# Analyst Sentiment in M&A Conference Calls


## Abstract

We use Large Language Models (LLMs) to analyze analyst sentiment during the unscripted Q&A sessions of M&A conference calls. Across 2,604 deals, we document that: while optimism validates synergies, analyst anxiety and fear serve as strong leading indicators of value destruction. The market reacts disproportionately to negative sentiment, consistent with a 'costly signaling' framework where analysts only break professional norms of politeness to flag severe risks. Beyond immediate returns, elevated anxiety predicts deal failure, delays, and long-run underperformance. Our results show that LLMs capture nuanced skepticism missed by traditional methods, highlighting the Q&A session as a critical governance channel.



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## 1. Introduction

Mergers and acquisitions (M&A) are among the most consequential yet opaque events in corporate finance. While management typically frames these transactions as synergistic, agency theory suggests that many deals are driven by empire building (Jensen, 1986) or managerial hubris (Roll, 1986; Malmendier and Tate, 2008). This conflict creates profound information asymmetry: acquirer management possesses private information regarding integration risks and target quality but has strong incentives to selectively disclose only favorable details, potentially obscuring negative signals (Myers and Majluf, 1984; Kimbrough and Louis, 2011; Ahern and Sosyura, 2014).

In this opaque setting, the interactive Q&A session of the M&A conference call serves as a critical governance mechanism. It is the moment where the scripted managerial narrative faces real-time scrutiny from financial analyst, who are sophisticated intermediaries tasked with discovering private information (Jensen, 1993; Chen, Harford, and Li, 2007). Unlike the prepared remarks, which are often scripted and optimistic (Matsumoto, Pronk, and Roelofsen, 2011), the Q&A session is an interactive, unscripted dynamic where soft information is revealed through the nuances of dialogue (Chen, Nagar, and Schoenfeld, 2018).

Consider two acquisitions where financial metrics such as deal size and premium are identical. In the first call, analysts query the deal terms with excitement, validating the strategic rationale. In the second, analysts probe the same metrics with anxiety and fear, pressing management on downside scenarios. We posit that these affective distinctions contain information distinct from the text itself. Specifically, we argue that analyst sentiment serves as a costly signal: analysts typically adhere to a "positivity bias" to maintain access to management (Mayew and Venkatachalam, 2012; Milian and Smith, 2017). Therefore, an analyst's expression of anxiety or fear is non-trivial: it signals that their private assessment of deal risk is severe enough to override professional norms of politeness.

This paper investigates whether discrete, multifaceted analyst sentiments expressed during the Q&A session are associated with market reactions and deal outcomes. While a rich literature establishes that market participants react to the tone of corporate filings (Loughran and McDonald, 2011) and media sentiment (Tetlock, 2007), we know little about the affective states of the analysts themselves as they perform their monitoring function. To capture these nuances, we employ Large Language Models (LLMs), specifically GPT-4.1, to score analyst inquiries on discrete affective

dimensions grounded in Russell's (1980) circumplex model of affect. This approach aligns with rapidly emerging evidence that generative AI provides psychologically valid emotion annotations that outperform traditional "bag-of-words" lexicons (e.g., Hansen and Kazinnik, 2024; Jha et al., 2024).

Analyzing 2,604 M&A deals from 2003 to 2023, we document a distinct asymmetry in information processing. We find that while analyst *Optimism* and *Excitement* are associated with modest positive cumulative abnormal returns (CARs), analyst *Anxiety* and *Fear* are associated with substantial value destruction. The market reaction to negative sentiment is disproportionately strong, consistent with the hypothesis that negative affect acts as an informative signal of latent risk in an environment characterized by cheap talk.

Beyond short-run price discovery, we find that analyst sentiment predicts real economic outcomes. High levels of analyst anxiety are significantly related to lower deal completion probabilities and longer times to completion. Furthermore, we link analyst sentiment to long-run beliefs; deals characterized by high analyst anxiety exhibit weaker post-call buy-and-hold abnormal returns (BHARs), particularly when the initial market reaction was positive. This suggests a "crash belief" channel (Goetzmann, Kim, and Shiller, 2024) where analysts sense risks, such as integration failure or overpayment, that the broader market initially ignores.

Our study contributes to the literature in three ways. First, we extend the work on M&A disclosure (Kimbrough and Louis, 2011) by shifting the focus from management tone to analyst interaction. We show that the "how" of analyst questioning, specifically the presence of fear and anxiety, reveals information to the "what" of the deal terms. Second, we provide micro-foundational evidence for the role of intermediaries in resolving information asymmetry (Healy and Palepu, 2001). We demonstrate that analysts function as active monitors whose real-time emotional reactions help price agency costs. Third, we advance the methodology of textual analysis in finance. By showing that LLM-based measures outperform standard dictionary methods (Loughran and McDonald, 2011) in explaining returns, we validate the utility of context-aware models in decoding high-stakes financial dialogue (Kim, Muhn, and Nikolaev, 2023; Lopez-Lira and Tang, 2023).

The remainder of the paper is organized as follows. Section 2 develops the conceptual framework. Section 3 describes the data and LLM measurement protocol. Section 4 presents

univariate evidence. Section 5 reports the main multivariate results linking sentiment to returns and deal outcomes. Section 6 provides cross-sectional tests on information asymmetry. Section 7 analyzes long-run performance, and Section 8 concludes.

## 2. Hypothesis Development

Our analysis is motivated by the unique friction of M&A transactions, where the twin forces of information asymmetry and agency conflict are most acute. We posit that financial analysts serve as a real-time governance mechanism during conference call Q&A sessions, and that their affective expressions, specifically deviations from professional norms, provide a credible signal of deal quality.

### 2.1. Agency Conflicts and the Information Gap

M&A is the classic setting for agency conflicts. As established by Jensen's (1986) free cash flow hypothesis and Roll's (1986) hubris hypothesis, managers frequently pursue acquisitions to expand the firm's boundaries (empire building) or because they overestimate their ability to manage the target, often at the expense of shareholder value. This conflict creates "motive uncertainty": investors must discern whether a deal is driven by sound economic logic or managerial self-interest (Malmendier and Tate, 2008).

Compounding this agency problem is profound information asymmetry (Myers and Majluf, 1984). Target firms often possess intangible assets or technological capabilities that are difficult for outsiders to value (Officer, Poulsen, and Stegemoller, 2009). Acquiring managers, possessing private information about the target, have a strategic incentive to selectively disclose positive information while obscuring integration risks (Kimbrough and Louis, 2011; Ahern and Sosyura, 2014). Consequently, the market faces a "lemons problem" where the credibility of the managerial narrative is fundamentally suspected.

### 2.2. The Analyst as Monitor and the "Costly Signaling" Mechanism

In this environment, the Q&A session serves as a critical monitoring channel. Unlike prepared remarks, which are scripted and strictly controlled (Matsumoto et al., 2011), the Q&A is an unscripted, interactive forum. Analysts function as information intermediaries, probing for

details on synergies and cost structures that management may have omitted (Huang, Zang, and Zheng, 2014; Twedt and Rees, 2012).

However, the information content of this interaction is not limited to the text of the questions. We argue that analyst sentiment acts as a distinct, high-fidelity signal due to the social structure of the analyst-manager relationship. Analysts are incentivized to maintain good relations with management to ensure future access to private information (Mayew and Venkatachalam, 2012). Consequently, they typically adhere to a "positivity bias," exhibiting norms of politeness and deference in public calls (Milian and Smith, 2017).

This institutional constraint creates a costly signaling framework. Because optimism is the "cheap talk" equilibrium (aligned with social norms and low proprietary costs), positive sentiment may simply reflect professional courtesy. In contrast, *Anxiety* and *Fear* represent costly deviations from the norm. When an analyst expresses anxiety (high arousal, negative valence) or fear, they are implicitly signaling that their concern regarding agency costs or valuation risk is severe enough to outweigh the reputational cost of challenging management publicly. [1]

### 2.3. Hypothesis

Based on this framework, we argue that analyst sentiment facilitates price discovery by revealing the market's real-time assessment of the deal's credibility.

First, if analysts successfully identify value-creating synergies or validate the strategic rationale, their optimism should facilitate positive price updates. Conversely, if their questioning reveals skepticism or anxiety, it signals unresolved risks, leading to negative price updates.

[1] We provide illustrative examples of these signals in Appendix D. In instances of positive sentiments, analyst validate the acquirer's strategic decision. For example, in the *PAR Technology* call, where management sought to deploy recently raised capital for a transformative acquisition, the analyst expresses *Excitement*, validating this desire as a "catalytic moment" that successfully shifts the firm "from point of defense to point of offense." Similarly, regarding *Salesforce'*s desire to expand into e-commerce via *Demandware*, an analyst displays *Optimism* by confirming that the "TAM is large enough" to justify the acquirer's move. Conversely, negative sentiments reveal a clash between the acquirer's intentions and the analyst's assessment. In the *Secure Computing* transaction, where management aimed to acquire *CipherTrust* to spur growth, the analyst expresses *Fear* by exposing the acquirer's hidden motive: using the deal to "layer on more revenue" to mask a "substantial slide in the organic business." Finally, in the *Insignia Solutions* call, while management sought to frame the sale as value-maximizing, the analyst expresses *Anxiety* regarding the lack of transparency, countering the acquirer's narrative by stating, "How can we be sure that this is the maximum value... We don't know what we're selling."

**Hypothesis 1a (The Informativeness Hypothesis):** *Acquirer conference call returns are positively associated with analyst positive sentiments (Optimism, Excitement) and negatively associated with analyst negative sentiments (Anxiety, Fear).*

Crucially, the "costly signaling" framework implies asymmetry. Because positive sentiment is the default social mode, it contains less distinctive information. Negative sentiment, being a violation of the positivity norm, is a "harder" signal of latent risk. Investors should therefore weigh negative affects more heavily than positive affects when updating valuations.

**Hypothesis 1b (The Asymmetry Hypothesis):** *The magnitude of the market reaction to analyst negative sentiments is significantly larger than the reaction to analyst positive sentiments.*

Finally, if analyst sentiment captures genuine private information regarding deal quality, rather than just temporary market noise, it should predict real economic outcomes. High levels of anxiety or fear in the Q&A suggest that sophisticated intermediaries perceive fundamental flaws in the deal structure. These frictions are likely to manifest as deal failures, delays, or long-run value destruction.

**Hypothesis 2 (The Real Outcomes):** *Negative analyst sentiments are associated with a lower probability of deal completion, longer time-to-completion, and lower long-run post-merger stock performance.*

## 3. Data, Sample, and Variables

### 3.1. Sample Selection and Data Sources

We construct a comprehensive sample of U.S. M&A conference calls by merging deal data from Refinitiv SDC Platinum with conference call transcripts from LSEG (formerly StreetEvents). Our sample period spans from October 2003, when LSEG coverage begins, through December 2023.

To ensure our sample reflects economically significant transactions, we apply standard filtering criteria following prior M&A literature (e.g., Moeller, Schlingemann, and Stulz, 2005; Dasgupta et al., 2024). We retain deals where: (i) the acquirer is a publicly traded U.S. firm listed on AMEX, NASDAQ, or NYSE; (ii) the transaction value exceeds $1 million; and (iii) the deal

represents a change in control (the acquirer owns less than 50% prior to the deal and 100% afterward). We further require the availability of stock return data from CRSP and financial data from Compustat, linked via the historical GVKEY-DealNumber mapping provided by Ewens, Peters, and Wang (2024).

A critical step in our sample construction is identifying the specific conference call dedicated to the M&A announcement. We match SDC announcement dates with LSEG transcripts and manually verify matches to ensure the call content primarily concerns the acquisition. Finally, we exclude transcripts that lack a Q&A session or where no analyst questions are recorded. The final sample consists of 2,604 deal-call observations. [2]

Table 1 displays the distribution of merger conference calls timing relative to the deal announcement date. In our sample, over two-thirds (about 69%) of calls were made on the same day as the deal announcement, with 23% occurring on the following day. About 4% of calls took place within 2 to 5 days after the announcement, with the remaining 4% occurring more than 5 days after the announcement. Thus, most of our M&A calls are tightly clustered around the first public disclosure of the deal, making them an ideal setting to study how analyst sentiments during real-time interaction relate to announcement (conference call)-window returns and subsequent outcomes.

### 3.2. Constructing the Analyst Sentiment Measures

Our primary independent variables are the affective states of financial analysts expressed during the Q&A session. While traditional textual analysis relies on "bag-of-words" approaches (e.g., Loughran and McDonald, 2011), these methods struggle to capture the nuance, pragmatics, and emotional intensity of spoken dialogue. To overcome this, we employ a Large Language Model (LLM) framework to capture these nuances through a three-step process: (1) speaker isolation, (2) context-aware inference, and (3) dimensional scoring.

#### 3.2.1. Speaker Isolation and Input Processing

[2] The final sample of 2,604 call-deal observations is consistent with recent M&A studies using similar transcript filtering. For comparison, Dasgupta et al. (2024) identify 2,559 deals after applying standard CRSP/Compustat requirements, while Cao et al. (2023) have a more restrictive sample of 1,152 deals after requiring matching SEC press releases.

A critical challenge in conference call analysis is attributing sentiment to the correct speaker. Standard sentiment classifiers often conflate management's optimistic answers with analysts' skeptical questions. To address this, we parse each transcript into a structured format, isolating the Q&A session from the prepared remarks. We then employ a roster-based matching algorithm to map each speaker to the participant list provided by LSEG. This allows us to filter out management responses and operator interjections, retaining only the text spoken by the analysts. This analyst-isolated text serves as the input for our measurement model.

### 3.2.2. The LLM Measurement Protocol

We measure sentiment using GPT-4.1, accessed via the API to ensure deterministic reproducibility (temperature set to zero). Unlike "bag-of-words" methods (e.g., Loughran and McDonald, 2011) that count isolated keywords, LLMs process the full semantic context of the dialogue. This is particularly vital in the Q&A setting, where meaning is often conveyed through pragmatics, such as the use of hedging ("I'm just trying to understand..."), repetition, or the framing of downside scenarios, rather than explicit negative vocabulary.

We employ a standardized zero-shot prompting strategy grounded in Russell's (1980) Circumplex Model of Affect. The model is instructed to act as an expert rater and evaluate the aggregate analyst dialogue along two axes: *Valence* (positivity/negativity) and *Arousal* (intensity). Within this framework, we extract four dimensions of sentiments: *Optimism, Excitement, Anxiety* and *Fear*. Importantly, rather than chunking the text into individual sentences, we pass the full analyst dialogue for each call as a single context window. This allows the model to detect affective states that emerge across multi-turn exchanges, such as when an analyst repeatedly presses management on a specific line of questioning.

### 3.2.3. Scoring and Variable Definition

For each call, the model outputs a continuous intensity score for each sentiment on a scale of [0, 100]. To facilitate economic interpretation, we rescale these scores to the unit interval [0, 1]. As reported in Table 2, the resulting measures reveal a distinct skew: while *Optimism* is pervasive (mean = 0.498), *Anxiety* (mean = 0.085) and *Fear* (mean = 0.072) are relatively rare. This distributional property supports our "costly signaling" framework: because analysts are professionally incentivized to be polite, the emergence of measurable fear or anxiety represents a significant deviation from the norm.

### 3.3. Dependent and Control Variables

Our primary dependent variable is the cumulative abnormal return (CAR) for the acquirer, calculated using the Fama-French three-factor model over the three-day window [–1, +1] centered on the conference call date. This short window minimizes the noise from confounding events while capturing the immediate price discovery facilitated by the call.

To isolate the information content of analyst sentiment, we control for a robust set of deal and firm characteristics. Firm-level controls include acquirer size (ln(AT)Acq), market-to-book ratio, ROA, and R&D intensity. Deal-level controls include the method of payment (stock percentage), the relative size of the deal, and indicators for whether the target is a public company or a U.S. entity. Detailed definitions for all variables are provided in Appendix B.

### 3.4. Summary Statistics

Table 2 reports summary statistics for the key variables used in our analysis. The sample consists of 2,604 deals from 2003 to 2023. The descriptive statistics for our LLM-based sentiment measures reveal an asymmetry consistent with professional norms in the finance industry. *Optimism* is the dominant sentiment, with a mean intensity of 0.498 and a median of 0.540. In contrast, negative sentiments are comparatively rare events: *Anxiety* has a mean of 0.085 and *Fear* has a mean of 0.072. The low baseline levels of negative affect support our theoretical framework, suggesting that analysts largely adhere to a "positivity bias." Consequently, the substantial standard deviations for *Anxiety* (0.048) and *Fear* (0.040) indicate meaningful cross-sectional variation, implying that deviations into negative affect are significant information events rather than noise.

The mean cumulative abnormal return (CAR) over the three-day window [–1, +1] is 1.0%, which is consistent with the generally modest positive returns to acquirers documented in recent decades (e.g., Alexandridis et al., 2017). However, the standard deviation of 8.4% indicates substantial heterogeneity in market reactions, which we aim to explain through analyst sentiment.

Finally, our sample is representative of the broader U.S. M&A universe. Approximately 39% of targets are public companies, and 85% are domestic U.S. firms. The average deal is significant relative to the acquirer, with a relative deal size (*DealVal/AcqME*) of 35%. Stock financing is used in roughly 26% of the deal value on average.

## 4. Empirical Results

### 4.1 Acquirer Market Reactions around Conference Calls: Event Study

To examine the market's real-time reaction to analyst sentiment, we compute cumulative abnormal returns (CARs) using the Fama–French three-factor model. Figure 1 plots the return paths over the event window [-5, +5] for deals partitioned by median sentiment intensity.

The visual evidence reveals a significant divergence in market pricing commencing on the conference call date (Day 0). Deals characterized by high analyst *Optimism* or *Excitement* exhibit a sustained upward drift in CARs relative to their low-sentiment counterparts. Conversely, calls marked by high *Anxiety* or *Fear* display a sharp reversal, with return paths flattening or declining immediately upon interaction. This pattern suggests that analyst sentiment effectively discriminates between value-creating and value-destroying deal narratives in real time.

Table 3 quantifies these cross-sectional differences using two-sample t-tests of the three-day CAR [-1, +1]. The return spreads are economically large and statistically significant across all affective dimensions. For positive sentiment, acquirers experience substantially higher returns when analysts validate the deal. The spread between high- and low-*Optimism* calls is 1.5 percentage points (t = 4.44), while the high-minus-low spread for *Excitement* is 1.0 percentage point (t = 3.03). Moreover, for negative sentiment, the market penalty for negative affect is particularly severe. High-Fear calls underperform low-*Fear* calls by 1.9 percentage points (t =-5.39). Similarly, the spread for *Anxiety* is −1.5 percentage points (t = -4.53).

Collectively, these univariate results corroborate our hypothesis that analyst sentiment serves as a strong leading indicator of the market's assessment of deal quality.

### 4.2. Multivariate Regression

#### 4.2.1. Stock Market Return

To assess whether analyst sentiments predict call-window returns after controlling for observable deal and firm characteristics, we estimate the following cross-sectional specification:

$$FF3\ CAR_{it}\ [-1,+1] = \alpha + \beta\ Sentiment_{it} + \gamma' X_{it} + FE_{Acquirer\ 1\text{-}digit\ SIC} + FE_{Target\ 1\text{-}digit\ SIC} + FE_{Conference\ Year} + \varepsilon_{it} \quad (1)$$

The dependent variable $FF3\ CAR_{it}\ [-1,+1]$is the acquirer's Fama–French three-factor cumulative abnormal return over the three-day window centered on the conference-call date. $Sentiment_{it}$ is one of the four analyst sentiment intensity measures—optimism, excitement, anxiety, or fear (scaled to the unit interval). The control vector $X_{it}$ controls for acquirer size, market-to-book ratio, profitability (ROA), R&D intensity, relative deal size, stock payment percentage, and target public status. All specifications include acquirer and target industry fixed effects and year fixed effects. Appendix B provides a detailed definition of these variables. Standard errors are clustered by acquirer's industry. [3]

Table 4 presents the results. Consistent with Hypothesis 1a, we find that all four affective dimensions are strong predictors of conference call returns. The coefficient of *Optimism* is positive and significant (t = 7.57). A one-standard-deviation increase in analyst optimism is associated with a 0.95 percentage point increase in CAR. Similarly, the positive and highly significant coefficient on *Excitement* suggests that acquirers experience higher cumulative abnormal returns when analysts exhibit greater excitement about the deal. Importantly, the coefficients on *Anxiety* and *Fear* are negative and highly significant (t = -5.25 and t = -5.21, respectively). Deals where analysts express elevated fear suffer significantly lower returns.

Crucially, the magnitude of the coefficients supports Hypothesis 1b. The market reaction to negative sentiment is noticeably stronger than the reaction to positive sentiment. This asymmetry is consistent with the "costly signaling" framework (Mayew and Venkatachalam, 2012): because analysts face social and professional incentives to remain polite, a deviation into anxiety or fear is an informative signal of severe latent risks.

### 4.2.2. Deal completion and timing

Table 5 examines our second set of hypotheses on whether analyst sentiments are associated with real deal outcomes. Panel A reports logit regressions where the dependent variable indicates whether the deal is completed. Positive sentiments (Columns 1 and 2) are not significantly related to completion. In contrast, negative sentiments (Columns 3 and 4) are strongly associated with deal failure. In addition, *Anxiety* and *Fear* have large negative coefficients (-3.275

[3] Our main evidences are robust to alternative clustering of standard errors. Specifically, our inferences remain unchanged when clustering at the acquirer-firm level, by year, or using multi-way clustering by acquirer firm and industry, firm and year, industry and year, and jointly by firm, industry, and year.

and -5.066; both statistically significant at 1 percent level), indicating substantially lower completion likelihood for deals in which analyst questioning reflects heightened concern.

To gauge economic magnitude, we evaluate the logit estimates at one standard deviation changes in the sentiment variables. A one-standard-deviation increase in anxiety (0.048) lowers the odds of completion by roughly 15 percent (odds ratio ≈ 0.85). A one-standard-deviation increase in fear (0.040) lowers completion odds by about 18 percent (odds ratio ≈ 0.82). Appendix E.3 shows that probit models produce the same inferences.

Panel B reports Cox proportional-hazards models where the outcome is the time from announcement to completion, with incomplete deals right-censored. Consistent with Panel A, *Anxiety* and *Fear* significantly reduce the completion hazard, implying slower completion and a higher risk of delay or failure. At one standard deviation changes, the implied hazard ratios are approximately 0.84 for anxiety and 0.86 for fear. Overall, our results show that negative analyst sentiments are associated not only with weaker call-window returns, but also with subsequent deal frictions that are economically meaningful.

The asymmetry in Table 5, with stronger effects for negative sentiments than for positive sentiments, is consistent with our second set of hypotheses that negative analyst sentiments in Q&A sessions of M&A conference calls could be more diagnostic of deal frictions that can derail or slow deal completion.

#### 4.2.3. Analyst Recommendations

Panel C of Table 5 examines whether analyst sentiments expressed during the call are followed by subsequent analyst recommendations, as an examination of consistency in analyst point of view towards the deal. The dependent variable is the consensus recommendation measured at month-end, with higher values reflecting more bearish views.

The results show that *Optimism* and *Excitement* lead to more favorable future recommendations. A one-standard-deviation increase in optimism (0.140) is associated with a decline of about 0.08 in the consensus rating, and a one-standard-deviation increase in excitement (0.107) is associated with a decline of about 0.07. *Anxiety* and *Fear* are followed by more bearish recommendations. A one-standard-deviation increase in anxiety (0.048) raises the rating by roughly 0.05, and a one-standard-deviation increase in fear (0.040) raises it by roughly 0.06. Taken

together, our results indicate that sentiments explain nontrivial variation in recommendations beyond fundamentals and deal characteristics.

### 4.3. Robustness Tests

We examine the robustness of our primary evidence in Table 4 by addressing potential concerns regarding measurement, specification, and identification. Specifically, Tables 6 and 7 investigate whether the baseline sentiment and return relation remains robust to alternative sentiment measurement techniques, alternative return definitions, and alternative identification strategies.

#### 4.3.1 Alternative Specifications

Table 6 evaluates robustness along three dimensions. First, Panel A addresses the concern that our estimates could reflect idiosyncratic features of a single proprietary LLM model, GPT 4.1. We re-estimate the baseline Fama–French 3 CAR [–1,+1] regressions using sentiment scores generated by two additional LLMs, Mistral-large-3 and Llama 3.1.[4] These models are distributed as open-weights systems, which improves transparency and replicability because model versions can be archived and re-run in controlled (local) environments. They therefore provide a natural benchmark for GPT-4.1, which is accessed through an API and is not distributed as an open-weight model. Across all three models, the results are consistent: *Optimism* and *Excitement* load positively on CARs, *Anxiety* and *Fear* load negatively, and magnitudes and significance are comparable. This cross-model stability reduces the likelihood that the relations in Table 4 are an artifact of a particular model's training data, inference heuristics, or implementation details.[5]

Second, Panels B–D report alternative event windows used to measure market reactions. Using Fama–French three-factor CAR [−2,+2] (Panel B) and CAR [−5,+5] (Panel C) yields coefficients with the same signs and similar statistical significance as in Table 4 (which uses Fama–French three-factor CAR [−1,+1]), indicating that the results are not specific to a narrow three-day window. Panel D reports Fama–French three-factor CAR [0,+2], which is particularly informative in our setting because it reduces sensitivity to the timing of the call relative to market hours. When

[4] Mistral Large 3 is a flagship model developed by Mistral AI, featuring 123 billion parameters and a native 128,000 token context window. It is optimized for multilingual reasoning and complex extraction tasks. Llama 3.1, developed by Meta AI, is a dense transformer-based model with 405 billion parameters in its largest configuration. Both models represent the state of the art in open weights architectures, allowing researchers to perform local inference.

[5] We do not use earlier small-context variants such as Mistral-v1 (e.g., Goetzmann et al., 2025) for the main robustness check because our measurement protocol relies on processing the full analyst Q&A without chunking. Models with materially smaller context windows would require splitting transcripts into multiple segments, reintroducing boundary artifacts and context loss that our approach is designed to avoid. Using long-context models for this exercise keeps the alternative-LLM comparison aligned with the core design choice of scoring the full Q&A in one pass.

a call occurs after the market close, the associated price response is mechanically reflected in the next trading day. The estimates in Panel D remain directionally and economically consistent with the baseline specifications in Table 4, indicating that the sentiment–return relation does not hinge on whether calls occur before trading hours or after the close. [6]

Third, Panel E replaces the Fama–French three-factor model with the market model. Appendices E.4 and E.5 provide additional benchmarks using a momentum-augmented factor model and market-adjusted returns. Across all these alternative abnormal-return definitions, sentiment coefficients preserve their signs and remain similar in magnitude and statistical significance (compared to our baseline specifications in Table 4), implying that the main inferences are not driven by a particular benchmark model.[7]

Finally, Panel F of Table 6 reports the baseline regressions (Table 4) using standardized sentiment measures (mean = zero, standard deviation = one). This rescaling puts all sentiments on a common unit and allows a direct comparison of economic magnitudes across dimensions that otherwise differ in dispersion. The standardized estimates confirm the central patterns in Table 4. *Optimism* and *Excitement* are positively related to call-window CARs, while *Anxiety* and *Fear* are negatively related. They also reinforce the asymmetry highlighted in the baseline results. A one-standard-deviation increase in negative sentiments is associated with a larger decline in Fama–French 3 CAR [–1,+1] than the corresponding increase associated with a one-standard-deviation increase in positive sentiments.

**4.3.2 Extended Controls and Within-Acquirer Fixed Effects**

Table 7 presents two additional robustness checks of the baseline results (Table 4). Panel A augments the baseline specification with additional deal and information-environment controls, macro controls, pre-call return controls, and call-structure controls. Beyond the baseline control variables, we add bidder status (*Bidder*), analyst coverage (*Analyst Coverage*), and analyst forecast accuracy (*Analyst Forecast Accuracy*) to control for variation in the information environment and uncertainty that can shape both analyst questioning and investor reactions. We also add aggregate sentiment (*Sentiment Index*), a recession indicator (*Recession Indicator*), employment growth (*Employment Growth*), and CPI inflation (*CPI Inflation*) to control for time-varying macro

[6] Our results remain robust to additional alternative event windows, such as [0, +1], [-2, +1], and [-1, +3].

[7] Our results are also robust to the choice of additional asset pricing model such as Fama–French five-factor model (Fama and French, 2015) and the Hou–Xue–Zhang q-factor model (Hou, Xue, and Zhang, 2015).

conditions that affect risk pricing and conference call returns. We further include Fama–French three-factor CAR[−4,−2] (*Fama–French 3 CAR [-4,-2]*) relative to the call date to address information leakage, rumors, or gradual incorporation of deal information before the Q&A. [8]

In addition, to disentangle analyst sentiment from managerial framing and disclosure structure, we control for several call-level features that plausibly move both analyst sentiments and investors' valuation updates. Managerial tone can shape the sentimental content of the Q&A mechanically: a manager who repeatedly "sells" synergies or expresses unusually strong optimism may invite skepticism or probing follow-ups, while a manager who provides concrete milestones and verifiable details may reduce uncertainty and limit the scope for anxious questioning. Because these disclosure choices are endogenous to deal complexity and information asymmetry, they are also likely to affect conference-window returns directly. We therefore include LLM-based measures of management optimism in the prepared remarks (*Management Optimism in Main*) and in the Q&A (*Management Optimism in Q&A*) to net out the portion of analyst sentiment that simply mirrors (or reflects) managerial tone.

We also control for the verifiability and quantitative specificity of the information disclosed during the call (*Hard Information Score*). Following Dasgupta et al. (2024), we include a hard-information score that captures the extent to which the call emphasizes contractible and verifiable content as opposed to qualitative narrative. In their framework, "hard" information reflects concrete, checkable details such as terms, financing, timing, regulatory steps, and other elements that can be validated ex post, whereas "soft" communication emphasizes broader strategic framing, integration narratives, or aspirational synergy language (Dasgupta et al., 2024). In our setting, this distinction matters because low hard-information intensity can both elevate analyst anxiety and fear (by leaving key uncertainties unresolved) and depress CARs (by increasing perceived information risk and execution uncertainty), creating an omitted-variables channel if disclosure structure is not accounted for.

Complementing this verifiability dimension, we also control for a numerical-information share (*Numerical Information Share*) following Campbell et al. (2025), who show that more

[8] To ensure our findings are not driven by extreme market volatility, we also re-estimate our baseline specifications (in Table 4) after excluding the Global Financial Crisis (2008–2009) and the COVID-19 pandemic period (2020). The coefficients on analyst sentiments and the resulting statistical inferences remain similar to those reported in the main regressions (Table 4).

extensive numerical disclosure is associated with stronger announcement-period returns and lower information risk proxies. In M&A calls, a higher numerical share similarly reflects greater quantitative grounding in the discussion, for example, explicit guidance about revenue synergies, margin targets, integration costs, timing, or unit economics. Such quantitative specificity can attenuate negative sentiments by narrowing the set of plausible downside scenarios, while also improving investors' ability to update valuations. Including these disclosure-structure controls, therefore, helps ensure that the estimated sentiment coefficients capture incremental information in how analysts react and probe, rather than simply proxy for whether management communicates in a vague, highly optimistic style versus a concrete, number-rich style.

Despite this substantial expansion of controls, the estimated return−sentiment relations remain both economically large and statistically significant (Columns 1-4 of Panel A, Table 7). *Optimism* continues to load positively on call-window performance, with a coefficient of 0.070 (t = 7.317), and *Excitement* shows a similarly positive association at 0.062 (t = 4.107). The negative sentiments retain the opposite pattern with larger magnitude in effect: *Anxiety* is −0.190 (t = −4.424), and *Fear* is −0.258 (t = −4.108). Thus, conditioning on a broad set of acquirer and deal observables, pre-call price dynamics, macro conditions, and detailed measures of managerial tone and disclosure structure, analyst sentiments retain significant explanatory power. Higher analyst optimism and excitement lead to stronger Fama–French 3 CAR [−1,+1], whereas elevated anxiety and fear lead to larger weaker market reactions.[9]

Our results in Panel A, Table 7, have two implications. First, they indicate that the informative content of analyst sentiments is not absorbed by richer proxies for the information environment or disclosure accuracy. In other words, analysts do not simply "sound" optimistic or anxious because managers provide more or less quantitative, verifiable information; nor do the coefficients reflect a mechanical correlation with pre-call run-ups or macro states. Second, the persistence of the negative-sentiment effects after these controls reinforces the interpretation that anxiety and fear capture meaningful downside-oriented assessment during the Q&A that investors

[9] Our results remain robust to several additional controls: transcript length (as measured by log token count), concurrent sentiment in press release (obtained from WRDS SEC Analytics Suite), concurrent news sentiment (obtained from RavenPack), macro level factors including economic policy uncertainty (Baker, Bloom, and Davis, 2016), the default spread, and the term spread (Loughran and McDonald, 2011; Cao et al., 2023).

incorporate into prices, over and above what is contained in the observable deal package and in management's own framing of the transaction.

In Panel B of Table 7, we replace acquirer industry fixed effects in our baseline model (Table 4) with acquirer firm fixed effects while retaining target one-digit SIC and conference-year fixed effects. This specification absorbs all time-invariant acquirer characteristics, including persistent differences in business model, governance, disclosure style, and the typical composition of the firm's analyst following. It also mitigates the concern that the documented effects could reflect stable analyst–industry (firm) pairings, where certain analyst groups are systematically more pessimistic or optimistic and repeatedly cover the same firms (Boni and Womack, 2006; Clarke, Khorana, Patel, and Rau, 2007). Under firm fixed effects, identification comes from within-firm variation in analyst sentiments across different M&A calls over time, holding constant persistent firm attributes and stable aspects of the analyst base.

Our results in Panel B, Table 7 remain economically and statistically meaningful: *Optimism* (0.069, t = 5.548) and *Excitement* (0.065, t = 3.446) remain positive, while *Anxiety* (−0.158, t = −3.127) and *Fear* (−0.200, t = −2.663) remain negative with higher magnitude. Importantly, the adjusted $R^2$ increases substantially (to 0.52), reflecting the explanatory power of firm fixed effects.

### 4.4. Endogeneity

In Table 8, we further address the concern that the baseline findings (Table 4) could be influenced by endogeneity, in the sense that unobserved deal attributes may jointly affect analysts' sentiments in the Q&A and investors' conference call-window valuation updates.

In Panel A, we apply Oster's (2019) coefficient-stability procedure under proportional selection (δ = 1), setting $R_{\max} = \min(1.3 \times R^2_{\text{full}}, 1)$. For each sentiment, we compare a "short" specification that includes the sentiment and the fixed effects to the baseline "full" specification that additionally includes the full set of control variables. The implied identified sets are tight and preserve the baseline signs. For *Optimism*, the coefficient increases from 0.0565 ( $R^2 = 0.047$) in the short model to 0.0675 ( $R^2 = 0.1008$) in the full model; the Oster-adjusted estimate is 0.0737, yielding an identified set of [0.0675, 0.0737]. *Excitement* displays a similar pattern: 0.0463 in the short model and 0.0624 in the full model, with an adjusted estimate of 0.0711 and an identified set of [0.0624, 0.0711]. For the negative sentiments, the identified sets remain strictly below zero.

*Anxiety* moves from −0.2567 to −0.2223, with an Oster-adjusted value of −0.1983 and an identified set of [−0.2223, −0.1983]. *Fear* moves from −0.3284 to −0.2856, with an adjusted value of −0.2549 and an identified set of [−0.2856, −0.2549]. Under this benchmark, selection on unobservables would need to be implausibly strong, relative to selection on observables, to eliminate the baseline effects.[10]

Panel B reports a falsification test that targets mechanical artifacts. We randomly permute each sentiment score across deals, preserving its marginal distribution but breaking any deal-level linkage to returns, and re-estimate our baseline regressions (Table 4). [11]The permuted coefficients are close to zero and statistically insignificant for all sentiments (*Optimism* −0.005, t = −0.352; *Excitement* 0.004, t = 0.245; *Anxiety* −0.016, t = −0.557; *Fear* −0.001, t = −0.027).

In Panels C through E, we further address the possibility that high- and low-sentiment calls differ systematically on observable firm and deal characteristics that also predict announcement-window returns. For each sentiment, we define treatment as being above the sample median and then balance treated and control observations on the baseline controls (Table 4). Specifically, in Panel C, we implement one-to-one nearest-neighbor propensity score matching and re-estimate Equation (1) on the matched sample. The estimated coefficients remain economically large and statistically significant, and they are close to the baseline magnitudes (*Optimism* 0.067, t = 7.751; *Excitement* 0.068, t = 3.014; *Anxiety* −0.273, t = −2.910; *Fear* −0.277, t = −4.829). Panel D applies coarsened exact matching (CEM), which mitigates model dependence by imposing strict comparability between treated and control groups. We coarsen continuous covariates into five bins and require exact matches for binary variables. Although this procedure yields reduced sample sizes (ranging from 2,063 to 2,100 observations), the CEM-weighted estimates remain robust and consistent with the baseline (*Optimism* 0.066, t = 6.472; *Excitement* 0.059, t = 2.824; *Anxiety* −0.159, t = −2.914; *Fear* −0.213, t = −2.725). Panel E employs entropy balancing, which reweights control observations to ensure that their covariate moments effectively match those of the treated group. The resulting estimates continue to mirror the baseline economic and statistical significance:

[10] This approach has become standard in recent empirical literature to assess the sensitivity of results to omitted variable bias (see, e.g., Gao and Huang, 2020; Sani, Shroff, and White, 2023).

[11] To ensure the replicability of this falsification test, we initialize the pseudo-random number generator with a fixed seed prior to the permutation procedure.

*Optimism* (0.065, t = 6.519), *Excitement* (0.061, t = 3.892), *Anxiety* (−0.223, t = −4.918), and *Fear* (−0.273, t = −4.655).[12]

Taken together, the coefficient-stability bounds, the placebo permutation, and three balancing approaches show that the relation between analyst sentiments in the Q&A and call-window abnormal returns is not explained by omitted-variable bias, mechanical artifacts, or systematic differences in observable deal and firm characteristics between high- and low-sentiment calls.

**5. Validation: LLM Sentiment vs. Loughran–McDonald (LM) Tone**

In Table 9, we evaluate whether dictionary-based tone, as measured by the Loughran and McDonald (2011) word lists applied to analyst speech in the Q&A, captures the return-relevant content of merger-call dialogue. Panel A shows that the standard Loughran and McDonald (2011) tone components (*Tone (LM)*) have limited explanatory power for call-window returns once we include baseline controls and the full set of fixed effects. In Columns (1) and (2), neither the positive-word share nor the negative-word share is reliably related to *Fama French 3 CAR [-1, +1]*, and net tone is at best weakly significant. This pattern is consistent with an important limitation of bag-of-words measurement in interactive settings. Analysts often communicate skepticism or confidence through question structure, conditional framing, and context-dependent implications rather than through isolated affect words. Consequently, word counts serve as a noisy proxy for the semantic content processed by investors.

Panel B conducts a direct horse race between dictionary tone and an LLM (GPT 4.1)-based measure of overall affect computed from the same analyst Q&A text. In our framework, *Valence* represents the pleasant–unpleasant dimension of affect in the Russell (1980) circumplex model; it summarizes whether the analyst dialogue reflects a favorable versus unfavorable affective evaluation (sentiment) of the deal. When we include both *Valence* and *Tone (LM)* in the same regression, *Valence* loads strongly and positively on *Fama French 3 CAR [-1, +1]*, whereas *Tone (LM)* becomes economically small and statistically indistinguishable from zero. The increase in

[12] Our results remain robust to alternative matching procedures. Following Lu, Zanutto, Hornik, and Rosenbaum (2001) and Armstrong, Jagolinzer, and Larcker (2010), we implement a non-bipartite matching algorithm that optimizes matched pairs by minimizing propensity score distances while maximizing treatment differences (Armstrong, Larcker, Ormazabal, and Taylor, 2013). This approach produces CAR–sentiment estimates nearly identical in magnitude and significance to our baseline findings (Table 4).

explanatory power relative to the LM-only specifications indicates that the LLM (GPT 4.1)-based construct captures return-relevant variation in analyst dialogue that dictionary tone fails to recover.

This evidence aligns with a broader theme in recent research. Model-based representations that utilize context and task-relevant learning materially outperform dictionary tone in settings where meaning is not well approximated by counts of pre-specified words. In asset-pricing applications, Ke, Kelly, and Xiu (2019) show that predictive signals extracted from text using modern machine-learning methods dominate traditional dictionary-style measures for return prediction. In accounting disclosure settings, Frankel, Jennings, and Lee (2022) document that machine-learning approaches outperform dictionary methods in measurement and validation exercises. More recently, work leveraging large language models emphasizes that LLMs can extract economically relevant information from the semantic structure of text by conditioning on context and discourse relations (Chen, Kelly, and Xiu, 2023).

Taken together with the discrete sentiment results, Table 9 indicates that the LLM approach is not simply a smoother version of dictionary tone. Rather, it recovers a richer, context-dependent affective signal from analyst dialogue. The optimism, excitement, anxiety, and fear scores can thus be interpreted as a structured decomposition of that signal into psychologically meaningful dimensions within the same valence–arousal framework (Russell, 1980).

## 6. Cross-Sectional Evidence

In Table 10, we explore whether the predictive power of analyst sentiments is stronger in settings characterized by high information asymmetry and valuation uncertainty. Our conceptual framework suggests that when formal disclosure is sparse or less reliable, investors place greater weight on the affective cues embedded in analyst management interactions to assess deal quality.

### 6.1. Public vs. Non-Public Targets

We first examine whether investors rely more on analyst sentiments when information asymmetry regarding the target is high by comparing acquisitions of public versus non-public firms. Panel A estimates the baseline *Fama French 3 CAR [-1, +1]* regressions separately for these two subsamples. Privately held companies are inherently more opaque because they lack the mandatory disclosure requirements of publicly traded firms. This scarcity of public information increases

investors' information search costs and makes the information revealed during conference calls valuable (Akerlof, 1978; Officer, 2007; Bargeron, Schlingemann, Stulz, and Zutter, 2008).

Columns (1) and (2) report the results for *Optimism*. The estimated coefficient is positive and statistically significant for private target deals (t = 5.963) but statistically insignificant for public target acquisitions. The difference between these subsample coefficients is statistically significant (p = 0.0175), indicating that analyst optimism is more informative when target side opacity is higher. We observe a similar pattern for *Excitement* in Columns (3) and (4) where the coefficient is positive and significant for non-public deals (t = 3.245) but insignificant for public deals (t= 1.180). Although the subsample difference is not statistically significant (p = 0.2075), the point estimate for private targets is more than twice the magnitude of the estimate for public targets.

The results for negative sentiments are even more pronounced. In Columns (5) and (6), the coefficient for *Anxiety* is strongly negative for private targets (t = -3.965) but insignificant for public targets, with a significant difference between groups (p = 0.0236). For *Fear*, presented in Columns (7) and (8), the pattern is similar. *Fear* carries a negatively statistically significant coefficient for private target deals (t= −5.765), whereas the coefficient for public targets is not statistically significant. The difference is highly significant (p = 0.0004). Collectively, these patterns demonstrate that analyst sentiments are most salient to investors when the target is opaque and traditional public information is limited.

### 6.2. Related vs. Unrelated Acquisitions

Panel B splits the sample by industry relatedness between the acquirer and the target (based on two-digit SIC code). In diversifying or unrelated acquisitions, synergies are often more idiosyncratic and integration risks are harder to evaluate ex ante (Servaes, 1996; Schoar, 2002). Since unrelated deals often suffer from greater agency problems and valuation complexity, investors rely more heavily on analyst signals to benchmark managerial narratives.

Consistent with this intuition, the relation between positive sentiments and *Fama French 3 CAR [-1, +1]* is significantly larger in magnitude for unrelated deals. Specifically, the coefficient for *Optimism* is 0.100 (t = 6.080) for unrelated deals versus 0.049 (t = 5.331) for related deals, a difference that is statistically significant (p = 0.0054). Similarly, the coefficient for *Excitement* is

0.113 (t = 5.371) in the unrelated subsample but drops to 0.037 (t = 1.945) for related deals, with a significant difference between coefficients (p = 0.0034).

For negative sentiments, the impact is also more salient in unrelated transactions. The coefficient on *Anxiety* is −0.296 (t = −4.978) for unrelated deals versus −0.188 (t = −4.259) for related deals (p = 0.0106). For *Fear*, the coefficients are −0.336 (t = −5.260) for unrelated deals and −0.263 (t = −4.405) for related deals (although the difference is not statistically significant). These findings suggest that when deal complexity is high and business models are less familiar, investors place extra weight on analysts' sentiments as a signal of underlying deal quality.

### 6.3. Accrual Quality

Panel C examines whether the informativeness of analyst sentiments depends on the acquirer's financial reporting quality, using the accrual quality measure of Dechow and Dichev (2002). Prior literature established accrual quality as a proxy for information asymmetry between management and market participants (Francis, LaFond, Olsson, and Schipper, 2005; Lee and Masulis, 2009; Bhattacharya, Desai, and Venkataraman, 2013). We argue that lower reporting quality heightens uncertainty about the true value of an acquisition, leading investors to seek supplementary cues from analyst-management interactions.

We estimate subsample regressions based on a median split of accrual quality. For positive sentiments, the coefficients are similar and statistically significant across both subsamples. However, the effects of negative sentiments are substantially stronger for the low quality accrual group. While *Anxiety* is statistically significant for both, the magnitude is considerably larger for firms with noisier accruals (p = 0.0354). Similarly, the coefficient for *Fear* is −0.425 (t = −9.103) for low quality accrual firms but attenuates to −0.186 (t = −3.588) for high quality firms, with the difference being statistically significant at the 1% level (p = 0.0054). These findings indicate that when accounting numbers are noisier or potentially more manipulable, investors rely more heavily on analysts' negative sentimental signals to assess risk. [13]

[13] Our results remain qualitatively similar when we use alternative proxies for financial reporting quality and accrual manipulation. Specifically, we re-estimate our regressions using the performance adjusted discretionary accruals model (Kothari, Leone, and Wasley, 2005) and the modified Jones model (Dechow, Sloan, and Sweeney, 1995). We continue to find that negative analyst sentiments carry greater weight for firms with lower reporting quality is robust across these different estimation methods.

## 7. Long-Run Performance and the Crash-Belief Channel

In Table 11, we link analyst sentiments to long-run post-conference call buy-and-hold abnormal returns (BHAR), measured using both value-weighted (BHAR_VW) and equal-weighted (BHAR_EW) portfolios rebalanced over the post-call horizon. Each specification includes a specific sentiment measure, the *Fama French 3 CAR [-1, +1]*, and the interaction between the sentiment and *Fama French 3 CAR [-1, +1]*, alongside the full set of firm- and deal-level controls and fixed effects.[14]

The results indicate a clear asymmetry between positive and negative sentiments. For positive sentiments (Columns 1, 2, 5, and 6), the main coefficients on *Optimism* and *Excitement* are small and statistically insignificant. The interaction terms with *Fama French 3 CAR [-1, +1]* are also insignificant, suggesting that once short-run returns are accounted for, positive sentiments do not provide additional predictive power for long-run performance.

In contrast, negative sentiments significantly predict long-run underperformance (as shown in Columns 3, 4, 7, and 8). For BHAR_VW, *Anxiety* has a coefficient of −0.345 (t = −2.213) and *Fear* has a coefficient of −0.428 (t = −2.970). For BHAR_EW, *Anxiety* has a coefficient of −0.484 (t = −3.567) and *Fear* has a coefficient of −0.380 (t = −2.512). This long-run drift suggests that negative analyst sentiments at the M&A announcement flag value-destroying potential in deals that the market only partially incorporates at the beginning (Loughran and Vijh, 1997; Rau and Vermaelen, 1998).

Importantly, the interaction terms between negative sentiments and *Fama French 3 CAR [-1, +1]* are all strongly negative and statistically significant. These significant negative interactions indicate that deals characterized by high short-run returns but high analyst anxiety or fear subsequently experience the most severe underperformance. This pattern is consistent with a crash-belief channel: analysts' negative sentiments reflect perceived tail risks or integration

[14] Our results are robust to alternative specifications of the long-run return window. Specifically, using non-rebalanced buy-and-hold abnormal returns (BHARs) instead of the rebalanced BHARs used in our primary analysis produces similar long-run relations between analyst sentiments and post-call performance.

problems that management may attempt to obscure through strategic disclosure (Jensen, 1986; Roll, 1986; Shleifer and Vishny, 2003).[15]

## 8. Conclusion and Implications

This paper documents that analysts' real-time sentiments during merger conference call Q&A sessions contain economically meaningful information about acquisition value and risk. Using 2,604 U.S. public acquirer observations from 2003 to 2023, we extract continuous measures of optimism, excitement, anxiety, and fear from analyst dialogue using an LLM-based protocol grounded in the Russell (1980) valence–arousal framework. We find that analyst sentiments are strongly associated with acquirer call-window returns. Higher optimism and excitement correlate with positive abnormal returns, while anxiety and fear correlate with significantly lower returns. These relations are robust to alternative return benchmarks, firm and deal controls, and within-acquirer fixed effects that absorb time-invariant acquirer characteristics. Importantly, the findings replicate across multiple LLM model families, ensuring the results are not artifacts of a single proprietary system.

Beyond short-run returns, these analyst sentiments signal consequential outcomes. Negative sentiments are followed by lower deal completion likelihood and longer closing times. Analyst anxiety and fear at the M&A announcement are also associated with post-completion long-run underperformance, particularly for deals where the market initially reacted positively despite analysts sounding worried. This pattern is consistent with a "crash-belief" channel, where affective cues flag integration or valuation risks that are only partially impounded at announcement (Loughran and Vijh, 1997; Rau and Vermaelen, 1998).

The evidence presented in this paper extends the mergers and acquisitions and information intermediary literature. First, our study moves beyond viewing conference calls as pure disclosure events by demonstrating that the interactional component of the call, how analysts question, challenge, hedge, and frame downside scenarios, contains priced information. This shifts attention from prepared remarks to what is revealed through unscripted real-time dialogue under uncertainty.

[15] In additional (unreported) analyses using a wide set of accounting performance measures, including return on assets (ROA) and operating cash flows, we do not find a statistically significant relation between analyst sentiments and long-run accounting outcomes.

Second, we provide micro-level evidence on a behavioral mechanism for heterogeneity in merger conference call returns. Investors learn from analysts' affective reactions, with negative sentiments carrying disproportionately higher weight than positive sentiments, consistent with the idea that downside-oriented signals are more diagnostic in high-stakes corporate events. Third, our analysis identifies when markets rely most on affective cues. The return-sentiment relation is strongest in settings with higher information asymmetry and valuation complexity, linking analyst dialogue to classic theories of agency problem, opacity and uncertainty in acquisitions and highlighting Q&A as a channel through which information is capitalized into prices. Fourth, our study bridges short-run price discovery and longer-run value materialization by documenting that analyst negative sentiments at the M&A announcement are associated with both completion risk and post-completion long-run underperformance, suggesting that analysts' anxiety and fear can flag latent deal problems that the market does not fully impound at announcement.

The paper also offers a methodological contribution to empirical finance by providing a scalable and reproducible approach to measuring economically interpretable constructs from dialogue. In interactive settings, meaning is conveyed through context, pragmatics, and discourse structure rather than isolated sentiment words. An LLM-based framework built on strict analyst isolation, standardized prompting, deterministic decoding, and machine-readable output captures this contextual content and outperforms dictionary tone in explaining call window returns. More broadly, it provides a template for studying belief formation and information processing in other high-stakes interactions where traditional text methods are poorly matched to conversational language.

Overall, our evidence implies that conference calls help markets learn not only from disclosed facts in management prepared remarks but also from how sophisticated intermediaries interact with management when they pressure test a deal in real time. Analysts' anxious and fearful questioning appears to summarize downside assessments that are followed by completion frictions and longer run value destruction. Measuring these affective signals from dialogue, therefore, opens a new window into the foundations of market learning in mergers and acquisitions and, more generally, into how information revealed through verbal interaction is incorporated into asset prices.

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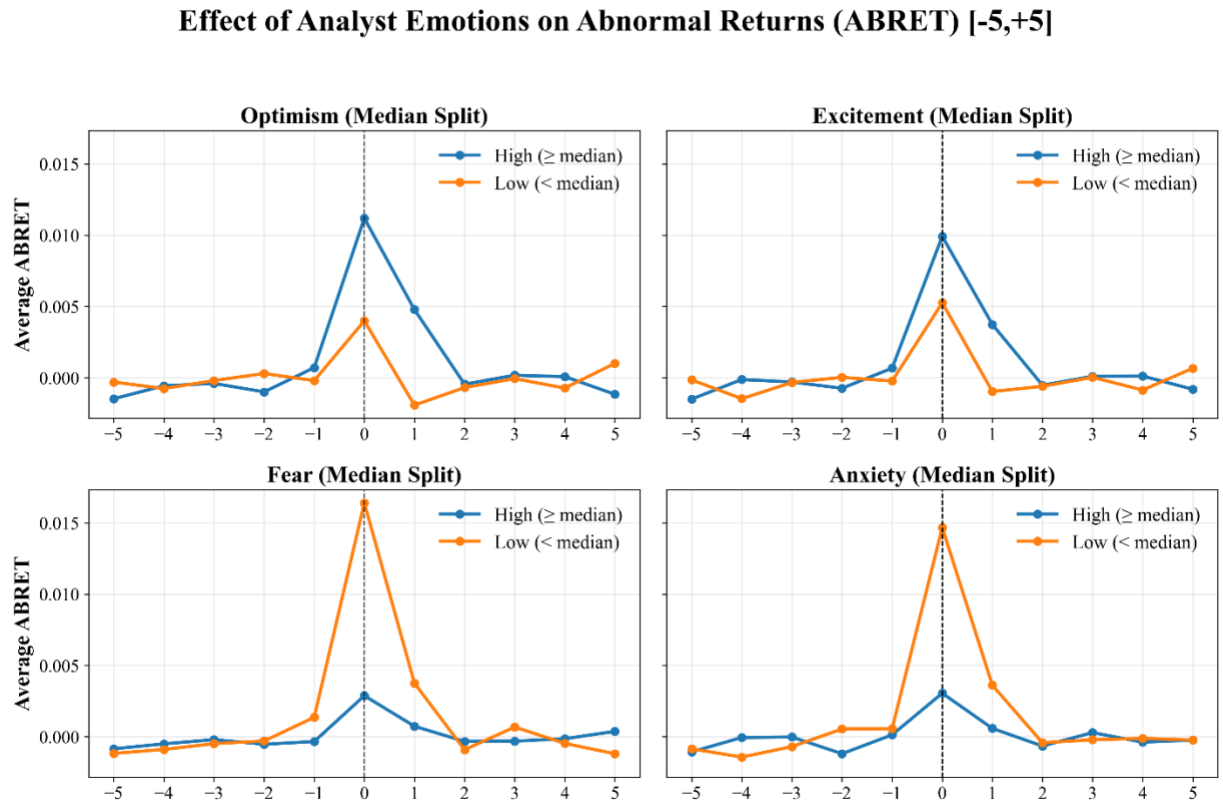
**Figure 1: Acquirer Market Reactions around Conference Calls by Analyst Sentiments**

This figure plots the acquirers' daily abnormal returns (Fama–French 3 ABRET [−5, +5]) and cumulative abnormal returns (Fama–French 3 CAR [−5, +5]) around conference calls for high- versus low-sentiment deals. For each analyst's sentiment, we classify deals into high- and low-sentiment groups based on a median split and compute the cross-sectional average Fama–French 3 ABRET or Fama–French 3 CAR for each event day separately for the two groups. The upper panels report results for positive sentiments (optimism and excitement), while the lower panels report results for negative sentiments (fear and anxiety). Day 0 denotes the conference day.



## Effect of Analyst Emotions on Cumulative Abnormal Returns ([-5,+5])

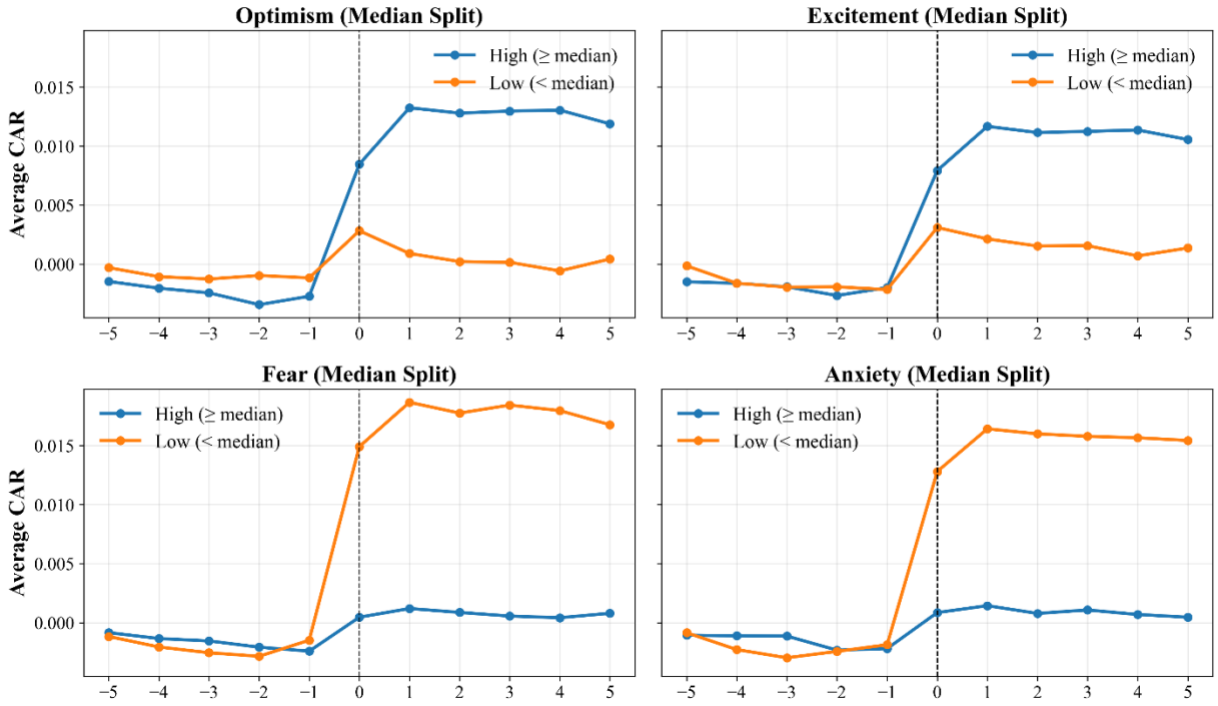


**Table 1. Timing of Calls**

This table reports the distribution of M&A conference calls by their timing relative to the corresponding deal announcement date. Most calls occur on the announcement day (about 69%), with an additional 23% held on the following day. The sample consists of 2,604 M&A conference call–deal observations.

| Days After | Frequency | Percent |
|---|---|---|
| 0 days | 1,788 | 68.66% |
| 1 day | 591 | 22.70% |
| 2–5 days | 113 | 4.34% |
| ≥ 6 days | 112 | 4.30% |
| Total | 2,604 | 100.00% |

**Table 2. Summary Statistics**

This table reports descriptive statistics for the analyst sentiment measures, the main acquirer return measure, and the control variables used in the analyses. For each variable, we report the mean, standard deviation, and the 25th, 50th (median), and 75th percentiles. The main return measure is the Fama–French three-factor cumulative abnormal return over the window [−1,+1] around the conference date.

| Variables | Mean | SD | P25 | P50 | P75 |
|---|---|---|---|---|---|
| Optimism | 0.498 | 0.140 | 0.400 | 0.540 | 0.600 |
| Excitement | 0.250 | 0.107 | 0.180 | 0.220 | 0.300 |
| Anxiety | 0.085 | 0.048 | 0.050 | 0.080 | 0.100 |
| Fear | 0.072 | 0.040 | 0.050 | 0.060 | 0.080 |
| FF3 CAR[–1,+1] | 0.010 | 0.084 | -0.029 | 0.005 | 0.043 |
| ln(AT)Acq | 7.995 | 1.824 | 6.756 | 7.983 | 9.254 |
| MTB Acq | 3.071 | 3.569 | 1.446 | 2.183 | 3.596 |
| ROA Acq | 0.018 | 0.136 | 0.006 | 0.038 | 0.081 |
| RD Acq | 0.050 | 0.086 | 0.000 | 0.004 | 0.071 |
| Tar Public | 0.394 | 0.489 | 0.000 | 0.000 | 1.000 |
| Tar US | 0.848 | 0.360 | 1.000 | 1.000 | 1.000 |
| Stock% | 26.096 | 37.291 | 0.000 | 0.000 | 50.000 |
| DealVal/AcqME | 0.348 | 0.455 | 0.086 | 0.192 | 0.431 |

**Table 3. Sentiments and Acquirer Conference Call Returns (Univariate Tests)**

This table reports univariate comparisons of acquirer conference call returns across high- and low-sentiment subsamples. For each sentiment measure, we split observations at the sample median and report the mean Fama–French 3 CAR[-1,+1] for the full sample, the low-sentiment group, and the high-sentiment group, along with the two-sample t-statistic for the difference in means. All variables are defined in Appendix B. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

| **Panel A. (Excitement)** | | | | |
|---|---|---|---|---|
| | All firms | Low Excitement | High Excitement | *t-statistic of difference* |
| | (N= 2,604) | (N= 1,018) | (N= 1,586) | |
| Fama–French 3 CAR [-1,+1] (Mean) | 0.010 | 0.004 | 0.014 | 3.032*** |

| **Panel B. (Optimism)** | | | | |
|---|---|---|---|---|
| | All firms | Low Optimism | High Optimism | *t-statistic of difference* |
| | (N= 2,604) | (N= 1,119) | (N= 1,485) | |
| Fama–French 3 CAR [-1,+1] (Mean) | 0.010 | 0.001 | 0.016 | 4.444*** |

| **Panel C. (Anxiety)** | | | | |
|---|---|---|---|---|
| | All firms | Low Anxiety | High Anxiety | *t-statistic of difference* |
| | (N=2,604) | (N= 1,130) | (N= 1,474) | |
| Fama–French 3 CAR [-1,+1] (Mean) | 0.010 | 0.018 | 0.003 | -4.532*** |

| **Panel D. (Fear)** | | | | |
|---|---|---|---|---|
| | All firms | Low Fear | High Fear | *t-statistic of difference* |
| | (N= 2,604) | (N= 1,005) | (N= 1,599) | |
| Fama–French 3 CAR [-1,+1] (Mean) | 0.010 | 0.0215 | 0.003 | -5.392*** |

**Table 4. Sentiments and Acquirer Conference Call Returns**

This table reports OLS regressions of acquirer cumulative abnormal returns (Fama–French 3 CAR [-1,1]) on analyst sentiment measures. Columns (1)–(2) focus on positive sentiments (optimism and excitement), while Columns (3)–(4) focus on negative sentiments (anxiety and fear). All specifications include the full set of deal and acquirer control variables, conference-year fixed effects, and acquirer and target one-digit SIC industry fixed effects. T-statistics, reported in parentheses, are based on robust standard errors clustered at the acquirer industry level. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

| | Positive sentiments | | Negative sentiments | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| **Variables** | Fama–French 3 CAR [-1,1] | | | |
| Optimism | 0.068*** | - | - | - |
| | (7.572) | | | |
| Excitement | - | 0.062*** | - | - |
| | | (4.165) | | |
| Anxiety | - | - | -0.222*** | - |
| | | | (-5.249) | |
| Fear | - | - | - | -0.286*** |
| | | | | (-5.211) |
| ln(AT)Acq | -0.003*** | -0.003** | -0.002 | -0.002 |
| | (-3.333) | (-3.222) | (-1.692) | (-1.532) |
| MTB Acq | 0.001* | 0.001* | 0.001* | 0.001* |
| | (2.179) | (2.156) | (2.201) | (2.197) |
| ROA Acq | -0.031*** | -0.029*** | -0.031*** | -0.030*** |
| | (-5.167) | (-4.384) | (-5.155) | (-4.972) |
| RD Acq | -0.033 | -0.033 | -0.027 | -0.026 |
| | (-1.424) | (-1.495) | (-1.363) | (-1.316) |
| Tar Public | -0.024*** | -0.024*** | -0.022*** | -0.022*** |
| | (-4.702) | (-4.681) | (-4.102) | (-4.001) |
| Tar US | 0.008 | 0.008 | 0.009 | 0.009 |
| | (1.662) | (1.736) | (1.777) | (1.755) |
| Stock% | -0.000** | -0.000** | -0.000** | -0.000** |
| | (-2.868) | (-2.733) | (-2.335) | (-2.299) |
| DealVal/AcqME | 0.022 | 0.022 | 0.024* | 0.024* |
| | (1.698) | (1.728) | (1.908) | (1.932) |
| Observations | 2,604 | 2,604 | 2,604 | 2,604 |
| Adjusted R-squared | 0.101 | 0.095 | 0.105 | 0.107 |
| Industry FE | Yes | Yes | Yes | Yes |
| Year FE | Yes | Yes | Yes | Yes |

**Table 5. Deal Outcomes**

**Panel A. Completion Probability**

This panel displays the estimation results of logistic regressions of the deal completion indicator (Completed_Deal) on analyst sentiment measures. Columns (1)–(2) focus on positive sentiments (optimism and excitement), while Columns (3)–(4) focus on negative sentiments (anxiety and fear). All regressions include conference-year fixed effects and acquirer and target one-digit SIC industry fixed effects. Z-statistics, reported in parentheses, are based on robust standard errors clustered at the acquirer industry level. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

| | Positive sentiments | | Negative sentiments | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| **Variables** | Completed_Deal | | | |
| Optimism | 0.315 | - | - | - |
| | (0.362) | | | |
| Excitement | - | 0.384 | - | - |
| | | (0.321) | | |
| Anxiety | - | - | -3.275*** | - |
| | | | (-2.917) | |
| Fear | - | - | - | -5.066*** |
| | | | | (-5.443) |
| ln(AT)Acq | 0.133* | 0.133* | 0.149** | 0.158** |
| | (1.850) | (1.891) | (2.305) | (2.386) |
| MTB Acq | -0.039** | -0.039* | -0.040** | -0.040** |
| | (-1.971) | (-1.960) | (-1.994) | (-2.001) |
| ROA Acq | 0.351 | 0.348 | 0.351 | 0.372 |
| | (0.471) | (0.465) | (0.488) | (0.516) |
| RD Acq | 0.045 | 0.032 | 0.153 | 0.118 |
| | (0.044) | (0.031) | (0.167) | (0.126) |
| Tar Public | -1.347*** | -1.347*** | -1.322*** | -1.315*** |
| | (-6.749) | (-6.749) | (-6.719) | (-6.688) |
| Tar US | 0.261 | 0.262 | 0.231 | 0.207 |
| | (0.762) | (0.760) | (0.688) | (0.609) |
| Stock% | -0.006 | -0.006 | -0.006 | -0.006 |
| | (-1.255) | (-1.291) | (-1.118) | (-1.078) |
| DealVal/AcqME | -0.529*** | -0.529*** | -0.521*** | -0.515*** |
| | (-3.646) | (-3.535) | (-3.666) | (-3.556) |
| Observations | 1,945 | 1,945 | 1,945 | 1,945 |
| Pseudo R-squared | 0.140 | 0.140 | 0.145 | 0.149 |
| Industry FE | Yes | Yes | Yes | Yes |
| Year FE | Yes | Yes | Yes | Yes |

**Panel B. Days to Completion**

This panel presents Cox proportional hazards regressions of deal completion time on analyst sentiment measures. Survival time is measured as the number of days from the announcement date to the completion date, with completed deals treated as failures and incomplete deals treated as right-censored observations. All regressions include acquirer and target one-digit SIC industry fixed effects and conference-year fixed effects. Z-statistics, reported in parentheses, are based on robust standard errors clustered at the acquirer industry level. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

| | Positive sentiments | | Negative sentiments | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| **Variables** | Days to Completion | | | |
| Optimism | 0.151 | - | - | - |
| | (0.466) | | | |
| Excitement | - | 0.134 | - | - |
| | | (0.317) | | |
| Anxiety | - | - | -3.512*** | - |
| | | | (-4.290) | |
| Fear | - | - | - | -3.765*** |
| | | | | (-5.885) |
| ln(AT)Acq | -0.135*** | -0.134*** | -0.125*** | -0.125*** |
| | (-7.454) | (-7.263) | (-6.279) | (-6.632) |
| MTB Acq | 0.004 | 0.004 | 0.007 | 0.007 |
| | (0.289) | (0.278) | (0.496) | (0.501) |
| ROA Acq | -0.152 | -0.151 | -0.196 | -0.148 |
| | (-0.813) | (-0.796) | (-1.365) | (-1.004) |
| RD Acq | -0.017 | -0.019 | 0.044 | 0.044 |
| | (-0.052) | (-0.059) | (0.146) | (0.140) |
| Tar Public | -0.484*** | -0.483*** | -0.465*** | -0.470*** |
| | (-6.210) | (-6.258) | (-6.718) | (-6.610) |
| Tar US | 0.227** | 0.225** | 0.227** | 0.219** |
| | (2.225) | (2.286) | (2.160) | (2.038) |
| Stock% | -0.007*** | -0.007*** | -0.007*** | -0.007*** |
| | (-3.032) | (-3.012) | (-3.128) | (-3.045) |
| DealVal/AcqME | -0.668*** | -0.668*** | -0.659*** | -0.651*** |
| | (-7.024) | (-6.993) | (-7.312) | (-6.994) |
| Observations | 1,333 | 1,333 | 1,333 | 1,333 |
| Wald $\chi^2$ | 108.25 | 55.04 | 113.95 | 669.90 |
| Industry FE | Yes | Yes | Yes | Yes |
| Year FE | Yes | Yes | Yes | Yes |

**Panel C. Analyst Recommendations**

This panel reports OLS regressions of analyst stock ratings on analyst sentiment measures. The dependent variable is the consensus analyst rating (1–5, with higher values indicating more bearish recommendations). Columns (1)–(2) focus on positive sentiments (optimism and excitement), while Columns (3)–(4) focus on negative sentiments (anxiety and fear). All regressions include acquirer and target one-digit SIC industry fixed effects and conference-year fixed effects. T-statistics, reported in parentheses, are based on robust standard errors clustered at the acquirer industry level. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

| | Positive sentiments | | Negative sentiments | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| **Variables** | Analyst Rating (1-5, higher = more bearish) | | | |
| Optimism | -0.578*** | - | - | - |
| | (-4.374) | | | |
| Excitement | - | -0.674*** | - | - |
| | | (-5.150) | | |
| Anxiety | - | - | 1.125*** | - |
| | | | (3.363) | |
| Fear | - | - | - | 1.437** |
| | | | | (3.289) |
| ln(AT)Acq | -0.000 | 0.001 | -0.005 | -0.005 |
| | (-0.000) | (0.063) | (-0.296) | (-0.326) |
| MTB Acq | -0.002 | -0.003 | -0.003 | -0.003 |
| | (-1.024) | (-1.073) | (-1.354) | (-1.354) |
| ROA Acq | -0.229* | -0.233* | -0.260** | -0.266** |
| | (-2.089) | (-2.187) | (-2.492) | (-2.579) |
| RD Acq | -0.612 | -0.572 | -0.623 | -0.632 |
| | (-1.371) | (-1.296) | (-1.533) | (-1.519) |
| Tar Public | -0.008 | -0.005 | -0.020 | -0.022 |
| | (-0.332) | (-0.190) | (-0.760) | (-0.799) |
| Tar US | 0.045 | 0.046 | 0.038 | 0.040 |
| | (0.871) | (0.864) | (0.772) | (0.814) |
| Stock% | 0.001 | 0.001 | 0.000 | 0.000 |
| | (0.913) | (0.896) | (0.518) | (0.479) |
| DealVal/AcqME | 0.001 | 0.003 | -0.013 | -0.017 |
| | (0.025) | (0.083) | (-0.363) | (-0.472) |
| Observations | 1,387 | 1,387 | 1,387 | 1,387 |
| Adjusted R-squared | 0.127 | 0.125 | 0.120 | 0.121 |
| Industry FE | Yes | Yes | Yes | Yes |
| Year FE | Yes | Yes | Yes | Yes |

**Table 6. Alternative Specifications**

**Panel A. Alternative LLM Models**

| | Mistral-large-3 | | | | Llama 3.1 | | | |
|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| | Fama–French 3 CAR [-1,1] | | | | | | | |
| Optimism | 0.029** | | | | 0.051*** | | | |
| | (2.916) | | | | (4.918) | | | |
| Excitement | | 0.019* | | | | 0.021* | | |
| | | (2.167) | | | | (2.114) | | |
| Anxiety | | | -0.166*** | | | | -0.158*** | |
| | | | (-6.232) | | | | (-5.919) | |
| Fear | | | | -0.213*** | | | | -0.286*** |
| | | | | (-4.182) | | | | (-3.923) |
| Controls | YES | YES | YES | YES | YES | YES | YES | YES |
| Observations | 2,604 | 2,604 | 2,604 | 2,604 | 2,604 | 2,604 | 2,604 | 2,604 |
| Adjusted R-squared | 0.092 | 0.091 | 0.110 | 0.099 | 0.098 | 0.091 | 0.103 | 0.100 |
| Industry FE | YES | YES | YES | YES | YES | YES | YES | YES |
| Year FE | YES | YES | YES | YES | YES | YES | YES | YES |

**Panel B. Alternative CAR Window [−2,+2]**

| | Positive sentiments | | Negative sentiments | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| **Variables** | Fama–French 3 CAR [-2,+2] | | | |
| Optimism | 0.064*** | - | - | - |
| | (6.545) | | | |
| Excitement | - | 0.060*** | - | - |
| | | (3.791) | | |
| Anxiety | - | - | -0.231*** | - |
| | | | (-5.365) | |
| Fear | - | - | - | -0.287*** |
| | | | | (-5.103) |
| Controls | Yes | Yes | Yes | Yes |
| Observations | 2,604 | 2,604 | 2,604 | 2,604 |
| Adjusted R-squared | 0.089 | 0.085 | 0.095 | 0.096 |
| Industry FE | Yes | Yes | Yes | Yes |
| Year FE | Yes | Yes | Yes | Yes |

**Panel C. Alternative CAR Window [−5,+5]**

| | Positive sentiments | | Negative sentiments | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| **Variables** | Fama–French 3 CAR [-5,+5] | | | |
| Optimism | 0.072*** | - | - | - |
| | (5.335) | | | |
| Excitement | - | 0.077*** | - | - |
| | | (4.256) | | |
| Anxiety | - | - | -0.197*** | - |
| | | | (-6.411) | |
| Fear | - | - | - | -0.245*** |
| | | | | (-5.597) |
| Controls | Yes | Yes | Yes | Yes |
| Observations | 2,604 | 2,604 | 2,604 | 2,604 |
| Adjusted R-squared | 0.073 | 0.070 | 0.073 | 0.073 |
| Industry FE | Yes | Yes | Yes | Yes |
| Year FE | Yes | Yes | Yes | Yes |

**Panel D. Alternative CAR Window [0,+2]**

| | Positive sentiments | | Negative sentiments | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| **Variables** | Fama–French 3 CAR [0,+2] | | | |
| Optimism | 0.066*** | - | - | - |
| | (8.712) | | | |
| Excitement | - | 0.060*** | - | - |
| | | (3.677) | | |
| Anxiety | - | - | -0.208*** | - |
| | | | (-4.269) | |
| Fear | - | - | - | -0.261*** |
| | | | | (-4.298) |
| Controls | Yes | Yes | Yes | Yes |
| Observations | 2,604 | 2,604 | 2,604 | 2,604 |
| Adjusted R-squared | 0.096 | 0.091 | 0.099 | 0.100 |
| Industry FE | Yes | Yes | Yes | Yes |
| Year FE | Yes | Yes | Yes | Yes |

**Panel E. Market-Model CARs**

| | Positive sentiments | | Negative sentiments | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| **Variables** | Market Model CAR [–1,+1] | | | |
| Optimism | 0.065*** | - | - | - |
| | (8.191) | | | |
| Excitement | - | 0.060*** | - | - |
| | | (4.340) | | |
| Anxiety | - | - | -0.222*** | - |
| | | | (-5.075) | |
| Fear | - | - | - | -0.283*** |
| | | | | (-4.941) |
| Controls | Yes | Yes | Yes | Yes |
| Observations | 2,604 | 2,604 | 2,604 | 2,604 |
| Adjusted R-squared | 0.100 | 0.095 | 0.105 | 0.106 |
| Industry FE | Yes | Yes | Yes | Yes |
| Year FE | Yes | Yes | Yes | Yes |

**Panel F. Standardized Sentiments**

| | Positive sentiments | | Negative sentiments | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| **Variables** | Fama–French 3 CAR [–1,+1] | | | |
| Optimism (Standardized) | 0.009*** | - | - | - |
| | (7.572) | | | |
| Excitement (Standardized) | - | 0.007*** | - | - |
| | | (4.165) | | |
| Anxiety (Standardized) | - | - | -0.011*** | - |
| | | | (-5.249) | |
| Fear (Standardized) | - | - | - | -0.011*** |
| | | | | (-5.211) |
| Controls | Yes | Yes | Yes | Yes |
| Observations | 2,604 | 2,604 | 2,604 | 2,604 |
| Adjusted R-squared | 0.101 | 0.095 | 0.105 | 0.107 |
| Industry FE | Yes | Yes | Yes | Yes |
| Year FE | Yes | Yes | Yes | Yes |

**Table 7. Robustness: Extended Controls and Within-Acquirer Fixed Effects**

**Panel A: Extended Control Set**

This table reports regressions of acquirer cumulative abnormal returns on analyst sentiment measures, controlling simultaneously for an expanded set of firm-, deal-, analyst-, macroeconomic-, management-sentiment, and information-structure variables. Columns (1)–(2) focus on positive analyst sentiments (optimism and excitement), whereas Columns (3)–(4) focus on negative analyst sentiments (anxiety and fear). The additional control set includes bidder status, analyst coverage, analyst forecast accuracy, macroeconomic sentiment, recession conditions, employment growth, CPI inflation, pre-conference Fama–French 3 CAR[−4,−2], management optimism in the main presentation and Q&A, the hard information score, and the numerical information share. All regressions include acquirer and target one-digit SIC industry fixed effects and conference-year fixed effects. Standard errors are clustered at the acquirer industry (one-digit SIC) level, and t-statistics are reported in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

| | Positive sentiments | | Negative sentiments | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| **Variables** | Fama–French 3 CAR [-1,+1] | | | |
| Optimism | 0.070*** | - | - | - |
| | (7.317) | | | |
| Excitement | - | 0.062*** | - | - |
| | | (4.107) | | |
| Anxiety | - | - | -0.190*** | - |
| | | | (-4.424) | |
| Fear | - | - | - | -0.258*** |
| | | | | (-4.108) |
| ln(AT)Acq | -0.001 | -0.001 | -0.001 | -0.001 |
| | (-0.867) | (-0.959) | (-0.484) | (-0.414) |
| MTB Acq | 0.002*** | 0.002*** | 0.002*** | 0.002*** |
| | (6.334) | (6.319) | (6.151) | (6.111) |
| ROA Acq | -0.040*** | -0.039*** | -0.042*** | -0.041*** |
| | (-3.597) | (-3.737) | (-3.608) | (-3.544) |
| RD Acq | -0.036 | -0.041 | -0.037 | -0.036 |
| | (-1.125) | (-1.276) | (-1.232) | (-1.200) |
| Tar Public | -0.023*** | -0.023*** | -0.021*** | -0.020*** |
| | (-4.318) | (-4.277) | (-3.894) | (-3.904) |
| Tar US | 0.010* | 0.010* | 0.011** | 0.011* |
| | (2.086) | (2.194) | (2.356) | (2.298) |
| Stock% | -0.000*** | -0.000*** | -0.000** | -0.000** |
| | (-3.561) | (-3.441) | (-2.954) | (-2.915) |
| DealVal/AcqME | 0.019 | 0.020 | 0.022* | 0.023* |
| | (1.741) | (1.821) | (2.080) | (2.128) |
| Bidder | -0.001 | -0.003 | -0.005 | -0.004 |
| | (-0.095) | (-0.205) | (-0.351) | (-0.300) |
| Analyst Coverage | -0.001 | -0.001 | -0.001 | -0.001 |
| | (-1.754) | (-1.584) | (-1.586) | (-1.586) |

| | | | | |
|---|---|---|---|---|
| Analyst Forecast Accuracy | 0.000 | 0.000 | 0.000 | 0.000 |
| | (0.641) | (0.384) | (0.313) | (0.268) |
| Sentiment Index | 0.003 | 0.002 | 0.004 | 0.004 |
| | (0.197) | (0.146) | (0.223) | (0.213) |
| Recession Indicator | -0.011 | -0.012 | -0.012 | -0.010 |
| | (-1.066) | (-1.194) | (-1.177) | (-1.018) |
| Employment Growth | -0.000*** | -0.000*** | -0.000*** | -0.000*** |
| | (-4.153) | (-3.784) | (-3.853) | (-3.896) |
| CPI Inflation | -0.002** | -0.002** | -0.002** | -0.002** |
| | (-2.570) | (-2.862) | (-3.062) | (-3.039) |
| Fama–French 3 CAR [-4,-2] | -0.062 | -0.063 | -0.058 | -0.059 |
| | (-1.157) | (-1.199) | (-1.115) | (-1.126) |
| Management Optimism in Main | 0.016 | 0.019 | 0.023 | 0.021 |
| | (0.955) | (1.121) | (1.406) | (1.348) |
| Management Optimism in Q&A | -0.066*** | -0.056*** | -0.040** | -0.040** |
| | (-5.077) | (-3.643) | (-2.567) | (-2.553) |
| Hard Information Score | 0.068 | 0.058 | -0.000 | -0.003 |
| | (1.479) | (1.224) | (-0.008) | (-0.061) |
| Numerical Information Share | | | | |
| | 1.364*** | 1.351*** | 1.479*** | 1.498*** |
| | (3.526) | (3.410) | (3.407) | (3.398) |
| Observations | 2,205 | 2,205 | 2,205 | 2,205 |
| Adjusted R-squared | 0.121 | 0.115 | 0.120 | 0.123 |
| Industry FE | Yes | Yes | Yes | Yes |
| Year FE | Yes | Yes | Yes | Yes |

**Panel B: Within-Acquirer Fixed Effects**

This table reports OLS regressions of acquirer cumulative abnormal returns (Fama–French 3 CAR [-1,1]) on analyst sentiment measures. Columns (1)–(2) focus on positive sentiments (optimism and excitement), while Columns (3)–(4) focus on negative sentiments (anxiety and fear). All specifications include the full set of deal and acquirer control variables, acquirer firm fixed effects, conference-year fixed effects, and target one-digit SIC industry fixed effects. T-statistics, reported in parentheses, are based on robust standard errors clustered at the acquirer industry level. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

| | Positive sentiments | | Negative sentiments | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| **Variables** | Fama–French 3 CAR [-1,1] | | | |
| Optimism | 0.069*** | - | - | - |
| | (5.548) | | | |
| Excitement | - | 0.065*** | - | - |
| | | (3.446) | | |
| Anxiety | - | - | -0.158** | - |
| | | | (-3.127) | |
| Fear | - | - | - | -0.200** |
| | | | | (-2.663) |
| ln(AT)Acq | -0.019** | -0.018* | -0.016* | -0.016* |
| | (-2.316) | (-2.214) | (-2.108) | (-2.190) |
| MTB Acq | 0.001 | 0.001 | 0.001 | 0.001 |
| | (0.967) | (0.994) | (0.798) | (0.776) |
| ROA Acq | -0.020 | -0.019 | -0.023 | -0.023 |
| | (-0.508) | (-0.436) | (-0.554) | (-0.556) |
| RD Acq | -0.036 | -0.036 | -0.033 | -0.039 |
| | (-0.408) | (-0.401) | (-0.361) | (-0.430) |
| Tar Public | -0.019* | -0.020** | -0.018* | -0.018* |
| | (-2.186) | (-2.273) | (-1.962) | (-1.979) |
| Tar US | 0.010 | 0.011 | 0.012 | 0.012 |
| | (1.304) | (1.436) | (1.493) | (1.447) |
| Stock% | -0.000** | -0.000** | -0.000** | -0.000** |
| | (-2.982) | (-2.855) | (-2.681) | (-2.704) |
| DealVal/AcqME | 0.020 | 0.020 | 0.022 | 0.023 |
| | (1.138) | (1.151) | (1.328) | (1.354) |
| Observations | 1,638 | 1,638 | 1,638 | 1,638 |
| Adjusted R-squared | 0.523 | 0.520 | 0.522 | 0.522 |
| Acquirer firm FE | Yes | Yes | Yes | Yes |
| Year FE | Yes | Yes | Yes | Yes |
| Target Industry FE | Yes | Yes | Yes | Yes |

**Table 8. Endogeneity Checks**

**Panel A. Oster (2019) Coefficient-Stability Analysis for Analyst Sentiments**

This panel implements the coefficient-stability approach of Oster (2019) to assess the sensitivity of the estimated effects of analyst sentiments on acquirer conference call returns to omitted-variable bias. For each sentiment, we report the coefficient from a "short" specification with only the sentiment and fixed effects and from the "full" specification with the baseline set of deal- and acquirer-level controls ($\beta\_full$, $R^2\_full$), as well as the Oster-adjusted coefficient $\beta^*$ under proportional selection ($\delta = 1$). Following Oster (2019), we set $R\_max = \min(1.3 \times R^2\_full, 1)$ and derive the identified set $[\beta_L, \beta_U]$for each sentiment's coefficient.

| **Sentiment** | **β_short** | **$R^2$_short** | **β_full** | **$R^2$_full** | **β* (Oster)** | ***Identified set* ([β_L,β_U ])** |
|---|---|---|---|---|---|---|
| Optimism | 0.0565 | 0.047 | 0.0675 | 0.1008 | 0.0737 | [0.0675, 0.0737] |
| Excitement | 0.0463 | 0.0422 | 0.0624 | 0.0952 | 0.0711 | [0.0624, 0.0711] |
| Anxiety | −0.2567 | 0.0598 | −0.2223 | 0.105 | −0.1983 | [−0.2223, −0.1983] |
| Fear | −0.3284 | 0.0621 | −0.2856 | 0.1067 | −0.2549 | [−0.2856, −0.2549] |

**Panel B. Placebo Test**

This panel reports a placebo test in which each sentiment variable is randomly permuted across deals, preserving its marginal distribution while severing any true relation to conference returns. We re-estimate the baseline regressions using these placebo sentiment measures. All regressions include acquirer and target one-digit SIC industry fixed effects and conference-year fixed effects. Standard errors are clustered at the acquirer industry (one-digit SIC) level, and t-statistics are reported in parentheses. *, **, and *** correspond to significance at the 10%, 5%, and 1% levels, respectively.

| | Positive sentiments | | Negative sentiments | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| **Variables** | Fama–French 3 CAR [-1,1] | | | |
| Optimism (Placebo) | -0.005 | - | - | - |
| | (-0.352) | | | |
| Excitement (Placebo) | - | 0.004 | - | - |
| | | (0.245) | | |
| Anxiety (Placebo) | - | - | -0.016 | - |
| | | | (-0.557) | |
| Fear (Placebo) | - | - | - | -0.001 |
| | | | | (-0.027) |
| ln(AT)Acq | -0.002** | -0.002** | -0.002** | -0.002** |
| | (-2.696) | (-2.672) | (-2.671) | (-2.663) |
| MTB Acq | 0.001* | 0.001* | 0.001* | 0.001* |
| | (2.201) | (2.200) | (2.192) | (2.195) |
| ROA Acq | -0.028*** | -0.028*** | -0.028*** | -0.028*** |
| | (-3.871) | (-3.993) | (-3.911) | (-3.915) |
| RD Acq | -0.028 | -0.028 | -0.028 | -0.028 |
| | (-1.404) | (-1.415) | (-1.415) | (-1.404) |
| Tar Public | -0.024*** | -0.024*** | -0.024*** | -0.024*** |
| | (-4.315) | (-4.325) | (-4.365) | (-4.331) |
| Tar US | 0.009* | 0.009* | 0.009* | 0.009* |
| | (1.962) | (1.955) | (1.974) | (1.981) |
| Stock% | -0.000** | -0.000** | -0.000** | -0.000** |
| | (-2.490) | (-2.468) | (-2.510) | (-2.490) |
| DealVal/AcqME | 0.023* | 0.023* | 0.023* | 0.023* |
| | (1.837) | (1.838) | (1.838) | (1.841) |
| Observations | 2,604 | 2,604 | 2,604 | 2,604 |
| Adjusted R-squared | 0.090 | 0.090 | 0.090 | 0.090 |
| Industry FE | Yes | Yes | Yes | Yes |
| Year FE | Yes | Yes | Yes | Yes |

**Panel C. Propensity Score Matching**

This panel examines robustness using a matched-sample design. For each sentiment measure, we define a treatment indicator equal to one for observations above the sample median and estimate propensity scores based on standard acquirer and deal characteristics. Treated and control deals are matched 1:1 using nearest-neighbor matching. We then re-estimate the baseline regressions on the matched samples using matching weights, including acquirer and target one-digit SIC industry fixed effects and conference-year fixed effects. Standard errors are clustered at the acquirer industry level (one-digit SIC). *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

| | Positive sentiments | | Negative sentiments | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| **Variables** | Fama–French 3 CAR [-1,1] | | | |
| Optimism | 0.067*** | - | - | - |
| | (7.751) | | | |
| Excitement | - | 0.068** | - | - |
| | | (3.014) | | |
| Anxiety | - | - | -0.273** | - |
| | | | (-2.910) | |
| Fear | - | - | - | -0.277*** |
| | | | | (-4.829) |
| ln(AT)Acq | -0.003** | -0.001 | -0.002 | -0.003 |
| | (-2.830) | (-0.680) | (-1.130) | (-1.791) |
| MTB Acq | 0.001 | 0.000 | -0.002 | 0.001 |
| | (1.306) | (0.672) | (-0.843) | (1.061) |
| ROA Acq | -0.022 | -0.039*** | -0.038*** | -0.025 |
| | (-1.620) | (-3.399) | (-3.903) | (-1.253) |
| RD Acq | -0.051 | -0.031 | 0.002 | 0.001 |
| | (-1.754) | (-1.564) | (0.039) | (0.020) |
| Tar Public | -0.026*** | -0.026*** | -0.025** | -0.023*** |
| | (-6.979) | (-3.362) | (-2.816) | (-4.409) |
| Tar US | 0.007 | 0.006 | 0.014** | 0.009 |
| | (1.202) | (1.110) | (2.580) | (1.727) |
| Stock% | -0.000 | -0.000*** | -0.000* | -0.000* |
| | (-1.767) | (-5.116) | (-2.117) | (-2.083) |
| DealVal/AcqME | 0.018 | 0.017 | 0.070 | 0.023 |
| | (1.396) | (1.154) | (1.721) | (1.288) |
| Observations | 2,198 | 2,262 | 2,156 | 2,247 |
| Adjusted R-squared | 0.108 | 0.106 | 0.337 | 0.122 |
| Industry FE | Yes | Yes | Yes | Yes |
| Year FE | Yes | Yes | Yes | Yes |

**Panel D. Coarsened Exact Matching**

This panel examines robustness using coarsened exact matching (CEM). For each sentiment, we define a treatment indicator equal to one when the sentiment is above its sample median and match treated and control deals using CEM on the full set of acquirer and deal characteristics. Continuous variables are coarsened into five bins and binary variables are matched exactly. We re-estimate the baseline regressions on the matched samples using CEM analytic weights, including acquirer and target one-digit SIC industry fixed effects and conference-year fixed effects. Standard errors are clustered at the acquirer industry level (one-digit SIC), and t-statistics are reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

| | Positive sentiments | | Negative sentiments | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| **Variables** | Fama–French3 CAR [-1,1] | | | |
| Optimism | 0.066*** | - | - | - |
| | (6.472) | | | |
| Excitement | - | 0.059** | - | - |
| | | (2.824) | | |
| Anxiety | - | - | -0.159** | - |
| | | | (-2.914) | |
| Fear | - | - | - | -0.213** |
| | | | | (-2.725) |
| ln(AT)Acq | -0.004*** | -0.004*** | -0.002 | -0.002 |
| | (-3.325) | (-3.544) | (-1.450) | (-1.580) |
| MTB Acq | 0.002* | 0.002* | 0.003** | 0.001 |
| | (2.121) | (2.187) | (2.823) | (1.304) |
| ROA Acq | -0.010 | 0.004 | -0.025** | -0.041* |
| | (-0.876) | (0.262) | (-2.332) | (-1.860) |
| RD Acq | -0.153*** | -0.183*** | -0.088** | -0.103** |
| | (-6.075) | (-8.060) | (-2.577) | (-2.399) |
| Tar Public | -0.017** | -0.016** | -0.018** | -0.016** |
| | (-2.775) | (-2.961) | (-2.907) | (-2.564) |
| Tar US | 0.010** | 0.010* | 0.011* | 0.010 |
| | (2.387) | (1.869) | (2.178) | (1.747) |
| Stock% | -0.000*** | -0.000*** | -0.000*** | -0.000*** |
| | (-5.654) | (-4.286) | (-5.130) | (-3.624) |
| DealVal/AcqME | 0.029 | 0.031 | 0.037 | 0.028 |
| | (1.391) | (1.389) | (1.485) | (1.082) |
| Observations | 2,084 | 2,071 | 2,100 | 2,063 |
| Adjusted R-squared | 0.125 | 0.124 | 0.125 | 0.111 |
| Industry FE | Yes | Yes | Yes | Yes |
| Year FE | Yes | Yes | Yes | Yes |

**Panel E. Entropy Balancing**

This panel applies entropy balancing as an additional robustness check. For each sentiment, we define a treatment indicator equal to one when the sentiment is above its sample median and use entropy balancing to reweight control observations so that their covariate means match those of the treated group. Treated deals receive weight one, and control deals receive entropy-balancing weights. We then re-estimate the baseline regressions on the weighted sample, including acquirer and target one-digit SIC industry fixed effects and conference-year fixed effects. Standard errors are clustered at the acquirer industry level (one-digit SIC), and t-statistics are reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

| | Positive sentiments | | Negative sentiments | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| **Variables** | Fama–French 3 CAR [-1,1] | | | |
| Optimism | 0.065*** | - | - | - |
| | (6.519) | | | |
| Excitement | - | 0.061*** | - | - |
| | | (3.892) | | |
| Anxiety | - | - | -0.223*** | - |
| | | | (-4.918) | |
| Fear | - | - | - | -0.273*** |
| | | | | (-4.655) |
| ln(AT)Acq | -0.003** | -0.002* | -0.002 | -0.002 |
| | (-2.530) | (-1.839) | (-1.431) | (-1.597) |
| MTB Acq | 0.001 | 0.001 | 0.001 | 0.001 |
| | (1.055) | (1.452) | (1.298) | (1.443) |
| ROA Acq | -0.027*** | -0.026*** | -0.038** | -0.046** |
| | (-4.689) | (-4.123) | (-2.894) | (-3.192) |
| RD Acq | -0.029 | -0.026 | -0.028 | -0.004 |
| | (-1.285) | (-0.982) | (-1.166) | (-0.146) |
| Tar Public | -0.024*** | -0.023*** | -0.021*** | -0.019*** |
| | (-4.846) | (-4.656) | (-3.666) | (-3.288) |
| Tar US | 0.008 | 0.008 | 0.008 | 0.008* |
| | (1.714) | (1.805) | (1.706) | (1.916) |
| Stock% | -0.000** | -0.000** | -0.000** | -0.000** |
| | (-2.600) | (-2.846) | (-2.861) | (-2.844) |
| DealVal/AcqME | 0.016 | 0.017 | 0.028 | 0.022 |
| | (1.351) | (1.411) | (1.751) | (1.584) |
| Observations | 2,604 | 2,604 | 2,604 | 2,604 |
| Adjusted R-squared | 0.094 | 0.088 | 0.121 | 0.115 |
| Industry FE | Yes | Yes | Yes | Yes |
| Year FE | Yes | Yes | Yes | Yes |

**Table 9. LLM Tone vs. Loughran–McDonald (LM) Tone**

**Panel A. CARs on Tone (LM)**

This panel examines whether traditional Loughran–McDonald (LM) sentiment measures predict acquirer conference call returns. We regress Fama–French 3 CAR [-1,1] separately on LM positive tone share, LM negative tone share, and LM net tone (Tone (LM)), controlling for the standard set of acquirer and deal characteristics. Each specification includes acquirer and target one-digit SIC industry fixed effects and conference-year fixed effects. Standard errors are clustered at the acquirer industry (one-digit SIC) level, and t-statistics are reported in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

| | (1) | (2) | (3) |
|---|---|---|---|
| **Variables** | Fama–French 3 CAR [-1,1] | | |
| Positive tone | 0.283 | - | - |
| | (0.907) | | |
| Negative tone | - | -1.704 | - |
| | | (-1.630) | |
| Tone (LM) | - | - | 0.457* |
| | | | (1.953) |
| ln(AT)Acq | -0.002** | -0.002** | -0.002** |
| | (-2.626) | (-2.499) | (-2.551) |
| MTB Acq | 0.001* | 0.001** | 0.001* |
| | (2.175) | (2.276) | (2.176) |
| ROA Acq | -0.028*** | -0.029*** | -0.029*** |
| | (-4.162) | (-3.893) | (-4.324) |
| RD Acq | -0.027 | -0.028 | -0.026 |
| | (-1.316) | (-1.343) | (-1.209) |
| Tar Public | -0.024*** | -0.023*** | -0.023*** |
| | (-4.380) | (-4.226) | (-4.376) |
| Tar US | 0.009* | 0.009* | 0.009* |
| | (2.002) | (1.937) | (2.013) |
| Stock% | -0.000** | -0.000** | -0.000** |
| | (-2.553) | (-2.513) | (-2.543) |
| DealVal/AcqME | 0.023 | 0.023* | 0.023 |
| | (1.831) | (1.842) | (1.829) |
| Observations | 2,604 | 2,604 | 2,604 |
| Adjusted R-squared | 0.090 | 0.092 | 0.091 |
| Industry FE | Yes | Yes | Yes |
| Year FE | Yes | Yes | Yes |

**Panel B. LLM Tone vs. LM Tone**

This panel compares the explanatory power of an LLM-based tone measure (Valence) with the traditional Loughran–McDonald (LM) net tone measure (Tone (LM)). The LLM tone variable (Valence) captures the overall positive–negative sentiment of the analyst's conference call text as assessed by a large language model on a continuous negative–to–positive scale. We jointly regress Fama–French 3 CAR [-1,1] on LLM-based tone (Valence) and the LM net tone (Tone (LM)), controlling for the standard set of acquirer and deal characteristics. All regressions include acquirer and target one-digit SIC industry fixed effects and conference-year fixed effects. Standard errors are clustered at the acquirer industry (one-digit SIC) level, and t-statistics are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

| **Variables** | Fama–French 3 CAR [-1,1] |
|---|---|
| LLM-based tone measure (Valence) | 0.100*** |
| | (11.735) |
| Tone (LM) | -0.216 |
| | (-0.994) |
| ln(AT)Acq | -0.002** |
| | (-2.306) |
| MTB Acq | 0.001* |
| | (2.158) |
| ROA Acq | -0.031*** |
| | (-6.081) |
| RD Acq | -0.030 |
| | (-1.327) |
| Tar Public | -0.023*** |
| | (-4.858) |
| Tar US | 0.007 |
| | (1.489) |
| Stock% | -0.000** |
| | (-2.829) |
| DealVal/AcqME | 0.022 |
| | (1.693) |
| Observations | 2,604 |
| Adjusted R-squared | 0.117 |
| Industry FE | Yes |
| Year FE | Yes |

**Table 10. Mechanism Tests**

**Panel A. Public vs. NonPublic Targets**

This panel reports estimates of the relation between analyst sentiments and conference call returns separately for acquisitions of non-public and public targets. All regressions include acquirer and target one-digit SIC industry fixed effects and conference-year fixed effects. Standard errors are clustered at the acquirer industry (one-digit SIC) level, and t-statistics are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

| | (1) | (2) | | (3) | (4) | | (5) | (6) | | (7) | (8) | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Nonpublic | Public | Difference (p-value) | Nonpublic | Public | Difference (p-value) | Nonpublic | Public | Difference (p-value) | Nonpublic | Public | Difference (p-value) |
| **Variables** | Fama–French 3 CAR [-1,1] | | | | | | | | | | | |
| Optimism | 0.090*** | 0.033 | 0.0175 | | | | | | | | | |
| | (5.963) | (1.836) | | | | | | | | | | |
| Excitement | | | | 0.085** | 0.032 | 0.2075 | | | | | | |
| | | | | (3.245) | (1.180) | | | | | | | |
| Anxiety | | | | | | | -0.351*** | -0.088 | 0.0236 | | | |
| | | | | | | | (-3.965) | (-1.465) | | | | |
| Fear | | | | | | | | | | -0.484*** | -0.100 | 0.0004 |
| | | | | | | | | | | (-5.765) | (-1.520) | |
| ln(AT)Acq | -0.003** | -0.003 | | -0.003** | -0.003 | | -0.002 | -0.002 | | -0.001 | -0.002 | |
| | (-2.398) | (-1.415) | | (-2.446) | (-1.383) | | (-1.290) | (-1.185) | | (-1.076) | (-1.161) | |
| MTB Acq | 0.001 | 0.001 | | 0.001 | 0.001 | | 0.001* | 0.001 | | 0.001* | 0.001 | |
| | (1.762) | (1.611) | | (1.755) | (1.608) | | (2.159) | (1.522) | | (2.240) | (1.544) | |
| ROA Acq | -0.016 | -0.028 | | -0.012 | -0.029 | | -0.018 | -0.027 | | -0.017 | -0.026 | |
| | (-0.715) | (-0.846) | | (-0.582) | (-0.835) | | (-0.879) | (-0.815) | | (-0.845) | (-0.800) | |
| RD Acq | -0.032 | -0.043 | | -0.034 | -0.043 | | -0.032 | -0.037 | | -0.030 | -0.038 | |
| | (-0.892) | (-1.086) | | (-0.919) | (-1.094) | | (-0.944) | (-0.985) | | (-0.897) | (-0.987) | |
| Tar US | 0.010 | 0.002 | | 0.010 | 0.002 | | 0.011 | 0.003 | | 0.011 | 0.003 | |
| | (1.543) | (0.242) | | (1.556) | (0.266) | | (1.797) | (0.295) | | (1.824) | (0.285) | |
| Stock% | -0.000 | -0.000*** | | -0.000 | -0.000*** | | 0.000 | -0.000*** | | 0.000 | -0.000*** | |
| | (-0.266) | (-5.268) | | (-0.157) | (-5.115) | | (0.215) | (-4.777) | | (0.256) | (-4.801) | |
| DealVal/AcqME | 0.042** | -0.004 | | 0.041** | -0.003 | | 0.044** | -0.002 | | 0.045** | -0.002 | |
| | (2.352) | (-0.655) | | (2.345) | (-0.612) | | (2.488) | (-0.434) | | (2.503) | (-0.388) | |
| Observations | 1,579 | 1,024 | | 1,579 | 1,024 | | 1,579 | 1,024 | | 1,579 | 1,024 | |
| Adjusted R-squared | 0.111 | 0.109 | | 0.102 | 0.107 | | 0.122 | 0.109 | | 0.129 | 0.109 | |
| Industry FE | YES | YES | | YES | YES | | YES | YES | | YES | YES | |
| Year FE | YES | YES | | YES | YES | | YES | YES | | YES | YES | |

**Panel B. Unrelated vs. Related Acquisitions**

This panel reports estimates of the relation between analyst sentiments and conference call returns for subsamples defined by deal relatedness (unrelated versus related acquisitions). All regressions include acquirer and target one-digit SIC industry fixed effects and conference-year fixed effects. Standard errors are clustered at the acquirer industry (one-digit SIC) level, and t-statistics are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

| | (1) | (2) | | (3) | (4) | | (5) | (6) | | (7) | (8) | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Unrelated | Related | Difference (p-value) | Unrelated | Related | Difference (p-value) | Unrelated | Related | Difference (p-value) | Unrelated | Related | Difference (p-value) |
| **Variables** | Fama–French 3 CAR [-1,1] | | | | | | | | | | | |
| Optimism | 0.100*** | 0.049*** | 0.0054 | | | | | | | | | |
| | (6.080) | (5.331) | | | | | | | | | | |
| Excitement | | | | 0.113*** | 0.037* | 0.0034 | | | | | | |
| | | | | (5.371) | (1.945) | | | | | | | |
| Anxiety | | | | | | | -0.296*** | -0.188*** | 0.0106 | | | |
| | | | | | | | (-4.978) | (-4.259) | | | | |
| Fear | | | | | | | | | | -0.336*** | -0.263*** | 0.1302 |
| | | | | | | | | | | (-5.260) | (-4.405) | |
| ln(AT)Acq | -0.004** | -0.003* | | -0.004** | -0.003* | | -0.002 | -0.002 | | -0.002 | -0.002 | |
| | (-2.792) | (-2.162) | | (-2.682) | (-2.044) | | (-1.620) | (-1.242) | | (-1.577) | (-1.096) | |
| MTB Acq | 0.002** | 0.001 | | 0.002** | 0.001 | | 0.002** | 0.001 | | 0.002** | 0.001 | |
| | (2.749) | (1.104) | | (2.849) | (1.061) | | (3.067) | (1.029) | | (2.949) | (1.011) | |
| ROA Acq | -0.075*** | -0.012 | | -0.074*** | -0.010 | | -0.075*** | -0.012 | | -0.074*** | -0.011 | |
| | (-4.007) | (-0.569) | | (-4.089) | (-0.465) | | (-3.843) | (-0.555) | | (-3.615) | (-0.525) | |
| RD Acq | -0.112* | -0.010 | | -0.119* | -0.009 | | -0.107* | -0.004 | | -0.111* | -0.003 | |
| | (-2.160) | (-0.304) | | (-2.283) | (-0.284) | | (-2.086) | (-0.167) | | (-2.235) | (-0.101) | |
| Tar Public | -0.014 | -0.029*** | | -0.015 | -0.029*** | | -0.011 | -0.027*** | | -0.012 | -0.026*** | |
| | (-1.161) | (-5.473) | | (-1.203) | (-5.324) | | (-1.069) | (-4.679) | | (-1.083) | (-4.476) | |
| Tar US | 0.014*** | 0.006 | | 0.014*** | 0.007 | | 0.016*** | 0.007 | | 0.016*** | 0.006 | |
| | (5.512) | (0.983) | | (4.845) | (1.024) | | (8.611) | (0.987) | | (8.417) | (0.934) | |
| Stock% | -0.000*** | -0.000** | | -0.000*** | -0.000** | | -0.000** | -0.000** | | -0.000** | -0.000** | |
| | (-3.969) | (-2.687) | | (-3.828) | (-2.579) | | (-2.534) | (-2.370) | | (-2.570) | (-2.354) | |
| DealVal/AcqME | -0.005 | 0.035** | | -0.006 | 0.035** | | -0.003 | 0.037** | | -0.003 | 0.037** | |
| | (-0.453) | (2.708) | | (-0.487) | (2.774) | | (-0.263) | (2.918) | | (-0.251) | (2.947) | |
| Observations | 864 | 1,739 | | 864 | 1,739 | | 864 | 1,739 | | 864 | 1,739 | |
| Adjusted R-squared | 0.122 | 0.123 | | 0.116 | 0.119 | | 0.126 | 0.127 | | 0.124 | 0.130 | |
| Industry FE | YES | YES | | YES | YES | | YES | YES | | YES | YES | |
| Year FE | YES | YES | | YES | YES | | YES | YES | | YES | YES | |

**Panel C. Accrual Quality (below- vs. above-median)**

This panel reports estimates of the relation between analyst sentiments and conference call returns for subsamples defined by accrual quality (below- versus above-median). All regressions include acquirer and target one-digit SIC industry fixed effects and conference-year fixed effects. Standard errors are clustered at the acquirer industry (one-digit SIC) level, and t-statistics are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

| | (1) | (2) | | (3) | (4) | | (5) | (6) | | (7) | (8) | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Below | Above | Difference (p-value) | Below | Above | Difference (p-value) | Below | Above | Difference (p-value) | Below | Above | Difference (p-value) |
| **Variables** | Fama–French 3 CAR [-1,1] | | | | | | | | | | | |
| Optimism | 0.074*** | 0.054*** | 0.4144 | | | | | | | | | |
| | (4.984) | (3.519) | | | | | | | | | | |
| Excitement | | | | 0.060** | 0.061*** | 0.9781 | | | | | | |
| | | | | (3.040) | (3.452) | | | | | | | |
| Anxiety | | | | | | | -0.311*** | -0.161** | 0.0354 | | | |
| | | | | | | | (-9.122) | (-3.064) | | | | |
| Fear | | | | | | | | | | -0.425*** | -0.186*** | 0.0054 |
| | | | | | | | | | | (-9.103) | (-3.588) | |
| ln(AT)Acq | -0.004** | -0.004*** | | -0.004** | -0.004*** | | -0.003* | -0.003** | | -0.003 | -0.003** | |
| | (-2.380) | (-4.156) | | (-2.401) | (-4.085) | | (-2.057) | (-2.784) | | (-1.768) | (-2.792) | |
| MTB Acq | 0.002 | 0.001 | | 0.002 | 0.001 | | 0.001 | 0.001 | | 0.001 | 0.001 | |
| | (1.393) | (1.262) | | (1.392) | (1.222) | | (1.208) | (1.523) | | (1.243) | (1.455) | |
| ROA Acq | -0.016 | -0.013 | | -0.014 | -0.012 | | -0.016 | -0.013 | | -0.015 | -0.013 | |
| | (-1.265) | (-0.693) | | (-1.028) | (-0.641) | | (-1.372) | (-0.710) | | (-1.281) | (-0.680) | |
| RD Acq | 0.022 | -0.136*** | | 0.023 | -0.142*** | | 0.028 | -0.138*** | | 0.027 | -0.137*** | |
| | (0.928) | (-3.462) | | (1.000) | (-3.498) | | (1.158) | (-3.572) | | (1.136) | (-3.558) | |
| Tar Public | -0.029*** | -0.014* | | -0.029*** | -0.014* | | -0.025*** | -0.012 | | -0.024*** | -0.012 | |
| | (-4.682) | (-1.958) | | (-4.560) | (-1.959) | | (-5.077) | (-1.572) | | (-5.072) | (-1.558) | |
| Tar US | 0.006 | 0.012 | | 0.006 | 0.012 | | 0.007 | 0.013* | | 0.006 | 0.013* | |
| | (0.807) | (1.743) | | (0.883) | (1.768) | | (0.951) | (2.082) | | (0.877) | (2.043) | |
| Stock% | -0.000** | -0.000** | | -0.000** | -0.000** | | -0.000* | -0.000* | | -0.000* | -0.000* | |
| | (-2.487) | (-2.739) | | (-2.363) | (-2.714) | | (-2.148) | (-2.037) | | (-2.140) | (-1.997) | |
| DealVal/AcqME | 0.048* | 0.005 | | 0.048* | 0.006 | | 0.049** | 0.007 | | 0.050** | 0.007 | |
| | (2.292) | (0.884) | | (2.277) | (0.969) | | (2.349) | (1.183) | | (2.347) | (1.254) | |
| Observations | 1,077 | 1,076 | | 1,077 | 1,076 | | 1,077 | 1,076 | | 1,077 | 1,076 | |
| Adjusted R-squared | 0.140 | 0.118 | | 0.134 | 0.116 | | 0.158 | 0.118 | | 0.163 | 0.117 | |
| Industry FE | YES | YES | | YES | YES | | YES | YES | | YES | YES | |
| Year FE | YES | YES | | YES | YES | | YES | YES | | YES | YES | |

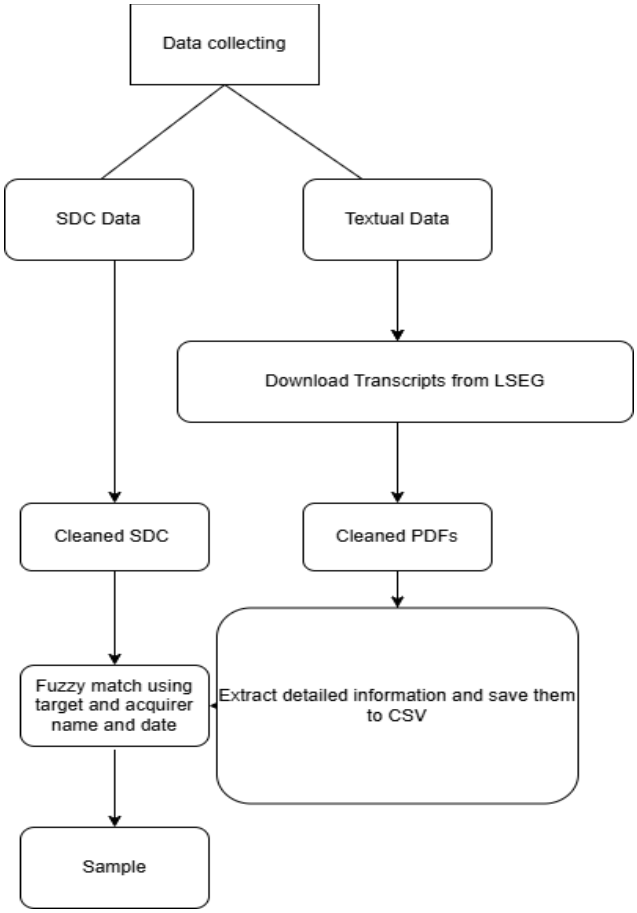
**Table 11. Analyst Sentiments and Post-Conference Call Buy-and-Hold Abnormal Returns**

This table reports regressions of post-conference call buy-and-hold abnormal returns (BHAR) on analyst sentiment measures. The dependent variables are rebalanced value-weighted BHARs (Columns (1)–(4)) and rebalanced equal-weighted BHARs (Columns (5)–(8)) over the post-conference call horizon. For each sentiment, the specification includes the sentiment measure, the short-window Fama–French three-factor CAR[–1,+1], and the interaction between the two. All regressions include acquirer and target one-digit SIC industry fixed effects and conference-year fixed effects. T-statistics, reported in parentheses, are based on robust standard errors clustered at the acquirer industry (one-digit SIC) level. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
|---|---|---|---|---|---|---|---|---|
| **Variables** | BHAR_VW | | | | BHAR_EW | | | |
| Optimism | -0.071 | | | | -0.074 | | | |
| | (-0.999) | | | | (-1.040) | | | |
| Optimism × CAR [–1, +1] | -1.173 | | | | -1.224 | | | |
| | (-0.820) | | | | (-0.869) | | | |
| Excitement | | -0.091 | | | | -0.095 | | |
| | | (-0.909) | | | | (-0.940) | | |
| Excitement × Fama French 3 CAR [-1, +1] | | -1.202 | | | | -1.189 | | |
| | | (-0.978) | | | | (-0.986) | | |
| Anxiety | | | -0.345* | | | | -0.484*** | |
| | | | (-2.213) | | | | (-3.567) | |
| Anxiety × Fama French 3 CAR [-1, +1] | | | -4.005** | | | | -4.297** | |
| | | | (-2.468) | | | | (-2.492) | |
| Fear | | | | -0.428** | | | | -0.380** |
| | | | | (-2.970) | | | | (-2.512) |
| Fear × Fama French 3 CAR [-1, +1] | | | | -4.436** | | | | -3.890** |
| | | | | (-2.496) | | | | (-2.502) |
| Fama–French 3 CAR [-1,1] | 0.910 | 0.611 | 0.633*** | 0.599** | 0.930 | 0.601 | 0.576** | 0.611*** |
| | (1.058) | (1.348) | (3.291) | (2.721) | (1.098) | (1.357) | (2.678) | (3.276) |
| ln(AT)Acq | 0.008 | 0.008 | 0.009* | 0.010* | 0.008 | 0.008 | 0.010* | 0.009* |

| | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | (1.609) | (1.629) | (1.949) | (2.009) | (1.489) | (1.502) | (1.956) | (1.871) |
| MTB Acq | 0.016** | 0.016** | 0.016** | 0.016** | 0.016** | 0.016** | 0.016** | 0.016** |
| | (2.341) | (2.328) | (2.326) | (2.333) | (2.372) | (2.357) | (2.362) | (2.354) |
| ROA Acq | 0.226** | 0.225** | 0.223** | 0.226** | 0.233** | 0.233** | 0.233** | 0.230** |
| | (3.015) | (2.928) | (2.585) | (2.635) | (3.002) | (2.927) | (2.628) | (2.583) |
| RD Acq | 0.163 | 0.164 | 0.155 | 0.154 | 0.139 | 0.140 | 0.130 | 0.131 |
| | (0.939) | (0.937) | (0.925) | (0.906) | (0.815) | (0.813) | (0.781) | (0.796) |
| Tar Public | -0.009 | -0.009 | -0.006 | -0.006 | -0.009 | -0.009 | -0.006 | -0.006 |
| | (-0.368) | (-0.364) | (-0.277) | (-0.284) | (-0.368) | (-0.365) | (-0.264) | (-0.261) |
| Tar US | 0.035* | 0.036 | 0.033 | 0.033 | 0.035 | 0.036 | 0.033 | 0.033 |
| | (1.839) | (1.807) | (1.743) | (1.707) | (1.717) | (1.687) | (1.562) | (1.600) |
| Stock% | -0.000 | -0.000 | -0.000 | -0.000 | -0.000 | -0.000 | -0.000 | -0.000 |
| | (-1.033) | (-1.015) | (-1.029) | (-1.014) | (-1.118) | (-1.096) | (-1.093) | (-1.106) |
| DealVal/AcqME | 0.074** | 0.073** | 0.073** | 0.074** | 0.072* | 0.071* | 0.073** | 0.071** |
| | (2.328) | (2.284) | (2.411) | (2.413) | (2.239) | (2.198) | (2.327) | (2.315) |
| Observations | 2,522 | 2,522 | 2,522 | 2,522 | 2,522 | 2,522 | 2,522 | 2,522 |
| Adjusted R-squared | 0.048 | 0.047 | 0.049 | 0.049 | 0.049 | 0.049 | 0.050 | 0.050 |
| Industry FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Year FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |

## Appendix A. Matching Process



**Appendix B. Variable Definitions**

| Variables | Definition |
|---|---|
| **Emotion Variables** | |
| Optimism | LLM-based score (0–1) for Optimism in analysts' Q&A questions. |
| Excitement | LLM-based score (0–1) for Excitement in analysts' Q&A questions. |
| Anxiety | LLM-based score (0–1) for Anxiety in analysts' Q&A questions. |
| Fear | LLM-based score (0–1) for Fear in analysts' Q&A questions. |
| Optimism (Standardized) | Z-score (mean 0, SD 1) of Optimism. |
| Excitement (Standardized) | Z-score (mean 0, SD 1) of Excitement. |
| Anxiety (Standardized) | Z-score (mean 0, SD 1) of Anxiety. |
| Fear (Standardized) | Z-score (mean 0, SD 1) of Fear. |
| Optimism (Placebo) | Placebo Optimism obtained by randomly permuting Optimism scores across deals. |
| Excitement (Placebo) | Placebo Excitement obtained by randomly permuting Excitement scores across deals. |
| Anxiety (Placebo) | Placebo Anxiety obtained by randomly permuting Anxiety scores across deals. |
| Fear (Placebo) | Placebo Fear obtained by randomly permuting Fear scores across deals. |
| Sadness | LLM-based score (0–1) for Sadness in analysts' Q&A questions. |
| Anger | LLM-based score (0–1) for Anger in analysts' Q&A questions. |
| Disgust | LLM-based score (0–1) for Disgust in analysts' Q&A questions. |
| Joy | LLM-based score (0–1) for Joy in analysts' Q&A questions. |
| **Return and Performance Variables** | |
| Fama–French 3 CAR [−n, +m] | Cumulative abnormal acquirer return from the Fama–French 3-factor model over days [−n, +m] around the conference call. |
| Fama–French 3 ABRET [−5, +5] | Daily Fama–French 3-factor abnormal acquirer returns over [−5, +5] around the call, used in event-time plots. |
| Fama–French 4 CAR [−1, +1] | Cumulative abnormal acquirer return from the Fama–French 4-factor model (including momentum) over [−1, +1] around the call. |
| Market Model CAR [−1, +1] | Cumulative abnormal acquirer return from a standard market model over [−1, +1] around the call. |
| Market-adjusted CAR [−1, +1] | Cumulative abnormal acquirer returns over [−1, +1] equal to raw return minus market index return each day, cumulated. |
| BHAR_VW | Rebalanced value-weighted post-call buy-and-hold abnormal return on the acquirer. |

| | |
|---|---|
| BHAR_EW | Rebalanced equal-weighted post-call buy-and-hold abnormal return on the acquirer. |
| **Deal Outcome Variables** | |
| Completed_Deal | Indicator equal to 1 if the M&A deal is completed and 0 otherwise. |
| Days to Completion | Calendar days from deal announcement to completion; incomplete deals are right-censored in duration models. |
| **Deal Characteristic Variables** | |
| Tar Public | Indicator equal to 1 if the target firm is public and 0 if the target is private. |
| Tar US | Indicator equal to 1 if the target firm is incorporated in the United States and 0 otherwise. |
| Stock% | Percentage of total deal consideration paid in acquirer stock. |
| DealVal/AcqME | Deal value divided by the acquirer's pre-announcement market equity. |
| **Acquirer (Firm) Characteristic Variables** | |
| ln(AT)Acq | Natural logarithm of the acquirer's total assets. |
| MTB Acq | Acquirer market-to-book ratio, measured as market value of equity divided by book value of equity. |
| ROA Acq | Acquirer return on assets, measured as income before extraordinary items divided by lagged total assets. |
| RD Acq | Acquirer R&D intensity, measured as R&D expenditures divided by lagged total assets. |
| **Analyst-Level Variables** | |
| Analyst Rating | Consensus analyst stock rating for the acquirer on a 1–5 scale (1 = strongest buy, 5 = strongest sell), measured as of the last trading day of the month of the conference call; higher values indicate more bearish views. |
| Analyst Coverage | Number of financial analysts covering the acquirer at the time of the conference call. |
| Analyst Forecast Accuracy | Measure of analyst earnings forecast accuracy for the acquirer, based on forecast errors as described in the text. |
| **Macroeconomic and Market-Level Controls** | |
| Sentiment Index | Aggregate macro or market sentiment index capturing overall economic or financial conditions. |

| | |
|---|---|
| Recession Indicator | Indicator equal to 1 if the conference year falls in a recession period and 0 otherwise. |
| Employment Growth | Macroeconomic measure of employment growth over the relevant period (e.g., annual percentage change in employment). |
| CPI Inflation | Inflation rate over the relevant period based on the Consumer Price Index. |
| **Management Sentiment and Information-Structure Variables** | |
| Management Optimism in Main | LLM-based optimism score for management language in the main presentation segment of the call. |
| Management Optimism in Q&A | LLM-based optimism score for management language in the Q&A segment of the call. |
| Hard Information Score | Index summarizing the share of verifiable, quantitative, or contractible information in the call; constructed following Dasgupta et al. (2024) |
| Numerical Information Share | Share of the call text that consists of numerical information; constructed following Campbell et al. (2025) |
| **Other Text-Tone Measures** | |
| Positive tone | Share of positive LM dictionary words in the *analyst* portion of the Q&A segment of the conference call. |
| Negative tone | Share of negative LM dictionary words in the *analyst* portion of the Q&A segment of the conference call. |
| Tone (LM) | Net LM tone in the analyst Q&A, defined as Positive tone minus Negative tone, where both components are computed using the analyst portion of the Q&A segment. |
| Valence | LLM-based overall sentiment measure (-1 to 1) that captures the positive–negative (pleasant–unpleasant) tone of the analyst's conference call text; higher values indicate more positive affect. |
| **Additional Variables** | |
| Bidder | Indicator equal to 1 if the acquirer is classified as a bidder in the deal and 0 otherwise. |
| Fama–French 3 CAR [−4, −2] | Pre-conference Fama–French 3-factor cumulative abnormal acquirer return over days [−4, −2] before the call. |

## Appendix C. GPT-Based Sentiment Extraction Procedure

We implement sentiment scoring using GPT-4.1 accessed via the application programming interface (API), rather than through the web interface, to maintain full control over model parameters and reproducibility. We set the temperature parameter to zero and fix the random seed, so that repeated calls with identical inputs return identical outputs.

Earlier work was constrained by relatively small context windows and therefore had to trim or chunk transcripts before processing. In contrast, the expanded context window of GPT-4.1 (up to 128,000 tokens, or around 96,000 words) allows us to pass the full analyst Q&A for each call without truncation or chunking. This design lets the model assess sentimental content using the entire dialogue and its context.

For each call, GPT-4.1 produces numerical scores on four discrete affective dimensions: optimism and excitement (positive sentiments) and anxiety and fear (negative sentiments). These dimensions are grounded in Russell's (1980) *Circumplex Model of Affect* and are intended to capture intensity rather than mere word counts.

## Appendix D. Example Transcript Segments with Labeled Sentiments

**Deal with high Anxiety score**

*FEBRUARY 23, 2007 / 9:30 PM GMT – Insignia Solutions Conference Call to Discuss Acquisition by Smith Micro Software, Inc.*

*Howard Prince – Analyst*

"Well, my question for you is how can we be sure that this is the maximum value that we're getting? We don't know what we're selling."

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**Deal with high Fear score**

*JULY 11, 2006 / 8:30 PM GMT – Secure Computing to Acquire CipherTrust and Announce Preliminary Second Quarter 2006 Results*

*Katherine Egbert, Jefferies – Analyst*

"Thank you. So the question I have regards to your core business. You bought CyberGuard and then you missed the March quarter, and now you missed again in June and you're attempting to buy CipherTrust. What gives investors comfort that this cycle is not going to repeat itself? There seems to be some substantial slide in the organic business and you seem to be acquiring to make up for that slide. And even the acquisitions aren't having the intended effect. So what comfort can you give us that the numbers for CipherTrust are right and this just isn't layering on or an attempt to layer on more revenue?"

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**Deal with high Excitement score**

*APRIL 8, 2021 / 2:30 PM GMT – PAR Technology Corp M&A Call*

*Adam David Wyden, ADW Capital Management LLC – Chief Compliance Officer, Founder & Managing Partner*

"I think many of us have been waiting a long time to see kind of the big deal, given the capital that was raised. And obviously, personally, I'm super excited because to me it's kind of the catalytic moment that we've successfully gone from point of defense to point of offense."

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**Deal with high Optimism score**

*JUNE 1, 2016 / 12:00 PM GMT – Salesforce.com Inc. to Acquire Demandware Inc.*

*Abhey Lamba, Mizuho Securities – Analyst*

"Thank you. Keith, you guys have been talking potential of e-commerce for a while. Did you see something in the market or at Demandware that catalyzed your decision to make a move now? Clearly the TAM is large enough for you to be excited about.

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## Appendix E. Additional Robustness Tests

### Appendix E.1. Sentiments and Acquirer Conference Call Returns (Univariate Tests)

This appendix reports univariate median tests comparing acquirer conference call returns across high- and low-sentiment groups. For each sentiment measure, observations are split at the sample median. We report the median Fama–French 3 CAR [-1, +1] for the full sample, the low-sentiment subsample, and the high-sentiment subsample. The final column reports the Wilcoxon rank-sum z-statistic for the difference in medians. All variables are defined in the Appendix. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

**Panel A. (Excitement)**

| | All firms | Low Excitement | High Excitement | z-statistic of difference |
|---|---|---|---|---|
| | (N=2,604) | (N= 1,119) | (N= 1,485) | |
| Fama–French 3 CAR[-1,+1] (Median) | 0.004 | 0.000 | 0.006 | 4.250*** |

**Panel B. (Optimism)**

| | All firms | Low Optimism | High Optimism | z-statistic of difference |
|---|---|---|---|---|
| | (N=2,604) | (N= 1,018) | (N= 1,586) | |
| Fama–French 3 CAR[-1,+1] (Median) | 0.004 | -0.000 | 0.006 | 3.352*** |

**Panel C. (Anxiety)**

| | All firms | Low Anxiety | High Anxiety | z-statistic of difference |
|---|---|---|---|---|
| | (N=2,604) | (N= 1,130) | (N= 1,474) | |
| Fama–French 3 CAR[-1,+1] (Median) | 0.004 | 0.010 | -0.000 | -5.399*** |

**Panel D. (Fear)**

| | All firms | Low Fear | High Fear | z-statistic of difference |
|---|---|---|---|---|
| | (N=2,604) | (N=1,005) | (N= 1,599) | |
| Fama–French 3 CAR[-1,+1] (Median) | 0.005 | 0.009 | 0.000 | -5.464*** |

**Appendix E.2. Additional Sentiments**

This appendix examines whether additional sentiment categories extracted by the LLM—sadness, anger, disgust, and joy—are associated with conference returns. For each of these sentiments, we regress Fama–French 3 CAR [-1, +1] on the corresponding sentiment score. All specifications include acquirer and target one-digit SIC industry fixed effects and conference-year fixed effects. Standard errors are clustered at the acquirer industry (one-digit SIC) level, and t-statistics are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| **Variables** | Fama–French 3 CAR [-1,1] | | | |
| Sadness | -0.247*** | - | - | - |
| | (-5.272) | | | |
| Anger | - | -0.259*** | - | - |
| | | (-5.320) | | |
| Disgust | - | - | -0.286** | - |
| | | | (-3.115) | |
| Joy | - | - | - | 0.126*** |
| | | | | (7.008) |
| ln(AT)Acq | -0.002* | -0.002** | -0.003** | -0.003** |
| | (-2.180) | (-2.306) | (-2.604) | (-3.224) |
| MTB Acq | 0.001** | 0.001** | 0.001* | 0.001* |
| | (2.276) | (2.281) | (2.225) | (2.234) |
| ROA Acq | -0.030*** | -0.029*** | -0.029*** | -0.029*** |
| | (-5.218) | (-4.438) | (-4.056) | (-4.566) |
| RD Acq | -0.026 | -0.030 | -0.031 | -0.031 |
| | (-1.323) | (-1.576) | (-1.621) | (-1.376) |
| Tar Public | -0.022*** | -0.022*** | -0.023*** | -0.024*** |
| | (-3.984) | (-4.066) | (-4.249) | (-4.972) |
| Tar US | 0.009 | 0.009 | 0.009 | 0.008 |
| | (1.738) | (1.820) | (1.823) | (1.668) |
| Stock% | -0.000** | -0.000** | -0.000** | -0.000** |
| | (-2.513) | (-2.422) | (-2.460) | (-2.827) |
| DealVal/AcqME | 0.023* | 0.023* | 0.023 | 0.022 |
| | (1.835) | (1.868) | (1.830) | (1.677) |
| Observations | 2,604 | 2,604 | 2,604 | 2,604 |
| Adjusted R-squared | 0.098 | 0.098 | 0.094 | 0.102 |
| Industry FE | Yes | Yes | Yes | Yes |
| Year FE | Yes | Yes | Yes | Yes |

**Appendix E.3. Probit Model**

This appendix examines the robustness of the deal completion results using probit specifications in place of the baseline logit models. For each analyst sentiment measure, we estimate a probit regression of the completion indicator on the respective sentiment variable and the standard set of acquirer and deal controls. All specifications include acquirer and target one-digit SIC industry fixed effects and conference-year fixed effects. Standard errors are clustered at the acquirer industry (one-digit SIC) level, and z-statistics are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

| | Positive sentiments | | Negative sentiments | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| **Variables** | Completed_Deal | | | |
| Optimism | 0.137 | - | - | - |
| | (0.360) | | | |
| Excitement | - | 0.143 | - | - |
| | | (0.268) | | |
| Anxiety | - | - | -1.700*** | - |
| | | | (-2.860) | |
| Fear | - | - | - | -2.773*** |
| | | | | (-5.230) |
| ln(AT)Acq | 0.064** | 0.064** | 0.072** | 0.077** |
| | (2.051) | (2.076) | (2.443) | (2.543) |
| MTB Acq | -0.016 | -0.016 | -0.017 | -0.017 |
| | (-1.484) | (-1.480) | (-1.525) | (-1.554) |
| ROA Acq | 0.135 | 0.138 | 0.133 | 0.137 |
| | (0.395) | (0.400) | (0.401) | (0.411) |
| RD Acq | -0.205 | -0.205 | -0.190 | -0.199 |
| | (-0.414) | (-0.395) | (-0.427) | (-0.439) |
| Tar Public | -0.606*** | -0.607*** | -0.591*** | -0.586*** |
| | (-6.568) | (-6.574) | (-6.415) | (-6.353) |
| Tar US | 0.095 | 0.095 | 0.081 | 0.073 |
| | (0.592) | (0.588) | (0.521) | (0.464) |
| Stock% | -0.003 | -0.003 | -0.003 | -0.003 |
| | (-1.182) | (-1.196) | (-1.051) | (-1.027) |
| DealVal/AcqME | -0.256*** | -0.255*** | -0.250*** | -0.244*** |
| | (-3.728) | (-3.633) | (-3.673) | (-3.552) |
| Observations | 1,945 | 1,945 | 1,945 | 1,945 |
| Industry FE | Yes | Yes | Yes | Yes |
| Year FE | Yes | Yes | Yes | Yes |

**Appendix E.4. Fama–French Momentum-Adjusted CARs**

This appendix examines whether the relation between analyst sentiments and conference call returns is robust to measuring abnormal performance using the Fama–French four-factor (FF4) model. All regressions include acquirer and target one-digit SIC industry fixed effects and conference-year fixed effects. Standard errors are clustered at the acquirer industry level (one-digit SIC), and t-statistics are reported in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

| | Positive sentiments | | Negative sentiments | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| **Variables** | Fama–French 4 CAR [-1,1] | | | |
| Optimism | 0.066*** | - | - | - |
| | (6.465) | | | |
| Excitement | - | 0.061*** | - | - |
| | | (3.994) | | |
| Anxiety | - | - | -0.225*** | - |
| | | | (-5.338) | |
| Fear | - | - | - | -0.289*** |
| | | | | (-5.142) |
| ln (AT)Acq | -0.003*** | -0.003*** | -0.002 | -0.002 |
| | (-3.564) | (-3.430) | (-1.794) | (-1.617) |
| MTB Acq | 0.001** | 0.001** | 0.001** | 0.001** |
| | (2.403) | (2.384) | (2.425) | (2.421) |
| ROA Acq | -0.032*** | -0.031*** | -0.032*** | -0.031*** |
| | (-4.755) | (-3.970) | (-4.629) | (-4.479) |
| RD Acq | -0.028 | -0.028 | -0.021 | -0.021 |
| | (-1.068) | (-1.129) | (-0.970) | (-0.935) |
| Tar Public | -0.024*** | -0.024*** | -0.022*** | -0.022*** |
| | (-4.780) | (-4.775) | (-4.205) | (-4.104) |
| Tar US | 0.008 | 0.008 | 0.008 | 0.008 |
| | (1.668) | (1.746) | (1.797) | (1.772) |
| Stock% | -0.000** | -0.000** | -0.000** | -0.000** |
| | (-3.057) | (-2.902) | (-2.468) | (-2.428) |
| DealVal/AcqME | 0.022 | 0.022 | 0.024* | 0.024* |
| | (1.680) | (1.709) | (1.889) | (1.913) |
| Observations | 2,604 | 2,604 | 2,604 | 2,604 |
| Adjusted R-squared | 0.099 | 0.094 | 0.104 | 0.106 |
| Industry FE | Yes | Yes | Yes | Yes |
| Year FE | Yes | Yes | Yes | Yes |

**Appendix E.5. Market-Adjusted CARs**

This appendix examines whether the relation between analyst sentiments and conference call returns is robust to measuring abnormal performance using a simple Market-adjusted CAR [–1,+1]. All regressions include acquirer and target one-digit SIC industry fixed effects and conference-year fixed effects. Standard errors are clustered at the acquirer industry level (one-digit SIC), and t-statistics are reported in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

| | Positive sentiments | | Negative sentiments | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| **Variables** | Market-adjusted CAR [-1,1] | | | |
| Optimism | 0.070*** | - | - | - |
| | (8.409) | | | |
| Excitement | - | 0.065*** | - | - |
| | | (4.801) | | |
| Anxiety | - | - | -0.230*** | - |
| | | | (-5.018) | |
| Fear | - | - | - | -0.294*** |
| | | | | (-4.977) |
| ln (AT)Acq | -0.003** | -0.003** | -0.002 | -0.001 |
| | (-2.859) | (-2.763) | (-1.425) | (-1.292) |
| MTB Acq | 0.001* | 0.001* | 0.001* | 0.001* |
| | (2.107) | (2.080) | (2.080) | (2.090) |
| ROA Acq | -0.024*** | -0.023*** | -0.024*** | -0.023*** |
| | (-4.210) | (-3.640) | (-4.219) | (-3.989) |
| RD Acq | -0.020 | -0.021 | -0.014 | -0.013 |
| | (-1.056) | (-1.130) | (-0.838) | (-0.791) |
| Tar Public | -0.024*** | -0.024*** | -0.022*** | -0.022*** |
| | (-4.697) | (-4.665) | (-4.013) | (-3.907) |
| Tar US | 0.009* | 0.009* | 0.010* | 0.010* |
| | (2.001) | (2.099) | (2.116) | (2.091) |
| Stock% | -0.000** | -0.000** | -0.000** | -0.000* |
| | (-2.838) | (-2.704) | (-2.285) | (-2.248) |
| DealVal/AcqME | 0.021 | 0.021 | 0.023* | 0.024* |
| | (1.691) | (1.723) | (1.907) | (1.930) |
| Observations | 2,604 | 2,604 | 2,604 | 2,604 |
| Adjusted R-squared | 0.099 | 0.093 | 0.103 | 0.105 |
| Industry FE | Yes | Yes | Yes | Yes |
| Year FE | Yes | Yes | Yes | Yes |