Mixed Messages: Strategic Tonal Inconsistency and Recovery of the PEAD Anomaly

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Abstract

Using conference call transcripts and contemporaneous press releases, I document that inconsistent managerial tone across these communication channels recovers a narrative-driven form of the Post-Earnings-Announcement Drift (PEAD) anomaly that remains potent where the Standardized Unexpected Earnings (SUE)-based drift has been arbitraged away. Specifically, a downward drift arises following tonally inconsistent disclosures. This delayed price decline for inconsistent announcements facilitates strategic and opportunistic insider trading and is robustly associated with subsequent adverse changes in firm fundamentals. I validate that the documented tonal inconsistency is a non-random phenomenon, rather than linguistic noise, using a Large Language Model (LLM)-based placebo test. I further find that tonally inconsistent messaging reflects a strategy that is employed in response to poor firm performance and partially engineered through topical divergence between the two disclosures. 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, which appear to be induced by ambiguity.

Keywords: Tonal Inconsistency, Post-Earnings-Announcement Drift (PEAD), Corporate Communication, Strategic Disclosures, Information Diffusion, Sentiment Analysis, Large Language Models (LLMs), Topic Modeling, Disclosure Processing Costs, Price Discovery, Market Efficiency, Insider Trading, Ambiguity.

JEL classification: G14, G34, G41, D82, D83, M41, C55, K22.

I. Introduction

For decades, the Post-Earnings-Announcement Drift (PEAD) stood as one of the most canonical asset pricing anomalies. Famously established by Fama, 1998 as a foundational challenge to the Efficient Market Hypothesis (EMH), the anomaly demonstrated that stock prices do not instantaneously impound all public information following an earnings announcement. However, the long-standing consensus regarding its persistence has been challenged by recent evidence of the drift's decline, particularly in an era of sophisticated arbitrage (e.g., Chordia et al., 2014, McLean and Pontiff, 2016, and Martineau, 2022).

Recent work has explored the predictability of returns following an earnings announcement by conditioning on the tonality of corporate communications (e.g., Tetlock, 2007, Cohen et al., 2020, and Meursault et al., 2021). I contribute to this literature by considering mixed tonality across contemporaneous communication channels, what I term *tonal inconsistency*, and show that this novel measure recovers the post-announcement drift. This finding suggests that while the classic, Standardized Unexpected Earnings (SUE)-based PEAD has attenuated, a narrative-driven form of the anomaly persists, conditional on managers' strategic communication choices.

This strategic behavior is facilitated by the modern information environment, where the volume and complexity of corporate disclosures 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).

This paper argues that this complexity provides the mechanism through which a qualitative form of PEAD persists. I propose that as arbitrage has corrected the market's historical underreaction to quantitative earnings surprises, the persistent, unarbitraged component of market inefficiency resides in the qualitative domain, where managers can strategically impose processing costs. The study investigates an unexplored dimension of this strategy: the deliberate engineering of tonal inconsistencies across simultaneously released disclosures. My findings indicate that this tactic successfully generates a predictable, delayed market reaction. By documenting that a classic PEAD pattern arises following tonally inconsistent announcements while a price reversal follows tonally consistent ones, this paper recovers the anomaly, suggesting the drift is not a ubiquitous market failure but a conditional response to strategic managerial communication.

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 conventional 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 investigates an unexplored dimension of strategic communication: the deliberate engineering of tonal inconsistencies across simultaneously released disclosures. While such inconsistencies could be dismissed as mere communicative noise, this study posits they represent a sophisticated, meta-level manipulation strategy. This proposition finds theoretical support in Harbaugh et al. (2016), who demonstrate that rational managers have mean-variance news preferences: they prefer to report bad news with high inconsistency (variance) to reduce the signal's precision and dampen the market's negative reaction. I investigate whether and how managers employ this tactic between the earnings press release and the contemporaneous conference call to 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. I validate this conclusion using a novel placebo test, prompting a Large Language Model to generate a non-strategic, tonally consistent press release from each earnings call transcript. The divergence between the high consistency of this Large Language Model (LLM)-generated benchmark and the low consistency observed in manager-authored documents confirms the phenomenon is not a random artifact. Instead, these inconsistencies 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, which takes approximately two months to be fully incorporated by the market. By demonstrating this, the paper identifies a novel, cross-disclosure channel of information manipulation, 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 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

[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 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 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 origins of tonal inconsistency confirm its strategic nature, revealing a clear profile of the conditions under which it is deployed. The use of this tactic is not primarily driven by stable, observable CEO traits but is a dynamic response to a firm's immediate circumstances. Specifically, managers resort to this sophisticated communication strategy when they have both a clear incentive, such as poor performance or financial distress, and the opportunity afforded by a high-uncertainty environment. Moreover, its increased use under heightened external scrutiny, for example from a large institutional investor base or a female CEO, supports the interpretation of tonal inconsistency as a calculated tactic rather than a random error.

Furthermore, the construction of this inconsistency appears to be a deliberate act of narrative engineering. An analysis of the thematic content of the disclosures reveals that tonal divergence is partially associated with shifts in topical focus between the press release and the conference call. Specifically, inconsistency is most pronounced when managers alter the emphasis on complex, subjective, and forward-looking topics, such as non-GAAP financial metrics, forward-looking statements, and expressions of managerial uncertainty, providing managers with room to craft an inconsistent tone between the two concurrent disclosures.

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 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, 1984). 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. Therefore, while the managers' strategic action exacerbates a powerful information asymmetry between insiders and all outsiders, the primary friction among external market participants is probably 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 implements robustness tests to ensure the findings are not driven by specific methodological choices. Section VII 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 managerial narratives as a critical tool for influencing markets. Within this context, the paper contributes to the literature on market anomalies by providing a narrative-driven mechanism that recovers the PEAD, showing that the anomaly persists where the classic, SUE-based drift has weakened.

Second, it extends the research on investor information processing costs by identifying a novel strategy, the strategic creation of tonal inconsistency, through which managers actively impose such costs to impede efficient price discovery.

Finally, by linking these inconsistencies to agency conflicts and insider trading, this study provides new evidence on opportunistic managerial behavior. This paper connects these strands by proposing that managers, driven by agency incentives, strategically manipulate the consistency of their qualitative disclosures, and that this unexplored strategy is a key driver of the unarbitraged component of post-announcement drift. 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.

This study directly addresses the central tension in the modern PEAD literature: the documented attenuation of the classic, SUE-based drift against the persistent and robust underreaction to qualitative information. While a growing body of work finds that the returns to a SUE-based PEAD strategy have declined in an era of sophisticated arbitrage (e.g., Chordia et al., 2014, McLean and Pontiff, 2016, and Martineau, 2022), a parallel stream of research demonstrates that significant market underreaction persists within the textual domain of corporate disclosures (e.g., Tetlock, 2007, Li, 2010, Davis et al., 2012b, Cohen et al., 2020, Druz et al., 2020, and Meursault et al., 2021). This paper bridges these two findings by proposing that the unarbitraged component of the anomaly stems from strategic managerial narratives, offering a new perspective on the enduring puzzle of what Fama famously posited as the "granddaddy of all market anomalies". My primary contribution is to identify a specific, previously unexplored mechanism, the strategic use of tonal inconsistency across contemporaneous disclosures, as a key driver explaining why this foundational anomaly persists in a narrative-based form.

This work builds on a literature exploring the link between textual content and PEAD. The studies most proximate to this one are those that identify a narrative-based underreaction. Meursault et al. (2021) show that a text-based measure of surprise from conference calls generates a robust drift, while Feldman et al. (2009) find that the temporal change in tone in the MD&A section from one year to the next predicts the anomaly. This paper complements these findings by confirming that a narrative-driven PEAD persists where the SUE-based drift has faded. I extend this literature by identifying a novel and distinct mechanism. While prior work has identified market underreaction to complex information in a single document (Meursault et al., 2021) or to a temporal change in tone over time (Feldman et al., 2009; Cohen et al., 2020), , this study proposes that the anomaly stems from a more deliberate friction that exploits the inherent imprecision of language—a quality Quine (1973) famously characterized as its original "sin". I argue that this friction is strategically engineered by managers through tonal inconsistency across different, contemporaneous disclosure documents. This distinction is critical, as it shifts the focus from an information-processing failure to a deliberate, cross-document communication strategy linked to agency incentives and opportunistic behavior.

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. Theoretical work by Harbaugh et al. (2016) suggests that such inconsistencies are a key tool for managers. They model a framework where managers maximize the impact of good news by being consistent, but minimize the impact of bad news by being strategically inconsistent. I investigate whether and how managers employ this tactic in the qualitative domain.

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; Cao et al., 2023; 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), with some studies directly linking this opportunistic trading to market anomalies like PEAD (Dargenidou et al., 2018). 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 (e.g., Bushee and Huang, 2024). 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 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;

[2]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/.

[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.

therefore, I retain `<img>` tags when they contain more than 100 words of textual content.

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 S&P 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.

Market data of stocks, including returns, prices, and trading volumes, are obtained from the Center for Research in Security Prices (CRSP). Accounting data 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 McDonald (Loughran and McDonald, 2011) Master Dictionary[6]. I obtain data on insider trading from the London Stock Exchange Group (LSEG). Executive compensation and CEO characteristics data are extracted from ExecuComp, and some of the corporate governance measures are constructed from the Harvard Law School Corporate Charter Governance (CCG) dataset (Frankenreiter et al., 2022), which contains raw corporate charter text used to calculate the G-index and E-index governance measures. Analyst coverage and estimates data are obtained from I/B/E/S Summary History files.

Sentiment scores of executives' language for both channels were computed using a lexicon-based approach, specifically employing the Loughran and McDonald dictionary, which is designed for financial text analysis. This dictionary classifies words into predefined sentiment categories

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

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

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 presentation or Q&A section, of firm j in quarter q of year t. I employ a standard Natural Language Processing (NLP) method to quantify the tone of corporate disclosures. 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]

[Insert Figure 1 about here]

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 inconsistencies between earnings press releases and sections of earnings conference calls have risen

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

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.

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.

[Insert Table I about here]

To illustrate my approach, consider the example 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 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. This drift illustrates a significant delay in price discovery. As shown in Panel B, the week following the earnings announcement experienced an abnormal volume of insider net sales, which exceeds the daily average net sales for Amazon's stock.

[Insert Figure 2 about here]

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.

To provide a deeper understanding of the prevalence and characteristics of tonal (in)consistencies 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. The data reveals over 17,000 firm-quarters with tonal inconsistencies, of which 954 are cases where a positive press release is paired with a negative earnings call presentation, a group for which my results are particularly pronounced.

[Insert Table II about here]

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 patterns 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.

To address the possibility that my measure of tonal inconsistency is capturing random linguistic variation rather than a deliberate strategic choice, I conduct a placebo test designed to establish a non-strategic benchmark. As shown in Panel C of Figure 1, the tonal divergence between press releases and earnings calls has widened over time. I therefore focus the analysis for this placebo test on a subsample of earnings calls from 2022, a recent year where the incidence of inconsistency is particularly high; this choice subjects the placebo methodology to a stringent test. If a synthetically generated, non-strategic counterpart is found to be highly consistent, even when based on transcripts from a period where manager-authored documents are highly inconsistent, it validates that my measure is correctly distinguishing between random linguistic noise and the potential layer of strategic framing added by managers. The goal is to determine the baseline rate of inconsistency that would occur if press releases were simply neutral, tonally consistent counterparts of their corresponding earnings calls, devoid of any strategic framing by management.

To generate this benchmark, I use a large language model (LLM), gpt-4.1-mini, and for each earnings call transcript in the 2022 subsample, I prompted the model with a set of specific, neutral instructions. These instructions required the model to create a press release based exclusively on the provided transcript, to add no outside information or sentiment, to ensure the tone was a faithful reflection of the source, and to factually report all financial results mentioned.[8] To construct this

[8]The model used is gpt-4.1-mini-2025-04-14 from OpenAI (https://platform.openai.com/). The exact prompt is as follows: *"Your task is to create a press release that is a direct and tonally consistent summary of the following earnings conference call transcript. Instructions: 1. Base the press release exclusively on the information provided in the transcript. 2. Do not add any outside information, speculation, or sentiment that is not present in the source text. 3. The tone of the press release must be a neutral and faithful reflection of the tone in the source transcript. 4. Factually report all financial results and management commentary mentioned in the transcript. Earnings Conference Call Transcript:"*

non-strategic benchmark, the full, unaltered text of executive remarks in the presentation section of earnings conference calls was provided to the LLM. I deliberately retained all firm- and time-specific information, as this context is essential for generating a realistic press release. Since my objective is the retrospective generalization of a known information event rather than prediction, traditional concerns of look-ahead bias are not applicable to this research design. In fact, to the extent that any such bias could exist (e.g., from the model's training data containing information beyond the transcript), it would likely cause the LLM to generate a document more akin to an actual, manager-authored press release. This potential effect would work against my hypothesis, making the research design more conservative and the large observed difference in inconsistency even more compelling.

This process effectively creates a placebo test. Since the LLM-generated press release is engineered to be a faithful reflection of the earnings call, any valid sentiment measure should find a high degree of tonal consistency between them. After generating this synthetic dataset of press releases, I applied the exact same Loughran and McDonald dictionary-based analysis to both the LLM-generated documents and the original earnings call transcripts to classify each pair as tonally consistent or inconsistent. This allows for a direct comparison between the high inconsistency rate observed in the real world and the baseline rate expected from purely non-strategic communication.

[Insert Table III about here]

Table III presents the results of this placebo test. Panel A shows that when comparing the LLM-generated press releases to the original earnings calls, my sentiment measure finds a high degree of consistency, with 91.1% of the pairs having the same tonal polarity. Panel B shows that for the original, real-world press releases, only 31.7% are tonally consistent with their corresponding earnings calls, while a substantial 68.3% are inconsistent. The dramatic divergence between the non-strategic benchmark (8.9% inconsistency) and the observed real-world rate (68.3% inconsistency) indicates that the high level of tonal mismatch in corporate disclosures is not random noise. Instead, it validates that the measure is capturing a phenomenon more consistent with a potential strategic choice than with random noise, which provides the basis for the subsequent analyses.

To further ensure that my inconsistency measure captures a meaningful divergence in narrative rather than a simple artifact of word counts, I analyze the underlying distributions of tonal imbalance. The robustness of the tonal classification methodology is underscored by the magnitude of these imbalances. Across the full sample, the mean absolute word difference is 18.92 for press releases, 42.55 for earnings call presentations, and 35.80 for Q&A sections. Figure 3, which plots the frequency distribution for absolute word differences up to a threshold of 50 words, provides further visual evidence confirming that the measure captures a non-trivial divergence in communicative posture across disclosure channels.

[Insert Figure 3 about here]

Table IV presents summary statistics for the key variables used in our analysis, partitioned by disclosure consistency. On initial inspection, the average polarity is consistently lower for the inconsistent group across all disclosure channels. The other notable differences appear to be in measures of performance and risk; firms issuing inconsistent disclosures tend to exhibit lower *SUE*, weaker financial performance, and higher volatility. These patterns suggest that tonal inconsistency is associated with adverse firm conditions, a finding that I explore in more detail in the subsequent sections.

[Insert Table IV about here]

The primary analysis relies on the Loughran and McDonald (2011) dictionary and classifies tonality using a zero threshold. To ensure the results are robust to this specification, I test several alternative measures. First, as an alternative to the Loughran and McDonald word lists, I employ Diego Garcia machine-learning-based dictionary (García, Hu, and Rohrer, 2023). Second, because the distribution of inconsistency groups under the simple zero threshold is not evenly distributed (as shown in Table II), I also consider four alternative benchmarks for classification to ensure the results are not driven by this concentration. These benchmarks are: (i) the firm-level time-series mean, (ii) the firm-level time-series median, (iii) the cross-sectional year–month level mean, and (iv) the cross-sectional year–month level median. Tonality is classified as "positive" if above a given benchmark and "negative" if below. These alternative benchmarks produce more evenly distributed inconsistency groups, and the main results are qualitatively similar across all specifications. Appendix Table A.II presents a correlation analysis of all binary polarity measures derived from the different dictionaries and benchmarks. The analysis shows that all measures are positively correlated, both in the aggregate and at the disclosure-channel level, confirming their suitability for robustness testing.

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-*.[9]

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

[9] 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.

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).[10] The announcement date is 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 4 provides initial visual support for **H1**. Panel A, which focuses on a window from a week before the earnings announcement to the announcement day, shows that the inconsistent groups experience a much less negative abnormal return than the *Negative Consistent* group. Importantly, while the pre-event returns of the four groups are not distinguishable, on the event day we see the result that one might expect from the work of Hirshleifer and Teoh (2003). This supports H1(a), suggesting that tonal inconsistency successfully moderates the immediate negative price response.[11]

However, an alternative interpretation could be that the tonally inconsistent announcements are simply communicating news that is fundamentally less negative than that of the uniformly negative announcements. In this view, the market's muted reaction is not a sign of investor confusion but an efficient response to mixed, rather than purely bad, news. To distinguish this possibility from a strategic obfuscation that causes investor underreaction, I look at the post-announcement period.

[10] 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.

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

If the market is perfectly efficient, there should be no subsequent price correction. The presence of a significant negative drift following the event, as predicted in **H1(b)**, would be inconsistent with an efficient market reaction and would support the theory that investors initially underreact to the complex signal.

Panel B plots the post-announcement cumulative abnormal returns (CAR) with 95% confidence intervals calculated using standard errors clustered by both date and firm, providing clear support for **H1(b)**. The results show a statistically significant downward drift for both inconsistency groups (EC -, PR + and EC +, PR -), with their confidence bands remaining entirely below zero throughout the 40-day window. This provides robust evidence that the initial underreaction is not a statistical artifact but a delayed absorption of negative information. The drift is most striking for the EC -, PR + group, whose CAR after two months falls below even that of the Negative Consistent group, indicating a more pronounced long-term correction. In contrast, the consistent groups show a pattern of reversal, aligning with well-documented investor overreaction behavior (Tetlock, 2007; Davis et al., 2012b; García, 2013), rather than a persistent drift. The statistical distinction between these patterns provides strong support for the hypothesis that tonal inconsistency is a key driver of the PEAD anomaly.

[Insert Figure 4 about here]

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:

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

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 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.[12] 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 and reversal 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 firm and date clustered standard errors, to address potential cross-sectional and temporal dependencies.

Table V 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 **H1(a)**. 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. However, this attenuation may simply reflect events that are fundamentally less negative than the consistent negative messaging events, a possibility that the test of PEAD will address.

[Insert Table V about here]

The subsequent columns test for the delayed drift predicted by **H1(b)**. Panel A, which uses non-

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

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 4.

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.

To complement the regression results and provide a dynamic visualization of the PEAD, Appendix Figure A.2 plots the daily evolution of this drift for the tonally inconsistent groups, with abnormal returns cumulated starting from the second trading day after the announcement. The plotted lines represent the coefficients on the tonal inconsistency indicators (β_2 for *EC+, PR-* and β_3 for *EC-, PR+*) from Equation 2. These coefficients are estimated from daily panel regressions that incorporate the full set of standard controls and include firm and year-month fixed effects, ensuring the depicted drift is not an artifact of omitted variables. The statistical significance of this drift is particularly strong for the *EC-, PR+* group, where the 95% confidence interval remains below zero for nearly the entire post-announcement period. For the *EC+, PR-* group, the negative drift becomes statistically significant in the second half of the window, reinforcing the delayed nature of the price correction.

This provides an evidence for my core argument that a narrative-driven form of the post-announcement drift persists, conditional on the strategic deployment of tonal inconsistency across communication channels. The figure plots the trajectory of this drift, illustrating the smooth and gradual incorporation of adverse information into the stock price over the 40-day window. This delayed price discovery, which persists after controlling for all standard risk factors, is characteristic of the classic PEAD anomaly. The evidence suggests that while arbitrage may have corrected market inefficiencies related to quantitative surprises, investor underreaction persists when faced with the qualitative complexity introduced by inconsistent managerial tone.

To ensure the observed market underreaction is not driven by investor inattention, I test whether the results are robust to controls for announcement timing. Panel A of Appendix Table A.III presents these results. The models include a set of controls that proxy for periods of potentially low investor attention or distraction. These include indicators for announcements made on Fridays or after market hours, times when investor attention is typically lower. Additionally, to account for potential distraction effects, the model controls for the time elapsed between the two disclosures and whether they occurred on different calendar days. Furthermore, I control for analyst coverage to ensure that the documented market underreaction is not merely a consequence of lack of analyst attention. The coefficients on the inconsistency variables remain largely unchanged, suggesting that inattention is not the primary driver of the documented drift.

Also, I address the alternative explanation that the cross-document tonal inconsistency I measure is merely a proxy for more established, conventional manipulation strategies within a single document. The existing literature has shown that managers can increase processing costs by making a single disclosure more complex or ambiguous. To isolate my proposed meta-level strategy, I explicitly control for these single-document tactics. Panel B of Appendix Table A.III shows that the predictive power of tonal inconsistency persists even after including a set of textual controls for linguistic ambiguity and complexity. These controls, derived from the Loughran and McDonald (Loughran and McDonald, 2011) Master Dictionary, include the frequency of words from distinct linguistic categories known to create uncertainty or increase processing costs, scaled by the total number of words in each document. These measures include the ratio of weak modal words (a proxy for hedging, e.g., "could", "might"), the ratio of uncertainty words (a proxy for vagueness, e.g., "approximately", "depends"), and the ratio of litigious words (a proxy for legal risk, e.g., "lawsuit", "allege"). Additionally, I control for textual complexity using the average number of syllables per word as a measure of readability. The robustness of the results indicates that the strategic conflict between disclosures is a distinct phenomenon, not subsumed by the baseline complexity or ambiguity of the individual documents.

Furthermore, I test whether the documented market underreaction is driven by the firm's underlying risk profile rather than the specific communication strategy. A firm's inherent uncertainty could confound the results if it is correlated with both the use of inconsistent language and a delayed price discovery process. To mitigate this concern, Panel C of Appendix Table A.III includes controls for the firm's lagged idiosyncratic return volatility and the volatility of its operating performance. The results show that the coefficients for tonal inconsistency remain significant, confirming that the effect is attributable to the strategic disclosure choice rather than the firm's overall risk environment. Finally, Panel D provides the most stringent test by including all attention, linguistic, complexity, and firm risk controls simultaneously, demonstrating that the predictive power of tonal inconsistency is robust even in this comprehensive "horse race" specification.

To ensure the results are not driven by CEO characteristics such as communication style, the model is re-estimated with CEO fixed effects. The findings, reported in Appendix Table A.IV, remain consistent, which suggests that the market's reaction can be attributed to the event-specific signal of tonal inconsistency, rather than to the time-invariant communication style of a particular CEO.

Having established that tonally inconsistent disclosures lead to an attenuated immediate price reaction followed by a subsequent negative drift (H1), I now seek to understand the drivers of this post-announcement correction. I hypothesize that the downward drift is primarily attributable to firms where tonal inconsistency is paired with fundamentally adverse earnings news. This analysis allows me to investigate whether the post-announcement drift is primarily driven by the subset of inconsistent disclosures that are accompanied by negative earnings surprises. To test this, the regression specification from Table V is augmented *Negative News* indicator and its interactions with the tonal consistency dummies. *Negative News* equals one if a firm's Standardized Unexpected Earnings for the current quarter falls within the bottom three deciles[13] of the SUE distribution from the same quarter of the previous year. This pre-determined cutoff is used to mitigate endogeneity concerns.

The findings in Table VI support this hypothesis, revealing that the post earnings announcement downward drift is exacerbated in firms that pair inconsistent tone with the most negative earnings surprises. Specifically, in the *CAR[21:40]* window, the coefficients on the interaction terms are negative for both inconsistent groups. The effect is particularly pronounced for the *Negative News* $\times$ *(EC -, PR +)* group, consistent with the baseline results in Table V where this group also exhibited

[13] The results are qualitatively the same when two or four decile cutoff points are considered instead.

the strongest negative drift. This indicates that the negative drift is significantly amplified for this group when they are also delivering adverse earnings news. This finding suggests that the market's delayed correction is a targeted response to the adverse fundamental news, which, in the presence of mixed tonal signals, was not efficiently impounded into prices during the event window.

[Insert Table VI about here]

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 inefficiency is not uniform; rather, it is significantly more pronounced when tonal inconsistency coincides with fundamentally adverse earnings news. This finding sharpens a critical question: are these mixed messages the result of accidental variation in tone, which leads to unanticipated price responses that may reflect market inefficiency but little else, or are they a deliberate strategy by managers using tonal inconsistency to obfuscate the market's perception of adverse performance? 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 apparent 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 first step, but tonal inconsistency is not necessarily 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 inconsistent narrative to create a window of mispricing, a 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:

H2(a): 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.

H2(b): 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 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 Difference-in-Differences style event-study framework, 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-announcement 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 date 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 **H2(a)** and **H2(b)** as well.

The results of this analysis are presented in Table VII. The first two columns provide strong support for **H2**. On an average day in the week following an inconsistent announcement (*Date[2:5]*), net sales are higher by \$0.75 million. The subsequent columns disaggregate these trades to test **H2(a)** and **H2(b)**.[14] This disaggregation reveals a clear divergence in behavior that aligns with

[14]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.

the refined hypotheses. In support of **H2(a)**, the average daily planned sales by top executives increase by a statistically significant \$0.01 million, a more than threefold increase relative to the sample's average daily planned sale by top executives of \$0.003 million. In support of **H2(b)**, the average daily unplanned sales by other insiders increase by a statistically 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 evidence that tonal inconsistency is a strategic tool which creates an information friction that widens the information asymmetry between insiders and outsiders.

[Insert Table VII about here]

An important question that follows is whether such strategic inconsistency also signals deteriorating fundamentals. 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 date level.

[Insert Table VIII about here]

The findings in Table VIII provide 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 VIII 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 view that managers strategically employ mixed messaging to obscure a negative outlook, thereby delaying full market recognition of real economic underperformance.

V. Mechanisms

The preceding sections establish that tonal inconsistency is a significant and strategic phenomenon with real market consequences. The findings, that it predicts negative future returns and facilitates opportunistic insider trading, strongly suggest that it is a deliberate act rather than random noise. A deeper understanding of this strategy, however, requires investigating the underlying mechanisms from multiple perspectives. This section, therefore, undertakes a three-part exploration. First, it investigates the origins of this behavior by identifying the *ex-ante* firm and CEO characteristics that predict the use of tonal inconsistency. Second, it examines how these mixed messages are engineered by analyzing the topical content of the disclosures. Finally, it suggests the channel of information friction through which these inconsistencies operate to impair market efficiency.

V.I. The Drivers of Strategic Inconsistency

If tonal inconsistency is indeed a strategic choice, as the evidence on insider trading and future fundamentals suggests, then its usage may be predictable based on a set of *ex-ante* firm and managerial characteristics that proxy for the incentives and opportunities to engage in such behavior. To test this prediction, I develop a panel logistic regression model where the dependent variable is a binary indicator for the presence of tonal inconsistency. The explanatory variables are drawn from four distinct channels identified in the literature that are likely to drive strategic disclosure choices: firm performance and financial distress, firm risk and uncertainty, corporate governance and monitoring, and the observable traits and incentives of the CEO. This framework allows for a direct test of the conditions under which managers are most likely to employ this sophisticated communication tactic.

The first channel I investigate is the influence of observable CEO characteristics. To capture a CEO's behavioral biases, demographics, and incentives, I test a set of standard variables from the literature. Overconfidence is a dummy variable that identifies CEOs with a revealed long-term optimism, constructed based on their tendency to hold stock options even when they are deep in the money (Malmendier and Tate, 2005). Female is a dummy variable for CEO gender, which a large body of literature links to systematic differences in managerial style, with female executives often found to be less overconfident and more risk-averse than their male counterparts (e.g., Huang and Kisgen, 2013; Faccio et al., 2016). CEO Tenure is included as a proxy for experience and potential entrenchment (Hermalin and Weisbach, 1998). Finally, to capture direct financial incentives, I include the Equity Pay Ratio, defined as the ratio of stock and option awards to total direct compensation, and CEO Ownership, the percentage of the firm's shares owned by the CEO. I also analyze the effect of CEO Age which is a common proxy for risk aversion based on the "career horizon" hypothesis (Yim, 2013); however, due to its high correlation with CEO Tenure, it is excluded from the main specifications to avoid multicollinearity. Untabulated robustness checks show that its inclusion does not alter the main fin

The results from the logit regressions, reported in Table IX, suggest that observable CEO traits are not the primary drivers of tonal inconsistency. The F-test for the joint significance of all CEO characteristics is not statistically significant (p-value = 0.112), indicating that this channel, as a whole, has limited explanatory power. Individually, most traits, including overconfidence and financial incentives, do not show a significant association with inconsistency. The one exception is the Female CEO indicator, which is positive and marginally significant. This finding aligns with the "scrutiny hypothesis", suggesting that female executives, who often face more intense monitoring from investors and boards (e.g., Farrell and Hersch, 2005; Adams and Ferreira, 2009), may be more likely to employ sophisticated communication strategies to manage perceptions, a behavior also observed in firms with high institutional ownership.

[Insert Table IX about here]

The second channel explores the role of corporate governance, which provides the formal framework of rules and monitoring that can either constrain or enable a manager's strategic behavior. I test four widely used governance measures. The G-Index and E-Index are indices of managerial entrenchment based on the number of anti-takeover provisions a firm has in place, where a higher score indicates weaker governance and greater managerial entrenchment (Gompers, Ishii, and Metrick, 2003; Bebchuk, Cohen, and Ferrell, 2009). To construct these measures, I use the raw text of corporate charters from the Harvard Law School CCG Corpus, which provides data until 2021 (Frankenreiter et al., 2022). Similar to text-based methodologies in the literature that extract quantitative measures from qualitative disclosures (e.g., Li, 2008; Tetlock et al., 2008), I employ a natural language processing (NLP) approach with regular expressions to identify each of the anti-takeover provisions within the charter text. To capture the effect of external monitoring, I also include Institutional Ownership, the percentage of shares held by institutional investors, and Analyst Coverage, the logarithm of one plus the number of analysts providing earnings forecasts for the firm. For both of these measures, a higher value is associated with stronger governance due to increased monitoring by sophisticated investores (Shleifer and Vishny, 1986; Hartzell and Starks, 2003) and greater scrutiny from information intermediaries (Yu, 2008).

The results for the governance channel, presented in Table IX, are jointly significant (p-value < 0.001) and reveal a nuanced story. Stronger internal governance, as measured by a lower *E-Index*, is associated with a lower likelihood of inconsistency, supporting the view that formal rules can constrain strategic communication. Due to the high collinearity between the *E-Index* and the broader *G-Index*, only the more focused *E-Index* is included in the main specification; untabulated results using the *G-Index* are qualitatively similar. The most striking finding, however, comes from external monitoring. *Institutional Ownership* is positive and highly significant, suggesting that firms with more sophisticated owners are more likely to exhibit tonal inconsistency. This result is consistent with the "scrutiny hypothesis" also observed for *Female CEOs*, where managers facing more intense monitoring may substitute away from more overt forms of management and instead employ more sophisticated communication strategies to shape the narrative when facing a more demanding audience.

Third, I examine the role of firm performance and financial distress. The link between poor corporate performance and the likelihood of manipulating disclosures is clear and well-established in the literature, as managers facing pressure have strong incentives to obfuscate or delay bad news to avoid negative career and capital market consequences (e.g., Fama, 1980; Healy, 1985; Kothari et al., 2009). To test this, I use a suite of standard performance measures. *ROA* (Return on Assets) and *ROE* (Return on Equity) capture quarterly profitability, while *CFOA* (Cash Flow on Assets) provides a less-manipulable measure of operating performance. *Sales Growth* measures the firm's growth trajectory. To capture financial distress risk, I use both the *Altman Z-Score* (Altman, 1968), where lower values indicate higher risk, and the *Ohlson O-Score* (Ohlson, 1980), where higher values indicate higher risk. To avoid issues of multicollinearity, not all measures are included in the same specification; Table IX shows the results for a representative set of measures, while untabulated tests for the remaining measures yield consistent results. The results in Table IX strongly support this channel. The F-test for the joint significance of all performance variables is highly significant (p-value < 0.001). Individually, lower profitability and higher financial distress risk are both associated with a significantly higher probability of using tonal inconsistency, confirming that this behavior is a response to poor underlying fundamentals.

Finally, I investigate the role of corporate risk and uncertainty. A volatile information environment provides managers with greater scope for manipulation, as inconsistent messaging can be more easily attributed to genuine business uncertainty rather than a deliberate strategic act by investors. I test this using three types of risk measures. *Idiosyncratic Volatility* measures firm-specific stock market risk by using the residuals from a Fama–French three-factor model, and *Operating ROA Volatility* measures fundamental business risk using the standard deviation of quarterly operating returns. I also examine *Total Return Volatility*, defined as the standard deviation of a firm's daily stock returns over the quarter. As shown in Table IX, this channel is a powerful predictor of inconsistency (joint F-test p-value < 0.001). Both higher idiosyncratic volatility and, more strongly, higher operating ROA volatility are significantly associated with a greater likelihood of using inconsistent messaging. Total Return Volatility yields qualitatively similar results, but due to high collinearity, it is excluded from the main specification; untabulated results confirm this finding. This suggests that tonal inconsistency is a strategy employed by managers in response to both market-perceived uncertainty and the instability of their core business operations.

Taken together, the evidence presented in this section provides a clear profile of the conditions under which managers are most likely to employ tonal inconsistency. The strategy is not primarily driven by the stable, observable traits of the CEO. Rather, it is a dynamic response to the firm's immediate circumstances and governance environment. The results strongly indicate that managers resort to this sophisticated communication tactic when they have both the incentive to do so—driven by poor performance and high financial distress risk—and the opportunity that a high-uncertainty environment provides. Furthermore, the evidence from variables linked to external monitoring constraints indicates that tonal inconsistency is a sophisticated strategy, employed more when managers face the heightened scrutiny.

V.II. Engineering Tonal Inconsistency

I now turn to the underlying mechanism of the construction of tonal inconsistency. For a manager to strategically craft a tonally inconsistent narrative, there are two primary levers at their disposal: lexical choice and thematic emphasis. First, a manager can engage in lexical framing by altering their word choice while discussing a consistent set of topics. Second, a manager can create tonal divergence by strategically shifting the thematic focus between disclosures; for example, by emphasizing topics that lend themselves to positive language in the press release while shifting to topics that require more cautious framing in the subsequent conference call. The Amazon.com Inc. example from Section III illustrates this clearly: the positive press release highlighted topics like "Kindle Fire HD" and "global expansion", while the more negative conference call omitted these and shifted its emphasis to operating income and cash flow challenges. This divergence in thematic emphasis is a plausible mechanism through which the overall tonal inconsistency is manufactured.

To quantify and test the role of this thematic emphasis lever, I employ topic modeling, a computational method that quantifies the thematic composition of each disclosure by representing it as a vector of topic weights that sum to one. This allows me to measure the degree to which different themes are emphasized in each document and, consequently, to test for divergence between them. I employ the Structural Topic Model (STM) (Roberts et al., 2014), which is a is a textual dimension reduction technique that automatically groups terms into interpretable themes based on their co-occurrences across the corpus. For example, terms such as "merger", "acquisition", and "deal" are automatically grouped by the model to form a single, coherent topic I subsequently label “M&A & Corporate Transactions.” STM is an extension of the widely-used Latent Dirichlet Allocation (LDA) model (Blei et al., 2003), which has become a standard tool for textual analysis (e.g., Bybee et al., 2023). While newer to finance, STM is a well-established methodology in other leading empirical social sciences such as political science (e.g., Mishler et al., 2015; Curry and Fix, 2019). STM offers two key advantages for this research context. First, it allows for the inclusion of metadata; specifically, I used time, firm size, and industry (using Fama-French 48-industry classifications[15](Fama and French, 1997)) as covariates in the estimation of topic prevalence. Second, it accounts for potential correlations between topics, which is a more realistic assumption for financial disclosures where subjects are often related (Ardia et al., 2022). These features make STM particularly well-suited for my analysis. The ability to incorporate covariates is crucial given the nature of my dataset, which spans a long time period (2006–2023), multiple industries, and firms of varying sizes. Thematic content in financial disclosures is not static; it evolves with macroeconomic conditions and technological shifts. For instance, topics related to “Macroeconomic Conditions” or “COVID-19 Pandemic Impact” are inherently time-dependent, while the prevalence of industry-specific topics will naturally differ across sectors.

To ensure a consistent thematic space, I estimate the topic model on the full corpus of disclosures by treating each document—the press release, the conference call presentation, and the conference call Q&A—as a distinct observation at the firm-quarter level, and apply a rigorous multi-stage search procedure to determine the optimal number of topics (K), guided by diagnostic metrics of semantic coherence and exclusivity.[16] This process identified $K = 43$ as the optimal number of distinct topics. The final model, estimated using spectral initialization for robustness, produces a vector of 43 topic proportions for each disclosure, representing the document’s thematic content.

This structured representation of thematic content allows me to test the extent to which managers rely on the lever of thematic emphasis to construct their narratives. I hypothesize that tonal inconsistency is constructed partially through a divergence in the topics discussed between disclosures. To test this, I calculate the cosine similarity between the 43-topic vectors of the press release and the conference call for each firm-quarter.

[15] The Fama-French 48-industry classifications are retrieved from Kenneth French’s online data library: `https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/Data_Library/det_48_ind_port.html`

[16] Semantic coherence measures the degree to which the most probable words within a topic frequently co-occur in the documents, indicating thematic consistency. Exclusivity measures how unique the top words of a topic are to that topic relative to others, ensuring the topics are distinct.

The results, presented in Table X, provide initial support for this hypothesis. In Panel A, which compares the press release to the presentation section of the conference call, the mean topic similarity for inconsistent announcements is statistically significantly lower than for consistent announcements. Panels B and C repeat this analysis for the Q&A section and the minimum similarity across both sections, respectively, finding a similarly significant pattern. These results suggest that tonal inconsistency is not merely a matter of word choice within topics but is associated with a broader divergence in the thematic content of the disclosures.

[Insert Table X about here]

While the univariate cosine similarity test confirms that tonal inconsistency is associated with greater thematic divergence overall, it does not reveal which specific topics are the primary drivers of this divergence. To identify these key topics, a multivariate approach is necessary. The primary challenge in this setting is the high dimensionality of the predictor space; a standard regression with 43 topic deltas and numerous controls risks overfitting and produces noisy, difficult-to-interpret results. To address this, I employ a Post-LASSO Linear Probability Model (LPM) (Belloni et al., 2014). This two-step procedure is well-suited for this descriptive task. In the first step, a LASSO (Least Absolute Shrinkage and Selection Operator) regression with 10-fold cross-validation performs objective variable selection, creating a parsimonious model by shrinking the coefficients of unimportant predictors to zero. In the second step, a standard linear regression is estimated using only this LASSO-selected subset of variables. I use an LPM framework as it correctly handles the high-dimensional firm and time fixed effects essential in a panel setting with a binary dependent variable. The empirical specification is as follows:

$$\text{Inconsistent}_{i,t} = \beta_0 + \sum_{j \in S} \beta_j (\Delta w_{i,t})_j + \gamma' \text{Controls}_{i,t} + \alpha_i + \lambda_t + \epsilon_{i,t} \tag{4}$$

where $\text{Inconsistent}_{i,t}$ is a dummy variable equal to one for tonally inconsistent announcements for firm i in quarter t. The key independent variables, $(\Delta w_{i,t})_j$, represent the j-th element of the topic delta vector for the subset of topics S selected by the LASSO procedure.[17] $\text{Controls}_{i,t}$ is

[17] To be consistent with the baseline analysis, which defines inconsistency when a press release's tone differs from either the presentation or Q&A section, the topic delta is constructed to capture the maximum divergence. For each of the 43 topics, I compute the difference between the press release's topic proportion and the proportions in both

a vector of standard firm-level controls, including standardized unexpected earnings (SUE), prior returns, institutional ownership, size, and book-to-market ratio. The model includes firm fixed and year-month fixed effects, and standard errors are clustered by date.

Table XI presents the results of the Post-LASSO LPM. The findings indicate that tonal inconsistency is not a random phenomenon but is systematically associated with thematic divergence in specific, economically meaningful areas. The topics that positively predict inconsistency are largely those that are complex, forward-looking, or subjective, providing managers with the greatest latitude to craft a mixed narrative. These include *Financial Metrics & Non-GAAP Measures*, *Financial Reporting & Forward-Looking Statements*, *Managerial Uncertainty & Qualifiers*, *Financial Performance & Restructuring*, and *M&A & Corporate Transactions*. The model demonstrates a clear, though modest, ability to distinguish between inconsistent and consistent events, achieving an AUC (Area Under the Curve, a measure of classification performance) of 0.621. Furthermore, the F-test for the joint significance of the selected topic deltas is significant, confirming that these thematic shifts, as a group, have explanatory power for tonal inconsistency.

[Insert Table XI about here]

This analysis dissects the construction of the aggregate tonal inconsistency, showing it is partially engineered through divergence in complex, forward-looking, and subjective topics. This identification of how a different tonal impression is constructed for each disclosure channel provides a more complete picture of the managerial strategy at play.

V.III. Market Channel

This section empirically investigates four potential channels through which tonal inconsistency impacts market price discovery: ambiguity, disagreement, information asymmetry, and inattention. Each channel generates distinct, and often competing, predictions for market behavior. By testing these predictions, I distinguish the primary mechanism at play and thereby explain the observed market underreaction. The subsequent analysis indicates that ambiguity is the dominant channel.

The theoretical channels of disagreement and ambiguity offer directly competing predictions regarding market activity. Disagreement theory, rooted in models of heterogeneous beliefs (Miller,

the presentation and Q&A sections. I then use the difference with the larger absolute magnitude as the final delta for that topic. The results are qualitatively similar when using the delta from either section alone.

1977; Varian, 1985), 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 Difference-in-Differences style event-study framework.

The regression results, presented in Table XII, 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 evidence for the ambiguity channel, suggesting that the informational conflict suppresses trading as investors adopt a cautious "wait-and-see" approach.

[Insert Table XII about here]

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 XII, 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 further 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 lens through which to test competing theories. To ensure the analysis captures the direct effect of the earnings announcement, all analyst-related measures are constructed using the first forecast each analyst issues for the next fiscal quarter following the announcement. Specifically, I examine four key metrics derived from analyst forecasts: *Dispersion*, *Consensus*, *Common Info Quality*, and *Private Info Quality* (denoted as d, ρ, h, and s, respectively, in Barron et al. (1998)). All measures are standardized by price, as is common in the literature.

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

[Insert Table XIII about here]

Finally, the analysis reveals that tonal inconsistency is associated with a statistically significant decline in the quality of both public and private information available to analysts. As shown in the final two columns of Table XIII, the coefficient on the *Inconsistent* indicator is -0.05 in the regression for *Common Info Quality* and -0.04 for *Private Info Quality.* This indicates that the ambiguity created by managers degrades the entire external information environment. It not only contaminates the public signals available to all investors but also diminishes the precision of the private information that analysts work to gather.

To further adjudicate between competing theories, I examine idiosyncratic return volatility (*IVOL*) and test for investor inattention. Disagreement and ambiguity theories offer competing predictions for idiosyncratic volatility. Disagreement theory posits that active trading on divergent beliefs should increase *IVOL*, whereas ambiguity theory, which predicts investor passivity, suggests that *IVOL* should remain stable or even decrease. My results in Table XIV show that the coefficient on *Inconsistent* is statistically insignificant for *IVOL* in both the *[0, 5]* and *[6, 20]* post-announcement windows. This statistically insignificant result fails to support a disagreement-based explanation but is consistent with the ambiguity-driven investor passivity channel.

[Insert Table XIV about here]

Investor inattention is another alternative explanation for the return drift following inconsistent messaging, as it has been documented to be associated with slow price adjustments (e.g., DellaVigna and Pollet, 2009; Hirshleifer et al., 2009). Perhaps situations of mixed messaging are associated with unimportant earnings news, leading to a spurious association with a return drift. This would be surprising, given that earnings announcements are high-salience events and my results are robust to standard inattention controls, but a direct test of this is still warranted. I 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 XIV, the coefficients on *Inconsistent* are insignificant for both measures. This indicates that investors are not displaying a drop in attention when we are witnessing a mixed messaging event. 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 evidence of decreased trading, wider bid-ask spreads, stability in investor attention and analyst forecasts support an ambiguity channel for the observed return drift following inconsistent messaging and make it unlikely that investor disagreement, information asymmetry, or investor inattention are behind this drift.

VI. Robustness Checks

The primary analysis throughout this paper relies on a baseline measure where tonal inconsistency is determined using a zero threshold for classifying sentiment for each disclosure. This section provides a series of robustness tests to ensure the main findings are not contingent on specific methodological choices. These tests address two key areas: first, the classification of inconsistency itself, and second, the model used for estimating abnormal returns.

To ensure the robustness of the sentiment classification, I test for sensitivity to both the choice of dictionary and the classification threshold. First, in addition to the baseline Loughran and McDonald dictionary, I re-calculate tonality using the machine-learning-based dictionary by García, Hu, and Rohrer, 2023. Second, I test four alternative thresholds for defining sentiments based on the tonality ratio defined in Equation 1. Instead of the baseline zero cutoff, I use benchmarks derived from the ratio's own distribution: the firm-level time-series mean and median across the entire 2006 to 2023 sample period, and the cross-sectional year-month mean and median. A disclosure's binary sentiment is then determined based on whether its tonality ratio is above or below these alternative thresholds, which in turn provides a new classification of tonally inconsistent observations for the analysis.

A preliminary visual inspection in Appendix Figure A.3 confirms that the results are consistent with Hypotheses 1 across all five alternative benchmarks. Regardless of the benchmark used, the immediate abnormal return on the announcement date for inconsistent disclosures is less negative than for consistently negative disclosures, consistent with **H1(a)**. Subsequently, these inconsistent groups exhibit a pronounced negative post-announcement drift for up to two months, supporting **H1(b)**. To formally test the robustness of the economic implications, I replicate the primary regression analysis for cumulative abnormal returns using each of these four alternative inconsistency classifications to verify that the results hold.

Table XV reports coefficient estimates from the panel regression model specified in Equation 2 using both the alternative dictionary and the four alternative benchmarks. The findings confirm that across all four benchmarks, the immediate market reaction, *CAR[-1:1]*, is significantly positive for both types of inconsistency, providing strong support for **H1(a)**. Furthermore, the results are consistent with the baseline findings regarding post-announcement drift, in support of **H1(b)**. The negative drift is particularly steep and statistically significant for the *EC -, PR +* group across all four specifications, confirming that this effect is robust to the method of classifying tonal inconsistency. Repeating the analyses that test whether tonal inconsistency predicts post-announcement insider selling and adverse future firm performance using these alternative benchmarks yields qualitatively similar results, though these are not tabulated for brevity.

[Insert Table XV about here]

Additionally, to test the sensitivity to the asset pricing model, I follow the approach of Tetlock et al. (2008) and re-estimate abnormal returns using the Fama-French five-factor model with an estimation window of [–252, –23] trading days relative to the earnings announcement, rather than the original three-factor model. The results of this test, illustrated in Appendix Table A.VI, are qualitatively the same as the baseline findings, confirming that the main conclusions are robust to the choice of asset pricing model.

VII. 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 a strategic choice with significant economic consequences. I show that these inconsistencies predict a narrative-driven form of the Post-Earnings-Announcement Drift, with the market taking approximately two months to fully incorporate the negative information. This recovery of PEAD, precisely where the classic quantitative drift has attenuated, suggests a novel, meta-level 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. 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.

The strategic nature of this behavior is further supported by an analysis of its origins and construction. The use of this tactic is predictable, arising from a dynamic response to poor firm performance and high uncertainty. Moreover, the inconsistency appears partially engineered through thematic divergence, with managers strategically shifting the focus between disclosures on complex, subjective, and forward-looking topics. Furthermore, this narrative strategy appears to operate primarily by creating ambiguity, which suppresses trading volume and widens bid-ask spreads, rather than through other channels like investor disagreement or inattention.

In sum, this paper makes several contributions to the literature on financial communication and market efficiency. First, by identifying the strategic engineering of tonal inconsistency across related disclosures, it recovers a narrative-driven form of the PEAD, demonstrating that the anomaly persists as an active, firm-initiated friction even as the passive, SUE-based drift has been arbitraged away. 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, I provide empirical evidence that ambiguity is the primary mechanism driving this delayed price discovery. 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. As such, this work has implications for policymakers seeking to protect market integrity, investors aiming to decode complex corporate narratives, and the broader social welfare that depends on fair and transparent markets.

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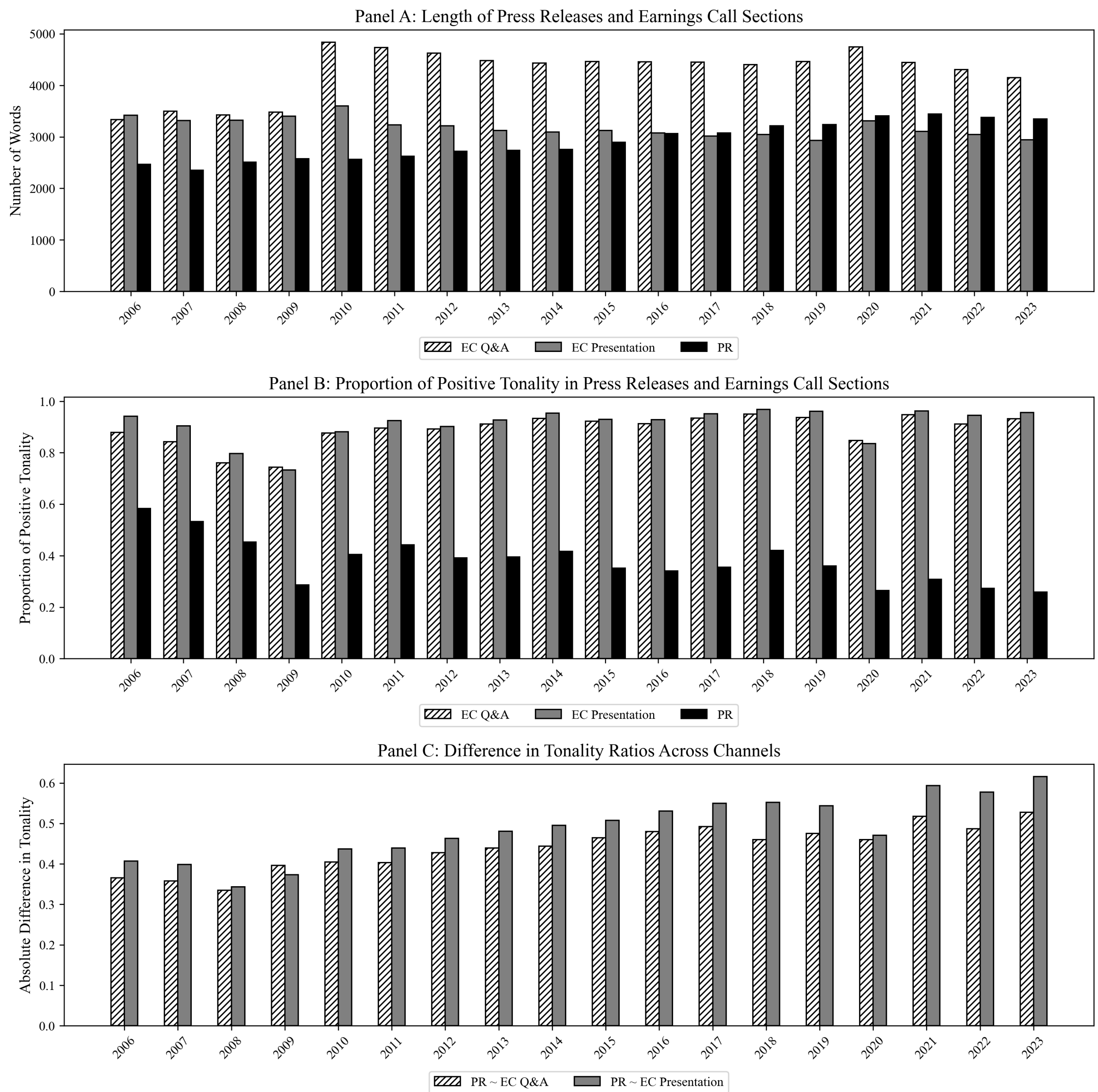


Figure 1. Descriptive Statistics of Key Tonal and Content Characteristics across Communication Mediums, specifically press releases (PR) and sections of earnings calls (EC), including the *presentation* and *Q&A* segments. Panel A shows the average number of words, comparing content length across these 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.

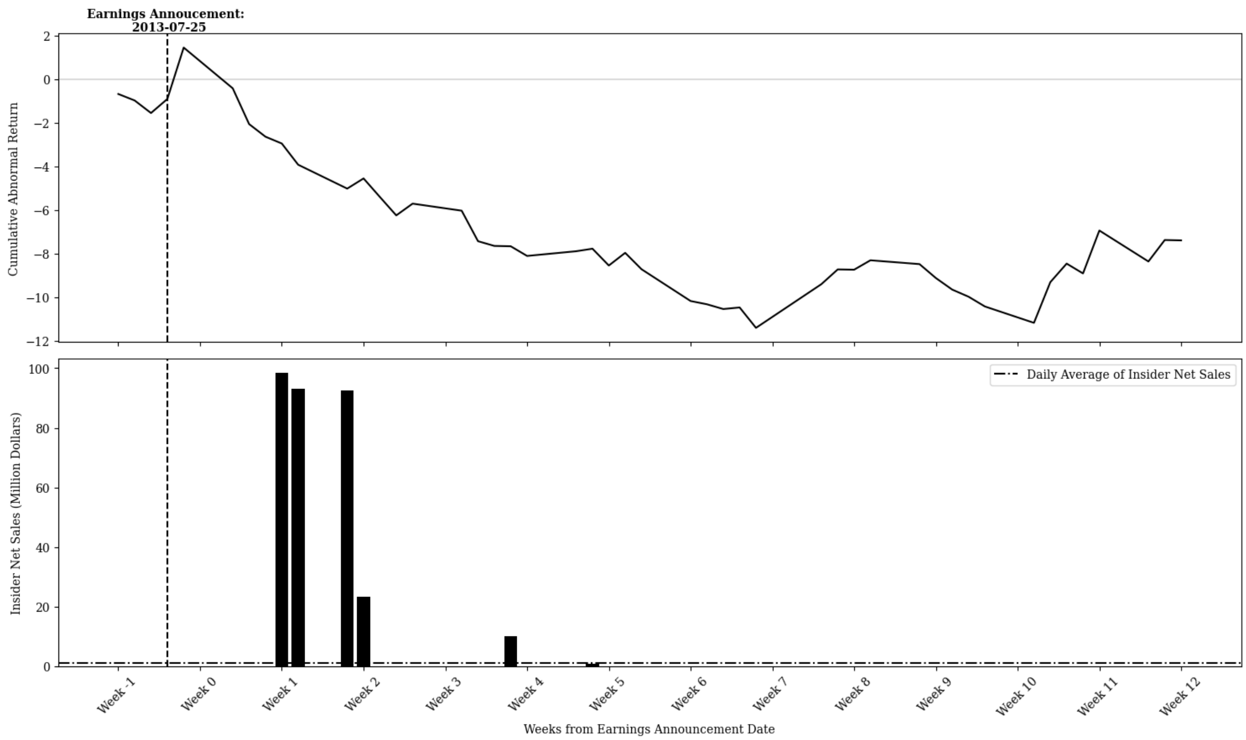


Figure 2. Amazon's CAR and Insider Net Sales Following Tonality Inconsistency Across Channels: This figure shows the cumulative abnormal returns and cumulative insider net sales of Amazon.com, Inc. (NASDAQ: AMZN) in the weeks following the release of Amazon's 2013Q2 earnings announcement. The announcement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

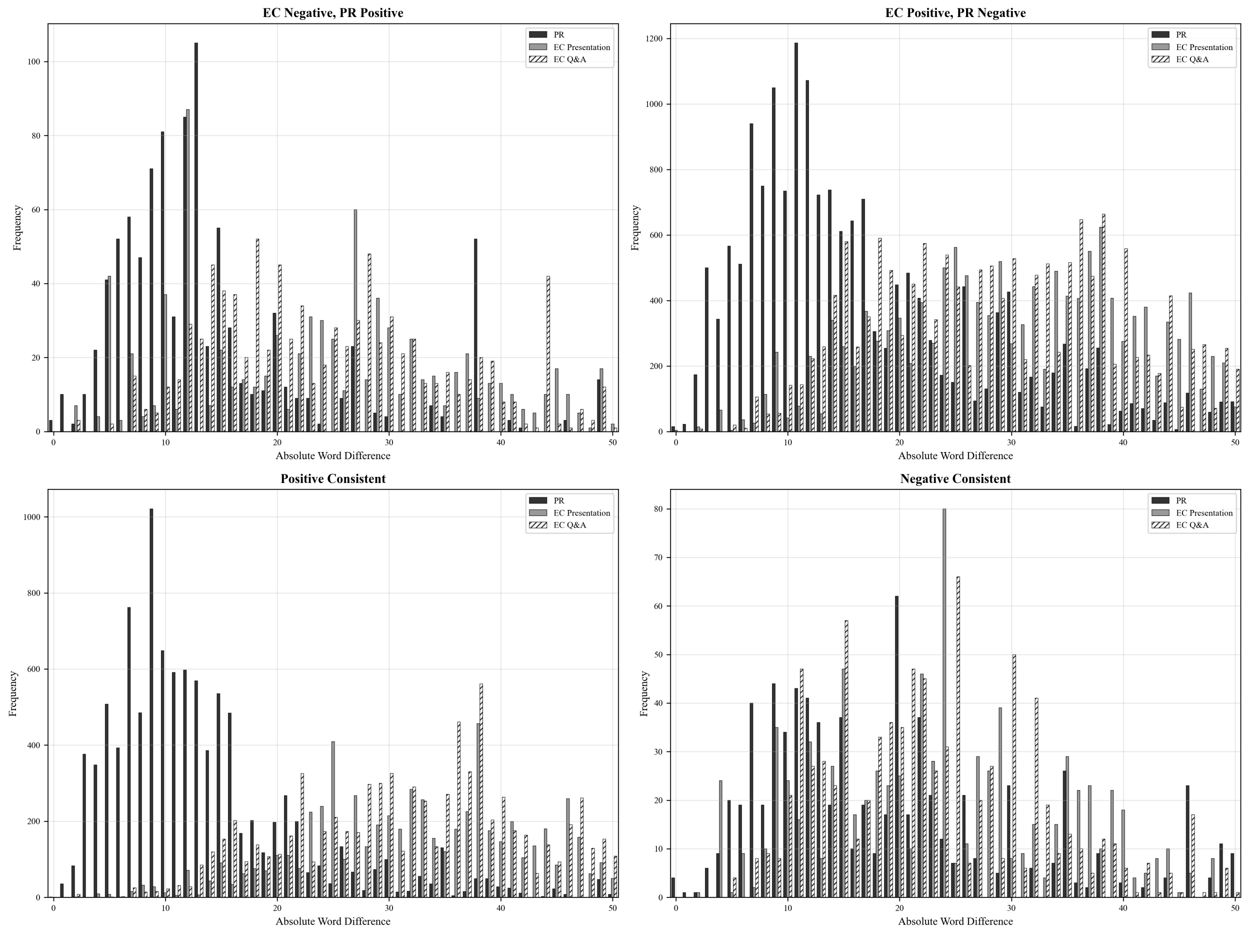
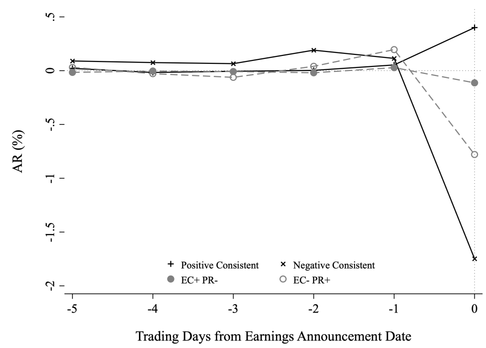


Figure 3. Distribution of Tonal Intensity by Consistency Category: This figure presents histograms of the absolute word difference (|Positive Words − Negative Words|) up to a threshold of 50 words for Press Releases (PR), Earnings Call (EC) Presentations, and EC Q&A sessions. The distributions are plotted separately for four consistency categories, defined by the tonal alignment between the press release and the earnings call: two inconsistent categories (top panels) and two consistent categories (bottom panels). The absolute word difference on the x-axis serves as a proxy for tonal intensity, where a higher value indicates a more tonally decisive or imbalanced document. 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.

Panel A: Daily Abnormal Returns around Announcement



Panel B: Drifts and Reversals with 95% Confidence Intervals

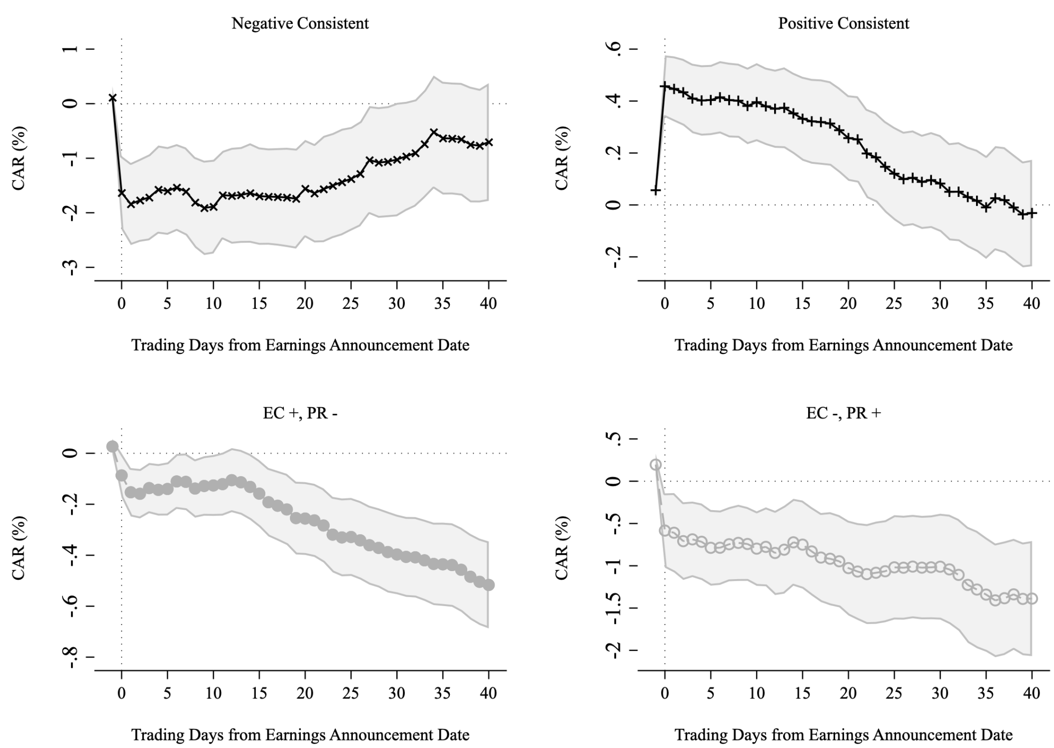


Figure 4. Abnormal Returns Across Consistency Groups: This figure plots the average abnormal returns for four categories based on the tonal consistency between the earnings conference call (EC) and the press release (PR). The sample includes S&P 500 firms from 2006Q1 to 2023Q3. Abnormal returns are estimated using the Fama-French five-factor model (Fama and French, 2015). Panel A plots the daily abnormal returns in the [-5, 0] window around the announcement. Panel B presents the cumulative abnormal returns (CAR), starting from one day before the announcement, for each of the four consistency groups separately, along with 95% confidence intervals calculated using standard errors clustered by both date and firm. The x-axis in Panel B indicates trading days post-announcement, where day 40 corresponds to approximately two months.

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

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

Table III

Placebo Test: Tonal Consistency Between LLM-Generated and Manager-Authored Press Releases vs Earnings Calls

This table reports a placebo test designed to establish a non-strategic benchmark for tonal consistency between press releases and earnings call presentations. Panel A compares LLM-generated press releases (created from earnings call transcripts using GPT-4.1-mini with instructions to base the press release exclusively on the transcript, add no outside information or sentiment, and ensure the tone is a faithful reflection of the source) with earnings call presentations. Panel B compares original, manager-authored press releases with earnings call presentations. Sentiment is measured using the Loughran-McDonald dictionary. The analysis is based on a subsample of earnings calls from 2022, a period of particularly high tonal divergence.

Panel A: LLM-Generated Press Releases vs Earnings Calls		
	Count	Percentage
Consistent	1722	91.1%
Inconsistent	169	8.9%
Panel B: Real Press Releases vs Earnings Calls		
	Count	Percentage
Consistent	599	31.7%
Inconsistent	1292	68.3%

Table IV

Summary Statistics by Disclosure Consistency

This table reports summary statistics for groups of observations classified by disclosure tonal consistency. *Inconsistent* observations are those where the press release tone has a different sign than either section of the earnings call (presentation or Q&A). Variables are defined as follows: *Polarity PR* is the tone of press releases; *Polarity EC Pres* and *Polarity EC Q&A* are the tones of earnings call presentation and Q&A sections, respectively; *SUE* is standardized unexpected earnings; *Size* is log market equity; *log(BM)* is log book-to-market ratio; *CAR Prev Month* and *CAR Past Year* are cumulative abnormal returns over the previous month and year; *G-Index* and *E-Index* are governance indices measuring anti-takeover provisions; *Institutional Ownership* is the percentage of shares held by institutional investors; *Analyst Coverage* is log-transformed number of analysts following the firm; *Overconfident CEO* is a dummy for CEOs who hold deep-in-the-money options until expiration; *Female CEO* is a dummy for female CEOs; *CEO Tenure* is years as CEO; *Equity Pay Ratio* is the ratio of equity-based to total compensation; *CEO Ownership %* is the percentage of shares owned by the CEO; *CEO Age* is the CEO's age; *ROA*, *ROE*, and *CFOA* are return on assets, return on equity, and cash flow from operations to assets; *Sales Growth* is year-over-year sales growth; *Altman Z-Score* and *Ohlson O-Score* are bankruptcy prediction models; *Total Volatility*, *Idiosyncratic Volatility*, and *Operating ROA Volatility* measure different aspects of firm risk. Continuous variables are winsorized at the 1%.

	Consistent			Inconsistent		
	Mean	Median	SD	Mean	Median	SD
Polarity Measures						
Polarity PR	0.206	0.188	0.274	-0.228	-0.219	0.213
Polarity EC Pres	0.466	0.520	0.269	0.352	0.374	0.256
Polarity EC Q&A	0.359	0.390	0.246	0.307	0.326	0.237
Control Variables						
SUE	1.414	1.015	2.685	1.258	0.882	3.097
Size	9.878	9.752	1.115	9.908	9.768	1.149
log(BM)	-1.186	-1.097	0.984	-1.004	-0.869	0.979
CAR Prev Month	-0.120	-0.004	6.321	-0.180	-0.121	6.231
CAR Past Year	0.473	0.345	22.687	-2.258	-1.799	22.704
Governance						
G-Index	3.099	3.000	1.900	2.999	3.000	1.882
E-Index	0.481	0.000	0.629	0.411	0.000	0.606
Institutional Ownership	0.784	0.812	0.153	0.778	0.810	0.160
Analyst Coverage	2.928	2.996	0.405	2.904	2.944	0.405
CEO Traits						
Overconfident CEO	0.075	0.000	0.264	0.063	0.000	0.244
Female CEO	0.037	0.000	0.189	0.055	0.000	0.228
CEO Tenure	6.656	5.000	6.054	6.276	5.000	6.290
Equity Pay Ratio	0.613	0.649	0.217	0.636	0.667	0.207
CEO Ownership %	0.663	0.104	2.300	0.620	0.092	2.379
CEO Age	57.220	58.000	6.273	57.412	57.000	5.992
Financial Performance						
ROA	0.020	0.018	0.025	0.014	0.012	0.030
ROE	0.059	0.046	0.102	0.043	0.036	0.135
CFOA	0.069	0.057	0.065	0.059	0.045	0.062
Sales Growth	0.100	0.067	0.316	0.072	0.040	0.410
Altman Z-Score	3.851	2.502	5.288	2.830	2.019	4.412
Ohlson O-Score	-2.087	-2.021	1.499	-1.930	-1.809	1.526
Volatility Measures						
Total Volatility	0.311	0.273	0.154	0.322	0.279	0.162
Idiosyncratic Volatility	0.241	0.214	0.118	0.248	0.219	0.121
Operating ROA Volatility	0.012	0.007	0.018	0.012	0.007	0.017

Table V

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 date level. t-Statistics are reported below the estimates. Statistical significance at the 1%, 5%, and 10% levels is indicated by ***, **, and *, respectively.

Panel A: CARs in non-Overlapping Windows

	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 V—Continued

Panel B: CARs in Overlapping Windows

	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

Table VI

Interaction Effects of Tonal Inconsistency and Negative Fundamental News

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 V is augmented with *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. All variable definitions, sample criteria, fixed effects, and standard error calculations are identical to those in Table V.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 VII

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. Daily averages of the dependent variables (in millions of dollars) are also reported in the table. Columns (1) examines net sales for all insiders. Columns (2) and (3) focus on sales by top executives, disaggregated into planned (Rule 10b5-1) and unplanned (discretionary) trades. Columns (4) and (5) 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 date 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	
	Net Sale	Planned	Unplanned	Planned	Unplanned
Inconsistent	0.01	-0.00	-0.01	-0.00	0.13*
	(0.09)	(-1.38)	(-0.49)	(-0.03)	(1.78)
Positive Consistent	-0.01	0.00	-0.02	-0.01	0.10
	(-0.03)	(0.95)	(-1.09)	(-0.78)	(0.81)
Date[-1:1]	0.04	-0.00	0.00	0.00	0.00
	(0.40)	(-0.35)	(0.31)	(0.63)	(0.07)
Date[2:5]	-0.28	0.00	0.01	0.00	-0.05
	(-1.01)	(0.56)	(0.91)	(0.42)	(-0.61)
Date[-1:1] × Inconsistent	0.11	0.00**	-0.00	0.00	0.03
	(0.81)	(2.11)	(-0.23)	(0.28)	(0.57)
Date[2:5] × Inconsistent	0.75**	0.01**	0.17	0.03	0.27***
	(2.21)	(2.10)	(1.22)	(1.20)	(2.70)
Date[-1:1] × Positive_Consistent	0.04	-0.00	-0.03	0.01	0.05
	(0.28)	(-0.15)	(-0.79)	(0.52)	(0.56)
Date[2:5] × Positive_Consistent	0.88**	-0.00	-0.01	0.07	0.45**
	(2.41)	(-1.31)	(-0.33)	(1.03)	(2.39)
Constant	-0.22	-0.17**	-0.20	0.07	0.18
	(-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
Daily Mean ($M)	0.284	0.003	0.031	0.010	0.200
Firm FE	✓	✓	✓	✓	✓
Year-Month FE	✓	✓	✓	✓	✓
Controls	✓	✓	✓	✓	✓
Adjusted R-sq	0.003	0.017	0.005	0.010	0.004

Table VIII

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 date 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

Table IX

Firm and CEO Characteristics and Tonal Inconsistency

This table presents panel logistic regression results examining the determinants of issuing tonally inconsistent disclosures across four channels: CEO characteristics, corporate governance, corporate performance, and corporate risk. The dependent variable, Inconsistent, is a binary indicator equal to one if the tone of a firm's earnings press release and its subsequent conference call are different, and zero otherwise. The sample consists of firm-quarter observations, restricted to observations with non-missing data for all variables. All control variables are winsorized at the 1% level. All regressions include firm and year-month fixed effects and a set of standard control variables. Standard errors are clustered at the date level. z-statistics are reported in parentheses. The bottom panel reports p-values for F-tests of the joint significance of each group of variables and the chi-squared p-value for the overall model. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)	(5)
CEO Characteristics					
Overconfidence	-0.18	-0.20			
	(-1.10)	(-1.22)			
Female CEO	0.25*	0.21			
	(1.70)	(1.48)			
CEO Tenure	-0.00	-0.00			
	(-0.09)	(-0.16)			
Equity Pay Ratio	0.18	0.22			
	(1.30)	(1.55)			
CEO Ownership	0.04*	0.04*			
	(1.94)	(1.92)			
Corporate Governance					
E-Index	-0.15**		-0.14**		
	(-2.12)		(-1.97)		
Analyst Coverage	0.19		0.18		
	(1.17)		(1.13)		
Institutional Ownership	1.48***		1.44***		
	(3.63)		(3.58)		
Corporate Performance					
ROA	-7.14***			-7.40***	
	(-5.11)			(-5.25)	
Altman Z-Score	-0.02*			-0.02*	
	(-1.89)			(-1.84)	
Sales Growth	0.02			0.03	
	(0.17)			(0.29)	
Corporate Risk					
Idiosyncratic Volatility	0.78*				1.11***
	(1.80)				(2.58)
Operating ROA Volatility	6.38***				5.72***
	(3.56)				(3.24)
Observations	16,983	16,983	16,983	16,983	16,983
Pseudo R-sq	0.314	0.310	0.310	0.312	0.311
F-test p-val (CEO Traits)	0.112	0.109			
F-test p-val (Governance)	0.000		0.001		
F-test p-val (Performance)	0.000			0.000	
F-test p-val (Risk)	0.000				0.000
Firm FE	✓	✓	✓	✓	✓
Year-Month FE	✓	✓	✓	✓	✓
Controls	✓	✓	✓	✓	✓
Pr > χ^2	0.000	0.000	0.000	0.000	0.000

Table X

Topic Similarity Mean Differences by Consistency Categories

This table reports mean differences in topic similarities between earnings conference calls and press releases, categorized by consistency patterns. Topic similarity scores are first computed by extracting topic weights for 43 topics from STM analysis for each document, then cosine similarity between each pair of documents is computed (Press Releases and Earnings Conference Calls Q&A, and Press Releases and Earnings Conference Calls Presentation). *Inconsistent* includes cases where EC and PR have opposite tones (EC negative/PR positive or EC positive/PR negative). *Consistent* includes cases where both EC and PR have the same tone (both negative or both positive). Panel A presents statistics for the presentation section of earnings conference calls, Panel B for the Q&A section, and Panel C reports the minimum similarity between press releases and both presentation and Q&A sections for each firm-quarter. The difference column shows the mean difference (Inconsistent - Consistent) with t-statistics in parentheses. Statistical significance at the 1%, 5%, and 10% levels is indicated by ***, **, and *, respectively.

Panel A: Press Releases and Earnings Conference Calls (Presentation)

	Inconsistent	**Consistent**	**Diff**
Topic Similarity	0.407	0.450	-0.043***
			(-14.63)

Panel B: Press Releases and Earnings Conference Calls (Q&A)

	Inconsistent	**Consistent**	**Diff**
Topic Similarity	0.269	0.305	-0.036***
			(-14.16)

Panel C: Minimum Similarity (Press Releases and Both EC Sections)

	Inconsistent	**Consistent**	**Diff**
Topic Similarity	0.264	0.301	-0.037***
			(-14.82)

Table XI

Thematic Drivers of Tonal Inconsistency

This table presents the results of a Post-LASSO Linear Probability Model (LPM), implemented excluding sector-related topics, where the dependent variable is a dummy equal to one for tonally inconsistent earnings announcements, and zero otherwise. The main independent variables are the differences in topic proportions between the conference call and the press release (Δw_i). The full set of 43 substantive topic deltas and other firm-level controls are used as potential predictors. For brevity, this table reports only those variables selected by the LASSO procedure that are subsequently found to be statistically significant in the LPM estimation. A comprehensive report listing all variables selected by LASSO (regardless of significance) can be found in Appendix Table A.V. The model includes firm and year-month fixed effects. Standard errors are clustered by date. The AUC and the p-value for a joint F-test of the selected topic deltas are reported at the bottom of the table. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Post-LASSO LPM Results with Fixed Effects

Topic Name	Coefficient
Financial Metrics & Non-GAAP Measures	0.81***
	(18.35)
Financial Reporting & Forward-Looking Statements	0.80***
	(12.70)
Financial Performance & Restructuring	0.99***
	(11.25)
COVID-19 Pandemic Impact	0.62***
	(4.40)
M&A & Corporate Transactions	0.38***
	(4.07)
Banking & Credit	0.33**
	(2.25)
Corporate Governance	0.25**
	(2.33)
Macroeconomic Conditions & Prudence	0.22***
	(3.21)
Managerial Uncertainty & Qualifiers	0.21***
	(4.20)
Pharmaceutical & Medical Devices	-0.72***
	(-4.45)
Corporate Culture & Leadership	-0.30***
	(-4.24)
Observations	22,926
Firm FE	✓
Year-Month FE	✓
AUC	0.621
F-test p-value	0.000
Pr > χ^2	0.000

Table XII

Trading Volume and Bid-Ask Spread

This table presents the results of Difference-in-Differences style event-study regressions, as specified in equation 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 date 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

Table XIII

Properties of Analysts' Information Environment

This 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*, *Common Info Quality*, and *Private Info Quality*. 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 date fixed effects and a set of control variables. Standard errors are clustered at both the firm and date 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

Table XIV

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 date level. t-statistics are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	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

Table XV

Robustness Tests: Analysis of Cumulative Abnormal Returns for Alternative Benchmarks for Tonal Inconsistency

This table reports results from panel regressions testing the robustness of the relationship between tonal inconsistency and Cumulative Abnormal Returns (CAR) using alternative classification benchmarks and an alternative sentiment dictionary. The sample consists of S&P 500 firms from 2006Q1 to 2023Q3. The regressions follow the specification in Equation 2, with Negative Consistent serving as the omitted category. For brevity, only the coefficients for the inconsistency dummies (*EC +, PR -* and *EC -, PR +*) are reported. Abnormal returns are estimated using the Fama-French (2015) five-factor model. The dependent variables are CARs over the event window *CAR[-1:1]* and three subsequent, overlapping windows measured up to one week (*CAR[2:5]*), one month (*CAR[2:20]*), and two months (*CAR[2:40]*). Panels A through D test alternative benchmarks to define inconsistency: firm-specific time-series mean (Panel A), firm-specific time-series median (Panel B), year-month cross-sectional mean (Panel C), and year-month cross-sectional median (Panel D). Panel E tests an alternative dictionary, using the machine-learning-based word lists from García, Hu, and Rohrer, 2023 with the baseline zero threshold. All models include the full set of controls, as well as firm and year-month fixed effects. Standard errors are clustered at the firm and date level. t-Statistics are reported in parentheses below the estimates. Statistical significance at the 1%, 5%, and 10% levels is indicated by ***, **, and *, respectively.

VARIABLES	CAR[-1:1]	CAR[2:5]	CAR[2:20]	CAR[2:40]
Panel A: Time-Series Mean Comparison				
EC +, PR -	1.31***	-0.05	-0.21	-0.18
	(9.56)	(-0.84)	(-1.62)	(-0.98)
EC -, PR +	0.85***	-0.10	-0.34**	-0.52**
	(6.54)	(-1.55)	(-2.53)	(-2.54)
Panel B: Time-Series Median Comparison				
EC +, PR -	1.30***	-0.05	-0.19	-0.16
	(10.11)	(-0.86)	(-1.44)	(-0.95)
EC -, PR +	0.86***	-0.13**	-0.41***	-0.57***
	(7.01)	(-2.23)	(-3.20)	(-3.11)
Panel C: Cross-Sectional Mean Comparison				
EC +, PR -	1.19***	0.00	-0.01	-0.06
	(8.91)	(0.08)	(-0.11)	(-0.37)
EC -, PR +	0.70***	-0.05	-0.21	-0.40**
	(4.94)	(-0.77)	(-1.43)	(-2.00)
Panel D: Cross-Sectional Median Comparison				
EC +, PR -	0.97***	-0.03	-0.04	-0.04
	(7.86)	(-0.45)	(-0.30)	(-0.27)
EC -, PR +	0.57***	-0.06	-0.27*	-0.31*
	(4.50)	(-0.97)	(-1.90)	(-1.68)
Panel E: Using Diego Garcia Dictionary				
EC +, PR -	1.52***	-0.46**	-0.16	-0.79
	(4.27)	(-1.97)	(-0.43)	(-1.60)
EC -, PR +	0.70	-0.60**	-0.59	-1.42**
	(1.64)	(-2.28)	(-1.30)	(-2.45)
Observations	24,638	24,638	24,638	24,638
Firm FE	✓	✓	✓	✓
Year-Month FE	✓	✓	✓	✓

Appendix

A Constructing Thematic Similarity and Divergence Measures

This appendix details the procedures for pre-processing the textual data, implementing the Structural Topic Model (STM), and constructing the primary measure of thematic divergence used in the main analysis.

A.1 Textual Data Cleaning and Pre-processing

The textual data is prepared for topic modeling through a multi-step pre-processing pipeline. The steps, applied sequentially to each document, are as follows:

1. Boilerplate Removal and Normalization: Remove common conversational artifacts and boilerplate language inherent in earnings call transcripts. Standardize mentions of specific fiscal periods to generic tokens (e.g., "Q1 2022" becomes "quarter") and convert all text to lowercase.

2. Named Entity Recognition (NER) and Filtering: Identify and remove tokens corresponding to personal names. For organization names, retain key regulatory and governmental institutions (e.g., "SEC," "Fed"), while replacing other company mentions with a generic <Company> tag.

3. Lemmatization: Lemmatize all remaining tokens to their base or dictionary form (e.g., "operating" and "operated" both become "operate").

4. Collocation Identification (N-grams): Identify and combine common adjacent words into meaningful two- and three-word phrases (e.g., "cash" and "flow" become "cash_flow") to preserve important financial terminology.

5. Customized Stopword Removal: Remove a standard list of English stopwords, augmented with a domain-specific list of terms common to financial disclosures that carry little semantic weight (e.g., "question," "operator"). A predefined set of over 50 value-relevant financial terms (e.g., "growth," "earnings") is explicitly preserved from removal.

6. Vocabulary Pruning by Document Frequency: Exclude terms appearing in fewer than 50 documents or in more than 85% of all documents in the corpus.

7. Final Vocabulary Refinement: Remove any remaining non-substantive tokens, including words containing digits, spelled-out numbers and ordinals (e.g., "four," "second"), and modal verbs (e.g., "could," "would").

This pipeline results in a clean, tokenized corpus where each document is represented as a sequence of meaningful unigrams, bigrams, and trigrams, forming the document-term matrix for the STM analysis.

A.2 Structural Topic Model Implementation

To quantify the thematic shift between a firm's earnings press release and its subsequent conference call, I employ a topic modeling approach.

A.2.1 Topic Modeling Framework

Topic models are a popular dimension-reduction technique from machine learning and natural language processing, designed to summarize dense verbal descriptions of documents. Much like Principal Component Analysis (PCA) condenses large data matrices into a smaller number of common factors, a topic model reduces the inherently high-dimensional representation of a text corpus into a relatively low-dimensional set of common "topics." A topic is defined as a distribution over words, where related terms (e.g., "merger," "acquisition," "deal") are grouped together. The model's second key element is to estimate the proportion of text dedicated to each of these topics within every individual document. This transforms each document into a structured numerical vector representing its thematic composition. The foundational model for this type of analysis, Latent Dirichlet Allocation (LDA), has become a standard tool in financial research.

A.2.2 The Structural Topic Model (STM)

For this study, I use the Structural Topic Model (STM), an extension of LDA. In practice, STM functions similarly to LDA but allows for the inclusion of document-level metadata as covariates in the estimation of topic prevalence. This feature is a crucial advantage for my research context, as it allows the model to account for known sources of heterogeneity in corporate disclosures.

Specifically, I leverage this capability by incorporating metadata—time (quarterly indicators), firm size (log market capitalization), and industry (Fama-French 48 classifications)—directly into the topic prevalence parameter. By doing so, the model explicitly controls for the fact that the thematic content of financial disclosures is not static. By modeling this heterogeneity, the STM provides a more precise and contextually aware measurement of a document's thematic content than a standard LDA model would. This enhanced precision is critical for isolating the strategic, firm-specific shifts in thematic emphasis that are the focus of this paper.

A.2.3 Selection of the Number of Topics (K)

A critical parameter in topic modeling is the number of topics, K. To select an optimal K that is both statistically sound and substantively meaningful, I employ a rigorous, data-driven search procedure. The objective is to identify a model that balances two competing goals: maximizing the interpretability of topics while minimizing the redundancy between them. To achieve this, I evaluate candidate models on both semantic coherence, which ensures that words within a topic are thematically related, and exclusivity, which ensures that topics are distinct from one another.

The selection process proceeds in three iterative stages to robustly identify the optimal K:

1. Stage 1 (Broad Search): I first conduct a coarse search over a wide range of K from 10 to 100 (in increments of 20) to identify a promising region of topic numbers.

2. Stage 2 (Focused Search): Based on the results of the initial search, I perform a more refined search with K ranging from 25 to 55 (in increments of 5).

3. Stage 3 (Granular Search): Finally, I conduct a granular search around the best-performing values from the second stage, examining K from 42 to 46.

At each stage, multiple models are estimated for each value of K using different random seeds to ensure the results are robust to initialization sensitivity. This multi-stage process revealed that a model with $K = 43$ provides the best balance between semantic coherence and exclusivity, yielding a thematically rich yet parsimonious set of topics for the main analysis.

A.2.4 Final Model Estimation and Interpretation

The final model with $K = 43$ is estimated using spectral initialization for robustness, as it is less sensitive to local optima than random initialization. The model's output is a vector of 43 topic proportions (θ) for each disclosure, representing the document's thematic content. Each of the 43 topics is assigned a meaningful label through a qualitative inspection of its most probable and exclusive (FREX) words; Appendix Table A.VII lists these topic labels and their justification words. In Appendix Figure A.4, the distribution of topic proportions is depicted, providing a visual overview of the relative importance of each identified theme.

A.2.5 Topic Similarity Calculation

In addition to divergence, I compute the thematic similarity between the press release and the conference call components using cosine similarity. This measure captures the alignment of topic vectors as the cosine of the angle between them, with a value of 1 indicating identical thematic focus and 0 indicating no shared themes. For each firm i in quarter t, the similarity between the press release ($\theta_{i,t}^{PR}$) and the conference call presentation ($\theta_{i,t}^{EC,Pres}$) is:

$$\text{TopicSimilarity}_{i,t}(PR, Pres) = \frac{\theta_{i,t}^{PR} \cdot \theta_{i,t}^{EC,Pres}}{\|\theta_{i,t}^{PR}\| \, \|\theta_{i,t}^{EC,Pres}\|}$$

Similarly, the similarity between the press release and the Q&A session ($\theta_{i,t}^{EC,QA}$) is:

$$\text{TopicSimilarity}_{i,t}(PR, QA) = \frac{\theta_{i,t}^{PR} \cdot \theta_{i,t}^{EC,QA}}{\|\theta_{i,t}^{PR}\| \, \|\theta_{i,t}^{EC,QA}\|}$$

A composite measure, representing the overall thematic similarity between the press release and the subsequent conference call, is constructed by taking the minimum of these two values. This conservative approach ensures that the final similarity score reflects the lower bound of alignment across both parts of the conference call.

$$\text{TopicSimilarity}_{i,t} = \min(\text{TopicSimilarity}_{i,t}(PR, Pres),\ \text{TopicSimilarity}_{i,t}(PR, QA))$$

A.2.6 Divergence Calculation

With the topic proportions for each document estimated, the thematic divergence between the press release and the two components of the conference call (the prepared presentation and the Q&A session) is calculated. For each firm i in quarter t, let $\theta_{i,t}^{PR}$, $\theta_{i,t}^{EC,Pres}$, and $\theta_{i,t}^{EC,QA}$ be the 43x1 vectors of topic proportions for the press release, conference call presentation, and conference call Q&A, respectively.

The primary measure of thematic divergence is the Manhattan distance (or L1 norm) between the topic proportion vectors, which captures the total absolute difference in topic weights. The divergence between the press release and the conference call presentation is:

$$\text{TopicDivergence}_{i,t}(PR, Pres) = \sum_{k=1}^{43} |\theta_{i,t,k}^{PR} - \theta_{i,t,k}^{EC,Pres}|$$

Similarly, the divergence between the press release and the Q&A session is:

$$\text{TopicDivergence}_{i,t}(PR, QA) = \sum_{k=1}^{43} |\theta_{i,t,k}^{PR} - \theta_{i,t,k}^{EC,QA}|$$

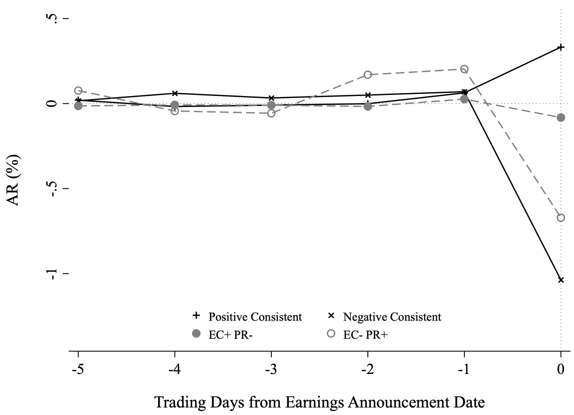
For the LASSO analysis, a composite topic-level divergence measure is constructed. This measure captures the maximum thematic shift for each topic between the press release and either part of the conference call. For each topic k, the divergence is defined as the maximum of the absolute difference between the press release and the presentation, and the press release and the Q&A session:

$$\text{TopicDivergence}_{i,t,k} = \max(|\theta_{i,t,k}^{PR} - \theta_{i,t,k}^{EC,Pres}|, |\theta_{i,t,k}^{PR} - \theta_{i,t,k}^{EC,QA}|)$$

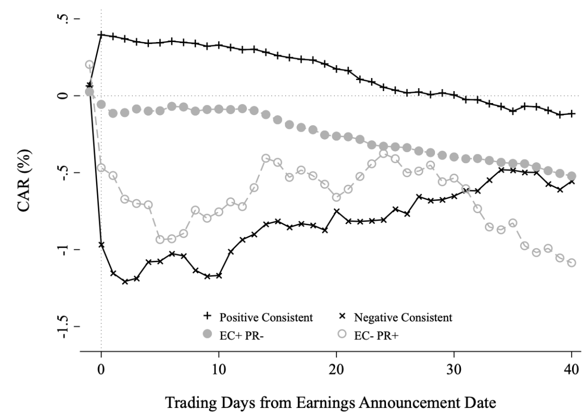
A score of zero indicates that the thematic content is identical, while a higher score indicates a greater aggregate divergence in thematic emphasis between the two disclosures.

Appendix Figures and Tables

Panel A: Consistency between Press Release and Presentation Section

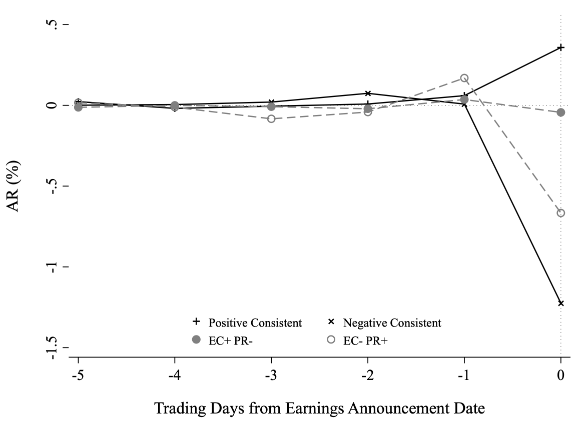


(a) Daily Abnormal Returns (AR)

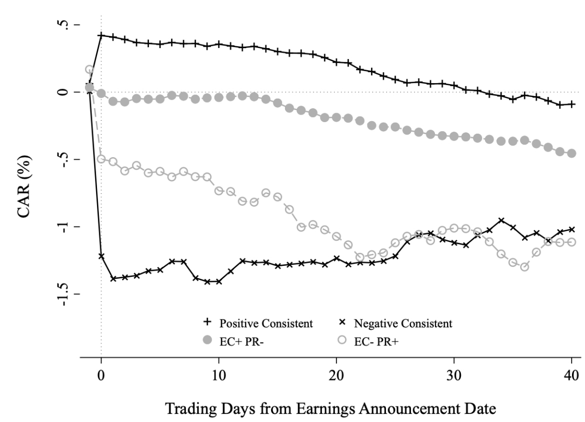


(b) Cumulative Abnormal Returns (CAR)

Panel B: Consistency between Press Release and QA Section



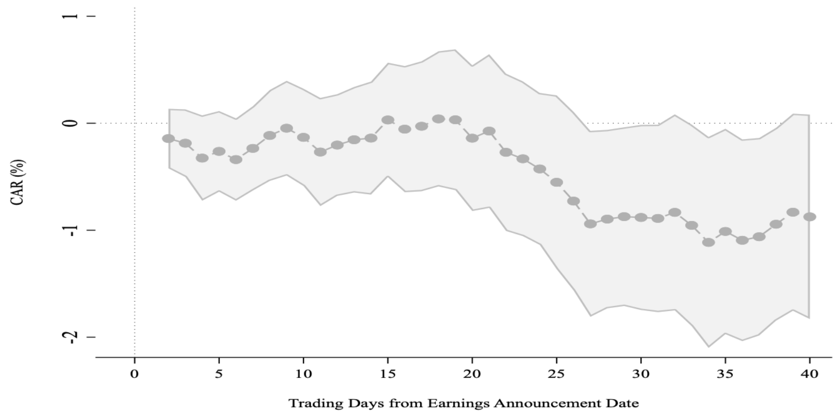
(c) Daily Abnormal Returns (AR)



(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).

Panel A: PEAD for *EC+, PR-*



Panel B: PEAD for *EC-, PR+*

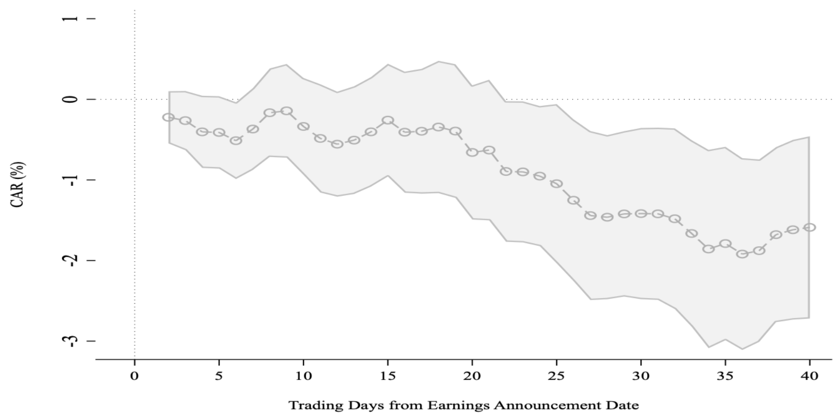
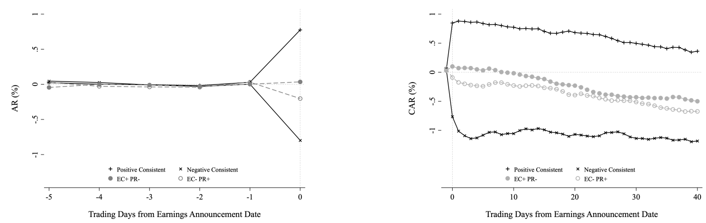
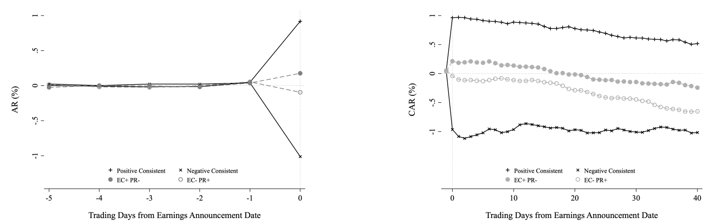


Figure A.2. Post-Earnings-Announcement Drift for Tonal Inconsistent Announcements: This figure plots abnormal returns cumulated starting from the second trading day after earnings announcements for firms with inconsistent sentiment between earnings calls and press releases. The sample includes S&P 500 firms from 2006Q1 to 2023Q3. Abnormal returns are estimated using the Fama-French five-factor model (Fama and French, 2015). Panel A plots the coefficients for *EC+, PR-* firms, while Panel B plots the coefficients for *EC-, PR+* firms. These coefficients (β_2 and β_3 from Equation 2) are estimated using panel regressions with firm and year-month fixed effects, controlling for all variables in Table V. Shaded areas represent 95% confidence intervals with standard errors two-way clustered by firm and date. The x-axis indicates trading days post-announcement, where day 40 corresponds to approximately two months.

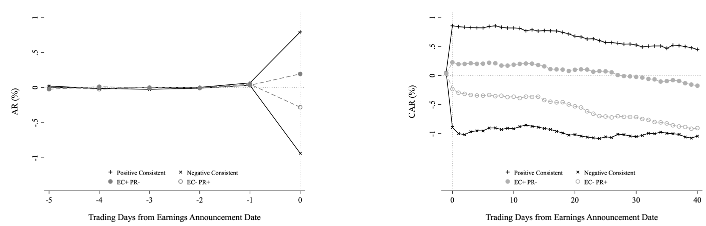
Panel A: Consistency Based on Time-Series Mean



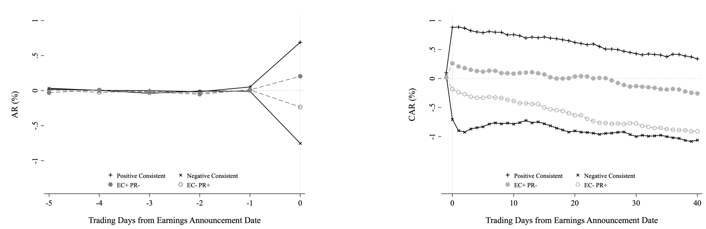
Panel B: Consistency Based on Time-Series Median



Panel C: Consistency Based on Cross-Sectional Mean



Panel D: Consistency Based on Cross-Sectional Median



Panel E: Consistency Based on Diego Garcia Dictionary

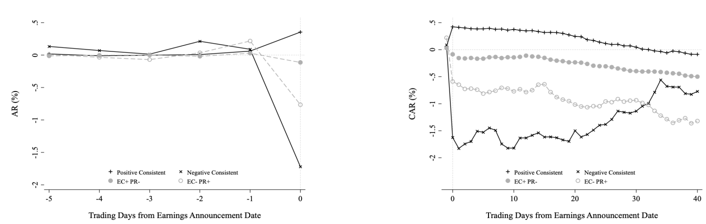


Figure A.3. Robustness of Abnormal Return Patterns to Alternative Consistency Definitions: Each panel reports average daily (left) and cumulative (right) abnormal returns for S&P 500 firms, 2006Q1–2023Q3, estimated using the Fama–French five-factor model. Consistency groups reflect agreement or disagreement in tone between the press release and the earnings call. Panels A-D define binary sentiment relative to four alternative benchmarks: (i) firm-level time-series mean, (ii) firm-level time-series median, (iii) cross-sectional year–month level mean, and (iv) cross-sectional year–month level median. Panel E uses an alternative definition of tonality based on the machine-learning-based dictionary from García, Hu, and Rohrer, 2023.

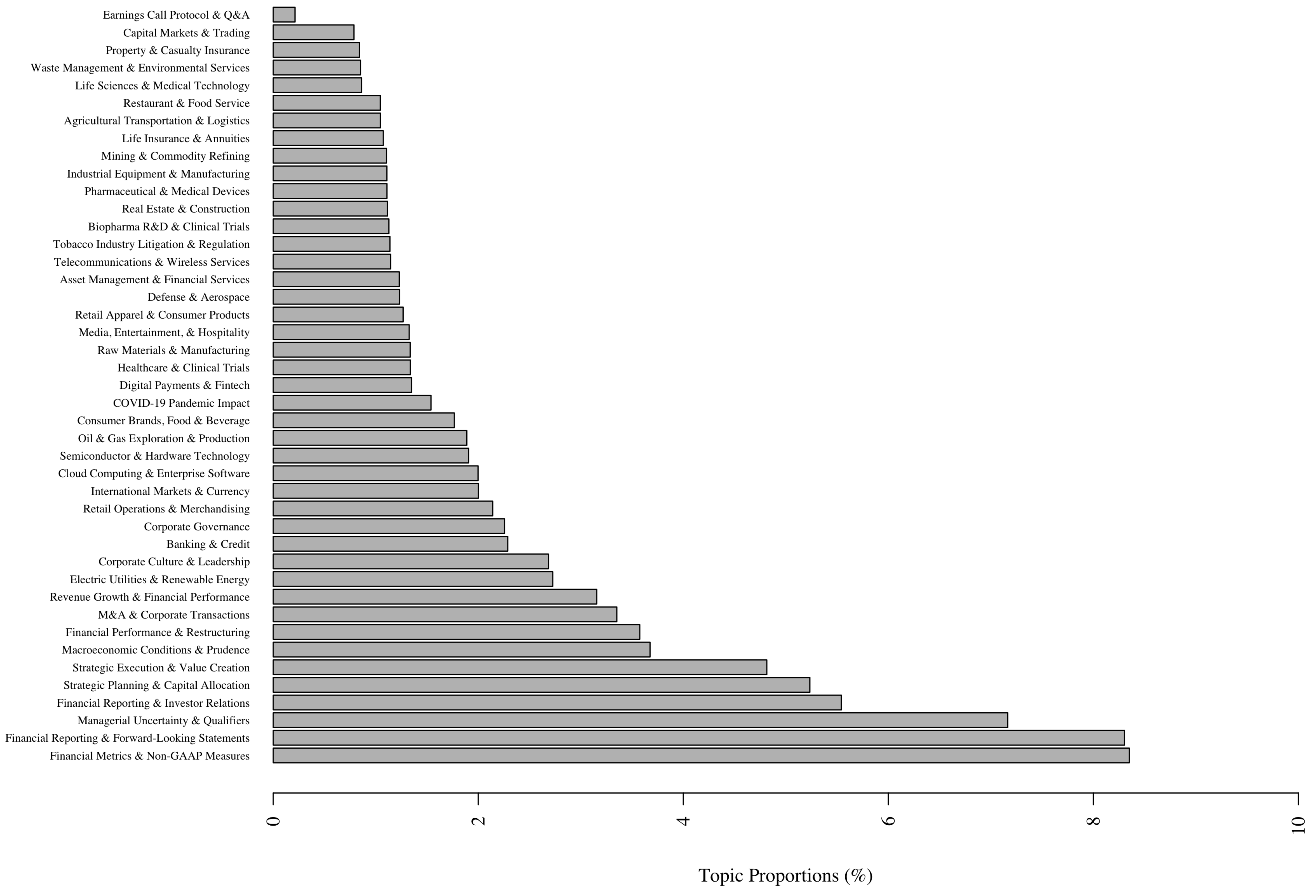


Figure A.4. Distribution of Topic Proportions Across the Corpus

This figure displays the average proportion of each of the 43 topics extracted from the Structural Topic Model (STM). The length of each bar indicates the topic's mean prevalence across all earnings call transcripts and press releases in the sample. This visualization highlights the relative prominence of each thematic dimension within the overall corporate discourse from 2006 to 2023.

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.

(Continued)

Table A.I – (Continued)

Area of Comparison	Earnings Press Release (Positive Tonality)	Earnings Conference Call (Neutral/Negative Tonality)
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.
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

Binary Polarity Measures and Garcia Dic Correlation Analysis

This table reports correlation analysis of binary polarity measures using the Loughran and McDonald (Loughran and McDonald, 2011) Master Dictionary and (García, Hu, and Rohrer, 2023) Dictionary Sentiment across different disclosure channels. The binary polarity measures using the Loughran and McDonald dictionary are computed as follows: *LM (zero)* uses a simple positive/negative classification based on raw polarity scores; *LM (TS mean)* uses firm-specific mean comparison over time; *LM (TS median)* uses firm-specific median comparison over time; *LM (CS mean)* uses year-month mean comparison across all firms; and *LM (CS median)* uses year-month median comparison across all firms. *Garcia (zero)* represents sentiment scores from the Diego Garcia dictionary. Binary sentiment is determined by comparing each observation to the respective benchmark (firm mean/median or period mean/median). Panel A presents the correlation matrix between these six types of polarity measures. Panel B provides summary statistics of these correlations by disclosure channel (Press Releases, Earnings Calls - Presentation, and Earnings Calls - Q&A).

Panel A: Correlation Matrix of Binary Polarity Measures and Garcia Dic

	LM (zero)	LM (TS mean)	LM (TS median)	LM (CS mean)	LM (CS median)	Garcia (zero)
LM (zero)	1.000					
LM (TS mean)	0.347	1.000				
LM (TS median)	0.294	0.890	1.000			
LM (CS mean)	0.474	0.520	0.494	1.000		
LM (CS median)	0.407	0.510	0.490	0.919	1.000	
Garcia (zero)	0.139	0.251	0.238	0.291	0.295	1.000

Panel B: Correlation Statistics by Channel

Channel	Count	Mean Corr.	Min Corr.	Max Corr.
Press Releases	29,583	0.505	0.222	0.934
Earnings Calls - Presentation	29,583	0.454	0.278	0.906
Earnings Calls - Q&A	29,583	0.457	0.252	0.922

Table A.III

Robustness Tests: Including Attention, Complexity, Uncertainty, and Risk Controls

This table reports results from panel regressions testing the robustness of the relationship between tonal inconsistency and Cumulative Abnormal Returns (CAR). The sample consists of S&P 500 firms from 2006Q1 to 2023Q3. The regressions follow the specification in Equation 2, with Negative Consistent serving as the omitted category. For brevity, only the coefficients for the inconsistency dummies (*EC +, PR -* and *EC -, PR +*) are reported. Abnormal returns are estimated using the Fama-French (2015) five-factor model. The dependent variables are CARs over the event window *CAR[-1:1]* and three subsequent, overlapping windows measured up to one week (*CAR[2:5]*), one month (*CAR[2:20]*), and two months (*CAR[2:40]*). **Panel A** reports results after including controls that proxy for low investor attention, such as indicators for announcements made on Fridays or after market hours, and measures of time elapsed between disclosures, and **Analyst Coverage** (the logarithm of one plus the number of analysts providing earnings forecasts for the firm).. **Panel B** includes detailed textual controls derived from the Loughran and McDonald (Loughran and McDonald, 2011) Master Dictionary; these consist of the frequency of words from distinct linguistic categories, scaled by the total number of words in each document, and include measures for weak modal words (a proxy for hedging, e.g., "could", "might"), uncertainty words (a proxy for vagueness, e.g., "approximately", "depends"), and litigious words (a proxy for legal risk, e.g., "lawsuit", "allege"). It also includes controls for textual complexity using the number of syllables in each document. All textual controls are measured separately for the press release (PR), the conference call presentation (Presentation), and Q&A (QA) sections. **Panel C** includes firm-specific risk controls, including lagged idiosyncratic return volatility and operating performance volatility. **Panel D** includes all controls from Panels A, B, and C simultaneously. All models include the full set of standard controls from Table V, as well as firm and year-month fixed effects. Standard errors are clustered at the firm and date level. t-Statistics are reported in parentheses below the estimates. Statistical significance at the 1%, 5%, and 10% levels is indicated by ***, **, and *, respectively.

VARIABLES	CAR[-1:1]	CAR[2:5]	CAR[2:20]	CAR[2:40]
Panel A: Including Investor Attention & Analyst Coverage Controls				
EC +, PR -	1.78***	-0.23	0.05	-0.84
	(4.37)	(-1.18)	(0.15)	(-1.60)
EC -, PR +	1.22***	-0.40*	-0.46	-1.47**
	(2.59)	(-1.69)	(-1.03)	(-2.36)
Panel B: Including Linguistic and Complexity Controls				
EC +, PR -	1.47***	-0.23	-0.13	-0.78
	(3.71)	(-1.23)	(-0.39)	(-1.60)
EC -, PR +	0.86*	-0.41*	-0.63	-1.51***
	(1.90)	(-1.81)	(-1.46)	(-2.61)
Panel C: Including Firm Risk Controls				
EC +, PR -	1.76***	-0.21	0.04	-0.58
	(4.39)	(-1.11)	(0.11)	(-1.17)
EC -, PR +	1.12**	-0.36	-0.43	-1.25**
	(2.49)	(-1.60)	(-1.03)	(-2.16)
Panel D: Including All Controls Simultaneously				
EC +, PR -	1.61***	-0.19	-0.00	-0.57
	(4.09)	(-1.03)	(-0.01)	(-1.15)
EC -, PR +	1.03**	-0.36	-0.47	-1.25**
	(2.30)	(-1.61)	(-1.11)	(-2.15)
Observations	24,645	24,645	24,645	24,645
Firm FE	✓	✓	✓	✓
Year-Month FE	✓	✓	✓	✓
Standard Controls	✓	✓	✓	✓

Table A.IV

Robustness to CEO-Specific Effects: Panel Regressions of Cumulative Abnormal Returns

This table presents a robustness check for the main results reported in Table V to ensure the findings are not driven by unobservable, time-invariant CEO characteristics. The baseline regression specification from Equation 2 is re-estimated, replacing firm fixed effects with CEO fixed effects. The key finding is that the coefficients on the tonal inconsistency dummies remain qualitatively and statistically similar to those reported in the main analysis. This persistence suggests that the market's reaction is attributable to the event-specific signal of tonal inconsistency, rather than to the time-invariant communication style of a particular CEO. All other variable definitions, sample criteria, and standard error calculations are identical to those in Table V. 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	2.44***	-0.32*	0.24	-0.75*
	(5.80)	(-1.68)	(0.65)	(-1.84)
EC +, PR -	1.73***	-0.28	0.35	-0.72*
	(4.20)	(-1.44)	(0.98)	(-1.77)
EC -, PR +	1.04**	-0.45*	-0.04	-0.96**
	(2.25)	(-1.94)	(-0.09)	(-1.98)
SUE	0.45***	0.02**	-0.00	-0.01
	(10.40)	(2.04)	(-0.12)	(-0.59)
CAR(-12,-1)	-0.02***	-0.01***	-0.01***	-0.02***
	(-7.38)	(-3.99)	(-3.02)	(-4.96)
CAR(-1,0)	-0.02*	-0.00	-0.01	-0.02
	(-1.73)	(-0.53)	(-0.71)	(-1.47)
Size	-0.32	0.06	0.16	-0.14
	(-1.55)	(0.55)	(0.93)	(-0.59)
log(BM)	-0.76***	-0.13*	-0.38***	-0.50***
	(-5.15)	(-1.80)	(-2.87)	(-2.83)
Inst Own	1.15*	-0.51*	0.50	0.01
	(1.94)	(-1.73)	(0.74)	(0.01)
Constant	-1.08	-0.07	-2.80	1.35
	(-0.53)	(-0.06)	(-1.60)	(0.53)
Observations	24,494	24,494	24,494	24,494
CEO FE	✓	✓	✓	✓
Year-Month FE	✓	✓	✓	✓
Adjusted R-sq	0.081	0.028	0.032	0.043

Table A.V

Comprehensive Thematic Drivers of Tonal Inconsistency

This table presents the results of a Post-LASSO Linear Probability Model (LPM), where the dependent variable is a dummy equal to one for tonally inconsistent earnings announcements, and zero otherwise. The main independent variables are the differences in topic proportions between the conference call and the press release (Δw_i). The full set of 43 substantive topic deltas and other firm-level controls are used as potential predictors. The reported variables are those selected by a LASSO procedure with 10-fold cross-validation. The model includes firm and year-month fixed effects. Standard errors are clustered by date. The AUC and the p-value for a joint F-test of the selected topic deltas are reported at the bottom of the table. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Post-LASSO LPM Results with Fixed Effects

Topic Name	Coefficient	Topic Name	Coefficient
Financial Metrics & Non-GAAP Measures	0.81***	Financial Reporting & Forward-Looking Statements	0.80***
	(18.35)		(12.70)
Financial Performance & Restructuring	0.99***	Tobacco Industry Litigation & Regulation	0.66***
	(11.25)		(9.25)
Life Insurance & Annuities	0.74***	COVID-19 Pandemic Impact	0.62***
	(4.27)		(4.40)
Oil & Gas Exploration & Production	0.47***	Agricultural Transportation & Logistics	0.41**
	(3.81)		(2.41)
M&A & Corporate Transactions	0.38***	Banking & Credit	0.33**
	(4.07)		(2.25)
Corporate Governance	0.25**	Macroeconomic Conditions & Prudence	0.22***
	(2.33)		(3.21)
Managerial Uncertainty & Qualifiers	0.21***	Electric Utilities & Renewable Energy	0.20
	(4.20)		(1.58)
Waste Management & Environmental Services	0.14	Raw Materials & Manufacturing	0.10
	(0.50)		(0.66)
Strategic Execution & Value Creation	0.08	Mining & Commodity Refining	0.08
	(1.50)		(0.41)
Consumer Brands, Food & Beverage	0.03	Pharmaceutical & Medical Devices	-0.72***
	(0.23)		(-4.45)
Corporate Culture & Leadership	-0.30***	Telecommunications & Wireless Services	-0.34*
	(-4.24)		(-1.67)
Earnings Call Protocol & Q&A	-0.57	Restaurant & Food Service	-0.18
	(-1.35)		(-0.96)
Media, Entertainment, & Hospitality	-0.13	Real Estate & Construction	-0.13
	(-0.77)		(-0.74)
Digital Payments & Fintech	-0.07	Strategic Planning & Capital Allocation	-0.01
	(-0.57)		(-0.24)
Biopharma R&D & Clinical Trials	-0.01		
	(-0.09)		
Observations		22,926	
Firm FE		✓	
Year-Month FE		✓	
AUC		0.621	
F-test p-value		0.000	
Pr > χ^2		0.000	

Table A.VI

Robustness to Asset Pricing Model: Panel Regressions of CAR following Tetlock (2008)

This table presents a robustness check for the main results reported in Table V to ensure the findings are not sensitive to the choice of asset pricing model. Following the approach of Tetlock et al. (2008), the baseline regression specification is replicated, but with cumulative abnormal returns (CAR) estimated using the Fama-French (2015) five-factor model. 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 under this alternative model provides strong evidence that the observed market reaction is robust to the asset pricing specification. 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[2:20]	CAR[2:40]
Positive Consistent	2.39***	-0.53***	-0.16	-0.72
	(5.96)	(-3.05)	(-0.45)	(-1.35)
EC +, PR -	1.71***	-0.47***	-0.04	-0.73
	(4.33)	(-2.65)	(-0.13)	(-1.42)
EC -, PR +	1.07**	-0.60***	-0.61	-1.35**
	(2.39)	(-2.73)	(-1.48)	(-2.25)
SUE	0.45***	0.01	0.00	-0.01
	(10.63)	(1.47)	(0.04)	(-0.38)
CAR(-12,-1)	-5.99***	-4.64***	-21.02***	-43.75***
	(-7.72)	(-10.58)	(-21.46)	(-30.58)
CAR(-1,0)	-0.01	0.01	0.00	-0.01
	(-0.60)	(0.94)	(0.15)	(-0.45)
Size	-0.36**	-0.01	0.30**	-0.20
	(-2.12)	(-0.09)	(1.97)	(-0.88)
log(BM)	-0.52***	-0.12**	-0.42***	-0.98***
	(-3.83)	(-2.14)	(-3.08)	(-4.84)
Inst Own	0.82	-0.23	-0.05	0.08
	(1.50)	(-0.96)	(-0.10)	(0.10)
Constant	-0.03	0.63	-3.21**	1.89
	(-0.02)	(0.76)	(-2.13)	(0.77)
Observations	24,638	24,638	24,638	24,638
Firm FE	✓	✓	✓	✓
Year-Month FE	✓	✓	✓	✓
Adjusted R-sq	0.071	0.035	0.096	0.170

Table A.VII

Topic Labels and Descriptions from Structural Topic Model Analysis

This table presents the 43 topics extracted from the Structural Topic Model (STM) analysis of earnings call transcripts and press releases. Each topic is labeled based on the most frequent and exclusive (FREX) words and represents a distinct thematic dimension of firm disclosures. The topics span various business domains including financial reporting, industry-specific operations, strategic planning, and market conditions. The analysis covers earnings calls and press releases from 2006-2023 for S&P 500 companies.

Topics	**Key Words**	**Topics**	**Key Words**
1. Waste Management & Environmental Services	waste, landfill, recycling, disposal, volume, republic, recycle	2. Financial Reporting & Investor Relations	statement, slide, website, president, chief, officer, press_release
3. Tobacco Industry Litigation & Regulation	cigarette, tobacco, court, plaintiff, investigation, defendant, lawsuit	4. Corporate Culture & Leadership	people, love, learn, incredible, amazing, idea, wonderful
5. Earnings Call Protocol & Q&A	caller, later, multi, caller, wide_variety, brief, limit	6. Strategic Execution & Value Creation	strategic, execute, execution, progress, leadership, discipline, strategy
7. Digital Payments & Fintech	debit, card, app, merchant, mobile, payment, mobile_app	8. Managerial Uncertainty & Qualifiers	guess, anything, cash_flow, happen, whatever, exactly, frankly
9. Property & Casualty Insurance	catastrophe, combine_ratio, accident, underwriting, allstate, property_casualty, reinsurance	10. Industrial Equipment & Manufacturing	aftermarket, engine, industrial, truck, equipment, aerospace, automotive
11. Pharmaceutical & Medical Devices	generic_competition, allergan, stent, neuromodulation, generic_competition, pacemaker, phase_study	12. Macroeconomic Conditions & Prudence	balance_sheet, stable, environment, conservative, cautious, recession, scenario
13. COVID-19 Pandemic Impact	pandemic, crisis, lockdown, virus, resilient, coronavirus, surge	14. Raw Materials & Manufacturing	raw_material, lithium, aluminum, steel, packaging, mill, chemical
15. Asset Management & Financial Services	client, institutional, inflow, outflow, fund, advisory, blackrock	16. Oil & Gas Exploration & Production	oil_equivalent, drill, wolfcamp, marcellus, drilling, basin, permian
17. Retail Operations & Merchandising	store, merchandise, comp, assortment, dollar_tree, remodel, merchandising	18. Healthcare & Clinical Trials	dose, readout, inhibitor, efficacy, study, antibody, placebo
19. Telecommunications & Wireless Services	broadband, postpaid, churn, verizon, wireless, tower, fiber	20. Revenue Growth & Financial Performance	revenue, organic, margin, adjusted, guidance, double_digit, expansion

Table A.VII – (Continued)

Topics	Key Words	Topics	Key Words
21. Capital Markets & Trading	clearing, trading, issuance, index, agency, s&p, derivative	22. Life Insurance & Annuities	variable_annuity, annuity, mortality, persistency, statutory, retirement, disability
23. Semiconductor & Hardware Technology	nanometer, foundry, memory, semiconductor, microchip, wafer, processor	24. Electric Utilities & Renewable Energy	megawatt, transmission, electric, utility, solar, renewable, nuclear
25. Real Estate & Construction	homebuilding, dealer, housing, land, builder, construction, texas	26. Biopharma R&D & Clinical Trials	pharmacy, health_care, cigna, generic, medical, healthcare, physician
27. Corporate Governance	stock, stockholder, compensation, document, quarterly, information, form	28. Life Sciences & Medical Technology	agilent, lab, invisalign, surgeon, instrument, procedure, diagnostic
29. Cloud Computing & Enterprise Software	cloud, software, saas, cisco, hardware, enterprise, subscription	30. Financial Reporting & Forward-Looking Statements	selling_price, price_realization, chairman_president, conference_call, forward, millions, week
31. Defense & Aerospace	airplane, award, dod, aircraft, missile, defense, unmanned	32. Financial Metrics & Non-GAAP Measures	measures, comparable, intangible, substitute, fair_value_adjustment, recurring, reconciliation
33. Banking & Credit	noninterest, loan, deposit, mortgage_banking, lending, banking, delinquency	34. Agricultural Transportation & Logistics	intermodal, railroad, corn, truckload, soybean, farmer, coal
35. Consumer Brands, Food & Beverage	cereal, soup, foodservice, beer, coffee, wine, chocolate	36. Mining & Commodity Refining	molybdenum, refining, newmont, refinery, copper, gold, crude
37. Retail Apparel & Consumer Products	footwear, beauty, apparel, woman, mall, timberland, makeup	38. Strategic Planning & Capital Allocation	standpoint, perspective, frankly, free_cash_flow, different, space, guide
39. Media, Entertainment, & Hospitality	hotel, movie, audience, programming, entertainment, netflix, studio	40. Restaurant & Food Service	restaurant, franchisee, monster, menu, olive_garden, energy_drink, breakfast
41. International Markets & Currency	latin_america, russia, brazil, europe, india, asia, china	42. Financial Performance & Restructuring	unfavorable, decrease, decline, restructuring, favorable, offset, currency_translation
43. M&A & Corporate Transactions	cash, flow, debt, integration, synergy, acquisition, merger		