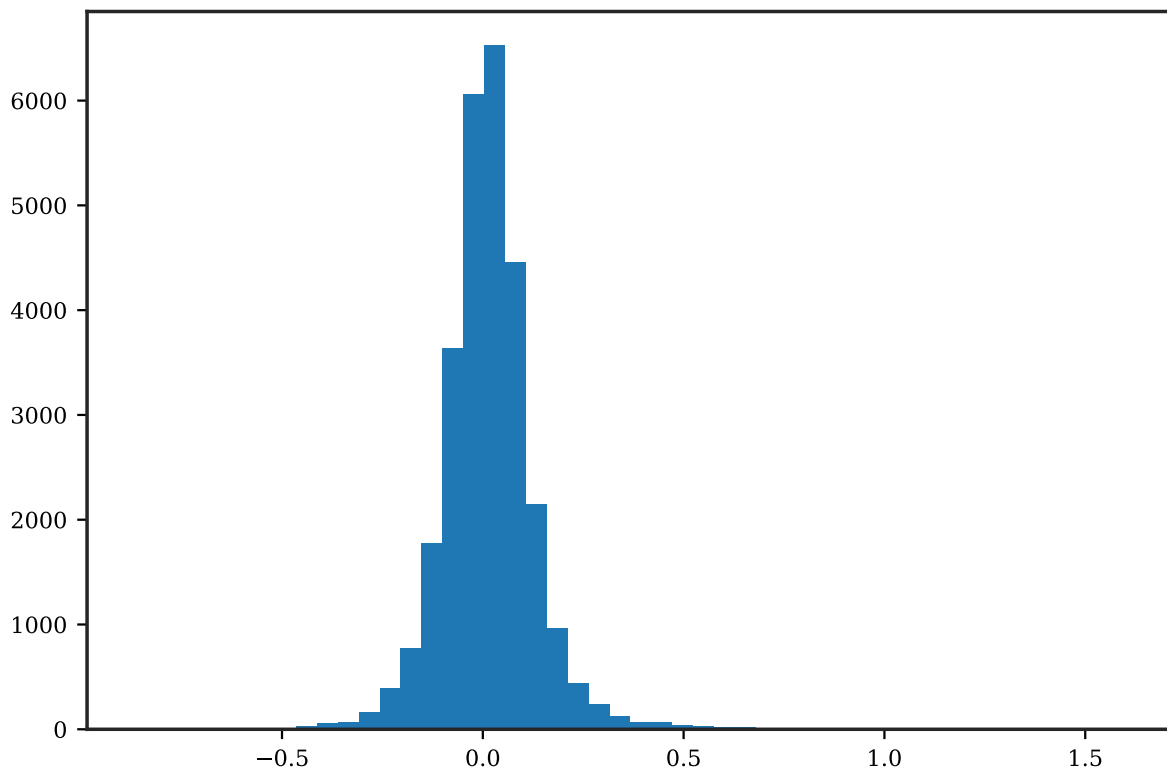


Fig. 1. Price Target Deviation

This figure shows the distribution of analysts' price target deviations from the consensus. The variable is measured as the difference between an analyst's individual expected return and the mean expected return across analysts for the same firm and call. Positive values indicate price targets above the consensus, while negative values indicate price targets below the consensus. The histogram illustrates how strongly individual analysts deviate from the consensus in their price target forecasts.

3.2. Topic Distribution

The prompting strategy in Section 2 generates 20 topical clusters (plus a catch-all category) that summarize the content of analysts' questions. These topics span a wide range of issues. They include, for example, questions about market performance and the com-

petitive environment, financial guidance and projections, supply-chain and operational problems, business segment performance and growth drivers, consumer behavior and market trends, cost management and efficiency, technological innovation, and environmental, social and governance (ESG) initiatives.

Table 1 summarizes how often each topic appears in analyst questions. Analysts focus most frequently on business segment performance and growth drivers (33.18% of all statements) and on financial metrics and performance analysis (31.47%). Questions about forward-looking financial guidance account for 21.07% of statements. Pricing strategy and gross margin implications (15.62%) and cost management and efficiency initiatives (11.11%) round out the top five topics. Other common topics include supply chain and operational issues (10.23%) and product development and launches (10.11%). Less common topics include investment plans and strategy (7.69%), technological advancements and innovation (6.01%), and international business and market conditions (5.38%). The catch-all “None of the above” category captures 9.73% of statements, indicating that our high-level taxonomy covers most of the questions.

Table 1: Analyst Topic Distribution

This table reports how often analysts talk about each of the topics. The table shows the proportions over all analyst interactions in the sample.

Topic	Average (%)
Business Segment Performance and Growth Drivers	33.18
Financial Metrics and Performance Analysis	31.47
Financial Guidance and Projections	21.07
Pricing Strategy and Gross Margin Implications	15.62
Cost Management and Efficiency Initiatives	11.11
Supply Chain and Operational Issues	10.23
Product Development and Launches	10.11
None of the above	9.73
Competitive Landscape and Market Share	8.84
Regulatory and Economic Impact	8.81
Capital Allocation and Shareholder Returns	8.77
Consumer Behavior and Market Trends	8.67
Mergers and Acquisitions (M&A) Strategy	8.15
Investment Plans and Strategy	7.69
Technological Advancements and Innovation	6.01
International Business and Market Conditions	5.38
Strategic Partnerships and Collaborations	4.70
Market Performance and Competitive Environment	3.67
Raw Materials and Commodity Prices	2.87
Advertising and Marketing Spend	1.92
Environmental, Social, and Governance (ESG) Initiatives	0.97

The dominance of performance-related questions echoes prior work showing that analysts emphasize near-term earnings and growth drivers and tend to avoid difficult or sensitive topics. Questions about ESG and advertising appear rarely, suggesting that such areas remain peripheral. Analysts’ emphasis on financial metrics and guidance is consistent with prior evidence that management favors optimistic questions. This may reflect management’s ability to select specific analysts when their questions are known in advance (Cohen et al., 2020).

Table 6 in Appendix A shows the results of descriptive regressions of the analyst topics on firm characteristics. We find that topics such as business segment performance and growth drivers are addressed significantly less often in calls of larger firms, but significantly more often in calls of firms with high momentum. Also, regulatory and economic impact is significantly more often addressed in calls of larger firms while consumer behavior and market trends more often in calls of smaller firms. Interestingly, product development is addressed significantly less often in calls of highly profitable firms. This coefficient is also among the largest in magnitude in the analysis.

3.3. Analyst Sentiment

The ChatGPT sentiment analysis assigns each analyst–firm–quarter interaction a tone of positive, neutral or negative. Across the sample we count 28,181 of these interactions. Neutral tone dominates, accounting for 76.92% of interactions. Positive sentiment represents 21.64% of interactions, while negative sentiment accounts for 1.44%. Analyst sentiment varies over time, dipping during the economic uncertainty of 2020 Q1 and Q2 and rebounding in later quarters. Negative tone by analysts remains relatively rare. Figure 2 shows the proportions of analyst interactions in Q&A sessions over one year. We find that neutral sentiment remains the dominant category when analyst interactions are aggregated by year. In every year, the share of positive interactions is higher than the share of negative interactions. Positive sentiment varies more noticeably over time and increases by several percentage points in some years, such as 2021. Negative sentiment, in contrast, remains relatively low and does not show increases of similar magnitude. When calculating the quarterly proportions the resulting figure looks quite similar as can be seen in Figure 4 in Appendix A.

We also regress the mean analyst sentiment score of each earnings call on firm characteristics. The results suggest that analyst sentiment is higher in calls of smaller firms and

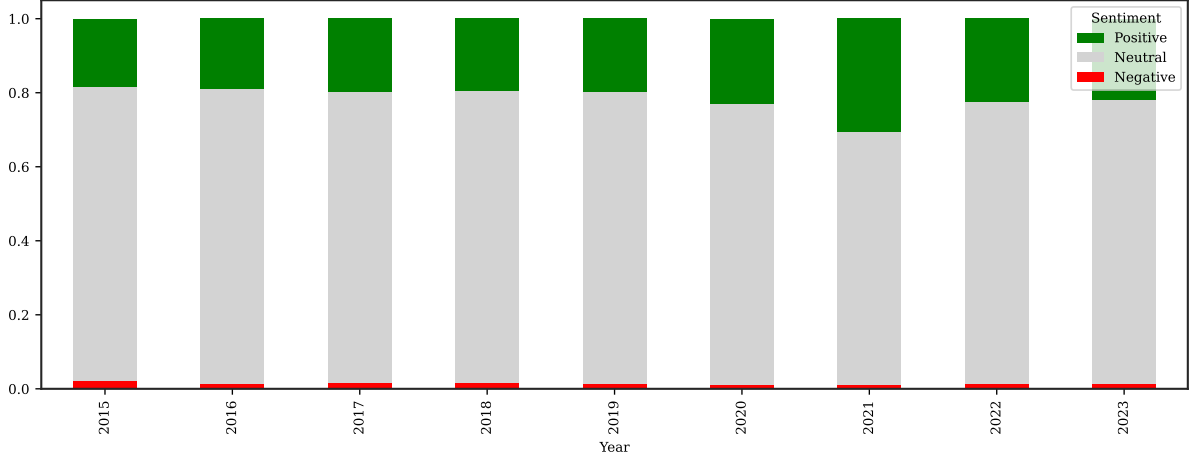


Fig. 2. Analyst Sentiment

This figure shows the yearly proportions of analyst interactions classified as *Negative*, *Neutral*, or *Positive*. For each year, we pool all analyst interactions across all earnings calls and compute the share of interactions in each sentiment category.

firms with stronger momentum. We also find that lower analyst dispersion is associated with a more positive tone, while interestingly, a higher analyst coverage is positively related to average call sentiment. The results can be found in Table 7 in Appendix A. This pattern hints towards strategic tone-setting by analysts that seek access or differentiation in more competitive information environments.

Table 2 reports the results from regressing analyst sentiment on question topics. The table shows that analyst sentiment differs substantially across question topics. We find that topics such as business segment performance and growth drivers, product development and launches, and ESG initiatives are associated with significantly more positive sentiment. In contrast, topics such as raw materials and commodity prices, as well as regulatory and economic impact, are associated with more negative sentiment. This pattern suggests that analysts adopt a more favorable tone when discussing growth opportunities, innovation, and strategic initiatives, while their tone becomes more negative when addressing operational constraints, margins, input costs, and financial performance. The results are consistent with the idea that analyst sentiment reflects not only the analyst’s general attitude toward the firm, but also the economic content and sensitivity of the question. Topics that allow management to emphasize future opportunities tend to be framed more positively, whereas topics that require discussion of current performance pressures or risks carry a less favorable tone. These findings complement the descriptive evidence on question topics. While analysts frequently focus on financial performance

Table 2: Analyst Topics & Sentiment

This table reports the regression results of analyst sentiment on question topics at the analyst-interaction level. Positive coefficients indicate that interactions mentioning the topic are associated with more positive analyst sentiment, while negative coefficients indicate more negative sentiment. *** (**, *) denotes statistical significance at the 1% (5%, 10%) level.

Topic	Sentiment
Business Segment Performance and Growth Drivers	0.06***
Financial Metrics and Performance Analysis	-0.05***
Financial Guidance and Projections	-0.05***
Pricing Strategy and Gross Margin Implications	-0.03***
Cost Management and Efficiency Initiatives	-0.06***
Supply Chain and Operational Issues	-0.06***
Product Development and Launches	0.10***
Competitive Landscape and Market Share	0.01
Regulatory and Economic Impact	-0.07***
Capital Allocation and Shareholder Returns	-0.02***
Consumer Behavior and Market Trends	0.02***
Mergers and Acquisitions (M&A) Strategy	-0.01
Investment Plans and Strategy	0.02*
Technological Advancements and Innovation	0.11***
International Business and Market Conditions	0.04***
Strategic Partnerships and Collaborations	0.12***
Market Performance and Competitive Environment	-0.04***
Raw Materials and Commodity Prices	-0.08***
Advertising and Marketing Spend	-0.02
Environmental, Social, and Governance (ESG) Initiatives	0.11***

and guidance, these topics are not necessarily associated with more positive sentiment. Instead, the most positive tone appears in questions related to growth narratives, innovation, partnerships, and ESG. This distinction is important because it suggests that analysts’ strategic communication operates along two dimensions: what topics they choose to raise and how favorably they frame those topics.

For comparison with more traditional models, we measure Q&A sentiment using FinBERT from ProsusAI (2020), a language model trained on financial text. To compare FinBERT with our ChatGPT-based measure, we aggregate analyst-level ChatGPT sentiment to the call level and compare it with FinBERT sentiment for the full Q&A session. The two measures agree in 46.69% of calls. Most disagreements arise when FinBERT classifies a Q&A session as *Neutral*, while ChatGPT classifies the aggregated analyst sentiment as *Positive*. This comparison should be interpreted with caution. The two models differ in architecture and training, and they are applied to different text units: ChatGPT measures analyst tone, whereas FinBERT measures sentiment for the full Q&A session,

including executives and moderators. We therefore use this exercise as a sanity check for the ChatGPT-based sentiment measure.

3.4. Brokerages

Another way to characterize analyst access is to examine brokerage affiliation. Our matching procedure links analyst-call observations to the brokerage employing the analyst, allowing us to observe not only which analyst speaks in a given call and after which price target, but also the analyst’s brokerage. The sample of appearances in S&P 500 earnings conference falls from 2015 to 2023 contains 118 brokerages. Goldman Sachs has the most appearances, with more than 2,900, followed by Bank of America Merrill Lynch with almost 2,500. Barclays and Deutsche Bank each account for roughly 1,700 appearances. Larger brokerages also appear to cover broader firm sets, with their analysts covering more than three firms on average, compared with about two firms or one firm for smaller brokerages. Table 8 in Appendix A provides an overview of the 50 largest brokerages, their total number of appearances, the number of analysts working for them, the number of firms they cover, and the average number of firms per analyst.

Table 9 in Appendix A summarizes analyst behavior at the brokerage level. The table shows whether brokerage affiliation is associated with systematic differences in price target optimism and sentiment. The largest brokerages exhibit only limited deviations from the price target consensus. Their average sentiment scores are also close to the sample mean of 0.22. Bank of America Merrill Lynch, Deutsche Bank, and JPMorgan are slightly below the mean, with average sentiment scores between 0.17 and 0.18, while Evercore ISI is above the mean at 0.27. Among the top 50 brokerages, Wolfe Research and Bernstein have relatively low sentiment scores of 0.12 and 0.06, whereas Oppenheimer and Canaccord Genuity stand out with higher scores of 0.37 and 0.43.

Figure 7 in Appendix A shows topic intensity across the 50 largest brokerages. The figure indicates that brokerage-level topic choices largely mirror the aggregate distribution of topics in the full sample. The most frequently discussed topics are broadly similar across brokerages, and the least frequently discussed topics are also consistently less common. Thus, the heatmap provides little evidence that large brokerages systematically specialize in distinct question topics.

Overall, the brokerage-level descriptives show that analyst access is concentrated among a small set of large brokerages, but that these brokerages do not differ sharply in their

average price target optimism, sentiment, or topic choices. The main brokerage-level difference is scale: larger brokerages account for more appearances and broader firm coverage. In contrast, analyst behavior appears broadly similar across major brokerages, suggesting that the key variation in our setting is more likely to arise at the analyst-firm level than at the brokerage level.

3.5. Analyst Reappearance

After applying our matching and filtering procedures, the final sample contains 2,577 unique analysts covering 294 unique companies. Coverage is uneven: almost 1,000 analysts appear only in a single company’s earnings calls, over 500 analysts appear in calls at two companies, and more than 1,000 analysts appear at three or more companies. On average, one analyst covers about 2.6 companies. This reflects the fact that brokerage houses assign analysts to cover multiple firms within a sector. The distribution also underscores that many analysts build long-term relationships with firms, a dynamic explored in the call-casting literature.

We measure analyst reappearance using a forward-looking score. For each analyst-firm-quarter observation, the score equals the fraction of the analyst’s future active quarters in which the analyst appears again in the same firm’s earnings call. We define an analyst as active in a quarter if the analyst appears in any S&P 500 earnings conference call.

$$\text{Reappearance}_{i,k,t}^+ = \frac{\sum_{\tau>t} \mathbb{1}\{k \text{ appears for firm } i \text{ in quarter } \tau\}}{\sum_{\tau>t} \mathbb{1}\{k \text{ appears in any earnings call in quarter } \tau\}} \quad (2)$$

The numerator in Eq. (2) counts the number of future quarters in which analyst k appears again in firm i ’s call. The denominator counts the number of future quarters in which analyst k is active in any S&P 500 call. The score ranges from zero to one. A value of zero means that the analyst does not return to the firm during the analyst’s remaining active time in the sample. A value of one means that the analyst appears in the firm’s call in every future quarter in which the analyst is active. We set the score to missing when the analyst has no future active quarters.

In total we count 24,670 analyst-firm-quarter combinations of reappearance. Figure 5 in Appendix A shows the distribution of those combinations. Averaged over all quarters, we see that reappearance is rather evenly distributed with a slight skew to the right. Yet still, several hundred observations correspond to analysts who reappear in almost

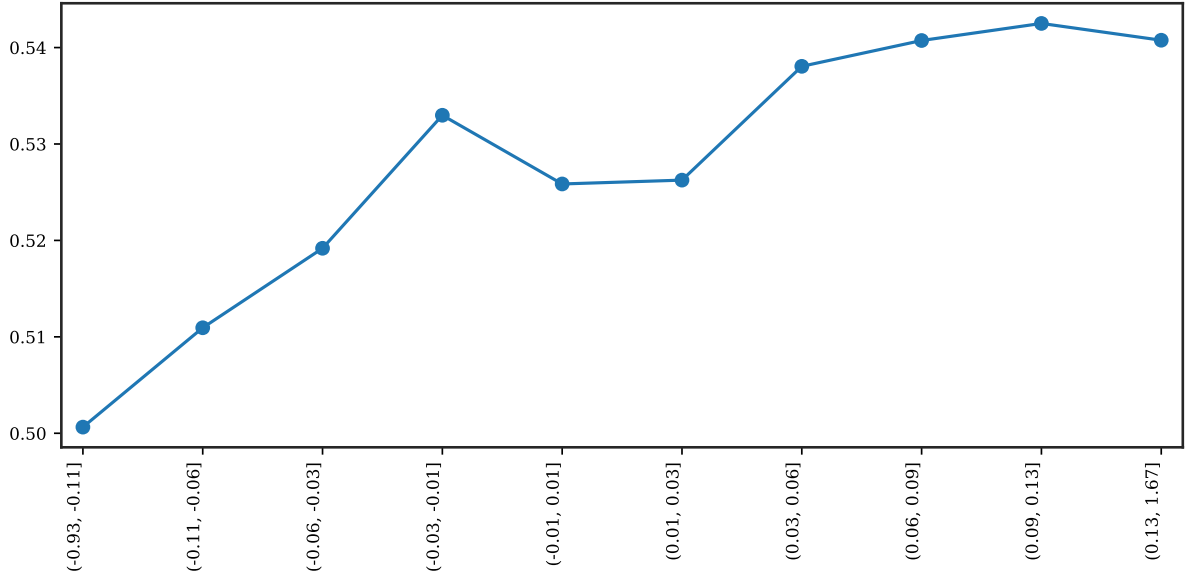


Fig. 3. Analyst Sentiment & Price Target Deviation

This figure shows the relationship between price target optimism and future reappearance. Analyst-firm-quarter observations are sorted into ten bins based on the analyst's price target deviation from the consensus. For each bin, the figure reports the average future reappearance score. The measure captures how often an analyst appears again for the same firm in future active quarters.

every future active quarter. The mean reappearance is at 0.53, the median is at 0.50, the standard deviation is at 0.34.

Figure 3 shows the relationship between analysts' price target deviations from the consensus and their forward-looking reappearance scores. The figure indicates a positive unconditional association between relative price target optimism and future reappearance. Analysts with higher price targets relative to the consensus tend to exhibit higher reappearance scores. This pattern appears to be driven particularly by analysts who issue price targets below the consensus, as these observations are associated with lower future reappearance in the absence of controls.

Figure 6 in Appendix A plots the mean future reappearance score for the three sentiment categories, where -1 denotes *Negative*, 0 denotes *Neutral*, and 1 denotes *Positive* analyst sentiment. In this unconditional comparison, future reappearance is higher for observations with positive sentiment than for observations with negative sentiment. The distribution of sentiment categories is highly uneven. ChatGPT classifies 368 analyst-firm-quarter observations as negative, 5,322 as positive, and 18,970 as neutral. Overall, the descriptive evidence suggests that analyst reappearance is positively related to above-consensus price targets and more positive sentiment.

3.5.1. Topics, Tone, and Reappearance

The descriptive evidence points to a clear pattern in analyst behavior. Analysts mostly ask about core financial topics. Business segment performance, financial metrics, and guidance are the most common topics. More sensitive or less central topics, such as ESG and advertising, appear much less often. This pattern is consistent with prior evidence that analysts focus on near-term earnings and growth drivers and often avoid more difficult topics.

Analyst tone also varies with question content. Questions about growth opportunities, product development, innovation, strategic partnerships, and ESG are associated with more positive sentiment. Questions about costs, supply chains, regulation, raw materials, margins, and financial performance are associated with more negative sentiment. Thus, analysts do not only choose which topics to raise. They also vary how favorably they frame those topics. This distinction is important for our setting because access may depend on both the content and the tone of analyst questions.

The reappearance patterns are consistent with this interpretation. Analysts who issue price targets above the IBES consensus tend to have higher future reappearance scores. Positive analyst sentiment is also associated with higher future reappearance in the unconditional evidence. These patterns suggest that more favorable analyst behavior may be related to future access to management. This interpretation aligns with the call-casting literature, which argues that managers can shape the Q&A by selecting analysts and may favor analysts who ask less confrontational or more supportive questions.

These descriptive results motivate our panel regressions. We expect future reappearance to be positively related to analyst optimism and favorable tone, after controlling for analyst, firm, and time variation. We also expect the relation to depend on question content. Topics that allow for growth-oriented or less confrontational framing should be associated with greater reappearance, while topics that emphasize risks, costs, or operational constraints may be associated with lower reappearance.

4. Empirical Results

This section presents the core empirical findings. We begin by outlining the econometric framework, linking the measurement strategy to our hypotheses. We then discuss the results of two panel regressions: one that explains analysts' reappearance scores in firms' earnings calls and another that uses a backward looking reappearance score to explain forecasting errors.

4.1. Empirical Framework

We analyze a panel of analyst–firm–quarter observations covering the years 2015–2023. The dependent variable in the first regression is a forward-looking measure. We calculate the analyst's rolling future reappearance score, defined as the number of times an analyst returns to a firm's earnings calls divided by the number of opportunities to do so (see Eq. (2)).

Price target optimism, sentiment, and topic choice are the main explanatory variables in our empirical framework. Price target optimism is measured as the analyst's current price target deviation from the consensus (see Eq. (1)). A positive value indicates that analyst k is more optimistic about firm i in quarter t than the consensus. If managers give more access to bullish analysts, we expect a positive coefficient on this variable.

To measure analysts' past behavior, most prior works focus on the past 12 months. We want to offer a more long-term perspective. In our study, sentiment captures the analyst's tone in past earnings calls with the same firm. Using ChatGPT, we classify each analyst's tone as positive, neutral, or negative, as described in Section 2. We code sentiment as $S_{i,k,t} = 1$ for positive tone, $S_{i,k,t} = 0$ for neutral tone, and $S_{i,k,t} = -1$ for negative tone. In the regressions, we use the analyst's average past sentiment in calls of the same firm:

$$\text{Sentiment}_{i,k,t}^- = \frac{1}{N_{i,k,t}^-} \sum_{\tau < t} \mathbb{1}\{k \text{ appears for firm } i \text{ in quarter } \tau\} S_{i,k,\tau}, \quad (3)$$

where $N_{i,k,t}^-$ is the number of prior quarters in which analyst k appears in firm i 's earnings call. We use past sentiment because we examine whether earlier behavior predicts future reappearance. If a more positive tone increases future access, we expect a positive

coefficient on sentiment.

Topic choice captures the topics that an analyst raised in past calls with the same firm. For each topic m , we measure the analyst's past topic exposure as the average share of prior interactions with firm i that discussed topic m :

$$\text{Topic}_{i,k,t}^{m,-} = \frac{1}{N_{i,k,t}^-} \sum_{\tau < t} \mathbb{1}\{k \text{ appears for firm } i \text{ in quarter } \tau\} T_{i,k,\tau}^m. \quad (4)$$

Here, $T_{i,k,\tau}^m$ is the share of analyst k 's interaction with firm i in quarter τ assigned to topic m . The denominator $N_{i,k,t}^-$ is the number of prior quarters in which analyst k appears in firm i 's earnings call. These variables capture whether the analyst's past question content predicts future reappearance. For example, topics such as mergers and acquisitions strategy or financial guidance and projections may be useful for managers because they allow them to discuss favorable information. The topic coefficients show whether past exposure to a given topic is associated with higher future reappearance.

We also include control variables. The control vector $C_{i,t}$ contains firm characteristics, analyst coverage, and standardized unexpected earnings. The firm characteristics are momentum, book-to-market, size, investment, profitability, maximum return, illiquidity, and price. Analyst coverage, following Zhang (2006), measures the number of analysts following the firm. Analyst dispersion, following Diether, Malloy, and Scherbina (2002), measures disagreement among analysts, defined as the standard deviation of analysts' earnings forecasts scaled by the absolute value of the mean forecast. We include standardized unexpected earnings to control for earnings news. We calculate this component following Engelberg, McLean, and Pontiff (2018). We use actual earnings and mean consensus forecast for firm i at time t :

$$\text{SUE}_{i,t} = \frac{\text{Actual Earnings}_{i,t} - \text{Analyst Mean Consensus}_{i,t-1}}{\text{Stock Price}_{i,t-1}}. \quad (5)$$

We use the most recent consensus forecast available before the earnings call, considering only forecasts issued between 90 days before the call and the day prior to the call. Quarter fixed effects absorb common time shocks. Analyst fixed effects absorb persistent analyst-level differences, such as baseline optimism, experience, skill, and general access advantages. Standard errors are two-way clustered by analyst and firm.

The reappearance regression thus takes the form

$$\begin{aligned} \text{Future Reappearance}_{k,i,t+1} = & \beta_1 \text{PTDeviation}_{k,i,t} + \beta_2 \text{Sentiment}_{k,i,t-1} + \beta_3' \text{Topics}_{k,i,t-1} \\ & + \boldsymbol{\theta}' C_{i,t} + \mu_k + \lambda_t + \varepsilon_{k,i,t}, \end{aligned} \quad (6)$$

where k indexes analysts, i indexes firms, and t indexes quarters. The dependent variable is the analyst's future cumulative reappearance for a given firm. $\text{PTDeviation}_{k,i,t}$ denotes the current one-year price target deviation from the consensus (see Eq. (1)), $\text{Sentiment}_{k,i,t-1}$ denotes past sentiment (see Eq. (3)), and $\text{Topics}_{k,i,t-1}$ is a vector of past topic-choice indicators (see Eq. (4)). The vector $C_{i,t}$ contains firm-level and analyst-level controls, while μ_k and λ_t denote analyst and quarter fixed effects, respectively. A positive coefficient indicates that the corresponding analyst behavior is associated with higher future cumulative reappearance. Our hypotheses predict that more optimistic price targets, more positive past tone, and certain supportive topic choices should increase reappearance scores.

The second regression examines whether access-related behavior comes at a cost to forecast accuracy. The dependent variable is the analyst's 12-month forecast error relative to the consensus forecast error. We measure relative forecast accuracy by comparing each analyst's forecast error with the forecast error of the IBES consensus. For analyst k covering firm i at time t , we define

$$\text{Relative Forecast Error}_{i,k,t} = \left| ER_{i,k,t}^{12m} - R_{i,t}^{12m} \right| - \left| \overline{ER}_{i,t}^{12m} - R_{i,t}^{12m} \right|. \quad (7)$$

Here, $ER_{i,k,t}^{12m}$ is the analyst's implied one-year expected return, $\overline{ER}_{i,t}^{12m}$ is the IBES consensus expected return, and $R_{i,t}^{12m}$ is the realized one-year stock return. Positive values indicate that the analyst is less accurate than the consensus. Negative values indicate that the analyst is more accurate than the consensus.

We regress this relative forecast error on past reappearance. Past reappearance is the backward-looking counterpart to the forward-looking reappearance score from Eq. (2). It measures how often analyst k has already appeared in firm i 's earnings calls, relative to the analyst's prior active quarters in the sample. We define it as

$$\text{Past Reappearance}_{i,k,t}^- = \frac{\sum_{\tau < t} \mathbb{1}\{k \text{ appears for firm } i \text{ in quarter } \tau\}}{\sum_{\tau < t} \mathbb{1}\{k \text{ appears in any earnings call in quarter } \tau\}}. \quad (8)$$

The numerator counts the number of prior quarters in which analyst k appeared in firm i 's call. The denominator counts the number of prior quarters in which analyst k was active in any S&P 500 earnings call. The measure is set to missing when the analyst has no prior active quarters. We then estimate

$$\text{Relative Forecast Error}_{i,k,t} = \gamma_1 \text{Past Reappearance}_{i,k,t}^- + \boldsymbol{\theta}' C_{i,t} + \mu_k + \lambda_t + \varepsilon_{i,k,t}. \quad (9)$$

We use the same controls as in the reappearance analysis. Under our hypothesis, access-seeking behavior may come at the cost of forecast accuracy. We therefore expect γ_1 to be positive.

4.2. Determinants of Reappearance

Table 3 reports the results of estimating equation (6). Column (1) includes price-target optimism, sentiment and the topic indicators using firm characteristics, analyst coverage, analyst dispersion, and quarter and analyst fixed-effects as controls; column (2) adds standardized unexpected earnings as an additional control. We add standardized unexpected earnings separately because earnings surprises may affect both analysts' behavior during the call and their future access. For example, managers may be more willing to engage with analysts after positive earnings news, while negative surprises may lead to more difficult or critical questions. Including SUE allows us to test whether the relation between analyst behavior and future reappearance is distinct from the information content of the earnings announcement. The results are consistent over the two specifications. First, we find that an analyst's price target relative to the consensus is strongly and positively associated with reappearance. A one-unit increase in price target optimism is associated with an increase of 9 percentage points in the reappearance score. The coefficient is statistically significant at the 1% level, supporting the hypothesis that managers reward bullish analysts. Second, the tone of an analyst's questions has a positive impact on reappearance. An analyst with more positive past sentiment in calls of

Table 3: Analyst Future Cumulative Reappearance

This table reports panel regressions of analysts' future cumulative reappearance on their current price target deviation from the consensus, past sentiment, and past topic choices. We control for differences in the characteristics of the affected firms (Chars), the analyst coverage (Cvg.) following Zhang (2006), analyst forecast dispersion (Disp.) following Diether et al. (2002), and the standardized unexpected earnings component (SUE) following the definition in Eq. (5). For all specifications we include analyst and calendar quarter fixed effects. Standard errors are two-way clustered by analyst and firm. *** (**, *) denotes statistical significance at the 1% (5%, 10%) level.

Future Cumulative Reappearance	(1)	(2)
Current Price Target - Mean	0.09***	0.09***
Past Sentiment	0.04***	0.04***
Business Segment Performance and Growth Drivers	0.04***	0.04***
Financial Metrics and Performance Analysis	0.04***	0.04***
Financial Guidance and Projections	0.03**	0.03**
Pricing Strategy and Gross Margin Implications	0.02	0.02
Other Topic	0.00	0.00
Cost Management and Efficiency Initiatives	0.01	0.01
Product Development and Launches	0.02	0.02
Supply Chain and Operational Issues	0.06***	0.06***
Competitive Landscape and Market Share	0.06***	0.06***
Regulatory and Economic Impact	-0.00	-0.00
Capital Allocation and Shareholder Returns	0.04*	0.04*
Consumer Behavior and Market Trends	0.01	0.01
Mergers and Acquisitions (M&A) Strategy	0.02	0.02
Investment Plans and Strategy	0.01	0.01
Technological Advancements and Innovation	0.03	0.03
International Business and Market Conditions	0.03	0.03
Strategic Partnerships and Collaborations	0.00	0.00
Market Performance and Competitive Environment	-0.00	-0.00
Raw Materials and Commodity Prices	0.03	0.03
Advertising and Marketing Spend	-0.01	-0.00
Environmental, Social, and Governance (ESG) Initiatives	-0.04	-0.04
Chars	×	×
Cvg., Disp.	×	×
SUE		×
Quarter	×	×
Analyst	×	×
R^2	0.02	0.02
N	16,963	16,963

the same firm has a higher future reappearance score. We find that a one-unit increase in sentiment corresponds to a 4-percentage-points higher reappearance score, while also significant at the 1% level. Third, the topic coefficients show that not all question topics are equally associated with future access. Analysts are more likely to reappear when they have previously asked about business segment performance, financial metrics, financial

guidance, supply chain issues, and the competitive landscape. These effects are positive and statistically significant at the 1% level, with coefficients between 0.03 and 0.06. Economically, this means that those analysts who more frequently raised these topics in past calls with the same firm have future reappearance scores that are about 3 to 6 percentage points higher. Capital allocation and shareholder returns is also positively related to reappearance, but only at the 10% level. In contrast, most other topics are small and statistically insignificant, suggesting that they do not meaningfully predict future access once price target optimism, past sentiment, controls, analyst fixed effects, and quarter fixed effects are included.

The inclusion of control variables and fixed effects (column (2)) leaves the main coefficients largely unchanged. The model's R^2 is low (around 0.02), suggesting that individual access depends on many unobserved factors (e.g. personal relationships, brokerage reputation). Nevertheless, the significant coefficients on price targets, sentiment and selective topics provide clear evidence that bullish analysts enjoy greater access.

4.3. Determinants of Forecast Errors

Table 4: Analyst Forecast Error

This table reports panel regressions of analysts' 12-month forecast errors relative to consensus forecast errors on their past cumulative reappearance. We control for differences in the characteristics of the affected firms (Chars), the analyst coverage (Cvg.) following Zhang (2006), analyst forecast dispersion (Disp.) following Diether et al. (2002), and the standardized unexpected earnings component (SUE) following the definition in Eq. (5). For all specifications we include analyst and calendar quarter fixed effects. Standard errors are two-way clustered by analyst and firm. *** (**, *) denotes statistical significance at the 1% (5%, 10%) level.

Relative Forecast Error	(1)	(2)
Past Cumulative Reappearance	0.01**	0.01**
Chars	×	×
Cvg., Disp.	×	×
SUE		×
Quarter	×	×
Analyst	×	×
R^2	0.00	0.00
N	21,185	21,185

We next turn to equation (9), which tests whether analysts' reappearance comes at the cost of forecast accuracy. Table 4 reports the results. Column (1) includes past cumulative reappearance, firm characteristics, analyst coverage, quarter fixed effects, and

analyst fixed effects. Column (2) adds standardized unexpected earnings as an additional control. The coefficient on past cumulative reappearance is positive and statistically significant at the 5% level in both specifications. This indicates that analysts with higher past cumulative reappearance tend to have higher relative forecast errors. Economically, a one-unit increase in past cumulative reappearance is associated with a 1-percentage-point increase in the analyst’s forecast error relative to the consensus forecast error. The result is consistent with the idea that greater access may come at a cost to forecast accuracy. The coefficient remains unchanged after adding standardized unexpected earnings, which suggests that the relation is not driven by earnings surprises.

As a robustness check, we re-estimate the main regressions using only analysts affiliated with the five largest brokerages. Table 12 in Appendix B reports regressions of future cumulative reappearance on current price target deviations from the consensus, past sentiment, and past topic choices. The main results are largely unchanged. Price target deviations, sentiment, and several topic variables remain positively associated with future reappearance, although statistical significance is generally weaker than in the full sample. At the same time, the R^2 increases from 2% to 3%. Interestingly, ESG-related questions are negatively associated with future reappearance in the top-five-brokerage sample. Whether this pattern reflects target-firm characteristics or brokerage-specific behavior is outside the scope of this analysis. Table 11 in Appendix B reports the forecast-accuracy regressions for analysts affiliated with the five largest brokerages. The results are broadly unchanged. Past cumulative reappearance remains positively associated with relative forecast error, although statistical significance declines from the 5% level in the full sample to the 10% level in the top-five-brokerage sample. The explanatory power remains limited, with an R^2 below 1%. The results are robust to alternative brokerage cutoffs. Both sets of regressions yield similar conclusions when restricting the sample to analysts affiliated with either the top-three or top-ten brokerages.

4.4. Interpretation and Discussion

The empirical evidence is consistent with the main prediction of the paper. Analysts with more optimistic price targets, more positive past tone, and certain topic choices are more likely to reappear in future earnings-call Q&A sessions. These results support the view that access to management is not randomly allocated. Instead, access appears to be related to observable analyst behavior.

This interpretation is closely related to the call-casting literature. Prior work shows that managers can shape the Q&A by deciding which analysts are allowed to speak (Cohen et al., 2020; Brown et al., 2019). Our evidence extends this argument from the level of a single call to the repeated interaction between analysts and firms. Analysts who appear today are more likely to reappear in the future when their behavior is more supportive of management. This suggests that call casting is not only a contemporaneous feature of the Q&A. It may also shape longer-term access relationships between analysts and firms.

The descriptive results help explain the mechanism. Analysts mostly ask about core financial topics, such as business segment performance, financial metrics, and guidance. These topics are central to investors and allow managers to discuss operating performance and forward-looking narratives. Analyst tone also differs across topics. Growth-oriented topics, such as business segment performance, product development, innovation, strategic partnerships, and ESG, are associated with more positive sentiment. More challenging topics, such as costs, supply chains, regulation, raw materials, margins, and financial performance, are associated with less favorable tone. Thus, analysts differ along two dimensions: what they ask and how they ask it.

The panel results show that both dimensions matter. Positive sentiment predicts future reappearance, even after controlling for price target optimism, topic choice, firm characteristics, analyst fixed effects, and quarter fixed effects. Several topics are also positively related to future access, including business segment performance, financial metrics, financial guidance, supply chain issues, and the competitive landscape. These topics are not all uniformly positive in tone. This distinction is important. It suggests that managers may value questions that are useful for communicating the firm narrative, not only questions that sound favorable. Some topics may provide managers with an opportunity to explain performance, address uncertainty, or redirect attention toward future prospects.

The results for ESG illustrate this distinction. In the descriptive analysis, ESG-related questions are associated with more positive sentiment. However, ESG questions are rare and do not consistently predict higher reappearance in the panel regressions. In the top-five-brokerage subsample, ESG is even negatively associated with future reappearance. This pattern suggests that positive tone alone is not sufficient to generate access. Topic relevance, firm context, and managerial incentives likely matter. ESG questions may be framed positively, but they may not always be central to the earnings narrative or useful for management in the same way as guidance, segment performance, or competitive

positioning.

Firm characteristics also matter for interpreting the topic and sentiment patterns. Larger firms face more questions about regulation and economic conditions, while smaller firms receive more questions about consumer behavior and market trends. High-momentum firms receive more questions about business segment performance and growth drivers. Sentiment is also higher in calls of smaller firms and firms with stronger momentum. These patterns suggest that analyst behavior reflects both strategic incentives and the information environment of the firm. Analysts do not choose topics in a vacuum. They respond to firm fundamentals, recent performance, and the issues that are most relevant for each call.

Brokerage-level evidence points to a similar conclusion. Access is concentrated among large brokerages, which account for many appearances and broader firm coverage. However, large brokerages do not differ sharply in average price target optimism, sentiment, or topic choices. The main brokerage-level difference is scale rather than style. This supports the use of analyst-level and analyst-firm-level variation in the panel regressions. The relevant variation appears to come less from broad brokerage policies and more from the repeated interactions between individual analysts and specific firms.

The forecast-error results add an important qualification. Analysts with greater past reappearance have higher relative forecast errors compared with the consensus. The effect is economically modest, but it is consistent with the idea that access can come at a cost to accuracy. This result connects the paper to prior evidence that analysts may trade off objectivity against incentives related to reputation, management access, and career concerns (Lim, 2001; Hilary and Hsu, 2013; Malmendier and Shanthikumar, 2014; Cen et al., 2016). In our setting, analysts who maintain access do not appear to produce more accurate price-target forecasts. If anything, repeated access is associated with lower relative accuracy.

The evidence suggests that the information revealed in earnings-call Q&A sessions depends partly on which analysts managers call on and how those analysts frame their questions. Analysts who are more optimistic, more positive, and who raise certain management-relevant topics are more likely to regain access. At the same time, repeated access is associated with less accurate forecasts. These findings imply that investors should interpret earnings-call participation and analyst price targets jointly. Access may reveal information about an analyst's relationship with management, but it does not

necessarily imply superior forecasting ability.

5. Conclusion

This paper studies the trade-off between analyst access and forecast accuracy in earnings-call Q&A sessions. We combine conference-call transcripts with IBES price-target data and use ChatGPT to measure analyst tone, topic choice, and identity in a setting where analyst and brokerage names are partly anonymized. This allows us to link analysts' behavior inside the call to their future reappearance and forecast accuracy.

The paper contributes by introducing analyst reappearance as a measure of repeated access to management. It also shows that future access is related to observable analyst behavior. Analysts with more optimistic price targets, more positive tone, and certain topic choices are more likely to reappear in later calls.

The central result is consistent with a trade-off between access and accuracy. Analysts with greater past reappearance have larger forecast errors relative to the consensus. This suggests that repeated access may not reflect superior forecasting ability. Instead, it may partly reflect incentives to maintain management relationships. Overall, the evidence points to a trade-off between gaining access and producing accurate forecasts.

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Appendix A. Further Descriptives

Table 5: Price Target Deviation & Firm Characteristics

This table reports descriptive regressions of price target deviations from the consensus on firm characteristics. The regressions include size, book-to-market, investment, profitability, momentum, maximum return, analyst dispersion following Diether et al. (2002), and analyst coverage following Zhang (2006). Coefficients indicate whether specific firm characteristics are associated with higher or lower analyst price target deviation from the consensus. *** (**, *) denotes statistical significance at the 1% (5%, 10%) level.

Variable	Size	B2M	Inv	Prof	Mom	MAX	DISP	Cvg
PT Deviation	0.00	0.01	0.01**	0.01***	0.00	0.01***	0.01***	0.01***

Table 6: Topics & Firm Characteristics

This table reports descriptive regressions of analyst question topics on firm characteristics. Each row corresponds to one topic category, and each column reports the coefficient on a firm characteristic. The regressions include size, book-to-market, investment, profitability, momentum, maximum return, analyst dispersion following Diether et al. (2002), and analyst coverage following Zhang (2006). Coefficients indicate whether specific firm characteristics are associated with more frequent mentions of a topic. The analyst topics are aggregated on a call level. *** (**, *) denotes statistical significance at the 1% (5%, 10%) level.

Topic	Size	B2M	Inv	Prof	Mom	MAX	DISP	Cvg
Business Segment Performance and Growth Drivers	-0.12***	0.04**	0.02*	0.04**	0.04***	0.01	-0.03*	-0.06***
Financial Metrics and Performance Analysis	0.00	0.15***	-0.02	0.02	-0.00	-0.04**	0.03*	-0.11***
Financial Guidance and Projections	0.00	0.07***	-0.00	0.00	-0.01	0.03**	-0.04***	-0.09***
Pricing Strategy and Gross Margin Implications	-0.07***	-0.05***	0.07***	0.05***	-0.00	-0.02*	-0.02**	-0.01
Cost Management and Efficiency Initiatives	-0.05***	0.08***	-0.02***	0.05***	-0.01	-0.01	-0.00	0.00
Supply Chain and Operational Issues	-0.04***	0.00	0.03***	0.01	0.00	0.03***	0.03***	0.02*
Product Development and Launches	0.06***	-0.18***	0.02***	-0.14***	-0.02**	0.04***	-0.01	-0.07***
None of the above	-0.06***	0.02*	0.02***	0.00	0.01*	-0.01	-0.01	-0.04***
Competitive Landscape and Market Share	-0.01	-0.09***	-0.02**	0.01	-0.02***	0.01	-0.01	-0.04***
Regulatory and Economic Impact	0.10***	0.11***	-0.01*	-0.03***	-0.00	-0.01	-0.04***	-0.13***
Capital Allocation and Shareholder Returns	0.00	0.14***	-0.03***	0.05***	0.02***	0.01	0.05***	-0.02**
Consumer Behavior and Market Trends	-0.08***	-0.03***	0.04***	0.05***	0.01	-0.01**	-0.02***	0.03***
Mergers and Acquisitions (M&A) Strategy	0.00	0.06***	-0.03***	0.01	-0.01	-0.03***	-0.00	-0.05***
Investment Plans and Strategy	0.00	0.07***	-0.01	0.01	0.03***	-0.01	0.00	-0.03***
Technological Advancements and Innovation	-0.02***	-0.07***	-0.01	-0.05***	0.01	0.02***	0.02***	0.01
International Business and Market Conditions	0.00	-0.06***	-0.01	-0.02**	-0.01	0.01	0.01*	-0.03***
Strategic Partnerships and Collaborations	-0.02***	-0.02***	-0.02***	-0.03***	0.01**	0.01	0.01	0.00
Market Performance and Competitive Environment	-0.02***	-0.01	0.00	0.00	-0.01	0.01*	-0.00	0.01**
Raw Materials and Commodity Prices	-0.02***	0.05***	0.01***	0.05***	0.01*	-0.01**	0.02***	-0.02***
Advertising and Marketing Spend	-0.01***	-0.05***	-0.01***	-0.01*	-0.01***	-0.02***	0.02***	0.00
Environmental, Social, and Governance (ESG) Initiatives	0.00*	0.03***	-0.01***	0.00	0.00	0.00	0.00	-0.01***

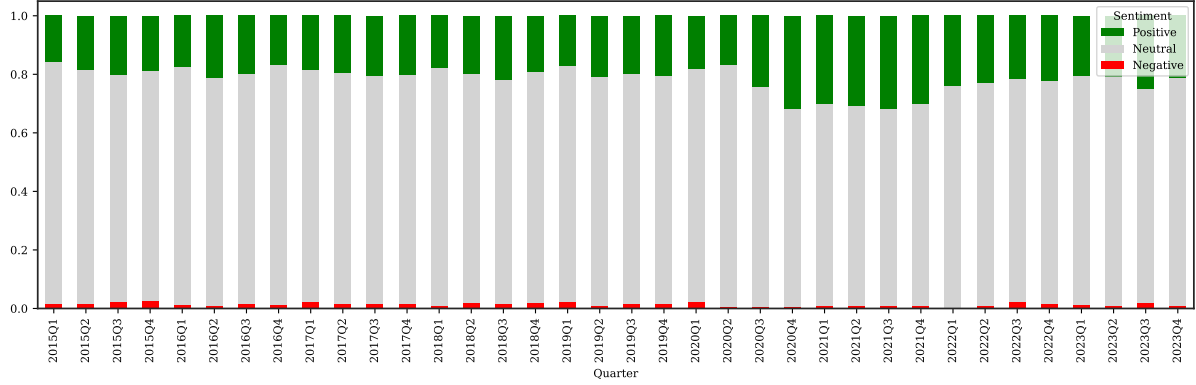


Fig. 4. Distribution of Sentiment by Quarter

This figure shows the quarterly proportions of analyst interactions classified as *Negative*, *Neutral*, or *Positive*. For each quarter, we pool all analyst interactions across all earnings calls and compute the share of interactions in each sentiment category.

Table 7: Sentiment & Firm Characteristics

This table reports descriptive regressions of analyst sentiment on firm characteristics. The regressions include size, book-to-market, investment, profitability, momentum, maximum return, analyst dispersion following Diether et al. (2002), and analyst coverage following Zhang (2006). Coefficients indicate whether specific firm characteristics are associated with higher or lower sentiment. The analyst sentiment is aggregated on a call level. *** (**, *) denotes statistical significance at the 1% (5%, 10%) level.

Variable	Size	B2M	Inv	Prof	Mom	MAX	DISP	Cvg
Sentiment	-0.06***	-0.18***	0.02	-0.18***	0.14***	0.06***	-0.04***	0.06***

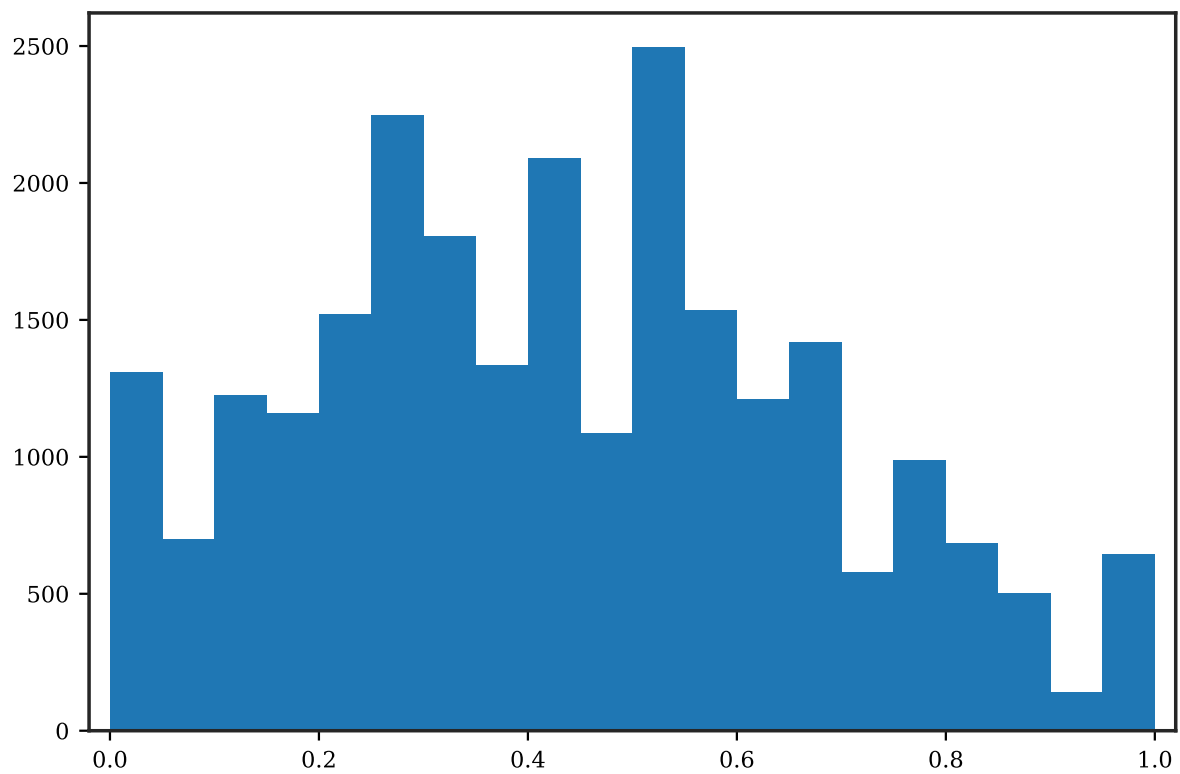


Fig. 5. Analyst Reappearance

This figure shows the distribution of analyst reappearance. Reappearance measures how often an analyst appears again for the same firm in subsequent quarters, scaled by the number of quarters in which the analyst is active anywhere in the dataset.

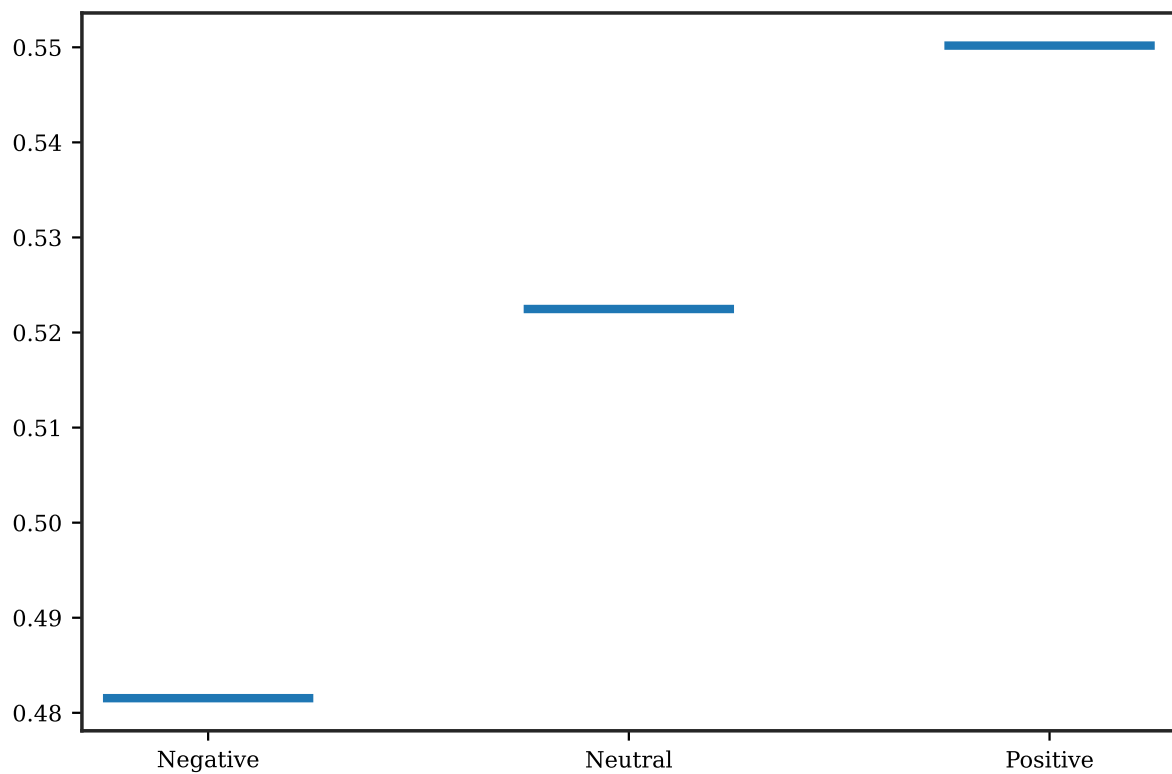


Fig. 6. Analyst Sentiment & Reappearance

This figure shows the average future reappearances score by analyst sentiment. Sentiment is grouped into three categories: *Negative*, *Neutral*, and *Positive*. For each category, the horizontal line reports the mean future reappearances score, which measures how often an analyst appears again for the same firm in future active quarters.

Table 8: Brokerage Distribution

This table reports the 50 largest brokerages in the sample by appearances in S&P 500 earnings conference calls. For each brokerage, the table reports the number of analyst appearances, the number of unique analysts observed, the number of unique firms covered, and the average number of firms per analyst. The table describes brokerage representation in the call sample and therefore reflects only analysts observed in our data, not total brokerage employment.

Brokerage	Appearances	Analysts	Firms	Firms per Analyst
Goldman Sachs	2,908	153	241	3.74
BofA Merrill Lynch	2,449	153	240	3.16
Barclays	1,709	118	211	3.53
Deutsche Bank	1,701	141	216	3.28
Evercore ISI	1,584	78	170	3.91
Credit Suisse	1,527	149	205	2.83
JPMorgan	1,444	122	224	3.56
Jefferies	1,396	133	196	2.59
RBC	1,226	118	163	2.74
Stifel Nicolaus	857	95	141	2.59
Wolfe Research	828	56	132	3.23
Bernstein	766	51	97	3.06
BMO	688	70	129	2.84
Piper Jaffray & Co.	664	92	124	2.18
Wells Fargo, LLC, Research Division	615	78	167	2.90
Stephens Inc.	434	48	74	2.23
Raymond James & Associates, Inc.	400	66	98	2.09
KeyBanc	396	62	78	2.05
Oppenheimer & Co.	384	43	71	2.47
Guggenheim	356	46	77	2.35
Vertical Research Partners	344	18	48	3.89
Susquehanna Financial Group	319	26	63	3.08
Keefe, Bruyette & Woods, Inc.	317	23	28	2.17
SunTrust Robinson Humphrey	300	45	73	2.29
Mizuho	247	37	69	2.68
Leerink Partners	229	24	30	2.88
Macquarie Research	195	44	68	1.95
Scotiabank	169	15	30	2.53
Wedbush	169	25	37	2.12
Buckingham Research Group	161	31	52	2.23
D.A. Davidson & Co.	153	28	39	2.00
Canaccord Genuity	138	31	30	1.68
Nomura	131	28	43	2.11
Sandler O'Neill & Partners	131	20	25	2.10
Loop	122	21	30	1.62
Global Hunter	117	22	33	2.00
Capital One	109	9	16	3.11
CLSA Limited	107	20	48	2.70
Berenberg Bank	105	26	35	1.62
Needham & Company	100	26	29	1.54
Tudor, Pickering, Holt & Co. Securities	97	12	14	1.92
Exane BNP Paribas	92	20	27	1.55
Longbow Research	90	17	21	1.94
Consumer Edge Research, LLC	88	15	24	2.20
Janney Montgomery Scott	88	12	19	2.33
Gordon Haskett Research Advisors	83	4	16	4.25
MoffettNathanson	73	10	14	1.90
Nephron Research	72	5	13	2.80
BTIG	64	20	31	1.85
Cantor Fitzgerald	59	17	24	1.65

Table 9: Brokerage Behavior

This table reports brokerage-level analyst behavior for the 50 largest brokerages in the sample, ranked by analyst-firm-quarter observations. For each brokerage, the table reports the average price target deviation from the consensus and the average sentiment score. Price target deviation measures relative optimism in analysts' forecasts, while sentiment captures the average tone of analyst interactions.

Brokerage	Price Target Deviation	Sentiment
Goldman Sachs	-0.00	0.21
BofA Merrill Lynch	0.02	0.17
Barclays	-0.01	0.18
Deutsche Bank	-0.00	0.16
Evercore ISI	-0.00	0.27
Credit Suisse	0.01	0.20
JPMorgan	0.01	0.17
Jefferies	0.02	0.20
RBC	0.01	0.22
Stifel Nicolaus	0.04	0.24
Wolfe Research	0.01	0.12
Bernstein	0.02	0.06
BMO	0.01	0.17
Piper Jaffray & Co.	0.03	0.31
Wells Fargo, LLC, Research Division	0.01	0.18
Stephens Inc.	0.04	0.32
Raymond James & Associates, Inc.	0.05	0.22
KeyBank	0.03	0.25
Oppenheimer & Co.	0.04	0.37
Guggenheim	0.05	0.24
Vertical Research Partners	0.00	0.22
Susquehanna Financial Group	0.05	0.11
Keefe, Bruyette & Woods, Inc.	0.03	0.11
SunTrust Robinson Humphrey	0.02	0.20
Mizuho	0.00	0.23
Leerink Partners	0.03	0.31
Macquarie Research	0.01	0.18
Scotiabank	0.02	0.08
Wedbush	0.01	0.17
Buckingham Research Group	0.02	0.16
D.A. Davidson & Co.	0.02	0.13
Canaccord Genuity	0.07	0.43
Sandler O'Neill & Partners	0.03	0.21
Nomura	0.01	0.14
Loop	0.01	0.20
Global Hunter	0.03	0.17
Capital One	-0.02	0.17
CLSA Limited	0.01	0.14
Berenberg Bank	0.01	0.09
Needham & Company	0.07	0.36
Tudor, Pickering, Holt & Co. Securities	0.03	0.18
Exane BNP Paribas	0.00	0.07
Longbow Research	0.08	0.31
Consumer Edge Research, LLC	0.01	0.14
Janney Montgomery Scott	-0.01	0.11
Gordon Haskett Research Advisors	-0.00	0.25
MoffettNathanson	0.00	0.27
Nephron Research	0.02	0.18
BTIG	0.04	0.28
Northcoast Research	0.06	0.36

Table 10: Broker IDs

This table reports the mapping between brokerage names and IBES brokerage identifiers for the 50 most frequently observed brokerages in the sample. Brokerages are selected based on the number of matched analyst-call observations. The table documents the brokerage-name translation used to link analyst appearances in earnings conference calls to brokerage identifiers in the IBES data.

Broker Name	Broker ID
BMO	BURNS
BTIG	BTIG
Barclays	FRCLAYSC
Berenberg Bank	BEREN
Bernstein	BERN
BofA Merrill Lynch	MERRILL
Buckingham Research Group	BUCK
CLSA Limited	CLALEXHK
Canaccord Genuity	CANACCOR
Cantor Fitzgerald	CANTORFZ
Capital One	SCOAST
Consumer Edge Research, LLC	CONSUMER
Credit Suisse	FBOSTON
D.A. Davidson & Co.	DAVIDSON
Deutsche Bank	LAWRENCE
Evercore ISI	EVERCO
Exane BNP Paribas	EXANE
Global Hunter	GHUNTER
Goldman Sachs	GOLDMAN
Gordon Haskett Research Advisors	HASKETT
Guggenheim	GUGGEL
JPMorgan	JPMORGAN
Janney Montgomery Scott	JANNEY
Jefferies	JEFFEREG
Keefe, Bruyette & Woods, Inc.	KEEFE
KeyBanc	MCDONALD
Leerink Partners	LEERINK
Longbow Research	Longbow
Loop	LOOPCAMA
Macquarie Research	MACQUARI
Mizuho	MIZUSEC
MoffettNathanson	MOFFETT
Needham & Company	NEEDHAM
Nephron Research	NEPHRON
Nomura	NOMURAUS
Oppenheimer & Co.	FAHN
Piper Jaffray & Co.	PIPER
RBC	RBCDOMIN
Raymond James & Associates, Inc.	RAYMOND
Sandler O'Neill & Partners	SANDLER
Scotiabank	MCLEOD
Stephens Inc.	STEPHENS
Stifel Nicolaus	STIFEL
SunTrust Robinson Humphrey	ROBINSON
Susquehanna Financial Group	SUSQUEH
Tudor, Pickering, Holt & Co. Securities	PICKERIN
Vertical Research Partners	VERTRESP
Wedbush	OLMSTEAD
Wells Fargo, LLC, Research Division	WHEAT
Wolfe Research	WOLFE

Appendix B. Robustness

Table 11: Top Brokerage Forecast Error

This table reports panel regressions of analysts' 12-month forecast errors relative to consensus forecast errors on their past cumulative reappearance. In this regression, only the analysts from the top five largest brokerages from our dataset are included. We control for differences in the characteristics of the affected firms (Chars), the analyst coverage (Cvg.) following Zhang (2006), analyst forecast dispersion (Disp.) following Diether et al. (2002), and the standardized unexpected earnings component (SUE) following the definition in Eq. (5). For all specifications we include analyst and calendar quarter fixed effects. Standard errors are two-way clustered by analyst and firm. *** (**, *) denotes statistical significance at the 1% (5%, 10%) level.

Relative Forecast Error	(1)	(2)
Past Cumulative Reappearance	0.01*	0.01*
Chars	×	×
Cvg., Disp.	×	×
SUE		×
Quarter	×	×
Analyst	×	×
R^2	0.00	0.00
N	8,100	8,100

Table 12: Top Brokerage Reappearance

This table reports panel regressions of analysts' future cumulative reappearance on their current price target deviation from the consensus, past sentiment, and past topic choices. In this regression, only the analysts from the top five largest brokerages from our dataset are included. We control for differences in the characteristics of the affected firms (Chars), the analyst coverage (Cvg.) following Zhang (2006), analyst forecast dispersion (Disp.) following Diether et al. (2002), and the standardized unexpected earnings component (SUE) following the definition in Eq. (5). For all specifications we include analyst and calendar quarter fixed effects. Standard errors are two-way clustered by analyst and firm. *** (**, *) denotes statistical significance at the 1% (5%, 10%) level.

Future Cumulative Reappearance	(1)	(2)
Current Price Target - Mean	0.08*	0.08*
Past Sentiment	0.05*	0.05*
Business Segment Performance and Growth Drivers	0.06***	0.06***
Financial Metrics and Performance Analysis	0.03	0.03
Financial Guidance and Projections	0.02	0.02
Pricing Strategy and Gross Margin Implications	-0.02	-0.02
Other Topic	-0.01	-0.01
Cost Management and Efficiency Initiatives	-0.00	-0.00
Product Development and Launches	-0.01	-0.01
Supply Chain and Operational Issues	0.03	0.03
Competitive Landscape and Market Share	0.09***	0.09***
Regulatory and Economic Impact	-0.01	-0.01
Capital Allocation and Shareholder Returns	0.03	0.03
Consumer Behavior and Market Trends	-0.02	-0.02
Mergers and Acquisitions (M&A) Strategy	0.00	0.00
Investment Plans and Strategy	0.03	0.03
Technological Advancements and Innovation	0.02	0.02
International Business and Market Conditions	0.02	0.02
Strategic Partnerships and Collaborations	0.02	0.01
Market Performance and Competitive Environment	-0.00	-0.00
Raw Materials and Commodity Prices	0.03	0.03
Advertising and Marketing Spend	-0.06	-0.05
Environmental, Social, and Governance (ESG) Initiatives	-0.13*	-0.13*
Chars	×	×
Cvg., Disp.	×	×
SUE		×
Quarter	×	×
Analyst	×	×
R^2	0.03	0.03
N	6,881	6,881