Mixed Messages by Firms' Managers: An Exploration into the Strategic Use of Tonal Inconsistency across Managerial Financial Communications

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Abstract

Using conference call transcripts and contemporaneous press releases for the same quarterly earnings announcement, I document that inconsistent managerial tone across these communication channels predicts future negative abnormal returns and influences the speed of market price responsiveness to earnings disclosures. My empirical results demonstrate that such tonal inconsistencies forecast significantly slower market reactions and are robustly associated with subsequent fundamental adverse changes in firm performance and profitability. I further find that these inconsistencies foster market ambiguity, thereby delaying investor responses and facilitating strategic and opportunistic insider trading that appears to capitalize on this delayed price incorporation. Overall, the evidence aligns with managers strategically employing mixed messaging in financial disclosures to mislead investors about underlying firm fundamentals by manipulating market perceptions and exploiting informational frictions induced by ambiguity.

Keywords: Tonal inconsistencies, Financial communication, Strategic disclosures, Information diffusion, Sentiment analysis, Ambiguity, Disclosure Processing Costs, Price Discovery, Market Efficiency, Insider trading
JEL classification: G14, G34, G41, D82, D83, M41, C55, K22.

I. Introduction

Over recent decades, the volume and complexity of corporate information dissemination have increased substantially. This environment presents a dual challenge for investors: not only must they navigate an increasingly complex informational landscape, but they must also contend with managerial incentives to subtly manipulate corporate communications. Contrary to classical assumptions of frictionless markets, this complexity means that information is not costlessly absorbed. Instead, investors face significant costs to monitor, acquire, and analyze firm disclosures. These frictions, collectively termed "disclosure processing costs", transform learning from a disclosure into an active economic choice rather than a passive absorption of public information (Blankespoor et al., 2020).

While traditional quantitative manipulation is often readily identifiable by markets and regulators, this paper explores whether managers exploit investor processing costs through more subtle, qualitative means. Existing literature confirms that managers strategically exploit their discretion in financial communications (e.g., Peng and Roell, 2014, Ahern and Sosyura, 2014); yet, this body of research has predominantly focused on what can be termed first-order manipulation strategies. These include altering the attributes of a single disclosure, such as the level of tone (Huang et al., 2014), or using the volume of unrelated concurrent disclosures to distract investors (Rawson et al., 2023).

This paper argues that a second-order strategy—the deliberate engineering of tonal inconsistencies across simultaneously released, related disclosures stemming from the same core event—remains a largely unexplored dimension of strategic financial communication. I investigate whether managers employ this tactic between the earnings press release and the contemporaneous conference call to create ambiguity and impede efficient price discovery. This study, therefore, seeks to determine whether tonal inconsistencies exist, ascertain their strategic nature, examine if they signal adverse future firm fundamentals, and understand how they impede efficient price discovery.

The contemporaneous nature of earnings press releases and conference calls provides a unique setting to examine such coordinated messaging strategies. My findings indicate that these inconsistencies are not merely random noise but carry strategic significance, as they predict delayed market reactions—specifically, post-event negative cumulative abnormal returns (CAR) that contribute to a negative post-earnings announcement drift (PEAD), which takes approximately two months to be fully incorporated by the market. By demonstrating this, the paper identifies a novel, second-order manipulation strategy, showing how the relationship between communications can itself be a powerful tool for imposing processing costs and creating predictable market inefficiencies.

The strategic nature of this behavior is further evidenced by two key patterns: first, tonally inconsistent announcements are followed by significantly elevated net selling from insiders within the subsequent week; second, these inconsistencies are linked to future adverse changes in firm fundamentals, including lower profitability and revenue growth. This behavior aligns with a rich literature on agency theory, which posits that managers have incentives to opportunistically delay the pricing of negative information to secure personal benefits, such as capitalizing on equity incentives, maximizing performance-based compensation, or mitigating damage to their career prospects and reputation (e.g., Watts and Zimmerman, 1978, Fama, 1980, Healy, 1985, Ke et al., 2003, Jagolinzer, 2009, Kothari et al., 2009, Niessner, 2014, Blankespoor et al., 2020, Rawson et al., 2023).

A key challenge is to distinguish whether the observed insider selling is merely an opportunistic reaction to a market delay or part of a strategic, pre-meditated plan. My findings reveal a nuanced pattern of behavior that points toward a coordinated strategy that facilitates both planned and opportunistic trading. The results show that following tonally inconsistent announcements, top executives who are defined as the CEO, CFO, COO, president, and chairman of the board (Rogers, 2008), engage in significant planned selling under the safe harbor of SEC Rule 10b5-1[1]. In contrast, non-strategic insiders (e.g., treasurers, secretaries), who are still informed but do not craft the disclosures, engage in significant unplanned, discretionary sales. This divergence provides compelling evidence of a sophisticated, two-tiered strategic behavior. The top executives as strategic insiders, who are mostly the architects of the inconsistent narrative (Brown et al., 2019), appear to pre-plan their trades under legal protection, suggesting a pre-meditated, two-step strategy of first creating the ambiguity and then executing a pre-arranged sale. Simultaneously, the ambiguity created by these disclosures is so effective at delaying the price reaction that it emboldens other, non-narrative-setting insiders with high confidence in their informational advantage. These insiders engage in opportunistic, discretionary selling, forgoing the legal protection of a 10b5-1 plan to gain

[1]SEC Rule 10b5-1, established in 2000, provides an affirmative legal defense (or "safe harbor") against insider trading allegations for trades that are executed under a pre-arranged written plan that was adopted when the insider was not in possession of material non-public information (U.S. Securities and Exchange Commission, 2000).

the flexibility to capitalize on the window of mispricing created by their senior colleagues. The fact that both planned strategic selling by narrative-setters and opportunistic discretionary selling by other insiders increase following tonal inconsistency provides strong evidence that the inconsistency itself is a deliberate strategic act, rather than an accident that is merely exploited.

The theoretical foundation for such strategic manipulation is grounded in understanding the market's processing of information and the established channels of information friction that managers can an potentially exploit. Foundational models of information economics that challenge the notion of costless price discovery establish that the very presence of processing costs ensures that prices cannot be fully and instantaneously informative (Grossman and Stiglitz, 1976). This is because rational investors, who have limited processing capacity, must strategically allocate their finite cognitive resources across a vast set of available information (Sims, 2003). When faced with disclosures that are difficult to analyze, such as those with conflicting signals, the cognitive effort required to form a coherent valuation—the "integration costs"—becomes particularly high (Verrecchia, 1982a). It is this rational investor response to costly and complex information that creates an opportunity for managers. By strategically introducing informational frictions, managers can influence the market's processing of disclosures and, consequently, the speed and efficiency of price discovery.

To determine which established channels of information friction are activated by tonal inconsistency, I investigate four potential mechanisms grounded in the literature, that affect the audience of these disclosures: ambiguity, disagreement, information asymmetry, and inattention. My empirical results allow me to distinguish between these competing channels, with the evidence pointing strongly to ambiguity as the primary mechanism through which tonal inconsistencies operate. The findings suggest that these inconsistencies create a pervasive ambiguity that increases the cognitive integration costs for the entire market. This conclusion is supported by several key findings.

First, the ambiguity and disagreement channels offer several competing theoretical predictions for market activity. Disagreement is expected to fuel trading volume, as investors with heterogeneous beliefs actively transact based on their differing interpretations, leading to higher trading volume (Varian, 1985; Bamber et al., 1997) and potentially higher idiosyncratic volatility (Diether et al., 2002; Atmaz and Buffa, 2024). In contrast, pervasive ambiguity is expected to induce passivity, leading to reduced trading volume (Dow and Werlang, 1992; Easley and O'Hara, 2009) and wider bid-ask spreads as investors adopt a "wait-and-see" approach. My findings of significantly lower abnormal trading volume and stable idiosyncratic volatility, coupled with wider bid-ask spreads and a lack of a systematic increase in analyst forecast dispersion, are inconsistent with a disagreement-based explanation and provide strong support for the ambiguity channel.

Second, my findings help to clarify the nature of the information asymmetry at play among outside investors. Analyst forecast analyses, guided by the Barron et al. (1998) framework, show that the precision of both public and private information declines post-inconsistency. This suggests the ambiguity is so effective it degrades the entire external information environment, affecting sophisticated and retail investors alike. This conclusion is reinforced by a within-channel analysis showing that inconsistencies between the presentation and Q&A portions of a single conference call—arguably consumed by a more homogeneous, sophisticated audience—still predict a delayed market reaction. This suggests the effect is driven by a universal integration cost rather than by different audiences consuming different disclosures. Therefore, while the managers' strategic action exacerbates a powerful information asymmetry between insiders and all outsiders, the primary friction among external market participants is ambiguity, not a widening information gap between sophisticated and retail investors.

Finally, inattention is also an unlikely driver given the high-salience nature of earnings announcements, as they are typically pre-scheduled (deHaan et al., 2015; Chapman, 2018) and therefore often specifically excluded from studies focusing on investor distraction or limited attention (e.g., Rawson et al., 2023). This conclusion is reinforced by my empirical results, which hold after controlling for proxies related to both major models of inattention: distraction (Hirshleifer et al., 2009) (proxied by competing announcements on the same day and the time elapsed between the press release and conference call) and work-vs-leisure preferences (DellaVigna and Pollet, 2009) (proxied by Friday or after-hours announcements). Furthermore, a direct test shows no abnormal investor inattention using the Abnormal Google Search Volume Index (SVI) (Da et al., 2011; Drake et al., 2012). Instead of investors overlooking information, the timing and nature of the tonal divergence I observe suggest a different strategic approach: managers may not be trying to divert attention away from the earnings news, but rather to create interpretive ambiguity or cognitive friction regarding the news itself, even among attentive participants, leading to a gradual diffusion of information into prices due to heightened ambiguity engendered by these strategic inconsistencies, thereby making inattention a less likely primary driver for the observed market behavior.

Taken together, these results indicate that tonal inconsistency is not merely noise but a deliberate strategy managers use to shape investor perceptions by creating ambiguity. The findings demonstrate that this strategy has multifaceted consequences: the inconsistency is a significant predictor of future adverse changes in firm fundamentals, it directly impairs market efficiency, and it creates opportunities for informed insider trading. By increasing the integration costs of processing disclosures, this tactic leads to a passive investor response and delayed price discovery.

This study contributes to the literature by identifying a novel channel through which managers exploit informational frictions—by creating a murky information environment through the strategic use of tonal inconsistency across concurrent disclosures about a single event—and by providing evidence that this previously unexplored dimension of qualitative disclosure is a key driver of the slow price responsiveness and impaired market efficiency documented in this paper.

The remainder of the paper is organized as follows. Section II provides background and reviews the related literature. Section III describes the sample and the construction of the tonal inconsistency measure. Section IV presents the primary empirical results, examining the effects of tonal inconsistency on market reactions, future firm performance, and insider trading to establish its strategic nature. Section V explores the mechanism driving my results in more detail. Section VI concludes.

II. Background and Related Literature

This paper is situated at the intersection of three active areas of research: the strategic use of qualitative information in corporate disclosures, the role of agency conflicts in shaping communication policy, and the impact of investor information processing costs on market efficiency. First, it builds on the extensive research into strategic corporate disclosure and the informational content of qualitative language, which establishes that managerial narratives are a critical tool for influencing markets. Second, it extends the literature on information processing costs by identifying a novel strategy through which managers impose such costs—the strategic creation of tonal inconsistency—to generate ambiguity and impede efficient price discovery. Third, by linking these inconsistencies to insider trading, this study informs the literature on agency theory and opportunistic managerial behavior. This paper connects these strands by proposing that managers, driven by agency conflicts, strategically manipulate the consistency of their qualitative disclosures to impose and exploit information processing costs on investors. While prior work has documented that managers manipulate the tone of individual disclosures, the strategic use of conflicting qualitative signals across contemporaneous, related disclosures remains unexplored. This study fills that gap.

A foundational body of research documents that the sentiment embedded in managerial language—often captured as "tone"—is a significant determinant of capital market outcomes. Early studies find that negative tone in corporate communications predicts lower stock returns and earnings (Tetlock, 2007; Demers and Vega, 2009; Price et al., 2012). This insight has been refined by work developing systematic methods to measure financial sentiment, demonstrating that even subtle tonal shifts significantly influence investor perceptions and behavior (Li, 2010; Loughran and McDonald, 2013). This line of inquiry highlights that not only the semantic content, but also the delivery characteristics of communication affect subsequent market dynamics (Tetlock et al., 2008; Lee, 2016). These collective findings establish that tone is not merely an atmospheric or stylistic artifact but is an informative, and therefore pliable, tool.

My study focuses on two of the most salient channels for managerial communication: earnings press releases and conference calls. Prior literature has largely examined the informational role of these outlets in isolation, focusing on their distinct characteristics. One stream of research establishes that the textual tone of earnings press releases is itself informative, predicting short-term market reactions (Henry, 2008; Davis et al., 2012b). A separate, parallel body of work validates the conference call as a critical disclosure event that impacts markets and information intermediaries (Tasker, 1998; Frankel et al., 1999; Bowen et al., 2002). This line of inquiry has explored the unique attributes of the conference call format, identifying the spontaneous Q&A session as a particularly rich source of information (Matsumoto et al., 2011) and even analyzing non-textual cues like the vocal affect of managers (Mayew and Venkatachalam, 2012). The adoption of Regulation Fair Disclosure by the U.S. Securities and Exchange Commission (SEC) (U.S. Securities and Exchange Commission, 2000), which broadened access to these calls (Bushee et al., 2003), makes this question all the more relevant for a wide investor audience. While these studies underscore that the conference call is a distinct and value-relevant event, their focus has been on the information contained within the call itself or its effect on specific user groups like analysts. This prior work, however, leaves unexamined the question of whether managers strategically create qualitative inconsistencies in textual tone between the simultaneously or near-simultaneously released outlets, and what the market consequences of such a strategy might be.

Recognizing this, a parallel stream of literature provides evidence that managers strategically manage tone to influence sentiment, often aligning with personal incentives (Huang et al., 2014; Arslan-Ayaydin et al., 2016; Li et al., 2023). These incentives are well-established, ranging from maximizing performance-based compensation (Watts and Zimmerman, 1978; Healy, 1985) and preserving reputational capital by delaying bad news (Fama, 1980; Graham et al., 2005; Kothari et al., 2009), to capitalizing on forthcoming news through insider trading.

A large body of work demonstrates that managers trade on negative private information long before it is publicly disclosed (Ke et al., 2003). A key focus of this literature is the strategic use of SEC Rule 10b5-1 plans, which investigates whether pre-planned trades are truly for uninformed diversification or constitute strategic trading. Jagolinzer (2009) defines strategic trade as a "trade executed non-randomly to enhance trade gains or mitigate holding losses." In his foundational study, he finds that even trades conducted under the supposed safe harbor of Rule 10b5-1 show evidence of this strategic behavior, as insiders using these plans earn abnormal returns, suggesting the plans are initiated based on material non-public information. Subsequent research provides further evidence of this strategic behavior, showing that managers coordinate these trading plans with disclosure timing—accelerating good news and delaying bad news (Shon and Veliotis, 2013)—and that plan-based trades often precede predictable, material corporate news releases (Henderson et al., 2015). This strategic timing of disclosures to benefit insider trading has been shown to occur on low-attention days, such as Fridays (Niessner, 2014). My results show that following tonally inconsistent announcements, top executives—defined as the CEO, CFO, COO, president, and chairman of the board (Rogers, 2008)—engage in significant planned selling under the safe harbor of SEC Rule 10b5-1, reinforcing the strategic nature of the disclosure choice. This discretion is central to agency conflicts, as managers can exploit the loose regulation of narrative disclosures to shape investor perceptions and valuations (Peng and Roell, 2014; Ahern and Sosyura, 2014), a strategy made more effective by investors' susceptibility to such manipulation due to "lazy" processing of complex information (Cohen et al., 2020).

The strategic incentive to manage disclosure tone is powerful because investors face significant costs to acquire, interpret, and analyze complex information. The existence of these "disclosure processing costs" means that learning from a disclosure is an active economic choice, not a passive absorption of public information. Seminal work by Blankespoor et al. (2020) demonstrates the real-world impact of these costs. They find that when an intermediary ("robo-journalism") synthesizes and disseminates earnings releases into a simpler format—thereby lowering processing costs—trading volume and liquidity increase significantly, even though no new information is created. This establishes that the cost of processing is a distinct and important friction in capital markets. While their work examines an intermediary that reduces these costs, this paper investigates the opposite: whether managers strategically increase processing costs by creating tonal inconsistencies to deliberately introduce friction and impair market efficiency.

This study investigates the information aggregation costs investors face when presented with conflicting qualitative signals. To isolate this friction, I employ a "same event, same time" framework by analyzing disclosures that are both contemporaneous and related to the same core event. This setting makes the attribution of any observed market friction to the conflict between signals tractable, allowing for a direct test of whether strategic inconsistencies impose aggregation costs on investors. This approach is distinct from prior work that has examined related but different phenomena. For instance, some studies analyze sequential disclosures separated by time and regulatory scrutiny, such as Davis and Tama-Sweet (2012a) who compare an early press release to the Management's Discussion and Analysis (MD&A) section of a formal SEC filing that is released days or weeks later, a setting which examines message evolution under different regulatory burdens rather than a real-time aggregation problem. Other research compares the same filing across different time periods, such as year-over-year changes to 10-K language (Cohen et al., 2020), which by definition studies different information events where a simultaneous processing cost is not definable. Finally, studies of concurrent disclosures have focused on a distraction mechanism, where managers issue unrelated press releases at the same time as a negative Form 8-K, a formal SEC filing to divert investor attention (Rawson et al., 2023). This unique "same event, same time" setting contributes to the literature by allowing for a test of whether managers strategically capitalize on the aggregation costs that arise from their own inconsistent messaging, providing evidence that such conflicts are not merely noise but a tool to impair market efficiency.

The theoretical underpinning for why such inconsistencies would impact market efficiency lies in four potential mechanisms. Tonal conflicts may generate ambiguity, a form of Knightian uncertainty where probabilities are difficult to assess (Knight, 1921), leading investors to adopt a passive "wait-and-see" approach (Dow and Werlang, 1992). They could also heighten information asymmetry, where the presence of informed traders creates adverse selection risk for market makers, leading to wider bid-ask spreads (Glosten and Milgrom, 1985; Krinsky and Lee, 1996; Hendershott et al., 2011). Alternatively, inconsistent signals could foster disagreement, where heterogeneous beliefs, as modeled by Miller (1977), lead to increased trading as investors act on their differing interpretations (Bamber et al., 1997). Finally, the delayed reaction could be a product of investor inattention, where cognitive constraints cause investors to defer processing complex signals, leading to gradual price adjustment (Hirshleifer et al., 2009). Distinguishing which of these frictions—ambiguity, information asymmetry, disagreement, or inattention—is the primary channel through which tonal inconsistency operates is an important empirical question of this paper. To the best of my knowledge, this is the first study to examine whether managers strategically vary the tone of contemporaneous, related disclosures as a tool to create these specific informational frictions, thereby providing new insights into the sophisticated ways managers exploit the costs of information processing.

III. Data and Summary Statistics

My sample includes all S&P 500 constituent firms from 2006Q1 to 2023Q3. The analysis centers on quarterly earnings press releases and their corresponding earnings conference calls. I focus on firms within the S&P 500 due to their substantial economic significance—collectively representing approximately 80% of U.S. market capitalization[2]—and high level of media and analyst coverage, which provides a rich setting for textual analysis.

I use a range of data sources to construct the sample. Earnings press releases are primarily retrieved from the SEC's EDGAR database[3]. Specifically, I download all relevant press releases filed by S&P 500 firms through Form 8-K, in accordance with Section 409 of the Sarbanes–Oxley Act, which mandates that public companies furnish earnings releases to the SEC within four business

[2]According to S&P Dow Jones Indices, the S&P 500 "covers approximately 80% of available market capitalization." See S&P Dow Jones Indices, S&P 500®, available at `https://www.spglobal.com/spdji/en/indices/equity/sp-500/`.

[3]https://www.sec.gov/edgar/.

days. [4]

To process these documents, I extract content tagged under <TYPE> EX 99.1 and transform it into textual representations using word vectorization techniques. This procedure aligns with established textual analysis methodologies in financial research (e.g., Henry, 2008; Davis and Tama-Sweet, 2012a; Davis et al., 2012b; Loughran and McDonald, 2011), but I adapt the process to address the unique features of my dataset. For instance, some press releases appear as image files; therefore, I retain `<img>` tags when they contain more than 100 words of textual content. I also normalize special characters (e.g., converting   to whitespace and &AMP to the ampersand symbol) into standard ASCII encoding.

Further preprocessing includes removing HTML `<table>` tags if over 10% of their non-blank content is numeric, as well as eliminating all other remaining HTML elements. The resulting clean text is then tokenized using a regular expression that isolates word tokens consisting of at least two alphabetic characters. These steps help ensure a consistent and analyzable text corpus while preserving the embedded financial narratives.

Earnings call transcripts are sourced from the Compustat Capital IQ database. Each transcript includes both the presentation (management's prepared remarks) and Q&A sections. The transcripts also specify the speaker type (e.g., operator, executive, analyst). I restrict my analysis to executives' speech, excluding content from operators and analysts in all sections. This results in a final sample of 33,374 earnings call transcripts, with 29,583 successfully matched to the corresponding earnings press releases associated with the same earnings announcement. The sample spans 701 unique firms over the full sample period.

Data on daily stock returns are obtained from the Center for Research in Security Prices (CRSP). Accounting data, including book value of equity and earnings per share, are sourced from the Compustat database. The factors required for implementing the Fama–French five-factor model (Fama and French, 2015) are retrieved from Kenneth French's online data library[5]. Additionally, I obtain the precise timestamps of press release dissemination from the Institutional Brokers' Estimate System (I/B/E/S). Sentiment categories are identified using the Loughran and

[4] Other studies use additional sources such as Businesswire (Huang et al., 2014) and Newswire (Davis and Tama-Sweet, 2012a; Davis et al., 2012b). See also Henry and Leon (2016) for a broader discussion on the information content of earnings press releases using SEC data.

[5] https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html

McDonald (Loughran and McDonald, 2011) Master Dictionary[6]. I obtain data on insider trading from the London Stock Exchange Group (LSEG).

Sentiment scores of executives' language for both channels were computed using a lexicon-based approach, specifically employing the Loughran and McDonald Dictionary, which is specifically designed for financial text analysis. This dictionary classifies words into predefined sentiment categories and the tone is measured as the difference between the number of positive and negative words, divided by the total number of positive and negative words. The sentiment classification and *Tone* calculations were applied to the processed earnings call transcripts and press release texts:

$$Tone_{j,q,t} = \frac{PW_{j,q,t} - NW_{j,q,t}}{PW_{j,q,t} + NW_{j,q,t}} \tag{1}$$

with $PW_{j,q,t}$ and $NW_{j,q,t}$ denoting the number of positive and negative words, respectively, in the context of interest—either the earnings press release or the earnings conference call presenation or Q&A section—of firm j in quarter q of year t. The formula is proposed by Henry (2008) and builds on earlier applications to auditors' opinion letters (Uang et al., 2006). The approach treats the document as a "bag of words," counting occurrences of words classified as positive or negative based on pre-defined dictionaries. The variable *Tone* ranges from 1 (fully positive) to –1 (fully negative). Sentiment scores for earnings call transcripts and press release articles are classified as either positive or negative, with neutral values assigned to the negative group, following Hollander et al. (2010). Observations are classified as positive if $Tone_{j,q,t} > 0$, and as negative otherwise.[7]

To illustrate the growing complexity faced by investors, Figure 1 highlights several key trends in the content and tone of corporate disclosures across press releases and earnings calls over the 18-year period. Panel A shows that over the past two decades, the average length of quarterly earnings press releases, measured by word count, has grown substantially. However, Panel B demonstrates that this increase in length of earnings press releases has been accompanied by a decline in the proportion of filings with net positive tonality. Notably, managers demonstrate very high tonal consistency within the different sections of earnings conference calls, as evidenced by little difference in positive tonality frequency in Panel B. Based on Panel C, the magnitude of tonal

[6]Available at: https://sraf.nd.edu/loughranmcdonald-master-dictionary/.

[7]For robustness, I also vary the classification threshold by using the median of *Tone* across the sample, and alternatively at the firm or quarter level for each disclosure type, and obtain qualitatively similar results.

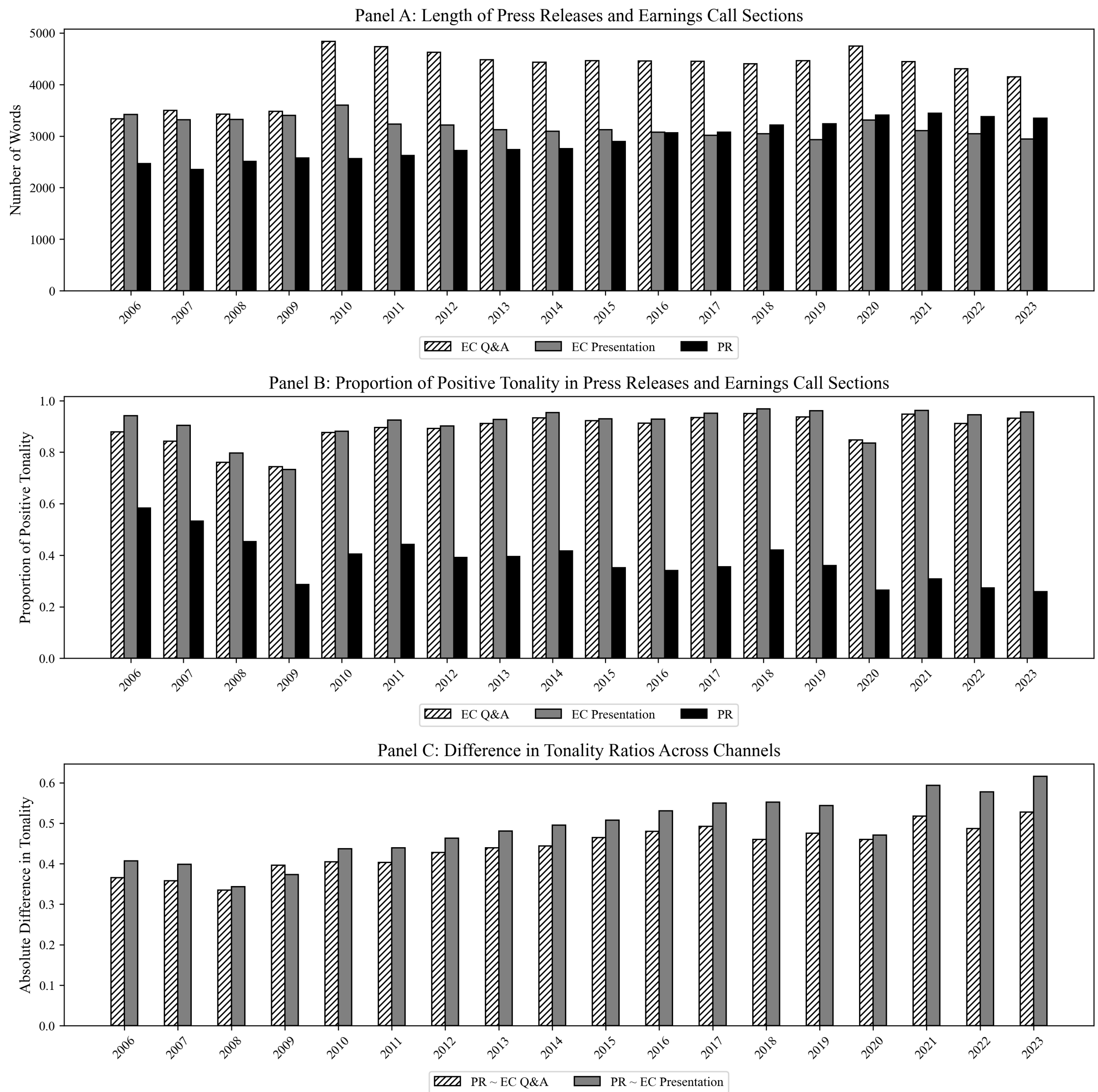


Figure 1. Descriptive Statistics of Key Tonal and Content Characteristics across Communication Mediums, specifically press releases (PR) and sections of earnings calls (EC), including the *presentation* and *Q&A* segments. Panel A shows the average number of words, comparing content length across these channels. Panel B illustrates the proportion of positive tonality, capturing the relative prevalence of optimistic sentiment. Panel C shows the absolute differences in *tone* between channels, with *tone* computed as described in Equation 1, reflecting the magnitude of divergence in sentiment. *EC* refers to earnings calls, where *EC Presentation* denotes the management's prepared remarks, and *EC Q&A* captures the interactive segment with analysts. *PR* refers to the corresponding earnings press releases. Observations are from S&P 500 firms between 2006Q1 and 2023Q3.

inconsistencies between earnings press releases and sections of earnings conference calls have risen over time. It also highlights that the tonal discrepancies between the presentation segments of earnings conference calls and press releases are consistently greater than those observed between the Q&A sections of the calls and press releases. This finding aligns with intuitive expectations, as the presentation portion is typically pre-scripted, whereas the Q&A segment tends to be more spontaneous and reactive in nature.

Table I provides summary statistics for quarterly earnings press releases and earnings conference call transcripts (presentation and Q&A sections) spanning from 2006Q1 to 2023Q3. Panels A to C illustrate attributes related to the length and tonal characteristics of these communication channels. Specifically, Q&A sections are longer than presentation segments and press releases on average. Tonal analysis indicates that press releases are generally more negative, with only 36% classified as positive compared to approximately 90% positivity in earnings calls (presentation and Q&A). I will document evidence that suggests this misalignment of tone across channels is the result of strategic behavior by senior executives. Panel D shows timing-related variables, revealing that earnings calls and press releases typically occur within approximately four hours of each other, highlighting their contemporaneous nature, with earnings calls occurring after press releases in more than half of the cases. These insights suggest strategic timing and deliberate tonal divergence by managers across these communication channels.

To illustrate this concept, consider the case of Amazon.com, Inc., a leading American multinational technology firm and a member of the S&P 500. The company's earnings disclosures have frequently demonstrated tonal inconsistencies between press releases and conference calls. The second quarter of 2013 provides a representative example from the sample. In this instance, the press release exhibited a markedly positive tone, highlighting several developments such as the *Kindle Fire HD*, partnerships with *Viacom Inc.*, new product launches like the *Comedy Pilots Alpha House*, and global expansion efforts. In contrast, the contemporaneous conference call presentation omitted these positive highlights, adopting a more negative tonality and suggesting a deliberate shift in emphasis.

Following the 2013Q2 earnings announcement, Amazon's stock experienced a notable market reaction. As illustrated in Panel A of Figure 2, cumulative abnormal returns initially rose before beginning a slow downward drift that continued without reversal over the subsequent quarter.

Table I

Summary Statistics of Disclosures' Tone and Timing

This table presents summary statistics based on a merged dataset of earnings press releases (PR) and earnings conference calls (EC) at the firm-quarter level, where both channels released earnings announcements. Positive and negative words were identified using the Loughran–McDonald dictionary, with *tone* computed as described in Equation 1. *Number of Words* counts all words in a document. *Positive Tonality* and *Negative Tonality* represent the share of positive and negative words, respectively. *Positive Tone Rate* is a binary indicator equal to one if tone is positive and zero otherwise. *Disclosure Time Gap* is the hour difference between a call and its corresponding press release. *EC After Hours Rate* and *PR After Hours Rate* indicate the fraction of events that occur after 4 p.m. Eastern Time (ET). *EC Before PR Rate* captures the fraction of calls that occur before the corresponding press release. Panel A reports statistics for press releases, Panel B for the presentation portion of earnings calls, Panel C for the Q&A portion, and Panel D for disclosure timing variables.

Panel A: Summary Statistics of Press Release

Variable	**Count**	**Mean**	**SD**	**25%**	**50%**	**75%**
Number of Words	29,583	2,978	1,987	1,800	2,625	3,620
Positive Tonality	29,583	0.464	0.156	0.353	0.451	0.561
Negative Tonality	29,583	0.536	0.156	0.439	0.549	0.647
Tone	29,583	-0.072	0.312	-0.294	-0.098	0.121
Positive Tone Rate	29,583	0.362	0.481	0.000	0.000	1.000

Panel B: Summary Statistics of Earnings Calls – Presentation

Number of Words	29,583	3,157	1,385	2,330	3,010	3,799
Positive Tonality	29,583	0.697	0.133	0.618	0.714	0.795
Negative Tonality	29,583	0.303	0.133	0.205	0.286	0.382
Tone	29,583	0.394	0.266	0.235	0.429	0.589
Positive Tone Rate	29,583	0.915	0.279	1.000	1.000	1.000

Panel C: Summary Statistics of Earnings Calls – Q&A

Number of Words	29,583	4,374	1,866	3,109	4,047	5,303
Positive Tonality	29,583	0.662	0.121	0.589	0.674	0.748
Negative Tonality	29,583	0.338	0.120	0.252	0.326	0.411
Tone	29,583	0.324	0.241	0.178	0.347	0.495
Positive Tone Rate	29,583	0.898	0.302	1.000	1.000	1.000

Panel D: Summary Statistics of Timing Variables

Disclosure Time Gap	29,583	3.946	11.004	-2.500	-0.483	11.917
EC After Hours Rate	29,583	0.644	0.479	0.000	1.000	1.000
PR After Hours Rate	29,583	0.387	0.487	0.000	0.000	1.000
EC Before PR Rate	29,583	0.462	0.499	0.000	0.000	1.000

This drift illustrates a significant delay in price discovery, as it took the market approximately two months to fully absorb the negative information from the inconsistent disclosures. As shown in

Panel B, the week following the earnings announcement experienced an abnormal volume of insider net sales, which significantly exceeds the daily average net sales for Amazon's stock.

It is important to emphasize that these inconsistencies pertain solely to tonal and linguistic differences, focusing on the emphasis and choice of words, rather than discrepancies in the quantitative information disclosed. Indeed, in the presented example, the underlying numerical data remains consistent across the channels. However, as evidenced by various comparative criteria (which I illustrate in Appendix Table A.I), the highlights and tonal framing of the language differ.

The Amazon case is illustrative of a broader pattern. Just as we see in the weeks following the mixed messaging of Amazon's corporate communications, the typical experience for firms with such tonal inconsistency in my sample of analysis is one of elevated insider trading and a subsequent slow drift downwards in price.

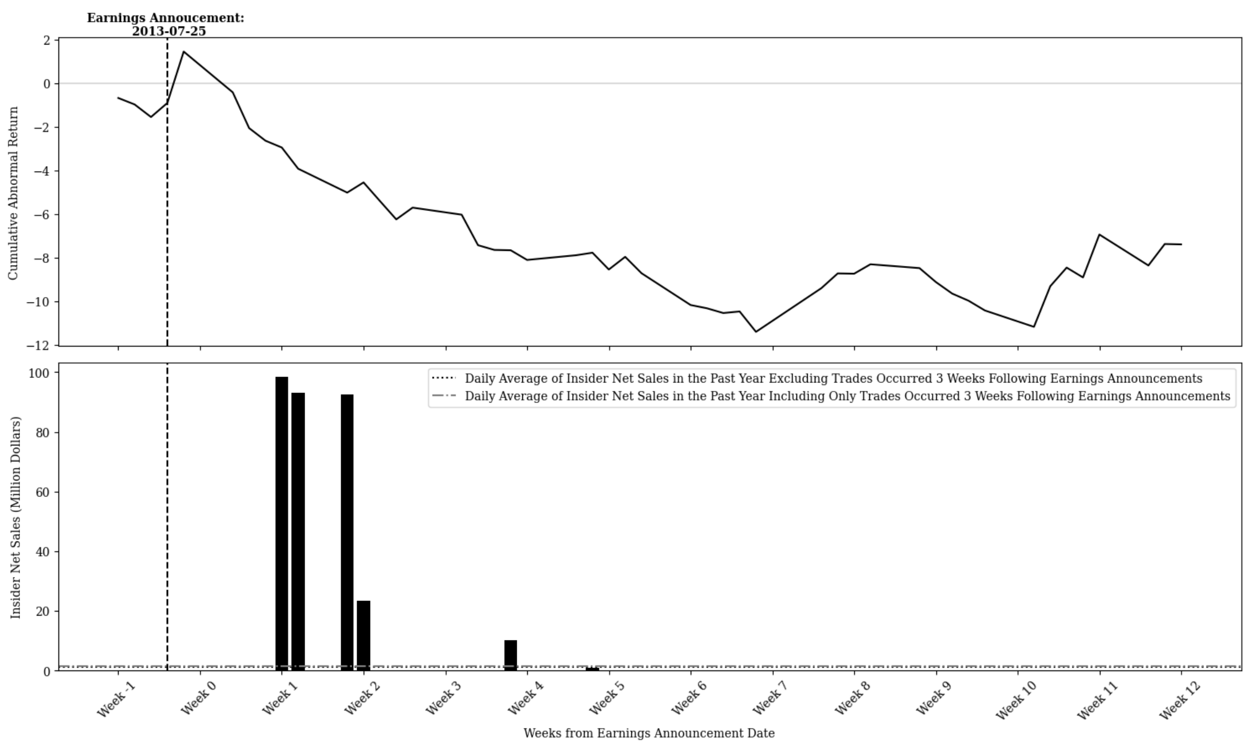


Figure 2. Amazon's CAR and Insider Net Sales Following Tonality Inconsistency Across Channels: This figure shows the cumulative abnormal returns (CAR) and cumulative insider net sales of Amazon.com, Inc. (NASDAQ: AMZN) in the weeks following the release of Amazon's 2013Q2 earnings announcement. The announcement exhibited a positive tonality in the earnings press release but a negative tonality in the presentation section of the conference call.

To provide a deeper understanding of the prevalence and characteristics of tonal (in)consistencies

Table II

Tonality Combinations in Earnings Conference Calls and Press Releases

This table reports the number of firm-quarter observations categorized by the tone of executive communication in earnings conference calls and press releases. Panel A presents the distribution of observations based on the tone in the presentation section of earnings conference calls in comparison with the tone in earnings press releases. Panel B focuses on the Q&A section of earnings conference calls for this comparison. Panel C examines whether the tone in earnings press releases is consistent with the tone in *either* the presentation or Q&A section of the corresponding earnings conference call. The tone in these communications is computed using Equation 1, and observations are from S&P 500 firms between 2006Q1 and 2023Q3. *Negative* and *Positive* classifications are determined based on the sign of the *tone* score as defined in Equation 1.

Panel A: Tonality in Earnings Press Releases and Earnings Conference Calls - Presentation

	Earnings Press Releases	
Earnings Calls - Presentation	**Negative**	**Positive**
Negative	2,142	377
Positive	16,731	10,333

Panel B: Tonality in Earnings Press Releases and Earnings Conference Calls - Q&A

	Earnings Press Releases	
Earnings Calls - Q&A	**Negative**	**Positive**
Negative	2,348	665
Positive	16,525	10,045

Panel C: Tonality in Earnings Press Releases and Earnings Conference Calls - All Sections

	Earnings Press Releases	
Earnings Calls - All Sections	**Negative**	**Positive**
Negative	887	954
Positive	17,986	9,756

across communication channels, I examine the distribution of firm-quarter observations categorized by their tonal alignment. This analysis sheds light on the frequency of consistent versus inconsistent tonalities between earnings conference calls and press releases, highlighting the strategic patterns of managerial communication. Table II presents the number of firm-quarter observations categorized by combinations of different tonalities in earnings conference calls and press releases. It captures both consistent tonalities, where both channels share the same positive or negative *tone*, and inconsistent tonalities, where one channel is positive while the other is negative. Importantly, only the parts of earnings call transcripts narrated by executives are considered in this analysis, whether for the presentation, or Q&A sections. This ensures that the tonal assessment reflects solely the communication from top management, filtering out any input from analysts or other participants.

Panel A focuses specifically on the presentation section of earnings conference calls, where only the scripted statements by executives are analyzed. The distribution in Panel A reveals that the majority of firm-quarters exhibit consistency between the tone of presentations and press releases, with over 10,000 observations showing positive tones across both channels and more than 2,000 firm-quarters reflecting negative tones in both. However, there are also several hundred firm-quarters showing tonal inconsistencies, such as cases where the tone is negative in press releases but positive in the presentation section, and vice versa.

Panel B, which covers the more spontaneous Q&A section of earnings calls, and Panel C, which defines inconsistency as a tonal mismatch between the press release and either the presentation or the Q&A section, show similar almost trends in the distribution of consistent and inconsistent tonalities. The observed distributions across all three panels suggest that contemporaneous tonal inconsistencies between earnings press releases and different sections of earnings conference calls are not uncommon. These observations provide a preliminary insight into how managers might communicate differently across these channels, potentially influencing market participants' perceptions. The analysis presented below suggests that these intriguing patterns are likely not accidental and motivates a deeper investigation into their strategic nature and market impact.

IV. Tonal Inconsistency and its Implications

The stocks are categorized into four distinct portfolios based on the alignment of managerial tonalities across the two disclosure channels. These include: (1) *Positive Consistent*, where both channels reflect positive tonality; (2) *Negative Consistent*, where both exhibit negative tonality; (3) *EC+, PR-*, where the tone is positive in earnings conference calls but negative in press releases; and (4) *EC-, PR+*, where the tone is negative in earnings conference calls but positive in press releases. These classifications are used throughout the remainder of the analysis.

I classify firm-quarter announcements as *Positive Consistent* (*Negative Consistent*) if all three sources—the presentation and Q&A sections of the earnings call, along with the press release—exhibit positive (negative) tonalities. If at least one section of the earnings call is negative while the concurrent press release is positive, the firm-quarter is classified as *EC-, PR+*. Conversely, if at least one section of the earnings call is positive while the press release is negative, the firm-quarter is classified as *EC+, PR-*.[8]

In some specifications, I also construct a binary indicator variable, *Inconsistent*, which equals one if either *EC+, PR-* or *EC-, PR+* classifications are observed, and zero otherwise. That is, the *Inconsistent* dummy captures all cases where the tone differs across disclosure channels, regardless of which channel is more positive. The omitted group in this specification comprises the *Positive Consistent* and *Negative Consistent* cases, collectively referred to as *Consistent*. This binary formulation allows me to study the effect of overall tonality inconsistency without distinguishing the direction of disagreement.

IV.I. Cumulative Abnormal Returns

To test whether tonal inconsistency between corporate disclosures affects stock prices, I draw on theories of information processing costs. This literature posits that when investors have limited attention and face cognitive costs to process information, they may initially underreact to public news (Hirshleifer and Teoh, 2003). As this conflict subsequently resolves, the price is expected to drift toward the level implied by the fundamental information. This theoretical framework gives rise to a specific, testable prediction regarding the market's response to tonally inconsistent announcements that contain negative elements. This leads to the first primary hypothesis of this study:

Hypothesis 1 (H1): Compared to a uniformly negative announcement, a tonally inconsistent announcement will exhibit **(a)** a less negative immediate stock price reaction, followed by **(b)** a significant negative post-announcement drift.

To test this hypothesis, I first examine the CARs of stocks in each of the four classes of tonal consistency. The analysis is conducted over multiple intervals—the day, week, month, and two months following the earnings announcement. Abnormal returns are computed using residuals from the Fama-French five-factor model (Fama and French, 2015).[9] The announcement date is

[8] I also considered another approach: I analyze each section of the presentation and Q&A separately and compare the tonalities from each section's transcript with the concurrent press releases to determine the appropriate classification at the firm-quarter level. Defining inconsistency groups using either of these robustness tests leads to qualitatively similar results.

[9] As a robustness check, I augment the approach of Tetlock et al. (2008) by estimating abnormal returns using the Fama-French five-factor model rather than their original three-factor model, with an estimation window of [–252, –23] trading days. I also extend this approach by using an alternative estimation window—from the day after the previous earnings announcement to 10 trading days before the current announcement—to fully exclude the pre-event period. Both approaches yield consistent results.

defined as the date of the earnings press release; if the release occurs after 4:00 PM ET, the standard market closing time, I treated the next trading day as the effective announcement date.

Figure 3 provides initial visual support for **H1**. Panel A, which focuses on a shorter event window of 10 trading days, provides support for **H1a**. On the announcement date, the inconsistent groups experience a much less negative abnormal return than the *Negative Consistent* group. This suggests that the tonal inconsistency successfully moderates the immediate negative price response, even for the *EC-, PR+* group that experiences the most significant long-term decline.[10]

Panel B then captures the longer-term post-announcement market reaction, providing clear support for **H1b**. The results reveal a pattern of swift reversals for the consistent groups, aligning with the well-documented overreaction behavior of investors (Tetlock, 2007; Davis et al., 2012b; Garcia, 2013). In contrast, both inconsistency groups experience a downward PEAD over the two-month period. The drift is most striking for the *EC -, PR +* group, whose cumulative abnormal return after two months falls below even that of the *Negative Consistent* group. This indicates that while mixed signals lead to a delayed absorption of negative information for both inconsistency groups, the effect is particularly severe when the conference call is negative and the press release is positive, resulting in a more pronounced long-term market correction.

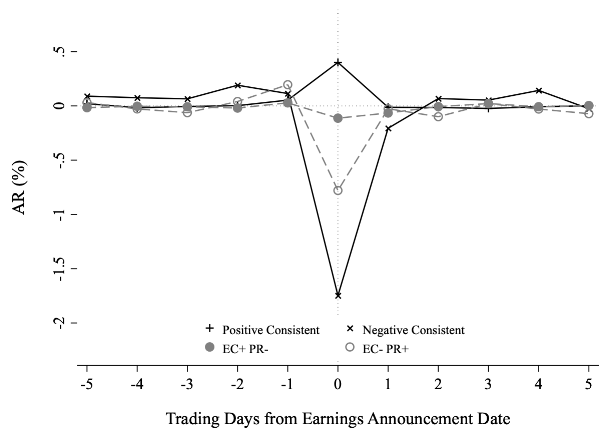
To empirically test the statistical significance of these patterns, I employ a panel time-series regression framework. I capture tonal inconsistency effects in managerial communication by introducing appropriate dummy variables that represent the four sentiment-based categories and the relevant event windows. This approach allows for a direct test of the persistence and structure of market responses to mixed signals across earnings disclosures. The empirical specification is as follows:

$$
\begin{aligned}
Y_{i,t,k} = \beta_0 + \beta_1 \text{PositiveConsistent}_{i,t} + \beta_2 \text{EC}^{+} PR^{-}_{i,t} + \beta_3 \text{EC}^{-} PR^{+}_{i,t} \\
+ \beta_4 Controls_{i,t} + \alpha_i + \gamma_t + \varepsilon_{i,t} \qquad (2)
\end{aligned}
$$

where $CAR_{i,t,k}$ represents the cumulative abnormal return of firm i at time t over a post-announcement horizon k, expressed as a percentage and scaled by 100. The key independent variables are dummies

[10]For an alternative classification of consistency groups which yields qualitatively similar results, see Appendix Figure A.1.

Panel A: Daily Abnormal Returns around the Announcement Date



Panel B: Cumulative Abnormal Returns from One Day Before to Two Months After the Announcement

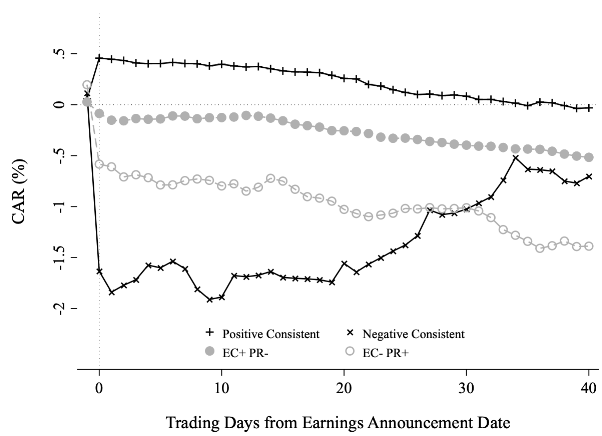


Figure 3. Abnormal Returns Across Consistency Groups: This figure plots the average abnormal returns for four categories of tonal consistency classifications. The sample includes S&P 500 firms from 2006Q1 to 2023Q3. Abnormal returns are estimated using the Fama-French five-factor model (Fama and French, 2015).Panel A focuses on a shorter event window of 10 trading days around the earnings announcement date (from day –5 to +5). Panel B presents cumulative abnormal returns from one trading day before to 40 trading days after the earnings announcement. The x-axis indicates relative trading days; for example, day 40 corresponds to approximately two months post-announcement.

for the tonal consistency groups, with the *Negative Consistent* group serving as the omitted category. The omitted category in the regression is the *Negative Consistent* case, where both disclosures convey a uniformly pessimistic tone.

The model includes controls for standardized unexpected earnings ($SUE_{i,t}$), which measures the magnitude of the earnings surprise by scaling the difference between reported earnings per share and the consensus analyst forecast by the stock price.[11] Given the strong empirical link between earnings surprises and abnormal returns, controlling for $SUE_{i,t}$ ensures that the estimated effects of tonal inconsistency are not confounded by fundamental earnings news. To account for potential momentum effects, the model also includes additional controls: $CAR(-1,0)_{i,t}$, which captures the firm's cumulative abnormal return in the month prior to the earnings announcement, and $CAR(-12,-1)_{i,t}$, which represents the cumulative abnormal return from 12 months to one month before the announcement. Other controls include last quarter's *size*,logarithm of market capitalization; *log(BM)*, the log book value of equity over market value of equity; and *Inst Own*, institutional ownership to proxy for the firm's information environment. All controls are winsorized at the 1% level. This specification also incorporates firm and month fixed effects as a Two-Way Fixed Effects (TWFE) estimator, with two-way standard errors clustered at both the firm and trading day levels to address potential cross-sectional and temporal dependencies.

Table III presents the regression results, which confirm the graphical evidence and provide strong support for **H1**. The estimated coefficients on the inconsistency dummies, β_2, and β_3, capture the differential impact of mixed messaging on cumulative abnormal returns relative to the omitted *Negative Consistent* group. In the event window (*CAR[-1:1]*), the coefficients on both inconsistency dummies are positive and significant, confirming the attenuation effect predicted by **H1a**. This provides strong evidence that the positive component of the inconsistent disclosures successfully attenuates the immediate market reaction to the negative information embedded in the other channel, leading to a slower initial price response compared to a uniformly negative announcement.

The subsequent columns test for the delayed drift predicted by **H1b**. Panel A, which uses non-overlapping windows, pinpoints the timing of the market reaction. For both inconsistent groups, the negative drift is concentrated in the second month following the announcement, as shown by the significant negative coefficients in the *CAR[21:40]* window. The effect is particularly steep for the *EC -, PR +* group, confirming the pattern shown in Figure 3. This pattern is particularly pronounced when the underlying earnings news is negative. As shown in Appendix Table A.II, the downward drift for inconsistent firms intensifies when the announcement's *SUE* falls within the

[11] $SUE_{i,t}$ is defined as the Compustat-based standardized unexpected earnings and is computed as in Livnat and Mendenhall (2006).

Table III

Main Results: Panel Time-series Regressions of Cumulative Abnormal Returns

This table reports results of panel time-series regressions of individual firm-level stock cumulative abnormal returns from a day before the earnings announcement to two months after. The sample consists of S&P 500 firms from 2006Q1 to 2023Q3. The consistency dummies are based on categories including *Positive Consistent* (both earnings call and press release are positive), *Negative Consistent* (both are negative), *EC -, PR +* (negative in earnings call and positive in press release), and *EC +, PR -* (positive in earnings call and negative in press release), with *Negative Consistent* serving as the omitted category in the panel regression analysis. Abnormal returns are estimated using the Fama-French (2015) five-factor model (Fama and French, 2015). *AR[-1]* is the abnormal return on the announcement day, while *CAR[-1:k]* represents the cumulative abnormal return from one day before the announcement until k trading days after that. The dependent variable, *CAR*, is expressed as a percentage. *CAR(–1,0)* represents the previous month's abnormal return, while *CAR(–12,–1)* is the cumulative return from month –12 to month –1. *SUE* (Standardized Unexpected Earnings) is computed as actual earnings per share minus the average analyst forecast earnings per share, divided by the stock's price. *Size* is log of last quarter's market value of equity, log(BM) is log of last quarter's book value of equity over market value of equity, and *Inst Own* is institutional ownership. Panel A reports results for the CAR in the event window *CAR[-1:1]* and three subsequent, non-overlapping windows: the first week (*CAR[2:5]*), the following three weeks (*CAR[6:20]*), and the second month (*CAR[21:40]*). Panel B reports results for the CAR in the earnings announcement event window *CAR[-1:1]* and three overlapping windows starting from the day after the event window, with cumulative returns measured up to approximately one week (*CAR[2:5]*), one month (*CAR[2:20]*), and two months later (*CAR[2:40]*). Firm and year-month fixed effects are included. Standard errors are clustered at the firm and trading day level. *t*-Statistics are reported below the estimates. Statistical significance at the 1%, 5%, and 10% levels is indicated by ***, **, and *, respectively.

Panel A: Based on the Presentation Section of Earnings Calls and Press Releases

	CAR[-1:1]	CAR[2:5]	CAR[6:20]	CAR[21:40]
Positive Consistent	2.28***	-0.31*	-0.01	-0.64
	(5.58)	(-1.70)	(-0.02)	(-1.54)
EC +, PR -	1.61***	-0.25	0.15	-0.71*
	(3.99)	(-1.32)	(0.44)	(-1.74)
EC -, PR +	0.94**	-0.41*	-0.19	-0.94**
	(2.09)	(-1.81)	(-0.47)	(-1.97)
SUE	0.45***	0.02*	-0.00	-0.01
	(10.73)	(1.80)	(-0.07)	(-0.69)
CAR(-12,-1)	-0.01***	-0.01***	-0.00	-0.01***
	(-5.22)	(-3.31)	(-1.39)	(-3.61)
CAR(-1,0)	-0.01	-0.00	-0.01	-0.02
	(-1.62)	(-0.48)	(-0.57)	(-1.38)
Size	-0.30*	0.01	0.29**	-0.28
	(-1.73)	(0.13)	(2.18)	(-1.63)
log(BM)	-0.58***	-0.13**	-0.31***	-0.52***
	(-4.31)	(-2.35)	(-2.99)	(-4.23)
Inst Own	0.80	-0.32	0.27	0.12
	(1.47)	(-1.36)	(0.56)	(0.20)
Constant	-0.70	0.23	-3.67***	2.61
	(-0.41)	(0.26)	(-2.65)	(1.41)
Observations	24,618	24,618	24,618	24,618
Firm FE	✓	✓	✓	✓
Year-Month FE	✓	✓	✓	✓
Adjusted R-sq	0.069	0.019	0.027	0.039

Table III—Continued

Panel B: Based on the Presentation Section of Earnings Calls and Press Releases

	CAR[-1:1]	CAR[2:5]	CAR[2:20]	CAR[2:40]
Positive Consistent	2.28***	-0.32*	-0.33	-0.97*
	(5.58)	(-1.72)	(-0.93)	(-1.90)
EC +, PR -	1.62***	-0.26	-0.11	-0.82*
	(4.01)	(-1.35)	(-0.33)	(-1.68)
EC -, PR +	0.95**	-0.42*	-0.61	-1.55***
	(2.10)	(-1.83)	(-1.45)	(-2.68)
SUE	0.45***	0.02*	0.02	0.00
	(10.73)	(1.86)	(0.96)	(0.16)
CAR(-12,-1)	-0.01***	-0.01***	-0.01***	-0.02***
	(-5.19)	(-3.31)	(-2.85)	(-4.51)
CAR(-1,0)	-0.02*	-0.00	-0.01	-0.03
	(-1.66)	(-0.48)	(-0.73)	(-1.59)
Size	-0.30*	0.01	0.30*	0.02
	(-1.74)	(0.10)	(1.87)	(0.07)
log(BM)	-0.58***	-0.13**	-0.45***	-0.97***
	(-4.28)	(-2.33)	(-3.63)	(-5.21)
Inst Own	0.81	-0.32	-0.03	0.08
	(1.47)	(-1.37)	(-0.06)	(0.09)
Constant	-0.69	0.26	-3.44**	-0.79
	(-0.40)	(0.29)	(-2.12)	(-0.31)
Observations	24,638	24,638	24,638	24,638
Firm FE	✓	✓	✓	✓
Year-Month FE	✓	✓	✓	✓
Adjusted R-sq	0.068	0.018	0.031	0.040

lowest deciles of the prior year's distribution—a pre-determined measure of *Negative News* designed to mitigate endogeneity concerns.

Panel B, which examines overlapping windows, then quantifies the full magnitude of this subsequent price drift. The results show that the *EC -, PR +* group experiences a non-annualized cumulative abnormal return that is 1.55 percentage points lower than the *Negative Consistent* group over the two months following the announcement (*CAR[2:40]*). This delayed price discovery for inconsistent announcements contrasts with the behavior of the *Positive Consistent* group. For these firms, while Panel B shows a marginally significant negative CAR over the full two months, Panel A clarifies that this is not a slow drift but a rapid price correction (reversal). The negative return is concentrated entirely in the week following the announcement (*CAR[2:5]*), illustrating a relatively swift reversal of the market's initial overreaction to good news.

The regression results remain qualitatively similar when these controls are excluded or when the model is extended with additional controls for announcement timing to account for potential investor inattention effects. These include indicators for announcements made on Fridays (*Friday*) or after market hours (*PR After Hour*, *EC After Hour*), times when investor attention is typically lower. Additionally, I control for the time elapsed between disclosures (*Time Difference*) and whether they occurred on different days (*Different Days*) to account for potential distraction effects that might otherwise confound the results. Results for regressions with these extended controls are tabulated in Appendix Table A.III. The results are robust and demonstrate that the inconsistency measures are the primary drivers of the cumulative abnormal returns, even after accounting for this stringent set of controls.

Taken together, the slow price responsiveness in the event window and the subsequent two-month period it takes for the market to fully incorporate the information serve as a stylized fact. These results demonstrate a persistent pattern of delayed market response to tonal inconsistencies across different corporate disclosures, pointing to a broader inefficiency in how the market processes dispersed disclosure content. This raises a critical question: are these mixed messages the result of accidental variation in tone, or do they reflect deliberate strategic behavior by managers? To explore this possibility, the following sub-sections examine insider trading activity and firm fundamentals to assess whether such patterns coincide with managerial incentives or signal deteriorating future performance. Furthermore, I will investigate the specific mechanism through which this information friction leads to the observed slow price discovery.

IV.II. Insider Trading

The finding that tonal inconsistency precedes a significant downward drift in abnormal returns is a crucial first step, but it does not, on its own, prove that the inconsistency is a deliberate strategic act. An alternative explanation could be that these inconsistencies are simply accidental noise that the market is slow to resolve. To distinguish between strategic action and unintentional noise, I now turn to an analysis of insider trading. If managers intentionally craft an ambiguous narrative to create a window of mispricing, a powerful test of this intent is to observe whether they—and their informed colleagues—systematically trade during this window. This leads to the second primary hypothesis of this study:

Hypothesis 2 (H2): Tonal inconsistency is followed by a significant increase in net insider selling in the post-announcement period.

While evidence supporting **H2** would be consistent with strategic behavior, it is not definitive. A general increase in selling could merely be an opportunistic reaction by insiders to a market delay they did not create. A more sophisticated test is required to disentangle pre-meditated strategy from simple opportunism. I achieve this by dissecting insider trades along two critical dimensions: the type of insider (strategic architects vs. other informed insiders) and the type of trade (planned vs. unplanned).

Top executives defined as the CEO, CFO, COO, president, and chairman of the board (Rogers, 2008) are the architects of the firm's disclosure strategy (Brown et al., 2019). If they engineer tonal inconsistency as part of a pre-meditated plan to delay negative price discovery, it is plausible they would also pre-arrange their own stock sales to capitalize on the strategy while minimizing legal risk under the safe harbor of SEC Rule 10b5-1. This suggests a deliberate, two-step strategy of first creating the information friction and then executing a pre-arranged sale. This leads to a specific prediction for this group:

Hypothesis 2a (H2a): Following tonally inconsistent announcements, top executives engage in significantly higher levels of planned (Rule 10b5-1) net selling.

Simultaneously, the heightened information processing cost created by these disclosures may be so effective at delaying the price reaction that it emboldens other, non-narrative-setting insiders who are still highly informed. Confident in their informational advantage, these insiders may choose to trade opportunistically and flexibly without the legal protections and constraints of a 10b5-1 plan. Their trading patterns would therefore be discretionary and unplanned.

Hypothesis 2b (H2b): Following tonally inconsistent announcements, other insiders engage in significantly higher levels of unplanned (discretionary) net selling.

Observing both patterns simultaneously—planned selling by the narrative-setting top executives and unplanned selling by other informed insiders—would provide compelling evidence that tonal inconsistency is not an accident. Instead, it would support the view that it is a deliberate and effective strategic act, designed to create a window of mispricing that is then exploited by insiders at multiple levels of the firm.

To test these hypotheses, I employ a staggered event-time Difference-in-Differences (DID) design, a standard framework for estimating treatment effects when the treatment is introduced at different times across different units (Angrist and Pischke, 2009), to examine insider trading behavior across different post-announcement windows. This framework allows for a direct test of whether the change in insider selling after an announcement differs for firms with inconsistent disclosures compared to those with consistent disclosures. The empirical specification is as follows:

$$\begin{aligned} Y_{i,t,k} = \beta_0 + \sum_j \beta_j \cdot D_k + \sum_m \gamma_m \cdot TONE\_GROUP^m_{i,t} \\ + \sum_{j,m} \delta_{jm}(D_k \times TONE\_GROUP^m_{i,t}) + \gamma Controls_{i,t} + \alpha_i + \lambda_t + \varepsilon_{i,t} \end{aligned} \tag{3}$$

where $Y_{i,t,k}$ is firm i's (net) insider sales in month t over interval k, D_k are post-annoucement interval dummies, and $TONE\_GROUP^m$ classifies tonal consistency types into *Inconsistent*, *Positive Consistent*. $Controls_{i,t}$ include the same standard controls used in the prior CAR analysis and are winsorized at the 1% level. This specification incorporates firm and month fixed effects. To ensure robust statistical inference in this DID setting, I follow the recommendations of Bertrand et al. (2004) and employ two-way standard errors clustered at both the firm and trading day levels to address potential cross-sectional and temporal dependencies.

The key parameter of interest is δ_{jm}, the coefficient on the interaction term between the post-announcement interval dummies and the tonal consistency group dummies. This coefficient captures the differential change in insider selling for a given consistency group after the announcement, relative to the base group (*Negative Consistent*). A positive and significant δ for the *Inconsistent* group would provide evidence in support of **H2**. By running this regression on different subsamples of insider trades (e.g., planned sales by top executives), this model provides a unified framework for testing **H2a** and **H2b** as well.

The results of this analysis are presented in Table IV. The first two columns provide strong support for **H2**. In the week following an inconsistent announcement (*Date[2:5]*), total insider sales increase by a significant \$0.45 million, and net sales increase by \$0.75 million. The subsequent columns disaggregate these trades to test **H2a** and **H2b**.[12] This disaggregation reveals a clear divergence in behavior that aligns precisely with the refined hypotheses. In support of **H2a**, top executives' planned sales increase by a statistically significant \$0.01 million in the week after an

[12]For the disaggregated analysis of planned versus unplanned trades, I focus on sales only. Including purchases in this detailed breakdown can introduce noise and complicate the interpretation of opportunistic and strategic motives. Robustness checks using net sales for these subsamples yield qualitatively similar results.

Table IV

Panel Time-series Regressions of Net Insider Sales

This table presents regression estimates of daily insider trading activity following earnings announcements. The dependent variables are the dollar volume of sales and net sales (sales minus purchases) in millions of dollars. The analysis uses a Difference-in-Differences (DID) specification where the key independent variables are the interactions between tonal consistency dummies (*Inconsistent* and *Positive Consistent*, with *Negative Consistent* as the omitted base group) and post-announcement event window dummies (*Date[-1:1]* and *Date[2:5]*). The analysis is performed on several subsamples. Columns (1) and (2) examine total and net sales for all insiders. Columns (3) and (4) focus on sales by top executives, disaggregated into planned (Rule 10b5-1) and unplanned (discretionary) trades. Columns (5) and (6) repeat this disaggregation for all other insiders. The sample consists of S&P 500 firms from 2006Q1 to 2023Q3. All specifications include the same control variables as in the CAR analysis, as well as firm and year-month fixed effects. Standard errors are clustered at the firm and year-month level. *t*-statistics are reported in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

	All Insiders		Top Executives Sale		Other Insiders Sale	
	Sale	Net Sale	Planned	Unplanned	Planned	Unplanned
Inconsistent	0.12	0.01	-0.00	-0.01	-0.00	0.13*
	(1.61)	(0.09)	(-1.38)	(-0.49)	(-0.03)	(1.78)
Positive Consistent	0.07	-0.01	0.00	-0.02	-0.01	0.10
	(0.54)	(-0.03)	(0.95)	(-1.09)	(-0.78)	(0.81)
Date[-1:1]	0.01	0.04	-0.00	0.00	0.00	0.00
	(0.12)	(0.40)	(-0.35)	(0.31)	(0.63)	(0.07)
Date[2:5]	-0.03	-0.28	0.00	0.01	0.00	-0.05
	(-0.35)	(-1.01)	(0.56)	(0.91)	(0.42)	(-0.61)
Date[-1:1] × Inconsistent	0.04	0.11	0.00**	-0.00	0.00	0.03
	(0.74)	(0.81)	(2.11)	(-0.23)	(0.28)	(0.57)
Date[2:5] × Inconsistent	0.45**	0.75**	0.01**	0.17	0.03	0.27***
	(2.53)	(2.21)	(2.10)	(1.22)	(1.20)	(2.70)
Date[-1:1] × Positive_Consistent	0.03	0.04	-0.00	-0.03	0.01	0.05
	(0.31)	(0.28)	(-0.15)	(-0.79)	(0.52)	(0.56)
Date[2:5] × Positive_Consistent	0.48**	0.88**	-0.00	-0.01	0.07	0.45**
	(2.19)	(2.41)	(-1.31)	(-0.33)	(1.03)	(2.39)
Constant	-0.03	-0.22	-0.17**	-0.20	0.07	0.18
	(-0.04)	(-0.20)	(-2.16)	(-0.76)	(1.01)	(0.30)
Observations	1,714,964	1,714,964	1,714,964	1,714,964	1,714,964	1,714,964
Firm FE	✓	✓	✓	✓	✓	✓
Year-Month FE	✓	✓	✓	✓	✓	✓
Controls	✓	✓	✓	✓	✓	✓
Adjusted R-sq	0.004	0.003	0.017	0.005	0.010	0.004

inconsistent announcement. In support of **H2b**, other insiders' unplanned sales increase by a highly significant $0.27 million during the same period. This two-tiered pattern, where narrative-setting executives engage in planned selling while other informed insiders trade opportunistically, provides compelling evidence that tonal inconsistency is a deliberate strategic tool, which serves as an opportunistic tool for non-top executives by creating an information friction that widens the information asymmetry between insiders and outsiders, providing a window to take advantage of this temporal gap.

An important question that follows is whether such strategic inconsistency also signals deteriorating fundamentals that managers are privately aware of—using mixed messaging as a means to delay full price adjustment and exit before bad news becomes publicly reflected in valuations. This motivates the next section, where we examine whether tonal inconsistency predicts future firm performance.

IV.III. Forecasting Firm Fundamentals through Tonal Discrepancies

To test whether tonal inconsistency is a strategic response to deteriorating firm prospects, I draw on disclosure and agency theories. These frameworks predict that managers have strong incentives to obscure negative information about future performance to protect their compensation, reputation, and career prospects. If tonal inconsistency is a tool used for this purpose, its presence should serve as a leading indicator of adverse future fundamentals. This theoretical linkage motivates the third primary hypothesis of this study:

Hypothesis 3 (H3): Tonally inconsistent announcements are followed by a decline in future firm operating performance.

To test this hypothesis, I examine whether firms that display tonal inconsistency between their earnings press releases and conference calls subsequently experience weaker operating performance. I define three forward-looking measures of firm fundamentals: operating income before depreciation (*Oibdpq*), net income (*Niq*), and sales (*Saleq*). Each measure is scaled by lagged total assets (*L1atq*) and measured one quarter ahead to capture future performance. The regressions include firm and year-month fixed effects, with standard errors clustered at both the firm and trading day level.

The findings in Table V provide strong support for **H3**, indicating that tonal inconsistency is a significant predictor of future performance deterioration. Specifically, firms with inconsistent messaging show significantly lower future profitability and revenue. These results persist even after controlling for earnings surprises, suggesting that tonal inconsistency provides incremental information beyond realized earnings performance. The results presented in Table V include standard controls and remain robust to the inclusion of the extended set of controls used in the appendix (Table A.III). This consistency across specifications strengthens the conclusion that tonal inconsistency serves as a reliable signal for adverse future fundamentals. Taken together, these results support the

Table V

Panel Regressions of Future Firm Fundamentals on Tonal Inconsistency

This table presents regression estimates of future firm fundamentals on tonal inconsistency between earnings press releases and earnings conference calls. The dependent variables are forward-looking measures of firm performance, each scaled by lagged total assets (*L1atq*): operating income before depreciation (*oibdpq*), net income (*niq*), and sales (*saleq*). These outcomes are measured one quarter ahead to capture forward-looking performance. The key independent variable is *Inconsistent*, a binary indicator equal to one when the tone differs across disclosure channels, and zero otherwise. The sample consists of S&P 500 firms from 2006Q1 to 2023Q3. All continuous variables are winsorized at the 1% level to mitigate the influence of outliers. Regressions include firm and year-month fixed effects, and standard errors are clustered at the firm and year-month level. Statistical significance at the 1%, 5%, and 10% levels is indicated by ***, **, and *, respectively.

	Oibdpq/L1atq	Niq/L1atq	Saleq/L1atq
Inconsistent	-0.14***	-0.11**	-0.49***
	(-2.59)	(-2.02)	(-3.10)
SUE	0.03***	0.02***	0.06***
	(4.80)	(3.06)	(4.82)
Size	0.47***	0.80***	-1.64***
	(4.80)	(7.69)	(-3.03)
log(BM)	-1.01***	-0.75***	-3.53***
	(-7.07)	(-5.45)	(-7.93)
Constant	-2.12**	-7.05***	32.52***
	(-2.27)	(-7.08)	(6.47)
Observations	24,747	24,747	24,747
Firm FE	✓	✓	✓
Year-Month FE	✓	✓	✓
Adjusted R-sq	0.440	0.252	0.911

view that managers strategically employ mixed messaging to obscure a negative outlook, thereby delaying full market recognition of real economic underperformance.

V. Mechanisms

This section empirically investigates the four primary channels through which tonal inconsistency could impact market price discovery: ambiguity, disagreement, information asymmetry, and inattention. As outlined in the introduction, each channel offers distinct and often competing predictions for market behavior. By systematically testing these predictions, I can distinguish the primary mechanism at play and provide a clear narrative for the observed market underreaction. The evidence presented below points overwhelmingly to ambiguity as the dominant channel, a conclusion that reshapes our understanding of the market's response to these strategic disclosures.

Table VI

Trading Volume and Bid-Ask Spread

This table presents the results of staggered event-time Difference-in-Differences (DiD) regressions, as specified in 2, examining the impact of tonal inconsistency on market liquidity and trading volume. The dependent variables are the *Standardized Spread*, *LVOL* (the natural logarithm of trading volume), and *MDAJVOL* (median-adjusted trading volume). The key independent variable is *Inconsistent*, a binary indicator equal to one when the tone differs across disclosure channels, and zero otherwise. The sample consists of S&P 500 firms from 2006Q1 to 2023Q3. All continuous variables are winsorized at the 1% level. All regressions include firm and year-month fixed effects, along with a set of control variables. Standard errors are clustered at both the firm and year-month level. t-statistics are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	Standardized Spread	LVOL	MDAJVOL
Inconsistent	-0.01**	0.00	-0.00
	(-2.44)	(0.58)	(-0.75)
Date[-1:1]	1.23***	0.55***	0.77***
	(48.27)	(55.19)	(27.44)
Date[2:5]	0.16***	0.17***	0.17***
	(12.18)	(32.54)	(22.28)
Date[-1:1] × Inconsistent	-0.01	-0.03***	-0.08***
	(-0.64)	(-3.53)	(-3.17)
Date[2:5] × Inconsistent	0.03***	-0.00	-0.01
	(2.74)	(-0.89)	(-0.97)
Constant	0.15**	2.10***	0.47***
	(2.55)	(10.48)	(5.54)
Observations	1,714,702	1,714,702	1,714,702
Firm FE	✓	✓	✓
Year-Month FE	✓	✓	✓
Controls	✓	✓	✓
Adjusted R-sq	0.274	0.589	0.138

The theoretical channels of disagreement and ambiguity offer directly competing predictions regarding market activity. Disagreement theory, rooted in models of heterogeneous beliefs (Varian, 1985; Miller, 1977), posits that conflicting signals should fuel trading as investors confidently act on their differing interpretations (Bamber et al., 1997; Kandel and Pearson, 1995). This would manifest as higher trading volume and potentially higher idiosyncratic volatility (Diether et al., 2002). In contrast, ambiguity theory predicts the opposite. Pervasive ambiguity, or Knightian uncertainty, leads to investor caution and passivity, as rational agents adopt a "wait-and-see" posture in the face of information that is difficult to price (Dow and Werlang, 1992; Epstein and Schneider, 2008). This should manifest as reduced trading volume and wider bid-ask spreads, as market makers increase spreads to compensate for their own uncertainty.

To test these competing predictions, I first examine trading volume around earnings announcements. I employ two standard measures of trading volume: *LVOL*, the natural logarithm of the percentage of shares outstanding traded, which corrects for the common positive skewness in volume data (Ajinkya and Jain, 1989); and *MDAJVOL*, the firm-specific median-adjusted percentage of shares traded, following Bamber et al. (1997). While prior work often cumulates volume over the 3-day event window ([-1, +1]) where trading is most concentrated, I compute these measures on a daily basis to implement a staggered event-time Difference-in-Differences (DiD) design.

The regression results, presented in Table VI, provide strong empirical support for the ambiguity channel. The coefficient on the event window indicator, *Date[-1:1]*, is positive and highly significant for both *LVOL* and *MDAJVOL*. This confirms the well-established finding that earnings announcements are high-information events that stimulate significant trading activity. The pivotal finding, however, emerges from the interaction term, *Date[-1:1]* $\times$ *Inconsistent*. For both volume measures, the coefficient on this interaction term is negative and statistically significant. This reveals that despite the general surge in trading during the announcement window, tonally inconsistent announcements are associated with a significant reduction in trading volume relative to their consistent counterparts. This finding of relative investor passivity directly contradicts the predictions of disagreement models, which posit heightened trading activity. Instead, it provides compelling evidence for the ambiguity channel, suggesting that the informational conflict suppresses trading as investors adopt a cautious "wait-and-see" approach.

To further test the ambiguity channel, I examine the standardized bid-ask spread. I measure the bid-ask spread using a standardized abnormal spread metric. This variable is constructed using a mean-adjusted model, where the abnormal spread for a given day is the raw spread minus the firm's average spread from a pre-event estimation window. This abnormal spread is then standardized by the standard deviation of the raw spread from the same estimation period, following the methodology of Corrado and Zivney (2000). Theoretically, ambiguity-induced information asymmetry is expected to create adverse selection risk for market makers, leading them to widen bid-ask spreads (Glosten and Milgrom, 1985; Krinsky and Lee, 1996; Hendershott et al., 2011). My findings are consistent with this prediction. As shown in Table VI, the standardized bid-ask spread is significantly wider in the week following tonally inconsistent announcements, providing further evidence that tonal inconsistency increases market friction and perceived uncertainty.

To more rigorously distinguish between the disagreement and ambiguity channels, I employ the diagnostic framework of Barron et al. (1998). This model allows for the decomposition of analyst forecast properties into underlying components of the information environment, providing a powerful lens through which to test competing theories. Specifically, I examine four key metrics derived from analyst forecasts: *Dispersion*, *Consensus* (ρ), *Common Info Quality* (h), and *Private Info Quality* (s). All measures are standardized by price, as is common in the literature.

Table VII

Properties of Analysts' Information Environment

TThis table presents Panel Time-series regression results examining the impact of tonal inconsistency on the properties of the analyst information environment, based on the diagnostic framework of Barron et al. (1998). The dependent variables are *Dispersion* (analyst forecast dispersion), *Consensus* (ρ), *Common Info Quality* (h), and *Private Info Quality* (s). The key independent variable is *Inconsistent*, a binary indicator equal to one when the tone differs across disclosure channels, and zero otherwise. The sample consists of S&P 500 firms from 2006Q1 to 2023Q3. All control variables are winsorized at the 1%. All regressions include firm and year-month fixed effects and a set of control variables. Standard errors are clustered at both the firm and year-month level. t-statistics are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	Dispersion	Consensus	Common Info Quality	Private Info Quality
Inconsistent	0.00	-0.00	-0.05***	-0.04**
	(0.96)	(-0.66)	(-2.97)	(-2.43)
Constant	0.03***	0.55***	-4.34***	-3.23***
	(7.23)	(6.37)	(-14.47)	(-10.96)
Observations	24,855	24,855	24,855	24,855
Firm FE	✓	✓	✓	✓
Year-Month FE	✓	✓	✓	✓
Controls	✓	✓	✓	✓
Adjusted R-sq	0.393	0.094	0.086	0.052

The results, presented in Table VII, provide robust evidence against the disagreement channel. The disagreement hypothesis predicts that tonal inconsistency should cause analysts' beliefs to diverge, leading to an increase in forecast *Dispersion*. My results show that the coefficient on *Inconsistent* in the *Dispersion* regression is statistically indistinguishable from zero. Furthermore, the Barron et al. (1998) framework provides a direct measure of analyst agreement, *Consensus* (ρ).

A decrease in ρ would signify an increase in disagreement. The results show that tonal inconsistency has no significant effect on ρ. The failure to find an increase in dispersion or a decrease in consensus provides strong, direct evidence against the disagreement channel.

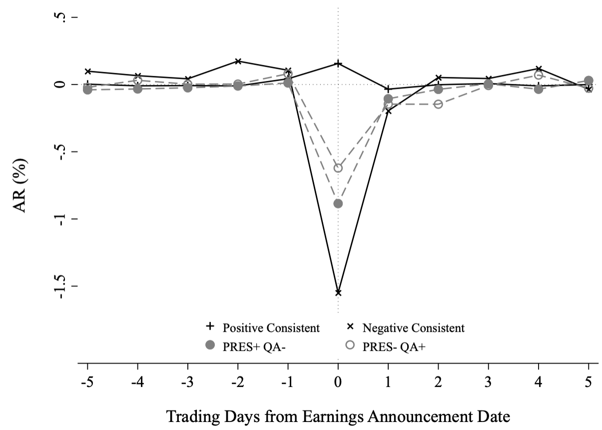
The framework also allows for a more nuanced understanding of uncertainty. The finding that tonal inconsistency does not significantly affect *Dispersion* or *Consensus* implies that it also does not increase analysts' perceptions of total uncertainty (V), as dispersion is a function of both total uncertainty and consensus. This result is crucial because it helps distinguish between two types of uncertainty: fundamental uncertainty about the firm's economic reality versus interpretive ambiguity about the signals provided by management. If inconsistency signaled higher fundamental risk, V would increase. The stability of V suggests that managers are not revealing new fundamental uncertainty but are instead creating interpretive ambiguity, making it difficult for analysts to process the information and update their beliefs. This is precisely the condition under which ambiguity theory predicts investor passivity.

Finally, the analysis reveals that tonal inconsistency is associated with a statistically significant decline in both *Common Info Quality* (h) and *Private Info Quality* (s). This indicates that the ambiguity created by managers is so pervasive that it degrades the entire external information environment. It contaminates not only the public signals available to all but also the private information that sophisticated analysts gather.

This conclusion is powerfully corroborated by a within-channel analysis focusing on inconsistencies between the prepared remarks (Presentation) and the Q&A session of a single conference call. As shown in Figure 4, these within-call inconsistencies—which are much rarer, occurring in about 20% of cases—still predict a similar negative post-announcement drift in cumulative abnormal returns. This finding further rules out explanations based on different audiences consuming different disclosure channels. It demonstrates that the effect is driven by the cognitive friction of integrating mixed signals, even when those signals are delivered to a homogeneous audience within the same session. Therefore, the primary friction is not a widening information gap between investors, but a shared state of ambiguity created by the cost of aggregating conflicting information.

To further adjudicate between competing theories, I examine idiosyncratic return volatility (*IVOL*) and directly test for investor inattention. An increase in *IVOL* could plausibly be predicted by disagreement theories (from active trading on divergent beliefs) or ambiguity theories (from price

Panel A: Daily Abnormal Returns around the Announcement Date



Panel B: Cumulative Abnormal Returns from One Day Before to Two Months After the Announcement

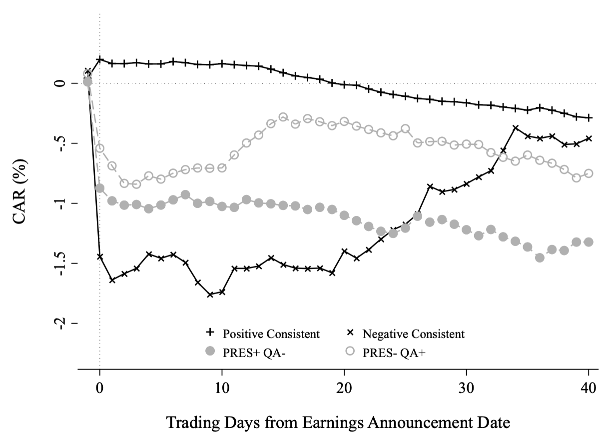


Figure 4. Abnormal Returns for Within-Conference Call Tonal Inconsistency: This figure plots the average abnormal returns for consistency groups defined by comparing the tone of the prepared remarks (Presentation) and the Q&A session of the same earnings conference call. This analysis serves as a robustness test to isolate the effect of conflicting signals within a single information event consumed by a relatively homogeneous audience. Abnormal returns are estimated using the Fama-French five-factor model (Fama and French, 2015) for S&P 500 firms from 2006Q1 to 2023Q3. Panel A shows daily abnormal returns around the announcement, while Panel B plots the cumulative abnormal returns for 40 trading days post-announcement.

oscillations as the market struggles to interpret the signal). My results in Table **??** show that the coefficient on *Inconsistent* is statistically insignificant for *IVOL* in both the *[0, 5]* and *[6, 20]* post-announcement windows. The absence of increased volatility provides further evidence against disagreement and is consistent with ambiguity-driven investor passivity.

A final alternative explanation is investor inattention, which is unlikely given that earnings announcements are high-salience events and my results are robust to standard inattention controls.

I directly test this channel using the Google Search Volume Index (*SVI*), a widely-used proxy for investor attention (Da et al., 2011; Drake et al., 2012). I measure both the raw *SVI* and Abnormal *SVI* (*ASVI*), which controls for day-of-the-week effects, over the [-1, 1] announcement window. As shown in Table VIII, the coefficients on *Inconsistent* are insignificant for both measures. This indicates that investors are not overlooking the information but are actively engaging with it at normal levels. The friction, therefore, appears to stem not from a lack of attention or volatility-inducing trading, but from the cognitive costs of integrating an ambiguous signal.

Table VIII

Idiosyncratic Volatility and Google Search Volume Index

This table presents Panel Time-series regression results examining the impact of tonal inconsistency on post-announcement idiosyncratic volatility and investor attention. The dependent variables are *IVOL[0:5]* and *IVOL[6:20]*, the annualized standard deviation of abnormal returns (estimated using the Fama-French (2015) five-factor model (Fama and French, 2015)) over the respective day windows. Other dependent variables are the *SVI*, the raw Google Search Volume Index, and the *ASVI*, the abnormal Google Search Volume Index. Both *SVI* and *ASVI* are aggregated over the three-day [-1, 1] earnings announcement window; *ASVI* is calculated by subtracting the average search volume from the same day of the week in the preceding month. The key independent variable is *Inconsistent*, a binary indicator equal to one when the tone differs across disclosure channels. The sample consists of S&P 500 firms from 2006Q1 to 2023Q3. All control variables are winsorized at the 1%. All regressions include firm and year-month fixed effects and a set of control variables. Standard errors are clustered at both the firm and year-month level. t-statistics are reported in parentheses. ***, **, and * denote statistical significance at the 1

	IVOL[0:5]	IVOL[6:20]	ASVI	SVI
Inconsistent	-0.01	-0.02	-0.10	0.09
	(-0.40)	(-1.13)	(-0.39)	(0.28)
Constant	7.26***	5.34***	-8.58*	41.24***
	(14.23)	(15.95)	(-1.89)	(6.32)
Observations	24,855	24,853	24,828	24,828
Firm FE	✓	✓	✓	✓
Year-Month FE	✓	✓	✓	✓
Controls	✓	✓	✓	✓
Adjusted R-sq	0.325	0.452	0.456	0.576

A final alternative explanation is investor inattention, which is unlikely given that earnings announcements are high-salience events and my results are robust to standard inattention controls. I directly test this channel using the Google Search Volume Index (*SVI*), a widely-used proxy for investor attention (Da et al., 2011; Drake et al., 2012). I measure both the raw *SVI* and Abnormal *SVI* (*ASVI*), which controls for day-of-the-week effects, over the [-1, 1] announcement window.

As shown in Table VIII, the coefficients on *Inconsistent* are insignificant for both measures. This indicates that investors are not overlooking the information but are actively engaging with it at normal levels. The friction, therefore, appears to stem not from a lack of attention or volatility-inducing trading, but from the cognitive costs of integrating an ambiguous signal.

The collective evidence from these tests provides a clear and coherent narrative. The empirical results systematically rule out disagreement, inattention, and information asymmetry between outside investors as the primary explanatory channels. Instead, the observed market behavior—suppressed trading volume, wider bid-ask spreads, and degraded information precision for all external agents—is uniquely consistent with ambiguity being the primary operative channel.

These findings provide strong empirical support for the formal theoretical proposition that strategic tonal inconsistency causes the asset price process to deviate from the pure random walk prescribed by the Efficient Market Hypothesis (Fama, 1970). In a perfectly efficient market, prices incorporate all new information instantaneously, with the information component of price changes following a process with no predictable drift:

$$P_{t+1} = P_t + \varepsilon_{t+1}, \quad \varepsilon_{t+1} \sim \mathcal{N}(0, \sigma^2) \tag{4}$$

where ε_{t+1} represents the unpredictable information innovation. However, the informational friction created by ambiguity breaks this assumption. The resulting investor passivity and gradual price discovery are better modeled by a Geometric Brownian Motion (GBM) (Merton, 1974) that includes a predictable drift component μ:

$$dP_t = \mu P_t \, dt + \sigma P_t \, dW_t \tag{5}$$

My findings provide strong support for the hypothesis that ambiguity induces a negative drift. This aligns with theoretical models where investors, faced with interpretive ambiguity, asymmetrically process information—underreacting to ambiguous good news while more fully incorporating ambiguous bad news (Epstein and Schneider, 2008). When tonal inconsistencies create such ambiguity, this asymmetric processing leads to a systematic underreaction and a gradual, predictable downward adjustment toward fundamental value.[13]

This validates the post-event price drift found in support of Hypothesis 1a. The cumulative abnormal returns documented in the two months post-disclosure are the empirical manifestation of this ambiguity-induced drift (Hypothesis 1b), governed by the process:

$$dP_t = -\alpha P_t \, dt + \sigma P_t \, dW_t, \quad \alpha > 0 \tag{8}$$

This negative drift represents the market's slow correction of an initial underreaction. As my findings on trading volume suggest, ambiguity leads to investor inaction, preventing the price from fully incorporating the negative signal on the announcement day. The subsequent, predictable drift is the price gradually adjusting downward toward the fundamental value that the tonal inconsistency implied.

This mechanism provides a theoretical rationale for phenomena like the post-earnings announcement drift. When an earnings announcement is ambiguous or confusing, the well-documented tendency for prices to drift in the direction of the surprise is especially pronounced. Epstein and Schneider (2008) formalize this idea: if investors receive a public signal of uncertain precision, prices adjust only partially at first, and subsequent corrections as uncertainty resolves create predictable post-event abnormal returns—a violation of the random walk.

It is important to note that rational investors are aware of this predictability, yet ambiguity itself prevents its complete arbitrage. While sophisticated investors may partially exploit these patterns—as evidenced by the gradual price correction over two months rather than indefinite persistence—several factors limit full arbitrage. First, ambiguity aversion is a first-order effect on investor behavior, unlike risk, which only has second-order (variance-proportional) effects (Jahan-

[13] Formally, consider the firm's fundamental value, V_t, evolving as a standard GBM:

$$dV_t = \mu_V V_t \, dt + \sigma_V V_t \, dW_t \tag{6}$$

Investors observe public signals s_t, with ambiguity about their precision σ_s^2. Following Epstein and Schneider (2008), ambiguity-averse investors price the asset based on a worst-case valuation within the set of possible signal precisions $[\underline{\sigma}_s^2, \overline{\sigma}_s^2]$. The ambiguity pricing rule is:

$$P_t = \min_{\sigma_s^2 \in [\underline{\sigma}_s^2, \overline{\sigma}_s^2]} \mathbb{E}_t[V_T \mid s_t, \sigma_s^2] e^{-r(T-t)} \tag{7}$$

This conservative updating implies that investors underreact to ambiguous good news (by assuming high variance) while more fully incorporating ambiguous bad news (by assuming low variance). This asymmetric response leads to a predictable negative drift in subsequent periods if the fundamental news is, on average, negative, or if ambiguity itself induces pessimism, a conclusion supported by the empirical findings of this study.

Parvar and Liu, 2014). Second, the very nature of ambiguous signals makes it difficult for arbitrageurs to distinguish between temporary mispricing and fundamental deterioration, creating uncertainty about the optimal timing and magnitude of contrarian positions. Third, investors demand compensation for bearing ambiguity—an "ambiguity premium"—which means ambiguous stocks can have higher expected returns as compensation for uncertainty (Jahan-Parvar and Liu, 2014).

This recognition of partial but incomplete arbitrage is consistent with the empirical patterns observed. The predictable drift documented in this study diminishes over time, suggesting that sophisticated investors do gradually exploit the mispricing, but the process is slow and incomplete due to the inherent uncertainty about the signal's interpretation. In asset-pricing terms, ambiguity is a priced factor: models that include an ambiguity factor help explain return patterns in equilibrium (Jahan-Parvar and Liu, 2014), implying that markets recognize ambiguity and price it in equilibrium, but this recognition does not eliminate the drift entirely because doing so would require taking on undesirable ambiguous risks. In other words, ambiguity itself creates a form of limits-to-arbitrage: even if a pattern is predictable, traders may rationally hesitate to bet against it when the information driving the pattern is unclear or non-verifiable.

Here, the negative drift term $-\alpha P_t \, dt$ represents the predictable downward price correction attributable to ambiguity aversion. This drift is not a classical arbitrage opportunity but rather compensation for bearing the Knightian uncertainty imposed by managers. The evidence of systematic insider selling post-disclosure, as documented, provides evidence consistent with managers being aware of this predictable downward trajectory and strategically creating the ambiguity to facilitate their trades at more favorable prices. The market's deviation from a random walk is, therefore, a direct consequence of the heightened cognitive integration costs that ambiguity imposes on market participants.

VI. Conclusion

This study provides evidence that tonal inconsistency between a firm's earnings press release and its contemporaneous conference call is not merely random noise, but rather appears to be a strategic choice with significant economic consequences. I show that these inconsistencies are a significant predictor of a subsequent downward drift in stock returns, with the market taking approximately two months to fully incorporate the negative information. This slow price adjustment suggests a novel, second-order manipulation strategy through which the relationship between disclosures may be used to impair market efficiency.

The strategic nature of this behavior is suggested by two key patterns. First, I document a significant increase in net selling by insiders following tonally inconsistent announcements. The data show a divergence in trading behavior that appears to align with insiders' roles in crafting the corporate narrative. I find that top executives—who are likely involved in crafting the disclosures—engage in significant planned selling under the safe harbor of SEC Rule 10b5-1, while other insiders engage in significant unplanned, opportunistic selling. Second, I show that these inconsistencies predict weaker future firm fundamentals, including lower profitability and revenue growth. Together, the combination of systematic insider selling and subsequent adverse firm performance provides evidence consistent with the view that tonal inconsistency reflects a deliberate strategy to exploit temporarily elevated valuations, rather than an incidental communication error.

Furthermore, this paper seeks to arbitrate between several competing theoretical channels through which such inconsistencies might affect markets. My results weigh against explanations based on investor disagreement or inattention. Instead of the heightened trading volume predicted by disagreement theories, I find significantly lower abnormal trading volume and wider bid-ask spreads, which is consistent with an investor retreat amid ambiguity. The high salience of earnings announcements, combined with a lack of abnormal search volume, suggests that inattention is an unlikely primary driver. The evidence, therefore, points toward ambiguity as the primary mechanism. By degrading the external information environment, these inconsistencies heighten the cognitive integration costs for market participants. This increase in ambiguity induces a deviation from a random walk, creating a predictable downward price drift. This drift persists because ambiguity itself creates limits to arbitrage; it is not a classical risk-based opportunity but reflects the market's slow correction of an initial underreaction to information shrouded in uncertainty. This interpretation is further supported by my finding that these inconsistencies also predict weaker future firm fundamentals, which suggests they convey substantive adverse information.

In sum, this paper makes several contributions to the literature on financial communication and market efficiency. First, I identify and provide a rich empirical account of a novel, second-order channel of information manipulation: the strategic engineering of inconsistency across related disclosures. Second, I quantify the consequences of this strategy, showing it creates a predictable, two-month downward price drift, widens bid-ask spreads, and suppresses trading volume. Third, by empirically distinguishing ambiguity from disagreement and inattention, I provide clear evidence for the specific mechanism through which this tactic operates. My findings underscore the importance of analyzing the qualitative dimensions of financial communication not just in isolation, but as an interconnected system where meaning is shaped by both content and consistency.

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Appendix

Table A.I

Contrast of Positively Stated points in Earnings Press Release with Negatively Stated Points in Earnings Conference Call for Amazon.com, Inc. (2013Q2)

This table contrasts the differences in tonal emphasis between Amazon's 2013Q2 earnings press release and its presentation section of conference call; the former tends to highlight positive aspects, while the latter reflects a more neutral or negative tone. Amazon.com, Inc., is a leading American multinational technology firm operating in e-commerce, cloud computing, online advertising, digital streaming, and artificial intelligence. Founded in 1994, Amazon trades on the NASDAQ under the ticker AMZN and is a member of the S&P 500.

Area of Comparison	**Earnings Press Release (Positive Tonality)**	**Earnings Conference Call (Negative Tonality)**
Operating Income	*"Operating income decreased 26% to $79 million in the second quarter, compared with $107 million in second quarter 2012. The unfavorable impact from year-over-year changes in foreign exchange rates throughout the quarter on operating income was $18 million."* Acknowledges the decrease but attributes a portion to unfavorable exchange rates, downplaying concerns about company performance.	*"GAAP operating income decreased 26% to $79 million or 0.5% of net sales."* Detailed mention of operating income as a small fraction of net sales, emphasizing a narrower margin and raising caution about profitability, also states the decrease without providing mitigating factors, emphasizing the decline as a potential issue.
Free Cash Flow	*"Free cash flow decreased 76% to $265 million for the trailing twelve months, compared with $1.10 billion for the trailing twelve months ended June 30, 2012. Free cash flow for the trailing twelve months ended June 30, 2013 includes fourth quarter 2012 cash outflows for purchases of corporate office space and property in Seattle, Washington, of $1.4 billion."* Presents free cash flow decrease but emphasizes that it's influenced by investment in corporate infrastructure, casting it as a strategic decision.	*"Trailing 12-month free cash flow decreased 76% to $265 million. Trailing 12-month capital expenditures were $4.27 billion. This amount includes $1.4 billion in purchases of previously leased corporate office space and property for development."* Reinforces the free cash flow decrease with specific capital expenditure details with a minor portion being allocated to corporate expenditures, reflecting caution regarding high expenditure without positive framing, highlighting significant cash outflows, which may concern investors.
Highlights and Achievements	*"Amazon and Viacom Inc. announced an expanded multi-year, multi-national digital video licensing agreement..." "Comedy pilots Alpha House and Betas... have been given the greenlight to begin production..." "Amazon announced that Kindle Fire HD and Kindle Fire HD 8.9" are now available to customers in over 170 countries..."* The press release extensively showcases positive developments, partnerships, product launches, and global expansions, emphasizing growth and innovation.	No mention of these highlights or services. Absence of any discussion on digital ecosystem or achievements, despite significant focus in the press release, suggesting a lack of emphasis on this area during the earnings call.
Operating Cash Flow	*"Operating cash flow increased 41% to $4.53 billion for the trailing twelve months, compared with $3.22 billion for the trailing twelve months ended June 30, 2012."* Emphasizes significant growth in operating cash flow, showcasing financial strength.	*"Trailing 12-month operating cash flow increased 41% to $4.53 billion."* States the increase but lacks enthusiastic language, presenting it in a neutral manner without positive emphasis.
Future Outlook on Operating Loss	*"No mention of estimated future operating losses."* The press release avoids discussing potential future losses, maintaining a positive tone by focusing on growth and customer-centric initiatives.	*"For Q3 2013, we expect... GAAP operating loss to be between $440 million and $65 million compared to $28 million in third quarter 2012."* Provides guidance that includes a significant potential operating loss, introducing a negative outlook for the upcoming quarter.

(Continued)

Table A.I – (Continued)

Area of Comparison	Earnings Press Release (Positive Tonality)	Earnings Conference Call (Neutral/Negative Tonality)
Forward-Looking Statements	*"Actual results could differ materially... including investments in new business opportunities, international growth and expansion, and management of growth."* Acknowledges unpredictability but focuses on growth factors, conveying optimism.	*"Our results are inherently unpredictable... including exchange rate fluctuations and consumer spending. It's not possible to accurately predict demand..."* Emphasizes uncertainties and external risks without mentioning growth, leading to a cautious tone.

Table A.II

Main Results: Panel Time-series Regressions of Cumulative Abnormal Returns

This table examines whether the market's response to tonal inconsistency is conditional on the nature of the underlying fundamental news. I create a *Negative News* indicator, which equals one if a firm's Standardized Unexpected Earnings (*SUE*) for the current quarter falls within the bottom three deciles of the SUE distribution from the same quarter of the previous year. This pre-determined cutoff is used to mitigate endogeneity concerns. The regression specification from Table III is augmented with this *Negative News* indicator and its interactions with the tonal consistency dummies. The key result is shown in the final column for the non-overlapping *CAR[21:40]* window. The coefficients on the interaction terms, particularly *Negative News × (EC -, PR +)*, are negative and statistically significant. This indicates that the delayed downward price drift following tonally inconsistent disclosures is significantly more pronounced when the firm is simultaneously delivering fundamentally negative news. This finding supports the hypothesis that managers use tonal inconsistency strategically to obfuscate the market's perception of adverse performance. All variable definitions, sample criteria, fixed effects, and standard error calculations are identical to those in Table III.Statistical significance at the 1%, 5%, and 10% levels is indicated by ***, **, and *, respectively.

	CAR[-1:1]	CAR[2:5]	CAR[6:20]	CAR[21:40]
Positive Consistent	2.41***	-0.12	0.18	0.22
	(5.42)	(-0.46)	(0.42)	(0.44)
EC +, PR -	1.74***	-0.02	0.33	0.12
	(3.92)	(-0.08)	(0.75)	(0.25)
EC -, PR +	0.92*	-0.09	-0.09	0.11
	(1.82)	(-0.29)	(-0.20)	(0.21)
Negative News	-1.33**	0.40	0.39	1.54*
	(-2.03)	(1.02)	(0.65)	(1.96)
Negative News × (Positive Consistent)	-0.84	-0.33	-0.41	-1.53*
	(-1.29)	(-0.84)	(-0.66)	(-1.91)
Negative News × (EC +, PR -)	-0.62	-0.44	-0.35	-1.47*
	(-0.95)	(-1.11)	(-0.57)	(-1.82)
Negative News × (EC -, PR +)	-0.40	-0.65	-0.09	-2.11**
	(-0.47)	(-1.51)	(-0.13)	(-2.45)
SUE	0.31***	0.02	0.00	-0.01
	(8.33)	(1.42)	(0.10)	(-0.29)
CAR(-12,-1)	-0.02***	-0.01***	-0.00	-0.01***
	(-5.68)	(-3.31)	(-1.34)	(-3.52)
CAR(-1,0)	-0.02**	-0.00	-0.01	-0.02
	(-2.20)	(-0.41)	(-0.55)	(-1.28)
Size	-0.37*	0.01	0.31**	-0.30*
	(-1.95)	(0.06)	(2.24)	(-1.68)
log(BM)	-0.59***	-0.14**	-0.31***	-0.51***
	(-4.06)	(-2.38)	(-2.88)	(-4.08)
Inst Own	0.80	-0.30	0.26	0.12
	(1.44)	(-1.28)	(0.54)	(0.19)
Constant	0.65	0.05	-3.99***	1.97
	(0.35)	(0.05)	(-2.77)	(1.04)
Observations	24,326	24,326	24,326	24,326
Firm FE	✓	✓	✓	✓
Year-Month FE	✓	✓	✓	✓
Adjusted R-sq	0.085	0.019	0.027	0.039

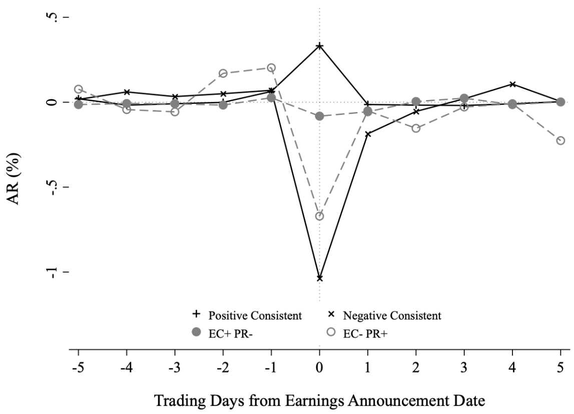
Table A.III

Main Results: Panel Time-series Regressions of Cumulative Abnormal Returns

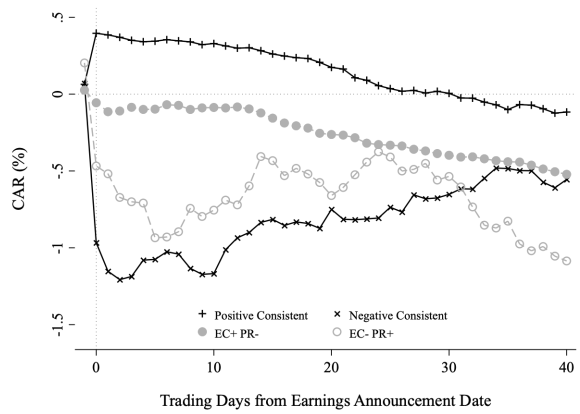
This table presents a robustness check for the main results reported in Table III to ensure the findings are not driven by investor inattention. The baseline regression specification is augmented with a set of controls that proxy for periods of potentially low investor attention or distraction. These include indicators for announcements made on Fridays (*Friday*) or after market hours (*PR After Hour*, *EC After Hour*). Additionally, to account for potential distraction effects, the model controls for the time elapsed between the two disclosures (*Time Difference*) and whether they occurred on different calendar days (*Different Days*). The key finding is that the coefficients on the tonal inconsistency dummies remain qualitatively similar to those reported in the main analysis. The persistence of the downward price drift for inconsistent announcements, even after accounting for these inattention proxies, provides strong evidence that the observed market reaction is driven by the strategic nature of the mixed messaging itself, rather than by simple investor distraction. All other variable definitions, sample criteria, fixed effects, and standard error calculations are identical to those in Table III. Statistical significance at the 1%, 5%, and 10% levels is indicated by ***, **, and *, respectively.

	CAR[-1:1]	CAR[2:5]	CAR[6:20]	CAR[21:40]
Positive Consistent	2.28***	-0.31*	-0.01	-0.65
	(5.58)	(-1.69)	(-0.02)	(-1.56)
EC +, PR -	1.61***	-0.25	0.15	-0.71*
	(3.99)	(-1.32)	(0.43)	(-1.74)
EC -, PR +	0.94**	-0.41*	-0.20	-0.95**
	(2.08)	(-1.80)	(-0.49)	(-1.98)
SUE	0.45***	0.02*	-0.00	-0.01
	(10.74)	(1.80)	(-0.07)	(-0.71)
CAR(-12,-1)	-0.01***	-0.01***	-0.00	-0.01***
	(-5.25)	(-3.36)	(-1.42)	(-3.59)
CAR(-1,0)	-0.01	-0.00	-0.01	-0.02
	(-1.64)	(-0.50)	(-0.57)	(-1.42)
Size	-0.29*	0.02	0.28**	-0.28
	(-1.71)	(0.23)	(2.07)	(-1.64)
log(BM)	-0.58***	-0.13**	-0.31***	-0.52***
	(-4.31)	(-2.36)	(-2.96)	(-4.28)
Inst Own	0.78	-0.33	0.27	0.11
	(1.43)	(-1.41)	(0.56)	(0.18)
PR After Hour	-0.00	0.13	-0.19	0.05
	(-0.00)	(1.13)	(-0.96)	(0.19)
EC After Hour	-0.28	-0.25*	0.07	-0.29
	(-1.39)	(-1.76)	(0.39)	(-1.02)
Time Difference	-0.01	-0.01	0.01	-0.04**
	(-0.99)	(-0.92)	(0.95)	(-2.27)
Different Days	0.13	0.03	-0.28*	0.67***
	(0.74)	(0.25)	(-1.79)	(2.60)
Friday	-0.29	-0.17	-0.02	0.15
	(-1.43)	(-1.32)	(-0.08)	(0.71)
Constant	-0.51	0.32	-3.43**	2.79
	(-0.30)	(0.36)	(-2.46)	(1.51)
Observations	24,618	24,618	24,618	24,618
Firm FE	✓	✓	✓	✓
Year-Month FE	✓	✓	✓	✓
Adjusted R-sq	0.069	0.019	0.027	0.039

Panel A: Consistency between Press Release and Presentation Section

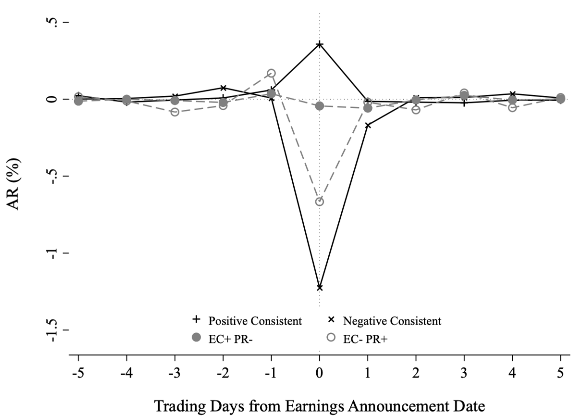


(a) Daily Abnormal Returns (AR)

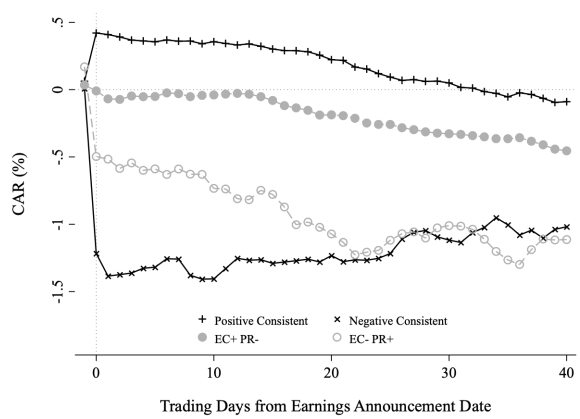


(b) Cumulative Abnormal Returns (CAR)

Panel B: Consistency between Press Release and QA Section



(c) Daily Abnormal Returns (AR)



(d) Cumulative Abnormal Returns (CAR)

Figure A.1. Abnormal Returns Across Consistency Groups with Different Classifications This figure plots the average abnormal returns for four categories of tonal consistency classifications. The sample includes S&P 500 firms from 2006Q1 to 2023Q3. Abnormal returns are estimated using the Fama-French five-factor model. Panel A presents results based on tonal consistency between the earnings press release and the presentation section of the conference call. Panel B presents results based on consistency with the Q&A section. Within each panel, the left plot shows daily Abnormal Returns (AR) and the right plot shows Cumulative Abnormal Returns (CAR).