Unusual Financial Communication:

ChatGPT, Earnings Calls, and Financial Markets

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Abstract

We devise a prompting strategy for ChatGPT to detect and analyze unusual aspects of financial communication in earnings calls. We identify 25 dimensions across four categories: unusual communication *styles* by executives and analysts, unusual *contents*, and technical difficulties. Unusual financial communication is common, correlates with certain firm characteristics and fluctuates with the business cycle. Financial markets respond negatively to both unusual communication styles and content, leading to decreased stock returns, increased trading activity, higher volatility and option-implied uncertainty, and downward revisions of next-quarter earnings forecasts by analysts. Our study demonstrates the potential of large language models to provide new insights into the interpretation of financial textual data.

1. Introduction

The introduction of ChatGPT has changed how humans process information. ChatGPT is the fastest-growing online service to date, reaching 100 million users just two months after its launch (Hu, 2023). Today, more than 180 million users are actively using ChatGPT. The service's success in making sense of textual data also has important repercussions for financial markets. Financial analysts can use large language models to comb through the ever-growing amounts of financial and economic textual data (Gentzkow, Kelly, and Taddy, 2019). To this end, Bloomberg, as a leading data and service provider to financial professionals, introduced BloombergGPT in March 2023 (Wu, Irsoy, Lu, Dabravolski, Dredze, Gehrmann, Kambadur, Rosenberg, and Mann, 2023) and JPMorgan followed suit in 2024 with its own model (Janakiram, 2024). The large language models are dedicated to performing well on the everyday tasks of financial analysts.[1] Similarly, Citadel is seeking an enterprise-wide license of ChatGPT (Doherty and Marques, 2023).

We leverage ChatGPT's general knowledge to understand the intricacies of financial communication using earnings calls as a laboratory. Earnings calls are the premier data source for this task, as the included Q&A session reflects dynamic interactions between financial analysts asking questions about the firm and members of the management team providing their answers. In general, we want to capture not only the unusualness of what is being said (content) and how it is said (tonality), but also identify unusual aspects that go beyond. Tesla's Q1-2018 earnings call is a prime example of unusual financial communication. CEO Elon Musk addressed an analyst's question about future capital requirements by "Excuse me. Next. Boring, bonehead questions are not cool. Next?". At the same time, Tesla's earnings call exemplifies how unusual communication can go beyond what has been said and how. Musk's remarks that he does not know the number of reservations for the Tesla Semi were supplemented by the CFO. This, in turn, indicates a lack of preparedness – another dimension of unusual financial communication identified by ChatGPT. Furthermore, Musk takes questions from a YouTuber, which ChatGPT also correctly identifies as unusual.

Our **first contribution** is in engineering a novel prompting approach for ChatGPT to identify and understand unusual communication in earnings calls. We devise a three-step prompting strategy, which is solely based on ChatGPT's general knowledge and

[1] Another recent development in the field that is likely to impact the work of financial analysts is Microsoft's development of "Copilot", a large language model for the company's office suite (Spataro, 2023).

does not require an external definition of what constitutes unusual communication. With this prompting strategy at hand, we feed the earnings call transcripts for firms in the S&P 500 through ChatGPT and extract a binary indication for various dimensions of unusual communication. Identified dimensions of unusual communication include a lack of preparedness by the firm's executives, repetitive questions asked by financial analysts, or surprising announcements. Apart from the binary indicator ("unusual" vs. "usual"), we also ask ChatGPT to provide a concise reason for why it believes an earnings call to be unusual in the respective dimension. Of course, our prompting strategy can also be applied to numerous other applications to make sense of textual data in the financial context. This underlines the potential of large language models such as ChatGPT for financial analysis.

As our **second contribution**, we identify unusual financial communication in earnings calls between 2018 and 2023 and investigate its correlation with firm characteristics, industry affiliation, and its fluctuation over the business cycle. In total, we identify 25 dimensions of unusual communication in earnings calls, which can be classified into four broader categories: unusual communication *styles* by executives and by financial analysts, unusual *contents*, and technical difficulties.[2] Firms with unusual communication are larger on average and more likely growth than value stocks. They also tend to experience some level of stress, for example in the form of deteriorating profit margins or a declining stock price. While there is some heterogeneity across industries, industry affiliation alone is unable to explain the occurrence of unusual financial communication. We also relate the different dimensions of unusual communication to various macroeconomic indicators and document that the degree of unusual communication varies with the business cycle. For example, discussions of unusual *contents* are more likely in high-VIX regimes and less likely in times of a high price-dividend ratio. Higher net share issuance is correlated with less unusual communication, particularly by firm executives, potentially in an effort to portray a stable picture of the company, especially when issuing or planning to issue additional shares (Pontiff and Woodgate, 2008).

As our **third contribution**, we investigate to which extent market participants react to unusual financial communication in earnings calls and if they do, which dimensions of unusual communication are responsible for this reaction. Unusual financial communication can be understood as an impediment to market participants in judging the quality and content of the provided information. As such, we can draw on the theory by Epstein

[2]The full list of identified dimensions is provided in Table 1.

and Schneider (2008) to guide our empirical analyses, which studies the implications of differential quality of information disclosures with ambiguity-averse investors.

In line with the theory, we find that the stock return reaction to unusual financial communication is significantly negative. This result is robust to equally- and value-weighting the respective firms and robust to controlling for various confounding effects, including differences in the characteristics of the affected firms, the standardized unexpected earnings component, how many analysts cover the firms, and how much these analysts disagree about next period's earnings-per-share. We also control for industry- and firm-specific effects. On average, the announcement return of firms with unusual communication patterns is -0.37% lower than the announcement response of firms with typical communication. A higher intensity of unusual financial communication – defined as the number of the 25 identified dimensions that ChatGPT flags as unusual in a firm's earnings call – plays an accelerating role in the announcement return response. We find a monotonically increasing negative announcement return response as the degree of unusual communication increases. For example, with 11 or more of 25 dimensions flagged as unusual, the average announcement response of the affected firms is -1.02% smaller than of firms with typical communication. This is further validation for our identification approach of unusual communication with ChatGPT: the more unusual the communication in a given earnings call, the more do market participants react to it. To ascertain that this market reaction is not simply the response to bad news or the revelation of significant events, which ChatGPT identifies as unusual *contents*, we investigate the incremental information conveyed by unusual *styles* of communicating. Conditional on the prevalence of unusual contents, we find that a repeated focus of financial analysts on specific participants or topics, repetitive questions, and especially a lack of critical questioning is associated with an additional and highly significant negative announcement return impact. Likewise, we find a negative incremental return impact whenever firm executives try to evade questions by financial analysts and if they appear unprepared. These results are intuitive and highlight important aspects of how analysts and executives communicate that investors should pay attention to. Finally, we find that the return reaction to unusual financial communication is negative, regardless of whether the news component of the earnings release was positive or negative for the firm, which follows directly from the theory of Epstein and Schneider (2008), and corroborates the idea that unusual financial communication is disliked by investors as it represents an impediment to judging the quality of the provided information.

Market participants increase their trading activity in response to unusual financial communication, in line with several empirical studies linking an increase in ambiguity to an initial increase in investor trading activity (Kostopoulos, Meyer, and Uhr, 2022; Barria, 2023). Likewise, models of investor disagreement also predict an elevated trading activity in the presence of unusual financial communication, should the unusual communication patterns elevate disagreement among investors (Kim and Verrecchia, 1991; Banerjee and Kremer, 2010). Empirically we find that firms with unusual communication experience significantly more trading activity during their earnings announcements, which survives the consideration of various controls, and is once again increasing in the intensity of unusual financial communication.

Other markets and market participants also react to unusual financial communication. We first show it significantly increases the stock's return volatility around the earnings announcement. Then, we find that the options market expects higher uncertainty going forward for firms with unusual communication patterns. On average, the at-the-money implied volatility of call options written on the affected firms increases by between 0.41 and 0.79 percentage points. As a final piece of evidence regarding the impact of unusual financial communication, we find that financial analysts significantly revise their forecasts of *next quarter's* earnings-per-share downward, showcasing how unusual communication and the discussion of unusual contents can impact the valuation of a firm's fundamentals.

Our use of ChatGPT to identify unusual financial communication comes with multiple advantages. First, we always rely on the same model for the decision of whether a particular earnings call was unusual or not. As human intuition is subjective, it can vary from day to day and from analyst to analyst. With the model's *temperature* set to zero and its *seed* fixed, the model produces the same output (is the call unusual?) for the same input (the transcript's Q&A session) and the same prompt. This reproducibility in the pipeline is key for the compliance of financial professionals. Second, the model processes textual information significantly faster than humans and combines much of the aggregate reasoning of how humans would process this information from its training corpus (de Kok, 2023). Third, we utilize GPT-4-Turbo. This version not only offers general enhancements over its predecessor, GPT-4, but most crucially, it can process texts of up to 128,000 tokens in a single prompt. Previous iterations of GPT-4 were limited to just 8,192 tokens, compelling many studies that utilized ChatGPT on earnings call transcripts to either shorten the length of the transcripts or use summarization techniques.

Such methods invariably led to a loss of important content and context.[3] Finally, we assure that our results hold when applied to a subsample of earnings calls collected after the training cutoff of our version of GPT-4-Turbo. While our carefully designed prompting approach already assures that ChatGPT is only asked about unusual aspects of a firm's earnings call, and not about how the model believes these aspects to be reflected in financial markets, this exercise nonetheless further cements the viability of our approach and results, and confirms the functionality of the ChatGPT prompting strategy.

Related Literature

Our paper is part of a young but growing literature that uses ChatGPT to understand vast amounts of economic and financial textual data. Lopez-Lira and Tang (2023) is the first to show that ChatGPT is capable of identifying short-term price movements in small stocks. Dong, Stratopoulos, and Wang (2023) provide a review of the recent studies. To address the criticism that information about a stock's realized return in a backtest may be part of ChatGPT's training corpus, Pelster and Val (2023) perform a live experiment to study ChatGPT's real-time ability to predict future stock returns. Kim (2023) asks ChatGPT to provide investment recommendations across asset classes.

Other studies focus on ChatGPT's ability to make sense of textual data. Impressively, Katz, Bommarito, Gao, and Arredondo (2023) show that GPT-4 passes the bar exam, while previous iterations of ChatGPT have failed to do so. We use the updated GPT-4-Turbo, which is another improvement over GPT-4 studied by the authors. In a similar vein, Kim, Muhn, and Nikolaev (2023b) show that ChatGPT-generated summaries of corporate disclosures better reflect the conveyed textual sentiment and, in turn, are more predictive of the stock market's reaction. They introduce a measure of information "bloat" and show that bloated disclosures are linked to lower stock price efficiency and higher information asymmetries. Kim, Muhn, and Nikolaev (2023a) use GPT-3.5 to measure a firm's exposure to several risks from the transcripts of earnings calls, while Bai, Boyson, Cao, Liu, and Wan (2023) use the textual distance between the answers given by firm executives and answers generated by ChatGPT and show that this human-AI distance can predict the stock's liquidity, abnormal returns around earnings announcements, and the accuracy of forecasts made by financial analysts. Jha, Qian, Weber,

[3]We discuss this circumstance in more detail in Section 2.2.

and Yang (2023) introduce an investment score from earnings calls using ChatGPT and show that this score is highly correlated with the expectations of CFOs. Finally, Bybee (2023) uses ChatGPT to generate economic expectations from historical newspaper articles. The author uses the generated economic expectations to study the origins of stock price bubbles.

Our study furthermore adds to the broader literature, which uses textual information for economic research. Gentzkow et al. (2019) provide an introduction to the topic. In an influential study, Baker, Bloom, and Davis (2016) construct economic policy uncertainty indexes from the mentions of certain topics in newspaper articles. Baker, Bloom, Davis, and Sammon (2021) study the origins of stock market jumps by identifying the dominant news story on the day after the jump occurred, and Gorodnichenko, Pham, and Talavera (2023) study the impact of the communication by the Federal Reserve chair. Bybee, Kelly, and Su (2023b) construct a latent factor model for the cross-section of stock returns from news topics, and Bybee, Kelly, Manela, and Xiu (2023a) use these news topics to forecast macroeconomic dynamics. Finally, Chen, Tang, Zhou, and Zhu (2023) show that news-based information extracted with the help of ChatGPT is related to macroeconomic conditions and the aggregate stock market.

Many studies make use of earnings call transcripts to obtain insights about the impact of manager communication. Hassan, Hollander, Van Lent, and Tahoun (2019) measure a firm's exposure to political risks from earnings call transcripts using a simple dictionary approach. Hassan, Hollander, Van Lent, and Tahoun (2020b) extend this idea to measure the perceived impact of Brexit and Hassan, Hollander, Van Lent, Schwedeler, and Tahoun (2020a) study the implications of firm-level exposure to pandemics. Li, Mai, Shen, and Yan (2021) use a simple machine learning approach to assess if earnings calls convey information about a firm's culture, and Breuer, Knetsch, et al. (2023) study the impact of managerial charisma.

Finally, we add to our understanding of the importance of event days. To this end, Savor and Wilson (2013) and Ernst, Gilbert, and Hrdlicka (2019) show that market returns are significantly higher on days with macroeconomic news releases and Liang (2003) argues that earnings announcements provide particularly important information to investors. Consistent with this, Savor and Wilson (2016) show that earnings announcement returns are significantly elevated and link this to investors revising their expectations for non-announcing firms. Engelberg, McLean, and Pontiff (2018) show that the returns of many prominent cross-sectional stock anomalies are significantly elevated on earnings

announcement days and favor an explanation based on the resolution of mispricing.

The rest of the paper is organized as follows: Section 2 introduces the data and the methodology, Section 3 discusses how often firms engage in unusual financial communication, and Section 4 investigates how financial markets react to it. Section 5 concludes.

2. Data and ChatGPT Processing

2.1. Data Description

We obtain transcripts of earnings calls held by firms in the S&P 500 from Refinitiv for the period of January 2018 to December 2023. A typical earnings call has two sections: first, a presentation by the firm's management, which provides a broad overview of the firm's current operations and its future trajectory. The second section is a Q&A session, as an interaction between financial analysts asking questions and members of the management team providing answers. We focus our analysis on this second section of the transcript, as the management's presentation tends to be tightly scripted and conveys less novel information (Lee, 2016; Li et al., 2021). Cao, Jiang, Yang, and Zhang (2023) show that firms adapt to the increasing use of machine learning tools by investors to process textual information and consequently change their writing in regulatory disclosures like 10Ks. Earnings calls are not affected by this catering to conveying specific information to machines as the Q&A sessions reflect live interactions between management and analysts.

The earnings call transcripts are provided by Refinitiv as .txt files. From each file, we extract a) the date and time of when the earnings call took place, b) the reporting quarter, and c) the company name and ticker. Finally, we split the transcript into the presentation part and the Q&A session and feed ChatGPT with the Q&A session only. In the future, we plan to provide a description of which earnings calls are unusual and why for public use.

We also collect stock return and volume information from CRSP, information about firm-level accounting data from Compustat, information about options trading on the stocks in the S&P 500 from OptionMetrics, and analyst forecasts from IBES.

2.2. ChatGPT

Accessing ChatGPT. We access ChatGPT via its application programming interface (API). Different from the web access, the API offers various additional functions. The *temperature* parameter defines the magnitude of stochastic answers. Asking the same question several times generates varying responses when *temperature* is high. We set this parameter to zero and set the *seed* parameter to a constant value to obtain answers as objective and reproducible as possible.

The model that we rely on is GPT-4-Turbo, which is an updated version of GPT-4. It was released on November 6, 2023, and is trained on data obtained until April of 2023, including earnings calls.[4] Whereas the previous iteration was limited to processing 8,192 tokens per prompt, the token limit has been increased to 128,000 for GPT-4-Turbo. This change alleviates the need to trim the transcripts or have ChatGPT process the information of a single transcript in chunks. With this, we are able to evade the downsides of chunking, which previous studies may have to resort to given the limitations of ChatGPT before GPT-4-Turbo.[5] GPT-4-Turbo is therefore able to comprehend the Q&A sessions in their entirety. This contributes to a model setup that is capable of identifying subtleties in both tone and language that may only stand out as unusual when the entire Q&A session is provided as context. In our dataset, 5,178 of the 11,134 Q&A sessions are longer than 8,192 tokens.[6]

ChatGPT Prompt Engineering. We need to find a suitable approach for ChatGPT to accurately and consistently assess the *unusualness* of a firm's earnings call. The analysis should not only examine what is said (content) and how it is said (tonality), but also uncover unusual aspects of earnings calls that go beyond that. In addition, we not only want to determine whether an earnings call is unusual, but also to understand the textual aspects that make it unusual. We propose a three-step prompting approach for this purpose:

[4]We use version `gpt-4-1106-preview`. Using earnings calls held after the cutoff date, we assure that our results are reproducible fully out-of-sample, see Section 4.5.

[5]Examples of studies resorting to "chunking" are Goyal, Li, and Durrett (2022), Kim et al. (2023a) Kim et al. (2023b) and Zhang, Ni, Yu, Zhang, Zhu, Deb, Celikyilmaz, Awadallah, and Radev (2021). Their solution to larger inputs is chunking about every 2,000 tokens and using summaries of the previous chunk to add to the recent 2,000 token chunks.

[6]The average token length is 8,146, which we calculate using the tokenizer provided by *OpenAI*, especially for the ChatGPT-4-Turbo model. The 90th (95th; 99th) percentile of the token length amounts to 11,162 (12,272; 14,608) tokens.

In the first step, we want to understand what is generally unusual in earnings call Q&A sessions. We feed ChatGPT a random sample of $n = 1000$ Q&A session transcripts and ask for the model's judgment of whether a particular Q&A session is usual or unusual.[7] If a Q&A session is found to be unusual in any way, ChatGPT is asked to provide a textual justification for this *unusualness*.

> **Prompt 1:** *Please read the following transcript of a Question-and-Answer session from the earnings conference call of company {firm} ({ticker}) carefully. Determine whether the Question-and-Answer session of this earnings conference call is 'usual' or 'unusual': If the Question-and-Answer session is classified as 'usual', state 'usual' without any justifications or further output. If the Question-and-Answer session is classified as 'unusual', state 'unusual' and provide a justification for this classification. Transcript of the Question-and-Answer Session: '{qa}'*

To illustrate that ChatGPT is able to identify unusual aspects during earnings calls, we showcase the ChatGPT output for the first prompt related to Tesla's Q1-2018 earnings call below.

> The Question-and-Answer session of Tesla's Q1-2018 earnings call is classified as 'unusual' for the following reasons:
>
> 1. CEO's Dismissive Attitude: Elon Musk, the CEO, displays a dismissive attitude towards analysts' questions, which is not typical for an earnings call. He refers to some questions as "boring," "dry," and "bonehead," which is highly unprofessional and not in line with the decorum usually maintained during such calls.
> 2. Refusal to Answer Questions: Musk refuses to answer certain questions or provides vague responses. For example, when asked about the timing for the Tesla Network, he says, "I haven't really thought about it," which is unexpected from a CEO discussing a significant aspect of their company's strategy.
> 3. Focus on Short-Term Stock Traders: Musk explicitly states that they have no interest in satisfying the desires of day traders and even suggests that those concerned about volatility should not buy Tesla stock. This is unusual as companies typically avoid making such direct and potentially discouraging statements to investors.
> 4. Lack of Specific Financial Details: There is a lack of specific financial details provided in some of Musk's responses. For instance, when discussing the potential cost savings from the Tesla Semi, he speaks in general terms rather than providing concrete numbers.
> 5. Hostile Responses: Musk's responses to analysts from Sanford C. Bernstein and RBC Capital Markets are notably hostile. He cuts off one analyst, saying, "Boring bonehead questions are not cool. Next," and dismisses another by moving to a YouTube questioner, which is highly unconventional and indicative of an unusual call.

[7] The results are robust to selecting different random samples in this step.

6. Diversion to YouTube Questioner: Musk takes a question from a YouTube questioner, which is atypical for an earnings call that usually prioritizes financial analysts and institutional investors.
7. Casual Language and Jokes: The language used by Musk and other executives is more casual and includes jokes, which is not typical of the formal tone expected in earnings calls.
8. Lack of Preparedness: Musk's statement that he does not know the number of reservations for the Tesla Semi and needs to be corrected by the CFO suggests a lack of preparedness, which is unusual for a CEO during an earnings call.

This brief example illustrates ChatGPT's ability to identify unusual aspects of financial communication in earnings calls. ChatGPT's assessment of Tesla's Q1 2018 earnings call illustrates its ability to detect deviations from standard communication patterns, such as the CEO's dismissive attitude towards analysts and unconventional responses. Most notably, ChatGPT captures not only unusual content, but also subtleties that are not immediately apparent, such as Elon Musk's general lack of preparation implied by his and other executives' statements. This example demonstrates ChatGPT's sophisticated ability to not only identify unusual content ("what is said") and tone ("how it is said"), but also to recognize deviations from communicative norms that go beyond.

In the second step, we want to find a way to systematize these unusual observations. To do this, we collect all justifications for unusual communication from the first step. These justifications are made available to ChatGPT in a new prompt. ChatGPT is then asked to form high-level categories from these justifications.

Prompt 2: *Please read the provided text file with justifications for unusual Q&A sessions from earnings conference calls carefully. What are high-level categories to identify unusual Q&A sessions? Make sure that each statement from the text file can be assigned to one of the categories.*

As a result, ChatGPT provides us with 25 high-level categories for the identification of unusual communication in the Q&A sessions for earnings call transcripts, which we further describe in Section 3.1.

In the third step, we then examine all Q&A sessions with regard to these identified categories that constitute the different dimensions of unusual communication in the earnings calls. We ask ChatGPT to provide a binary assessment of whether the transcript in question is unusual with respect to each of the categories. For each category, if ChatGPT rates the Q&A session of the respective earnings call as usual, ChatGPT will label it as "usual" without further explanation. However, if ChatGPT classifies the Q&A session

of the respective earnings call as unusual, it will be labeled as "unusual," and ChatGPT is required to justify this classification. Examples of these justifications are shown in Table A.1 in Appendix A.

> **Prompt 3:** *Please read the following transcript of a Question-and-Answer session from the earnings conference call of company {firm} (ticker) carefully. Determine whether the Question-and-Answer session of this earnings conference call is 'usual' or 'unusual' in the following {len(categories)} categories: {categories}*
> *For each category, state whether the Question-and-Answer session is 'usual' or 'unusual'. If the Question-and-Answer session is classified as 'usual' in the respective category, state 'usual' without any justifications or further output. If the Question-and-Answer session is classified as 'unusual' in the respective category, state 'unusual', print a '/,' and provide a justification for this classification. Transcript of the Question-and-Answer Session: '{qa}'*

Why ChatGPT? Relying on ChatGPT to identify unusual financial communication comes with multiple advantages. First, we always rely on the same model for the decision of whether a particular earnings call is unusual or not. With the model's *temperature* set to zero and the *seed* fixed, the model always produces the same output (is the call unusual?) for the same input (the transcript's Q&A session) and the same prompt (shown above). This reproducibility in the pipeline is key for the compliance of financial professionals. Second, the model performs significantly faster in interpreting textual information than humans and combines much of the aggregate reasoning, with which humans would process this information, from its training corpus (de Kok, 2023). Besides being faster, our approach is also more accurate and cheaper than employing a large team of analysts to comb through textual data (Baker et al., 2016), or using simple dictionary-based approaches (Loughran and McDonald, 2011), which disregard contextual information. Of course, the prompting approach we devise above can be used for numerous other applications to make sense of textual data in the financial context. Applications range from risk assessment and management to the optimization of investment portfolios and the construction of profitable trading strategies. We leave these for future research.

3. Unusual Financial Communication

In this section, we provide a description of what constitutes unusual financial communication and how prevalent it is among firms in the S&P 500. We start with the general questions of what unusual financial communication is and how often it happens. We then assess which firms are more likely to engage in unusual financial communication and consider its aggregate variation over time.

3.1. Dimensions of Unusual Financial Communication

Our ChatGPT prompting approach provides us with 25 identified dimensions of unusual financial communication in the Q&A sessions of earnings calls. The dimensions can roughly be clustered into four broader categories: 1) unusual financial communication by the firm's executives (*executives*); 2) unusual financial communication by financial analysts (*analysts*); 3) unusual contents that were being discussed (*content*); and 4) technical difficulties (*technical*). Table 1 provides an overview of the identified 25 dimensions of unusual financial communication along with their frequency in the average calendar quarter.

ChatGPT identifies several dimensions of unusual financial communication by *executives*. For example, responses to analyst questions may be too lengthy, emotional, or even contain conflicting information or be evasive. ChatGPT also identifies whether the management team appeared unprepared. Unusual communication by *analysts* comes in the form of off-topic or repetitive questions, a particularly large volume of questions, a repeated focus on specific participants or topics, frequent queries about non-financial issues, and a lack of critical questions. Unusual *contents* can range from corporate changes and changes in the leadership team, over providing strategic insights and the discussion of legal and regulatory issues, to issues in the operations and among management. Furthermore, ChatGPT can identify unusual patterns in the firm's analysis of the markets it operates in, a particularly detailed discussion of certain (financial or non-financial) topics, the impact of external events, macroeconomic considerations, and surprising announcements, as well as detailed discussions of the firm's products or services. Finally, ChatGPT also identifies *technical* difficulties.

For each of these 25 dimensions, Table A.1 in Appendix A shows three illustrative rationales that ChatGPT provides for why it has identified a particular Q&A session as

Table 1: Dimensions & Frequency of Unusual Financial Communication

The table shows the frequency with which we identify unusual financial communication in general, along the four broader categories and the 25 dimensions of *unusualness*, as well as each dimension's abbreviation. We show how many firms engage in unusual financial communication in a typical calendar quarter ("N"), and their median fraction ("Median").

Dimension	Abbreviation	N	Q50
Unusual		197.4	0.43
Executives		116.0	0.25
Lengthy Responses	Lengthy	85.0	0.18
Informal Tone	Informal	44.8	0.09
Unusual Dialogue Patterns	Dial	30.5	0.06
Emotional Responses	Emotion	17.8	0.04
Management Evasiveness	Evasive	16.0	0.04
Management Unpreparedness	Unprep	7.5	0.02
Conflicting Information	Conflict	3.5	0.01
Analysts		85.5	0.18
Repeated Focus on Specific Participants or Topics	RepPart	78.1	0.16
Repetitive Questions	RepQ	19.9	0.04
High Volume of Questions	QVolume	11.3	0.02
Off-Topic Questions	Off-Top	11.0	0.02
Lack of Critical Questioning	LackCrit	3.3	0.01
Unusual Financial Queries	FinQuery	3.0	0.01
Content		146.5	0.31
Detailed Discussion on Non-Financial Topics	NonFin	86.6	0.18
In-Depth Product or Service Discussions	ProdDisc	79.2	0.16
Detailed Financial Discussions	FinDisc	77.7	0.16
Forward-Looking Statements and Strategic Insights	Strategy	76.6	0.16
Significant Leadership or Corporate Changes	Changes	67.5	0.14
Macroeconomic Considerations	Macro	65.5	0.14
External Events Impact	Extern	63.1	0.12
Competitive and Market Analysis	Market	57.0	0.12
Operational and Management Issues	OpIssue	49.5	0.11
Legal or Regulatory Issues	Legal	25.7	0.06
Surprising Announcements	Surprise	17.9	0.04
Technical		50.8	0.11
Technical Difficulties and Disruptions	TechDiff	50.8	0.11

unusual.

Within a typical calendar quarter, the communication of 197 (out of roughly 500) firms is considered unusual along at least one of the 25 dimensions. The median amounts to 43% of the considered firms. For a typical calendar quarter, 116 firms show some unusual patterns in their communication by *executives*. Most commonly, ChatGPT identifies lengthy responses (18%), an informal tone (9%), or unusual dialogue patterns (6%). Less common are emotional responses (4%), evasive behavior (4%), and unpreparedness (2%) of executives, and the provision of conflicting information (1%). In an average calendar

quarter, ChatGPT identifies unusual financial communication by *analysts* for 85 firms. The most common is a repeated focus on specific call participants or specific topics, which afflicts 16% of firms on average. Other dimensions of unusual behavior by *analysts* are far less common: for only 4% of firms, ChatGPT identifies repetitive questions, 2% a high volume of questions, and off-topic questions. The least common are unusual financial queries and a lack of critical questioning (1%). The *content* of what is discussed is flagged as unusual most often. In the average quarter, 146 firms are identified as such. There is a lot more homogeneity in the frequency with which the different content-based dimensions are flagged as unusual. Most common are detailed discussions of (non-) financial topics (18%), in-depth product or service discussions (16%), detailed financial discussions (16%), and forward-looking statements and strategic insights (16%). The least common are surprising announcements (4%) and a discussion of legal or regulatory issues (6%). Around 11% of firms experience some form of *technical* difficulties during their earnings calls, which disrupts the flow of conversation.

In Table 2, we show how likely it is that a firm with unusual financial communication along one dimension also engages in unusual financial communication patterns along another dimension of the same category. For example, how often do firm *executives* who give lengthy responses also provide emotional or informal responses? We find that 16.24% of all earnings calls are unusual along just one dimension, and 4.39% (1.95%) along 2 (3). We find unusual financial communication along 12 or more dimensions for a total of 4.77% of earnings calls in our sample. The co-occurrence of unusual financial communication is also prevalent within the four categories. For example, for 15.12% of earnings calls, we identify unusual communication along one dimension in the *executives* category, for 4.05% (3.60%) we identify 2 (3) dimensions, and 0.74% of transcripts include unusual financial communication along 5 or more dimensions of that category.

Table 2: Co-Occurrence of Unusual Financial Communication

The table shows how frequently multiple dimensions of unusual financial communication are identified for the same earnings call in general and within each of the four broader categories. For example, for 15.12% of earnings calls, we identify *unusualness* along one dimension in the *executives* category, for 4.05% (3.60%) we identify 2 (3) dimensions, and so forth.

Dimension	0	1	2	3	4	5	6	7	8	9	10	11	12+
Unusual	57.45	16.24	4.39	1.95	1.15	1.01	0.81	1.28	2.14	2.78	3.40	2.63	4.77
Executives	75.00	15.12	4.05	3.60	1.48	0.43	0.09	0.22					
Analysts	81.56	12.64	4.10	1.02	0.25	0.21	0.22						
Content	68.43	10.19	2.91	1.21	0.93	1.80	2.71	4.13	4.61	2.04	0.66	0.39	
Technical	89.04	10.96											

We see a similar aggregation for unusual financial communication by *analysts*. 12.64% of earnings calls are identified as unusual along one dimension, 4.10% along two, and 1.02% along three. Unusual *content* is identified for roughly 31% of calls, with 10.19% identified as unusual along one dimension, 2.91% along two dimensions, and 16.34% along five or more dimensions.

In Table 3, we also investigate how often firms with unusual financial communication in at least one dimension of a particular category (e.g., *executives*) also communicate unusually along another category (e.g., *analysts*). From the table we learn that unusual financial communication by *executives* is accompanied by some degree of unusual financial communication by *analysts* in 70.64% of occasions. *Technical* difficulties co-arise in 15.24% of these cases, and unusual *content* is discussed by 83.94% of these firms. Interestingly, when we condition on the circumstance of unusual financial communication by *analysts*, we find that *executives* also communicate in unusual ways in 95.76% of cases and that the *content* is unusual in 96.01% of cases. This suggests that financial analysts are important to set the tone of the discussions during the earnings call. Unusual *contents* are accompanied by unusual financial communication of *executives* in 66.46% and of *analysts* in 56.07% of cases. *Technical* difficulties co-arise in just 10.27% of these cases.

Table 3: Cross-Category Occurrence of Unusual Financial Communication

The table shows the co-occurrence of unusual financial communication across the four identified broader categories, *executives, analysts, technical,* and *content*. For example, if a firm's *executives* communicate unusually, in 70.64% of cases, we also find unusual financial communication along at least one of the dimensions in the *analysts* category.

Dimension	Executives	Analysts	Content	Technical
Executives	–	95.76	66.46	34.75
Analysts	70.64	–	56.07	19.43
Content	83.94	96.01	–	29.59
Technical	15.24	11.54	10.27	–

3.2. Which Firms Communicate Unusually?

We now analyze if specific firms are more prone to engaging in unusual financial communication by understanding if systematic differences arise in financial ratios and market-based firm characteristics among firms with and without unusual financial communication patterns across each of the four categories and 25 dimensions. For example, one could expect a greater prevalence of unusual financial communication among firms with a deteriorat-

ing profit margin or a declining stock price, indicating some level of stress the firm is experiencing. We consider the firms' market capitalization (Size), book-to-market ratio (B2M), investment behavior (Inv) and profitability (Prof), return momentum (Mom), 21-day MAX return following Bali, Cakici, and Whitelaw (2011), analyst forecast dispersion (Disp., following (Diether, Malloy, and Scherbina, 2002)) and analyst coverage (Cvg., following (Zhang, 2006)). We then regress the dummies for unusual communication along the four broader categories ($\mathbb{1}_{cat}$) on each of the firm characteristics (C), which we cross-sectionally rank-standardize to lie between -0.5 and $+0.5$:

$$\mathbb{1}_{cat_{i,t}} = \alpha + \theta C_{i,t} + \varepsilon_{i,t} \tag{1}$$

Table 4: Unusual Financial Communication & Firm Characteristics

The table shows the results of regressing the occurrence of unusual financial communication along each of the four broader categories, as well as *unusualness* in general on a constant and market-based firm characteristics. For a given earnings call, we measure the firm characteristics on the last trading day of the previous month. Each characteristic is cross-sectionally rank-standardized between -0.5 and $+0.5$ across the firms currently in the S&P 500. The construction of the firm characteristics follows Jensen, Kelly, and Pedersen (2023). We include market capitalization (Size), book-to-market ratio (B2M), investment behavior (Inv), profitability (Prof), return momentum (Mom), and 21-day MAX return following Bali et al. (2011). We also add analyst dispersion (DISP) following Diether et al. (2002) and analyst coverage (Cvg) following Zhang (2006). *** (**, *) denotes that the respective characteristic differs significantly between "unusual" and "usual" firms at the 1% (5%, 10%) level.

Dimension	Size	B2M	Inv	Prof	Mom	MAX	DISP	Cvg
Unusual	0.03	-0.07^{***}	-0.01	-0.09^{***}	-0.08^{***}	0.03^{*}	0.02	-0.01
Executives	0.05^{***}	-0.06^{***}	0.01	-0.10^{***}	-0.04^{**}	0.03^{**}	0.04^{***}	-0.00
Analysts	0.06^{***}	-0.05^{***}	0.02	-0.08^{***}	-0.03^{**}	0.03^{*}	0.02	0.02
Content	0.05^{***}	-0.07^{***}	-0.01	-0.09^{***}	-0.09^{***}	0.03^{*}	0.01	0.02
Technical	0.01	-0.01	0.00	-0.01	0.00	0.02^{*}	0.01	-0.00

The results are provided in Table 4. We find that firms with unusual communication tend to have significantly lower book-to-market ratios, are significantly less profitable, and are more likely to be momentum losers. Given that we rank-standardize each characteristic in the cross-section to lie between -0.5 and $+0.5$, this shows that firms with the lowest profitability within the S&P 500 are on average 9% more likely to engage in some form of unusual financial communication than firms with the highest profitability.

We again let our analysis be guided by the broader categories of unusual financial communication by *executives, analysts, technical* and *content*. Firms with unusual financial communication by their *executives* are on average significantly less profitable, tend to be larger, momentum losers, have a higher maximum return in the past 21 days, and have

a lower book-to-market ratio. Similar differences emerge for unusual communication by *analysts*. Interestingly, we find that the identification of unusual communication by *executives* is more likely for firms with a higher disagreement of *analysts*. Larger firms, with lower book-to-market ratio and profitability, and momentum losers discuss unusual *contents* more frequently. We find no significant differences in firm characteristics for the identification of *technical* difficulties.[8]

3.3. When is Financial Communication Unusual?

Figure 1 shows the relative occurrence of unusual financial communication along the four broader categories *executives*, *analysts*, *content*, and *technical* over time. While there is a slight peak in the identification of unusual *contents*, which coincides with the onset of the global COVID-19 pandemic, we generally find that the identification of unusual communication patterns is fairly stable over time.

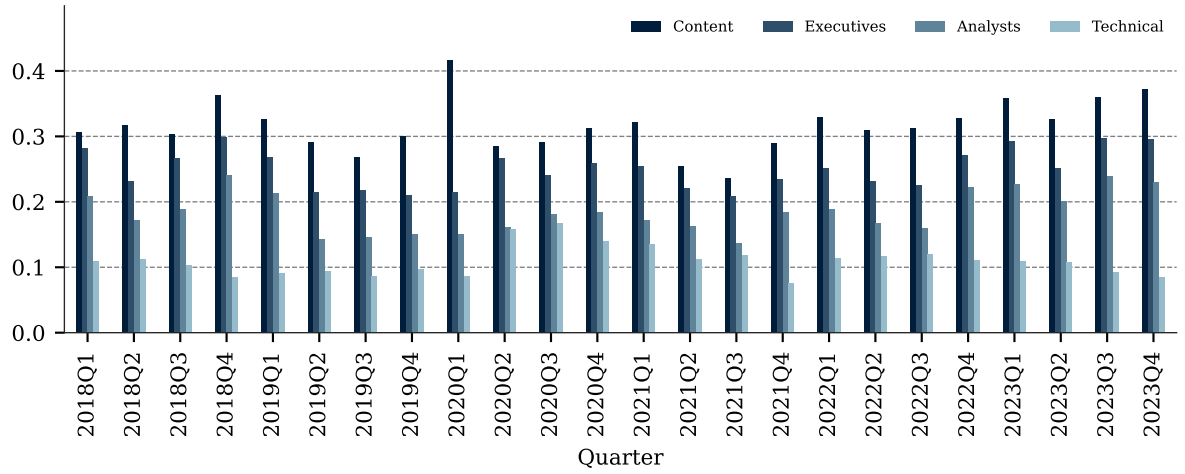


Fig. 1. Unusual Financial Communication – Broader Categories Over Time

The figure shows the temporal evolution of the relative occurrence of unusual financial communication along each of the four broader categories *executives*, *analysts*, *content*, and *technical*.

However, it is likely that some dimensions of unusual financial communication will vary over time according to external conditions. For example, in hindsight, we would expect more in-depth discussions of the implications of the Coronavirus pandemic in 2020. At the start of the pandemic, this additional emphasis on a single topic is far from the norm and consequently unusual. To get a feel for the time-variation in individual dimensions

[8]In Appendix IA.2 in the Internet Appendix, we show differences in the occurrence of unusual financial communication across industries.

of unusual financial communication, Figure 2 plots the fraction of firms with unusual patterns in their communication on the impact of external events between Q1-2018 and Q4-2023. An unusual discussion of the impact of external events is identified for around 10% of firms in 2018 and 2019 but peaks in Q1-2020 to above 25% – predominantly, of course, due to the fallout of the COVID crisis. Interestingly, however, ChatGPT does not consider the communication style along this dimension to be unusual for all firms but only for around a quarter of the firms in the S&P 500. Unusual discussions of the impact of external events remain elevated throughout 2020, calm down in much of 2021, and peak once more in early-2022, as the Russian war in Ukraine generates additional uncertainty also for U.S.-based firms.

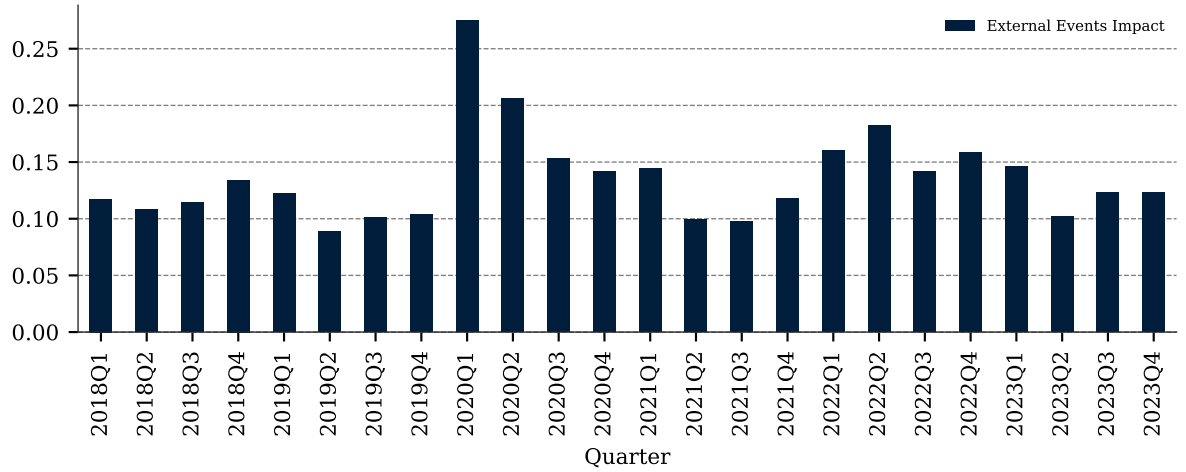


Fig. 2. Unusual Financial Communication – External Events Impact Over Time

The figure shows the temporal evolution of the relative occurrence of unusual financial communication regarding the impact of external events.

To understand if unusual financial communication varies with the business cylce, we aggregate the fraction of firms for which ChatGPT flags unusual financial communication patterns for each of the 25 identified dimensions in each calendar quarter and regress this fraction on various macroeconomic indicators and a constant. We include Cboe's VIX, the default spread, the price-dividend ratio of the S&P 500, net share issuance, and the term spread. Because many of the macroeconomic indicators are highly correlated, we perform univariate regressions but show the results in a condensed table to save space. Specifically, we run a contemporaneous regression of the average proportion of earnings calls within each quarter with unusual financial communication on each macroeconomic

variable:

$$\frac{1}{N_t}\sum_{i\in\mathcal{S}_t}\mathbb{1}_{cat_{i,t}} = \alpha + \delta M_t + \varepsilon_t^M, \tag{2}$$

where $\mathcal{S}_t$ are the N_t stocks in the S&P 500 at time t and M_t is one of the macroeconomic indicators. Macroeconomic indicators are averaged within each calendar quarter and subsequently normalized. Table 5 shows the results.

Table 5: Unusual Financial Communication & the Business Cycle

The table shows the results of regressing the per-quarter fraction of firms with unusual financial communication in general and along each of the four broader categories on a constant and various macroeconomic indicators. We include the price-dividend ratio of the S&P 500, net share issuance, and the term and default spread, all of which are taken from Welch and Goyal (2008). We also include Cboe's VIX. Measures of unusual communication are first averaged across firms within each calendar quarter and then normalized. Macroeconomic indicators are first averaged within each calendar quarter and then normalized. *** (**, *) denotes statistical significance at the 1% (5%, 10%) level.

Dimension	VIX	dfy	pd	ntis	tms
Unusual	0.65***	−0.66	−0.80**	−0.58*	−0.21
Executives	0.02	−0.47	−0.39	−0.61**	0.15
Analysts	−0.09	−0.22	−0.20	−0.53*	0.14
Content	0.50**	−0.41	−0.79**	−0.57*	−0.36
Technical	0.44*	−0.66	0.20	0.18	0.25

We find that an elevated VIX is associated with a larger degree of unusual communication, which is predominantly driven by the discussion of unusual *contents*. A one standard deviation increase in VIX is associated with a 0.65 standard deviation increase in the fraction of firms with unusual communication and a 0.50 standard deviation increase in the fraction of firms that discuss unusual *contents*. Both the default (dfy) and term spreads (tms) are unrelated to the degree of unusual communication. Instead, a larger price-dividend ratio (pd) which indicates improved economic conditions, is associated with a significantly lower degree of unusual communication, which is driven by a less frequent discussion of unusual *contents*. Interestingly, higher net share issuance (ntis) corresponds to a lower probability of firm *executives* communicating in unusual ways. A one standard deviation increase in ntis corresponds to a 0.61 standard deviation decrease in unusual communication by firm *executives*. Management may decide to issue additional shares in particularly rosy times. Alternatively, executives may be keen on portraying a stable picture of the company during earnings calls, especially when issuing or planning to issue shares (Pontiff and Woodgate, 2008; Greenwood and Hanson, 2012; McLean, Pontiff, and Reilly, 2020).

4. Reacting to Unusual Financial Communication

As the next step, we turn to how financial markets react to unusual financial communication. The impact of it can be understood through the lens of uncertain information quality and ambiguity-averse investors. Several theoretical and empirical studies guide us in the exploration of how investors react to an unusual communication of financial results.

Epstein and Schneider (2008) study the theoretical implications of differential quality of informational disclosures in conjunction with ambiguity-averse investors. In their model, investors learn about future stock returns:

$$r_{t+1} = \theta_t + \varepsilon_{t+1}, \quad \varepsilon \sim \mathcal{N}(0, \sigma_s^s), \quad \sigma_s^2 \in \left[\underline{\sigma}_s^2, \overline{\sigma}_s^2\right] \tag{3}$$

The quality of the announced information is captured by the range of the signal's precision, $[1/\overline{\sigma}_s^2, 1/\underline{\sigma}_s^2]$. Investors not only care about how quickly they expect uncertainty to be resolved (location of the interval) but also the reliability of the signal (width of the interval). Unusual financial communication potentially impacts both aspects of the signal quality. If, for example, a firm announces surprising information, investors may be unsure about its impact on the firm's operations, elevating uncertainty going forward. Similarly, investors may question the reliability of the information provided if for exa, for example, a firm's executives give evasive answers. In the model by Epstein and Schneider (2008), the mere presence of ambiguous information will increase average excess stock returns – potentially resulting in the elevated stock return response to the average earnings announcement (Savor and Wilson, 2016). If, instead, the information conveyed is ambiguous or of low quality, we should observe a negative return response. Likewise, the model suggests that ambiguous information can elevate the volatility of stock returns.

While the theory by Epstein and Schneider (2008) is silent about the impact of ambiguous information on the trading activity of investors, several other studies point out that an increase in ambiguity is empirically linked to an initial increase in investor trading activity (Kostopoulos et al., 2022; Barria, 2023). Models in which investors disagree about the interpretation of public information – in our case, the information released and discussed in the earnings call – also predict an elevated trading activity in the presence of unusual financial communication, should the unusual communication patterns elevate disagreement among investors (Kim and Verrecchia, 1991; Banerjee and Kremer, 2010).

The empirical analysis that follows is guided by these considerations. We investigate the impact of unusual financial communication in earnings calls on a) stock returns, b) the trading activity of the affected stocks, and c) return volatility and implied volatilities of equity options as a measure of uncertainty. We also investigate if d) financial analysts respond to unusual financial communication and analyze how they revise their forecast of next quarter's earnings release.

4.1. Announcement Returns

We start by studying how the stock market reacts to unusual financial communication. As the first step, we use daily stock prices and calculate the cumulative stock return for firm i over a three-day window from $t-1$ to $t+1$ for the earnings call on day t.[9] We then compute the equally- and value-weighted returns of stocks with unusual communication along each of the 25 identified dimensions, as well as the four broader categories, and stocks with usual communication patterns. We also report the difference between the two groups of stocks and assess the statistical significance of the return patterns.

Figure 3 produces several interesting findings: most importantly, we find that unusual communication patterns are associated with significantly lower announcement returns. Whereas the average firm with standard communication patterns experiences a positive earnings announcement return (Savor and Wilson, 2016), we find that the average return of firms with unusual communication is indistinguishable from zero.[10] Both the equally- and the value-weighted difference between firms with unusual and firms with usual financial communication are negative and statistically significant, averaging -0.37% and -0.56% in the three-day window surrounding the announcement, respectively.

Turning to the four categories of unusual communication, we find that unusual communication by firm *executives* is associated with significantly smaller announcement returns, which holds true when equally- and value-weighting firms. On average, a firm with unusual communication by its *executives* experiences -0.54% smaller announcement returns (value-weighted: -0.74%). We find that unpreparedness and evasive responses have the largest negative return impact, of -1.10% and -1.04%, respectively. In contrast, executives' informal tone, unusual dialogue patterns, or conflicting information do

[9] For earnings calls that take place after 4 p.m., i.e., after the close of the New York Stock Exchange, we use the next trading day as the event day.

[10] The tabulated form of these results including the mentioned t-values is shown in Table B.1 in Appendix B.

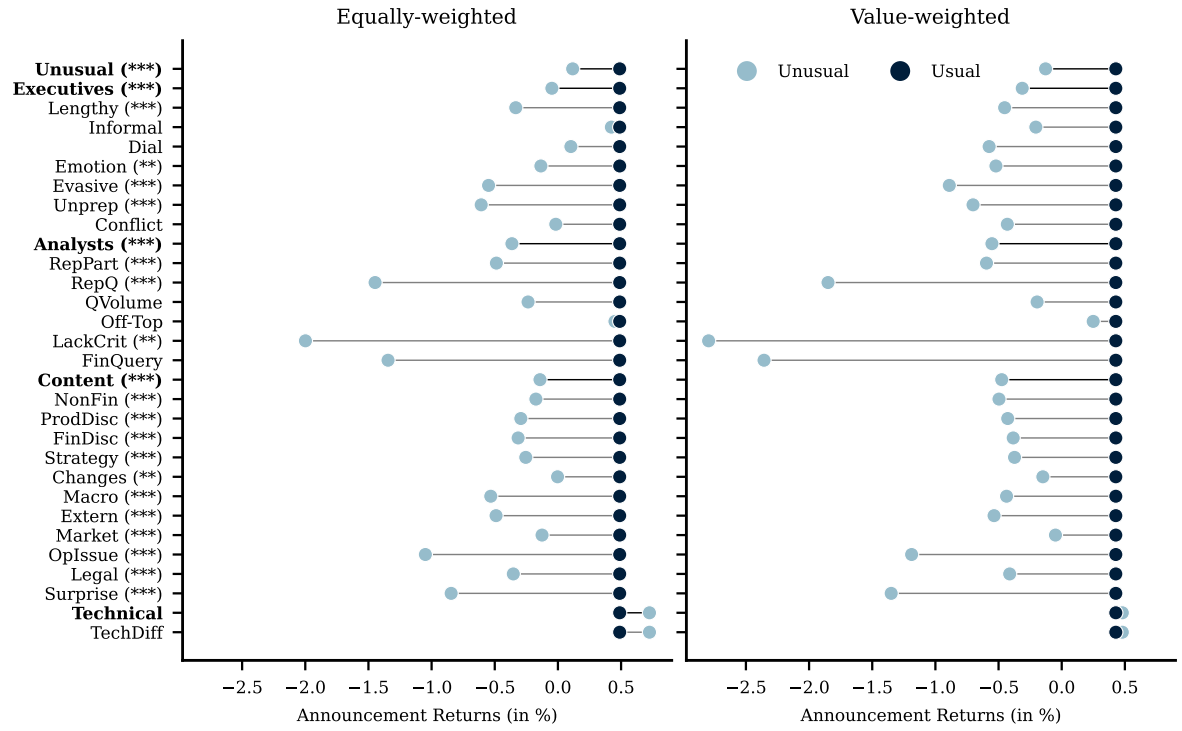


Fig. 3. Unusual Financial Communication & Earnings Announcement Returns

The figure shows the average cumulative earnings announcement return from $t-1$ to $t+1$ for firms with Unusual communication along each of the 25 identified dimensions, as well as along the four broader categories and along *unusualness* in general, and compares it to the cumulative returns of stocks with no indication of unusual financial communication. In the panel on the left, we equally-weight firms in the two portfolios, in the panel on the right, we value-weight firms by their market capitalization at the end of the previous month. *** (**, *) denotes the statistical significance of the difference between the two (Unusual − Usual) at the 1% (5%, 10%) level (shown for the equally-weighted results in the panel on the left). The results are also tabulated in Table B.1 in Appendix B.

not significantly impact announcement returns.

Unusual communication by financial *analysts* is also associated with a negative return impact of −0.85% equally-weighted and −0.98% value-weighted. A lack of critical questioning and repetitive questions have the largest negative return impact of −2.49% and −1.94%, respectively. The impact of a high volume of questions, off-topic discussions, and unusual financial queries is statistically indistinguishable from zero.

Unusual *contents* also generate significantly smaller announcement returns of −0.63% equally-weighted and −0.90% value-weighted. The equally- and value-weighted return impact of all but one dimension within the *content* category is significantly negative at the 5%-level or below. The largest return impact is produced by discussions of operating issues (−1.54%), surprising announcements (−1.33%), external events impacts (−0.98%),

legal issues (−0.84%), and macroeconomic considerations (−1.02%). As a sanity check for our approach, we can show that firms that experience *technical* difficulties during their earnings calls do not exhibit significantly different announcement return responses, neither when equally- nor when value-weighting the firms in question. Overall, these results show that the stock market reacts to cues of unusual communication during earnings calls.

In our baseline specification in Table B.1 in Appendix B, we show the results for cumulative event returns from one day before to one day after the earnings announcement date. We also calculate cumulative *abnormal* returns using the three Fama and French (1993) factors plus momentum. Beta coefficients to calculate expected returns are estimated over a 200-day period ending 30 days before the event day t, for which we require a minimum of 100 valid returns in the estimation window. In Table B.2, we show the results for an event window starting at $t-1$ and ending at $t+1$. Table B.3 and Table B.4 replicate the analysis extending the event window to $t+3$ and $t+10$, respectively. The results agree with our baseline assessment.

Controls. To rule out confounding effects, we now turn to panel regressions of the announcement return response on the prevalence of unusual financial communication and several controls. The panel regressions take the following form:

$$r_{i,t-1:t+1} = \beta \mathbb{1}_{\text{Unusual}_{i,t}} + \theta C_{i,t} + FE_{i,t} + \varepsilon^r_{i,t}, \tag{4}$$

where C is a vector of control variables and $\mathbb{1}_{\text{Unusual}}$ is a dummy indicating if ChatGPT flagged the communication in a given earnings call as unusual. We separately consider the overall *unusual* dummy and the three broader categories capturing unusual communication by *executives*, by financial *analysts*, and the discussion of unusual *content*. For all panel regressions, we include quarter fixed effects.

We ensure that differences in characteristics of firms with and without unusual communication do not drive our results. We control for the firms' market capitalization, book-to-market ratio, investment growth, profitability, return momentum, 21-day MAX return following Bali et al. (2011), illiquidity following Amihud (2002), and the stock's nominal share price. Characteristics are measured at the end of the month preceding the earnings announcement day and cross-sectionally rank standardized to lie between −0.5 and +0.5 to make them comparable over time. We also control for whether the surprise

component of the earnings news itself is driving our result. For this, we follow Engelberg et al. (2018) and calculate the standard unexpected earnings component (SUE) of stock i using analyst forecasts made up to the day before the announcement on day t:

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

We require that we have valid forecasts made by at least five analysts that have been updated within the past 90 days. We also add analyst disagreement measured on day $t-1$, using the analyst forecast dispersion measure (Disp.) of Diether et al. (2002), and the number of analysts covering a firm (Cvg.) as a proxy for information asymmetries, following Zhang (2006).[11]

Table 6: Unusual Financial Communication & Announcements Returns

The table shows the results of regressing the cumulative earnings announcement return from $t-1$ to $t+1$ on dummies for different categories of unusual financial communication. We control for differences in characteristics of the affected firms ("Chars"), the standardized unexpected earnings component, following the definition in Eq. (5), analyst forecast dispersion, following Diether et al. (2002), and the number of analysts covering each firm (Zhang, 2006). For all specifications we include calendar quarter fixed effects. Standard errors are clustered by calendar quarter. *** (**, *) denotes statistical significance at the 1% (5%, 10%) level.

Category	(1)	(2)	(3)	(4)
$\mathbb{1}_{\text{Unusual}}$	-0.38^{***}			
$\mathbb{1}_{\text{Executives}}$		-0.56^{***}		
$\mathbb{1}_{\text{Analysts}}$			-0.82^{***}	
$\mathbb{1}_{\text{Content}}$				-0.74^{***}
Chars	×	×	×	×
SUE Disp. Cvg.	×	×	×	×
Quarter	×	×	×	×
R^2	1.22	1.28	1.38	1.42
N	9,512	9,512	9,512	9,512

The results are provided in Table 6 and confirm that unusual financial communication triggers a highly significant negative reaction by the stock market, even after the inclusion of various controls. The affected stock's returns are negative, for the unusualness indicator in general, and the three broader categories capturing unusual communication by executives and analysts, and the discussion of unusual contents. In fact, the presence

[11] In Table B.5 we show that the results are unaffected by considering individual groups of control variables, and also consider the impact of firm fixed effects to assure that individual firms for which ChatGPT frequently flags their communication style as unusual are not driving the results, and industry fixed effects.

of unusual communication leads to returns of −0.38% even after we control for the surprise component of the earnings release, as well as characteristics of the firm. We find the largest singular impact of unusual communication by analysts at −0.82%.

Intensity of Unusual Financial Communication. As a next step, we investigate if the intensity of unusual communication plays an exacerbating role in this return response. If, for example, ChatGPT flags all of the 25 dimensions shown in Table 2 as unusual, we would naturally expect an exaggerated response by market participants. To this end, we define the intensity of unusual communication as the number of dimensions of unusual communication $\mathcal{D}$ flagged by ChatGPT for each earnings call:

$$\text{Unusual}_{i,t}^{\#} = \sum_{dim \in \mathcal{D}} \mathbb{1}_{dim} \tag{6}$$

Table 7: Intensity of Unusual Financial Communication & Announcement Returns

The table shows the average earnings announcement return from $t-1$ to $t+1$ for firms with unusual and firms with usual financial communication. We separately show the average returns of firms for which we identify 1:2 (3:5, 6:10, $\geq$ 11) of the 25 dimensions of unusual financial communication. We also show the difference between the two (Unusual − Usual). In the columns on the left, we equally-weight firms in the two portfolios, in the column on the right we value-weight firms by their market capitalization at the end of the previous month. *** (**, *) denotes statistical significance at the 1% (5%, 10%) level.

	Equally-weighted			Value-weighted		
Dimension	Unusual	Usual	Diff	Unusual	Usual	Diff
Unusual	0.12	0.49***	−0.37***	−0.13	0.43**	−0.56**
$\text{Unusual}_{1:2}^{\#}$	0.51***	0.49***	0.02	0.21	0.43**	−0.21
$\text{Unusual}_{3:5}^{\#}$	−0.05	0.49***	−0.54	−0.17	0.43**	−0.60
$\text{Unusual}_{6:10}^{\#}$	−0.22	0.49***	−0.71***	−0.45	0.43**	−0.88***
$\text{Unusual}_{11:}^{\#}$	−0.53*	0.49***	−1.02***	−0.49	0.43**	−0.92**

We find a monotonically decreasing return difference between firms with unusual and firms with usual communication as we increase the intensity of unusual communication. The results are shown in Table 7. If only 1 or 2 ($\text{Unusual}_{1:2}^{\#}$) of the 25 dimensions are flagged as unusual by ChatGPT, we find no statistically nor economically significant difference between the two groups of firms. For firms for which ChatGPT flags between 3 and 5 dimensions as unusual ($\text{Unusual}_{3:5}^{\#}$), we find an economically meaningful difference, which is not statistically significant, however. As soon as we consider firms with between 6 and 10 flagged dimensions of unusual communication ($\text{Unusual}_{6:10}^{\#}$), however, we find that their return response is significantly more negative than that of firms with usual

communication patterns. The difference amounts to -0.71% for the average earnings announcement. Increasing the number of flagged dimensions of unusual communication further ($\text{Unusual}^{\#}_{11:}$), further increases the return difference to -1.02%, providing substantial evidence for the idea that the identified dimensions of unusual communication reinforce each other, and culminate in a significantly negative stock return reaction. Value-weighted results are comparable.

Unusual Contents vs. Unusual Communication Styles. A possible concern with our identification of unusual communication and the proposed link to financial markets is that ChatGPT merely flags earnings calls as unusual whenever firms report bad news or face significant events. The market reaction may then simply be the response to this news but not to other aspects of unusual communication, especially unusual communication styles by executives and financial analysts. Of course, a consistent and concise identification of unusual contents discussed in an earnings call is important and one of our contributions. To understand the incremental information content of unusual communication styles, we select those earnings calls for which ChatGPT has identified at least one dimension in the *content* category as unusual. We then investigate the incremental announcement return impact of the individual dimensions of unusual communication styles by analysts and executives in panel regressions (see Eq. (4)).

The results of this exercise are found in Table 8. ChatGPT identifies a discussion of unusual contents for a little over 3,000 earnings calls. Within this subset, Panel A shows a pronounced additional impact of unusual communication by financial analysts. As we zoom in on the individual dimensions in this category, we can understand which unusual communication styles convey valuable information to equity market participants. Above and beyond the negative impact of unusual contents (see Figure 3), we find an additional negative return impact of -0.7% whenever analysts repeatedly focus on specific participants or topics (RepPart). Repetitive Questions (RepQ) also trigger a significant additional return impact. On average, firms for which we flag unusual contents experience an additional negative announcement return impact of -1.89%. We find the largest incremental return impact for a lack of critical questioning by financial analysts (LackCrit). This result is intuitive. Sufficient scrutiny in the questioning of the executive team is essential to uncovering new information about the firm and probing executives about conflicting results. If financial analysts fail in their investigative role, we observe an outsized negative incremental return response of -3.87%. A large volume of ques-

Table 8: Impact of Unusual Communication Styles Conditional on Unusual Contents

The table shows the results of regressing the cumulative earnings announcement return from $t-1$ to $t+1$ on dummies for different dimensions of unusual communication styles by analysts (Panel A) and executives (Panel B). To understand the incremental impact of unusual communication *styles*, we condition on the prevalence of unusual *contents*. We control for differences in characteristics of the affected firms ("Chars"), the standardized unexpected earnings component, following the definition in Eq. (5), analyst forecast dispersion, following Diether et al. (2002), and the number of analysts covering each firm (Zhang, 2006). For all specifications we include calendar quarter fixed effects. Standard errors are clustered by calendar quarter. *** (**, *) denotes statistical significance at the 1% (5%, 10%) level.

Panel A: Unusual Communication by Analysts

Dimension	(1)	(2)	(3)	(4)	(5)	(6)
$\mathbb{1}_{\text{RepPart}}$	-0.70^{***}					
$\mathbb{1}_{\text{RepQ}}$		-1.89^{***}				
$\mathbb{1}_{\text{QVolume}}$			-0.15			
$\mathbb{1}_{\text{Off-Top}}$				0.94^{*}		
$\mathbb{1}_{\text{LackCrit}}$					-3.87^{***}	
$\mathbb{1}_{\text{FinQuery}}$						-3.07^{*}
Chars	×	×	×	×	×	×
SUE Disp. Cvg.	×	×	×	×	×	×
Quarter	×	×	×	×	×	×
R^2	1.30	1.80	1.06	1.17	1.58	1.37
N	3,010	3,010	3,010	3,010	3,010	3,010

Panel B: Unusual Communication by Executives

Dimension	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$\mathbb{1}_{\text{Lengthy}}$	-0.36						
$\mathbb{1}_{\text{Informal}}$		0.61^{**}					
$\mathbb{1}_{\text{Dial}}$			0.34				
$\mathbb{1}_{\text{Emotion}}$				-0.17			
$\mathbb{1}_{\text{Evasive}}$					-1.54^{***}		
$\mathbb{1}_{\text{Unprep}}$						-1.39^{**}	
$\mathbb{1}_{\text{Conflict}}$							-0.40
Chars	×	×	×	×	×	×	×
SUE Disp. Cvg.	×	×	×	×	×	×	×
Quarter	×	×	×	×	×	×	×
R^2	1.12	1.19	1.09	1.06	1.36	1.17	1.06
N	3,010	3,010	3,010	3,010	3,010	3,010	3,010

tions (QVolume) has no incremental impact on announcement returns, the prevalence of off-topic questions (Off-Top) has a marginally significant positive impact, and unusual

financial queries (FinQuery) have a marginally significant negative impact.

In Panel B we repeat the above exercise for the individual dimensions of unusual communication styles by firm executives. We find a large negative incremental return impact whenever executives show evasive behavior (Evasive). Their attempt to dodge the questions by financial analysts is associated with an additional negative announcement return impact of -1.54%. Likewise, if executives appear unprepared (Unprep) we also find a negative response of -1.39%. Both of these results are intuitive. If executives are unwilling (Evasive) are unable (Unprep) to answer the questions posed by financial analysts, investors' ability to learn from the interactions in the Q&A sessions of earnings calls is significantly muted. Not only do these categories speak to a lack of professional behavior, but they may also cover an attempt to cover up uncomfortable information. Interestingly, an informal tone of executives (Informal) has a significantly positive return impact, which is potentially reflective of executives being willing to share more detailed information if they feel comfortable in their exchange with the financial analysts present in the call. For the remaining categories of unusual communication styles by executives, we find no additional return impact.

These results present evidence that it is not solely the revelation of material or bad news that financial markets and ChatGPT equally respond to. Instead, our nuanced assessment of unusual communication *styles* triggers an additional negative return impact. Those dimensions identified by ChatGPT that trigger an additional return impact are intuitive and correspond to important aspects of the communication of analysts and executives to which investors should pay attention.

Ambiguity Aversion and Unusual Financial Communication. To explore a potential explanation for the pronounced market reaction to unusual financial communication, we examine how the announcement return response to these unusual communication patterns varies depending on the magnitude of the earnings surprise (SUE). For example, the model of Epstein and Schneider (2008) suggests that the initial announcement response does not necessarily reflect the average response to the announcement, as models of investor disagreement would imply (Kim and Verrecchia, 1991). Instead, low information quality, in our case in the form of unusual communication, may give rise to a negative announcement return response, even if the information itself was positive for the firm, as investors fear the prospect of elevated uncertainty going forward. Favoring this explanation, we show in Section 4.3 that the options market values uncertainty about

the firm's stock price higher after an earnings call with unusual financial communication.

To generate additional evidence in this direction, we investigate if unusual financial communication triggers a negative return response, even if the released information itself was perceived as positive. For this, we regress the cumulative earnings announcement return from $t-1$ to $t+1$ on dummies, indicating if the announcement news was positive (SUE > 0) or negative (SUE < 0) as well as their interactions with the relative intensity of unusual communication. The relative intensity of unusual communication is simply defined as the average dimensions of unusual communication flagged by ChatGPT:

$$\text{Unusual}^{\%}_{i,t} = \frac{1}{|\mathcal{D}|} \sum_{dim \in \mathcal{D}} \mathbb{1}_{dim}. \tag{7}$$

It ranges from 0 (no dimensions flagged as unusual) to 1 (all 25 dimensions flagged as unusual) and captures the amplified impact of unusual communication whenever multiple dimensions are identified as such (Table 7). We also control for firm characteristics, analyst forecast dispersion and analyst coverage, industry affiliation, and firm and quarter fixed effects:

$$\begin{aligned} r_{i,t-1:t+1} = {} & \beta^{+}\mathbb{1}_{\text{SUE}_{i,t}>0} + \gamma^{+}\left(\mathbb{1}_{\text{SUE}_{i,t}>0} \times \text{Unusual}^{\%}_{i,t}\right) \\ & + \beta^{-}\mathbb{1}_{\text{SUE}_{i,t}<0} + \gamma^{-}\left(\mathbb{1}_{\text{SUE}_{i,t}<0} \times \text{Unusual}^{\%}_{i,t}\right) + \theta C_{i,t} + FE_{i,t} + \varepsilon^{\text{SUE}}_{i,t}, \end{aligned} \tag{8}$$

where C contains the vector of control variables and $\mathbb{1}_{\text{SUE}>0}$ and $\mathbb{1}_{\text{SUE}<0}$ are dummies indicating if the standardized earnings surprise of firm i is positive or negative. Following the insights of the model of Epstein and Schneider (2008), we would expect $\gamma^{\pm} < 0$.

Consistent with the model of Epstein and Schneider (2008) we find that unusual communication triggers a more negative announcement return, regardless of whether the news conveyed at the announcement measured by SUE is positive or negative. Both interaction effects shown in Table 9 are negative and significant for all regression specifications run. Even if the earnings news was positive (SUE > 0), if we find a large intensity of unusual communication in the subsequent earnings call, the announcement return response is significantly lower. The coefficient on the interaction ranges from -1.95%, controlling for the dispersion of analyst forecasts and how many analysts cover the firm in (3), to -2.73% when adding firm fixed effects in the specification (5). If, for example, ChatGPT flags 10 out of the 25 dimensions as unusual ($10/25 = 40\%$), the average announcement return response for a positive SUE ranges from 0.24% in (1) to 0.41% in (5), being significantly

Table 9: Unusual Communication, Earnings Surprises & Announcements Returns

The table shows the results of regressing the cumulative earnings announcement return from $t-1$ to $t+1$ on two dummies indicating whether the earnings surprise (SUE) was positive or negative, as well as their interactions with the relative intensity of unusual financial communication, $\text{Unusual}^{\%}_{i,t}$. For SUE, we use the definition in Eq. (5). In (2) we control for differences in characteristics of the affected firms ("Chars"). In (3) we control for the dispersion of analyst forecasts following Diether et al. (2002), and the number of analysts covering a particular firm (Zhang, 2006). We also control for the firm's industry affiliation in (4) and firm fixed effects in (5). For all specifications we include calendar quarter fixed effects. Standard errors are clustered by calendar quarter. *** (**, *) denotes statistical significance at the 1% (5%, 10%) level.

Category	(1)	(2)	(3)	(4)	(5)
$\mathbb{1}_{\text{SUE}_{i,t}>0}$	1.05^{***}	1.21^{***}	1.31^{***}	1.12^{***}	1.50^{***}
$\mathbb{1}_{\text{SUE}_{i,t}>0} \times \text{Unusual}^{\%}$	-2.02^{***}	-2.08^{***}	-1.95^{***}	-2.09^{***}	-2.73^{***}
$\mathbb{1}_{\text{SUE}_{i,t}<0}$	-1.29^{***}	-1.16^{***}	-1.10^{***}	-1.25^{***}	-1.13^{***}
$\mathbb{1}_{\text{SUE}_{i,t}<0} \times \text{Unusual}^{\%}$	-1.38^{***}	-1.42^{***}	-1.44^{***}	-1.38^{***}	-2.09^{***}
Chars		×			
Disp. Cvg.			×		
Industry				×	
Firm					×
Quarter	×	×	×	×	×
R^2	3.34	3.81	3.55	3.37	3.87
N	10,722	10,722	9,637	10,722	10,722

depressed from the average response of firms with typical communication patterns.[12]

The negative announcement return impact of unusual communication is also large in the face of negative earnings news (SUE < 0). The coefficient of the interaction ranges from -1.38% for specifications (1) and (4) to -2.09% in specification (5). For the same intensity of unusual financial communication of 40%, the average announcement return for a negative SUE ranges from -1.68% to -2.0%.[13] The asymmetry in the response is in line with the model by Epstein and Schneider (2008), which postulates that ambiguity averse investors will respond more negatively to information of uncertain quality when faced with negative information, as they base their judgment off of the worst-case scenario.

4.2. Announcement Trading Activity

Announcement returns are significantly smaller for many dimensions of unusual communication. But do market participants also increase their trading activity upon encountering this unusual information? The literature has proposed trading volume as a measure for

[12] $1.05\% + 40\% \times (-2.02\%) = 0.242\%$ in (1); $1.5\% + 40\% \times (-2.73\%) = 0.408\%$ in (5).

[13] $-1.1\% + 40\% \times (-1.44\%) = -1.676\%$ in (3); $-1.13\% + 40\% \times (-2.09\%) = -1.966\%$ in (5).

disagreement across investors (Goetzmann and Massa, 2005; Banerjee and Kremer, 2010; Banerjee, 2011). Hong and Stein (2007) argue that disagreement may arise when investors possess different information sets or if they update their beliefs based on new information. Earnings calls are, of course, an important source of information for investors, and investors may have a harder time interpreting the information when it is communicated in unusual ways, or the content is unusual itself. Several empirical papers on the impact of ambiguity also find that an increase triggers an initial elevation in the trading activity of investors (Kostopoulos et al., 2022; Barria, 2023).

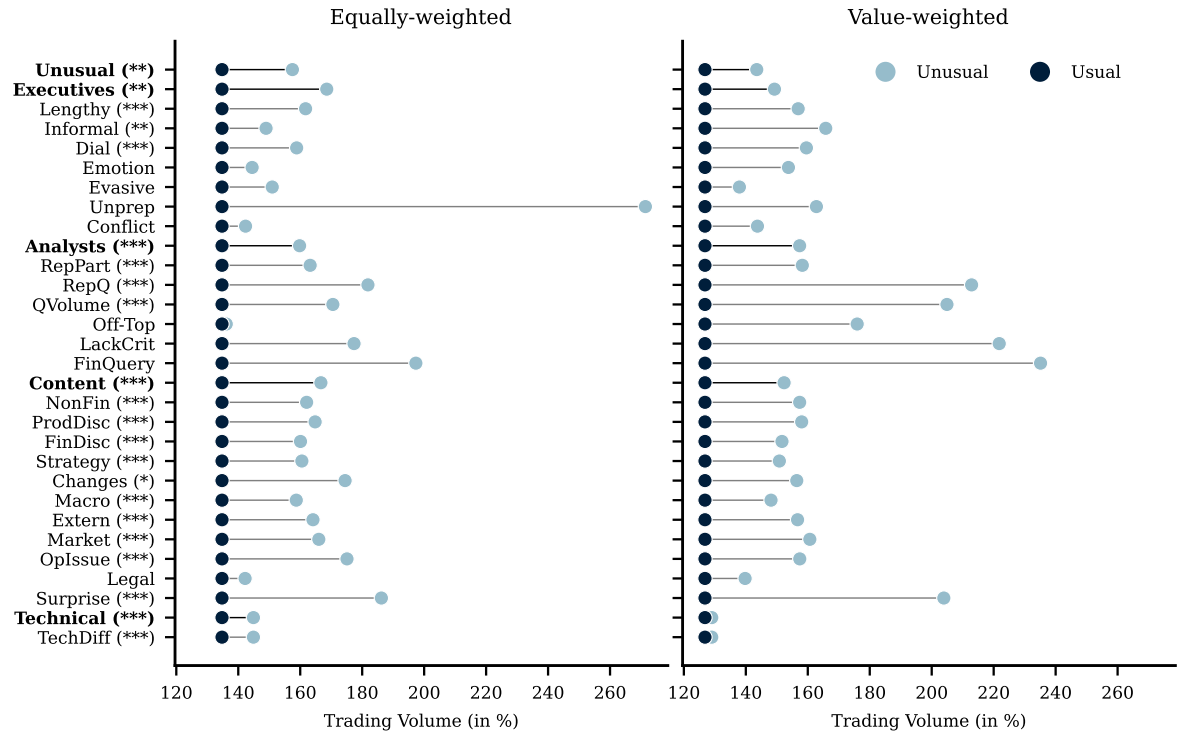


Fig. 4. Unusual Financial Communication & Earnings Announcement Trading Activity

The figure shows the announcement day relative trading activity for firms with Unusual communication along each of the 25 identified dimensions, as well as along the four broader categories and along *unusualness* in general, and compares it to the relative trading activity of stocks with no indication of unusual financial communication. We compare the total dollar volume in the event window to the average over the 30 days before it, leaving a gap of five days. In the panel on the left, we equally-weight firms in the two portfolios, in the panel on the right, we value-weight firms by their market capitalization at the end of the previous month. *** (**, *) denotes the statistical significance of the difference between the two (Unusual − Usual) at the 1% (5%, 10%) level (shown for the equally-weighted results in the panel on the left). The results are also tabulated in Table C.1 in Appendix C.

Our empirical results, depicted in Figure 4 and tabulated in Table C.1 in Appendix C, agree with this: firms with unusual communication experience significantly more trading activity than those with usual communication. We compare the trading activity

of the announcement day to the average dollar trading volume measured over the past 30 days, leaving a gap of five days. The announcement trading volume of firms with standard communication patterns amounts to 134.76% of this baseline, for firms with unusual communication, this number increases to 157.48% – a highly significant 22.72 percentage point (*pp*) increase. Unusual communication by firm *executives* elevates the trading activity in the affected stocks by 33.80*pp* when equally-weighting and 22.43*pp* when value-weighting. A perceived unpreparedness of the management team, lengthy responses, informal responses, unusual dialogue patterns, and evasiveness of the management team lead to the largest increases in trading. For all those categories, except the perceived evasiveness and unpreparedness of the management team, the differences are statistically significant when equally- and value-weighting firms. Emotional responses show a significant difference only when value-weighting. The other categories do not show significant differences.

A repeated focus by financial *analysts* on specific topics or participants, as well as repetitive questions and a high volume of questions, lead to significantly elevated trading activity in the affected stocks. For example, repetitive questions increase the trading activity to 181.86% compared to the baseline of the past 30 days, which is 47.10*pp* larger than for firms without unusual communication. Overall, unusual communication by *analysts* leads to 25.04*pp* higher trading volume when equally-weighting firms and 30.55*pp* when value-weighting firms.

Technical difficulties give rise to an increase in the trading activity of market participants when equally-weighting the firms, which is washed out as soon as we value-weight the respective firms. This, in turn corroborates the idea that the elevated trading volume we observe around unusual earnings calls is driven by participants disagreeing about the provided information. In contrast, unusual *contents* are once again associated with an elevated trading activity regardless of whether we equally-weight (an increase of 31.92*pp*) or value-weight the firms in question (an increase of 25.53*pp*). Surprising announcements, the discussion of operating issues, and corporate changes drive the largest significant increases. Equally- and value-weighted results show a high agreement. Overall, the trading activity of firms with unusual communication is significantly elevated at the 5%-level for 16 (equally-weighted; 17 when value-weighting) out of the 25 dimensions.

Once more, we rule out confounding effects, to ascertain that unusual financial communication is the driving force behind the elevated trading activity we observe. Results from the corresponding panel regressions are shown in Table C.2 in the appendix and

show that unusual communication significantly elevates the trading activity around the earnings announcements, even when considering the impact of the various control variables.

Echoing the results of Section 4.1 that a greater intensity of unusual communication triggers an exaggerated negative return response, we find that a greater intensity also leads to even larger trading activity. Table C.3 shows virtually the same pattern: the more dimensions of unusual communication ChatGPT identifies for a firm's earnings call, the higher the resulting trading activity by stock market participants. With 3 to 5 flagged dimensions, the relative trading activity is elevated by 20.18*pp*, with 6 to 10 by 24.58*pp*, and with more than 11 flagged dimensions by 31.55*pp*. Each of these differences is statistically significant, and value-weighting leads to an even greater volume response.

4.3. Announcement Volatility and Uncertainty

To see if the incorporation of information of uncertain quality into market prices elevates the stock's volatility, we run panel regressions of the absolute earnings announcement return on dummies for unusual financial communication and the set of controls C:

$$|r_{i,t-1:t+1}| = \beta \mathbb{1}_{\text{Unusual}_{i,t}} + \theta C_{i,t} + FE_{i,t} + \varepsilon^{|r|}_{i,t}, \tag{9}$$

We also investigate if the options market reacts to unusual financial communication. For this, we collect the implied volatility (IV) of the at-the-money call option written on stock i that expires on the third Friday of the month following the next, both one day before the earnings call and one day after. We then run panel regressions of the change in the IV on the unusualness dummies and control variables:

$$\text{IV}_{i,t+1} - \text{IV}_{i,t-1} = \beta \mathbb{1}_{\text{Unusual}_{i,t}} + \theta C_{i,t} + FE_{i,t} + \varepsilon^{\text{IV}}_{i,t}. \tag{10}$$

The results in Table 10 paint a clear picture: unusual financial communication not only increases the return volatility surrounding the earnings announcements but also triggers investors in the options market to increase their estimate of future uncertainty about the firm's stock price. If the communication in an earnings call is unusual, absolute announcement returns of the affected firms increase by a highly significant 0.32%, their implied volatility by a marginally significant 0.43%. Across the three categories, we find that the announcement volatility is amplified most by unusual behavior by analysts

Table 10: Unusual Financial Communication, Volatility & Firm-Level Uncertainty

The panel on the left shows the results of regressing the absolute cumulative earnings announcement return from $t-1$ to $t+1$ on dummies for different categories of unusual financial communication. The panel on the right shows the results of regressing the change of the implied volatility around the earnings announcement from $t-1$ to $t+1$ of the at-the-money call option that matures on the third Friday of the month after the next on the same set of dummy variables. We control for differences in characteristics of the affected firms ("Chars"), the standardized unexpected earnings component, following the definition in Eq. (5), analyst forecast dispersion, following Diether et al. (2002), and the number of analysts covering a particular firm (Zhang, 2006). For all specifications we include calendar quarter fixed effects. Standard errors are clustered by calendar quarter. Coefficients are multiplied by 100 for better readability. *** (**, *) denotes statistical significance at the 1% (5%, 10%) level.

	Announcement Volatility				Change in Uncertainty			
Category	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\mathbb{1}_{\text{Unusual}}$	0.32^{***}				0.41^{*}			
$\mathbb{1}_{\text{Executives}}$		0.36^{***}				0.60^{**}		
$\mathbb{1}_{\text{Analysts}}$			0.53^{***}				0.40	
$\mathbb{1}_{\text{Content}}$				0.46^{***}				0.79^{***}
Chars	×	×	×	×	×	×	×	×
SUE Disp. Cvg.	×	×	×	×	×	×	×	×
Quarter	×	×	×	×	×	×	×	×
R^2	6.49	6.49	6.58	6.60	6.38	6.44	6.35	6.57
N	9,512	9,512	9,512	9,512	5,438	5,438	5,438	5,438

(+0.53%, highly significant), while implied volatilities are most elevated if the earnings call's contents are unusual (+0.79%, highly significant). The stock market is not the only market that reacts to unusual financial communication of a firm. We also find a pronounced response in the market for equity options, with an elevated valuation of future uncertainty about the firm's stock price.

4.4. Analyst Forecast Revisions

As a final step to highlight the implications of unusual financial communication, we turn to how financial analysts respond by revising their earnings-per-share forecasts. Once more, we do so by running panel regressions of the change in the analysts' consensus forecast from one day before to one day after the earnings announcement day on the unusualness dummies and control variables:

$$\text{Consensus}_{i,t+1}^{q+1} - \text{Consensus}_{i,t-1}^{q+1} = \beta \mathbb{1}_{\text{Unusual}_{i,t}} + \theta C_{i,t} + FE_{i,t} + \varepsilon_{i,t}^{\text{Consensus}}. \tag{11}$$

Here, Consensus is the average of all earnings-per-share forecasts made by financial analysts within the past 90 days for *next quarter's* $(q+1)$ earnings announcement. With this, we wish to understand if ambiguous information triggers a revision of future expected earnings above and beyond the information contained in today's unexpected earnings figures (SUE), for which we control. For each analyst, we retain the most recent forecast made for the next quarter and scale the mean consensus forecast by the stock price one day before the announcement day to ease the cross-sectional comparison. We require at least five valid forecasts to compute the mean consensus.

Table 11: Unusual Financial Communication & Analyst Forecast Revisions

The table shows the results of regressing the change in the mean analyst forecast consensus of *next period's* earnings-per-share around the earnings announcement from $t-1$ to $t+1$ on dummies for different categories of unusual financial communication. We control for differences in characteristics of the affected firms ("Chars"), standardized unexpected earnings, following the definition in Eq. (5), analyst forecast dispersion, following Diether et al. (2002), and the number of analysts covering a particular firm (Zhang, 2006). For all specifications we include calendar quarter fixed effects. Standard errors are clustered by calendar quarter. *** (**, *) denotes statistical significance at the 1% (5%, 10%) level.

Category	(1)	(2)	(3)	(4)
$\mathbb{1}_{\text{Unusual}}$	-1.18^{**}			
$\mathbb{1}_{\text{Executives}}$		-2.33^{***}		
$\mathbb{1}_{\text{Analysts}}$			-1.77^{**}	
$\mathbb{1}_{\text{Content}}$				-1.50^{**}
Chars	×	×	×	×
SUE Disp. Cvg.	×	×	×	×
Quarter	×	×	×	×
R^2	11.29	11.37	11.30	11.31
N	8,956	8,956	8,956	8,956

Table 11 shows that financial analysts respond significantly to unusual financial communication. If at least one of the 25 dimensions is identified as unusual by ChatGPT, analysts revise their next-period earnings-per-share forecast downward by a significant -1.18% relative to the stock's price. The impact of the individual categories varies between a downward revision of -1.50% for discussing unusual contents, to -1.77% for unusual behavior by analysts and -2.33% for unusual communication by executives. Just like the stock's price is depressed in response to unusual financial communication, financial analysts also incorporate this cue into their next-period forecasts, showcasing how communication styles and deviations from agreed-upon norms can impact the valuation of a firm's fundamentals.

4.5. Results After ChatGPT's Training Cutoff

One concern with many studies using large language models like ChatGPT is that the validity of the results may be confined to the sample period on which the model was trained. Of course, our prompting strategy carefully assures that we only ask ChatGPT about unusual aspects of a firm's earnings call, and not about how the model believes this unusualness to be reflected in the firm's stock price, or in other financial markets. Therefore, the concern that some of our results may arise because ChatGPT potentially knows about the stock market's response to earnings calls from news headlines is significantly attenuated. We nonetheless replicate our main results for all earnings calls after the cutoff date for the training of the version of ChatGPT-4-Turbo that we have used for this paper. The cutoff date is the end of April 2023, fully ruling out that ChatGPT is basing its judgment on in-sample information.[14] This is in addition to the previous analyses for all earnings calls between 2018 and 2023. We analyze the distribution of unusual communication, the differential return response, and the elevated trading activity for stocks with unusual vs. usual communication for May through December of 2023. To preserve space, we show the results in Appendix D and only describe them here verbally.

We first assure that the general frequency with which ChatGPT identifies unusual financial communication is comparable between the full sample and the post-cutoff period (Table D.1). Between May and December 2023, we identify unusual communication among at least one of the 25 dimensions on average for 165 firms in the S&P 500. Unusual communication by *executives* is found for 106 firms, unusual communication by financial *analysts* for 85 firms, and discussions with unusual *content* for 131 firms. The distribution of which dimensions of unusual communication are identified agrees well with those obtained from the full sample starting in January 2018.

In Table D.2, we show that unusual communication by *executives* and *analysts*, and unusual communication among several dimensions of category *content* lead to significantly lower announcement returns. Driven by the shorter sample period and the naturally resulting decrease in statistical power, the overall significance levels partially drop but, importantly, remain statistically significant for many of the 25 dimensions. Our result that investors trade significantly more when confronted with unusual communication patterns in earnings calls is also evident in the post-cutoff period, as shown in Table D.3. On average, unusual communication by *executives* triggers a volume increase of 39.37*pp*,

[14]The version of ChatGPT-4-Turbo used is `gpt-4-1106-preview`.

unusual communication by *analysts* of 44.48*pp*, and unusual *content* by 35.89*pp*.

By showing that the patterns of unusual financial communication and its subsequent impact on announcement returns and trading volumes observed in the initial sample also persist after the training cutoff of ChatGPT-4-Turbo, we mitigate possible concerns about the validity of our results and confirm the functionality of our ChatGPT prompting strategy.

5. Conclusion

We systematically identify 25 dimensions of unusual financial communication using earnings calls of S&P 500 companies and study how participants in financial markets react to it. Traditionally, financial analysts in particular try to identify unusual patterns in earnings calls. This approach is inherently subjective, however, with the resulting assessment potentially varying substantially between analysts and over time. This subjectivity can lead to biases in perception. In contrast, the use of ChatGPT provides us with a standardized and consistent approach to identifying unusual financial communication patterns, which minimizes the subjectivity of the analyses. In addition, GPT-4-Turbo's ability to process large bodies of text allows for a more comprehensive and in-depth analysis of financial communication than the model's previous iterations.

Our research makes a substantial contribution by expanding the understanding of the impact of financial communication on market dynamics. On the one hand, we uncover unusual communication patterns that have been elusive to prior research. On the other hand, our findings provide a more detailed understanding of how unusual communication is perceived by market participants. We find a robust negative stock market reaction to various dimensions of unusual communication, including unusual communication *styles* by the firm's executives and financial analysts, as well as the discussion's *content*. The more dimensions of unusual communication we identify, the larger this negative stock return reaction. At the same time, the trading activity in the affected stocks increases significantly, as market participants interpret the information provided in the earnings call. We also find that stock market volatility and uncertainty about future stock returns, which we measure using actively traded options contracts, increase due to unusual financial communication. Finally, we showcase that financial analysts substantially revise their forecasts of *next quarter* earnings-per-share downward, stressing how communica-

tion styles and deviations from agreed-upon norms can impact the valuation of firm fundamentals. Our empirical results agree well with models in which the quality of provided information is uncertain, and investors are averse to ambiguity. Unusual contents and unusual styles of communicating represent an impediment to judging the quality of information provided.

The study expands our understanding of the potential applications of modern machine learning tools in financial market research. Tools like ChatGPT are particularly useful in extracting information from large and diverse textual datasets. With this, our study also has important implications for practitioners. Financial analysts, asset managers, and other market participants can use our prompting approach for ChatGPT to identify unusual financial communication patterns, which allows them to make more informed decisions. Our study highlights just one aspect of how artificial intelligence can benefit the day-to-day business of financial analysts.

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Appendix

A. Unusual Financial Communication

Table A.1: Examples of ChatGPT Output

For each dimension within the four broader categories of unusual financial communication, *executives*, *analysts*, *content* and *technical* the table shows three illustrative justifications that ChatGPT provides for classifying a Q&A session as "unusual".

Firm (Quartal)	ChatGPT Output
Executives	
Lengthy Responses	
EXR (2020-Q3)	Some responses, particularly the answer to question [17] regarding the bridge loan program, are notably detailed and lengthy, which is somewhat unusual as earnings calls typically aim for concise answers to cover more questions.
NOC (2018-Q1)	Some responses, particularly from Wesley G. Bush, are quite detailed and lengthy, providing extensive context and information beyond the immediate scope of the questions asked.
HSIC (2022-Q2)	The CEO, Stanley M. Bergman, provides detailed and lengthy responses to questions, particularly in [3], [8], [10], [18], [24], and [26], which is somewhat unusual as executives often keep their answers concise in earnings calls.
Informal Tone	
DOV (2018-Q3)	The use of informal language such as "I'm as pissed off as everybody" and "dog's breakfast" is not typical for the formal setting of an earnings call.
JPM (2022-Q2)	The language used by James Dimon at times is less formal and more direct, which is not typical for an earnings call. For example, he uses phrases like "we're going to manage the hell out of the rest of the stuff" and describes regulatory requirements as "ridiculous."
FRT (2018-Q1)	The use of phrases like "I can't help myself," "hanging around the hoop," and "I am kind of done with those people for now" indicates a more informal tone than typically found in earnings calls.
Unusual Dialogue Patterns	
MCHP (2019-Q1)	The dialogue includes several instances where the management team corrects itself or provides clarifications, which is not typical of a standard earnings call.
CB (2020-Q1)	There are instances where the CEO asks for clarification or repeats questions, such as in [13], [43], and [70], which is not typical in a structured earnings call.
WFC (2019-Q1)	The dialogue includes follow-up questions where analysts repeat or rephrase their questions for additional clarity, indicating that the initial responses may not have fully addressed their inquiries.
Emotional Responses	
BLK (2020-Q1)	The response from Laurence Douglas Fink in [15] shows a level of emotion when he describes a question as "insulting."
VTR (2019-Q3)	There is a sense of frustration and insistence on patience from the CEO, Debra A. Cafaro, when repeatedly asked for 2020 guidance.
L (2021-Q2)	The use of "WTF" in response [2] is highly unprofessional and emotional for an earnings call.

Continued on next page

Table A.1 – continued from previous page

Firm (Quartal)	ChatGPT Output
Management Evasiveness	
MNST (2018-Q1)	Management avoids giving specific guidance on gross margins and does not provide a clear answer regarding potential price increases.
F (2017-Q4)	There is a noticeable avoidance by management to provide specific details on the 6 global fitness redesign initiatives, despite being pressed by analysts.
PCAR (2021-Q1)	The CEO, R. Preston Feight, avoids giving a direct answer to Jerry David Revich's question about quantifying assembly efficiency gains and proprietary parts content, suggesting the answer is complicated (response [10]).
Management Unpreparedness	
TSN (2018-Q1)	Management seemed unprepared to address the specifics of the sales guidance changes for AdvancePierre and Chicken, as indicated by the need to follow up after the call [24].
S0 (2018-Q2)	Thomas A. Fanning did not have specific numbers on hand when asked about the number of additional hires needed, indicating a moment of unpreparedness.
RF (2021-Q4)	CFO David Jackson Turner admits to not remembering the payback period for deals, which could indicate a lack of preparedness.
Conflicting Information	
WRK (2022-Q1)	There seems to be a discrepancy regarding margin guidance, with one participant noting a difference in the expected margin range and the company representatives acknowledging the need to double-check the numbers (responses [23], [24], [25]).
TSLA (2018-Q3)	There is a moment where Elon Musk corrects J.B. Straubel about the impact of cell supply constraints on Model 3 production, indicating a slight discrepancy in their statements.
TDG (2019-Q1)	There is a moment of conflicting information regarding the acquisition expenses for Esterline. Michael Lisman mentions higher-than-typical expenses due to the size of the acquisition, but Kevin Stein then says the fees are not different than expected, which Lisman confirms.
Analysts	
Repeated Focus on Specific Participants or Topics	
ECL (2022-Q1)	There is a repeated focus on the topic of inflation, energy surcharges, and the impact of the war in Eastern Europe, as seen in responses [3], [6], [11], [18], [23], [33], [41], [44], [51], [53], [56], [60], [63], [65], [68], [70], [72], [75], [77], [78], and [81]. This indicates a significant concern and interest from the participants regarding these issues.
L (2018-Q3)	The entire Q&A focused on a single analyst and a narrow set of topics related to CNA's valuation and investment portfolio, which is unusual as earnings calls typically cover a broader range of topics and participants.
CPRT (2019-Q1)	The repeated focus on the German market and the company's strategy there is unusual, as earnings calls typically cover a broader range of topics.

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Table A.1 – continued from previous page

Firm (Quartal)	ChatGPT Output
Repetitive Questions	
EXR (2020-Q3)	There are several follow-up questions regarding the bridge loan program [16][18][21][22][25][26], indicating a repeated focus on this topic, which is somewhat unusual as it suggests a particular interest or concern from the analysts.
CB (2021-Q2)	There are multiple questions about pricing and loss trends ([2], [4], [7], [19], [21], [22]), indicating a repetitive focus on this topic.
SO (2018-Q3)	There are multiple questions regarding the Vogtle project's construction schedule and labor demands, indicating a repetitive focus on this topic (responses [4], [9], [11], [13], [17], [20], [21], [22], [23], [59], [60], [61], [62], [63]).
High Volume of Questions	
FRT (2021-Q2)	The transcript indicates a high volume of questions from various analysts, suggesting an unusually engaged Q&A session.
CSX (2017-Q4)	The call includes a high volume of questions from analysts, indicating significant interest and scrutiny from the investment community.
MAA (2017-Q4)	The number of questions, especially those seeking clarification, suggests a higher-than-usual volume of inquiries.
Off-Topic Questions	
CRM (2019-Q2)	There are questions that veer off from typical financial inquiries, such as the question about Marc Benioff's personal growth as a CEO and the broader impact of the company's activism.
C (2020-Q3)	Questions about the CEO's compensation and suggestion to step aside are not typical for an earnings call and are off-topic from the financial results.
STX (2021-Q3)	The question about cryptocurrency and the company's stake in Ripple (questions [24] and [25]) is somewhat off-topic as it deviates from the core business and financial performance discussions typically expected in an earnings call.
Lack of Critical Questioning	
CRM (2020-Q4)	The questions from analysts are generally supportive and lack a critical edge, which is somewhat unusual as analysts often challenge executives on their performance and strategies.
EVRG (2022-Q3)	The transcript shows only one analyst asking questions, and there is no evidence of critical questioning, which is unusual as earnings calls typically feature multiple analysts asking probing questions.
L (2022-Q3)	The questions asked during the call seem to lack depth and do not challenge the management on the performance or strategies, which is unusual as earnings calls typically include more critical and probing questions from analysts and investors.
Unusual Financial Queries	
STT (2022-Q2)	There are detailed questions about the held-to-maturity (HTM) portfolio, risk-weighted assets (RWAs), and specific currency mix of deposits, which are more technical and granular than typical earnings call questions.
SPG (2020-Q2)	Analysts ask for specific financial details and clarifications that are not typically disclosed, such as the exact percentage of rent abatements and detailed breakdowns of tenant negotiations.
LUV (2018-Q3)	The financial queries are focused on specific concerns such as the 3% CASM ex growth and the impact of new initiatives, which is more detailed than typical earnings calls.

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Table A.1 – continued from previous page

Firm (Quartal)	ChatGPT Output
Content	
Detailed Discussion on Non-Financial Topics	
EIX (2018-Q3)	There is a detailed discussion on the wildfires, which is a non-financial topic, and this level of detail is unusual for an earnings call.
LUV (2018-Q1)	The detailed discussion of the accident, safety procedures, and engine inspections is not typical for an earnings call focused on financials.
FE (2022-Q2)	The discussion is heavily focused on non-financial topics, specifically the legal issues and the company's political activities, which is not typical for an earnings call.
In-Depth Product or Service Discussions	
MCD (2019-Q2)	The executives discuss specific products and services, such as the Filet-O-Fish promotion and McCafé initiatives, in greater detail than is typical for an earnings call.
BA (2022-Q3)	There is an in-depth discussion about specific products like the 737 MAX and defense programs, which is unusual as earnings calls typically summarize rather than delve into product specifics.
KO (2018-Q2)	There is a detailed discussion about the sports drink category, POWERADE's performance, and packaging changes in North America, which is more in-depth than typically found in earnings calls.
Detailed Financial Discussions	
BA (2022-Q3)	The call includes detailed financial discussions, particularly around free cash flow and debt, which is unusual as it indicates a strong emphasis on these areas due to the company's current financial position.
PFE (2022-Q3)	The call includes detailed financial discussions, including specific questions about sales numbers for NURTEC in Q3 and projections for COMIRNATY and PAXLOVID sales in 2030, which is more granular than usual.
COF (2022-Q4)	The discussion around the reserve build, CECL accounting, and the detailed explanation of the factors affecting the allowance coverage ratio by Andrew M. Young [51] are more in-depth than typically found in earnings calls.
Forward-Looking and Strategic and Strategic Insights	
HSIC (2022-Q2)	The CEO provides extensive forward-looking statements and strategic insights, particularly in [26] and [30], which is unusual as companies often limit the scope of forward-looking statements due to uncertainty and legal considerations.
FMC (2021-Q1)	The call includes forward-looking statements and strategic insights, particularly regarding the company's pricing strategy, market outlook, and long-term plans, which is not unusual for an earnings call but is noteworthy for the level of detail provided.
CPRT (2019-Q1)	There are several forward-looking statements and strategic insights provided, especially regarding the German market and the company's plans, which is somewhat unusual as companies often limit such disclosures.
Significant Leadership or Corporate Changes	
ARE (2018-Q1)	There is discussion about recent management changes and clarification of roles within the C-suite (lines 43-51).
MRK (2018-Q3)	The question from Vamil Divan regarding the CEO's extended tenure could indicate a significant leadership change or at least a deviation from the expected retirement timeline, which could have implications for the company's strategy.
IBM (2018-Q4)	The discussion includes significant corporate changes such as the acquisition of Red Hat and divestitures, which are not typical for every earnings call.

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Table A.1 – continued from previous page

Firm (Quartal)	ChatGPT Output
External Events Impact	
CPRT (2019-Q1)	There is a discussion about the potential impact of Brexit on the U.K. business, which is an external event that could have significant implications for the company.
AVGO (2020-Q1)	The discussion frequently references the impact of COVID-19, which is an external event affecting the business outlook and operations. This is a significant focus throughout the Q&A session.
EPAM (2022-Q1)	The discussion frequently references the impact of the conflict in Ukraine, which is an external event affecting the company's operations, client relations, and employee relocations.
Macroeconomic Considerations	
CL (2018-Q1)	There are several references to macroeconomic factors such as commodity cost pressures, inflation, and category growth rates in different markets ([3], [5], [8], [14], [17], [20], [23], [26], [31], [34], [37]).
FRT (2022-Q1)	The management team frequently references macroeconomic factors such as inflation, interest rates, and the potential for a recession, which is more than what is typically discussed in earnings calls.
IFF (2022-Q3)	There is a significant focus on macroeconomic factors such as inflation, interest rates, and consumer behavior, as seen in [10], [13], and [35], which is more detailed than usual.
Competitive and Market Analysis	
RHI (2018-Q4)	The management discusses competition with the Big Four and the unique positioning of Protiviti in [43], which is a more in-depth competitive analysis than typically found in earnings calls.
TEL (2023-Q4)	The executives provide a competitive and market analysis, especially when discussing the global position of the automotive business, EV trends, and China's market dynamics, which is more in-depth than typically found in earnings calls.
PG (2021-Q2)	There is a detailed discussion on market share, retailer behavior, and competitive positioning, especially in the context of e-commerce and private label, which is more in-depth than usual.
Operational and Management Issues	
MGM (2018-Q1)	The discussion includes detailed explanations of operational challenges, such as the disruptions at Monte Carlo and Mandalay Bay, which are more in-depth than usual.
FDX (2020-Q2)	The management openly discusses operational and management issues, particularly related to cost underestimation and the impact of the shorter peak season, which is not typically discussed in depth.
AAL (2022-Q2)	There is an extensive discussion on operational issues, such as the impact of weather on operations, the challenges at London Heathrow, and the airline's strategy to manage capacity and resources.
Legal or Regulatory Issues	
UHS (2018-Q1)	There is a detailed discussion about an ongoing government investigation and settlement negotiations, which is not a typical topic in earnings calls unless a company is facing significant legal or regulatory scrutiny.
CB (2020-Q1)	There is extensive discussion of potential legal and regulatory challenges related to business interruption claims, as seen in [5], [17], and [43].
AAL (2022-Q4)	There is discussion about the legal scrutiny of the Northeast Alliance (NEA) and the company's confidence in prevailing against the DOJ lawsuit.

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Table A.1 – continued from previous page

Firm (Quartal)	ChatGPT Output
Surprising Announcements	
DHR (2018-Q2)	The timing of the Dental spin-off seems to have been a surprise to analysts, as indicated by the first question.
TSLA (2023-Q2)	Elon Musk announces a one-time amnesty for transferring FSD (Full Self-Driving) to new vehicles, which is a significant and unexpected policy change.
WTW (2022-Q3)	The revised fiscal '24 targets and the impact of the Russian divestiture seem to be surprising to the analysts, prompting multiple questions for clarification.
Technical	
Technical Difficulties and Disruptions	
ABT (2018-Q1)	There is a moment where an analyst, David Lewis, experiences technical difficulties, which disrupts the flow of the call.
CHTR (2019-Q1)	There was a technical difficulty mentioned when trying to open the line for John Hodulik from UBS, which is not common in earnings calls.
IFF (2021-Q2)	There was an instance where the operator had to ask a participant to rejoin the line, indicating a minor technical issue or disruption ([14], [15]).

B. Announcement Returns

Table B.1: Unusual Financial Communication & Announcement Returns

The table shows the average cumulative earnings announcement return from $t-1$ to $t+1$ for firms with ('Unusual') and without ('Usual') *unusualness* in each of the 25 identified dimensions, as well as the four broader categories and *unusualness* in general. We also show the difference between the two (Unusual − Usual). In the columns on the left, we equally-weight firms in the two portfolios, in the column on the right we value-weight firms by their market capitalization at the end of the previous month. *** (**, *) denotes statistical significance at the 1% (5%, 10%) level.

	Equally-weighted			Value-weighted		
Dimension	Unusual	Usual	Diff	Unusual	Usual	Diff
Unusual	0.12	0.49***	−0.37***	−0.13	0.43**	−0.56**
Executives	−0.05	0.49***	−0.54***	−0.31	0.43**	−0.74***
Lengthy	−0.33	0.49***	−0.82***	−0.45	0.43**	−0.88***
Informal	0.42*	0.49***	−0.07	−0.20	0.43**	−0.63
Dial	0.10	0.49***	−0.39	−0.57	0.43**	−1.00*
Emotion	−0.13	0.49***	−0.62**	−0.52	0.43**	−0.95
Evasive	−0.55	0.49***	−1.04***	−0.89	0.43**	−1.32*
Unprep	−0.61	0.49***	−1.10***	−0.70	0.43**	−1.13*
Conflict	−0.02	0.49***	−0.49	−0.43	0.43**	−0.88
Analysts	−0.36*	0.49***	−0.85***	−0.55*	0.43**	−0.98***
RepPart	−0.49**	0.49***	−0.98***	−0.60*	0.43**	−1.02***
RepQ	−1.45***	0.49***	−1.94***	−1.85*	0.43**	−2.28**
QVolume	−0.24	0.49***	−0.73	−0.19	0.43**	−0.62
Off-Top	0.45	0.49***	−0.04	0.25	0.43**	−0.18
LackCrit	−2.00*	0.49***	−2.49**	−2.80	0.43**	−3.22*
FinQuery	−1.34	0.49***	−1.86	−2.36	0.43**	−2.75
Content	−0.14	0.49***	−0.63***	−0.47**	0.43**	−0.90***
NonFin	−0.17	0.49***	−0.66***	−0.50*	0.43**	−0.92***
ProdDisc	−0.29	0.49***	−0.78***	−0.43	0.43**	−0.86***
FinDisc	−0.31	0.49***	−0.80***	−0.38	0.43**	−0.81***
Strategy	−0.25	0.49***	−0.74***	−0.37	0.43**	−0.80**
Changes	−0.00	0.49***	−0.49**	−0.15	0.43**	−0.58**
Macro	−0.53**	0.49***	−1.02***	−0.44	0.43**	−0.86***
Extern	−0.49**	0.49***	−0.98***	−0.54	0.43**	−0.96**
Market	−0.13	0.49***	−0.61***	−0.05	0.43**	−0.48
OpIssue	−1.05***	0.49***	−1.54***	−1.19***	0.43**	−1.62***
Legal	−0.35	0.49***	−0.84***	−0.41	0.43**	−0.84**
Surprise	−0.85**	0.49***	−1.33***	−1.35*	0.43**	−1.78**
Technical	0.72***	0.49***	0.24	0.48	0.43**	0.05
TechDiff	0.72***	0.49***	0.24	0.48	0.43**	0.05

Table B.2: Unusual Financial Communication & Abnormal Returns – FF4 $(-1/+1)$

The table shows the average cumulative abnormal earnings announcement return from $t-1$ to $t+1$ for firms with ('Unusual') and without ('Usual') *unusualness* in each of the 25 identified dimensions, as well as the four broader categories and *unusualness* in general. We also show the difference between the two (Unusual − Usual). In the columns on the left, we equally-weight firms in the two portfolios, in the column on the right we value-weight firms by their market capitalization at the end of the previous month. We use the Fama and French (1993) factor model augmented with momentum and estimated over a 200-day period ending 30 days before event day t to generate abnormal returns. We require at least 100 valid return observations during this period. *** (**, *) denotes statistical significance at the 1% (5%, 10%) level.

	Equally-weighted			Value-weighted		
Dimension	Unusual	Usual	Diff	Unusual	Usual	Diff
Unusual	−0.07	0.26*	−0.33***	−0.27	0.27**	−0.54**
Executives	−0.25*	0.26*	−0.51***	−0.41	0.27**	−0.68**
Lengthy	−0.50***	0.26*	−0.76***	−0.41	0.27**	−0.69**
Informal	0.16	0.26*	−0.10	−0.45	0.27**	−0.73
Dial	−0.06	0.26*	−0.32	−0.70	0.27**	−0.98*
Emotion	−0.33	0.26*	−0.59**	−0.61	0.27**	−0.89
Evasive	−0.60**	0.26*	−0.86***	−1.01	0.27**	−1.28*
Unprep	−0.54	0.26*	−0.80***	−0.52	0.27**	−0.80
Conflict	0.18	0.26*	−0.06	−0.06	0.27**	−0.38
Analysts	−0.53***	0.26*	−0.78***	−0.55*	0.27**	−0.83**
RepPart	−0.63***	0.26*	−0.88***	−0.55**	0.27**	−0.82***
RepQ	−1.55***	0.26*	−1.80***	−1.78*	0.27**	−2.05**
QVolume	−0.47	0.26*	−0.72*	−0.43	0.27**	−0.70
Off-Top	0.26	0.26*	−0.00	0.23	0.27**	−0.05
LackCrit	−1.30	0.26*	−1.56	−1.96	0.27**	−2.23
FinQuery	−1.42	0.26*	−1.69	−2.50	0.27**	−2.80
Content	−0.30***	0.26*	−0.56***	−0.55***	0.27**	−0.82***
NonFin	−0.37***	0.26*	−0.63***	−0.52*	0.27**	−0.79**
ProdDisc	−0.45***	0.26*	−0.71***	−0.38	0.27**	−0.65**
FinDisc	−0.48***	0.26*	−0.74***	−0.40	0.27**	−0.68**
Strategy	−0.42***	0.26*	−0.68***	−0.39	0.27**	−0.66**
Changes	−0.16	0.26*	−0.42**	−0.35	0.27**	−0.62***
Macro	−0.68***	0.26*	−0.94***	−0.45	0.27**	−0.72**
Extern	−0.64***	0.26*	−0.90***	−0.61*	0.27**	−0.89**
Market	−0.26	0.26*	−0.52***	−0.09	0.27**	−0.36
OpIssue	−1.22***	0.26*	−1.47***	−1.26***	0.27**	−1.53***
Legal	−0.36*	0.26*	−0.62***	−0.63*	0.27**	−0.90**
Surprise	−1.06***	0.26*	−1.31***	−1.58**	0.27**	−1.86***
Technical	0.47**	0.26*	0.21	0.23	0.27**	−0.05
TechDiff	0.47**	0.26*	0.21	0.23	0.27**	−0.05

Table B.3: Unusual Financial Communication & Abnormal Returns – FF4 $(-1/+3)$

The table shows the average cumulative abnormal earnings announcement return from $t-1$ to $t+3$ for firms with ('Unusual') and without ('Usual') *unusualness* in each of the 25 identified dimensions, as well as the four broader categories and *unusualness* in general. We also show the difference between the two (Unusual − Usual). In the columns on the left, we equally-weight firms in the two portfolios, in the column on the right we value-weight firms by their market capitalization at the end of the previous month. We use the Fama and French (1993) factor model augmented with momentum and estimated over a 200-day period ending 30 days before event day t to generate abnormal returns. We require at least 100 valid return observations during this period. *** (**, *) denotes statistical significance at the 1% (5%, 10%) level.

	Equally-weighted			Value-weighted		
Dimension	Unusual	Usual	Diff	Unusual	Usual	Diff
Unusual	−0.07	0.25*	−0.33***	−0.22	0.17	−0.39**
Executives	−0.23	0.25*	−0.49***	−0.33	0.17	−0.50*
Lengthy	−0.52***	0.25*	−0.77***	−0.42	0.17	−0.59*
Informal	0.11	0.25*	−0.14	−0.46	0.17	−0.63
Dial	−0.02	0.25*	−0.28	−0.56	0.17	−0.73
Emotion	−0.25	0.25*	−0.51	−0.43	0.17	−0.60
Evasive	−0.67**	0.25*	−0.93***	−0.70	0.17	−0.87
Unprep	−0.39	0.25*	−0.64*	−0.12	0.17	−0.29
Conflict	0.08	0.25*	−0.14	−0.17	0.17	−0.38
Analysts	−0.51***	0.25*	−0.76***	−0.43	0.17	−0.60*
RepPart	−0.63***	0.25*	−0.88***	−0.53	0.17	−0.70**
RepQ	−1.59***	0.25*	−1.84***	−1.93**	0.17	−2.10**
QVolume	−0.62	0.25*	−0.87**	−0.73	0.17	−0.90
Off-Top	0.32	0.25*	0.07	0.50	0.17	0.33
LackCrit	−1.66	0.25*	−1.91*	−2.60	0.17	−2.78
FinQuery	−1.29	0.25*	−1.57	−2.75	0.17	−2.95
Content	−0.33***	0.25*	−0.58***	−0.52**	0.17	−0.69***
NonFin	−0.38**	0.25*	−0.64***	−0.42	0.17	−0.59*
ProdDisc	−0.47**	0.25*	−0.72***	−0.39	0.17	−0.56
FinDisc	−0.49***	0.25*	−0.75***	−0.42	0.17	−0.59*
Strategy	−0.43***	0.25*	−0.68***	−0.34	0.17	−0.51
Changes	−0.19	0.25*	−0.44**	−0.41	0.17	−0.58**
Macro	−0.65***	0.25*	−0.90***	−0.46	0.17	−0.63**
Extern	−0.64***	0.25*	−0.90***	−0.58	0.17	−0.76*
Market	−0.28	0.25*	−0.53***	−0.08	0.17	−0.25
OpIssue	−1.21***	0.25*	−1.46***	−1.08***	0.17	−1.25***
Legal	−0.30	0.25*	−0.56**	−0.37	0.17	−0.54
Surprise	−1.06***	0.25*	−1.31***	−1.52**	0.17	−1.69**
Technical	0.51**	0.25*	0.26	0.48	0.17	0.31
TechDiff	0.51**	0.25*	0.26	0.48	0.17	0.31

Table B.4: Unusual Financial Communication & Abnormal Returns – FF4 $(-1/+10)$

The table shows the average cumulative abnormal earnings announcement return from $t-1$ to $t+10$ for firms with ('Unusual') and without ('Usual') *unusualness* in each of the 25 identified dimensions, as well as the four broader categories and *unusualness* in general. We also show the difference between the two (Unusual − Usual). In the columns on the left, we equally-weight firms in the two portfolios, in the column on the right we value-weight firms by their market capitalization at the end of the previous month. We use the Fama and French (1993) factor model augmented with momentum and estimated over a 200-day period ending 30 days before event day t to generate abnormal returns. We require at least 100 valid return observations during this period. *** (**, *) denotes statistical significance at the 1% (5%, 10%) level.

	Equally-weighted			Value-weighted		
Dimension	Unusual	Usual	Diff	Unusual	Usual	Diff
Unusual	−0.11	0.19	−0.30**	−0.25	−0.09	−0.15
Executives	−0.34	0.19	−0.52***	−0.44	−0.09	−0.35
Lengthy	−0.64***	0.19	−0.82***	−0.58	−0.09	−0.48
Informal	−0.08	0.19	−0.27	−0.54	−0.09	−0.44
Dial	−0.39	0.19	−0.57***	−0.71	−0.09	−0.62
Emotion	−0.66*	0.19	−0.85**	−0.48	−0.09	−0.38
Evasive	−0.81*	0.19	−0.99**	−0.14	−0.09	−0.04
Unprep	−0.57	0.19	−0.76	0.28	−0.09	0.37
Conflict	−0.17	0.19	−0.29	−0.15	−0.09	−0.08
Analysts	−0.63***	0.19	−0.82***	−0.61	−0.09	−0.52
RepPart	−0.71***	0.19	−0.90***	−0.69*	−0.09	−0.60
RepQ	−1.47***	0.19	−1.65***	−1.86**	−0.09	−1.77*
QVolume	−1.20**	0.19	−1.38***	−1.14	−0.09	−1.04
Off-Top	−0.02	0.19	−0.20	0.71	−0.09	0.80
LackCrit	−1.70	0.19	−1.89	−2.18	−0.09	−2.09
FinQuery	−1.37	0.19	−1.63	−2.27	−0.09	−2.20
Content	−0.39**	0.19	−0.58***	−0.59***	−0.09	−0.50*
NonFin	−0.52***	0.19	−0.70***	−0.56	−0.09	−0.47
ProdDisc	−0.53**	0.19	−0.71***	−0.49	−0.09	−0.39
FinDisc	−0.59**	0.19	−0.77***	−0.46	−0.09	−0.37
Strategy	−0.52**	0.19	−0.71***	−0.47	−0.09	−0.37
Changes	−0.27	0.19	−0.45**	−0.40	−0.09	−0.30
Macro	−0.73***	0.19	−0.91***	−0.47	−0.09	−0.37
Extern	−0.65**	0.19	−0.84***	−0.49	−0.09	−0.40
Market	−0.36	0.19	−0.54**	−0.18	−0.09	−0.09
OpIssue	−1.17***	0.19	−1.36***	−1.08**	−0.09	−0.99*
Legal	−0.20	0.19	−0.39	−0.52	−0.09	−0.43
Surprise	−1.43***	0.19	−1.62***	−2.07**	−0.09	−1.97**
Technical	0.45	0.19	0.26	0.38	−0.09	0.47
TechDiff	0.45	0.19	0.26	0.38	−0.09	0.47

Table B.5: Unusual Financial Communication & Announcements Returns

The table shows the results of regressing the cumulative earnings announcement return from $t-1$ to $t+1$ on a dummy for unusual financial communication. In (2) we control for differences in characteristics of the affected firms ("Chars"). In (3) we control for standardized unexpected earnings, following the definition of Engelberg et al. (2018), analyst forecast dispersion, following Diether et al. (2002), and the number of analysts covering a particular firm, following the definition by Zhang (2006). We also control for the firm's industry affiliation in (4) and firm fixed effects in (5). For all specifications we include calendar quarter fixed effects. Standard errors are clustered by calendar quarter. *** (**, *) denotes statistical significance at the 1% (5%, 10%) level.

Category	(1)	(2)	(3)	(4)	(5)
$\mathbb{1}_{\text{Unusual}}$	-0.37^{***}	-0.39^{***}	-0.35^{**}	-0.37^{***}	-0.43^{***}
Chars		×			
SUE Disp. Cvg.			×		
Industry				×	
Firm					×
Quarter	×	×	×	×	×
R^2	0.08	0.51	0.85	0.08	0.10
N	11,134	11,134	9,512	11,134	11,134

C. Announcement Trading Activity

Table C.1: Unusual Financial Communication & Announcement Trading Activity

The table shows the announcement day trading activity for firms with ('Unusual') and without ('Usual') *unusualness* in each of the 25 identified dimensions, as well as the four broader categories and *unusualness* in general. We compare the total dollar volume in the event window to the average over the 30 days before it, leaving a gap of two days. We also show the difference between the two (Unusual − Usual). In the columns on the left, we equally-weight firms in the two portfolios, in the column on the right we value-weight firms by their market capitalization at the end of the previous month. *** (**, *) denotes statistical significance at the 1% (5%, 10%) level.

	Equally-weighted			Value-weighted		
Dimension	Unusual	Usual	Diff	Unusual	Usual	Diff
Unusual	157.48***	134.76***	22.72**	143.53***	126.82***	16.71***
Executives	168.56***	134.76***	33.80**	149.25***	126.82***	22.43***
Lengthy	161.73***	134.76***	26.98***	156.90***	126.82***	30.08***
Informal	148.97***	134.76***	14.21**	165.80***	126.82***	38.98***
Dial	158.85***	134.76***	24.09***	159.56***	126.82***	32.74***
Emotion	144.48***	134.76***	9.72	153.76***	126.82***	26.94**
Evasive	150.97***	134.76***	16.21	137.93***	126.82***	11.11
Unprep	271.42**	134.76***	136.66	162.79***	126.82***	35.97
Conflict	142.36***	134.76***	6.00	143.76***	126.82***	14.74
Analysts	159.80***	134.76***	25.04***	157.37***	126.82***	30.55***
RepPart	163.21***	134.76***	28.45***	158.24***	126.82***	31.42***
RepQ	181.86***	134.76***	47.10***	212.88***	126.82***	86.06***
QVolume	170.53***	134.76***	35.78***	204.92***	126.82***	78.10**
Off-Top	136.12***	134.76***	1.36	175.94***	126.82***	49.12*
LackCrit	177.37***	134.76***	42.61	221.80***	126.82***	94.98*
FinQuery	197.33***	134.76***	62.31	235.13***	126.82***	108.58
Content	166.67***	134.76***	31.92***	152.35***	126.82***	25.53***
NonFin	162.07***	134.76***	27.31***	157.38***	126.82***	30.56***
ProdDisc	164.81***	134.76***	30.05***	158.03***	126.82***	31.21***
FinDisc	160.09***	134.76***	25.33***	151.67***	126.82***	24.85***
Strategy	160.53***	134.76***	25.77***	150.83***	126.82***	24.01***
Changes	174.48***	134.76***	39.72*	156.44***	126.82***	29.62***
Macro	158.73***	134.76***	23.97***	148.14***	126.82***	21.32***
Extern	164.12***	134.76***	29.36***	156.70***	126.82***	29.88***
Market	166.00***	134.76***	31.24***	160.66***	126.82***	33.84***
OpIssue	175.09***	134.76***	40.34***	157.41***	126.82***	30.59***
Legal	142.21***	134.76***	7.45	139.77***	126.82***	12.95
Surprise	186.20***	134.76***	51.44***	203.91***	126.82***	77.09***
Technical	144.89***	134.76***	10.13***	129.01***	126.82***	2.19
TechDiff	144.89***	134.76***	10.13***	129.01***	126.82***	2.19

Table C.2: Unusual Financial Communication & Trading Volume

The table shows the results of regressing the dollar trading volume on the announcement day on dummies for different categories of unusual financial communication. We compare the total dollar volume on the announcement day to the average over the 30 days before it, leaving a gap of five days. We control for differences in characteristics of the affected firms ("Chars"), standardized unexpected earnings, following the definition in Eq. (5), analyst forecast dispersion, following Diether et al. (2002), and the number of analysts covering a particular firm, following the definition by Zhang (2006). For all specifications we include calendar quarter fixed effects. Standard errors are clustered by calendar quarter. *** (**, *) denotes statistical significance at the 1% (5%, 10%) level.

Category	(1)	(2)	(3)	(4)
$\mathbb{1}_{\text{Unusual}}$	14.87***			
$\mathbb{1}_{\text{Executives}}$		19.21***		
$\mathbb{1}_{\text{Analysts}}$			24.82***	
$\mathbb{1}_{\text{Content}}$				22.01***
Chars	×	×	×	×
SUE Disp. Cvg.	×	×	×	×
Quarter	×	×	×	×
R^2	9.44	9.51	9.61	9.66
N	9,512	9,512	9,512	9,512

Table C.3: Intensity of Unusual Financial Communication & Trading Volume

The table shows the relative increase in the trading volume on the earnings announcement day for firms with unusual and firms with usual financial communication. We compare the total dollar volume on the announcement day to the average over the 30 days before it, leaving a gap of five days. We separately show the increase in the trading activity of firms for which we identify 1:2 (3:5, 6:10, $\geq$ 11) of the 25 dimensions of unusual financial communication. We also show the difference between the two (Unusual − Usual). In the columns on the left, we equally-weight firms in the two portfolios, in the column on the right we value-weight firms by their market capitalization at the end of the previous month. *** (**, *) denotes statistical significance at the 1% (5%, 10%) level.

	Equally-weighted			Value-weighted		
Dimension	Unusual	Usual	Diff	Unusual	Usual	Diff
Unusual	157.48***	134.76***	22.72**	143.53***	126.82***	16.71***
$\text{Unusual}^{\#}_{1:2}$	151.58***	134.76***	16.82	130.09***	126.82***	3.27
$\text{Unusual}^{\#}_{3:5}$	154.94***	134.76***	20.18***	157.36***	126.82***	30.54**
$\text{Unusual}^{\#}_{6:10}$	159.34***	134.76***	24.58***	149.16***	126.82***	22.34***
$\text{Unusual}^{\#}_{11:}$	166.31***	134.76***	31.55***	168.24***	126.82***	41.42***

D. Post Cutoff Analysis

Table D.1: Post-Cutoff: Dimensions & Frequency of Unusual Financial Communication

The table shows overall *unusualness*, the four broader categories and the 25 identified dimensions of *unusualness*, their abbreviation, how many firms engage in unusual financial communication in a typical calendar quarter ("N"), and their median fraction ("Median").

Dimension	Abbreviation	N	Q50
Unusual		165.3	0.45
Executives		106.7	0.3
Lengthy Responses	Lengthy	83.0	0.23
Informal Tone	Informal	35.3	0.1
Unusual Dialogue Patterns	Dial	27.3	0.06
Emotional Responses	Emotion	12.0	0.04
Management Evasiveness	Evasive	10.3	0.02
Management Unpreparedness	Unprep	4.3	0.02
Conflicting Information	Conflict	4.0	0.01
Analysts		85.0	0.23
Repeated Focus on Specific Participants or Topics	RepPart	79.7	0.22
Repetitive Questions	RepQ	19.0	0.06
High Volume of Questions	QVolume	10.7	0.03
Off-Topic Questions	Off-Top	10.3	0.03
Lack of Critical Questioning	LackCrit	4.7	0.01
Unusual Financial Queries	FinQuery	3.7	0.01
Content		131.3	0.36
Detailed Discussion on Non-Financial Topics	NonFin	82.0	0.23
Detailed Financial Discussions	FinDisc	80.0	0.21
In-Depth Product or Service Discussions	ProdDisc	78.7	0.21
Forward-Looking Statements and Strategic Insights	Strategy	76.3	0.21
Macroeconomic Considerations	Macro	63.0	0.18
Significant Leadership or Corporate Changes	Changes	60.0	0.15
Competitive and Market Analysis	Market	56.7	0.15
Operational and Management Issues	OpIssue	46.7	0.13
External Events Impact	Extern	43.3	0.12
Legal or Regulatory Issues	Legal	26.7	0.07
Surprising Announcements	Surprise	15.7	0.04
Technical		33.7	0.09
Technical Difficulties and Disruptions	TechDiff	33.7	0.09

Table D.2: Post-Cutoff: Unusual Financial Communication & Announcement Returns

The table shows the average cumulative earnings announcement return from $t-1$ to $t+1$ for firms with ('Unusual') and without ('Usual') *unusualness* in each of the 25 identified dimensions, as well as the four broader categories and *unusualness* in general. We also show the difference between the two (Unusual − Usual). In the columns on the left, we equally-weight firms in the two portfolios, in the column on the right we value-weight firms by their market capitalization at the end of the previous month. *** (**, *) denotes statistical significance at the 1% (5%, 10%) level.

	Equally-weighted			Value-weighted		
Dimension	Unusual	Usual	Diff	Unusual	Usual	Diff
Unusual	−0.92	−0.35	−0.57	−1.13	0.57*	−1.71
Executives	−1.44***	−0.35	−1.09**	−0.73	0.57*	−1.30
Lengthy	−1.75***	−0.35	−1.40**	−0.68	0.57*	−1.25
Informal	−1.24***	−0.35	−0.89	−3.01***	0.57*	−3.59***
Dial	−2.34*	−0.35	−1.99	−4.19**	0.57*	−4.77***
Emotion	−2.43***	−0.35	−2.09***	−7.51***	0.57*	−8.08***
Evasive	−2.23***	−0.35	−1.88***	−5.18***	0.57*	−5.76***
Unprep	−1.95***	−0.35	−1.60***	−0.31	0.57*	−0.88
Conflict	−3.61	−0.35	−3.26	−2.95	0.57*	−3.52
Analysts	−1.74***	−0.35	−1.39**	−0.69	0.57*	−1.26
RepPart	−1.90***	−0.35	−1.55***	−0.72	0.57*	−1.29
RepQ	−1.92	−0.35	−1.57	−0.09	0.57*	−0.67
QVolume	−2.41**	−0.35	−2.06	0.37	0.57*	−0.20
Off-Top	−1.10	−0.35	−0.75	−5.14***	0.57*	−5.71***
LackCrit	−4.07*	−0.35	−3.72	1.05	0.57*	0.47
FinQuery	−5.67*	−0.35	−5.34	−7.91	0.57*	−8.30
Content	−1.00*	−0.35	−0.65	−0.67	0.57*	−1.24
NonFin	−1.47***	−0.35	−1.12**	−0.70	0.57*	−1.27
FinDisc	−1.64***	−0.35	−1.29**	−0.54	0.57*	−1.11
ProdDisc	−1.84***	−0.35	−1.49**	−0.79	0.57*	−1.37
Strategy	−1.66**	−0.35	−1.31	−0.67	0.57*	−1.24
Macro	−2.47***	−0.35	−2.12***	−2.79**	0.57*	−3.36**
Changes	−0.57	−0.35	−0.22	−0.18	0.57*	−0.75
Market	−1.69	−0.35	−1.34	1.47	0.57*	0.90
OpIssue	−3.04***	−0.35	−2.69***	−4.43***	0.57*	−5.01***
Extern	−2.49***	−0.35	−2.14**	−4.48***	0.57*	−5.06***
Legal	0.18	−0.35	0.53	−0.42	0.57*	−1.00
Surprise	−2.63**	−0.35	−2.28*	−1.46	0.57*	−2.03
Technical	−1.87***	−0.35	−1.52***	−2.44**	0.57*	−3.01**
TechDiff	−1.87***	−0.35	−1.52***	−2.44**	0.57*	−3.01**

Table D.3: Post-Cutoff: Unusual Communication & Announcement Trading Volume

The table shows the announcement day trading activity for firms with ('Unusual') and without ('Usual') *unusualness* in each of the 25 identified dimensions, as well as the four broader categories and *unusualness* in general. We compare the total dollar volume on the event day to the average over the 30 days before it, leaving a gap of 5 days. We also show the difference between the two (Unusual − Usual). In the columns on the left, we equally-weight firms in the two portfolios, in the column on the right we value-weight firms by their market capitalization at the end of the previous month. *** (**, *) denotes statistical significance at the 1% (5%, 10%) level.

	Equally-weighted			Value-weighted		
Dimension	Unusual	Usual	Diff	Unusual	Usual	Diff
Unusual	170.18***	147.84***	22.34***	164.35***	145.69***	18.66
Executives	187.21***	147.84***	39.37***	182.22***	145.69***	36.53
Lengthy	206.31***	147.84***	58.47***	190.62***	145.69***	44.93
Informal	170.98***	147.84***	23.14	173.48***	145.69***	27.78
Dial	173.89***	147.84***	26.05	183.31***	145.69***	37.62
Emotion	148.41***	147.84***	0.57	179.26**	145.69***	33.57
Evasive	180.50***	147.84***	32.66	109.74***	145.69***	−35.95***
Unprep	173.51***	147.84***	25.67	199.48***	145.69***	53.78
Conflict	175.78***	147.84***	27.94**	132.97***	145.69***	−12.72
Analysts	192.32***	147.84***	44.48***	183.22***	145.69***	37.53
RepPart	199.99***	147.84***	52.15***	187.39***	145.69***	41.69
RepQ	224.29***	147.84***	76.45**	224.56***	145.69***	78.87
QVolume	212.98***	147.84***	65.14	202.67***	145.69***	56.97
Off-Top	143.75***	147.84***	−4.09	102.78***	145.69***	−42.92***
LackCrit	235.98***	147.84***	88.14	240.34**	145.69***	94.64
FinQuery	311.84***	147.84***	171.13*	349.27**	145.69***	208.55
Content	183.73***	147.84***	35.89***	177.02***	145.69***	31.33
NonFin	200.54***	147.84***	52.70***	190.15***	145.69***	44.45
FinDisc	206.79***	147.84***	58.95***	190.90***	145.69***	45.21
ProdDisc	204.14***	147.84***	56.30***	189.13***	145.69***	43.43
Strategy	207.21***	147.84***	59.37***	194.56***	145.69***	48.87
Macro	211.18***	147.84***	63.34***	194.80***	145.69***	49.11
Changes	158.98***	147.84***	11.14***	157.35***	145.69***	11.66
Market	204.26***	147.84***	56.42***	192.48***	145.69***	46.78
OpIssue	226.19***	147.84***	78.35***	215.02***	145.69***	69.33
Extern	218.93***	147.84***	71.09***	204.25***	145.69***	58.56
Legal	167.30***	147.84***	19.46**	214.21***	145.69***	68.52**
Surprise	272.27***	147.84***	124.43***	275.01***	145.69***	129.31**
Technical	138.08***	147.84***	−9.76	118.99***	145.69***	−26.70**
TechDiff	138.08***	147.84***	−9.76	118.99***	145.69***	−26.70**

Internet Appendix for

Unusual Financial Communication:
ChatGPT, Earnings Calls, and Financial Markets

Not for Publication

This Internet Appendix provides additional results concerning the impact of unusual financial communication.

- Appendix IA.1 provides a breakdown of the 25 identified dimensions of unusual financial communication, clustered by the four broader categories *executives*, *analysts*, *content*, and *technical*.

- Appendix IA.2 investigates whether systematic differences in the propensity to engage in unusual financial communication exist for firms in different industries.

- Appendix IA.3 replicates our main results using the intensity of unusual financial communication as opposed to the dummy variables used in the main text.

Appendix IA.1. Dimensions of Unusual Financial Communication

Table IA.1.1: Dimensions of Unusual Financial Communication

The table shows the 25 identified dimensions of unusual financial communication, clustered by the four broader categories *executives*, *analysts*, *content* and *technical*.

Executives	**Analysts**
1) Lengthy Responses	1) Repeated Focus on Specific Participants or Topics
2) Informal Tone	2) Repetitive Questions
3) Unusual Dialogue Patterns	3) High Volume of Questions
4) Emotional Responses	4) Off-Topic Questions
5) Management Evasiveness	5) Lack of Critical Questioning
6) Management Unpreparedness	6) Unusual Financial Queries
7) Conflicting Information	
Content	**Technical**
1) Detailed Discussion on Non-Financial Topics	1) Technical Difficulties & Disruptions
2) In-Depth Product or Service Discussions	
3) Detailed Financial Discussions	
4) Forward-Looking Statements & Strategic Insights	
5) Significant Leadership or Corporate Changes	
6) External Events Impact	
7) Macroeconomic Considerations	
8) Competitive & Market Analysis	
9) Operational & Management Issues	
10) Legal or Regulatory Issues	
11) Surprising Announcements	

Appendix IA.2. Unusual Financial Communication Across Industries

In Table IA.2.1, we investigate if systematic differences in the propensity of engaging in unusual financial communication exist for firms in different industries. For this, we collect SIC codes for each firm in our sample and place them in one of twelve industries, using the definition by Kenneth French.[1] Overall, unusual financial communication is relatively unrelated to a firm's industry affiliation. We find the lowest propensity for the Energy sector (34%) and the highest for Chemicals (51%). There is, however, some heterogeneity across industries when it comes to unusual financial communication by firm *executives*. Here, we find the lowest values for Energy firms and firms in the Shops industry (18% for both). The highest prevalence instead is found for Consumer Durables (34%) and Chemicals (36%). For financial *analysts*, we find the lowest shares of unusual communication for Energy (11%), Shops (13%), and Manufacturing and Business Equipment (16%), and the highest once more for Consumer Durables and Chemicals at 29% each. *Technical* difficulties arise with roughly equal probability regardless of the firm's industry. Finally, unusual *contents* occur most frequently for Chemicals (41%), Consumer Durables (35%), Other (35%), Consumer Non-Durables (34%) and Health (33%). Discussions of Energy firms least frequently have unusual *contents* (21%). Overall, these results show that unusual financial communication is not exclusive to certain industries. While there is some heterogeneity in the propensity with which firms of a particular industry show signs of unusual financial communication in their earnings calls, industry affiliation alone is insufficient to explain its occurrence.

Table IA.2.1: Unusual Financial Communication & Industries

The table shows the quarterly relative occurrences of *unusualness* in general and along the four broader categories for stocks in each of the twelve industries, using the definition from Kenneth French's website.

Dimension	NoDur	Durbl	Manuf	Enrgy	Chems	BusEq	Telcm	Utils	Shops	Hlth	Money	Other
Unusual	0.43	0.45	0.41	0.34	0.51	0.42	0.41	0.43	0.40	0.42	0.42	0.46
Executives	0.24	0.34	0.22	0.18	0.36	0.22	0.28	0.24	0.18	0.27	0.26	0.32
Analysts	0.17	0.29	0.16	0.11	0.29	0.16	0.24	0.18	0.13	0.22	0.19	0.21
Content	0.34	0.35	0.30	0.21	0.41	0.32	0.32	0.30	0.28	0.33	0.31	0.35
Technical	0.09	0.12	0.09	0.12	0.13	0.11	0.09	0.09	0.12	0.11	0.12	0.10

[1] `https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/Data_Library/det_12_ind_port.html`.

Appendix IA.3. Intensity of Unusual Financial Communication

In this section, we replicate our main results using the intensity of unusual financial communication as defined in Eq. (7) instead of the dummies. The intensity measures range between 0, when none of the dimensions of unusual communication are flagged as such, and 1, if all dimensions are flagged.

Table IA.3.1: Intensity: Unusual Financial Communication & Announcement Returns

The table shows the results of regressing the cumulative earnings announcement return from $t-1$ to $t+1$ on the relative intensity each of the broader categories of unusual financial communication. We control for differences in characteristics of the afflicted firms ("Chars"), standardized unexpected earnings, following the definition in Eq. (5), analyst forecast dispersion, following Diether et al. (2002), and the number of analysts covering a particular firm, following the definition by Zhang (2006). For all specifications we include calendar quarter fixed effects. Standard errors are clustered by calendar quarter. *** (**, *) denotes statistical significance at the 1% (5%, 10%) level.

Category	(1)	(2)	(3)	(4)
Unusual$^{\%}$	-2.25^{***}			
Executives$^{\%}$		-1.73^{***}		
Analysts$^{\%}$			-3.54^{***}	
Content$^{\%}$				-1.50^{***}
Chars	×	×	×	×
SUE Disp. Cvg.	×	×	×	×
Quarter	×	×	×	×
R^2	1.46	1.27	1.52	1.48
N	9,512	9,512	9,512	9,512

Table IA.3.2: Intensity: Unusual Financial Communication & Trading Volume

The table shows the results of regressing the dollar trading volume on the announcement day on the relative intensity of different categories of unusual financial communication. We compare the total dollar volume on the announcement day to the average over the 30 days before it, leaving a gap of five days. We control for differences in characteristics of the afflicted firms ("Chars"), standardized unexpected earnings, following the definition in Eq. (5), analyst forecast dispersion, following Diether et al. (2002), and the number of analysts covering a particular firm, following the definition by Zhang (2006). For all specifications we include calendar quarter fixed effects. Standard errors are clustered by calendar quarter. *** (**, *) denotes statistical significance at the 1% (5%, 10%) level.

Category	(1)	(2)	(3)	(4)
Unusual$^{\%}$	74.06^{***}			
Executives$^{\%}$		66.44^{***}		
Analysts$^{\%}$			101.03^{***}	
Content$^{\%}$				46.68^{***}
Chars	×	×	×	×
SUE Disp. Cvg.	×	×	×	×
Quarter	×	×	×	×
R^2	9.84	9.56	9.78	9.81
N	9,512	9,512	9,512	9,512

Table IA.3.3: Intensity: Unusual Communication, Volatility, & Firm-Level Uncertainty

The panel on the left shows the results of regressing the absolute cumulative earnings announcement return from t-1 to t+1 on the relative intensity of different categories of unusual financial communication. The panel on the right shows the results of regressing the change of the implied volatility around the earnings announcement from t-1 to t+1 of the at-the-money call option that matures on the third Friday of the month after the next on the same set of categories of unusual financial communication. We control for differences in characteristics of the afflicted firms ("Chars"), standardized unexpected earnings, following the definition in Eq. (5), analyst forecast dispersion, following Diether et al. (2002), and the number of analysts covering a particular firm, following the definition by Zhang (2006). For all specifications we include calendar quarter fixed effects. Standard errors are clustered by calendar quarter. *** (**, *) denotes statistical significance at the 1% (5%, 10%) level.

	Announcement Volatility				Change in Uncertainty			
Category	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Unusual$^{\%}$	1.45***				1.55***			
Executives$^{\%}$		1.35***				1.60**		
Analysts$^{\%}$			2.28***				1.09	
Content$^{\%}$				0.86***				1.12***
Chars	×	×	×	×	×	×	×	×
SUE Disp. Cvg.	×	×	×	×	×	×	×	×
Quarter	×	×	×	×	×	×	×	×
R^2	6.66	6.54	6.71	6.61	6.43	6.40	6.34	6.46
N	9,512	9,512	9,512	9,512	5,438	5,438	5,438	5,438

Table IA.3.4: Intensity: Unusual Financial Communication & Analyst Forecast Revisions

The table shows the results of regressing the change in analyst forecast consensus of *next period´s* earnings-per-share around the earnings announcement from t-1 to t+1 on the relative intensity of different categories of unusual financial communication. We control for differences in characteristics of the afflicted firms ("Chars"), standardized unexpected earnings, following the definition in Eq. (5), analyst forecast dispersion, following Diether et al. (2002), and the number of analysts covering a particular firm, following the definition by Zhang (2006). For all specifications we include calendar quarter fixed effects. Standard errors are clustered by calendar quarter. *** (**, *) denotes statistical significance at the 1% (5%, 10%) level.

Category	(1)	(2)	(3)	(4)
Unusual$^{\%}$	−6.60***			
Executives$^{\%}$		−6.76**		
Analysts$^{\%}$			−7.18**	
Content$^{\%}$				−4.22***
Chars	×	×	×	×
SUE Disp. Cvg.	×	×	×	×
Quarter	×	×	×	×
R^2	11.39	11.35	11.33	11.38
N	8,956	8,956	8,956	8,956