Essays on Corporate Disclosure, Innovation, and Environmental Strategy

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Abstract

This dissertation comprises three essays that examine how corporate communication and strategic firm behavior shape market outcomes, real investment, and environmental performance.

Chapter 1: Mixed Messages: Strategic Tonal Inconsistency and Recovery of the PEAD Anomaly. 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. A downward drift arises following tonally inconsistent disclosures, facilitating strategic insider trading and predicting subsequent adverse changes in firm fundamentals. The evidence aligns with managers strategically employing mixed messaging to exploit informational frictions induced by ambiguity.

Chapter 2: Echoing Messages: Narrative Trend-Following, Real Innovation, and Mispricing. I develop a firm-level measure of narrative trend-following from the topical overlap between managers' prepared earnings-call remarks and lagged analyst discourse. Narrative trend-following is associated with lower R&D, capital expenditure, and patent output, a shift from product toward process inventions, higher near-term profitability with slower sales growth, and negative risk-adjusted returns over the two quarters following the call. The evidence is consistent with thematic echoing as a substitute for economic substance rather than a signal of innovative capacity.

Chapter 3: The Green Side of the China Shock: Environmental Responses of U.S. Firms to Import Competition. Co-authored with Ali Ahmadi, Rui Duan, Ambrus Kecskés, and Phuong-Anh Nguyen, this essay examines the causal effect of import competition from China on the environmental outcomes and performance of U.S. manufacturing firms. Firms in industries exposed to greater import penetration significantly reduce pollution. Firms with stronger initial environmental credentials exhibit superior performance under competitive shocks and respond by emphasizing exploitative green innovation that leverages existing green technologies.

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Chapter 1:

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

Elham Tabatabaei

November 2025

Link to Latest Version

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

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 52 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., 28, 99, and 95).

Recent work has explored the predictability of returns following an earnings announcement by conditioning on the tonality of corporate communications (e.g., 101, 29, and 101). 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 (17).

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., 107, 2); 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 (76), or using the volume of unrelated concurrent disclosures to distract investors (110).

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. (65), 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., 125, 50, 67, 84, 80, 83, 105, 17, 110).

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 (113), 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 (22), appear to pre-plan their trades under legal protection, suggesting a pre-meditated, two-step strategy of first creating the ambiguity and then executing a pre-arranged sale. Simultaneously, the ambiguity created by these disclosures is so effective at delaying

[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 (122).

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 (63). This is because rational investors, who have limited processing capacity, must strategically allocate their finite cognitive resources across a vast set of available information (93). 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 (124). 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 (123; 9) and potentially higher idiosyncratic volatility (41; 8). In contrast, pervasive ambiguity is expected to induce passivity, leading to reduced trading volume (42; 46) 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. (11) 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 announce-

ments, as they are typically pre-scheduled (38; 27) and therefore often specifically excluded from studies focusing on investor distraction or limited attention (e.g., 110). This conclusion is reinforced by my empirical results, which hold after controlling for proxies related to both major models of inattention: distraction (74) (proxied by competing announcements on the same day and the time elapsed between the press release and conference call) and work-vs-leisure preferences (39) (proxied by Friday or after-hours announcements). Furthermore, a direct test shows no abnormal investor inattention using the Abnormal Google Search Volume Index (SVI) (32; 43). 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., 28, 99, and 95), a parallel stream of research demonstrates that significant market underreaction persists within the textual domain of corporate disclosures (e.g., 101, 89, 35, 29, 44, and 101). 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. (101) show that a text-based measure of surprise from conference calls generates a robust drift, while Feldman et al. (55) 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 (101) or to a temporal change in tone over time (55; 29), , this study proposes that the anomaly stems from a more deliberate friction that exploits the inherent imprecision of language—a quality Quine (109) 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 (101; 40; 108). 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 (89; 93). This line of inquiry highlights that not only the semantic content, but also the delivery characteristics of communication affect subsequent market dynamics (120; 72). 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 (70; 35). A separate, parallel body of work validates the conference call as a critical disclosure event that impacts markets and information intermediaries (118; 57; 20). 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 (97) and even analyzing non-textual cues like the vocal affect of managers (98). The adoption of Regulation Fair Disclosure by the U.S. Securities and Exchange Commission (SEC) (122), which broadened access to these calls (23), 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. (65) 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 (76; 7; 26; 90). These incentives are well-established, ranging from maximizing performance-based compensation (125; 67) and preserving reputational capital by delaying bad news (50; 64; 83), 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 (84), with some studies directly linking this opportunistic trading to market anomalies like PEAD (37). 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 (80) 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 (116), and that plan-based trades often precede predictable, material corporate news releases (69). This strategic timing of disclosures to benefit insider trading has been shown to occur on low-attention days, such as Fridays (105). My results show that following tonally inconsistent announcements, top executives, defined as the CEO, CFO, COO, president, and chairman of the board (113), 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 (107; 2), a strategy made more effective by investors' susceptibility to such manipulation due to "lazy" processing of complex information (29).

The strategic incentive to manage disclosure tone is powerful because investors face significant costs to acquire, interpret, and analyze complex information (e.g., 25). 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. (17) 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 (34) 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 (29), 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 (110). 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 (85), leading investors to adopt a passive "wait-and-see" approach (42). 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 (61; 86; 68). Alternatively, inconsistent signals could foster disagreement, where heterogeneous beliefs, as modeled by Miller (102), lead to increased trading as investors act on their differing interpretations (9). 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 (74). 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., 70; 34; 35; 92), but I adapt the process to address the unique features of my dataset. For instance, some press releases appear as image files; therefore, I retain `<img>` tags when they contain more than 100 words of textual content.

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

[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 (76) and Newswire (34; 35). See also (71) for a broader discussion on the information content of earnings press releases using SEC data.

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 (53) 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 (92) 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 (58), 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 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 (70) and builds on earlier applications to auditors' opinion letters (121). The approach treats the

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

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

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. (75). Observations are classified as positive if $Tone_{j,q,t} > 0$, and as negative otherwise.[7] I recognize that any dictionary-based polarity classification is subject to measurement error: bag-of-words tone can mislabel documents near the classification threshold, miss context or negation, and treat modest lexical differences as a sign change. The remainder of this section therefore implements an LLM-based placebo test against linguistic noise and alternative dictionaries and classification thresholds. These checks reduce the concern that the results are an artifact of a particular coding rule, but they cannot eliminate measurement error entirely.

[*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 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.

[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.

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 1 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.II), 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 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

[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:"*

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 linguistic noise. The placebo therefore addresses a leading source of measurement error in the inconsistency classification, namely that a dictionary applied to two related documents about the same event might mechanically generate sign disagreements. It does not, however, rule out remaining measurement error in the tone scores themselves. 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 (60). 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.III 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. Taken together, the placebo test and the alternative dictionaries and thresholds indicate that the findings are not an artifact of a single coding rule. Residual measurement error in textual tone remains possible, as with any lexicon-based classification, and should be kept in mind when interpreting the magnitude of the estimates.

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

[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.

Negative Consistent cases, collectively referred to as *Consistent*. This binary formulation allows me to study the effect of overall tonality inconsistency without distinguishing the direction of disagreement.

IV.I. Cumulative Abnormal Returns

To test whether tonal inconsistency between corporate disclosures affects stock prices, I draw on theories of information processing costs. This literature posits that when investors have limited attention and face cognitive costs to process information, they may initially underreact to public news (73). 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 (53).[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 (73). This supports H1(a), suggesting that tonal inconsistency successfully moderates the immediate negative price response.[11]

[10] As a robustness check, I augment the approach of Tetlock et al. (120) 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

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. 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 (101; 35; 59), 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

Figure A.1.

responses to mixed signals across earnings disclosures. The empirical specification is as follows:

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

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

[12] $SUE_{i,t}$ is defined as the Compustat-based standardized unexpected earnings and is computed as in Livnat and Mendenhall (91).

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-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.IV 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.IV 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 (92) 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.IV 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.V, 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 × (EC -, PR +)* group, consistent with the baseline results in Table V where this group also exhibited 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.

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

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 (113) are the architects of the firm's disclosure strategy (22). 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 (4), 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:

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

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. (16) 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 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

[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.

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.IV). 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 (94). 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., 78; 48). CEO Tenure is included as a proxy for experience and potential entrenchment (72). 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 (127); 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 finding.

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., 54; 1), 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 (62; 13). To construct these measures, I use the raw text of corporate charters from the Harvard Law School CCG Corpus, which provides data until 2021 (58). Similar to text-based methodologies in the literature that extract quantitative measures from qualitative disclosures (e.g., 88; 120), 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 (115; 66) and greater scrutiny from information intermediaries (104).

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., 50; 67; 83). 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* (3), where lower values indicate higher risk, and the *Ohlson O-Score* (106), 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) (112), 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 (18), which has become a standard tool for textual analysis (e.g., 24). While newer to finance, STM is a well-established methodology in other leading empirical social sciences such as political science (e.g., 103; 31). 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](51)) 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 (6). 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

[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

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.

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) (14). 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

[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.

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 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

[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 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.

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 (102; 123), posits that conflicting signals should fuel trading as investors confidently act on their differing interpretations (9; 81). This would manifest as higher trading volume and potentially higher idiosyncratic volatility (41). 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 (42; 47). 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 (5); and *MDAJVOL*, the firm-specific median-adjusted percentage of shares traded, following Bamber et al. (9). 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]* × *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 (30). Theoretically, ambiguity-induced information asymmetry is expected to create adverse selection risk for market makers, leading them to widen bid-ask spreads (61; 86; 68). 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. (11). 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. (11)). 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. (11) 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., 39; 74). 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 (32; 43). 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. Because this binary classification can contain measurement error, 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, including alternative dictionaries and thresholds, 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 60. 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. (120) 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.VII, 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 recognize that dictionary-based tone is measured with error; an LLM placebo test and alternative dictionaries and classification thresholds reduce the concern that the results reflect linguistic noise or a particular threshold, though some measurement error may remain. 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.

Bibliography

[1] Adams, Renée B. and Daniel Ferreira. 2009. Women in the boardroom and their impact on governance and performance. *Journal of Financial Economics* 94(2), 291–309.

[2] Ahern, Kenneth and Denis Sosyura. 2014. Who Writes the News? Corporate Press Releases during Merger Negotiations. *Journal of Finance* 69, 241–291.

[3] Altman, Edward I. 1968. Financial Ratios, Discriminant Analysis and the Prediction of Corporate Bankruptcy. *The Journal of Finance* 23(4), 589–609.

[4] Angrist, Joshua D. and Jörn-Steffen Pischke. 2009. Mostly Harmless Econometrics: An Empiricist's Companion. *Princeton University Press*.

[5] Ajinkya, Bipin B. and Prem C. Jain. 1989. The Behavior of Daily Stock Market Trading Volume. *Journal of Accounting and Economics* 11(4), pp. 331–359.

[6] Ardia, David, Keven Bluteau, and Kris Boudt. 2022. Media abnormal tone, earnings announcements, and the stock market. *Journal of Financial Markets* 61, 100683.

[7] Arslan-Ayaydin, Ozgur, Kris Boudt, and James Thewissen. 2016. Managers Set the Tone: Equity Incentives and the Tone of Earnings Press Releases. *Journal of Banking and Finance* 72, S132–S147.

[8] Atmaz, A., and A. M. Buffa. 2024. Volatility Disagreement and Asset Prices. *Working Paper*.

[9] Bamber, L. S., O. E. Barron, and T. L. Stober. 1997. Trading Volume and Different Aspects of Disagreement Coincident with Earnings Announcements. *The Accounting Review* 72(4), 575–597.

[10] Barber, Brad M. and Terrance Odean. 2008. All That Glitters: The Effect of Attention and News on the Buying Behavior of Individual and Institutional Investors. *Review of Financial Studies* 21(2), 785–818.

[11] Barron, O. E., O. Kim, S. C. Lim, and D. E. Stevens. 1998. Using Analysts' Forecasts to Measure Properties of Analysts' Information Environment. *The Accounting Review* 73(4), 421–433.

[12] Beaver, William H. 1977. The Information Content of Annual Earnings Announcements. *Journal of Finance* 32(1), 65–92.

[13] Bebchuk, Lucian, Alma Cohen, and Allen Ferrell. 2009. What Matters in Corporate Governance?. *The Review of Financial Studies* 22(2), 783–827.

[14] Belloni, Alexandre and Victor Chernozhukov and Christian Hansen. 2014. High-Dimensional Methods and Inference on Treatment and Structural Effects. *Journal of Economic Perspectives* 28, 29–50.

[15] Bernard, Victor L. and Jacob K. Thomas. 1989. Post-Earnings-Announcement Drift: Delayed Price Response or Risk Premium. *Journal of Accounting Research* 27, 1–36.

[16] Bertrand, Marianne; Duflo, Esther; and Mullainathan, Sendhil. 2004. How Much Should We Trust Differences-in-Differences Estimates?. *The Quarterly Journal of Economics* 119(1), pp. 249–275.

[17] Blankespoor, Elizabeth, Ed deHaan, and Christina Zhu. 2020. Capital Market Effects of Media Synthesis and Dissemination: Evidence from Robo-Journalism. *Journal of Accounting and Economics* 69(2–3), 101312.

[18] Blei, David M., Andrew Y. Ng, and Michael I. Jordan. 2003. Latent Dirichlet Allocation. *Journal of Machine Learning Research* 3, 993–1022.

[19] Boudt, Kris, James Thewissen, and Wouter Torsin. 2008. When Does the Tone of Earnings Press Releases Matter? *International Review of Financial Analysis* 57, 231–245.

[20] Bowen, Robert M., Angela K. Davis, and Dawn A. Matsumoto. 2002. Do Conference Calls Affect Analysts' Forecasts? *The Accounting Review* 77(2), 285–316.

[21] Brown, Stephen V. and Jennifer Wu Tucker. 2011. Large-Sample Evidence on Firms' Year-Over-Year MD&A Modifications. *Journal of Accounting Research* 49, 309–346.

[22] Brown, Lawrence D.; Call, Andrew C.; Clement, Michael B.; and Sharp, Nathan Y. 2019. Managing the Narrative: Investor Relations Officers and Corporate Disclosure. *Journal of Accounting and Economics* 67(1), pp. 58–79.

[23] Bushee, Brian J., Dawn A. Matsumoto, and Gregory S. Miller. 2003. Open Versus Closed Conference Calls: The Determinants and Effects of Broadening Access to Disclosure. *Journal of Accounting and Economics* 34(1–3), 149–180.

[24] Bybee, Leland, Bryan Kelly, and Yinan Su. 2023. Narrative asset pricing: Interpretable systematic risk factors from news text. *The Review of Financial Studies* 36(12), 4759–4787.

[25] Bushee, Brian J., and Gus Zhenyu Huang. 2024. Do Analysts and Investors Efficiently Respond to Conference Call Linguistic Complexity? *The Accounting Review* 99 (4), 143–172.

[26] Cao, Qiaozhi, Jason S. H. Kwan, and Kai S. E. Li. 2023. Are There Any Differences in the Time Series, Particularly Around Introduction of Loughran and McDonald (2011)? *Review of Financial Studies* 36 (9), 3603–3611.

[27] Chapman, Kimball L. 2018. Earnings Notifications, Investor Attention, and the Earnings Announcement Premium. *Journal of Accounting and Economics* 66(1), 222–243.

[28] Chordia, Tarun, Avanidhar Subrahmanyam, and Qing Tong. 2014. Have Capital Market Anomalies Attenuated in the Recent Era of High Liquidity and Trading Activity? *Journal of Accounting and Economics* 58(1), 41–58.

[29] Cohen, Lauren, Christopher Malloy, and Quoc Nguyen. 2020. Lazy Prices. *The Journal of Finance* 75(3), 1371–1415.

[30] Corrado, Christos I. and Terry L. Zivney. 2000. Detecting Abnormal Bid-Ask Spread: A Comparison of Event Study Methods. *Review of Quantitative Finance and Accounting* 14(1), pp. 45–65.

[31] Curry, Todd, and Michael P. Fix. 2019. All the President's Words: The Effect of Presidential Use of Force Rhetoric on the US Supreme Court. *The Journal of Politics* 81(1), 227–241.

[32] Da, Zhi; Engelberg, Joseph; and Gao, Pengjie. 2011. In Search of Attention. *The Journal of Finance* 66(5), pp. 1461–1499.

[33] Dang, Tung Lam, Fariborz Moshirian, and Bohui Zhang. 2015. Commonality in News Around the World. *Journal of Financial Economics* 116(1), 82–110.

[34] Davis, Angela K., Isho Tama-Sweet Ge, Dawn Matsumoto, and Jenny Li Zhang. 2012a. Managers' Use of Language Across Alternative Disclosure Outlets: Earnings Press Releases Versus MD&A. *Contemporary Accounting Research* 29(3), 804–837.

[35] Davis, Angela K., Jeremy M. Piger, and Lisa M. Sedor. 2012b. Beyond the Numbers: Measuring the Information Content of Earnings Press Release Language. *Contemporary Accounting Research* 29(3), 845–868.

[36] Davis, Angela K., Weili Ge, Dawn Matsumoto, and Jenny Li Zhang. 2015. The Effect of Manager-Specific Optimism on the Tone of Earnings Conference Calls. *Review of Accounting Studies* 20(2), 639–673.

[37] Dargenidou, Charoula, Yaniv Konchitchki, and Ioannis P. Tampakoudis. 2018. Insider trading and the post-earnings announcement drift. *Journal of Business Finance & Accounting* 45 (1-2), 101–129.

[38] deHaan, Ed, Terry Shevlin, and Jacob Thornock. 2015. Market (In)Attention and the Strategic Scheduling and Timing of Earnings Announcements. *Journal of Accounting and Economics* 60(1), 36–55.

[39] DellaVigna, Stefano and Joshua M. Pollet. 2009. Investor Inattention and Friday Earnings Announcements. *The Journal of Finance* 64(2), pp. 709–749.

[40] Demers, Elizabeth and Clara Vega. 2009. Soft Information in Earnings Announcements: News or Noise? Meeting Papers, 80, *Society for Economic Dynamics*.

[41] Diether, Karl B.; Malloy, Christopher J.; and Scherbina, Anna. 2002. Differences of Opinion and the Cross Section of Stock Returns. *The Journal of Finance* 57(5), pp. 2113–2141.

[42] Dow, James and Sérgio Ribeiro da Costa Werlang. 1992. Uncertainty Aversion, Risk Aversion, and the Optimal Choice of Portfolio. *Econometrica* 60(1), pp. 197–204.

[43] Drake, Michael S.; Roulstone, Darren T.; and Thornock, Jacob R. 2012. Investor Information Demand: Evidence from Google Searches around Earnings Announcements. *Journal of Accounting Research* 50(4), pp. 1001–1040.

[44] Druz, Mikhail, Petya Petzev, Alexander F. Wagner, and Richard J. Zeckhauser. 2020. When Managers Change Their Tone, Analysts and Investors Change Their Tune. *Financial Analysts Journal* 76(2), 85–106.

[45] Duan, Lini, Lingyi Li, Kyung-Hye Park, and Di Wu. 2023. Muddy the Waters to Conceal Information? Evidence from Firms' Inconsistent Answers during Q&A. *Finance Research Letters* 51, 103415.

[46] Easley, David and Maureen O'Hara. 2009. Ambiguity and Asset Prices: An Experimental Perspective. *The Review of Financial Studies* 22(5), pp. 1757–1796.

[47] Epstein, Larry G. and Martin Schneider. 2008. Ambiguity, Information Quality, and Asset Pricing. *The Journal of Finance* 63(1), pp. 197–228.

[48] Faccio, Mara, Maria-Teresa Marchica, and Roberto Mura. 2016. CEO gender and corporate risk-taking. *Journal of Financial Economics* 122(1), 82–109.

[49] Fama, Eugene F. 1970. Efficient Capital Markets: A Review of Theory and Empirical Work. *The Journal of Finance* 25(2), pp. 383–417.

[50] Fama, Eugene F. 1980. Agency Problems and the Theory of the Firm. *Journal of Political Economy* 88(2), pp. 288–307.

[51] Fama, Eugene F. and Kenneth R. French. 1997. Industry Costs of Equity. *Journal of Financial Economics* 43, 153–193.

[52] Fama, Eugene F. 1998. Market efficiency, long-term returns, and behavioral finance. *Journal of Financial Economics* 49(3), 283–306.

[53] Fama, Eugene F. and Kenneth R. French. 2015. A Five-Factor Asset Pricing Model. *Journal of Financial Economics* 116(1), 1–22.

[54] Farrell, Kathleen A. and Philip L. Hersch. 2005. Additions to corporate boards: the effect of gender. *Journal of Corporate Finance* 11(1-2), 85–106.

[55] Feldman, Ronen, Suresh Govindaraj, Joshua Livnat, and Benjamin Segal. 2010. Management's Tone Change, Post-Earnings Announcement Drift, and Accruals. *Review of Accounting Studies* 15(4), 915–953.

[56] Foster, George, Chris Olsen, and Terry Shelvin. 1984. Earnings Releases, Anomalies, and the Behavior of Security Returns. *The Accounting Review* 59, 574–603.

[57] Frankel, Richard, Marilyn Johnson, and Douglas J. Skinner. 1999. An Empirical Examination of Conference Calls as a Voluntary Disclosure Medium. *Journal of Accounting Research* 37, 133–150.

[58] Frankenreiter, Jens, Cathy Hwang, Yaron Nili, and Eric Talley. 2022. "Charters Corpus from: Cleaning Corporate Governance", Harvard Dataverse, V3, https://doi.org/10.7910/DVN/GX5URZ.

[59] García, Diego. 2013. Sentiment during Recessions. *The Journal of Finance* 68(3), pp. 1267–1300.

[60] García, Diego; Xiaowen Hu; and Maximilian Rohrer. 2023. The colour of finance words. *Journal of Financial Economics* 147(3), 525–549.

[61] Glosten, Lawrence R. and Paul R. Milgrom. 1985. Bid, Ask and Transaction Prices in a Specialist Market with Heterogeneously Informed Traders. *Journal of Financial Economics* 14(1), 71–100.

[62] Gompers, Paul, Joy Ishii, and Andrew Metrick. 2003. Corporate Governance and Equity Prices. *The Quarterly Journal of Economics* 118(1), 107–156.

[63] Grossman, Sanford J. and Joseph E. Stiglitz. 1976. Information and Competitive Price Systems. *The American Economic Review* 66, 246–253.

[64] Graham, John R.; Harvey, Campbell R.; and Rajgopal, Shiva. 2005. The Economic Implications of Corporate Financial Reporting. *Journal of Accounting and Economics* 40(1-3), pp. 3–73.

[65] Harbaugh, Rick, John W. Maxwell, and Kelly Shue. 2016. Consistent Good News and Inconsistent Bad News. *NBER Working Paper* No. 22522.

[66] Hartzell, Jay C. and Laura T. Starks. 2003. Institutional Investors and Executive Compensation. *The Journal of Finance* 58(6), 2351–2374.

[67] Healy, Paul M. 1985. The Effect of Bonus Schemes on Accounting Decisions. *Journal of Accounting and Economics* 7(1-3), pp. 85–107.

[68] Hendershott, Terrence; Jones, Charles M.; and Menkveld, Albert J. 2011. Does Algorithmic Trading Improve Liquidity?. *The Journal of Finance* 66(1), pp. 1–33.

[69] Henderson, Andrew C.; Jagolinzer, Alan D.; and Muller, Karl A. III. 2015. Trading Activity, Information Asymmetry, and Corporate Disclosure. *Journal of Financial Economics* 118(2), pp. 363–380.

[70] Henry, Elaine. 2008. Are Investors Influenced by How Earnings Press Releases Are Written? *Journal of Business Communication* 45(4), 363–407.

[71] Henry, Elaine and Andrew J. Leone. 2016. Measuring Qualitative Information in Capital Markets Research: Comparison of Alternative Methodologies to Measure Disclosure Tone. *The Accounting Review* 491(1), 153–178.

[72] Hermalin, Benjamin E. and Michael S. Weisbach. 1998. Endogenously Chosen Boards of Directors and Their Monitoring of the CEO. *The American Economic Review* 88(1), 96–118.

[73] Hirshleifer, David and Siew Hong Teoh. 2003. Limited Attention, Information Disclosure, and Financial Reporting. *Journal of Accounting and Economics* 36(1-3), pp. 337–386.

[74] Hirshleifer, David, Sonya Seongyeon Lim, and Siew Hong Teoh. 2009. Driven to Distraction: Extraneous Events and Underreaction to Earnings News. *Journal of Finance* 64(5), 2289–2325.

[75] Hollander, Stephan, Maarten Pronk, and Erik Roelofsen. 2010. Does Silence Speak? An Empirical Analysis of Disclosure Choices during Conference Calls. *Journal of Accounting Research* 48(3), 531–563.

[76] Huang, Xuan, Siew Hong Teoh, and Yinglei Zhang. 2014. Tone Management. *The Accounting Review* 89(3), 1083–1113.

[77] Huang, Allen H., Hui Wang, and Yi Yang, 2022, FinBERT: A large language model approach to extracting information from financial text, *Contemporary Accounting Research* 40, pp. 806–841.

[78] Huang, Jiekun and David J. Kisgen. 2013. Gender and corporate finance: Are male executives overconfident relative to female executives?. *Journal of Financial Economics* 108(3), 822–839.

[79] Jahan-Parvar, Mohammad R. and Liu, Hening. 2014. Ambiguity Aversion and Asset Prices in Production Economies. *The Review of Financial Studies* 27(10), pp. 3060–3097.

[80] Jagolinzer, Alan D. 2009. SEC Rule 10b5-1 and Insiders' Strategic Trading. *Management Science* 55(2), pp. 224–239.

[81] Kandel, Eugene and Neil D. Pearson. 1995. Differential Interpretation of Public Signals and Trade in Speculative Markets. *Journal of Political Economy* 103(4), pp. 831–872.

[82] Kanelis, Dimitrios, and Pierre L. Siklos, 2025, The ECB press conference statement: deriving a new sentiment indicator for the euro area, *International Journal of Finance & Economics* 30(1), pp. 652–664.

[83] Kothari, S. P.; Shu, Susan; and Wysocki, Peter D. 2009. Do Managers Withhold Bad News? *Journal of Accounting Research*.

[84] Ke, Bin; Huddart, Steven; and Petroni, Kathy. 2003. What Insiders Know About Future Earnings and How They Use It: Evidence from Insider Trades. *Journal of Accounting and Economics* 35(3), pp. 315–346.

[85] Knight, Frank H. 1921. *Risk, Uncertainty, and Profit*. Boston, MA: Houghton Mifflin Company.

[86] Krinsky, Itzhak and Jason Lee. 1996. Earnings Announcements and the Components of the Bid-Ask Spread. *The Journal of Finance* 51(4), pp. 1523–1535.

[72] Lee, Joshua. 2016. Can Investors Detect Managers' Lack of Spontaneity? Adherence to Predetermined Scripts during Earnings Conference Calls. *The Accounting Review* 91(1), 229–250.

[88] Li, Feng. 2008. Annual report readability, current earnings, and earnings persistence. *Journal of Accounting and Economics* 45(2-3), 221–247.

[89] Li, Feng. 2010. The Information Content of Forward-Looking Statements in Corporate Filings: A Naïve Bayesian Machine Learning Approach. *Journal of Accounting Research* 48(5), 1049–1102.

[90] Li, Jing, Nan Li, Tongshui Xia, and Jinjin Guo. 2023. Textual Analysis and Detection of Financial Fraud: Evidence from Chinese Manufacturing Firms. *Economic Modelling* 126, 106428.

[91] Livnat, Joshua and Richard Mendenhall. 2006. Comparing the Post-Earnings Announcement Drift for Surprises Calculated from Analyst and Time-Series Forecasts. *Journal of Accounting Research* 44(1), pp. 177–205.

[92] Loughran, Tim and Bill McDonald. 2011. When Is a Liability Not a Liability? Textual Analysis, Dictionaries, and 10-Ks. *Journal of Finance* 66, 35–65.

[93] Loughran, Tim and Bill McDonald. 2013. IPO First-Day Returns, Offer Price Revisions, Volatility, and Form S-1 Language. *Journal of Financial Economics* 109(2), 307–326.

[94] Malmendier, Ulrike and Geoffrey Tate. 2005. CEO Overconfidence and Corporate Investment. *The Journal of Finance* 60(6), 2661–2700.

[95] Martineau, Charles. 2021. Rest in Peace Post-Earnings Announcement Drift. . *Critical Finance Review* 11, 613–646.

[96] Masulis, Ronald W., Cong Wang, and Fei Xie. 2007. Corporate Governance and Acquirer Returns. *The Journal of Finance* 62(4), 1851–1889.

[97] Matsumoto, Dawn, Maarten Pronk, and Erik Roelofsen. 2011. What Makes Conference Calls Useful? The Information Content of Managers' Presentations and Analysts' Discussion Sessions. *The Accounting Review* 86(4), 1383–1414.

[98] Mayew, William J. and Mohan Venkatachalam. 2012. The Power of Voice: Managerial Affective States and Future Firm Performance. *Journal of Finance* 67(1), 1–43.

[99] McLean, R. David, and Jeffrey Pontiff. 2016. Does Academic Research Destroy Stock Return Predictability? *The Journal of Finance* 71(1), 5–32.

[100] Merton, Robert C. 1974. On the Pricing of Corporate Debt: The Risk Structure of Interest Rates. *The Journal of Finance* 29(2), pp. 449–470.

[101] Meursault, Vitaly, Pierre Jinghong Liang, Bryan R. Routledge, and Madeline Marco Scanlon. 2021. PEAD.txt: Post-Earnings-Announcement Drift Using Text. *Working Paper*.

[102] Miller, Edward M. 1977. Risk, Uncertainty, and Divergence of Opinion. *The Journal of Finance* 32(4), pp. 1151–1168.

[103] Mishler, William, and Richard Rose. 2015. Learning and unlearning democracy. *Journal of Elections, Public Opinion and Parties* 25(1), 21–42.

[104] Mitu, Dragos. 2022. Do insiders time Rule 10b5-1 plan adoptions? *Journal of Accounting and Economics* 73(2-3), 101469.

[105] Niessner, Marina. 2015. Strategic Disclosure Timing and Insider Trading. *SSRN Working Paper*.

[106] Ohlson, James A. 1980. Financial Ratios and the Probabilistic Prediction of Bankruptcy. *Journal of Accounting Research* 18(1), 109–131.

[107] Peng, Lin and Ailsa Roell. 2014. Managerial Incentives and Stock Price Manipulation. *Journal of Finance* 69(2), 487–526.

[108] Price, S. McKay, James S. Doran, David R. Peterson, and Barbara A. Bliss. 2012. Earnings Conference Calls and Stock Returns: The Incremental Informativeness of Textual Tone. *Journal of Banking and Finance* 36(4), 992–1011.

[109] Quine, Willard V. 1973. *The Roots of Reference*. La Salle, IL: Open Court.

[110] Rawson, Caleb, Brady J. Twedt, and Jessica Watkins, 2023, Managers' strategic use of concurrent disclosure: Evidence from 8-K filings and press releases, *The Accounting Review* 98(4), pp. 345–371.

[111] Rendleman Jr., Richard J., Charles P. Jones, and Henry A. Latané. 1982. Empirical Anomalies Based on Unexpected Earnings and the Importance of Risk Adjustments. *Journal of Financial Economics* 10, 269–287.

[112] Roberts, Margaret E., Brandon M. Stewart, and Dustin Tingley. 2014. Structural Topic Models for Open-Ended Survey Responses. *American Journal of Political Science* 58(4), 1064–1082.

[113] Rogers, Jonathan L. 2008. Disclosure Quality and Management Trading Incentives. *Journal of Accounting Research* 46(5), pp. 1265–1296.

[114] Rybinski, Krzysztof. 2020. The Forecasting Power of the Multi-Language Narrative of Sell-Side Research: A Machine Learning Evaluation. *Finance Research Letters* 34, 101261.

[115] Shleifer, Andrei and Robert W. Vishny. 1986. Large Shareholders and Corporate Control. *Journal of Political Economy* 94(3), 461–488.

[116] Shon, John J. and Stavros Veliotis. 2013. Rule 10b5-1 Plans and the Timing of Corporate Disclosures. *The Accounting Review* 88(6), pp. 2213–2244.

[93] Sims, Christopher A. 2003. Implications of Rational Inattention. *Journal of Monetary Economics* 50(3), pp. 665–690.

[118] Tasker, Sarah C. 1998. Bridging the Information Gap: Quarterly Conference Calls as a Medium for Voluntary Disclosure. *Review of Accounting Studies* 3(1–2), 137–167.

[101] Tetlock, Paul C. 2007. Giving Content to Investor Sentiment: The Role of Media in the Stock Market. *Journal of Finance* 62, 1139–1168.

[120] Tetlock, Paul C., Maytal Saar-Tsechansky, and Sofus Macskassy. 2008. More Than Words: Quantifying Language to Measure Firms' Fundamentals. *Journal of Finance* 63, 1437–1467.

[121] Uang, Jinn-Yang, David B. Citron, Sudi Sudarsanam, and Richard J. Taffler. 2006. Management Going-Concern Disclosures: Impact of Corporate Governance and Auditor Reputation. *European Financial Management* 12(5), 789–816.

[122] U.S. Securities and Exchange Commission. 2000. Final Rule: Selective Disclosure and Insider Trading. *U.S. Securities and Exchange Commission Release Nos. 33-7881, 34-43154*.

[123] Varian, Hal R. 1985. Divergence of Opinion in Complete Markets: A Note. *The Journal of Finance* 40(1), pp. 309–317.

[124] Verrecchia, Robert E. 1982. Information Acquisition in a Noisy Rational Expectations Economy. *Econometrica* 52(6), pp. 1562-1570.

[125] Watts, Ross L. and Jerold L. Zimmerman. 1978. Towards a Positive Theory of the Determination of Accounting Standards. *The Accounting Review* 53(1), pp. 112–134.

[126] Wu, Di, Shenghao Gao, Kam C. Chan, and Xiaoke Cheng. 2022. Do Firms Strategically Respond to Retail Investors on the Online Interactive Information Disclosure Platform? *Finance Research Letters* 47, 102631.

[127] Yim, Se-Eun. 2013. The acquisitiveness of youth: CEO age and acquisition behavior. *Journal of Financial Economics* 108(1), 250–273.

[104] Yu, Frank. 2008. Analyst coverage and earnings management. *Journal of Financial Economics* 88(2), 245–271.

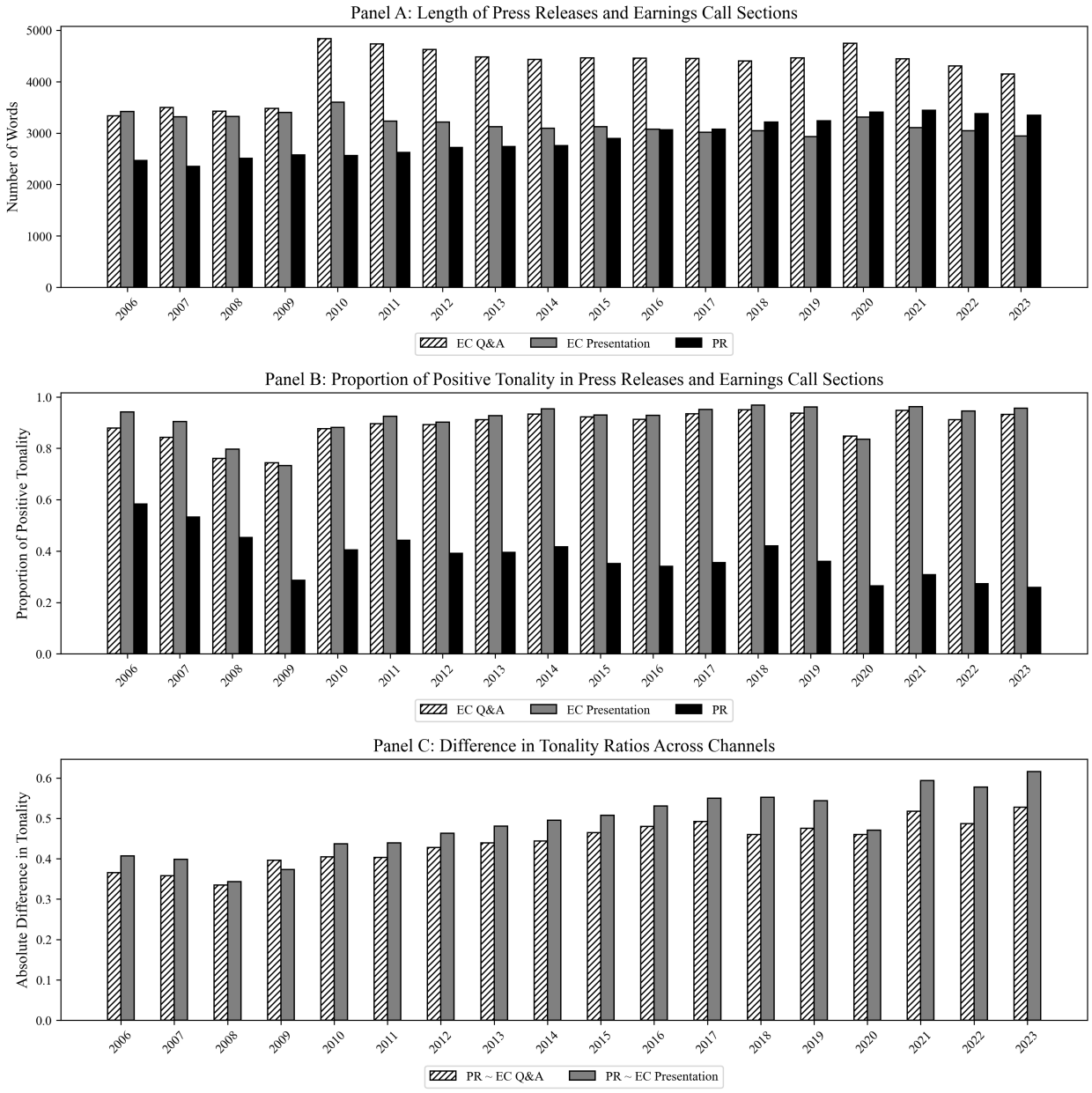


Figure 1. Descriptive Statistics of Key Tonal and Content Characteristics across Communication Mediums, specifically press releases (*PR*) and sections of earnings calls (*EC*), including the *presentation* and *Q&A* segments. Panel A shows the average number of words, comparing content length across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

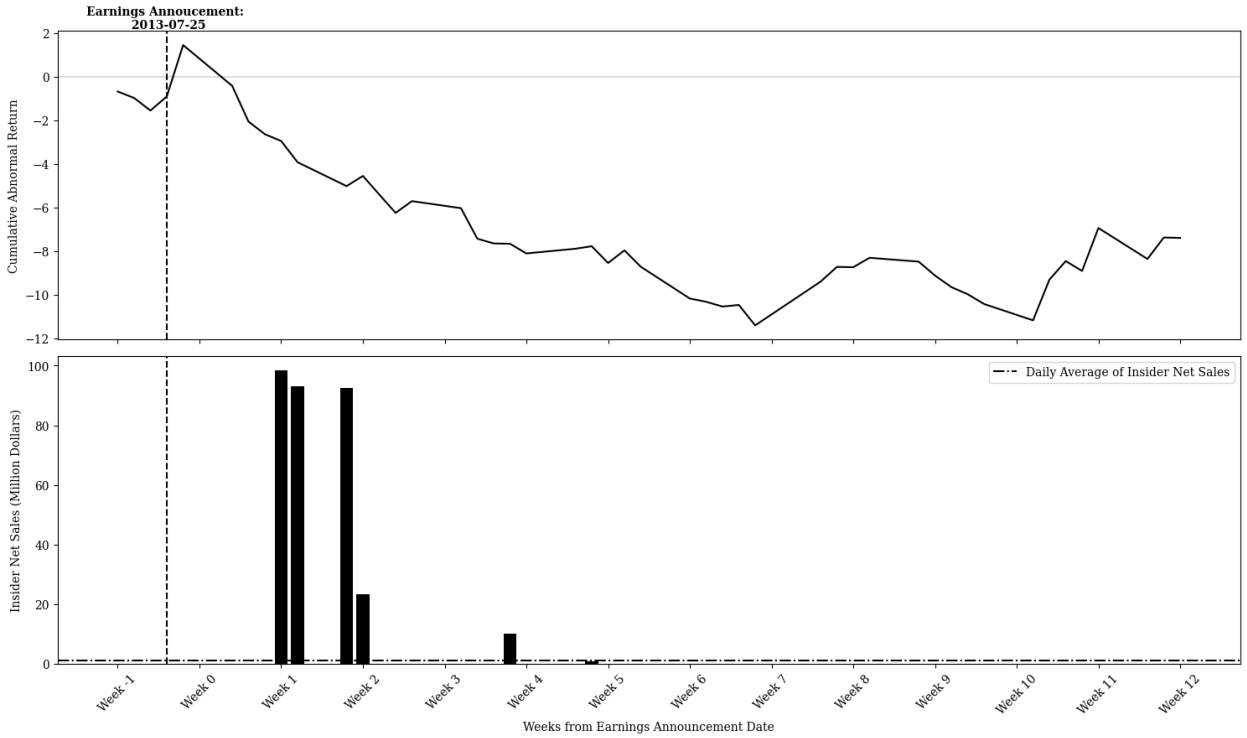


Figure 2. Amazon's CAR and Insider Net Sales Following Tonality Inconsistency Across Channels: This figure shows the cumulative abnormal returns and cumulative insider net sales of Amazon.com, Inc. (NASDAQ: AMZN) in the weeks following the release of Amazon's 2013Q2 earnings announcement. The announcement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

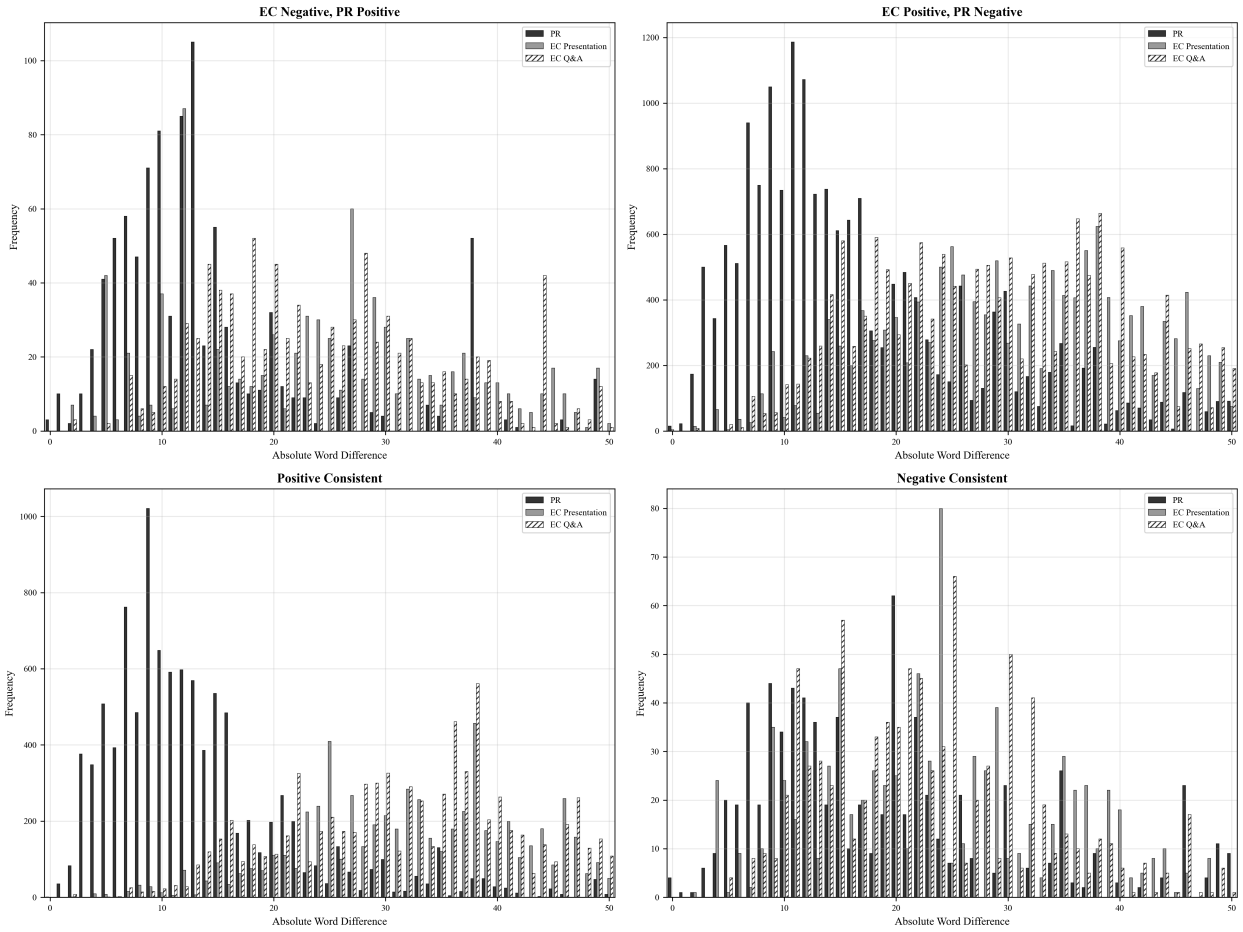
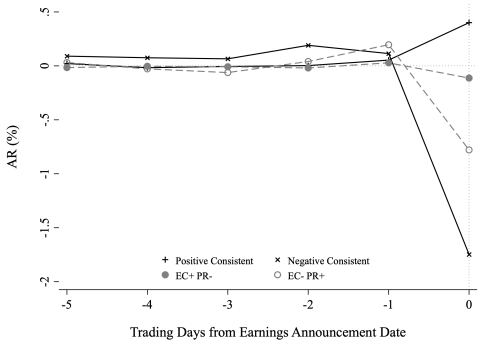


Figure 3. Distribution of Tonal Intensity by Consistency Category: This figure presents histograms of the absolute word difference (|Positive Words − Negative Words|) up to a threshold of 50 words for Press Releases (PR), Earnings Call (EC) Presentations, and EC Q&A sessions. The distributions are plotted 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

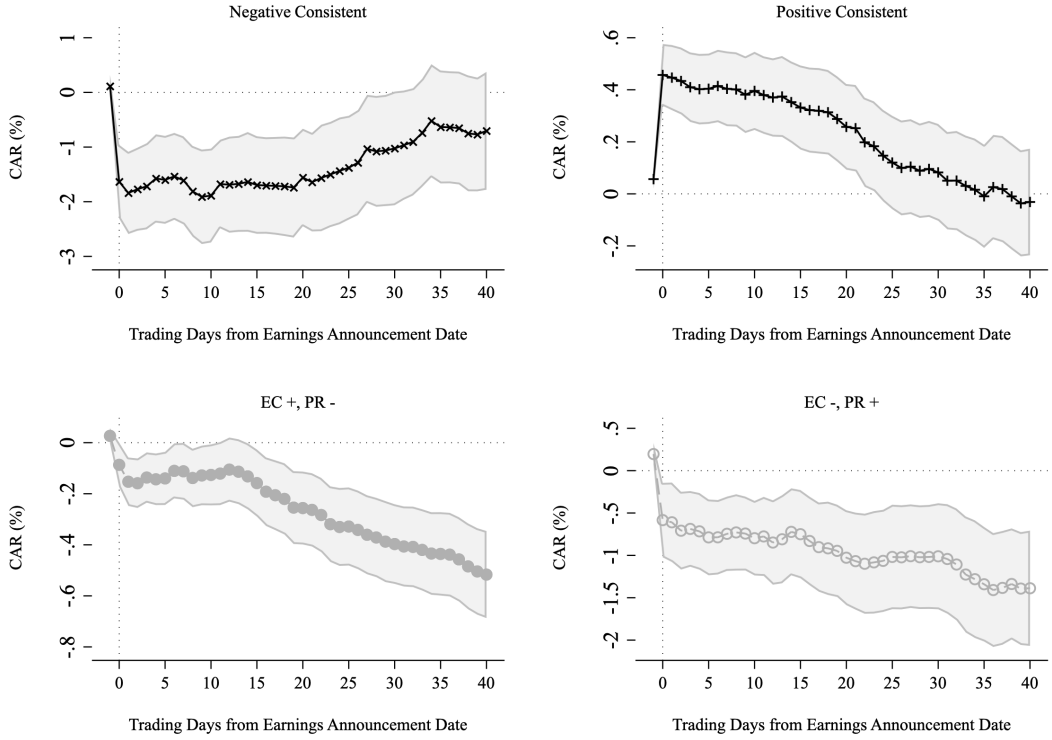


Figure 4. Abnormal Returns Across Consistency Groups: This figure plots the average abnormal returns for four categories based on the tonal consistency between the earnings conference call (EC) and the press release (PR). The sample includes S&P 500 firms from 2006Q1 to 2023Q3. Abnormal returns are estimated using the Fama-French five-factor model (53). 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 (53). *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	✓	✓	✓	✓	✓
$\Pr > \chi^2$	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.VI. 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
$\Pr > \chi^2$	0.000

Table XII

Panel Regressions of Abnormal Trading Volume and Bid-Ask Spreads on Tonal Inconsistency

This table presents regression estimates of abnormal trading volume and bid-ask spreads following earnings announcements. The dependent variables are Abnormal Volume (Abn Vol), defined as the firm's trading volume on the announcement day minus its average volume over the prior 60 trading days, and Abnormal Bid-Ask Spread (Abn Spread), defined as the bid-ask spread on the announcement day minus its average over the prior 60 trading days. 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 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.

	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

Panel Regressions of Analyst Forecast Properties on Tonal Inconsistency

This table presents regression estimates of analyst forecast properties following earnings announcements. The dependent variables are analyst forecast dispersion (Disp), the precision of public information (Pub Prec), and the precision of private information (Priv Prec), following the Barron et al. (11) framework. 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 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.

	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

Panel Regressions of Idiosyncratic Volatility and Search Volume on Tonal Inconsistency

This table presents regression estimates of idiosyncratic volatility and Google Search Volume Index (SVI) following earnings announcements. The dependent variables are idiosyncratic volatility (iVol) and Abnormal SVI (ASVI). 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 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.

	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 60 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.6 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:

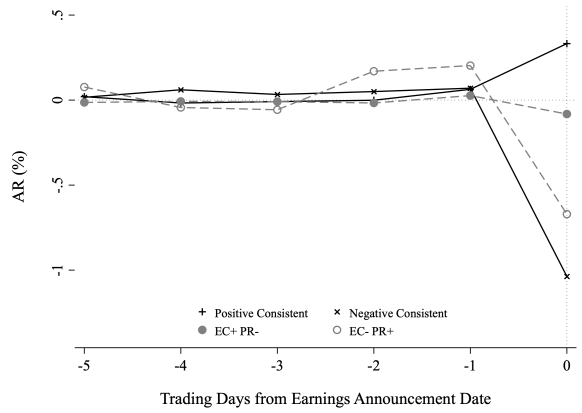
$$\text{TopicDivergence}_{i,t}(PR, QA) = \sum_{k=1}^{43} |\theta_{i,t,k}^{PR} - \theta_{i,t,k}^{EC,QA}|$$

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:

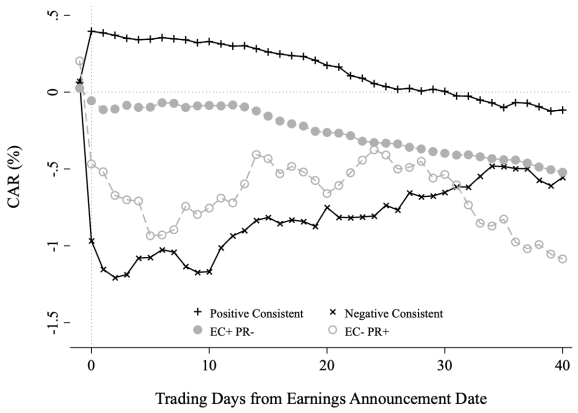
$$\text{TopicDivergence}_{i,t,k} = \max(|\theta_{i,t,k}^{PR} - \theta_{i,t,k}^{EC,Pres}|,\ |\theta_{i,t,k}^{PR} - \theta_{i,t,k}^{EC,QA}|)$$

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.

Panel A: Consistency between Press Release and Presentation Section

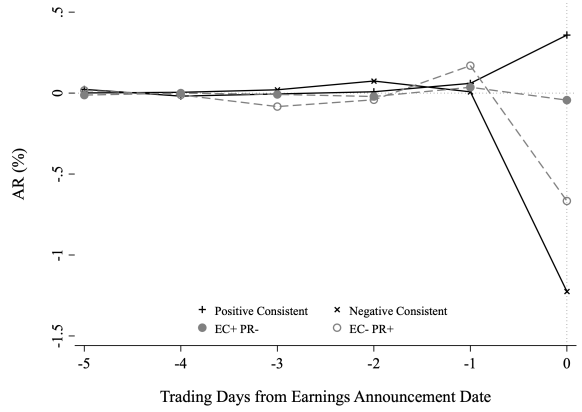


(a) Daily Abnormal Returns (AR)

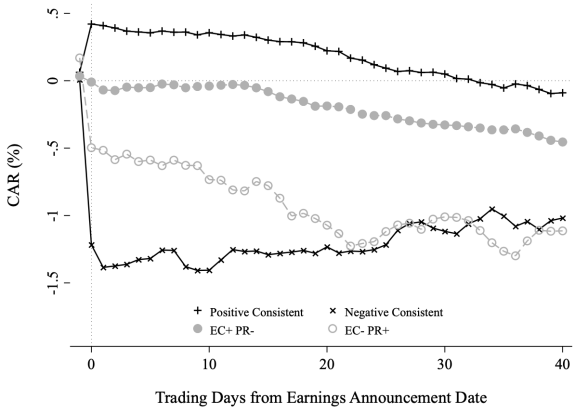


(b) Cumulative Abnormal Returns (CAR)

Panel B: Consistency between Press Release and Q&A 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).

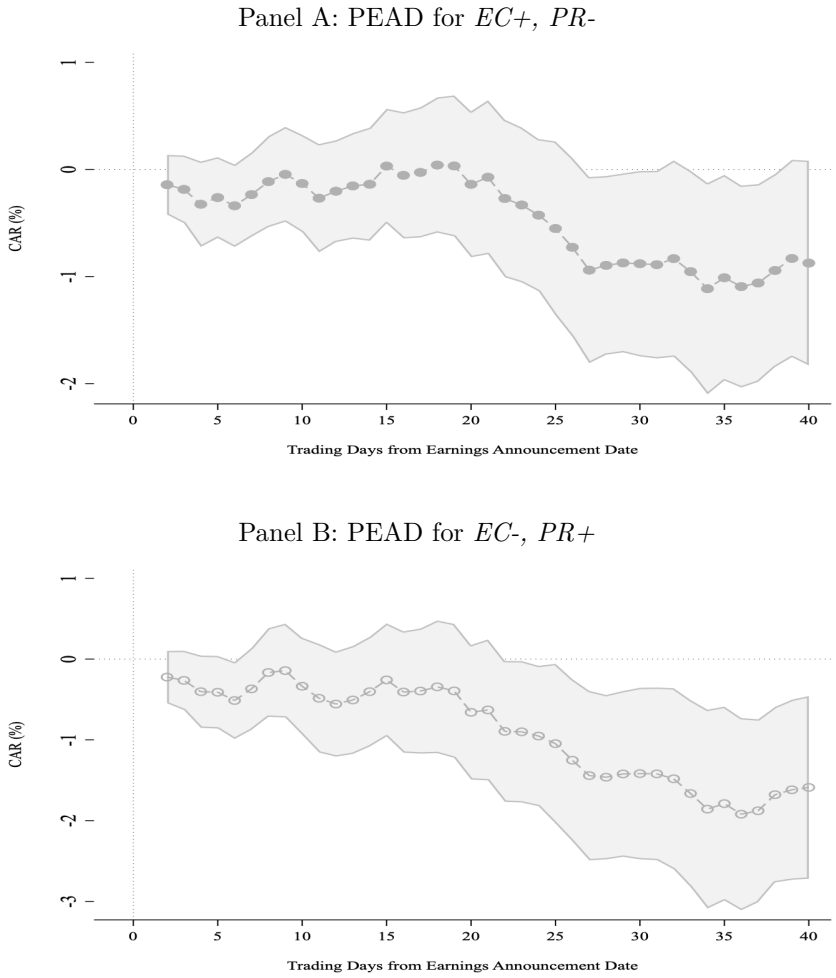


Figure A.2. Post-Earnings-Announcement Drift for Tonal Inconsistent Announcements: This figure plots abnormal returns cumulated starting from the second trading day after earnings announcements for firms with inconsistent sentiment between earnings calls and press releases. The sample includes S&P 500 firms from 2006Q1 to 2023Q3. Abnormal returns are estimated using the Fama-French five-factor model (53). 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.

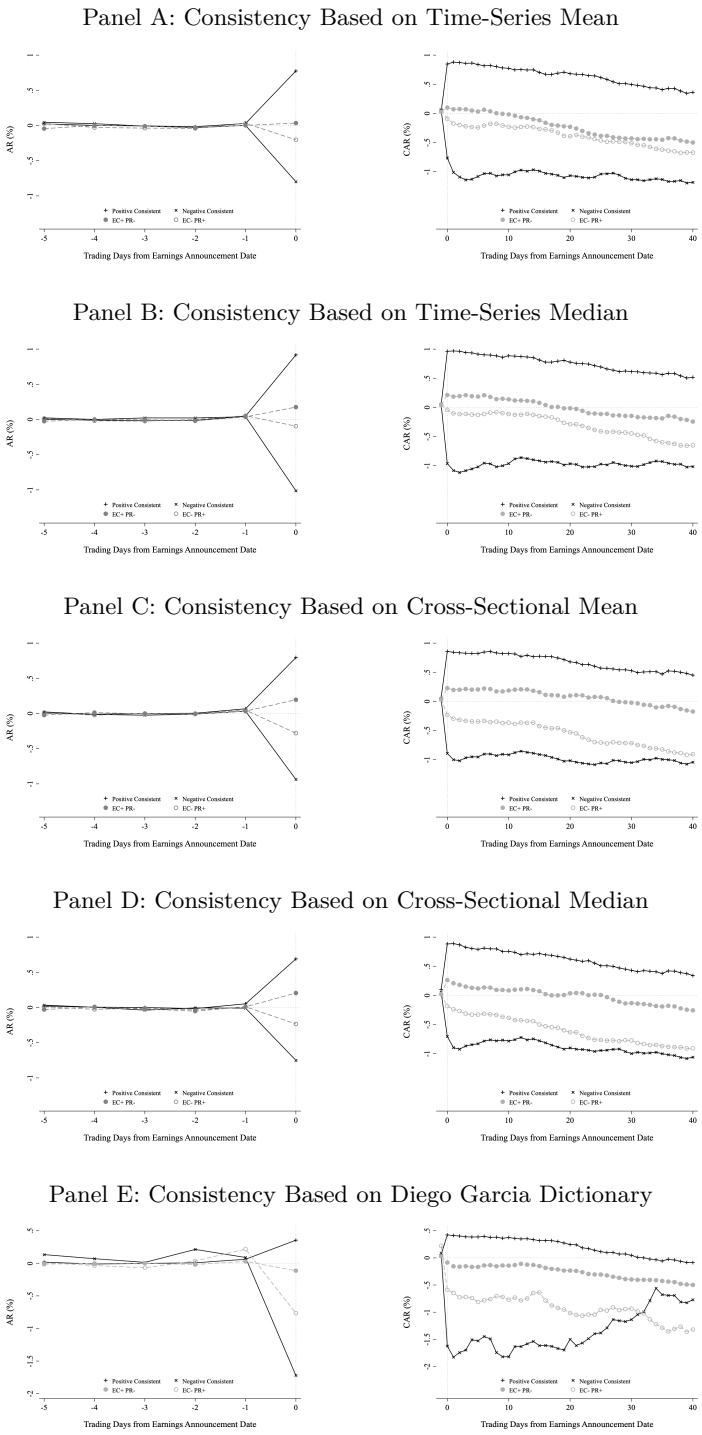


Figure A.3. Robustness of Abnormal Return Patterns to Alternative Consistency Definitions: Each panel reports average daily (left) and cumulative (right) abnormal returns for S&P 500 firms, 2006Q1–2023Q3, estimated using the Fama–French five-factor model. Consistency groups reflect agreement or disagreement 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 60.

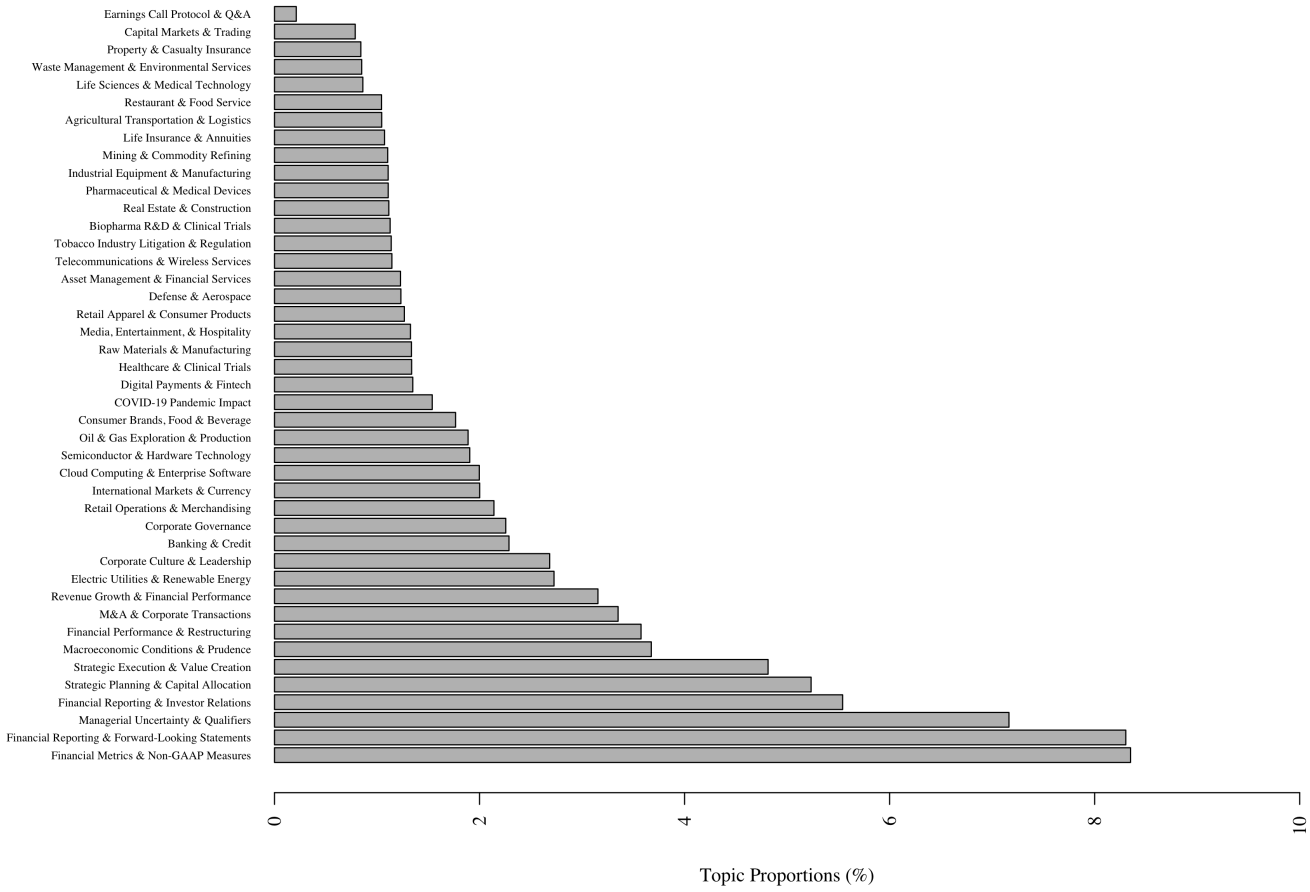


Figure A.4. Distribution of Topic Proportions Across the Corpus

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.II

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

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

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

(Continued)

Table A.II – (Continued)

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

Table A.III

Binary Polarity Measures and Garcia Dic Correlation Analysis

This table reports correlation analysis of binary polarity measures using the Loughran and McDonald (92) Master Dictionary and (60) 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.IV

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 (92) 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.V

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.VI

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	
$\Pr > \chi^2$		0.000	

Table A.VII

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. (120), 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.VIII

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
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		

Chapter 2:

Echoing Messages: Narrative Trend-Following, Real Innovation, and Mispricing

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Link to Latest Version

Echoing Messages: Narrative Trend-Following, Real Innovation, and Mispricing

Abstract

Corporate disclosure can track prevailing market themes without reflecting underlying innovation. This paper develops a firm-level measure of narrative trend-following, which I call *thematic alignment*, from the topical overlap between managers' prepared earnings-call remarks and lagged analyst discourse. Thematic alignment is associated with lower research and development, capital expenditure, and patent output, along with weaker subsequent investment. Furthermore, among patenting firms, it predicts a shift from product toward process inventions. The same firms subsequently exhibit higher near-term profitability and slower sales growth, consistent with harvesting existing operations rather than expanding them. The substitution is concentrated among smaller and less widely covered firms, where narrative verification is hardest. Portfolios sorted on thematic alignment earn negative risk-adjusted returns that are statistically significant over the two quarters following the call and decay thereafter. The evidence is more consistent with thematic echoing as a substitute for economic substance than as a signal of innovative capacity.

Keywords: Thematic alignment; Narrative trend-following; Cheap talk; Earnings conference calls; Corporate innovation; Textual analysis

JEL Classification: D82, G12, G14, G31, M41, O32

1 Introduction

Innovation is the principal engine of long-run economic growth, and the efficient allocation of capital toward the firms that produce it is a foundational premise of asset pricing theory (66). For that allocation to work, market participants must be able to distinguish firms engaged in genuinely distinctive, value-creating research and development from firms that merely look the part. The task is difficult because the primary channel through which managers communicate forward-looking strategy, the quarterly earnings conference call, is composed of discretionary, largely unverifiable narrative. While backward-looking financial statements are constrained by accounting standards and auditing, the prepared-remarks section of the call is subject to no comparable discipline: its thematic content is neither standardized nor subject to ex-post verification, and it is legally shielded by safe-harbor provisions (48; 103). The economics of cheap talk establish that when messages are costless and the interests of sender and receiver are imperfectly aligned, full revelation is unattainable: communication is at best coarse, and the set of equilibria ranges from partially informative to entirely uninformative (37). The question that motivates this paper is where the thematic content of corporate disclosure, the particular topics a firm emphasizes relative to the topics the market is already focused on, sits along that range: does it convey real economic substance, or does it substitute for it?

I show that thematic alignment, a firm-level measure of how closely a manager's narrative tracks the themes analysts were probing in the prior quarter, is a substitute for real innovation, not a signal of it. Firms whose conference-call narratives most closely mirror prevailing market themes invest less in R&D and capital expenditure, produce fewer patents, and tilt whatever patenting remains toward process-oriented rather than product-oriented inventions, the operational signature of harvesting existing capabilities rather than building new market-facing products (87; 14). Over the following year these firms harvest their existing operations by posting higher near-term profitability alongside slower sales growth, rather than building new productive capacity. The market does not see through this in real time: value-weighted

portfolios of the most thematically aligned firms earn negative risk-adjusted returns over the two quarters following the call, consistent with gradual incorporation of narrative content into prices. The pattern is difficult to reconcile with a signaling account in which alignment credibly conveys superior prospects. It is consistent instead with managers who lack distinctive firm-specific substance echoing the consensus, and with investors who impound the implications of that echo only gradually. These two components make different demands on rationality, and Section 2.5 separates them explicitly: the real-investment results are compatible with a fully rational signal-jamming equilibrium, whereas the return predictability is not, and I identify the information-processing and arbitrage frictions that it requires.

The cost of this behavior is a misallocation of attention and capital. R&D and intangible capital are now the dominant forms of corporate investment, and the firms that build them drive aggregate productivity growth (66). When disclosure rewards firms for sounding like the consensus rather than for building distinctive capacity, three groups bear the cost. First, investors who buy the narrative are hurt: the most aligned firms subsequently underperform by roughly 0.4% per month on a risk-adjusted basis over the two quarters following the call. Second, genuinely innovative but thematically differentiated firms are crowded out of market attention even though the data show they are the firms actually investing, the disclosure-side counterpart of the market's well-documented tendency to underprice real innovation (31; 56). Third, to the extent that managers respond to the capital that narrative conformity attracts, the result is a myopic equilibrium of the kind formalized by Stein (97): managers sacrifice long-term investment to deliver the short-term margins demanded by the investor base that their own disclosure has attracted (24; 4), the real-investment analog of catering to mispricing (11; 83). The economic magnitudes are not trivial: a one-standard-deviation increase in thematic alignment is associated with a 0.18 to 0.27 percentage-point reduction in R&D, capital expenditure, and patenting relative to assets, holding firm and time effects fixed.

I construct a quarterly panel of roughly 3,800 U.S. firms spanning 2010 through 2023 and use the earnings conference call as a single source of two complementary text inputs. Managers' prepared remarks measure the firm's narrative; the analyst questions in the Q&A

segment, aggregated across the universe of calls in the prior quarter, measure the themes the market is actively probing. The earnings call is well suited to both tasks: it occurs at quarterly frequency, the prepared remarks are the segment over which managers exercise the most thematic discretion (77), and the Q&A questions reveal in real time which issues professional intermediaries consider timely and insufficiently addressed (77; 22). I fit a Structural Topic Model (85) to the analyst corpus and project each manager's prepared remarks onto the resulting thematic basis. The headline measure, *thematic alignment*, is the cosine similarity between a firm's topic vector and the prior-quarter market-attention vector; a complementary main-table measure, *thematic conformity*, captures the same idea through distributional distance in topic space (Section 4). A within-quarter top-quintile indicator provides a non-parametric version. Appendix 2 defines *abnormal alignment* and the further robustness indicators in Appendix Table A.2. Section 4 and Appendix 1 describe the STM estimation in detail.

The evidence comes in six linked steps. First, thematic alignment is robustly negatively related to R&D, capital expenditure, and patent output scaled by assets, after absorbing firm and industry-by-month fixed effects (Section 5.1); Figure 2 shows the relationship is monotone across alignment quintiles. Second, within the patenting subsample, alignment predicts a compositional shift away from product patents and toward process patents (Section 5.2), sharpening the interpretation that aligned firms are optimizing operations rather than creating distinctive new products. Third, the negative relationship persists when the dependent variable is innovation investment one to four quarters *ahead*, so alignment is not merely coincident with low investment but precedes it (Section 5.3). Fourth, aligned firms subsequently show higher near-term return on assets but slower sales growth, the operating signature of harvesting existing operations, exactly the pattern produced by cutting discretionary R&D and capital to boost current margins (97; 86) (Section 5.4). Fifth, the real-investment effect concentrates in opaque firms, those with low analyst coverage, high forecast dispersion, and small size, where outsiders can least verify narrative content against fundamentals (104; 62) (Section 5.5). Sixth, a long-short portfolio that buys the most aligned firms and sells the least aligned

earns negative CAPM, three-factor, and five-factor alpha over the two quarters following the call, with the correction decaying thereafter, the slow-information-incorporation pattern documented by Cohen et al. (32) (Section 5.6). The six steps trace a single arc: narrative conformity stands in for real substance, and the market corrects the gap with a lag.

The paper makes three contributions. First, it introduces *thematic alignment* as a within-firm measure of how closely a firm's disclosure tracks prevailing market themes, conceptually distinct from disclosure tone (74; 64; Tabatabaei), readability and processing costs (18), machine-readability (28), within-firm textual change (23; 32), and cross-firm product similarity (58). Where the existing literature studies *how* firms talk or whether they repeat themselves, I study whether *what* they talk about converges on the consensus, and I tie that convergence to real outcomes. Second, it documents that this convergence is a substitute for, not a signal of, real innovation: aligned firms invest and patent less, shift patent output toward process rather than product inventions (14), and harvest near-term profitability at the expense of growth, connecting the disclosure literature to the real-effects-of-innovation literature (66; 56; 31). Third, it shows the capital market misprices this convergence, earning negative alpha on the most aligned firms, an extrapolation-and-reversal pattern in the spirit of Lakonishok et al. (70) and Bordalo et al. (21) but driven by the substance of disclosure rather than by realized growth or analyst forecasts.

The remainder of the paper proceeds as follows. Section 2 develops the related literature and the hypotheses. Section 3 describes the data. Section 4 defines the alignment measures and empirical design; Appendix Table A.1 lists all variable definitions. Section 5 reports the results. Section 6 concludes.

2 Related Literature and Hypotheses

This paper sits at the intersection of four literatures: the economics of strategic corporate disclosure, attention-driven capital allocation and catering, the real effects and pricing of innovation, and extrapolation-driven mispricing. I review each in turn and synthesize the

testable predictions that the empirical design takes to the data.

2.1 Strategic Disclosure and the Economics of Cheap Talk

The theoretical framework for understanding how unverifiable narrative can substitute for substance begins with the economics of cheap talk. Crawford and Sobel (37) establish that when a better-informed sender and an uninformed receiver have imperfectly aligned interests, costless and unverifiable communication is only partially informative in equilibrium: the sender conveys at most the interval of the state space in which his type lies, so receivers cannot fully separate high-quality agents from low-quality imitators.[18] The earnings conference call embodies this environment. While backward-looking financial statements are audited and constrained by GAAP, the prepared-remarks section is neither mandated in its thematic content nor subject to ex-post verification; it is the segment over which managers exercise the greatest discretion (77), and that discretion is strategic: Hollander et al. (60) document that managers make strategic participation choices on calls, and Lee (72) shows that they allocate Q&A access to favorable analysts. Almazan et al. (5) formalize the downstream consequence: managers deploy discretionary, unverifiable announcements specifically to attract market attention, and this cheap talk can produce large valuation effects even when it conveys no verifiable information, provided that subsequent monitoring is costly. The broader disclosure literature confirms that the framing, salience, and accessibility of disclosure matter for capital allocation even when the underlying facts are truthful (103; 18).

A large text-as-data literature has studied the *style* dimensions of this discretionary communication: tone (101; 74; 64; Tabatabaei), readability (18), adaptation to machine readers (28), and within-firm textual change over time. Brown and Tucker (23) measure

[18] Two features of that result bear on how it should be used here. First, the equilibrium set is a family of partition equilibria indexed by the number of intervals, bounded above by a maximum that shrinks as interests diverge; an entirely uninformative babbling equilibrium always exists alongside partition equilibria that remain informative but coarser. The theory therefore does not select a unique outcome, and I do not claim to identify which equilibrium the data reflect. What it rules out is full revelation. Second, receivers in *any* such equilibrium hold correct beliefs given the message they observe: coarse communication leaves them uninformed, not misled, and generates no predictable revision of prices after the fact. Section 2.5 returns to this distinction, which matters for interpreting the pricing results.

year-over-year MD&A modification and show that "sticky" disclosures produce muted price reactions; Lang and Stice-Lawrence (71) link boilerplate language to decreased liquidity; Dyer et al. (41) document the secular rise of standardized, uninformative language in 10-Ks; and Cohen et al. (32) show that changes to 10-K language predict large future returns yet draw no detectable announcement-window reaction, an inattention anomaly. Hoberg and Phillips (58, 59) introduce abnormal product-market similarity from 10-K text. These papers study whether firms *change their own narratives* or *how they frame* information. The present paper studies a conceptually different dimension: whether a firm's *thematic substance*, which topics it emphasizes, converges on the themes the market is already focused on, and whether that convergence predicts less real investment. This is the Crawford and Sobel (37) pooling prediction applied to the thematic content of disclosure.

> **H1 (Substitution).** Thematic alignment is negatively related to contemporaneous real innovation (R&D, capital expenditure, patents): firms with less distinctive substance tilt their narratives toward prevailing themes.

2.2 Attention, Narratives, and the Catering Channel

A central prediction of the limited-attention literature is that capital flows toward salient signals regardless of their fundamental content. Sims (93) formalizes attention as a scarce cognitive resource; Hirshleifer and Teoh (57) show that when processing capacity is limited, salience and framing matter for prices as much as statistical content; and Barber and Odean (13) document that both retail and institutional investors concentrate their buying in attention-grabbing stocks. Attention operates not only at the level of individual firms but at the level of broad themes: Shiller (91) argues that economic narratives propagate contagiously across market participants until they become shared focal points, and Bybee et al. (25) and Manela and Moreira (75) show that aggregate narrative content prices in the cross-section. Da et al. (39) establish a direct link between collective attention (measured by Google search volume) and subsequent fund flows, and Merton (78) formalizes the investor-recognition

channel through which visibility affects equilibrium prices.

On the corporate supply side, the catering literature shows that managers adjust real decisions to exploit time-varying, attention-driven investor demand: Baker and Wurgler (12) for dividends, Polk and Sapienza (83) for investment, and Stein (97) for the myopic equilibrium in which managers sacrifice long-term investment to inflate short-term earnings. Stein (97) is particularly relevant: in his signal-jamming model, managers cut R&D to boost current margins even though the market rationally discounts this behavior, because failing to do so would make the firm look even worse. Aghion and Stein (4) generalize this to a growth-versus-margins feedback loop in which firms give the stock market what it wants, whichever metric currently attracts the most attention, creating excess volatility in real investment. Baker et al. (11) show that non-fundamental stock-price movements distort the real investment of equity-dependent firms, and Bushee (24) documents that the presence of institutional investors with high portfolio turnover creates pressure on managers to cut R&D to meet short-term earnings targets. The extreme form of this catering behavior is purely cosmetic: Cooper et al. (34) document that firms adding ".com" to their corporate names during the late-1990s Internet boom earned cumulative abnormal returns of roughly 74% in the ten days around the announcement, regardless of their actual involvement with the Internet. Thematic alignment is a continuous, high-dimensional version of this cosmetic catering: instead of a binary name change, firms tilt the entire thematic distribution of their quarterly narrative toward whichever topics the market currently emphasizes.

Why does this work? Peng and Xiong (81) show that attention-constrained investors rationally adopt category-level learning, processing market-wide and sector-wide themes rather than firm-specific fundamentals because category-level data provides a higher marginal reduction in portfolio uncertainty per unit of cognitive effort. This endogenous information-processing structure implies that investors evaluate firms primarily by their adherence to broad themes rather than by their unique substance. A manager whose firm lacks distinctive R&D output therefore faces a strong incentive not to discuss complex, firm-specific advances that the market lacks the capacity to process, but instead to align the corporate narrative

with the category-level keywords investors are already monitoring, precisely the behavior thematic alignment measures. Narrative is a far more flexible margin than payout or capacity: a firm can re-tilt its thematic emphasis at essentially zero cost from one quarter to the next, making the earnings call the natural setting in which the cheap-talk and catering channels intersect.

> **H2 (Forward substitution).** Thematic alignment predicts *lower future* innovation investment, not higher, over the following quarters.

2.3 Innovation, Real Substance, and Managerial Myopia

A firm's real economic substance, its investment in R&D, capital, and patented technology, is observable and measurable. Kogan et al. (66) show that the private economic value of patents tracks firm growth, factor reallocation, and aggregate productivity; Hirshleifer et al. (56) show that innovative efficiency (patents per R&D dollar) predicts both operating performance and stock returns, partly because limited investor attention leaves it underpriced; and Cohen et al. (31) demonstrate that the market systematically ignores firms' track records in converting R&D expenditure into realized output, so that genuine innovators are undervalued. Not all patents measure the same kind of substance. A long tradition in the economics of innovation distinguishes *product* inventions, which create new goods or services intended for external sale, from *process* inventions, which improve internal production methods and cost efficiency (87; 43). Bena et al. (14) operationalize this distinction at scale by classifying U.S. patent claims with a text-based algorithm: product patents describe what the firm sells; process patents describe how it produces. In their setting, firms increase process innovation when labor-market frictions make cost-saving production methods especially valuable, and the resulting shift raises labor productivity and operating performance without expanding the product frontier. If thematic alignment substitutes for building distinctive new products, the prediction is not merely fewer patents but a *compositional* shift toward process-oriented output, the patent-level analogue of harvesting margins rather than investing for growth.

H3 (Harvesting). Thematically aligned firms subsequently raise near-term profitability while their growth slows, the operating signature of harvesting existing operations rather than investing for the future.

H4 (Patent composition). Conditional on patenting, thematic alignment is negatively related to the product-patent share and positively related to the process-patent share.

The accounting literature provides the operating diagnostic for distinguishing substance from its appearance. Sloan (95) establishes that earnings components with weaker fundamental backing (accruals) reverse in subsequent returns; Roychowdhury (86) documents real-activities management in which firms cut discretionary expenditures to boost current earnings at the expense of future profitability; and Graham et al. (50) report that 78% of surveyed CFOs would sacrifice long-term value to meet short-term earnings targets. The signal-jamming framework of Stein (97) shows that this myopia can be an equilibrium outcome even with rational markets: because R&D depresses current-period earnings, cutting it mechanically raises near-term margins, and the market, unable to observe the true allocation, discounts earnings by the expected manipulation. If thematic alignment substitutes for substance, aligned firms should display the operating fingerprint of this myopic trade-off: higher current profitability alongside slower growth, the combination that Aghion and Stein (4) predict when firms give the market what it currently wants.

2.4 Verification Frictions and Extrapolation-Driven Mispricing

Whether narrative can substitute for substance without immediate penalty depends on how easily outsiders can verify the underlying economics. The opacity literature establishes that mispricing is largest where verification is hardest: Hong et al. (63) show that information diffuses slowly in low-analyst-coverage firms; Yu (104) documents that weaker analyst coverage is associated with stronger earnings management; Hong and Kacperczyk (62) link fewer analysts to less informative prices; and Diether et al. (40) show that high analyst-forecast

dispersion, a proxy for investor disagreement about fundamentals, predicts low future returns, consistent with the overvaluation mechanism of Miller (79). The Almazan et al. (5) framework predicts exactly this pattern: the effectiveness of cheap talk in attracting attention depends on the cost of subsequent verification, so firms where monitoring is expensive enjoy the widest latitude for narrative pooling.

The asset-pricing literature disciplines the signaling-versus-substitution interpretation. Under a signaling account, trend-aligned firms should earn neutral-to-positive abnormal returns; under substitution, prices should reverse as fundamentals arrive. Sloan (95) and Hirshleifer et al. (55) establish the template for soft-information reversal: earnings components unsupported by fundamentals predict negative future alpha. Lakonishok et al. (70) and Skinner and Sloan (94) document the extrapolation-and-correction pattern for growth stocks, and Bordalo et al. (21) provide the belief-formation mechanism: analysts overweight recently salient information, exaggerating the probability of states that have become objectively more likely, a "kernel of truth" bias that predicts initial overvaluation followed by reversal. Cohen et al. (32) show that narrative content in 10-Ks predicts large future returns yet produces no announcement-window reaction, consistent with slow information incorporation. If thematic alignment captures a similar narrative dimension, the mispricing should manifest as a post-disclosure drift rather than an immediate price correction.

H5 (Opacity). The substitution effect is stronger in opaque firms, where the narrative is hardest to verify against fundamentals.

H6 (Mispricing). The most thematically aligned firms earn *negative* future risk-adjusted returns as fundamentals reveal the gap between narrative and substance.

2.5 Equilibrium Interpretation and Its Limits

The six hypotheses do not make uniform demands on the rationality of market participants, and it is worth separating them before turning to the data. Hypotheses H1 through H5, which

concern the association between narrative conformity and real investment, are compatible with fully rational behaviour on both sides of the market. The signal-jamming equilibrium of Stein (97) is the relevant benchmark: managers curtail long-horizon investment to raise current margins, the market correctly anticipates that they will do so and discounts reported performance accordingly, and no participant is deceived. The equilibrium persists because unilateral deviation is unattractive: a manager who declines to jam is pooled with the firms that could not, so the behaviour survives even though it leaves everyone weakly worse off. Thematic echoing is the disclosure-side analogue. A firm whose narrative departed from the prevailing consensus while its peers converged would forgo attention without an offsetting gain in credibility, because the thematic content of prepared remarks cannot be verified ex post. On this reading, the market's understanding that echoing accompanies weak investment is fully consistent with firms continuing to echo.

Hypothesis H6 is different in kind, and I state the difference plainly rather than leaving it implicit. Predictable risk-adjusted returns are by construction a departure from a rational-expectations equilibrium: were investors to know the mapping from thematic alignment to subsequent innovation, they would impound it at the announcement and leave no drift to measure. Documenting post-disclosure alpha therefore commits me to a friction, and the friction I have in mind operates on the receiving side and is one of costly information processing rather than of irrationality as such. Recovering a firm's position in a thirty-three-dimensional topic space from a conference-call transcript, and comparing it against a market-wide attention vector estimated over the preceding quarter, is not free. Peng and Xiong (81) show that investors facing such costs optimally learn at the category level and rationally neglect the firm-specific dimensions that a complete solution would require, which is precisely the margin thematic alignment occupies. The relevant themes also rotate from quarter to quarter (Figure 1), so the environment is non-stationary and offers no stable regularity that repeated exposure would teach.

Two further considerations bound how large a departure the evidence actually requires. First, what the data describe is incomplete and delayed adjustment, not the absence of

adjustment. The announcement-day reaction in Figure 3 is correctly signed: on the day of the call, the most aligned firms earn the most negative abnormal return, so prices move in the direction fundamentals warrant, merely by too little. Second, the drift is short-lived and modest in magnitude: the long-short alpha is statistically significant over the first two post-formation quarters and decays to insignificance thereafter (Section 5.6). The object of study is a partial correction completed within roughly half a year, not a standing arbitrage opportunity. That it is not competed away sooner does not, however, require the drift to be concentrated in hard-to-arbitrage securities, and I do not claim that it is: subsample splits of the portfolio tests by size and by forecast dispersion yield uniformly insignificant estimates and are not reported, so the calendar-time results should be read as a full-cross-section phenomenon rather than an opacity-driven one. The obstacles to arbitrage are more mundane. Capturing the drift requires a long-short position whose short leg carries borrowing costs, the estimated magnitude is modest and confined to two quarters, and, most to the point, the signal must be constructed before it can be traded: ranking firms on thematic alignment presupposes fitting a topic model to the full transcript universe and re-estimating the market-attention vector every quarter. The processing cost that keeps the marginal investor at the category level is the same cost that raises the barrier for the arbitrageur who would eliminate the drift (92).

3 Data and Sample

The sample consists of U.S. common stocks listed on NYSE, AMEX, or NASDAQ (CRSP share codes 10 and 11) with at least three earnings conference calls carrying analyst Q&A text in the Compustat Capital IQ transcript database during the prior quarter, so that the aggregate analyst-attention vector is estimable. I require non-missing Compustat quarterly fundamentals (total assets, common equity, revenue) and CRSP returns for the control set. The resulting panel spans 2010:Q2 through 2023:Q4 and covers roughly 3,800 unique firms. The sample is coverage-driven rather than index-based, which avoids the survivorship and

reconstitution biases of index-membership filters (44).

Conference-call transcripts are obtained from Compustat Capital IQ, which provides speaker-tagged transcripts with separate prepared-remarks and Q&A fields. The *manager narrative* is the prepared-remarks section (Capital IQ component type 2), where executives present results and forward-looking commentary; the *analyst discourse* is the analyst-question segment of the Q&A (component type 3). For each firm-quarter, I aggregate the manager's prepared remarks into one document; for the market-theme benchmark, I aggregate all analyst questions across the universe of calls in the prior calendar quarter into one cross-sectional document. Both streams are tokenized, lemmatized, and processed through a Structural Topic Model (85) (Section 4 and Appendix 1).

Real-outcome and fundamental data come from Compustat (R&D, capital expenditure, total and intangible assets, revenue, return on assets), patent and citation data from the U.S. Patent and Trademark Office (USPTO), matched to CRSP/Compustat identifiers, the Hoberg and Phillips (59) text-based product-uniqueness score, CRSP (returns, market capitalization), and IBES (analyst coverage, forecast dispersion, and standardized unexpected earnings, SUE). For the patent-composition tests I merge firm-year measures from the Bena et al. (14) classification of U.S. utility-patent applications (1991 to 2022), which assigns each patent to product or process categories using the legal language of patent claims and aggregates to gvkey×fyear shares of product and process patents among utility-patent applications; the fiscal-year snapshot is mapped to each earnings call in that year. This subsample covers roughly 998 firms and 19,000 firm-quarters with non-missing composition data, a strict subset of the main panel because patent decomposition requires matched Compustat and patent linkages and at least one classified filing in the fiscal year. I construct log market capitalization and log book-to-market at the end of the fiscal quarter preceding each call, and contemporaneous SUE, as controls, and use R&D, capital expenditure, patents, product uniqueness, and intangibles scaled by assets, return on assets, and year-over-year sales growth as outcomes. Monthly stock returns and Fama and French (45) five-factor data (MKT, SMB,

HML, RMW, CMA) are from CRSP and Kenneth French's data library[19] and are used in the calendar-time portfolio tests. All continuous variables are winsorized at the 1st and 99th percentiles within quarter. Variable definitions are in Appendix Table A.1.

[*Insert Table 1 about here*]

Table 1 reports summary statistics and Table 2 reports pairwise correlations.

[*Insert Table 2 about here*]

4 Measuring Thematic Alignment

4.1 Topic Model

The thematic content of both manager narratives and analyst discourse is represented through a Structural Topic Model (STM; 85). STM is an extension of Latent Dirichlet Allocation (LDA; 19), which has become a standard tool for large-scale textual analysis in finance and economics (e.g., 25). While newer to finance, STM is well established in political science and related fields (e.g., 80; 38). STM offers two advantages that are central to this setting. First, topic prevalence can depend on document-level metadata: I include calendar quarter (via a spline), Fama-French 48-industry classification, and log market capitalization as prevalence covariates, so that topic vectors are not mechanically driven by secular trends, sectoral composition, or firm size (8). Second, STM permits correlated topic proportions, which is more realistic for financial disclosures where subjects such as revenue growth, capital allocation, and guidance are inherently related.

The model is trained on 101,693 analyst-question firm-quarter documents from the all-US sample (roughly 4,700 firms; 2010:Q1 through 2023:Q4). Raw transcripts undergo a standard NLP preprocessing pipeline: boilerplate removal, spaCy lemmatisation with named-entity

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

redaction (person, organisation, monetary, and date entities), bigram and trigram detection via Gensim phrase models, stopword removal, and extreme-frequency filtering. The number of topics K is selected via a Pareto-front elbow rule applied jointly to normalised semantic coherence and exclusivity over a 15-value grid $K \in \{10, 20, 27, \ldots, 100\}$, evaluated on a 30% year-quarter-stratified subsample. The global elbow falls on $K = 33$, which I adopt as the primary specification. Appendix 1 provides the full preprocessing protocol, the K-selection diagnostics (Figure A.1), and the complete list of 33 topics with representative FREX words[20] (Table A.6).

The trained model yields a K-dimensional topic-proportion vector $\boldsymbol{\theta}_d$ for each document d, where $\theta_{d,k}$ is the estimated share of document d devoted to topic k. Manager topic vectors are obtained by applying the trained model to each firm-quarter's prepared remarks via out-of-sample document fitting (85), which infers posterior topic proportions using the fixed word-topic distribution learned from the analyst corpus. This two-stage design (train on analyst text, infer on manager text) ensures that the topic basis reflects the thematic structure of market discourse rather than the idiosyncratic language of any individual firm.

[*Insert Figure 1 about here*]

Figure 1 plots the evolution of aggregate topic prevalence in analyst discourse and shows the substantial thematic rotation (the rise and fall of pandemic, supply-chain, cloud, and energy themes) that the alignment measures exploit: a firm registers high alignment in a given quarter precisely when its narrative loads on whichever themes are then prominent.

4.2 Alignment Measures

For each calendar quarter q, the aggregate analyst-attention vector $\bar{\boldsymbol{\theta}}_q^A$ is the average posterior topic proportion across all analyst-question documents in q. The manager's vector

[20]FREX (Frequency and Exclusivity) ranks vocabulary terms by combining how often a word loads on a topic with how exclusive that word is to the topic among all topics, yielding interpretable top words for labelling each topic (85).

for firm i in q is $\boldsymbol{\theta}^{M}_{i,q}$. Alignment is measured against the *prior*-quarter $(q-1)$ attention vector. This one-quarter lag serves three purposes. First, it ensures strict temporal precedence: analyst themes are fully realised before the manager speaks. Second, it avoids mechanical endogeneity from firm i's own call contributing to the contemporaneous aggregate analyst corpus. Third, it matches the catering hypothesis: managers can tilt their narratives only toward themes that are already observable in the prior quarter's market discourse.

The headline measure, *thematic alignment*, is the cosine similarity between the manager's topic vector and the prior-quarter analyst-attention vector:

$$Alignment_{i,q} = \cos\Big(\boldsymbol{\theta}^{M}_{i,q},\, \bar{\boldsymbol{\theta}}^{A}_{q-1}\Big). \tag{1}$$

Higher values indicate that the manager's prepared remarks load on the same topics analysts were probing in the prior quarter. This geometric benchmark enters the main real-outcome regressions in Table 3, Panel A, and underlies the within-quarter quintile sorts in Panel C and Figure 2.

The second main-table measure, *thematic conformity*, captures alignment through topic *coverage* rather than vector angle. I compute the asymmetric Kullback-Leibler divergence of the prior-quarter analyst-attention distribution from the manager's topic distribution,

$$KL_{i,q} = \sum_{k=1}^{K} \bar{\theta}^{A}_{q-1,k}\, \log \frac{\bar{\theta}^{A}_{q-1,k}}{\theta^{M}_{i,q,k}}, \tag{2}$$

and define conformity as its negative,

$$Conformity_{i,q} = -\, KL_{i,q}. \tag{3}$$

The direction $\bar{\boldsymbol{\theta}}^{A}_{q-1} \,\|\, \boldsymbol{\theta}^{M}_{i,q}$ penalises managers who under-weight topics that analysts emphasised: if analysts devote substantial attention to topic k but the manager barely mentions it, $KL_{i,q}$ rises and $Conformity_{i,q}$ falls. Topics the manager discusses but analysts did not ask about contribute less, because $\bar{\theta}^{A}_{q-1,k} \approx 0$ down-weights those terms in the sum. Conformity therefore

measures whether the firm *covers* the themes the market is already focused on, complementing the cosine measure, which treats all topic co-movements symmetrically through the angle between vectors. Table 3, Panel B, reports this distributional benchmark alongside Panel A.

Portfolio sorts for the mispricing tests (Section 5.6) use *abnormal alignment*, a Hoberg–Phillips-style residual that subtracts each firm's average cosine similarity to all other analyst-quarter vectors from Eq. (1); Appendix 2 gives the formula and defines the remaining indicators in Appendix Table A.2. All continuous alignment measures used in regressions are standardized to zero mean and unit variance within the estimation sample, so coefficients are per one-standard-deviation increase. The non-parametric companion sorts firms into within-quarter quintiles of *thematic alignment* and includes indicators for Q2 through Q5 with the bottom quintile (Q1, least aligned) as the omitted baseline; Panel C of Table 3 reports the Q5 coefficient.

4.3 Empirical Design

The baseline specification regresses a real outcome on standardized alignment with firm and time fixed effects:

$$Y_{i,q} = \alpha_i + \alpha_t + \beta\, Alignment^{z}_{i,q} + \boldsymbol{\gamma}'\mathbf{X}_{i,q} + \varepsilon_{i,q}, \tag{4}$$

where Y is R&D, capital expenditure, patents, product uniqueness, or intangibles scaled by assets; α_i and α_t are firm and industry-by-year-month fixed effects; and $\mathbf{X}$ contains lagged log market equity, lagged log book-to-market (both measured at the end of fiscal quarter $q-1$), and contemporaneous SUE in the call quarter. Standard errors are two-way clustered by firm and call date (82; 26). Firm fixed effects are important in this setting: they absorb time-invariant firm characteristics that could lead some firms to exhibit systematically higher thematic alignment, such as a stable communication style, a persistently consensus-oriented disclosure policy, or an industry niche whose vocabulary overlaps with recurring market themes. The identifying variation is therefore within-firm, within-industry-month: a firm

whose remarks are unusually theme-aligned *for that firm*, in a month where industry-wide shocks are absorbed. For the forward tests (H2) and fundamentals (H3), Y is measured at $q+h$, $h=1,\ldots,4$. For patent composition (H4), Y is the fiscal-year share of product or process patents. For opacity (H5), I estimate equation (4) within the most-opaque and most-transparent within-quarter terciles of analyst coverage, forecast dispersion, and size. For mispricing (H6), I sort firms into alignment quintiles each quarter, form a top-minus-bottom portfolio held over month h after the call, and estimate its CAPM, three-factor, and Fama and French (45) five-factor alpha with Newey and West standard errors.

4.4 Robustness and Appendix Evidence

The main tables prioritize standardized alignment measures so coefficients are directly comparable across outcomes. Additional checks are collected in the appendix rather than repeated in every table. Table 3 already reports three complementary headline specifications in its panels: cosine-based thematic alignment (Panel A), distributional conformity (Panel B), and a within-quarter top-quintile indicator (Panel C). Appendix Table A.2 extends this battery to eight further *standardized* alignment constructions defined in Appendix 2—*abnormal alignment*, *residual alignment*, *trend-shock exposure*, *top-3 trend coverage*, *net trend-following*, and a *novelty residual*, alongside the headline cosine and conformity measures—each re-estimating the Table 3 real-outcome regressions under the same firm and industry-by-month fixed effects and controls. The negative substitution pattern for R&D, capital expenditure, and patents is robust across the cosine-based and residual variants; *abnormal alignment* is weaker on R&D and capital expenditure but remains negative for patents, which helps distinguish broad thematic proximity from quarter-specific tilts and from generic exposure to salient topics.

Appendix Table A.3 reports the same Table 3 specifications using *thematic alignment* and *thematic conformity* in *levels* rather than z-scores. Because full-sample standardization is an affine transform of the regressor only, t-statistics and inference are unchanged; the

levels table is provided so readers can interpret effects per unit of alignment rather than per standard deviation. It is not an independent statistical robustness test. Appendix Table A.4 re-estimates the forward-investment tests (H2) with the contemporaneous level of each outcome included as a control, following the persistence-control practice used in forward-fundamentals work (86); the negative forward pattern is largely unchanged, especially for patent output and capital expenditure through $h = 3$.

Appendix 1 documents the STM estimation pipeline—the preprocessing protocol, the $K = 33$ selection diagnostic (Figure A.1), and the complete topic list with representative words (Table A.6)—referenced in Section 4.

5 Empirical Results

5.1 Thematic Alignment and Real Innovation

[*Insert Table 3 about here*]

Table 3 reports the baseline estimates. Across Panels A, B, and C the message is the same: firms whose narratives align with prevailing market themes invest and innovate less. In Panel A, a one-standard-deviation increase in thematic alignment is associated with a 0.18 percentage-point reduction in R&D-to-assets ($t = -2.69$), a 0.20-point reduction in capital expenditure ($t = -6.11$), and a 0.27-point reduction in patent output ($t = -3.40$), all relative to assets and net of firm and industry-by-month fixed effects. The thematic-conformity measure (Panel B) and the top-quintile indicator (Panel C) deliver the same negative pattern for R&D, capital expenditure, and patents, confirming that the result is not an artifact of the particular alignment metric. Appendix Table A.2 confirms the pattern across eight alternative standardized alignment indicators (Section 4.4); Appendix Table A.3 reports the same estimates in levels for economic interpretation.

[*Insert Figure 2 about here*]

Figure 2 shows the relationship is monotone: average R&D, capital expenditure, and patent output decline steadily from the least-aligned quintile (Q1) to the most-aligned (Q5).

Two coefficients are positive: intangible assets rise with alignment, and product uniqueness rises with conformity. Both are consistent with the substitution interpretation rather than against it; each requires a distinct explanation.

Intangibles on the balance sheet are dominated by acquired goodwill and purchased intangibles, so the positive loading indicates that aligned firms lean on *bought* rather than *built* intangible capital, the opposite of organic R&D. The contrast, less internally generated innovation alongside more acquired intangibles, is itself the footprint of firms whose growth story outruns their own laboratory.

The product-uniqueness result is more subtle. Product uniqueness from Hoberg and Phillips (59) measures how few close product-market rivals a firm has in the text-based network of 10-K product descriptions; it captures the distinctiveness of the firm's competitive *position*, not the flow of new innovation. Crucially, the positive loading appears only for conformity (Panel B, $t = 3.51$), not for cosine alignment (Panel A, $t = -0.26$), and the distinction between the two measures is informative. Conformity penalises managers who fail to *cover* topics that analysts emphasised, whereas alignment measures the overall geometric proximity of topic vectors. A firm in a differentiated product niche may devote most of its narrative to specialised subjects that keep its cosine similarity to the broad market low, while still ensuring that every trending theme receives at least a mention, which raises conformity without raising alignment. The positive coefficient therefore indicates that niche firms (precisely those whose distinctiveness makes them harder for generalist investors to evaluate) compensate by covering whichever topics the audience is already monitoring, the attention-seeking behaviour predicted by Peng and Xiong (81) and Merton (78) when investors process information at the category level. There is also a stock-versus-flow dimension: a firm can inherit a differentiated market position from past innovation while currently under-investing in R&D to sustain that differentiation. High product uniqueness alongside high conformity and lower R&D captures firms that rest on an existing competitive niche while echoing consensus themes rather than

funding the innovation that would preserve their distinctiveness, reinforcing the harvesting profile documented below.

5.2 Patent Composition: Product versus Process

Table 3 establishes that aligned firms patent less in the aggregate.

[*Insert Table 4 about here*]

Table 4 asks whether the remaining patent output is directed toward building new products or toward refining production processes. A one-standard-deviation increase in thematic alignment is associated with a 1.2-percentage-point decline in the share of product patents ($t = -2.35$) and a 1.2-percentage-point increase in the share of process patents ($t = 2.35$), holding firm and industry-by-month fixed effects and the baseline controls fixed. The coefficients are equal in magnitude because product and process shares sum to one within firm-year; what matters economically is the *reallocation*. Product patents, in the taxonomy of Scherer (87) and Bena et al. (14), describe inventions intended for external sale or use and are the patent analogue of product-market differentiation and future growth; process patents describe internal production methods and are the patent analogue of cost efficiency and margin expansion. The compositional shift therefore sharpens the substitution interpretation from Section 5.1: thematically aligned firms are not merely doing less innovation, they are doing a different *kind* of innovation, one oriented toward harvesting existing operations rather than creating distinctive new products. The result is specific to the headline alignment measure and appears only in the patenting subsample, but it aligns cleanly with the harvesting profile documented in Section 5.4.

5.3 Future Innovation Investment

A natural concern is reverse causation: perhaps firms that have already cut investment then adopt consensus language.

[*Insert Table 5 about here*]

Table 5 addresses this by replacing the contemporaneous outcome with innovation investment one to four quarters *ahead*. Thematic alignment continues to predict lower future R&D, capital expenditure, and patenting, with the negative coefficients persisting across horizons. Because current alignment precedes the investment shortfall, the evidence is consistent with H2: narrative conformity is not merely coincident with low substance but forecasts it. Appendix Table A.4 shows the pattern is not driven by mechanical persistence alone: patent output and capital expenditure remain negatively related to alignment when the contemporaneous outcome at the call quarter is included as a control.

5.4 Harvesting, Not Building

If alignment substitutes for substance, the operating consequence should be visible in the split between profitability and growth. A firm that diverts resources away from R&D and capital expenditure mechanically raises its near-term margins, because discretionary investment depresses current earnings, while sacrificing the future growth that the investment would have funded (86).

[*Insert Table 6 about here*]

Table 6 shows exactly this pattern. Future return on assets is significantly *higher* for aligned firms at every horizon (Panel A, $t = 2.5$ to 3.0), while year-over-year sales growth is *lower*, with negative point estimates throughout and statistical significance at $q{+}2$ ($t = -1.82$). The combination, stronger near-term profitability alongside weaker growth, is the fundamental fingerprint of harvesting rather than building: aligned firms are not investing in the future, they are extracting more from the assets they already have. This profile is the operating counterpart of the under-investment in Sections 5.1 through 5.3 and of the price reversal documented below, and it is consistent with the real-activities trade-off of Roychowdhury

(86), the executive preference for current targets over long-run value documented by Graham et al. (50), and the growth-versus-margins feedback loop formalized by Aghion and Stein (4).

5.5 Where the Effect Concentrates: Opacity

H5 predicts that substitution is easiest where the narrative is hardest to check.

[*Insert Table 7 about here*]

Table 7 re-estimates the R&D, capital-expenditure, and patenting regressions separately within the most-opaque and most-transparent within-quarter terciles of three information-environment proxies: analyst coverage, forecast dispersion, and firm size. The pattern is sharpest for patent output, where the baseline effect among transparent firms is economically and statistically indistinguishable from zero across all three proxies (coefficients of -0.06, -0.01, and -0.01); transparent firms do not substitute narrative for product innovation. The entire substitution effect is concentrated among opaque firms: the patent coefficient among high-dispersion firms is -0.47 ($t = -3.17$), among low-coverage firms -0.24 ($t = -2.94$), and among small firms -0.60 ($t = -3.49$). R&D shows the same qualitative pattern, albeit with smaller gaps between opaque and transparent firms.

Capital expenditure, by contrast, is negative and significant in *both* terciles, and the opaque coefficient is not consistently larger. This is economically plausible: capital expenditures fund long-lived property, plant, and equipment whose planning horizons and contractual commitments make them less sensitive to the information environment than discretionary R&D or patent filings. Managers cannot readily adjust a multi-year factory build to offset a narrative gap in the same way they can modulate the timing of a research programme.

Appendix Table A.5 formalises the comparison with pooled interaction-term specifications that multiply *Thematic Alignment* by opacity-tercile indicators. The formal tests confirm the subsample pattern selectively: the interaction is significant for patents through coverage ($t = -3.17$) and size ($t = -2.53$), and for R&D through size ($t = -2.81$), while CAPX

interactions are uniformly insignificant. The interaction results therefore sharpen, rather than overturn, the split-sample evidence: the opacity channel operates most strictly through firm size and analyst coverage and manifests most clearly in patent output and R&D, the discretionary margins where information frictions give managers the widest latitude to substitute narrative for substance (5; 104; 62; 40).

5.6 Mispricing: Negative Future Alpha

The sharpest test of whether alignment signals quality or substitutes for it is the cross-section of returns. Under a signaling account, the most aligned firms should not be penalized; under substitution, their prices should reverse as fundamentals arrive (95; 55; 21).

[*Insert Figure 3 about here*]

Figure 3 summarizes the return dynamics. Panel A plots daily five-factor abnormal returns around the earnings announcement: on day 0 the most aligned firms (Q5) earn the most negative abnormal return while the least aligned (Q1) earn a positive return, so the market reacts in the correct direction; but the 95% confidence bands overlap zero, the hallmark of a signal the market only partially impounds at disclosure (32). Panel B traces cumulative abnormal return from the announcement through four post-formation months, anchoring at the day-0 reaction and adding monthly FF5 alphas thereafter. Panel C reports month-by-month FF5 alphas by quintile; Panel D cumulates those factor-adjusted alphas from portfolio formation, with Q1 drifting up and Q5 drifting down. Portfolio quintiles are formed each quarter on *abnormal alignment* in levels (Appendix 2), using within-quarter ranks.

[*Insert Table 8 about here*]

Table 8 reports calendar-time alphas of the long-short portfolio that buys the most aligned quintile and sells the least aligned. In the first two post-formation quarters the portfolio

earns negative CAPM, three-factor, and five-factor alpha of roughly -0.37 to -0.41% per month, statistically significant at the 5% level (t-statistics between -2.18 and -2.45). At horizons $h = 3$ and $h = 4$ the alphas remain negative (-0.23 to -0.34%) but lose statistical significance (t-statistics around -1.2 to -1.5), indicating that the bulk of the correction is absorbed within two quarters of the call, the horizon over which the gradual-incorporation mechanism of Cohen et al. (32) predicts the market should update on narrative content. The negative sign at short horizons, the consistent direction across all factor models, and the decay toward zero at longer horizons jointly weigh against signaling and support H6.

5.7 Taking Stock

The six tests trace one arc. Firms whose narratives converge on prevailing market themes invest and patent less (Section 5.1), shift patent output toward process and away from product inventions (Section 5.2), and the shortfall persists in forward investment (Section 5.3); they harvest near-term profitability while their growth slows (Section 5.4); the patent and R&D substitution concentrates in opaque firms where outsiders cannot verify it, while rigid capital expenditure is less sensitive to the information environment (Section 5.5); and the market corrects the gap with negative future alpha (Section 5.6). The pattern is difficult to reconcile with the view that thematic alignment credibly conveys good news. It is consistent with a simpler account, in which firms with little distinctive substance talk like the consensus, and capital and attention follow the talk until fundamentals catch up. As Section 2.5 sets out, the first five results sit comfortably inside a rational signal-jamming equilibrium; only the return predictability requires a departure from it, and the departure the data describe is a bounded one, correctly signed at announcement and fully dissipated within about two quarters.

6 Conclusion

This paper asks whether the substance of corporate disclosure, which themes a firm emphasizes relative to the market's prevailing focus, reveals real economic substance or

substitutes for it. Using earnings conference calls to measure both a firm's narrative and the market's themes, I construct within-firm measures of *thematic alignment* and trace their consequences through real investment, patent composition, fundamentals, and prices. The answer is consistent across all six tests: thematically aligned firms invest less in R&D, capital, and patents; among patenting firms they tilt output toward process rather than product inventions; they harvest near-term profitability while their growth slows; the effect concentrates where the narrative is hardest to verify; and their stocks subsequently underperform on a risk-adjusted basis. Talk, in short, stands in for substance.

The findings carry implications for three audiences. For *investors*, thematic alignment is a measurable predictor of weak real investment and negative future alpha, and a contrarian tilt toward differentiated firms, those whose narratives do not echo the consensus, is associated with both more real innovation and more favorable subsequent pricing. For *managers*, the results expose a tension between attracting near-term attention through narrative conformity and creating long-run value through investment; the capital that conformity attracts is not ultimately supported by fundamentals. For *regulators and standard setters*, the evidence that unverifiable narrative substance affects capital allocation, and that the real-investment response is concentrated among smaller and less widely covered firms, speaks to the ongoing debate over the comparability and informativeness of narrative disclosure. Several extensions follow naturally: linking alignment to governance and compensation, examining other text sources such as 10-Ks and earnings releases, and testing the mechanism in non-U.S. markets with different disclosure regimes.

Bibliography

[1] Acemoglu, D., Autor, D., Dorn, D., Hanson, G. H., and Price, B. (2016). Import competition and the great US employment sag of the 2000s. *Journal of Labor Economics*, 34(S1):S141–S198.

[2] Aghion, P., Bloom, N., Blundell, R., Griffith, R., and Howitt, P. (2005). Competition and innovation: An inverted-U relationship. *The Quarterly Journal of Economics*, 120(2):701–728.

[3] Aghion, P. and Howitt, P. (1992). A model of growth through creative destruction. *Econometrica*, 60(2):323–351.

[4] Aghion, P. and Stein, J. C. (2008). Growth versus margins: Destabilizing consequences of giving the stock market what it wants. *The Journal of Finance*, 63(3):1025–1058.

[5] Almazan, A., Banerji, S., and De Motta, A. (2008). Attracting attention: Cheap managerial talk and costly market monitoring. *The Journal of Finance*, 63(3):1399–1436.

[6] Ambec, S. and Lanoie, P. (2008). Does it pay to be green? a systematic overview. *Academy of Management Perspectives*, 22(4):45–62.

[7] Antweiler, W., Copeland, B. R., and Taylor, M. S. (2001). Is free trade good for the environment? *American Economic Review*, 91(4):877–908.

[8] Ardia, D., Bluteau, K., Boudt, K., and Inghelbrecht, K. (2022). Climate change concerns and the performance of green vs. brown stocks. *Management Science*, 69(12):7607–7632.

[9] Autor, D. H., Dorn, D., and Hanson, G. H. (2013). The china syndrome: Local labor market effects of import competition in the united states. *American Economic Review*, 103(6):2121–2168.

[10] Autor, D. H., Dorn, D., and Hanson, G. H. (2016). The china shock: Learning from labor-market adjustment to large changes in trade. *Annual Review of Economics*, 8:205–240.

[11] Baker, M., Stein, J. C., and Wurgler, J. (2003). When does the market matter? stock prices and the investment of equity-dependent firms. *The Quarterly Journal of Economics*, 118(3):969–1005.

[12] Baker, M. and Wurgler, J. (2004). A catering theory of dividends. *The Journal of Finance*, 59(3):1125–1165.

[13] Barber, B. M. and Odean, T. (2008). All that glitters: The effect of attention and news on the buying behavior of individual and institutional investors. *The Review of Financial Studies*, 21(2):785–818.

[14] Bena, J., Ortiz-Molina, H., and Simintzi, E. (2022). Shielding firm value: Employment protection and process innovation. *Journal of Financial Economics*, 146(2):637–664.

[15] Bena, J. and Simintzi, E. (2024). Machines could not compete with Chinese labor: Evidence from U.S. firms' innovation. SSRN Working Paper.

[16] Benner, M. J. and Tushman, M. L. (2002). Process management and technological innovation: A longitudinal study of the photography and paint industries. *Administrative Science Quarterly*, 47(4):676–706.

[17] Bernard, A. B., Jensen, J. B., and Schott, P. K. (2006). Survival of the best fit: Exposure to low-wage countries and the (uneven) growth of U.S. manufacturing plants. *Journal of International Economics*, 68(1):219–237.

[18] Blankespoor, E., deHaan, E., and Marinovic, I. (2020). Disclosure processing costs, investors' information choice, and equity market outcomes: A review. *Journal of Accounting and Economics*, 70(2-3):101344.

[19] Blei, D. M., Ng, A. Y., and Jordan, M. I. (2003). Latent Dirichlet allocation. *Journal of Machine Learning Research*, 3:993–1022.

[20] Bloom, N., Draca, M., and Van Reenen, J. (2016). Trade induced technical change? the impact of Chinese imports on innovation, IT and productivity. *The Review of Economic Studies*, 83(1):87–117.

[21] Bordalo, P., Gennaioli, N., La Porta, R., and Shleifer, A. (2019). Diagnostic expectations and stock returns. *The Journal of Finance*, 74(6):2839–2874.

[22] Bowen, R. M., Davis, A. K., and Matsumoto, D. A. (2002). Do conference calls affect analysts' forecasts? *The Accounting Review*, 77(2):285–316.

[23] Brown, S. V. and Tucker, J. W. (2011). Large-sample evidence on firms' year-over-year MD&A modifications. *Journal of Accounting Research*, 49(2):309–346.

[24] Bushee, B. J. (1998). The influence of institutional investors on myopic R&D investment behavior. *The Accounting Review*, 73(3):305–333.

[25] Bybee, L., Kelly, B. T., Manela, A., and Xiu, D. (2023). Business news and business cycles. *The Journal of Finance*. Forthcoming.

[26] Cameron, A. C., Gelbach, J. B., and Miller, D. L. (2011). Robust inference with multiway clustering. *Journal of Business & Economic Statistics*, 29(2):238–249.

[27] Campello, M., Graham, J. R., and Harvey, C. R. (2010). The real effects of financial constraints: Evidence from a financial crisis. *Journal of Financial Economics*, 97(3):470–487.

[28] Cao, S., Jiang, W., Yang, B., and Zhang, A. L. (2023). How to talk when a machine is listening: Corporate disclosure in the age of AI. *The Review of Financial Studies*, 36(9):3603–3642.

[29] Chava, S., Oettl, A., Subramanian, A., and Wilson, K. (2013). The real effects of financial shocks: Evidence from the tsunami. *The Review of Financial Studies*, 26(4):1048–1085.

[30] Cherniwchan, J. (2017). Trade liberalization and the environment: Evidence from NAFTA and U.S. manufacturing. *Journal of International Economics*, 105:130–149.

[31] Cohen, L., Diether, K. B., and Malloy, C. J. (2013). Misvaluing innovation. *The Review of Financial Studies*, 26(3):635–666.

[32] Cohen, L., Malloy, C. J., and Nguyen, Q. (2020). Lazy prices. *The Journal of Finance*, 75(3):1371–1415.

[33] Cohen, W. M. and Levinthal, D. A. (1990). Absorptive capacity: A new perspective on learning and innovation. *Administrative Science Quarterly*, 35(1):128–152.

[34] Cooper, M. J., Dimitrov, O., and Rau, P. R. (2001). A rose.com by any other name. *The Journal of Finance*, 56(6):2371–2388.

[35] Copeland, B. R. and Taylor, M. S. (1994). North-south trade and the environment. *The Quarterly Journal of Economics*, 109(3):755–787.

[36] Cornaggia, J., Mao, Y., Tian, X., and Wolfe, B. (2021). Financing and appropriability of innovation. *Journal of Financial and Quantitative Analysis*, 56(8):2739–2773.

[37] Crawford, V. P. and Sobel, J. (1982). Strategic information transmission. *Econometrica*, 50(6):1431–1451.

[38] Curry, J. M. and Fix, M. P. (2019). May it please the twitterverse: The use of twitter by state high court judges. *Journal of Law and Courts*, 7(1):1–22.

[39] Da, Z., Engelberg, J., and Gao, P. (2011). In search of attention. *The Journal of Finance*, 66(5):1461–1499.

[40] Diether, K. B., Malloy, C. J., and Scherbina, A. (2002). Differences of opinion and the cross section of stock returns. *The Journal of Finance*, 57(5):2113–2141.

[41] Dyer, T., Lang, M., and Stice-Lawrence, L. (2017). The evolution of 10-K textual disclosure: Evidence from Latent Dirichlet Allocation. *Journal of Accounting and Economics*, 64(2-3):221–245.

[42] Ederington, J. and Minier, J. (2003). Is environmental policy a secondary trade barrier? an empirical analysis. *Canadian Journal of Economics*, 36(1):137–154.

[43] Eswaran, M. and Gallini, N. (1996). Patent policy and the direction of technological change. *The RAND Journal of Economics*, 27(4):722–746.

[44] Fama, E. F. and French, K. R. (1993). Common risk factors in the returns on stocks and bonds. *Journal of Financial Economics*, 33(1):3–56.

[45] Fama, E. F. and French, K. R. (2015). A five-factor asset pricing model. *Journal of Financial Economics*, 116(1):1–22.

[46] Fazzari, S. M., Hubbard, R. G., and Petersen, B. C. (1988). Financing constraints and corporate investment. *Brookings Papers on Economic Activity*, 1988(1):141–195.

[47] Flammer, C. (2015). Does product market competition foster corporate social responsibility? evidence from trade liberalization. *Strategic Management Journal*, 36(10):1469–1485.

[48] Frankel, R., Johnson, M., and Skinner, D. J. (1999). An empirical examination of conference calls as a voluntary disclosure medium. *Journal of Accounting Research*, 37(1):133–150.

[49] Gao, Y. and You, F. (2019). The effect of the US-China trade war on corporate innovation. *Journal of Corporate Finance*, 58:744–764.

[50] Graham, J. R., Harvey, C. R., and Rajgopal, S. (2005). The economic implications of corporate financial reporting. *Journal of Accounting and Economics*, 40(1-3):3–73.

[51] Grinstein, Y. and Larkin, I. (2022). Competition and pollution. SSRN Working Paper.

[52] Hall, B. H., Jaffe, A., and Trajtenberg, M. (2005). Market value and patent citations. *The RAND Journal of Economics*, 36(1):16–38.

[53] Hart, S. L. (1995). A natural-resource-based view of the firm. *Academy of Management Review*, 20(4):986–1014.

[54] Hassan, T. A., Hollander, S., van Lent, L., and Tahoun, A. (2019). Firm-level political risk: Measurement and effects. *The Quarterly Journal of Economics*, 134(4):2135–2202.

[55] Hirshleifer, D., Hou, K., Teoh, S. H., and Zhang, Y. (2004). Do investors overvalue firms with bloated balance sheets? *Journal of Accounting and Economics*, 38:297–331.

[56] Hirshleifer, D., Hsu, P.-H., and Li, D. (2013). Innovative efficiency and stock returns. *Journal of Financial Economics*, 107(3):632–654.

[57] Hirshleifer, D. and Teoh, S. H. (2003). Limited attention, information disclosure, and financial reporting. *Journal of Accounting and Economics*, 36(1-3):337–386.

[58] Hoberg, G. and Phillips, G. (2010). Product market synergies and competition in mergers and acquisitions: A text-based analysis. *The Review of Financial Studies*, 23(10):3773–3811.

[59] Hoberg, G. and Phillips, G. (2016). Text-based network industries and endogenous product differentiation. *Journal of Political Economy*, 124(5):1423–1465.

[60] Hollander, S., Pronk, M., and Roelofsen, E. (2010). Does silence speak? an empirical analysis of disclosure choices during conference calls. *Journal of Accounting Research*, 48(3):531–563.

[61] Hombert, J. and Matray, A. (2018). Can innovation help U.S. manufacturing firms escape import competition from china? *The Journal of Finance*, 73(5):2003–2039.

[62] Hong, H. and Kacperczyk, M. (2010). Competition and bias. *The Quarterly Journal of Economics*, 125(4):1683–1725.

[63] Hong, H., Lim, T., and Stein, J. C. (2000). Bad news travels slowly: Size, analyst coverage, and the profitability of momentum strategies. *Journal of Finance*, 55(1):265–295.

[64] Huang, X., Teoh, S. H., and Zhang, Y. (2014). Tone management. *The Accounting Review*, 89(3):1083–1113.

[65] Katila, R. and Ahuja, G. (2002). Something old, something new: A longitudinal study of search behavior and new product introduction. *Academy of Management Journal*, 45(6):1183–1194.

[66] Kogan, L., Papanikolaou, D., Seru, A., and Stoffman, N. (2017a). Technological innovation, resource allocation, and growth. *The Quarterly Journal of Economics*, 132(2):665–712.

[67] Kogan, L., Papanikolaou, D., Seru, A., and Stoffman, N. (2017b). Technological innovation, resource allocation, and growth. *The Quarterly Journal of Economics*, 132(2):665–712.

[68] Kong, D., Lin, C., Wu, J., and Zhang, T. (2022). Trade liberalization and firm-level toxic emissions: Evidence from China's WTO accession. *Journal of International Economics*, 139:103673.

[69] Lacy, P., Cooper, T., Hayward, R., and Neuberger, L. (2010). A new era of sustainability: UN global compact-accenture CEO study 2010.

[70] Lakonishok, J., Shleifer, A., and Vishny, R. W. (1994). Contrarian investment, extrapolation, and risk. *The Journal of Finance*, 49(5):1541–1578.

[71] Lang, M. and Stice-Lawrence, L. (2015). Textual analysis and international financial reporting: Large-sample evidence. *Journal of Accounting and Economics*, 60(2-3):110–135.

[72] Lee, J. (2016). Can investors detect managers' lack of spontaneity? Evidence from cues in conference calls. *The Accounting Review*, 91(1):229–250.

[73] Lileeva, A. and Trefler, D. (2010). Improved access to foreign markets raises plant-level productivity... for some plants. *The Quarterly Journal of Economics*, 125(3):1051–1099.

[74] Loughran, T. and McDonald, B. (2011). When is a liability not a liability? Textual analysis, dictionaries, and 10-Ks. *The Journal of Finance*, 66(1):35–65.

[75] Manela, A. and Moreira, A. (2017). News implied volatility and disaster concerns. *Journal of Financial Economics*, 123(1):137–162.

[76] March, J. G. (1991). Exploration and exploitation in organizational learning. *Organization Science*, 2(1):71–87.

[77] Matsumoto, D., Pronk, M., and Roelofsen, E. (2011). What makes conference calls useful? The information content of managers' presentations and analysts' discussion sessions. *The Accounting Review*, 86(4):1383–1414.

[78] Merton, R. C. (1987). A simple model of capital market equilibrium with incomplete information. *The Journal of Finance*, 42(3):483–510.

[79] Miller, E. M. (1977). Risk, uncertainty, and divergence of opinion. *Journal of Finance*, 32(4):1151–1168.

[80] Mishler, A., Crabb, E. S., Paletz, S. B. F., Heffernan, B., and Petroff, M. (2015). Using structural topic modeling to detect events and cluster twitter users in the ukrainian crisis. *Proceedings of the Workshop on Computational Linguistics and Clinical Psychology*, pages 80–87.

[81] Peng, L. and Xiong, W. (2006). Investor attention, overconfidence and category learning. *Journal of Financial Economics*, 80(3):563–602.

[82] Petersen, M. A. (2009). Estimating standard errors in finance panel data sets: Comparing approaches. *The Review of Financial Studies*, 22(1):435–480.

[83] Polk, C. and Sapienza, P. (2009). The stock market and corporate investment: A test of catering theory. *The Review of Financial Studies*, 22(1):187–217.

[84] Porter, M. E. and van der Linde, C. (1995). Toward a new conception of the environment-competitiveness relationship. *Journal of Economic Perspectives*, 9(4):97–118.

[85] Roberts, M. E., Stewart, B. M., Tingley, D., Lucas, C., Leder-Luis, J., Gadarian, S. K., Albertson, B., and Rand, D. G. (2014). Structural topic models for open-ended survey responses. *American Journal of Political Science*, 58(4):1064–1082.

[86] Roychowdhury, S. (2006). Earnings management through real activities manipulation. *Journal of Accounting and Economics*, 42(3):335–370.

[87] Scherer, F. M. (1984). Using linked patent and R&D data to measure interindustry technology flows. In Griliches, Z., editor, *R&D, Patents, and Productivity*, pages 417–464. University of Chicago Press, Chicago.

[88] Schmidt, K. M. (1997). Managerial incentives and product market competition. *The Review of Economic Studies*, 64(2):191–213.

[89] Seru, A. (2014). Firm age, corporate governance, and innovation. *Journal of Financial Economics*, 112(3):429–450.

[90] Shapiro, J. S. (2021). Trade and the environment: A review. *Annual Review of Economics*, 13:149–173.

[91] Shiller, R. J. (2017). Narrative economics. *The American Economic Review*, 107(4):967–1004.

[92] Shleifer, A. and Vishny, R. W. (1990). Equilibrium short horizons of investors and firms. *The American Economic Review*, 80(2):148–153.

[93] Sims, C. A. (2003). Implications of rational inattention. *Journal of Monetary Economics*, 50(3):665–690.

[94] Skinner, D. J. and Sloan, R. G. (2002). Earnings surprises, growth expectations, and stock returns or don't let an earnings torpedo sink your portfolio. *Review of Accounting Studies*, 7(2-3):289–312.

[95] Sloan, R. G. (1996). Do stock prices fully reflect information in accruals and cash flows about future earnings? *The Accounting Review*, 71(3):289–315.

[96] Staw, B. M., Sandelands, L. E., and Dutton, J. E. (1981). Threat-rigidity effects in organizational behavior: A multilevel analysis. *Administrative Science Quarterly*, 26(4):501–524.

[97] Stein, J. C. (1989). Efficient capital markets, inefficient firms: A model of myopic corporate behavior. *The Quarterly Journal of Economics*, 104(4):655–669.

[98] Stoughton, N. M., Wong, K. P., and Yi, X. (2020). Committing to corporate social responsibility in a competitive industry. SSRN Working Paper.

[99] Strumsky, D., Lobo, J., and van der Leeuw, S. E. (2012). Using patent technology codes to study the dynamics of technological progress. *Research Policy*, 41(9):1717–1735.

[Tabatabaei] Tabatabaei, E. Mixed messages: Strategic tonal inconsistency and recovery of the PEAD anomaly. Working paper, Schulich School of Business. Available at SSRN: https://ssrn.com/abstract=5381754 or http://dx.doi.org/10.2139/ssrn.5381754.

[101] Tetlock, P. C. (2007). Giving content to investor sentiment: The role of media in the stock market. *The Journal of Finance*, 62(3):1139–1168.

[102] Valta, P. (2012). Competition and the cost of debt. *Journal of Financial Economics*, 105(3):661–682.

[103] Verrecchia, R. E. (2001). Essays on disclosure. *Journal of Accounting and Economics*, 32(1-3):97–180.

[104] Yu, F. F. (2008). Analyst coverage and earnings management. *Journal of Financial Economics*, 88(2):245–271.

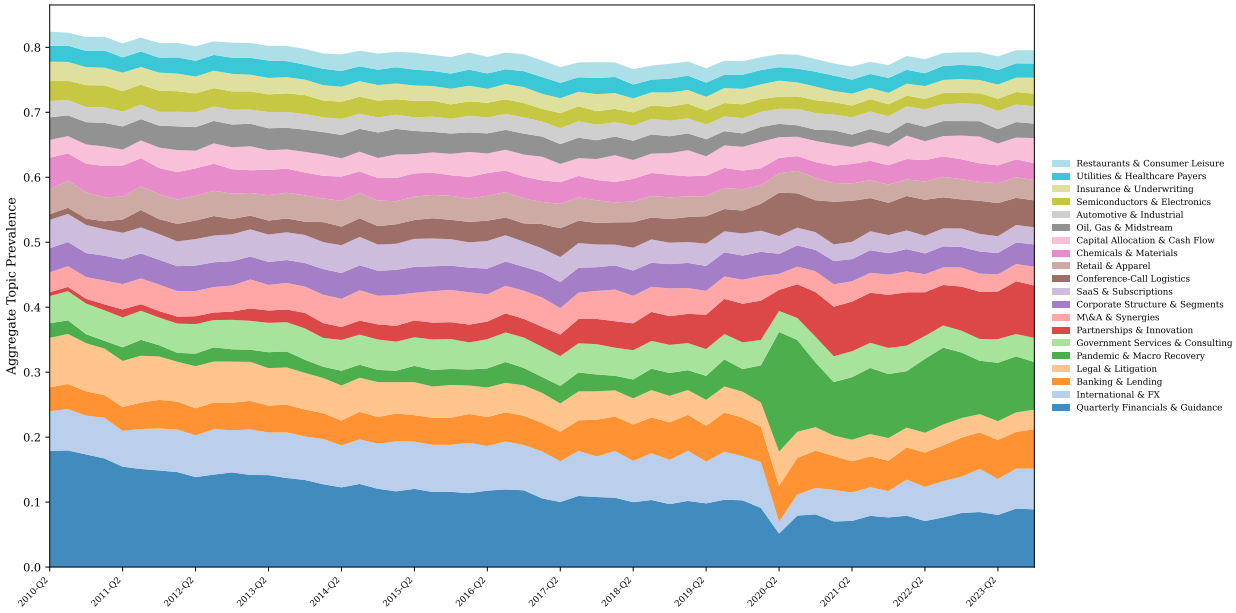

Figure 1: Aggregate Topic Prevalence in Analyst Discourse Over Time

This figure plots the aggregate prevalence of the 33 Structural Topic Model topics in the analyst-question corpus across sample quarters (2010:Q2 through 2023:Q4). The figure illustrates the thematic rotation in market discourse that the alignment measures exploit: a stable "Quarterly Financials & Guidance" anchor of roughly 11% in every quarter, the surge of pandemic and macro-recovery themes in 2020, the secular rise of cloud and cybersecurity themes after the mid-2010s, and commodity-driven spikes in energy topics. A firm whose prepared remarks load on whichever themes are currently prominent registers high thematic alignment in that quarter, regardless of its long-run thematic profile. See Section 4 and Appendix 1 for the model and topic inventory (Table A.6).

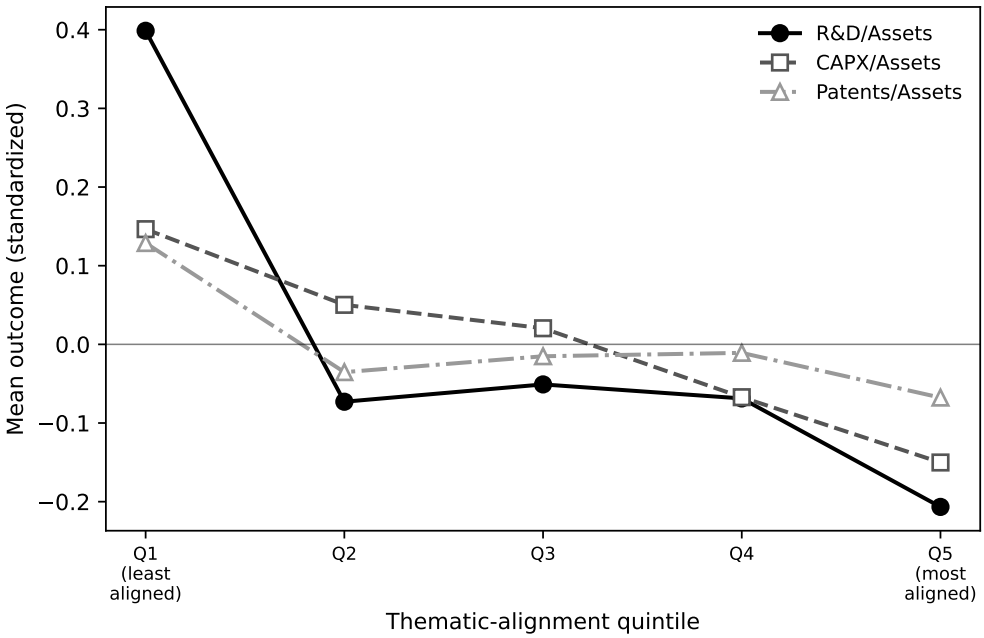

Figure 2: Real Innovation Outcomes Across Thematic-Alignment Quintiles
Each line plots the within-sample mean (standardized to zero mean and unit variance) of a real-outcome variable across quintiles of *Thematic Alignment*, where Q1 contains the least thematically aligned firm-quarters and Q5 the most. R&D, capital expenditure, and patent output are each scaled by total assets. The monotone decline shows that firms whose narratives most resemble prevailing market themes invest and innovate least.

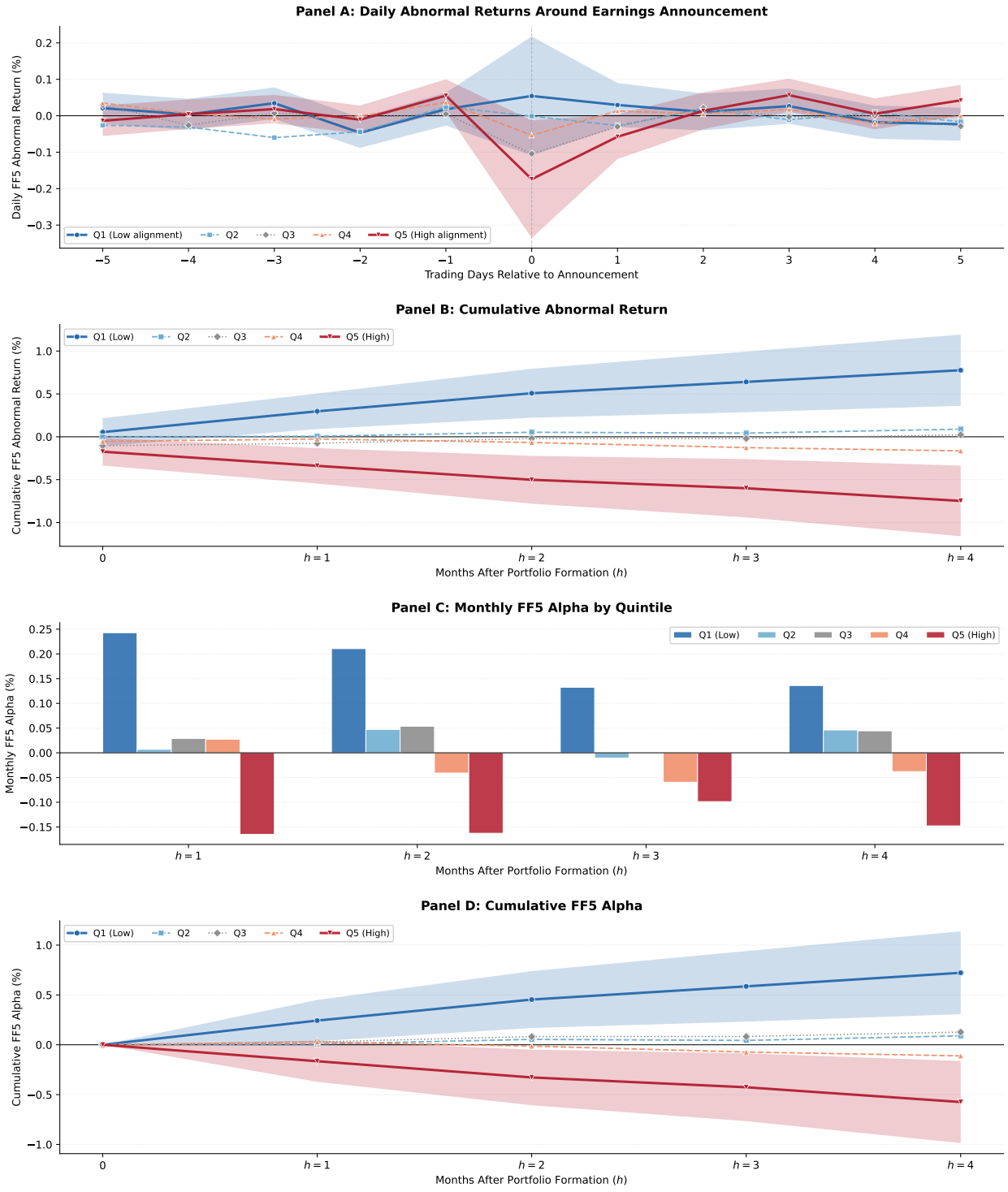

Figure 3: Abnormal Returns by Alignment Quintile

Each calendar quarter, firms are sorted into quintiles of abnormal thematic alignment (Eq. A.1; *sim_abnormal* in levels; Q1 = least aligned, Q5 = most aligned). Panel A plots average daily Fama and French (45) five-factor abnormal returns over $[-5, +5]$ trading days around the earnings announcement. Panel B cumulates FF5 abnormal returns from the announcement through $h = 4$, anchoring $h = 0$ at the day-0 abnormal return and adding portfolio FF5 alphas each month. Panel C reports value-weighted monthly FF5 alphas at $h = 1, \ldots, 4$. Panel D cumulates those monthly alphas from portfolio formation. Shaded bands in Panels A, B, and D show 95% confidence intervals for Q1 and Q5. See Table 8 for formal long-short (Q5−Q1) tests.

Table 1: Summary Statistics

This table reports summary statistics for the estimation sample, a quarterly panel of U.S. common stocks (CRSP share codes 10 and 11) with at least three prior-quarter earnings conference calls carrying analyst Q&A text, spanning 2010:Q2 through 2023:Q4. *Thematic Alignment* is the cosine similarity between a firm's prepared-remarks topic vector and the prior-quarter aggregate analyst-attention vector; *Thematic Conformity* is the negative Kullback-Leibler divergence of the firm's topic distribution from the prior-quarter analyst-attention distribution. Both are standardized to zero mean and unit variance (z). Accounting variables are from Compustat, returns from CRSP, and analyst variables from IBES; all are winsorized at the 1st and 99th percentiles within quarter. N is the number of firm-quarters.

	N	Mean	SD	P25	Median	P75
Panel A: Thematic alignment measures						
Thematic Alignment (z)	97,905	-0.021	1.008	-0.728	0.035	0.760
Thematic Conformity (z)	97,905	-0.023	1.005	-0.606	0.080	0.681
Panel B: Real innovation outcomes						
R&D/Assets	102,377	0.040	0.084	0.000	0.000	0.042
CAPX/Assets	102,377	0.037	0.045	0.009	0.024	0.048
Patents/Assets	102,357	0.008	0.056	0.000	0.000	0.002
Product uniqueness	96,777	0.083	0.121	0.008	0.030	0.100
Intangibles/Assets	102,377	0.178	0.170	0.021	0.131	0.308
Panel C: Firm and information-environment controls						
Log market equity	104,379	7.781	1.674	6.584	7.640	8.823
Log book-to-market	104,379	-0.992	1.017	-1.509	-0.848	-0.303
Earnings surprise (SUE)	104,379	1.199	5.773	-0.500	1.000	2.600
Log analyst coverage	104,379	2.086	0.722	1.609	2.079	2.639
Analyst forecast dispersion	103,848	0.270	1.265	0.036	0.077	0.185

Table 2: Pairwise Correlations

This table reports Pearson correlation coefficients among the two headline thematic-alignment measures and the principal real-outcome variables, computed over the estimation sample. *Thematic Alignment* and *Thematic Conformity* are standardized as described in Table 1.

	(1)	(2)	(3)	(4)	(5)
(1) Thematic Alignment	1.00				
(2) Thematic Conformity	0.66	1.00			
(3) R&D/Assets	-0.25	-0.28	1.00		
(4) Patents/Assets	-0.08	-0.08	0.27	1.00	
(5) Product uniqueness	0.32	0.36	-0.18	-0.05	1.00

Table 3: Thematic Alignment and Real Innovation Outcomes

This table reports estimates from firm-quarter panel regressions of real innovation outcomes on standardized thematic-alignment measures. The dependent variables are the log ratios of R&D, capital expenditure, patent output, and intangible assets to total assets, and the Hoberg and Phillips product-uniqueness score. Each column is a separate regression. Panel A uses *Thematic Alignment* (cosine similarity to prior-quarter market themes); Panel B uses *Thematic Conformity* (negative KL divergence from the market topic distribution); Panel C replaces the continuous measure with within-quarter quintile indicators (Q2–Q5), omitting the bottom quintile (Q1, least aligned) as the baseline; the reported coefficient is the top quintile (Q5), so the comparison is the most trend-aligned firms versus the least trend-aligned. All specifications include firm and industry×year-month fixed effects and control for lagged log market equity, lagged log book-to-market, and the contemporaneous earnings surprise. Coefficients are multiplied by 100. Standard errors are two-way clustered by firm and call date; t-statistics are in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

	R&D	CAPX	Patents	Product Uniqueness	Intangibles
	(1)	(2)	(3)	(4)	(5)
Panel A: Thematic Alignment					
Thematic Alignment	-0.181^{***}	-0.198^{***}	-0.269^{***}	-0.021	$+0.473^{***}$
	(-2.69)	(-6.11)	(-3.40)	(-0.26)	(4.34)
Panel B: Thematic Conformity					
Thematic Conformity	-0.179^{***}	$+0.009$	-0.217^{***}	$+0.213^{***}$	$+0.321^{***}$
	(-3.46)	(0.40)	(-3.09)	(3.51)	(3.77)
Panel C: High-alignment indicator					
High-Alignment (Q5)	-0.084^{***}	-0.089^{**}	-0.087^{***}	$+0.136$	$+0.549^{***}$
	(-2.98)	(-2.54)	(-2.68)	(0.86)	(3.78)
Controls	$\log(\text{ME})_{q-1}$, $\log(\text{BM})_{q-1}$, SUE_q				
Firm FE	✓	✓	✓	✓	✓
Industry×Month FE	✓	✓	✓	✓	✓
N (firm-quarters)	96,398	96,398	96,385	91,045	96,398
Firms	3,736	3,736	3,736	3,698	3,736
Within R^2	0.89	0.82	0.60	0.81	0.90

Table 4: Thematic Alignment and Patent Composition: Product versus Process

This table reports estimates from firm-quarter panel regressions of the composition of patent output on standardized *Thematic Alignment*. The dependent variables are the share of a firm's annual utility-patent applications classified as product-oriented versus process-oriented, following the claim-text algorithm of Bena et al. (14); product patents describe inventions intended for external sale or use, whereas process patents describe internal production methods (87). Shares are measured at the fiscal-year level and mapped to each call quarter in that year. All specifications include firm and industry×year-month fixed effects and the baseline controls of Table 3; coefficients are in percentage points. Standard errors are two-way clustered by firm and call date; t-statistics in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

	Thematic Alignment
Product patents / total	-1.22^{**}
	(-2.35)
Process patents / total	$+1.22^{**}$
	(2.35)
Controls	$\log(\text{ME})_{q-1}$, $\log(\text{BM})_{q-1}$, SUE_q
Firm FE	✓
Industry×Month FE	✓
N (firm-quarters)	18,736
Firms	989

Table 5: Thematic Alignment and Future Innovation Investment

This table reports estimates from firm-quarter panel regressions of *future* innovation investment on current thematic alignment. The dependent variables, measured $q + h$ quarters after the call, are quarterly R&D and capital expenditure scaled by assets and log patent output scaled by assets. Panel A uses *Thematic Alignment* and Panel B uses *Thematic Conformity*, both standardized. All specifications include firm and year-month fixed effects and the baseline controls of Table 3. Coefficients are multiplied by 100. Standard errors are two-way clustered by firm and call date; t-statistics in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Horizon	R&D	CAPX	Patents
Panel A: Thematic Alignment			
$q+1$	-0.067^{***}	-0.104^{***}	-0.235^{***}
	(-2.95)	(-3.98)	(-3.23)
$q+2$	-0.051^{**}	-0.108^{***}	-0.189^{***}
	(-2.38)	(-4.18)	(-2.88)
$q+3$	-0.049^{**}	-0.171^{***}	-0.157^{***}
	(-2.19)	(-6.30)	(-2.75)
$q+4$	-0.026	-0.044^{*}	-0.137^{**}
	(-1.22)	(-1.68)	(-2.52)
Panel B: Thematic Conformity			
$q+1$	-0.072^{***}	-0.002	-0.190^{***}
	(-4.20)	(-0.11)	(-2.76)
$q+2$	-0.053^{***}	$+0.011$	-0.184^{***}
	(-3.22)	(0.51)	(-2.65)
$q+3$	-0.044^{***}	$+0.006$	-0.157^{***}
	(-2.58)	(0.33)	(-2.61)
$q+4$	-0.027	$+0.028$	-0.136^{***}
	(-1.53)	(1.48)	(-2.59)
Controls	$\log(\text{ME})_{q-1}$, $\log(\text{BM})_{q-1}$, SUE_q		
Firm FE	✓	✓	✓
Year-Month FE	✓	✓	✓
N (firm-quarters)	94,428	94,222	92,692
Firms	3,746	3,745	3,688
Within R^2	0.75	0.69	0.59

Table 6: Thematic Alignment and Future Fundamentals: Harvesting, Not Building

This table reports estimates from firm-quarter panel regressions of future operating fundamentals on current thematic alignment. The dependent variables, measured $q + h$ quarters ahead, are return on assets and year-over-year sales growth (in percentage points). Panel A uses *Thematic Alignment* and Panel B uses *Thematic Conformity*, both standardized. All specifications include firm and year-month fixed effects and the baseline controls of Table 3. Return-on-assets coefficients are multiplied by 100. Standard errors are two-way clustered by firm and call date; t-statistics in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Horizon	Return on Assets	Sales Growth
Panel A: Thematic Alignment		
$q+1$	$+0.112^{***}$	-1.096
	(2.58)	(-1.29)
$q+2$	$+0.106^{**}$	-1.222^{*}
	(2.47)	(-1.83)
$q+3$	$+0.112^{**}$	-0.996
	(2.56)	(-1.62)
$q+4$	$+0.136^{***}$	-0.601
	(2.97)	(-1.25)
Panel B: Thematic Conformity		
$q+1$	$+0.079^{**}$	-0.645
	(2.24)	(-0.82)
$q+2$	$+0.098^{***}$	-1.096
	(2.71)	(-1.56)
$q+3$	$+0.069^{*}$	-0.869^{*}
	(1.94)	(-1.81)
$q+4$	$+0.071^{*}$	-0.688
	(1.81)	(-1.05)
Controls	$\log(\text{ME})_{q-1}$, $\log(\text{BM})_{q-1}$, SUE_q	
Firm FE	✓	✓
Year-Month FE	✓	✓
N (firm-quarters)	94,386	81,933
Firms	3,746	3,258
Within R^2	0.47	0.10

Table 7: Real Effects by Information Environment

This table reports the *Thematic Alignment* coefficient from separate regressions of three real-outcome variables (R&D/Assets, CAPX/Assets, and Patents/Assets) within the most-opaque and most-transparent within-quarter tercile of three information-environment proxies. Opaque firms are defined as those in the bottom analyst-coverage tercile, the top forecast-dispersion tercile, or the bottom market-cap tercile. Each estimate comes from a regression with firm and year-month fixed effects and the baseline controls of Table 3; coefficients are multiplied by 100. Standard errors are two-way clustered by firm and call date; t-statistics in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

	Opaque	Transparent
Analyst coverage		
R&D	-0.167^{**}	-0.056
	(-1.98)	(-1.07)
CAPX	-0.136^{***}	-0.211^{***}
	(-2.94)	(-4.74)
Patents	-0.239^{***}	-0.056
	(-2.94)	(-1.53)
N (firm-quarters)	28,955	33,879
Firms	2,247	1,489
Forecast dispersion		
R&D	-0.281^{**}	-0.058^{**}
	(-2.30)	(-2.24)
CAPX	-0.287^{***}	-0.104^{***}
	(-4.99)	(-3.26)
Patents	-0.474^{***}	-0.006
	(-3.17)	(-0.52)
N (firm-quarters)	32,049	31,077
Firms	3,195	2,293
Firm size		
R&D	-0.149	-0.038
	(-1.37)	(-0.91)
CAPX	-0.172^{***}	-0.206^{***}
	(-2.84)	(-4.72)
Patents	-0.600^{***}	-0.013
	(-3.49)	(-1.39)
N (firm-quarters)	26,394	36,611
Firms	2,279	1,505
Controls	$\log(\text{ME})_{q-1}$, $\log(\text{BM})_{q-1}$, SUE_q	
Firm FE	✓	
Year-Month FE	✓	

Table 8: Calendar-Time Portfolio Alphas of Alignment-Sorted Portfolios

At the end of each calendar quarter, firms with a conference call in that quarter are sorted into quintiles on *Abnormal Alignment* (Appendix 2). The long-short portfolio buys the top quintile (firms whose narratives most closely exceed their typical proximity to market themes) and sells the bottom quintile, and is held over the three calendar months of the quarter h quarters after the call. Alphas are intercepts from time-series regressions of the monthly long-short return on the CAPM, the Fama and French (1993) three-factor model, and the Fama and French (45) five-factor model, estimated with Newey and West standard errors (3 lags), and are reported in percent per month. t-statistics in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

	$h = 1$	$h = 2$	$h = 3$	$h = 4$
CAPM α	-0.38^{**}	-0.34^{**}	-0.24	-0.34
	(-2.21)	(-2.18)	(-1.24)	(-1.52)
FF3 α	-0.40^{**}	-0.36^{**}	-0.23	-0.31
	(-2.29)	(-2.28)	(-1.20)	(-1.42)
FF5 α	-0.41^{**}	-0.37^{**}	-0.23	-0.28
	(-2.45)	(-2.45)	(-1.30)	(-1.41)
Weighting		Value-weighted		
N (months)	159	156	153	150
Adj. R^2 (FF5)	0.02	0.02	0.02	0.03
Newey–West lags		3		

Appendix

1 Structural Topic Model: Estimation Details

Corpus and design. The STM is estimated on the analyst-question corpus only. Each firm-quarter with a Capital IQ transcript contributes one document formed by concatenating all analyst questions from that call. The training sample contains 101,693 such documents from roughly 4,700 unique firms over 2010:Q1 through 2023:Q4. Manager prepared remarks are *not* used to estimate the model; they are mapped onto the trained topic basis in a second stage so that the thematic dimensions reflect market discourse rather than any single firm's idiosyncratic language. This two-stage design mirrors the measurement logic in the main text: the analyst corpus defines *what* the market is asking about; manager remarks are scored by how closely they load on those same dimensions.

Text preprocessing. The analyst-question corpus undergoes a multi-stage NLP pipeline before estimation. Raw transcript text is cleaned of boilerplate headers, footers, and operator instructions; processed with spaCy for lemmatisation and named-entity redaction (person, organisation, monetary, percentage, date, cardinal, and geopolitical entities are removed so the model clusters on themes rather than proper nouns); augmented with bigrams and trigrams via Gensim `Phrases` models; and filtered of stopwords and extreme-frequency terms. The resulting vocabulary contains 51,770 terms across the 101,693 training documents.

Estimation and topic count. The model is estimated with the `stm` R package (85) using spectral initialisation. Prevalence covariates are calendar year-quarter (spline), Fama-French 48-industry classification, and log market capitalisation, so that estimated topic proportions are not mechanically driven by secular trends, sector composition, or firm size. STM also allows correlated topic proportions, which is appropriate when disclosure themes (for example,

revenue growth, capital allocation, and guidance) co-occur in practice.

The number of topics K is selected from a 15-value grid $K \in \{10, 20, 27, \ldots, 100\}$ by a Pareto-front rule applied jointly to normalised semantic coherence and exclusivity, evaluated on a 30% year-quarter-stratified subsample of the analyst corpus. The global Pareto-undominated point is $K = 33$ (Figure A.1), which I use in all main-text analyses.

Manager-side inference. After estimation, each firm-quarter's prepared remarks are tokenised with the *same* preprocessing pipeline and dictionary used at training time. Posterior topic proportions for manager documents are inferred via out-of-sample document fitting (85), holding the word-topic distribution fixed at its analyst-corpus estimate. Aggregate analyst-attention vectors $\bar{\boldsymbol{\theta}}_q^A$ are then formed by averaging analyst-question topic vectors within calendar quarter q, and alignment measures in Section 4 compare each manager vector $\boldsymbol{\theta}_{i,q}^M$ to the lagged market vector $\bar{\boldsymbol{\theta}}_{q-1}^A$.

2 Alternative Alignment Indicators

Appendix Table A.2 re-estimates the headline real-outcome regressions of Table 3 using eight standardized alignment indicators that isolate different facets of "manager echoes market themes." This section defines each construction. Unless noted, all measures compare the manager vector $\boldsymbol{\theta}_{i,q}^M$ to the lagged analyst-attention vector $\bar{\boldsymbol{\theta}}_{q-1}^A$ or to transformations of the analyst series. Continuous indicators are z-scored over the estimation sample before entering regressions.

Abnormal alignment. Following Hoberg and Phillips (58), abnormal alignment nets out each firm's typical proximity to market discourse, leaving only the quarter-specific tilt toward the relevant analyst benchmark:

$$AbnormalAlignment_{i,q} = \cos\Big(\boldsymbol{\theta}_{i,q}^M, \bar{\boldsymbol{\theta}}_{q-1}^A\Big) - \frac{1}{T-1} \sum_{s \neq q-1} \cos\Big(\boldsymbol{\theta}_{i,q}^M, \bar{\boldsymbol{\theta}}_s^A\Big). \tag{A.1}$$

Mispricing portfolios in Section 5.6 sort on this measure in levels (within-quarter ranks).

Residual alignment. Residual alignment removes firm-specific and calendar-quarter means from thematic alignment (Eq. 1), isolating within-firm, within-quarter variation in cosine similarity:

$$ResidualAlignment_{i,q} = Alignment_{i,q} - \overline{Alignment}_i - \overline{Alignment}_q + \overline{Alignment}, \tag{A.2}$$

where bars denote sample averages by firm, by quarter, and overall.

Trend-shock exposure. Let the analyst *trend shock* be the deviation of lagged market attention from its recent baseline,

$$\Delta\bar{\boldsymbol{\theta}}^A_{q-1} = \bar{\boldsymbol{\theta}}^A_{q-1} - \frac{1}{4}\sum_{j=2}^{5}\bar{\boldsymbol{\theta}}^A_{q-j}. \tag{A.3}$$

Trend-shock exposure is the manager's loading on recently surging analyst topics, normalised by the shock magnitude:

$$TrendShockExposure_{i,q} = \frac{\boldsymbol{\theta}^M_{i,q}\cdot\Delta\bar{\boldsymbol{\theta}}^A_{q-1}}{\|\Delta\bar{\boldsymbol{\theta}}^A_{q-1}\|}. \tag{A.4}$$

High values place managerial emphasis on themes whose market-wide attention has just risen, rather than on the full analyst distribution.

Top-3 trend coverage. *Top-3 trend coverage* sums the manager's topic weight on the three topics with the largest positive entries in $\Delta\bar{\boldsymbol{\theta}}^A_{q-1}$:

$$Top3Coverage_{i,q} = \sum_{k\in\mathcal{T}_3(q-1)}\theta^M_{i,q,k}, \tag{A.5}$$

where $\mathcal{T}_3(q-1)$ indexes the three fastest-rising analyst topics in quarter $q-1$. This non-parametric measure asks how much narrative mass the manager allocates to the themes

analysts are most actively pivoting toward.

Net trend-following. *Net trend-following* contrasts backward- and forward-looking cosine similarity:

$$NetTrendFollow_{i,q} = \cos\Big(\boldsymbol{\theta}^{M}_{i,q},\, \bar{\boldsymbol{\theta}}^{A}_{q-1}\Big) - \cos\Big(\boldsymbol{\theta}^{M}_{i,q},\, \bar{\boldsymbol{\theta}}^{A}_{q+1}\Big). \tag{A.6}$$

A positive value indicates that the narrative loads more on lagged than on leading market themes. The forward-looking term serves as a built-in placebo: coincidence with future analyst discourse should not reflect strategic catering to themes already observable when the manager speaks.

Novelty residual. *Novelty residual* projects the manager's *new* thematic tilt—relative to the firm's own narrative over the prior four quarters—onto the analyst trend shock:

$$NoveltyResidual_{i,q} = \frac{\Big(\boldsymbol{\theta}^{M}_{i,q} - \bar{\boldsymbol{\theta}}^{M}_{i,q-1:q-4}\Big)\cdot \Delta\bar{\boldsymbol{\theta}}^{A}_{q-1}}{\|\Delta\bar{\boldsymbol{\theta}}^{A}_{q-1}\|}, \tag{A.7}$$

where $\bar{\boldsymbol{\theta}}^{M}_{i,q-1:q-4}$ is the average manager topic vector over quarters $q-4$ through $q-1$. This measure is positive when the firm shifts *new* narrative mass toward themes analysts have recently elevated.

Headline measures in levels. Appendix Table A.3 repeats the Table 3 specifications using *thematic alignment* and *thematic conformity* in levels rather than z-scores. Because full-sample standardization is an affine transform of the regressor only, t-statistics are unchanged; the levels table is provided for economic interpretation.

Topic labelling. Table A.6 lists all 33 topics with representative FREX (Frequency and Exclusivity) words used to assign economic labels. FREX ranks terms by combining within-topic frequency with exclusivity across topics, yielding interpretable top words for each dimension (85).

3 Variable Definitions

Table A.1: Variable Definitions

This table defines all variables used in the main text and appendix tables. Unless noted, the unit of observation is a firm-quarter indexed to the earnings conference call in calendar quarter q. Compustat annual items are merged by fiscal year; patent composition and product-uniqueness measures are fiscal-year snapshots mapped to each call quarter in that year. Continuous accounting and IBES variables are winsorized at the 1st and 99th percentiles within calendar quarter. Alignment measures used in regressions are standardized to zero mean and unit variance over the estimation sample (z). Coefficients on log-ratio outcomes are reported multiplied by 100 in the tables.

Variable	Definition
Panel A: Sample	
Estimation sample	U.S. common stocks (CRSP share codes 10 and 11) with at least three prior-quarter earnings calls carrying analyst Q&A text in Compustat Capital IQ, non-missing Compustat quarterly fundamentals (assets, equity, revenue), and CRSP returns for the baseline control set. Sample period: 2010:Q2–2023:Q4.
Manager narrative	Prepared-remarks section of the earnings conference call (Capital IQ component type 2), aggregated to one document per firm-quarter.
Analyst-attention benchmark	All analyst questions from the Q&A segment (component type 3), aggregated across all calls in calendar quarter q to form the market-theme vector $\bar{\boldsymbol{\theta}}_q^A$ (Appendix 1).
Panel B: Thematic alignment measures	

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Table A.1 — *continued from previous page*

Variable	Definition
Thematic Alignment (z)	Cosine similarity between the manager topic vector and the lagged analyst-attention vector, $\cos(\boldsymbol{\theta}^{M}_{i,q}, \bar{\boldsymbol{\theta}}^{A}_{q-1})$; Eq. (**??**). Used in Table 3, Panel A, and related regressions.
Thematic Conformity (z)	Negative Kullback–Leibler divergence of the prior-quarter analyst-attention distribution from the manager topic distribution, $-KL(\bar{\boldsymbol{\theta}}^{A}_{q-1} \,\|\, \boldsymbol{\theta}^{M}_{i,q})$; Eqs. (**??**)–(**??**). Used in Table 3, Panel B.
High-alignment indicator	Indicator equal to one if *Thematic Alignment* places the firm in the top within-calendar-quarter quintile (Q5); the regression includes indicators for Q2–Q5 with Q1 (least aligned) as the omitted baseline. Table 3, Panel C reports the Q5 coefficient.
Abnormal Alignment	Hoberg–Phillips-style residual cosine similarity: thematic alignment minus the firm's average cosine similarity to all other analyst-quarter vectors in the sample; Eq. (A.1) in Appendix 2. Used to form mispricing portfolios (Table 8, Figure 3).
Alternative alignment indicators	Eight standardized robustness measures defined in Appendix 2 and reported in Appendix Table A.2.
Panel C: Real innovation outcomes	
R&D/Assets	$\ln(1 + \text{XRD}_{i,t}/\text{AT}_{i,t})$, where XRD is research and development expense and AT is total assets from Compustat annual fundamentals for fiscal year t mapped to call quarter q.

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Table A.1 — *continued from previous page*

Variable	**Definition**
CAPX/Assets	$\ln(1 + \text{CAPX}_{i,t}/\text{AT}_{i,t})$, capital expenditure scaled by total assets (Compustat annual).
Patents/Assets	$\ln(1 + P_{i,t}/\text{AT}_{i,t})$, where $P_{i,t}$ is the count of patent applications filed by firm i in fiscal year t, summed from quarterly USPTO–CRSP/Compustat matched patent data and scaled by total assets.
Product Uniqueness	Text-based product-market differentiation from the TNIC-3 network of Hoberg and Phillips (59): for each firm-year, count rivals with pairwise product similarity above the TNIC threshold and define $\textit{Uniqueness}_{i,t} = 1/(1 + N_{i,t}^{\text{rivals}})$. Higher values indicate greater distinctiveness from product-market peers. Fiscal-year measure mapped to call quarters.
Intangibles/Assets	$\ln(1 + \text{INTAN}_{i,t}/\text{AT}_{i,t})$, balance-sheet intangible assets scaled by total assets (Compustat annual).
Panel D: Patent composition (Bena–Simintzi subsample)	

continued on next page

Table A.1 — *continued from previous page*

Variable	Definition
Product patents / total	Share of utility-patent *applications* filed in fiscal year t classified as product patents: $ProductShare_{i,t} = N_{i,t}^{\text{product}}/(N_{i,t}^{\text{product}} + N_{i,t}^{\text{process}})$. Classification follows the claim-text algorithm of Bena et al. (14), which assigns each patent to product or process categories from the legal language of patent claims (green patents, classified separately in their framework, are excluded from the denominator). Product patents describe inventions intended for external sale or use; process patents describe internal production methods (87).
Process patents / total	$ProcessShare_{i,t} = 1 - ProductShare_{i,t}$. Table 4. Subsample: firm-quarters with matched Compustat, patent linkages, and at least one classified filing in the fiscal year (≈998 firms).
Panel E: Forward outcomes and fundamentals	
Forward R&D, CAPX, Patents	Outcome measured $h = 1, \ldots, 4$ calendar quarters after the call quarter. Quarterly Compustat flows (XRDQ, CAPXY) enter at the corresponding future quarter; annual outcomes (R&D/Assets, Patents/Assets) use the fiscal-year snapshot attached to the future quarter. Tables 5, A.4.
Return on Assets	Quarterly ROA = $\text{NIQ}_{i,q+h}/\text{ATQ}_{i,q+h}$, income before extraordinary items divided by total assets (Compustat quarterly), measured h quarters ahead. Table 6, Panel A.

continued on next page

Table A.1 — *continued from previous page*

Variable	**Definition**
Sales Growth	Year-over-year growth in quarterly revenue, $(\text{REVTQ}_{i,q+h} - \text{REVTQ}_{i,q+h-4})/\text{REVTQ}_{i,q+h-4}$, measured h quarters ahead. Table 6, Panel B.
Panel F: Controls and information-environment proxies	
Log market equity	Natural logarithm of CRSP compound market equity (`me_comp`) at the end of the quarter preceding the call, matched to Compustat via the CRSP/Compustat Merged link.
Log book-to-market	Natural logarithm of the ratio of book equity to market equity at the end of the quarter preceding the call. Book equity is Compustat stockholders' equity plus deferred taxes (annual), forward-filled within firm and divided by contemporaneous `me_comp`.
Earnings surprise (SUE)	Standardized unexpected earnings in the call quarter: (Actual EPS − Median forecast)/Forecast standard deviation, using IBES summary statistics for the fiscal period ending closest to the call; forecasts are taken from the last consensus update on or before the actual announcement date.
Log analyst coverage	Natural logarithm of the number of IBES analysts issuing annual earnings forecasts within 90 days before the call (`numest`).

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Table A.1 — *continued from previous page*

Variable	Definition
Analyst forecast dispersion	Coefficient of variation of analyst forecasts in the 90 days before the call: standard deviation of estimates divided by the absolute value of the median estimate (40).
Opacity splits	Within each calendar quarter, firms are sorted into terciles of analyst coverage, forecast dispersion, or log market equity. *Opaque* denotes the bottom coverage tercile, top dispersion tercile, or bottom size tercile; *transparent* denotes the opposite tail. Table 7.
Panel G: Portfolio return tests	
Alignment-sorted quintiles	Each calendar quarter, firms with a conference call are sorted into quintiles on *Abnormal Alignment* in levels (within-quarter ranks). Q5 (most aligned) minus Q1 (least aligned) forms the long-short portfolio.
Portfolio return	Value-weighted (Panels A–B of Table 8) or equal-weighted (Panel C) monthly CRSP return of the long-short portfolio over the three calendar months of quarter h after the call.
CAPM / FF3 / FF5 α	Intercept from a time-series regression of the monthly long-short portfolio excess return on the market factor (CAPM), the Fama and French (1993) three factors, or the Fama and French (45) five factors. Alphas are in percent per month; standard errors are Newey–West with three lags.
Small-cap subsample	Firms in the bottom within-quarter tercile of log market equity when portfolios are formed.

continued on next page

Table A.1 — *continued from previous page*

Variable	**Definition**
High-dispersion subsample	Firms in the top within-quarter tercile of analyst forecast dispersion when portfolios are formed.
Panel H: Econometric specifications	
Baseline regression	$Y_{i,q} = \alpha_i + \alpha_t + \beta\, Alignment^{z}_{i,q} + \boldsymbol{\gamma}'\mathbf{X}_{i,q} + \varepsilon_{i,q}$; Eq. (**??**).
Fixed effects	α_i: firm fixed effects (gvkey). α_t: in main tables, Fama–French 48-industry × call-year-month fixed effects; in Table 7, call-year-month fixed effects only.
Controls $\mathbf{X}$	Baseline vector: log market equity, log book-to-market, and SUE, all measured relative to the call quarter as defined above.
Standard errors	Two-way clustered by firm (gvkey) and earnings-call date (call_date), following Petersen (82); Cameron et al. (26).

Appendix Figures

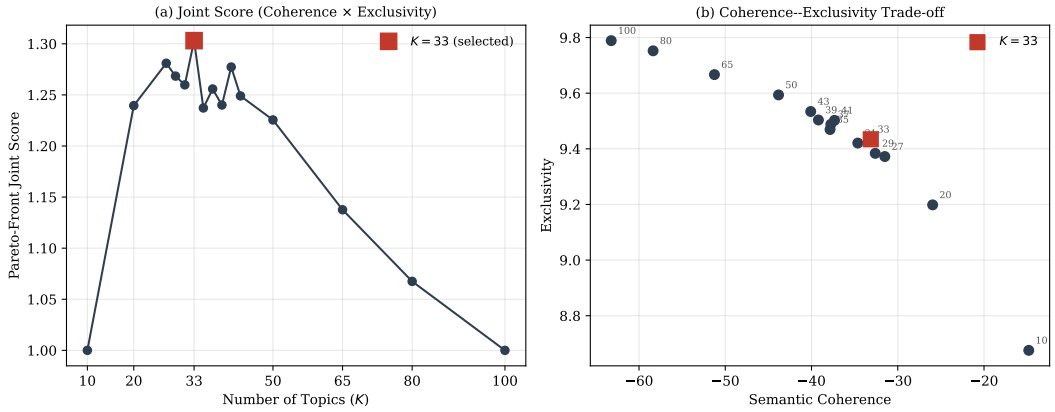

Figure A.1: K-Selection Diagnostic: Semantic Coherence versus Exclusivity
This figure plots the Pareto-front joint score (normalised semantic coherence and exclusivity) against the number of topics K for the 15-value grid evaluated on a 30% year-quarter-stratified subsample of the analyst-question corpus. The global maximum at $K = 33$ is marked. See Appendix 1.

Appendix Tables

Appendix Table A.1 defines all variables used in the paper. Appendix 2 defines the alternative alignment indicators in Appendix Table A.2. Appendix Table A.3 repeats the headline specifications in levels for coefficient interpretation; inference is unchanged from the main-text z-scored estimates (Section 4.4). Appendix Table A.4 adds contemporaneous innovation outcomes as controls in the forward-investment regressions (Table 5). Appendix Table A.5 reports pooled interaction-term specifications that formally test whether the relationship between thematic alignment and real outcomes differs between opaque and transparent firms (Section 5.5). Table A.6 lists all STM topics with representative words.

Table A.2: Robustness Across Alternative Alignment Indicators

This table re-estimates the headline real-outcome regressions of Table 3 (industry×month fixed-effects specification) using eight alternative standardized alignment indicators that capture complementary facets of thematic alignment. All specifications include firm and industry×year-month fixed effects and the baseline controls; coefficients are multiplied by 100. Standard errors are two-way clustered by firm and call date; t-statistics in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

	R&D	CAPX	Patents	Product Uniqueness	Intangibles
Thematic Alignment (cosine)	-0.181^{***}	-0.198^{***}	-0.269^{***}	-0.021	$+0.473^{***}$
	(-2.69)	(-6.11)	(-3.40)	(-0.26)	(4.34)
Residual Alignment	-0.089^{***}	-0.098^{***}	-0.133^{***}	-0.010	$+0.234^{***}$
	(-2.69)	(-6.11)	(-3.40)	(-0.26)	(4.34)
Abnormal Alignment	-0.002	-0.010	-0.110^{***}	-0.090	-0.206^{**}
	(-0.05)	(-0.44)	(-2.69)	(-1.11)	(-2.19)
Trend-Shock Exposure	-0.013	$+0.045^{**}$	$+0.116^{***}$	$+0.022$	$+0.034$
	(-0.42)	(2.32)	(4.07)	(0.53)	(0.70)
Top-3 Trend Coverage	-0.028	-0.031^{***}	$+0.066^{***}$	$+0.067^{***}$	$+0.024$
	(-1.07)	(-2.58)	(3.77)	(2.65)	(0.76)
Net Trend-Following	$+0.034^{**}$	-0.005	-0.027	-0.087^{***}	-0.004
	(2.14)	(-0.48)	(-1.52)	(-2.72)	(-0.12)
Novelty-Residual	$+0.017$	-0.000	-0.013	-0.017	$+0.016$
	(1.29)	(-0.03)	(-0.76)	(-0.68)	(0.67)
Thematic Conformity (KL)	-0.179^{***}	$+0.009$	-0.217^{***}	$+0.213^{***}$	$+0.321^{***}$
	(-3.46)	(0.40)	(-3.09)	(3.51)	(3.77)
Controls	$\log(\text{ME})_{q-1}$, $\log(\text{BM})_{q-1}$, SUE_q				
Firm FE	✓	✓	✓	✓	✓
Industry×Month FE	✓	✓	✓	✓	✓
N (firm-quarters)	96,398	96,398	96,385	91,045	96,398
Firms	3,736	3,736	3,736	3,698	3,736
Within R^2	0.89	0.82	0.60	0.81	0.90

Table A.3: Headline Measures in Levels

This table re-estimates the headline real-outcome regressions of Table 3 using the two headline alignment measures in levels (not standardized). Because full-sample standardization is an affine transform of the regressor only, t-statistics match the corresponding z-scored specifications in Table 3; coefficients are reported in levels for economic interpretation only. All specifications include firm and industry×year-month fixed effects and the baseline controls; coefficients are multiplied by 100. Standard errors are two-way clustered by firm and call date; t-statistics in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

	R&D	CAPX	Patents	Product Uniqueness	Intangibles
Thematic Alignment (level)	-1.285^{***}	-1.408^{***}	-1.915^{***}	-0.148	$+3.366^{***}$
	(-2.69)	(-6.11)	(-3.40)	(-0.26)	(4.34)
Thematic Conformity (level)	-0.437^{***}	$+0.022$	-0.531^{***}	$+0.520^{***}$	$+0.785^{***}$
	(-3.46)	(0.40)	(-3.09)	(3.51)	(3.77)
Controls	$\log(\text{ME})_{q-1}$, $\log(\text{BM})_{q-1}$, SUE_q				
Firm FE	✓	✓	✓	✓	✓
Industry×Month FE	✓	✓	✓	✓	✓
N (firm-quarters)	96,398	96,398	96,385	91,045	96,398
Firms	3,736	3,736	3,736	3,698	3,736
Within R^2	0.89	0.82	0.60	0.81	0.90

Table A.4: Forward Innovation Investment with Contemporaneous Outcome Controls

This table replicates Table 5 but adds the contemporaneous (call-quarter) level of each dependent variable as an additional control: quarterly R&D and capital expenditure scaled by assets, and log patent output scaled by assets. The specification is $Y_{i,q+h} = \alpha_i + \alpha_t + \beta\, Alignment^z_{i,q} + \delta Y_{i,q} + \boldsymbol{\gamma}'\mathbf{X}_{i,q} + \varepsilon_{i,q}$, so β captures incremental forward investment conditional on the firm's current position. Panel A uses *Thematic Alignment*; Panel B uses *Thematic Conformity*. Firm and year-month fixed effects and baseline controls match Table 5. Coefficients are multiplied by 100. Standard errors are two-way clustered by firm and call date; t-statistics in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Horizon	R&D	CAPX	Patents
Panel A: Thematic Alignment			
$q+1$	-0.047^{***}	-0.065^{***}	-0.047^{***}
	(-2.70)	(-3.38)	(-2.95)
$q+2$	-0.036^{**}	-0.100^{***}	-0.045^{**}
	(-1.99)	(-4.14)	(-1.99)
$q+3$	-0.034^{*}	-0.156^{***}	-0.050^{**}
	(-1.74)	(-6.19)	(-2.09)
$q+4$	-0.007	$+0.016$	-0.059^{**}
	(-0.41)	(0.89)	(-1.98)
Panel B: Thematic Conformity			
$q+1$	-0.054^{***}	-0.002	-0.031^{*}
	(-3.80)	(-0.11)	(-1.75)
$q+2$	-0.039^{***}	$+0.011$	-0.063^{**}
	(-2.72)	(0.54)	(-2.24)
$q+3$	-0.032^{**}	$+0.006$	-0.070^{**}
	(-2.06)	(0.33)	(-2.43)
$q+4$	-0.012	$+0.026^{*}$	-0.074^{**}
	(-0.84)	(1.88)	(-2.42)
Lagged Y (contemporaneous)		Yes	
Controls	$\log(\text{ME})_{q-1}$, $\log(\text{BM})_{q-1}$, SUE_q		
Firm FE	✓	✓	✓
Year-Month FE	✓	✓	✓
N (firm-quarters)	94,418	94,139	92,691
Firms	3,746	3,744	3,688
Within R^2	0.77	0.73	0.86

Table A.5: Opacity Interaction Tests

This table reports estimates from pooled firm-quarter panel regressions that interact standardized *Thematic Alignment* with within-quarter opacity-tercile indicators. For each information-environment proxy (analyst coverage, forecast dispersion, firm size), a within-quarter tercile classification assigns firms to opaque, medium, and transparent groups. The specification includes *Thematic Alignment*, its interaction with the opaque and medium indicators, the tercile main effects, and the baseline controls of Table 3. Transparent firms are the omitted baseline, so the interaction coefficient measures the *incremental* alignment effect in opaque (or medium) firms relative to transparent firms. All specifications include firm and year-month fixed effects. Coefficients are multiplied by 100. Standard errors are two-way clustered by firm and call date; t-statistics in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

	R&D	CAPX	Patents
Analyst coverage			
Thematic Alignment	-0.205^{***}	-0.175^{***}	-0.095
	(-3.43)	(-3.79)	(-1.25)
Alignment × Opaque	$+0.069$	-0.022	-0.393^{***}
	(0.82)	(-0.37)	(-3.17)
Alignment × Medium	$+0.045$	-0.059	-0.118
	(0.60)	(-1.23)	(-1.37)
N (firm-quarters)		96,398	
Firms		3,736	
Forecast dispersion			
Thematic Alignment	-0.150^{***}	-0.200^{***}	-0.243^{***}
	(-2.88)	(-6.12)	(-3.94)
Alignment × Opaque	-0.022	$+0.002$	-0.071
	(-0.34)	(0.06)	(-0.93)
Alignment × Medium	-0.040	-0.009	$+0.053$
	(-1.07)	(-0.38)	(1.57)
N (firm-quarters)		95,914	
Firms		3,732	
Firm size			
Thematic Alignment	-0.063	-0.247^{***}	-0.115^{*}
	(-1.15)	(-5.58)	(-1.88)
Alignment × Opaque	-0.280^{***}	$+0.083$	-0.330^{**}
	(-2.81)	(1.30)	(-2.53)
Alignment × Medium	-0.100	$+0.066$	-0.162
	(-1.12)	(1.21)	(-1.37)
N (firm-quarters)		96,398	
Firms		3,736	
Controls		$\log(\text{ME})_{q-1}$, $\log(\text{BM})_{q-1}$, SUE_q	
Tercile main effects		Yes	
Firm FE		✓	
Year-Month FE		✓	

Table A.6: STM Topic Labels and Representative Words

This table lists the 33 topics estimated by the Structural Topic Model (STM) trained on 101,693 analyst-question firm-quarter documents from the allUS primary universe (2010:Q1 to 2023:Q4). For each topic, I report a human-assigned label and the seven highest-FREX words. FREX (Frequency-Exclusivity) balances how common a word is within a topic against how exclusive it is to that topic (85). Topic 18 captures transcription noise and is retained in the model to prevent contamination of substantive topics.

No.	Label	Top FREX Words
1	Corporate Structure & Segments	<competitor_org>, division, include, announce, segment, announcement, billion
2	Automotive & Industrial	community_count, aftermarket, oe, builder, vehicle, dealer, hvac
3	SaaS & Subscriptions	billing, subscription, renewal, upsell, saas, suite, salesperson
4	Payments & Credit Cards	card, merchant, timeshare, debit, search, homeaway, marriott
5	Insurance & Underwriting	reinsurance, insurance, loss, claim, worker_comp, accident, underwriting
6	Capital Allocation & Cash Flow	cash, flow, free, dividend, buyback, repurchase, pension
7	Conference-Call Logistics	join, welcome, fireside_chat, investor, minute, ceo, webcast
8	Partnerships & Innovation	congrat, congratulation, awesome, super, echo, motion, partnership
9	M&A & Synergies	synergy, debt, transaction, pro_forma, accretion, combined, the_pro_forma
10	Chemicals & Materials	containerboard, caustic, wallboard, propylene, paperboard, mill, bromine
11	Quarterly Financials & Guidance	fourth, million, quarter, fiscal_period, sequentially, third, sequential
12	Media & Entertainment	retran, pandora, hulu, cable, directv, subscriber, mvpd
13	Diagnostics & Medical Devices	cologuard, liquid_biopsy, omnipod, lab, generic, pama, resmed
14	Asset Management & ETFs	trading, institutional, adviser, etf, advisory, etfs, advisor
15	Oncology & Pharma Pipelines	melanoma, cabo, chemo, esmo, revlimid, parp, tumor
16	Surgical & MedTech Devices	surgeon, procedure, knee, invisalign, hernia, implant, spine
17	Restaurants & Consumer Leisure	franchisee, restaurant, beef, macau, casino, chicken, menu
18	Audio Artifacts (Noise)	indiscernible, ph, presentation, audio_gap, breakout, room, breakout_session
19	Pandemic & Macro Recovery	pandemic, april, pre_covid, reopen, recovery, stimulus, recession
20	Cloud Computing & Cybersecurity	azure, workload, cloud, cisco, firewall, hardware, software
21	Utilities & Healthcare Payers	mlr, centene, ppa, hospice, utility, megawatt, renewable
22	Biotech & Vaccines	mrna, booster, eylea, vaccine, cdmo, abbvie, gene_therapy
23	Consumer Packaged Goods	soup, tobacco, snack, cagny, cigarette, foodservice, beer
24	Legal & Litigation	agreement, legal, litigation, settlement, resolution, resolve, review
25	International & FX	currency, europe, organic, double_digit, mid_single_digit, single_digit, americas
26	Oil, Gas & Midstream	acreage, marcellus, wolfcamp, haynesville, delaware_basin, lateral_length, midstream
27	Semiconductors & Electronics	notebook, microcontroller, baseband, optical, datacom, microchip, roadm
28	Clinical Trials & Rare Disease	schizophrenia, oca, pruritus, placebo, zuranolone, ahus, proteinuria
29	Transportation & Logistics	intermodal, truckload, aircraft, fleet, airline, rail, railroad
30	Government Services & Consulting	award, recompete, bidding, win, bid, dod, outsourcing
31	Banking & Lending	loan, deposit, origination, mortgage, branch, commercial_real_estate, mortgage_banking
32	Retail & Apparel	apparel, footwear, department_store, denim, assortment, merchandise, markdown
33	Memory & Chip Equipment	nand, advanced_packaging, dram, memory, equipment, oled, etch

Chapter 3:

The Green Side of the China Shock: Environmental Responses of U.S. Firms to Import Competition

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The Green Side of the China Shock: Environmental Responses of U.S. Firms to Import Competition

Abstract

We examine the causal effect of import competition from China on the environmental outcomes and performance of U.S. manufacturing firms. We find that firms in industries exposed to greater import penetration significantly reduce their pollution. We identify a firm's pre-existing environmental record as the mechanism driving this strategic response. Firms with lower pollution emissions or higher levels of green innovation exhibit superior performance when confronted with competitive shocks, making them more resilient. We show that, when exposed to competition shocks, firms with a history of green patents emphasize exploitative innovation, leveraging their existing green technologies rather than engaging in costly exploratory innovation. This strategic focus manifests in both green process innovations, which enhance efficiency, and green product innovations, which create market differentiation. As a result, these firms maintain more stable sales and profits under heightened competition, ultimately achieving superior financial performance: preserving market value, safeguarding R&D, and being viewed as less risky. Overall, our findings highlight environmental performance as a key dimension of competitive resilience in a globalized market.

Keywords: Import Competition; China Shock; Environmental Performance; Green Innovation; Exploitative Innovation; Exploratory Innovation; Product Innovation; Process Innovation; Corporate Resilience; Pollution Emissions; Porter Hypothesis; Pollution Haven Hypothesis

JEL Classification: F14, F18, F61, L25, O31, Q55

1 Introduction

A firm's response to a severe competitive shock provides a revealing lens on its capital allocation strategy. The shock creates a central tension: the same competitive pressure that creates powerful incentives for long-term strategic investment (e.g., Porter and van der Linde 84; Aghion et al. 2; Bloom et al. 20) simultaneously erodes profitability, increases the likelihood of firm exit (Bernard et al. 17; Autor et al. 10), and tightens the financial constraints that limit the ability to make such investments (e.g., Fazzari et al. 46; Valta 102; Campello et al. 27). This tension is particularly salient for non-market strategies, such as environmental performance, where the strategic path is not pre-determined, as theory offers conflicting predictions and the empirical evidence is divided. One stream of theory, rooted in the work of Porter and van der Linde (84), predicts that competition acts as a disciplinary force, compelling firms to invest in innovation and efficiency to differentiate their products and "escape competition" (20).

Conversely, a substantial body of work documents that intense pressure on profitability severely constrains a firm's capacity for long-term investment. Declining internal funds tighten financial constraints, forcing managers to forgo positive net present value projects for short-term survival (e.g., Fazzari et al., 1988; Campello et al., 2010). Consistent with this, empirical work on the U.S. response to trade shocks finds that firms often react with a broad-based contraction, cutting discretionary investments like R&D to conserve capital (10). This creates a fundamental tension in capital allocation between long-term strategic investment and short-term survival. How firms resolve this tension with respect to non-market strategies, such as environmental performance, remains largely under-explored. This is particularly salient as the strategic role of corporate environmentalism itself is debated; while some models posit it as a defensive tool in competitive markets, others frame it as an offensive strategy best suited for firms in concentrated industries seeking to deter entry (98).

This paper enters this debate by examining the strategic environmental choices firms make when confronted by intense foreign competition. Globalization fundamentally alters

the strategic calculus of firms by creating a critical trade-off: do firms invest in domestic capabilities to "fight" back, or do they leverage global value chains to "flee" by offshoring production? The "fight" response involves costly and uncertain investments in innovation or differentiation (Bloom et al. 20; Flammer 47), where environmental standards themselves can be used as a strategic tool to create a non-price competitive advantage (42). Our analysis complements and refines foundational research by Flammer (47), who provides causal evidence that trade liberalization prompts U.S. firms to increase their overall Corporate Social Responsibility (CSR) as a differentiation strategy. Our paper refines this insight by focusing specifically on environmental outcomes, a dimension that paper finds firms do not necessarily prioritize, and shows that the more intense "China Shock" drives a distinctly environmental response. This competes for capital with the "flee" response, which involves shifting production to lower-cost locations, a strategy often associated with the Pollution Haven Hypothesis (35).

This paper investigates how firms navigate this strategic crossroads. We hypothesize that, on average, U.S. firms resolve this trade-off with a "fight" strategy of environmental upgrading, and further, that the market selects for firms whose pre-existing capabilities, proxied by their initial environmental performance, make them better suited for this fight. The question of how firms manage their environmental footprint is therefore not merely an operational concern; it is a critical strategic decision that sits at the nexus of these competing capital allocation choices.

This paper investigates these questions by examining the causal effect of import competition from China on the environmental outcomes of U.S. manufacturing firms. Drawing upon granular data on toxic chemical releases at the chemical-firm level, we ask three core questions. First, what is the average effect of a competition shock on firms' pollution emission? Second, does this effect vary based on a firm's initial environmental performance, suggesting that a firm's environmental standing is a source of competitive resilience? Finally, we investigate the specific innovation strategies that drive these environmental responses, seeking to understand whether firms pursue costly exploratory innovation or focus on exploitative innovation that

leverages their existing green technologies. To answer these questions, our empirical strategy isolates the causal effect of competition by employing the canonical instrumental variable approach from the trade literature. We extend this framework to provide a comprehensive view of competitive pressure, analyzing not only the direct effect of import penetration but also the indirect effects that propagate through upstream and downstream supply-chain linkages.

We find robust evidence that heightened import competition leads to a significant reduction in chemical-firm-level and firm-level pollution, suggesting that, on average, firms engage in a "fight" response through environmental upgrading. This greening effect is not uniform; our analysis uncovers that a firm's pre-existing environmental record is a key determinant of its strategic response. Firms with stronger initial environmental credentials, either low pollution intensity or a stock of green patents, exhibit superior operational and financial performance when confronted with competitive shocks. This finding resonates with work by Hombert and Matray (61), who show that firms with stronger pre-shock innovation capabilities were more resilient to the China shock, underscoring the protective role of established strategic capabilities.

This operational resilience translates directly into superior financial outcomes: these firms are better able to preserve their market value, protect strategic R&D budgets from cuts, and are perceived by the market as being fundamentally less risky. Taken together, these findings identify a firm's environmental standing not merely as a non-market outcome, but as a core dimension of its competitive resilience in a globalized market.

This paper moves beyond asking whether firms innovate to ask how they innovate, and specifically, why they pursue green innovation as a strategic response. We hypothesize that to escape the intense, price-based competition of the China Shock, firms turned to green innovation as a differentiation strategy, a path that allowed them to lower pollution and capture greater market value. By developing products with superior environmental attributes, firms can build a distinct brand identity, foster customer loyalty among environmentally conscious consumers, and create a defensible market niche where competition is based on

values rather than solely on price (6). This view aligns with the Natural Resource-Based View (53), which frames a firm's unique and inimitable environmental capabilities as a source of sustained competitive advantage. Having established why firms would strategically choose green innovation, the critical question becomes what kind of green innovation they pursue.

To understand the specific nature of this innovative response, we employ the theoretical lens of exploitative versus exploratory innovation (76). Exploratory innovation is a high-risk search for new knowledge, while exploitative innovation is the lower-risk refinement of existing capabilities. This distinction is critical because the China Shock created a "Green Innovation Paradox": the need to differentiate created a demand for radical, exploratory innovation, but the financial constraints it imposed (10) simultaneously undermined firms' ability to fund such risky, long-term projects. We argue that this paradox pushed firms toward a more defensive strategy: focusing on exploitative innovation that leveraged their proven green technologies to secure more certain, short-term gains. This aligns with the concept of "threat rigidity," where organizations under pressure revert to well-understood routines (96).

This theoretical framework, of a financially constrained, exploitative green response, allows us to test a novel hypothesis about firm resilience. Using the patent citation methodology of Benner and Tushman (16), which operationalizes March's (1991) framework by classifying patents based on their knowledge inputs, we can unpack the precise mechanism through which environmental capabilities translate into a competitive advantage.

Delving deeper into the innovation channel, we find a specific strategy at play. Rather than engaging in costly and uncertain exploratory innovation, resilient firms focus on exploitative innovation. That is, they leverage and refine their existing green technologies, a strategy that enhances product differentiation and builds on established capabilities without requiring massive new capital outlays in a constrained environment. This strategic focus on exploiting existing green knowledge strengthens their competitive moat, fostering greater customer loyalty and allowing them to better defend their sales and profit margins.

Our analysis derives these findings by leveraging the integration of China into the global economy as a powerful quasi-natural experiment. This setting is ideal for examining

these strategic firm responses, and our long sample period from 1991 to 2022 allows for a comprehensive analysis of firm responses across distinct economic and policy regimes. The period begins with the initial "China shock" of the 1990s, an era characterized by high political risk for firms building China-centric supply chains (54), and its dramatic acceleration following China's 2001 accession to the World Trade Organization (WTO). This event locked in low tariffs and, perhaps more importantly, eliminated significant trade policy uncertainty for U.S. firms (e.g., Pierce and Schott, 2016; Handley and Limão, 2017; Amiti and Khandelwal, 2013). The analysis extends through the pre-crisis maturation of global supply chains in the mid-2000s, an era characterized by the increasing complexity of global value chains (e.g., Koopman et al., 2014; Baldwin, 2016), the major demand-side disruption of the Global Financial Crisis of 2008-2009 (e.g., Mian and Sufi, 2010; Bems et al., 2011), the subsequent post-crisis period of slower trade growth and recalibration of global value chains (e.g., Constantinescu et al., 2015), and concludes with the sharp reversal of trade liberalization during the U.S.-China Trade War that began in 2018 (e.g., Flaaen et al., 2020; Cavallo et al., 2021). This later period represents a distinct economic shock, characterized by significant costs passed on to U.S. firms and consumers and a different of strategic incentives that, in some cases, spurred innovation as a competitive response to protectionism (49).

This extended timeframe allows us to move beyond a static analysis of a single shock and instead examine how firms' strategic environmental policies evolve under varying competitive pressures, policy uncertainty, and macroeconomic conditions. This event unleashed a trade shock of unprecedented scale and speed, fundamentally reshaping the competitive landscape for firms in high-income nations. The surge in Chinese manufacturing exports, which grew from 2.3% of the world total in 1991 to a commanding 18.3% by 2014, was driven largely by internal productivity gains and market-oriented reforms, providing a unique quasi-natural experiment for researchers (10). It allows for the examination of causal firm responses to an intense, sustained, and largely exogenous increase in product market competition.

An extensive and influential body of literature has meticulously documented the consequences of this "China shock". Seminal work by Autor et al. (9) established its powerful and

often disruptive impact on local labor markets, linking it to higher unemployment, lower wages, and the long-term decline of manufacturing sectors. Parallel research has explored firm-level responses, uncovering a complex picture of both contraction and strategic adaptation. In the United States, the dominant finding is one of contraction, with firms in exposed industries experiencing declines in employment, sales, profitability, and even innovation, as measured by R&D expenditure and patenting (10). This stands in contrast to initial findings from Europe, which suggested that competition spurred technological upgrading as firms sought to "escape competition" (20).

While these lines of inquiry are well-developed, the strategic response of firms along the environmental margin remains a critical but comparatively under-explored dimension. The literature on the "China shock" is vast and methodologically sophisticated, yet its primary focus has been on labor market outcomes and broad measures of innovation. Similarly, the literature on trade and the environment has developed powerful theoretical frameworks like the Pollution Haven Hypothesis, but has often been hampered by challenges in achieving clean causal identification and separating the scale, composition, and technique effects of trade (Copeland and Taylor 35; Shapiro 90). Finally, the literature on strategic Corporate Social Responsibility (CSR) has identified competition as a key driver of corporate behavior, but often without the benefit of a large-scale, quasi-experimental shock to test its propositions (47).

In doing so, this paper makes several distinct contributions. First, we provide robust evidence that firms respond to intense import competition by becoming cleaner. Our finding of a widespread positive environmental response suggests that the competitive shock induces greening through broad strategic channels, moving beyond the specific, cost-based mechanism tested by Grinstein and Larkin (51), where such outcomes are conditional on the relative cost of available clean technology. Second, we identify a firm's initial environmental performance as a novel source of competitive resilience, showing that initially cleaner firms exhibit superior financial performance when hit by the trade shock. Finally, we contribute to the long-standing debate between the Pollution Haven Hypothesis and the Porter Hypothesis by disentangling

the mechanisms of greening, providing evidence that firms achieve environmental upgrading through a strategy of exploitative innovation, leveraging their existing green technologies, rather than through a simple outsourcing of polluting activities.

2 Data and Sample

The sample period spans from 1991 to 2022 and covers all U.S. publicly traded manufacturing firms, defined as firms with Standard Industrial Classification (SIC) codes between 2000 and 3999. To construct our chemical-firm-year level panel, we begin by measuring environmental outcomes using data from the U.S. Environmental Protection Agency's (EPA) Toxics Release Inventory (TRI). The TRI offers detailed annual data on toxic chemical releases by individual facilities, which we aggregate from the facility and chemical level to the parent firm level each year. Firm data come from Compustat.

Our primary measures of innovation are constructed using patent and citation data from the U.S. Patent and Trademark Office (USPTO). In addition to general innovation metrics, we construct specific measures of green innovation. Green patents are identified through a systematic classification approach using both International Patent Classification (IPC) and Cooperative Patent Classification (CPC) codes, following established methodologies in the environmental innovation literature. This process involves mapping patents to technology classes designated for environmental applications, such as air and water pollution abatement, climate change mitigation, and renewable energy. Using both IPC and CPC systems ensures comprehensive and robust identification. For all innovation measures, our baseline analysis uses patent filing (application) dates to timestamp innovation activities, as this most closely corresponds to the timing of the invention. We verify the robustness of our results using patent grant dates in supplementary tests.

Our key independent variable measures an industry's exposure to import penetration from China. To construct this variable, we follow the methodology established by Autor et al. (9) and Acemoglu et al. (1). We begin with product-level trade data from the UN

Comtrade database for the period 1991–2022, recorded at the 6-digit Harmonized System (HS) level. To link this trade data to U.S. firms, we map the HS product codes to U.S. SIC-87 industry classifications using the crosswalk files provided on David Dorn's website. This allows for the aggregation of import values to the industry level corresponding to each firm's primary segment. For each manufacturing industry j and year t, we define the direct import penetration from China (IP_{jt}) as the value of U.S. imports from China in that industry, normalized by the industry's total absorption (shipments + imports – exports). All import amounts are inflated to 2007 U.S. dollars using the Personal Consumption Expenditure deflator. Following Autor et al. (9), we use initial absorption levels from the base year 1991 to mitigate concerns that changes in domestic absorption are themselves driven by import shocks. The choice of 1991 as the starting point for our analysis is dictated by data availability. Formally, the import penetration ratio is:

$$IP_{jt} = \frac{M_{jt}^{\text{US}\leftarrow\text{CN}}}{S_{j,1991} + M_{j,1991} - E_{j,1991}}$$

where $M_{jt}^{\text{US}\leftarrow\text{CN}}$ is the value of imports from China in industry j and year t, and $S_{j,1991}$, $M_{j,1991}$, and $E_{j,1991}$ are total industry shipments, imports, and exports in the base year 1991, respectively.

Table 1 provides summary statistics for this import penetration measure. Panel A reveals substantial heterogeneity in import exposure across industries. Low-tech, labor-intensive sectors such as Toys and Textiles experienced the highest average import penetration over the full sample period, while more capital-intensive sectors like Chemicals and Food Products faced minimal direct import competition. Panel B documents the dramatic temporal evolution of this shock. Across nearly all industries, import penetration from China increased substantially following its accession to the WTO in 2001. This descriptive evidence underscores the pronounced and asymmetric nature of the China trade shock. Our long sample period, which captures the evolution of this shock across distinct economic and policy regimes, provides an ideal setting to conduct a comprehensive analysis of firm strategic responses.

[*Insert Table 1 about here*]

To address the endogeneity of import penetration, we instrument for U.S. imports from China using the contemporaneous imports from China into other high-income countries, following the strategy pioneered by Autor et al., (2013). This instrumental variable approach is designed to isolate the supply-driven component of Chinese exports. The instrument's validity rests on the assumption that the simultaneous growth of Chinese imports across developed economies is primarily driven by supply-side shocks within China, rather than by correlated demand shocks across these destination markets. The dramatic rise in China's export capacity during our sample period provides strong support for this identifying assumption, as it was fueled by a sequence of internal and global policy events. This began with market-oriented reforms and technological assimilation in the 1990s and dramatically accelerated following China's 2001 accession to the WTO. This event was pivotal, as it not only locked in low tariffs but also eliminated significant trade policy uncertainty for U.S. firms (e.g., Pierce and Schott, 2016; Handley and Limão, 2017), further cementing China's role as a global manufacturing hub driven by its own supply-side evolution. We construct the instrument using UN Comtrade data on imports from China into a balanced panel of eight other developed countries (Australia, Denmark, Finland, Germany, Japan, New Zealand, Spain, and Switzerland), aggregated to the four-digit SIC industry level.

[*Insert Figure 1 about here*]

Having detailed the construction of our import competition measures, we now introduce the data for our primary outcome variable, toxic chemical emissions. Table 2 presents descriptive statistics on this relationship. Panel A documents a consistent negative relationship between import competition and toxic emissions. Industries in quintiles with higher import competition exhibit lower average toxic emissions, and this differential grows over the sample period. For instance, the average log TRI emissions in the highest-competition quintile declined by more than half between the pre-WTO period and the 2018–2022 period, a substantially larger

reduction than that observed for the lowest-competition quintile. Panel B indicates that this negative correlation is present within most industry categories, despite significant variation in baseline emission levels. For example, while Chemicals and Clay/Stone are high-emission sectors, they still show lower average emissions in high-competition quintiles compared to low-competition quintiles. These unconditional patterns provide initial evidence of a potential link between import competition and domestic environmental outcomes, which we investigate more rigorously in our main analysis.

[*Insert Table 2 about here*]

Beyond the direct impact of import competition within a firm's own industry, we also account for indirect exposure transmitted through supply-chain networks. To capture these effects, we utilize the 1992 U.S. Input-Output (I–O) table from the U.S. Bureau of Economic Analysis (BEA). These tables allow us to measure the propagation of competition shocks from a firm's downstream (customer) and upstream (supplier) industries. For each industry, we calculate the share of its inputs sourced from every other industry and the share of its output sold to every other industry. To capture the full cascade of these inter-industry relationships, we compute the Leontief inverse of the I–O matrix, a method applied in this context by Acemoglu et al. (1). This provides a comprehensive measure of an industry's total exposure to competition shocks throughout its entire production network, accounting for not just immediate customers and suppliers but also the suppliers of suppliers and customers of customers.

[*Insert Table 3 about here*]

Finally, to set the stage for our analysis of how firms' strategic responses to the trade shock affect their performance, Table 3 presents summary statistics for key firm-level financial and performance variables. The table reports the means of these variables for the full sample and for sub-samples of firms grouped by their exposure to import penetration and their

pollution intensity, based on whether they are above or below the industry-year median. The descriptive statistics reveal systematic differences across these groups. For instance, firms in high import penetration (High IP) industries are, on average, smaller (Log Assets, Log Sales), have lower market valuations (Log Market-to-Book Ratio), and invest less in both innovation (Log R&D Expenditures / Assets) and capital (Log Capex / Assets) compared to their counterparts in low import penetration industries. These preliminary patterns suggest that import competition is associated with significant differences in firm characteristics and investment strategies, motivating the deeper investigation into firm performance that follows in our main analysis.

3 Methodology

3.1 Competition and Environmental Performance

The literature presents two contrasting narratives about how firms respond to intense competitive pressure. One view, consistent with U.S. evidence, posits that firms are overwhelmed, leading to a general contraction of operations, including R&D and innovation (10). The opposing "escape competition" view, prominent in initial European studies, argues that competition acts as a catalyst, forcing firms to innovate and upgrade (20). This empirical tension is rooted in a long-standing theoretical debate. A Schumpeterian perspective argues that since the prospect of future monopoly rents drives innovation, intense competition erodes these rents and thus stifles investment (3). Conversely, the Porter Hypothesis offers a "Darwinian" view, positing that it is precisely the pressure of stiff competition that forces firms to shed inefficiencies and innovate to survive (84).

This paper first seeks to establish the dominant average effect in the context of environmental outcomes. The logic of the Porter Hypothesis, combined with strategic management theories, suggests that competition can induce a "greening" of operations. The pressure to survive in a low-margin environment can force firms to eliminate managerial slack (88) and

optimize production processes, leading to the adoption of cleaner technologies, a "technique effect" (7). Furthermore, when price competition becomes untenable, firms may differentiate by investing in their environmental reputation and CSR, a strategy supported by both empirical evidence and CEO surveys (Flammer 47; Lacy et al. 69). Recent work confirms that trade liberalization can indeed lead to significant reductions in pollution intensity (Cherniwchan 30; Kong et al. 68). This leads to our first hypothesis, which tests the average environmental response to competition:

Hypothesis 1: Firms facing greater import competition from China exhibit lower levels of pollution.

We present illustrative evidence of the relationship between import competition and pollution in Figure 2. Panel A plots the evolution of average firm-level pollution over our sample period, grouping firms into quintiles based on the level of import penetration in their industry. The figure reveals a clear and persistent pattern: firms in industries facing higher levels of competition (the High and Medium-High quintiles) systematically exhibit lower average pollution than firms in less competitive industries. This gap appears to widen, particularly after the early 2000s, consistent with an intensified response following China's accession to the WTO. Panel B complements this time-series view with a cross-sectional scatterplot of industry-year import penetration against average pollution, revealing a strong negative correlation. Taken together, this raw correlational evidence provides compelling initial support for our hypothesis. We now turn to a formal econometric analysis to establish whether this relationship holds in a causal framework.

[*Insert Figure 2 about here*]

To test our primary hypothesis (H1) that firms facing greater import competition reduce their pollution, our specification examines future pollution responses over multiple horizons. Specifically, we estimate the following event-style model at the chemical-firm level:

$$\text{Pollution}_{i,c,t+k} = \alpha + \beta_k IP_{jt} + \gamma' X_{it} + \mu_i + \lambda_{c,t+k} + \eta_{s,t+k} + \epsilon_{i,c,t+k}, \quad \text{for } k = 1, 2, 3 \qquad (1)$$

where the dependent variable, $\text{Pollution}_{i,c,t+k}$, is the logarithm of toxic releases of chemical c by firm i, k years after period t. The key independent variable, IP_{jt}, and controls X_{it} (log of total assets and firm age) are measured in period t. A key challenge in estimating the causal effect of import penetration is that it may be endogenous, as an unobserved U.S. industry shock could affect both imports and pollution. To address this, we employ a two-stage least squares (2SLS) framework following Autor et al. (9), instrumenting U.S. import penetration with Chinese import penetration in other high-income countries. The model includes firm fixed effects μ_i, chemical-by-year fixed effects $\lambda_{c,t+k}$, and 2-digit SIC industry-by-year fixed effects $\eta_{s,t+k}$. A negative and statistically significant coefficient on the instrumented variable would indicate that higher exposure to Chinese import competition leads to lower pollution in subsequent years. Standard errors are clustered at the industry-year level, and all continuous variables are winsorized at the 1% and 99% levels.

The results of this chemical-firm level analysis, presented in Table 4, provide strong initial support for our proposition. Panel A presents the results where pollution intensity is scaled by total assets. The coefficient on direct competition is negative and highly statistically significant across all three subsequent years, indicating a robust and persistent reduction in pollution for specific chemicals following a competitive shock. The economic magnitude is substantial; for instance, the coefficient of -0.286 in column (1) for year t+1 implies a meaningful immediate effect. This core finding is robust to the inclusion of controls for supply chain pressures (even-numbered columns), confirming that the direct effect is not simply an artifact of upstream or downstream dynamics.

[*Insert Table 4 about here*]

The granular chemical-level results demonstrate a robust pollution reduction in response to competition. To determine whether these specific actions translate into a broader, firm-wide strategic shift, we next aggregate the analysis to the firm level. This allows us to test whether the greening effect holds for a firm's total pollution output. Accordingly, we estimate an

analogous set of firm-level regressions:

$$\text{Pollution}_{i,t+k} = \alpha + \beta_k IP_{jt} + \gamma' X_{it} + \mu_i + \delta_{j,t+k} + \epsilon_{i,t+k}, \quad \text{for } k = 1, 2, 3 \tag{2}$$

where $\text{Pollution}_{i,t+k}$ is the logarithm of total toxic releases by firm i in year $t+k$, and $\delta_{j,t+k}$ denotes industry-by-year fixed effects.

Table 5 presents the results of our 2SLS firm-level regressions. The odd-numbered columns report results from a baseline specification including only the direct effect of import competition, while the even-numbered columns present the comprehensive specification that simultaneously accounts for direct, upstream (supplier), and downstream (customer) competition. Panel A scales pollution intensity by total assets, while Panel B scales it by sales.

[*Insert Table 5 about here*]

In the baseline specifications (columns 1, 3, and 5), we find strong support for our hypothesis. Across both panels, the coefficient on the direct competition variable is consistently negative and statistically significant. For example, in Panel B, the coefficient is -0.074 in year t+1 and remains significant through t+3. This indicates that firms facing greater direct import competition from China significantly reduce their overall pollution intensity. The robustness of this finding across both asset- and sales-based measures suggests a genuine "greening" effect that is not merely an artifact of changes in firm size or sales.

The comprehensive models in the even-numbered columns confirm and enrich these findings. First, the coefficient on direct competition remains negative and significant across most specifications, and its magnitude often increases, demonstrating that the greening response is a robust phenomenon, not an artifact of supply chain spillovers. Second, the results reveal the powerful influence of downstream competition. The coefficient on the downstream variable is negative and highly significant across both panels and all time horizons, indicating that when a firm's customers face intense competition, this pressure is

transmitted up the supply chain, compelling the firm to also reduce its pollution. Conversely, the effect of upstream competition is positive and significant in Panel B, suggesting a more complex dynamic where pressure on suppliers may lead to higher pollution, possibly due to changes in input quality or cost.

Our analysis so far assumes a stable, time-invariant response to import competition. However, the nature of the "China Shock" and the broader economic environment evolved significantly over our sample period. To investigate whether firms' environmental responses varied across these distinct economic regimes, we augment our firm-level specification by interacting the import penetration variable with dummy variables for four distinct periods: the post-WTO accession boom (2002-2007), the Global Financial Crisis (2008-2012), the post-crisis recovery (2013-2016), and the recent period marked by the U.S.-China trade war (2017-2022). The pre-WTO period (1991-2001) serves as the omitted baseline. This dynamic specification allows us to test whether the greening effect intensified, weakened, or changed in nature as the competitive and macroeconomic landscape shifted. We estimate the following 2SLS model:

$$\begin{aligned} \text{Pollution}_{i,t+k} = \alpha + \beta_k IP_{jt} + \sum_p \gamma_{p,k} \, \text{Period}_p \times IP_{jt} + \sum_p \rho_{p,k} \, \text{Period}_p \\ + \zeta \, \text{Pollution}_{i,t-1} + \mu_i + \delta_{j,t+k} + \epsilon_{i,t+k}, \quad \text{for } k = 1, \ldots, 5 \end{aligned} \tag{3}$$

where Period_p represents the four period dummies. The coefficients of interest, the $\gamma_{p,k}$'s, capture the differential effect of import competition in each period relative to the pre-WTO baseline.

Table 6 reports the results of this dynamic analysis. A consistent finding across all three panels is that the coefficients on the interaction terms are positive, indicating that the environmental response to import competition in all periods after 2001 was different from the response during the baseline pre-WTO period. In Panel A, which examines the level of absolute pollution, the interaction coefficients are positive and statistically significant across all four periods and for nearly all time horizons. The magnitude of these coefficients generally

increases over time, with the largest effects observed in the "Recent" period (2017-2022). This suggests that any pollution-reducing effect of import competition was strongest in the initial 1991-2001 period and has subsequently weakened or even reversed. In the later periods, an increase in import competition is associated with a relative increase in absolute pollution compared to the baseline era's response.

[*Insert Table 6 about here*]

The results for pollution intensity, shown in Panels B and C, present a more nuanced picture. For much of the sample, the interaction terms for pollution scaled by assets (Panel B) and sales (Panel C) are not statistically significant, suggesting the intensity response did not differ materially from the pre-WTO baseline through the post-crisis era. This indicates that the core greening effect is not driven by any single period, but is a persistent phenomenon. However, the effect does appear to be most pronounced in the "Recent" period, where the positive coefficients on the interaction term ($IP_{ft} \times \mathbb{1}_{\text{Recent}}$) become statistically significant at longer time horizons (t+3 to t+5). This is particularly evident in Panel C, where the coefficient is 1.755 and significant at the 1% level by year t+5. This pattern suggests an attenuation of the greening effect over time, with the change becoming most pronounced and statistically identifiable in recent years, hinting that the strategic incentives for firms' environmental responses may have evolved.

Taken together, the results provide robust and multi-faceted support for our first hypothesis. Our analysis establishes a causal link between heightened import competition and a significant reduction in firm pollution, a finding that is consistent at both the granular chemical-firm level and the aggregate firm-level. This core "greening" effect is not only robust to the inclusion of complex supply chain pressures but is often amplified when these dynamics are taken into account. Furthermore, our dynamic analysis reveals that this is not an artifact of a specific economic era; while the intensity of the response has evolved, the pollution-reducing effect is a persistent phenomenon throughout our sample period. Having established this

average effect, we now turn to the critical question of which firms are mostly driving this environmental response.

3.2 The Role of a Firm's Initial Environmental Record

While our initial hypothesis posits an average greening effect, firm heterogeneity theory suggests this response is unlikely to be uniform. The logical next step is to identify which firms are the primary drivers of this aggregate trend. We argue that the observed reduction in pollution is disproportionately driven by firms possessing a superior pre-existing environmental "infrastructure." This infrastructure is built on two pillars: operational excellence, proxied by low initial pollution, and technological capability, proxied by a stock of green innovation. Firms with low initial pollution have likely already invested in efficient processes and a culture of waste reduction. This pre-existing "absorptive capacity" (33) makes them better able to identify and implement further efficiency gains when faced with a competitive shock. This logic aligns with evidence from the trade literature showing that it is the most productive and capable firms that are best positioned to adapt and benefit from competitive shocks through innovation and upgrading (73).

A firm's accumulated stock of innovation, particularly as codified in patents, functions as a critical strategic infrastructure. This intellectual capital is not merely a measure of past success but a reservoir of technological options that can be deployed proactively to build a competitive advantage (67). This view is supported by robust findings that a strong patent portfolio is linked to higher firm value (52) and that R&D-intensive firms are more resilient to competitive shocks (61). We extend this logic to posit that a stock of green innovation represents a uniquely valuable form of this infrastructure. Faced with a price-based trade shock, green technologies offer a dual pathway to "escape competition": they enable non-price product differentiation (47) and can simultaneously unlock process efficiencies that lower costs (84). For firms already possessing these capabilities, responding to the shock by becoming cleaner was not a radical departure but a strategic leveraging of their established

technological path.

> **Hypothesis 2: The competition-induced reduction in pollution is more pronounced for firms with stronger initial environmental credentials, defined as: (a) lower initial levels of pollution, (b) a higher prior level of green innovation.**

To test our second hypothesis, we estimate a difference-in-differences model that interacts the import competition shock with a firm's pre-shock environmental performance. The specification is as follows:

$$\begin{aligned}\text{Pollution}_{i,t+k} = \alpha + \beta_1 IP_{jt} + \beta_2 \text{InitialRecord}_{i,t-5} + \beta_3 IP_{jt} \times \text{InitialRecord}_{i,t-5} \\ + \gamma' X_{it} + \mu_i + \delta_{j,t+k} + \epsilon_{i,t+k}, \quad k = 1, \ldots, 5\end{aligned} \tag{4}$$

where $\text{InitialRecord}_{i,t-5}$ represents the firm's pre-shock environmental standing. The measurement of this variable differs for each sub-hypothesis. For H2(a), which examines operational history, we measure $\text{InitialRecord}_{i,t-5}$ as the firm's pollution level at year $t-5$. Using a deep lag ensures the measure is predetermined and mitigates concerns that serial correlation in pollution could mechanically drive the interaction term. For H2(b), which examines technological capability, $\text{InitialRecord}_{i,t-5}$ is the average number of green patents filed by the firm over the five-year period from $t-5$ to $t-1$. A five-year window is used because innovation is a cumulative process; this average provides a more stable and representative measure of a firm's established technological infrastructure than the patenting activity of any single year. The coefficient of interest is β_3, which captures the interaction effect. This term captures the heterogeneous effect of the import shock conditional on a firm's initial environmental standing. The model includes the same controls X_{it} and fixed effects (μ_i for firm and $\delta_{j,t+k}$ for industry-by-year) as the baseline firm-level regression.

The results, presented in Table 7, reveal a nuanced picture of the role of initial conditions. Panel A tests H2(a) by interacting import competition with lagged pollution levels. The coefficient on the interaction term is negative and statistically significant across all three

dependent variables (log pollution, and pollution scaled by assets and sales) and for all five time horizons. This indicates that the pollution-reducing effect of import competition is significantly stronger for firms that were initially more polluting. This suggests that the greening effect is partly driven by firms with more room for improvement, those with higher initial emissions, undertaking more substantial clean-up efforts when faced with competitive pressure.

[*Insert Table 7 about here*]

Panels B and C test H2(b) by interacting import competition with measures of a firm's prior stock of green innovation, normalized by detailed and broad technology classes, respectively. In both panels, the coefficient on the interaction term is consistently negative. In Panel B, using the detailed normalization, the coefficient is statistically significant for the absolute pollution measure for years t+1 through t+4, and for pollution per assets at t+1 and t+5. In Panel C, using the broad normalization, the effect is also negative and significant for absolute pollution across all horizons. These results provide direct support for H2b: the pollution-reducing effect of import competition is more pronounced for firms that enter the period with a larger stock of green innovation. This confirms that a pre-existing technological infrastructure dedicated to environmental topics is a key enabler of a firm's greening response to a competitive shock. Having established which firms drive the greening response, we now investigate whether these environmental credentials translate into superior performance.

3.3 Environmental Credentials and Firm Resilience

The critical question that follows is whether this environmental positioning, driven by firms with distinct initial credentials, translates into tangible competitive resilience. Understanding the performance consequences of these initial conditions is essential for reconciling the competing "contraction" versus "escape competition" paradigms. The theoretical synthesis proposed by Aghion et al. (2) suggests the response to competition is not linear but depends

on a firm's initial conditions. The empirical literature has consistently shown that the impact of a trade shock is not uniform; firms with greater pre-existing capabilities are better equipped to handle the pressure. For example, R&D-intensive firms experience smaller declines in sales and profitability because their innovation stock allows for greater product differentiation (61), while capital-intensive plants are more likely to survive and grow (17).

We extend this established logic by proposing that a firm's initial environmental performance is a previously unexplored, yet critical, dimension of this strategic resilience. If lower pollution signals higher resource efficiency and a stronger environmental reputation provides a strategic buffer (47), then firms with these characteristics should exhibit superior performance. Likewise, if a stock of green patents represents a unique, inimitable resource that insulates a firm from price-based competition (53), these firms should be better able to defend their market position and financial health. This logic leads to our third hypothesis, which moves from identifying the drivers of greening to testing the performance outcomes of these environmental credentials:

> **Hypothesis 3: Firms with stronger initial environmental credentials perform better when exposed to greater import competition from China, where stronger credentials are defined as: (a) lower initial levels of pollution, (b) a higher prior level of green innovation.**

To test this hypothesis, we estimate a difference-in-differences model that interacts the import competition shock with a firm's pre-shock environmental performance. The specification is just like equation (4), with

$$\begin{aligned} Y_{i,t+k} = \alpha + \beta_1 IP_{jt} + \beta_2 \text{InitialRecord}_{i,t-5} + \beta_3 IP_{jt} \times \text{InitialRecord}_{i,t-5} \\ + \theta Y_{i,t-1} + \gamma' X_{it} + \mu_i + \delta_{j,t+k} + \epsilon_{i,t+k}, \quad k = 1, \ldots, 5 \end{aligned} \tag{5}$$

where $Y_{i,t+k}$ is a measure of firm performance (e.g., market-to-book ratio, sales growth) for firm i in year $t+k$. The key variable of interest is the interaction term, $IP_{jt} \times \text{InitialRecord}_{i,t-5}$, where $\text{InitialRecord}_{i,t-5}$ is defined as in equation (4). This term captures the heterogeneous

effect of the import shock conditional on a firm's initial environmental standing. Also $Y_{i,t-1}$ is included on the right-hand side as the lagged dependent variable, which accounts for persistence in firm performance and helps to mitigate concerns that the results are driven by serial correlation rather than the effect of import competition. The model includes the same controls X_{it} and fixed effects (μ_i for firm and $\delta_{j,t+k}$ for industry-by-year) as before.

Our proposition of environmental resilience yields specific predictions for the sign of the interaction term's coefficient, β_3, depending on the nature of the outcome variable, $Y_{i,t+k}$. For performance measures where higher values are favorable (e.g., market-to-book ratio, sales, R&D), we expect β_3 to be negative. A negative coefficient would imply that the adverse performance effect of import competition is exacerbated for firms that were initially more polluting. Conversely, for measures of risk or cost inefficiency where higher values are unfavorable (e.g., volatility, cost of goods sold (COGS)/sales), we expect β_3 to be positive. A positive coefficient in this context would imply that the increase in risk or costs associated with the competitive shock is magnified for more polluting firms. In both cases, the results would provide direct support for the idea that strong environmental performance is a source of competitive resilience.

Table 8 presents the results from estimating this model for a range of firm performance outcomes. Panel A reports results where initial pollution is scaled by assets, while Panel B uses pollution scaled by sales; the findings are qualitatively similar across both panels. We focus on the coefficient on the interaction term which captures the differential effect of import competition conditional on a firm's initial pollution intensity. The results provide strong support for our central proposition: a firm's pre-existing environmental performance is a significant determinant of its competitive resilience.

[*Insert Table 8 about here*]

We first examine firm valuation and scale. For the market-to-book ratio, the interaction term is negative and becomes highly statistically significant three to five years after the shock. For instance, in Panel B at year I+5, the coefficient is -2.379. This indicates that the

negative valuation consequences of an import shock are significantly more severe for firms that were initially more polluting. Cleaner firms, in contrast, are better able to preserve their market value. This narrative is reinforced by firm scale. For both log assets and log sales, the interaction term is negative and statistically significant in most post-shock years, particularly in Panel B. This demonstrates that more polluting firms experience a substantially larger contraction in their asset base and sales revenue compared to their cleaner peers.

Next, we investigate how the competitive shock differentially affects corporate investment and operating policies. For R&D expenditures, the interaction term is negative and becomes highly significant from year t+3 onward, indicating that more polluting firms cut their R&D spending significantly more than their cleaner rivals. This suggests that cleaner firms are better able to protect their long-term innovative capacity. A similar pattern holds for operating profitability (OIBDA), where the negative and significant coefficients in later years show that profitability declines more sharply for initially polluting firms. The results for cost of goods sold (COGS) scaled by assets are negative and significant, suggesting that initially polluting firms engage in deeper, potentially distress-driven, cost-cutting in their asset base compared to cleaner firms.

Finally, we examine the impact on firm risk and volatility. The results provide consistent evidence that initially polluting firms become riskier. The interaction term is positive and significant for the volatility of total, systematic, and idiosyncratic stock returns, particularly in the immediate aftermath of the shock (year t+1). This indicates that the market perceives initially polluting firms as being more risky when faced with an intense competitive shock. This market-based evidence is corroborated by operational data: the volatility of a firm's operating profit margin also shows a positive and significant interaction effect that emerges and persists over time. This indicates that the increase in financial and operational risk associated with the competitive shock is significantly greater for firms with a weaker initial environmental record. Collectively, these results across valuation, investment, and risk metrics provide strong and consistent support for H3(a): a cleaner initial pollution emission record is a source of competitive resilience.

We now turn to the second pillar of our resilience hypothesis, a firm's pre-existing stock of green innovation. Table 9 presents the results from interacting import competition with a firm's lagged green innovation, where Panel A uses a measure normalized by detailed technology class and Panel B uses a broader normalization. The results are largely consistent across both panels and provide strong support for H3(b). For measures of valuation and scale, we find positive and significant interaction coefficients for market-to-book ratio, log assets, and log sales. This indicates that firms with a stronger initial stock of green innovation exhibit superior performance, preserving their market value and growing their asset and sales base more effectively than less innovative firms.

[*Insert Table 9 about here*]

The analysis of investment and operating policies reinforces this finding. The interaction term for R&D expenditures is negative and highly significant, indicating that firms with a weaker stock of green innovation are forced to cut R&D spending more, while those with a stronger innovation base are better able to protect this critical long-term investment. Furthermore, the positive and significant coefficients for OIBDA show that firms with more green innovation maintain stronger operating profitability. The results for cost of goods sold scaled by sales are negative and significant, suggesting that these firms are also better able to defend their profit margins.

Finally, we find evidence that a stronger green innovation record is associated with lower risk. The interaction term is negative and significant for systematic, idiosyncratic, and total return volatility, indicating that the market perceives firms with a greater stock of green innovation as being less risky and more stable in the face of the competitive shock. Together, these results provide compelling evidence that, consistent with H3(b), a pre-existing stock of green innovation is a critical source of competitive resilience, enabling firms to better withstand and adapt to intense import competition.

In sum, the evidence provides a comprehensive confirmation of our third hypothesis. We find that a firm's initial environmental performance, whether measured by low prior pollution

or a strong stock of green innovation, is a crucial dimension of strategic resilience. Faced with an intense competitive shock, firms with stronger environmental credentials exhibit superior outcomes across valuation, operations, investment, and risk. Having established that environmentally leading firms are more resilient, we now turn to the final piece of our inquiry.

4 Mechanisms

Our findings establish that a pre-existing stock of green innovation is a key source of firm resilience. This raises a foundational question for understanding the mechanism: does this innovation infrastructure also enable firms to produce more green innovation when faced with a competitive shock? A competitive shock does not create innovative capabilities from scratch; rather, it activates and amplifies a firm's existing technological infrastructure. Firms with a history of green innovation possess the necessary "absorptive capacity", the specialized human capital, established R&D processes, and relevant technological knowledge—to effectively recognize and pursue new innovative opportunities when faced with an existential threat (33). This path-dependent view of innovation suggests that competitive pressure will induce the most significant innovative response from firms that are already at the technological frontier in a given domain (Aghion et al. 2; Bloom et al. 20).

This perspective is consistent with a large body of literature showing that a firm's existing technological and R&D capabilities are key determinants of its ability to adapt to shocks. For instance, Hombert and Matray (61) find that R&D-intensive firms were better able to withstand the China shock by differentiating their products, a strategy that inherently relies on leveraging and expanding their existing knowledge base. Similarly, studies on technological adoption and productivity gains consistently find that firms with greater pre-existing capabilities are the ones that benefit most from new market opportunities or competitive pressures (73). We therefore hypothesize that firms with a stronger initial stock of green innovation will exhibit a more pronounced increase in their subsequent green patenting activity when exposed to import competition.

To test this, we estimate a 2SLS interaction model analogous to our previous specifications, where the dependent variable is now a measure of green innovation output in the years following the shock. The key independent variable is the interaction between import competition and the firm's lagged average green innovation intensity. A positive and significant coefficient on this interaction term would indicate that the innovation-inducing effect of competition is stronger for firms that enter the period with a more developed green technology infrastructure.

Table 10 presents the results of this analysis. Panel A and Panel B report results using lagged green innovation measures normalized by detailed and broad technology classes, respectively. The dependent variables are the log number of green patents and the log of green innovation intensity which is the log ratio of green patents to total patents. The results across both panels provide consistent support for our proposition. The coefficient on the interaction term is positive and, in most specifications, highly statistically significant from year t+2 onward. For example, in Panel B, for Log Green Innovation Intensity, the coefficient is 2.941 in year t+1 and remains large and significant across all five subsequent years. This indicates that firms with a stronger pre-existing green innovation capacity respond to import competition by significantly increasing both the absolute number of green patents they produce and the intensity of their green innovation relative to their overall patenting portfolio.

[*Insert Table 10 about here*]

Having established that the competitive shock induces a greater quantity of green innovation from firms already active in the domain, we now proceed to the core of our mechanistic analysis. The crucial question is not just whether firms innovate more, but what type of innovation they pursue. As theorized in our introduction, the intense financial constraints imposed by the China Shock (10) create a "Green Innovation Paradox" that pushes firms away from costly, high-risk exploratory innovation. Instead, we argue that firms pivot to a more defensive strategy of exploitative green innovation, leveraging their existing green

technologies and knowledge to make incremental but certain improvements (March 76; Benner and Tushman 16).

Our study advances this inquiry by examining not just the quantity of green innovation, but its strategic character. This connects directly to our argument in H2 regarding a firm's pre-existing environmental infrastructure. It is precisely this infrastructure—the established stock of green knowledge and patents—that makes an exploitative strategy both feasible and rational in a time of distress. By operationalizing the distinction between exploitative and exploratory innovation using patent citation patterns, we investigate whether the observed greening is driven by firms deepening their existing technological trajectories. This allows us to test the core theoretical argument that, under intense competitive threat, firms strategically leverage their established knowledge base to become cleaner and more efficient.

To distinguish between different types of innovation, we classify each patent as either exploratory or exploitative. Our approach operationalizes the conceptual framework of exploration and exploitation (e.g., Benner and Tushman 16) by employing a citation-based classification method. This technique, which uses citation patterns to measure an invention's novelty, is well-established in the innovation literature (e.g., Katila and Ahuja 65; Strumsky et al. 99) and has been widely adopted in finance to study how financing constraints and corporate governance shape firms' innovation strategies (e.g., Chava et al. 29; Seru 89; Cornaggia et al. 36). First, for each firm-year, we define the firm's "existing expertise" as its portfolio of all patents filed and their outward citations during the prior five-year window, from year t-7 to t-3. This temporal separation is crucial for ensuring that current innovation is benchmarked against a clearly demarcated and pre-existing knowledge base. Second, we identify a cohort of "current" patents as those filed in the subsequent window from t-2 to t.

For each current patent, we then compute the share of its citations that draw upon the firm's existing expertise. A patent is classified as exploitative if at least 80% of its citations reference patents within the firm's established knowledge base. Conversely, a patent is classified as exploratory if at least 80% of its citations are to knowledge outside of this base (i.e., a self-citation share of 20% or less). Patents with no citations are conservatively

classified as exploratory, reflecting a departure from existing knowledge streams. Finally, we aggregate these patent-level classifications to the firm-year level. We construct our primary innovation measures as the proportion of a firm's current patents classified as exploratory and the proportion classified as exploitative, using the 80% citation threshold. The raw USPTO citation data are thoroughly cleaned, deduplicated, and processed to ensure one-to-one patent-firm-year assignments before applying the classification algorithm.

Table 11 presents the results of this final analysis, testing how the interaction of import competition and initial green innovation capacity affects the production of exploratory versus exploitative green patents. Panel A and B again show results for initial innovation normalized by detailed and broad technology classes. The dependent variables are the log number of exploratory and exploitative patents, and these measures scaled by assets. The results reveal a clear and striking asymmetry. The coefficient on the interaction term for Log Green Exploitative Patents is positive and highly statistically significant across all five years in both panels. In contrast, the coefficient for Log Green Exploratory Patents is positive but generally smaller in magnitude and less statistically robust, particularly in Panel B where it is not significant in any year. This pattern is even sharper when innovation is scaled by assets. The interaction for exploitative patents per asset is positive and significant, while for exploratory patents per asset it is negative and significant.

[*Insert Table 11 about here*]

The combined evidence from this section provides a clear, step-by-step account of the innovation mechanism at play. First, we established that firms with a stronger initial green innovation infrastructure respond to competition by producing a greater quantity of green patents. Second, the results in Table 10 reveal the strategic character of this response: the increase in innovation is driven almost entirely by a surge in exploitative patenting, which builds on the firm's existing knowledge base. Meanwhile, high-risk exploratory innovation, which seeks to create new knowledge, either stagnates or is actively reduced. This provides direct, fact-based support for our core theoretical argument that under the financial and

competitive pressures of the China Shock, firms adopted a defensive innovation strategy, leveraging their established green technologies to become cleaner and more resilient.

Having established that firms pursue a strategy of exploitative innovation, we can further refine our understanding of this mechanism by distinguishing between the types of green technologies they develop. The distinction between process and product innovation offers a deeper lens through which to view a firm's strategic response. Green process innovations, which improve how a firm produces its goods, are often linked to the Porter Hypothesis's "win-win" scenario, where firms cut costs and pollution simultaneously by increasing operational efficiency. This aligns with a defensive, cost-cutting response to intense price competition. In contrast, green product innovations, which change what a firm sells, are a direct form of non-price differentiation aimed at capturing environmentally conscious consumers and creating new market niches. While the financial pressures of the shock might favor cost-saving process innovations, the strategic need to "escape competition" necessitates product differentiation. Therefore, we investigate whether firms with strong initial green innovation capacity pursue both strategies.

To test this, we distinguish between green process and product innovation using a precise, claim-based classification methodology developed by Bena and Simintzi (15). Using comprehensive data from the USPTO, we analyze the content of each patent's claims. A green patent is classified as a "process innovation" if it contains one or more claims related to a method or process of manufacturing. Patents with zero process claims are classified as "product innovations". This approach provides a more accurate and economically meaningful distinction than methods based solely on technology codes, as it directly reflects the intended application of the patented technology. We then construct firm-year measures for the number and intensity of both green process and green product patents to analyze how import competition differentially affects these distinct innovation strategies.

Table 12 presents the results for this analysis, again interacting import competition with lagged green innovation capacity. The dependent variables are the log number of green process patents and green product patents, as well as these counts scaled by assets. The

results in both Panel A and Panel B show that the coefficient on the interaction term is positive and highly statistically significant for both Log Green Process Patents and Log Green Product Patents across most time horizons. This indicates that firms with a stronger initial green innovation base respond to competition by increasing their innovation output along both strategic dimensions.

[*Insert Table 12 about here*]

The findings from this section provide a multi-layered view of the innovation mechanism. The evidence confirms that the competitive shock induces a greater quantity of green innovation from firms with a strong pre-existing technological infrastructure. This increase is driven primarily by exploitative innovation, where firms leverage their existing knowledge. Delving deeper, we find that this exploitative strategy is not confined to one type of technology; rather, these firms increase their output of both green process innovations, aimed at improving efficiency, and green product innovations, aimed at differentiation. This suggests that resilient firms adopt a comprehensive innovation strategy, simultaneously pursuing cost efficiencies and market-creating differentiation to navigate the competitive landscape.

5 Conclusion

This paper investigates the strategic environmental responses of U.S. manufacturing firms to the profound competitive shock of rising import penetration from China. We ask whether intense competition forces firms to contract and abandon non-market strategies or whether it disciplines them to upgrade their environmental performance as a competitive tool. Our findings provide robust evidence for the latter. We establish a causal link between greater import competition and a significant reduction in toxic chemical emissions at both the chemical-firm and aggregate firm level. This "greening" effect suggests that, on average, U.S. firms engaged in a "fight" response through environmental upgrading rather than a "flee" response by offshoring polluting activities.

Our analysis reveals that this aggregate trend is driven by a distinct set of firms. The competition-induced reduction in pollution is significantly more pronounced for firms with stronger pre-existing environmental credentials—either a history of low pollution intensity or a well-developed stock of green patents. This initial environmental standing proves to be a crucial source of competitive resilience. When confronted with the trade shock, these initially "cleaner" or "greener" firms exhibit superior financial and operational performance. They are better able to preserve their market valuation, safeguard strategic R&D investments, maintain sales and profitability, and are perceived by the market as being fundamentally less risky.

We then unpack the specific mechanism driving this resilience. We find that the competitive shock induces a significant increase in green innovation, but only among firms that already possess a strong green technology infrastructure. Critically, we show that the character of this innovation is primarily exploitative. Rather than engaging in costly and uncertain exploratory innovation, resilient firms strategically leverage and refine their existing green technologies. This defensive innovation strategy, which encompasses both process improvements and product differentiation, allows firms to enhance efficiency and create a defensible market niche without requiring massive new capital outlays in a financially constrained environment.

These findings contribute to several strands of literature. We add a crucial environmental dimension to the extensive literature on the "China shock," which has largely focused on labor market and broad innovation outcomes. We also contribute to the long-standing debate between the Porter Hypothesis and the Pollution Haven Hypothesis, providing evidence that intense competition can induce domestic environmental upgrading, and we identify exploitative innovation as a key channel. Finally, we identify a firm's environmental record as a novel and significant source of strategic resilience, complementing work that has identified R&D intensity and capital intensity as determinants of firm survival and performance in the face of trade shocks.

Our results have important implications for managers, investors, and policymakers. For corporate managers, our findings suggest that environmental performance should not be

viewed as a peripheral non-market issue, but as a core dimension of competitive strategy that builds resilience against severe economic shocks. For investors, a firm's environmental and green innovation record serves as a valuable, forward-looking indicator of its ability to withstand competitive pressures. For policymakers, our analysis highlights that trade policy has profound and nuanced environmental consequences, suggesting that policies aimed at fostering domestic green technological capabilities may enhance the resilience of the industrial base in an increasingly globalized and competitive market.

Bibliography

[1] Acemoglu, D., Autor, D., Dorn, D., Hanson, G. H., and Price, B. (2016). Import competition and the great US employment sag of the 2000s. *Journal of Labor Economics*, 34(S1):S141–S198.

[2] Aghion, P., Bloom, N., Blundell, R., Griffith, R., and Howitt, P. (2005). Competition and innovation: An inverted-U relationship. *The Quarterly Journal of Economics*, 120(2):701–728.

[3] Aghion, P. and Howitt, P. (1992). A model of growth through creative destruction. *Econometrica*, 60(2):323–351.

[4] Aghion, P. and Stein, J. C. (2008). Growth versus margins: Destabilizing consequences of giving the stock market what it wants. *The Journal of Finance*, 63(3):1025–1058.

[5] Almazan, A., Banerji, S., and De Motta, A. (2008). Attracting attention: Cheap managerial talk and costly market monitoring. *The Journal of Finance*, 63(3):1399–1436.

[6] Ambec, S. and Lanoie, P. (2008). Does it pay to be green? a systematic overview. *Academy of Management Perspectives*, 22(4):45–62.

[7] Antweiler, W., Copeland, B. R., and Taylor, M. S. (2001). Is free trade good for the environment? *American Economic Review*, 91(4):877–908.

[8] Ardia, D., Bluteau, K., Boudt, K., and Inghelbrecht, K. (2022). Climate change concerns and the performance of green vs. brown stocks. *Management Science*, 69(12):7607–7632.

[9] Autor, D. H., Dorn, D., and Hanson, G. H. (2013). The china syndrome: Local labor market effects of import competition in the united states. *American Economic Review*, 103(6):2121–2168.

[10] Autor, D. H., Dorn, D., and Hanson, G. H. (2016). The china shock: Learning from labor-market adjustment to large changes in trade. *Annual Review of Economics*, 8:205–240.

[11] Baker, M., Stein, J. C., and Wurgler, J. (2003). When does the market matter? stock prices and the investment of equity-dependent firms. *The Quarterly Journal of Economics*, 118(3):969–1005.

[12] Baker, M. and Wurgler, J. (2004). A catering theory of dividends. *The Journal of Finance*, 59(3):1125–1165.

[13] Barber, B. M. and Odean, T. (2008). All that glitters: The effect of attention and news on the buying behavior of individual and institutional investors. *The Review of Financial Studies*, 21(2):785–818.

[14] Bena, J., Ortiz-Molina, H., and Simintzi, E. (2022). Shielding firm value: Employment protection and process innovation. *Journal of Financial Economics*, 146(2):637–664.

[15] Bena, J. and Simintzi, E. (2024). Machines could not compete with Chinese labor: Evidence from U.S. firms' innovation. SSRN Working Paper.

[16] Benner, M. J. and Tushman, M. L. (2002). Process management and technological innovation: A longitudinal study of the photography and paint industries. *Administrative Science Quarterly*, 47(4):676–706.

[17] Bernard, A. B., Jensen, J. B., and Schott, P. K. (2006). Survival of the best fit: Exposure to low-wage countries and the (uneven) growth of U.S. manufacturing plants. *Journal of International Economics*, 68(1):219–237.

[18] Blankespoor, E., deHaan, E., and Marinovic, I. (2020). Disclosure processing costs, investors' information choice, and equity market outcomes: A review. *Journal of Accounting and Economics*, 70(2-3):101344.

[19] Blei, D. M., Ng, A. Y., and Jordan, M. I. (2003). Latent Dirichlet allocation. *Journal of Machine Learning Research*, 3:993–1022.

[20] Bloom, N., Draca, M., and Van Reenen, J. (2016). Trade induced technical change? the impact of Chinese imports on innovation, IT and productivity. *The Review of Economic Studies*, 83(1):87–117.

[21] Bordalo, P., Gennaioli, N., La Porta, R., and Shleifer, A. (2019). Diagnostic expectations and stock returns. *The Journal of Finance*, 74(6):2839–2874.

[22] Bowen, R. M., Davis, A. K., and Matsumoto, D. A. (2002). Do conference calls affect analysts' forecasts? *The Accounting Review*, 77(2):285–316.

[23] Brown, S. V. and Tucker, J. W. (2011). Large-sample evidence on firms' year-over-year MD&A modifications. *Journal of Accounting Research*, 49(2):309–346.

[24] Bushee, B. J. (1998). The influence of institutional investors on myopic R&D investment behavior. *The Accounting Review*, 73(3):305–333.

[25] Bybee, L., Kelly, B. T., Manela, A., and Xiu, D. (2023). Business news and business cycles. *The Journal of Finance*. Forthcoming.

[26] Cameron, A. C., Gelbach, J. B., and Miller, D. L. (2011). Robust inference with multiway clustering. *Journal of Business & Economic Statistics*, 29(2):238–249.

[27] Campello, M., Graham, J. R., and Harvey, C. R. (2010). The real effects of financial constraints: Evidence from a financial crisis. *Journal of Financial Economics*, 97(3):470–487.

[28] Cao, S., Jiang, W., Yang, B., and Zhang, A. L. (2023). How to talk when a machine is listening: Corporate disclosure in the age of AI. *The Review of Financial Studies*, 36(9):3603–3642.

[29] Chava, S., Oettl, A., Subramanian, A., and Wilson, K. (2013). The real effects of financial shocks: Evidence from the tsunami. *The Review of Financial Studies*, 26(4):1048–1085.

[30] Cherniwchan, J. (2017). Trade liberalization and the environment: Evidence from NAFTA and U.S. manufacturing. *Journal of International Economics*, 105:130–149.

[31] Cohen, L., Diether, K. B., and Malloy, C. J. (2013). Misvaluing innovation. *The Review of Financial Studies*, 26(3):635–666.

[32] Cohen, L., Malloy, C. J., and Nguyen, Q. (2020). Lazy prices. *The Journal of Finance*, 75(3):1371–1415.

[33] Cohen, W. M. and Levinthal, D. A. (1990). Absorptive capacity: A new perspective on learning and innovation. *Administrative Science Quarterly*, 35(1):128–152.

[34] Cooper, M. J., Dimitrov, O., and Rau, P. R. (2001). A rose.com by any other name. *The Journal of Finance*, 56(6):2371–2388.

[35] Copeland, B. R. and Taylor, M. S. (1994). North-south trade and the environment. *The Quarterly Journal of Economics*, 109(3):755–787.

[36] Cornaggia, J., Mao, Y., Tian, X., and Wolfe, B. (2021). Financing and appropriability of innovation. *Journal of Financial and Quantitative Analysis*, 56(8):2739–2773.

[37] Crawford, V. P. and Sobel, J. (1982). Strategic information transmission. *Econometrica*, 50(6):1431–1451.

[38] Curry, J. M. and Fix, M. P. (2019). May it please the twitterverse: The use of twitter by state high court judges. *Journal of Law and Courts*, 7(1):1–22.

[39] Da, Z., Engelberg, J., and Gao, P. (2011). In search of attention. *The Journal of Finance*, 66(5):1461–1499.

[40] Diether, K. B., Malloy, C. J., and Scherbina, A. (2002). Differences of opinion and the cross section of stock returns. *The Journal of Finance*, 57(5):2113–2141.

[41] Dyer, T., Lang, M., and Stice-Lawrence, L. (2017). The evolution of 10-K textual disclosure: Evidence from Latent Dirichlet Allocation. *Journal of Accounting and Economics*, 64(2-3):221–245.

[42] Ederington, J. and Minier, J. (2003). Is environmental policy a secondary trade barrier? an empirical analysis. *Canadian Journal of Economics*, 36(1):137–154.

[43] Eswaran, M. and Gallini, N. (1996). Patent policy and the direction of technological change. *The RAND Journal of Economics*, 27(4):722–746.

[44] Fama, E. F. and French, K. R. (1993). Common risk factors in the returns on stocks and bonds. *Journal of Financial Economics*, 33(1):3–56.

[45] Fama, E. F. and French, K. R. (2015). A five-factor asset pricing model. *Journal of Financial Economics*, 116(1):1–22.

[46] Fazzari, S. M., Hubbard, R. G., and Petersen, B. C. (1988). Financing constraints and corporate investment. *Brookings Papers on Economic Activity*, 1988(1):141–195.

[47] Flammer, C. (2015). Does product market competition foster corporate social responsibility? evidence from trade liberalization. *Strategic Management Journal*, 36(10):1469–1485.

[48] Frankel, R., Johnson, M., and Skinner, D. J. (1999). An empirical examination of conference calls as a voluntary disclosure medium. *Journal of Accounting Research*, 37(1):133–150.

[49] Gao, Y. and You, F. (2019). The effect of the US-China trade war on corporate innovation. *Journal of Corporate Finance*, 58:744–764.

[50] Graham, J. R., Harvey, C. R., and Rajgopal, S. (2005). The economic implications of corporate financial reporting. *Journal of Accounting and Economics*, 40(1-3):3–73.

[51] Grinstein, Y. and Larkin, I. (2022). Competition and pollution. SSRN Working Paper.

[52] Hall, B. H., Jaffe, A., and Trajtenberg, M. (2005). Market value and patent citations. *The RAND Journal of Economics*, 36(1):16–38.

[53] Hart, S. L. (1995). A natural-resource-based view of the firm. *Academy of Management Review*, 20(4):986–1014.

[54] Hassan, T. A., Hollander, S., van Lent, L., and Tahoun, A. (2019). Firm-level political risk: Measurement and effects. *The Quarterly Journal of Economics*, 134(4):2135–2202.

[55] Hirshleifer, D., Hou, K., Teoh, S. H., and Zhang, Y. (2004). Do investors overvalue firms with bloated balance sheets? *Journal of Accounting and Economics*, 38:297–331.

[56] Hirshleifer, D., Hsu, P.-H., and Li, D. (2013). Innovative efficiency and stock returns. *Journal of Financial Economics*, 107(3):632–654.

[57] Hirshleifer, D. and Teoh, S. H. (2003). Limited attention, information disclosure, and financial reporting. *Journal of Accounting and Economics*, 36(1-3):337–386.

[58] Hoberg, G. and Phillips, G. (2010). Product market synergies and competition in mergers and acquisitions: A text-based analysis. *The Review of Financial Studies*, 23(10):3773–3811.

[59] Hoberg, G. and Phillips, G. (2016). Text-based network industries and endogenous product differentiation. *Journal of Political Economy*, 124(5):1423–1465.

[60] Hollander, S., Pronk, M., and Roelofsen, E. (2010). Does silence speak? an empirical analysis of disclosure choices during conference calls. *Journal of Accounting Research*, 48(3):531–563.

[61] Hombert, J. and Matray, A. (2018). Can innovation help U.S. manufacturing firms escape import competition from china? *The Journal of Finance*, 73(5):2003–2039.

[62] Hong, H. and Kacperczyk, M. (2010). Competition and bias. *The Quarterly Journal of Economics*, 125(4):1683–1725.

[63] Hong, H., Lim, T., and Stein, J. C. (2000). Bad news travels slowly: Size, analyst coverage, and the profitability of momentum strategies. *Journal of Finance*, 55(1):265–295.

[64] Huang, X., Teoh, S. H., and Zhang, Y. (2014). Tone management. *The Accounting Review*, 89(3):1083–1113.

[65] Katila, R. and Ahuja, G. (2002). Something old, something new: A longitudinal study of search behavior and new product introduction. *Academy of Management Journal*, 45(6):1183–1194.

[66] Kogan, L., Papanikolaou, D., Seru, A., and Stoffman, N. (2017a). Technological innovation, resource allocation, and growth. *The Quarterly Journal of Economics*, 132(2):665–712.

[67] Kogan, L., Papanikolaou, D., Seru, A., and Stoffman, N. (2017b). Technological innovation, resource allocation, and growth. *The Quarterly Journal of Economics*, 132(2):665–712.

[68] Kong, D., Lin, C., Wu, J., and Zhang, T. (2022). Trade liberalization and firm-level toxic emissions: Evidence from China's WTO accession. *Journal of International Economics*, 139:103673.

[69] Lacy, P., Cooper, T., Hayward, R., and Neuberger, L. (2010). A new era of sustainability: UN global compact-accenture CEO study 2010.

[70] Lakonishok, J., Shleifer, A., and Vishny, R. W. (1994). Contrarian investment, extrapolation, and risk. *The Journal of Finance*, 49(5):1541–1578.

[71] Lang, M. and Stice-Lawrence, L. (2015). Textual analysis and international financial reporting: Large-sample evidence. *Journal of Accounting and Economics*, 60(2-3):110–135.

[72] Lee, J. (2016). Can investors detect managers' lack of spontaneity? Evidence from cues in conference calls. *The Accounting Review*, 91(1):229–250.

[73] Lileeva, A. and Trefler, D. (2010). Improved access to foreign markets raises plant-level productivity... for some plants. *The Quarterly Journal of Economics*, 125(3):1051–1099.

[74] Loughran, T. and McDonald, B. (2011). When is a liability not a liability? Textual analysis, dictionaries, and 10-Ks. *The Journal of Finance*, 66(1):35–65.

[75] Manela, A. and Moreira, A. (2017). News implied volatility and disaster concerns. *Journal of Financial Economics*, 123(1):137–162.

[76] March, J. G. (1991). Exploration and exploitation in organizational learning. *Organization Science*, 2(1):71–87.

[77] Matsumoto, D., Pronk, M., and Roelofsen, E. (2011). What makes conference calls useful? The information content of managers' presentations and analysts' discussion sessions. *The Accounting Review*, 86(4):1383–1414.

[78] Merton, R. C. (1987). A simple model of capital market equilibrium with incomplete information. *The Journal of Finance*, 42(3):483–510.

[79] Miller, E. M. (1977). Risk, uncertainty, and divergence of opinion. *Journal of Finance*, 32(4):1151–1168.

[80] Mishler, A., Crabb, E. S., Paletz, S. B. F., Heffernan, B., and Petroff, M. (2015). Using structural topic modeling to detect events and cluster twitter users in the ukrainian crisis. *Proceedings of the Workshop on Computational Linguistics and Clinical Psychology*, pages 80–87.

[81] Peng, L. and Xiong, W. (2006). Investor attention, overconfidence and category learning. *Journal of Financial Economics*, 80(3):563–602.

[82] Petersen, M. A. (2009). Estimating standard errors in finance panel data sets: Comparing approaches. *The Review of Financial Studies*, 22(1):435–480.

[83] Polk, C. and Sapienza, P. (2009). The stock market and corporate investment: A test of catering theory. *The Review of Financial Studies*, 22(1):187–217.

[84] Porter, M. E. and van der Linde, C. (1995). Toward a new conception of the environment-competitiveness relationship. *Journal of Economic Perspectives*, 9(4):97–118.

[85] Roberts, M. E., Stewart, B. M., Tingley, D., Lucas, C., Leder-Luis, J., Gadarian, S. K., Albertson, B., and Rand, D. G. (2014). Structural topic models for open-ended survey responses. *American Journal of Political Science*, 58(4):1064–1082.

[86] Roychowdhury, S. (2006). Earnings management through real activities manipulation. *Journal of Accounting and Economics*, 42(3):335–370.

[87] Scherer, F. M. (1984). Using linked patent and R&D data to measure interindustry technology flows. In Griliches, Z., editor, *R&D, Patents, and Productivity*, pages 417–464. University of Chicago Press, Chicago.

[88] Schmidt, K. M. (1997). Managerial incentives and product market competition. *The Review of Economic Studies*, 64(2):191–213.

[89] Seru, A. (2014). Firm age, corporate governance, and innovation. *Journal of Financial Economics*, 112(3):429–450.

[90] Shapiro, J. S. (2021). Trade and the environment: A review. *Annual Review of Economics*, 13:149–173.

[91] Shiller, R. J. (2017). Narrative economics. *The American Economic Review*, 107(4):967–1004.

[92] Shleifer, A. and Vishny, R. W. (1990). Equilibrium short horizons of investors and firms. *The American Economic Review*, 80(2):148–153.

[93] Sims, C. A. (2003). Implications of rational inattention. *Journal of Monetary Economics*, 50(3):665–690.

[94] Skinner, D. J. and Sloan, R. G. (2002). Earnings surprises, growth expectations, and stock returns or don't let an earnings torpedo sink your portfolio. *Review of Accounting Studies*, 7(2-3):289–312.

[95] Sloan, R. G. (1996). Do stock prices fully reflect information in accruals and cash flows about future earnings? *The Accounting Review*, 71(3):289–315.

[96] Staw, B. M., Sandelands, L. E., and Dutton, J. E. (1981). Threat-rigidity effects in organizational behavior: A multilevel analysis. *Administrative Science Quarterly*, 26(4):501–524.

[97] Stein, J. C. (1989). Efficient capital markets, inefficient firms: A model of myopic corporate behavior. *The Quarterly Journal of Economics*, 104(4):655–669.

[98] Stoughton, N. M., Wong, K. P., and Yi, X. (2020). Committing to corporate social responsibility in a competitive industry. SSRN Working Paper.

[99] Strumsky, D., Lobo, J., and van der Leeuw, S. E. (2012). Using patent technology codes to study the dynamics of technological progress. *Research Policy*, 41(9):1717–1735.

[Tabatabaei] Tabatabaei, E. Mixed messages: Strategic tonal inconsistency and recovery of the PEAD anomaly. Working paper, Schulich School of Business. Available at SSRN: https://ssrn.com/abstract=5381754 or http://dx.doi.org/10.2139/ssrn.5381754.

[101] Tetlock, P. C. (2007). Giving content to investor sentiment: The role of media in the stock market. *The Journal of Finance*, 62(3):1139–1168.

[102] Valta, P. (2012). Competition and the cost of debt. *Journal of Financial Economics*, 105(3):661–682.

[103] Verrecchia, R. E. (2001). Essays on disclosure. *Journal of Accounting and Economics*, 32(1-3):97–180.

[104] Yu, F. F. (2008). Analyst coverage and earnings management. *Journal of Financial Economics*, 88(2):245–271.

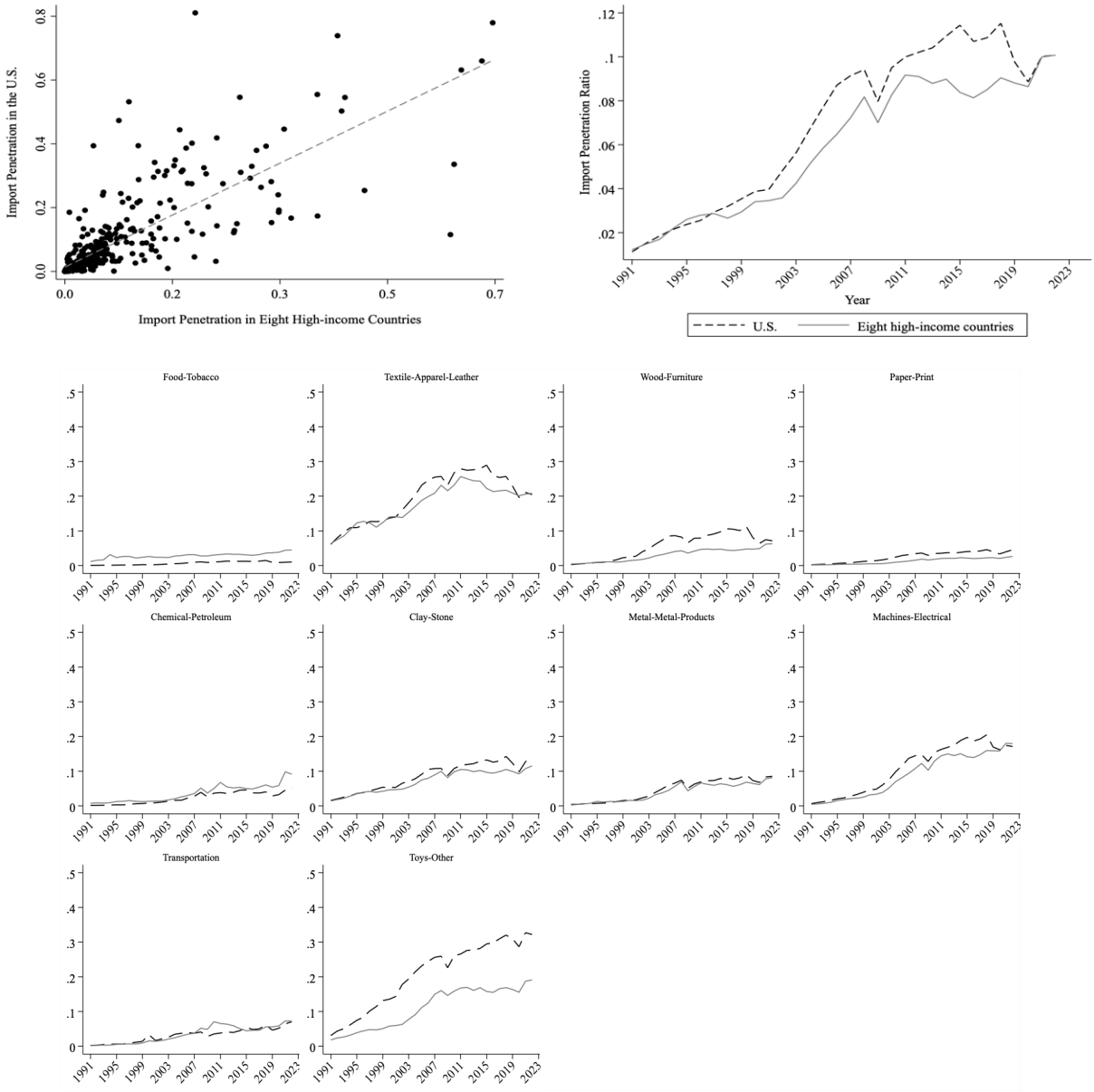

Figure 1: Manufacturing Imports from China: United States vs. Other High-Income Economies

This figure shows the evolution and cross-country comparison of China's import penetration in manufacturing from 1991 to 2022. Panel A plots the import-penetration ratio, Chinese imports divided by total domestic absorption (production + imports − exports), for the United States and for eight high-income economies (Australia, Denmark, Finland, Germany, Japan, New Zealand, Spain, and Switzerland). Panel B shows the cross-sectional relationship between U.S. and peer import penetration across NBER technology classes (industry groups), with a fitted least-squares line. Panel C presents time series by NBER technology classes (industry groups), reporting import penetration for both the United States and the eight-country group.

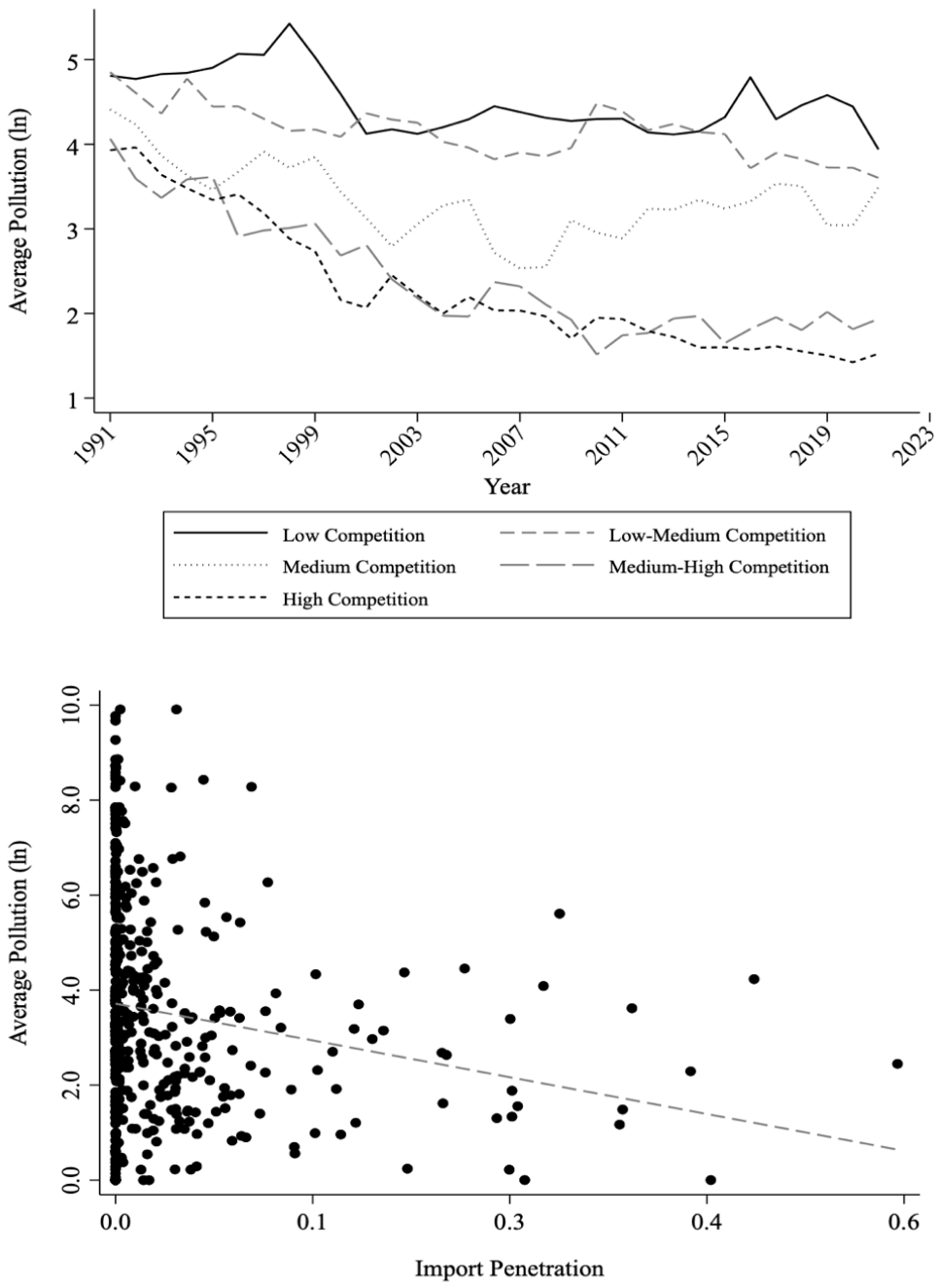

Figure 2: Import Penetration and Firm Pollution: Time Trends by IP Quintiles and Cross-Sectional Relationship

This figure shows the evolution of firms' average pollution and its relation to import competition across quintiles of import penetration (IP) from China. Panel A plots annual means of log TRI emissions for U.S. manufacturing firms from 1991–2022, grouping firm–industry–year observations into five equal-sized IP quintiles (labeled Low to High Competition). The series exhibit a broad decline over time and a clear gradient: industries facing higher import competition have lower average emissions, particularly after the early 2000s. Panel B displays the cross-sectional association between industry-year IP and average (log) TRI emissions, with a fitted least-squares line showing a negative slope. Import penetration is defined as Chinese imports divided by domestic absorption.

Table 1: Import Penetration Ratio by Industry

This table presents statistics on the import penetration from China across U.S. manufacturing industries, classified by NBER technology class, for the period 1991–2022. The import penetration ratio is defined as the value of U.S. imports from China divided by an industry's total domestic absorption (production + imports – exports). Panel A reports summary statistics, including the count of unique 4-digit industries, the mean, standard deviation, and key percentiles, for the full sample period. Panel B shows the evolution of the mean import penetration ratio over four distinct sub-periods: Pre-WTO (1991–2001), Post-WTO (2002–2008), Financial Crisis and Post-Crisis (2009–2017), and Recent (2018–2022). All statistics are calculated at the 4-digit SIC industry level and aggregated by NBER technology class.

Panel A: Summary Statistics of Import Penetration Ratio by NBER Technology Class

Industry	Count	Mean	Standard deviation	25th	Median	75th
Toys, Other	16	0.206	0.187	0.044	0.171	0.313
Textile, Apparel, Leather	54	0.196	0.205	0.032	0.127	0.275
Machines, Electrical	101	0.109	0.118	0.03	0.058	0.139
Clay, Stone	38	0.086	0.137	0.006	0.05	0.088
Wood, Furniture	23	0.057	0.079	0.007	0.018	0.066
Metal, Metal Products	46	0.047	0.062	0.007	0.025	0.068
Transportation	16	0.032	0.071	0.000	0.007	0.024
Paper, Print	24	0.026	0.045	0.001	0.009	0.023
Chemical, Petroleum	33	0.023	0.034	0.004	0.011	0.03
Food, Tobacco	46	0.007	0.018	0.000	0.001	0.006

Panel B: Mean Import Penetration Ratio by Industry Category and Time Period

Industry	1991–2001	2002–2008	2009–2017	2018–2022
Toys, Other	0.088	0.225	0.277	0.313
Textile, Apparel, Leather	0.112	0.219	0.268	0.219
Machines, Electrical	0.026	0.112	0.173	0.176
Clay, Stone	0.038	0.089	0.119	0.126
Wood, Furniture	0.013	0.068	0.090	0.081
Metal, Metal Products	0.010	0.048	0.072	0.080
Transportation	0.010	0.034	0.042	0.059
Paper, Print	0.008	0.027	0.037	0.041
Chemical, Petroleum	0.004	0.021	0.038	0.040
Food, Tobacco	0.002	0.007	0.012	0.011

Table 2: Mean Pollution Levels by Import Competition Level

This table presents summary statistics on the relationship between import competition from China and industrial pollution, measured as the natural logarithm of Toxic Release Inventory (TRI) emissions, for the period 1991–2022. For the analysis, industries are sorted into quintiles each year based on their import penetration ratio from China. Panel A reports the mean pollution levels for each competition quintile across four distinct economic periods: Pre-WTO (1991–2001), Post-WTO (2002–2008), Financial Crisis and Post-Crisis (2009–2017), and Recent (2018–2022). Panel B shows the mean pollution levels across both competition quintiles and NBER industry technology classes, averaged over the full sample period.

Panel A: Mean Pollution Levels by Import Competition Quintiles and Time Periods

Competition Quintiles	1991–2001	2002–2008	2009–2017	2018–2022
Low-Competition	4.867	4.270	4.289	4.365
Low-Medium-Competition	4.430	4.029	4.137	3.722
Medium-Competition	3.769	2.909	3.190	3.264
Medium-High-Competition	3.279	2.190	1.807	1.890
High-Competition	3.209	2.133	1.724	1.503

Panel B: Mean Pollution Levels by Import Competition Quintiles and Industry Categories

Industry	Low Competition	Low-Medium Competition	Medium Competition	Medium-High Competition	High Competition
Food-Tobacco	5.079	4.074	4.044	5.045	4.457
Textile-Apparel-Leather	3.869	4.097	3.524	3.565	3.803
Wood-Furniture	4.323	3.753	3.653	2.642	0.561
Paper-Print	2.073	2.679	2.392	2.075	1.958
Chemical-Petroleum	5.68	4.522	4.125	3.142	2.264
Clay-Stone	5.492	6.455	4.154	1.581	3.595
Metal-Metal-Products	3.067	4.038	4.049	3.490	3.477
Machines-Electrical	1.349	2.041	3.322	2.119	2.194
Transportation	5.001	3.603	3.752	2.409	4.319
Toys-Other	4.388	3.660	5.777	4.236	3.756

Table 3: Summary Statistics for Performance Variables by Import Penetration and Pollution Groups

This table presents summary statistics for performance variables used in the analysis. High IP and Low IP groups are defined based on whether import penetration is above or below the industry-year median. High Pollution and Low Pollution groups are defined based on whether firm-level pollution intensity is above or below the firm-year median. The variables include measures of firm valuation and size (the natural logarithm of the market-to-book ratio, total assets, and net sales), investment (the natural logarithm of R&D expenditures and capital expenditures, both scaled by assets), profitability (operating income before depreciation and amortization and cost of goods sold, each scaled by both assets and sales), and volatility measures, including the annualized standard deviation of total, systematic, and idiosyncratic stock returns, and operating profit margin.

Performance Variable	No. Obs.	All	High IP	Low IP	High Pollution	Low Pollution
Log Market-to-Book Ratio	19,579	0.722	0.693	0.755	0.732	0.711
Log Assets	20,319	0.400	0.080	0.774	1.125	−0.533
Log Sales	20,297	0.412	0.074	0.809	1.155	−0.389
Log R&D Expenditures / Assets	20,340	−4.681	−4.539	−4.972	−4.853	−4.407
Log Capex / Assets	20,360	−3.225	−3.245	−3.201	−3.164	−3.258
OIBDA / Assets	20,278	0.142	0.142	0.141	0.146	0.138
OIBDA / Sales	20,255	0.130	0.131	0.129	0.138	0.122
Cost of Goods Sold / Assets	20,316	0.830	0.785	0.882	0.879	0.786
Cost of Goods Sold / Sales	20,293	0.675	0.661	0.691	0.704	0.645
Vol Total Returns	20,292	0.028	0.030	0.026	0.025	0.031
Vol Systematic Returns	20,292	0.012	0.012	0.011	0.012	0.012
Vol Idiosyncratic Returns	20,292	0.025	0.026	0.023	0.028	0.027
Vol Operating Profit Margin	18,452	0.031	0.032	0.031	0.027	0.036

Table 4: Effects of Import Competition on Chemical-Firm-Level Pollution Outcomes

This table reports chemical–firm–level 2SLS estimates of the effect of import competition at time t on pollution from year $t+1$ to $t+3$. The dependent variable is chemical–firm pollution intensity, measured as toxic releases of a given chemical at a firm scaled by total assets (Panel A) or by sales (Panel B). For each horizon, the first column reports the effect of direct competition only, while the second column reports the combined effect including direct, upstream (supplier), and downstream (customer) spillovers. All regressions include firm fixed effects, industry–year fixed effects, and chemical–year fixed effects. Standard errors, shown in parentheses, are clustered at the 2-digit SIC industry–year level. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	$t+1$		$t+2$		$t+3$	
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Pollution Intensity (Scaled by Assets)						
Direct	-0.286^{***}	-0.284^{***}	-0.247^{***}	-0.231^{***}	-0.172^{***}	-0.151^{***}
	(-5.46)	(-5.04)	(-4.67)	(-4.11)	(-3.34)	(-2.75)
Upstream		-0.205^{*}		-0.312^{***}		-0.366
		(-1.69)		(-3.10)		(-1.19)
Downstream		0.174		-0.202		-0.291^{***}
		(0.51)		(-0.68)		(-2.73)
Ind-Year FE	✓	✓	✓	✓	✓	✓
Firm FE	✓	✓	✓	✓	✓	✓
Chemical-Year FE	✓	✓	✓	✓	✓	✓
No. Obs.	685,958	685,958	643,684	643,684	602,742	602,742
Adjusted R2	0.007	0.007	0.005	0.005	0.003	0.003
Panel B: Pollution Intensity (Scaled by Sales)						
Direct	-0.243^{***}	-0.253^{***}	-0.214^{***}	-0.208^{***}	-0.151^{***}	-0.139^{***}
	(-5.10)	(-4.86)	(-4.38)	(-3.97)	(-3.09)	(-2.66)
Upstream		-0.101		-0.207^{**}		-0.183^{*}
		(-0.84)		(-2.06)		(-1.74)
Downstream		0.434		0.019		-0.181
		(1.32)		(0.07)		(-0.66)
Ind-Year FE	✓	✓	✓	✓	✓	✓
Firm FE	✓	✓	✓	✓	✓	✓
Chemical-Year FE	✓	✓	✓	✓	✓	✓
No. Obs.	685,941	685,941	643,631	643,631	602,664	602,664
Adjusted R2	0.008	0.008	0.004	0.004	0.003	0.003

Table 5: Effects of Import Competition on Firm-Level Pollution Outcomes

This table reports firm-level 2SLS regression results for the effect of import competition at time t on firm pollution from year $t+1$ to $t+3$. The dependent variable is pollution intensity, measured as toxic releases scaled by total assets (Panel A) and by sales (Panel B). For each horizon, the first column reports the effect of direct competition only, while the second column reports the combined effect including direct, upstream (supplier), and downstream (customer) spillovers. All regressions include firm and industry-year fixed effects. Standard errors, reported in parentheses, are clustered at the 2-digit SIC industry-year level. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	$t+1$		$t+2$		$t+3$	
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Pollution Intensity (Scaled by Assets)						
Direct	-0.073^{**}	-0.088^{**}	-0.066^{*}	-0.086^{**}	-0.033	-0.055
	(-2.18)	(-2.16)	(-1.94)	(-2.04)	(-1.00)	(-1.31)
Upstream		0.200		0.322		0.314
		(0.69)		(1.14)		(1.15)
Downstream		-0.325^{***}		-0.323^{***}		-0.277^{***}
		(-3.63)		(-3.93)		(-3.42)
Ind-Year FE	✓	✓	✓	✓	✓	✓
Firm FE	✓	✓	✓	✓	✓	✓
No. Obs.	20,113	20,113	18,782	18,782	17,492	17,492
Adjusted R2	0.008	0.008	0.004	0.004	0.002	0.002
Panel B: Pollution Intensity (Scaled by Sales)						
Direct	-0.074^{**}	-0.096^{**}	-0.072^{**}	-0.101^{**}	-0.058^{*}	-0.091^{**}
	(-2.39)	(-2.52)	(-2.31)	(-2.57)	(-1.84)	(-2.32)
Upstream		0.561^{**}		0.617^{**}		0.635^{***}
		(2.17)		(2.47)		(2.65)
Downstream		-0.248^{***}		-0.251^{***}		-0.223^{***}
		(-3.18)		(-3.88)		(-3.59)
Ind-Year FE	✓	✓	✓	✓	✓	✓
Firm FE	✓	✓	✓	✓	✓	✓
No. Obs.	20,079	20,079	18,762	18,762	17,480	17,480
Adjusted R2	0.001	0.001	0.001	0.001	0.002	0.002

Table 6: Import Competition and Pollution: Time-Period Heterogeneity in Environmental Responses

This table reports firm-level 2SLS regression results for the interaction effects between import competition and lagged pollution intensity on subsequent pollution outcomes from year $t+1$ to $t+5$, allowing the effects to vary across distinct historical periods. The dependent variables are alternative measures of firm pollution: (a) total pollution, (b) pollution scaled by assets, and (c) pollution scaled by sales. Interaction terms are constructed by interacting direct import competition (IP) with indicator variables for the Post-WTO period (2002–2007), the Global Financial Crisis (2008–2012), the Post-Crisis recovery (2013–2016), and the Recent period (2017–2022). The omitted baseline category is the Pre-WTO period (1991–2001). Each cell reports the coefficient on the respective interaction term. All regressions include firm and industry-year fixed effects and control for lagged firm performance. Standard errors, reported in parentheses, are clustered at the 2-digit SIC industry-year level. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Dependent Variables	Interaction Term	$t+1$	$t+2$	$t+3$	$t+4$	$t+5$
a. Log Pollution						
	Post-WTO × IP	2.247***	1.663**	2.278***	1.943***	1.770***
		(3.11)	(2.33)	(3.30)	(2.95)	(2.64)
	Crisis × IP	2.392***	2.095**	2.963***	2.441***	2.251***
		(2.76)	(2.48)	(3.60)	(3.12)	(2.98)
	Post-Crisis × IP	3.265***	2.472**	3.580***	3.280***	3.689***
		(2.84)	(2.14)	(3.24)	(3.10)	(3.43)
	Recent × IP	4.913***	5.467***	8.660***	11.859***	22.228***
		(3.60)	(3.61)	(4.91)	(4.84)	(3.83)
b. Log Pollution per Assets						
	Post-WTO × IP	0.103	0.056	0.161	0.087	0.133
		(0.65)	(0.39)	(1.12)	(0.73)	(1.34)
	Crisis × IP	0.174	0.153	0.299*	0.204	0.249**
		(0.94)	(0.95)	(1.87)	(1.54)	(2.33)
	Post-Crisis × IP	0.257	0.215	0.379*	0.278	0.398***
		(1.02)	(0.95)	(1.72)	(1.51)	(2.61)
	Recent × IP	0.363	0.433	0.782**	0.885**	1.887***
		(1.21)	(1.47)	(2.32)	(2.40)	(3.03)
c. Log Pollution per Sales						
	Post-WTO × IP	0.028	0.033	0.174	0.147	0.163*
		(0.24)	(0.29)	(1.47)	(1.42)	(1.68)
	Crisis × IP	0.069	0.100	0.283**	0.228**	0.234**
		(0.49)	(0.78)	(2.11)	(2.00)	(2.23)
	Post-Crisis × IP	0.087	0.086	0.316*	0.271*	0.322**
		(0.46)	(0.47)	(1.72)	(1.74)	(2.18)
	Recent × IP	0.142	0.222	0.620**	0.866***	1.755***
		(0.63)	(0.95)	(2.19)	(2.70)	(2.89)
Industry-Year FE		✓	✓	✓	✓	✓
Firm FE		✓	✓	✓	✓	✓

Table 7: Import Competition and Pollution: Initial Green Innovation and Pollution Intensity Effects

This table reports firm-level 2SLS regression results for the interaction effects between import competition and lagged measures of environmental credentials on subsequent pollution outcomes from year $t+1$ to $t+5$. The dependent variables are alternative measures of firm pollution, including total pollution, pollution scaled by assets, and pollution scaled by sales. Panel A shows results for interactions with lagged pollution intensity measured five years prior to the shock. Panel B shows results for interactions with average of previous 5 years of green innovation normalized by detailed technology class (6-digit IPC/CPC subclass codes), where each patent is weighted by the inverse of total patents in its specific subclass-year. Panel C shows results for interactions with average of previous 5 years of green innovation normalized by broad technology class (4-digit IPC/CPC main class codes), where each patent is weighted by the inverse of total patents in its broader category-year. Each cell reports the coefficient on the interaction term between direct import competition (IP) and the respective lagged environmental credential. All regressions include firm and industry-year fixed effects. Standard errors, reported in parentheses, are clustered at the 2-digit SIC industry-year level. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Dependent Variables	$t+1$	$t+2$	$t+3$	$t+4$	$t+5$
Panel A: Lagged Pollution (Intensity) Interacted by IP					
a. Log Pollution	-0.188^{***}	-0.313^{***}	-0.387^{***}	-0.416^{***}	-0.380^{***}
	(-2.59)	(-3.87)	(-4.50)	(-5.33)	(-4.99)
b. Log Pollution per Assets	-1.490^{***}	-2.151^{***}	-2.039^{***}	-1.872^{***}	-1.853^{***}
	(-4.32)	(-5.24)	(-4.79)	(-5.28)	(-5.20)
c. Log Pollution per Sales	-1.587^{***}	-2.098^{***}	-1.808^{***}	-1.591^{***}	-1.651^{***}
	(-4.57)	(-4.52)	(-4.26)	(-3.82)	(-3.68)
Panel B: Lagged Mean Green Innovation (Normalized by Detailed Technology Class) Interacted by IP					
a. Log Pollution	-0.762^{**}	-1.232^{***}	-1.520^{***}	-1.269^{**}	-0.959
	(-2.07)	(-2.90)	(-3.09)	(-2.33)	(-1.55)
b. Log Pollution per Assets	-0.073^{*}	-0.073	-0.084^{*}	-0.065	-0.084^{*}
	(-1.95)	(-1.63)	(-1.73)	(-1.42)	(-1.92)
c. Log Pollution per Sales	-0.041	-0.067	-0.078	-0.065	-0.082^{*}
	(-1.22)	(-1.53)	(-1.61)	(-1.43)	(-1.92)
Panel C: Lagged Mean Green Innovation (Normalized by Broad Technology Class) Interacted by IP					
a. Log Pollution	-2.085^{**}	-3.038^{***}	-4.060^{***}	-3.779^{***}	-3.057^{**}
	(-1.97)	(-2.59)	(-3.01)	(-2.88)	(-2.32)
b. Log Pollution per Assets	-0.189^{**}	-0.164	-0.185	-0.118	-0.124
	(-2.04)	(-1.57)	(-1.62)	(-1.11)	(-1.33)
c. Log Pollution per Sales	-0.100	-0.127	-0.160	-0.126	-0.144
	(-1.08)	(-1.18)	(-1.39)	(-1.18)	(-1.55)
Industry-Year FE	✓	✓	✓	✓	✓
Firm FE	✓	✓	✓	✓	✓

Table 8: Import Competition and Firm Performance: Conditioning on Initial Pollution Intensity

This table reports firm-level 2SLS regression results for the interaction effects between import competition and lagged pollution intensity (measured five years prior to the shock) on firm performance outcomes from year $t+1$ to $t+5$. The dependent variables are various firm performance measures. Panel A shows results for interactions with lagged pollution intensity scaled by assets, Panel B shows results for interactions with lagged pollution intensity scaled by sales. Each cell reports the coefficient from equation (5), capturing the interaction term between direct import competition (IP) and lagged pollution intensity. All regressions include firm and industry-year fixed effects and control for log of total assets and firm age. Standard errors, reported in parentheses, are clustered at the 2-digit SIC industry-year level. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Lagged Pollution Intensity (Scaled by Assets) Interacted by IP

Dependent Variables	$t+1$	$t+2$	$t+3$	$t+4$	$t+5$
Valuation and Scale					
a. Log Market-to-Book Ratio	0.043	−0.090	−0.971*	−1.749***	−2.383***
	(0.08)	(−0.15)	(−1.85)	(−2.93)	(−4.28)
b. Log Assets	−0.095	−0.367	−0.481	−0.428	−0.292
	(−0.55)	(−1.25)	(−1.53)	(−1.11)	(−0.60)
c. Log Sales	−0.541*	−0.851*	−1.052**	−1.295***	−1.652***
	(−1.67)	(−1.72)	(−2.23)	(−2.61)	(−2.95)
Investment and Operating Policies					
d. Log R&D Expenditures / Assets	−0.135	−0.699	−1.234**	−1.256**	−1.501**
	(−0.33)	(−1.08)	(−1.98)	(−2.01)	(−2.12)
e. Log CAPEX / Assets	−0.773	−0.232	0.440	0.389	0.421
	(−1.33)	(−0.41)	(0.65)	(0.49)	(0.51)
f. OIBDA / Assets	−0.094	−0.066	−0.128	−0.215**	−0.259***
	(−1.01)	(−0.69)	(−1.25)	(−2.53)	(−2.99)
g. OIBDA / Sales	−0.045	−0.089	−0.129**	−0.177**	−0.188**
	(−0.75)	(−1.37)	(−2.13)	(−2.46)	(−2.11)
h. Cost of Goods Sold / Assets	−0.420	−0.523	−0.650*	−0.990***	−1.330***
	(−1.64)	(−1.53)	(−1.72)	(−2.85)	(−3.18)
i. Cost of Goods Sold / Sales	0.095*	0.099*	0.057	0.096	0.083
	(1.70)	(1.88)	(1.08)	(1.49)	(1.21)
Risk and Volatility Exposures					
j. Volatility of Total Returns	0.032**	0.018	0.019	0.020**	0.019
	(2.46)	(1.01)	(1.60)	(2.03)	(1.53)
k. Volatility of Systematic Returns	0.010**	0.001	0.000	−0.000	−0.008
	(2.12)	(0.10)	(0.04)	(−0.00)	(−1.07)
l. Volatility of Idiosyncratic Returns	0.029**	0.019	0.021*	0.024**	0.028**
	(2.23)	(1.08)	(1.77)	(2.53)	(2.32)
m. Volatility of Operating Profit Margin	0.035	0.012	0.096**	0.241***	0.306***
	(0.91)	(0.28)	(2.50)	(3.06)	(2.95)
Industry-Year FE	✓	✓	✓	✓	✓
Firm FE	✓	✓	✓	✓	✓

Table 8 — Continued

Panel B: Lagged Pollution Intensity (Scaled by Sales) Interacted by IP					
Dependent Variables	$t+1$	$t+2$	$t+3$	$t+4$	$t+5$
Valuation and Scale					
a. Log Market-to-Book Ratio	−0.124	−0.247	−0.842	−1.608**	−2.379***
	(−0.17)	(−0.34)	(−1.22)	(−2.09)	(−3.51)
b. Log Assets	−0.175	−0.670*	−0.930**	−0.919**	−0.753
	(−0.75)	(−1.87)	(−2.31)	(−2.00)	(−1.37)
c. Log Sales	−0.624*	−1.063**	−1.258***	−1.264**	−1.377**
	(−1.79)	(−2.18)	(−2.65)	(−2.50)	(−2.40)
Investment and Operating Policies					
d. Log R&D Expenditures / Assets	0.058	−0.575	−1.242*	−1.318**	−1.547**
	(0.13)	(−0.87)	(−1.81)	(−2.02)	(−2.10)
e. Log CAPEX / Assets	−0.849	−0.761	0.363	0.200	0.339
	(−1.06)	(−1.05)	(0.41)	(0.22)	(0.38)
f. OIBDA / Assets	−0.070	−0.081	−0.135	−0.207*	−0.248**
	(−0.47)	(−0.65)	(−0.98)	(−1.77)	(−2.42)
g. OIBDA / Sales	0.071	−0.054	−0.115	−0.127	−0.106
	(0.54)	(−0.57)	(−1.17)	(−1.21)	(−1.02)
h. Cost of Goods Sold / Assets	−0.844***	−0.781**	−0.827*	−1.004***	−1.231***
	(−2.68)	(−1.99)	(−1.86)	(−2.72)	(−2.83)
i. Cost of Goods Sold / Sales	0.013	0.098	0.021	0.055	0.012
	(0.11)	(1.33)	(0.27)	(0.60)	(0.15)
Risk and Volatility Exposures					
j. Volatility of Total Returns	0.047***	0.022	0.019	0.007	0.002
	(2.78)	(0.93)	(0.99)	(0.44)	(0.10)
k. Volatility of Systematic Returns	0.019***	0.004	0.000	−0.002	−0.023**
	(2.84)	(0.54)	(0.00)	(−0.33)	(−2.29)
l. Volatility of Idiosyncratic Returns	0.041**	0.021	0.019	0.012	0.016
	(2.39)	(0.87)	(1.02)	(0.76)	(0.92)
m. Volatility of Operating Profit Margin	0.078	0.040	0.063	0.252***	0.327***
	(1.04)	(0.57)	(0.92)	(3.39)	(3.00)
Industry-Year FE	✓	✓	✓	✓	✓
Firm FE	✓	✓	✓	✓	✓

Table 9: Import Competition and Firm Performance: Conditioning on Initial Normalized Green Innovation

This table reports firm-level 2SLS estimates of import competition interacted with five-year lagged green innovation on firm performance from $t+1$ to $t+5$. Panel A normalizes green innovation by detailed technology class (6-digit IPC/CPC); Panel B uses broad class (4-digit IPC/CPC). Each cell gives the IP interaction coefficient from equation (5). Specifications include firm and industry-year fixed effects with log assets and firm age controls. Standard errors (in parentheses) are clustered at the 2-digit SIC industry-year level. ***, **, and * denote significance at the 1%, 5%, and 10% levels.

Panel A: Lagged Mean Green Innovation (Normalized by Detailed Technology Class) Interacted by IP

Dependent Variables	$t+1$	$t+2$	$t+3$	$t+4$	$t+5$
Valuation and Scale					
a. Log Market-to-Book Ratio	0.945***	1.062***	1.030***	0.761**	0.581*
	(3.94)	(3.15)	(2.95)	(2.10)	(1.85)
b. Log Assets	0.250***	0.461***	0.653***	0.852***	0.860***
	(3.00)	(3.90)	(3.92)	(4.57)	(4.50)
c. Log Sales	−0.328***	−0.021	0.271	0.654***	0.731***
	(−3.37)	(−0.16)	(1.62)	(3.43)	(3.60)
Investment and Operating Policies					
d. Log R&D Expenditures / Assets	−0.499***	−0.830***	−0.912***	−0.913***	−0.955***
	(−2.98)	(−4.23)	(−3.79)	(−3.37)	(−3.78)
e. Log CAPEX / Assets	0.173	0.269	0.267	0.101	−0.190
	(1.02)	(1.31)	(1.20)	(0.48)	(−0.86)
f. OIBDA / Assets	0.157***	0.249***	0.297***	0.282***	0.245***
	(4.01)	(5.62)	(6.24)	(5.78)	(4.57)
g. OIBDA / Sales	0.238***	0.280***	0.282***	0.298***	0.285***
	(7.48)	(7.88)	(7.38)	(6.83)	(5.63)
h. Cost of Goods Sold / Assets	−0.089	−0.096	−0.055	−0.040	−0.036
	(−1.45)	(−1.49)	(−0.73)	(−0.43)	(−0.39)
i. Cost of Goods Sold / Sales	−1.464***	−1.049***	−0.469	−0.231	−0.229
	(−3.09)	(−2.59)	(−1.13)	(−0.68)	(−0.74)
Risk and Volatility Exposures					
j. Volatility of Total Returns	0.005	0.000	−0.005	−0.008**	−0.009**
	(1.45)	(0.06)	(−1.39)	(−1.98)	(−2.29)
k. Volatility of Systematic Returns	−0.003	−0.000	−0.003	−0.005*	−0.007**
	(−1.13)	(−0.16)	(−0.98)	(−1.76)	(−2.33)
l. Volatility of Idiosyncratic Returns	0.004	−0.002	−0.006**	−0.009**	−0.008**
	(1.20)	(−0.62)	(−2.03)	(−2.37)	(−2.33)
m. Volatility of Operating Profit Margin	−0.609	−0.054	−0.290	−0.643*	−0.423
	(−1.58)	(−0.15)	(−0.79)	(−1.71)	(−1.17)
Industry-Year FE	✓	✓	✓	✓	✓
Firm FE	✓	✓	✓	✓	✓

Table 9 — Continued

Panel B: Lagged Mean Green Innovation (Normalized by Broad Technology Class) Interacted by IP

Dependent Variables	$t+1$	$t+2$	$t+3$	$t+4$	$t+5$
Valuation and Scale					
a. Log Market-to-Book Ratio	1.340**	1.250	0.918	0.180	0.148
	(2.10)	(1.51)	(1.06)	(0.19)	(0.18)
b. Log Assets	0.287	0.464	0.870*	1.219**	1.133**
	(1.22)	(1.36)	(1.93)	(2.38)	(2.08)
c. Log Sales	−0.802***	−0.265	0.020	0.771	0.885
	(−2.67)	(−0.65)	(0.04)	(1.39)	(1.53)
Investment and Operating Policies					
d. Log R&D Expenditures / Assets	−1.880***	−2.524***	−2.659***	−2.673***	−2.750***
	(−4.38)	(−4.84)	(−4.32)	(−3.87)	(−4.07)
e. Log CAPEX / Assets	−0.199	0.072	0.196	−0.237	−0.970*
	(−0.42)	(0.13)	(0.35)	(−0.43)	(−1.65)
f. OIBDA / Assets	0.299***	0.468***	0.578***	0.539***	0.473***
	(2.83)	(4.32)	(5.51)	(5.05)	(4.11)
g. OIBDA / Sales	0.648***	0.744***	0.633***	0.674***	0.640***
	(6.66)	(6.82)	(5.20)	(5.02)	(4.46)
h. Cost of Goods Sold / Assets	−0.198	−0.115	0.094	0.148	0.111
	(−1.26)	(−0.71)	(0.47)	(0.58)	(0.48)
i. Cost of Goods Sold / Sales	−3.976***	−2.690***	−0.901	−0.097	−0.155
	(−3.36)	(−2.69)	(−0.81)	(−0.11)	(−0.18)
Risk and Volatility Exposures					
j. Volatility of Total Returns	0.006	−0.008	−0.018*	−0.016	−0.012
	(0.58)	(−0.78)	(−1.67)	(−1.35)	(−1.08)
k. Volatility of Systematic Returns	−0.015**	−0.012	−0.015*	−0.019**	−0.022***
	(−2.08)	(−1.53)	(−1.74)	(−2.21)	(−2.78)
l. Volatility of Idiosyncratic Returns	0.008	−0.008	−0.018*	−0.014	−0.005
	(0.83)	(−0.83)	(−1.82)	(−1.25)	(−0.55)
m. Volatility of Operating Profit Margin	−2.271**	−0.513	−0.582	−1.321	−1.071
	(−2.10)	(−0.70)	(−0.63)	(−1.42)	(−1.17)
Industry-Year FE	✓	✓	✓	✓	✓
Firm FE	✓	✓	✓	✓	✓

Table 10: Import Competition and Green Innovation Outcomes: Conditioning on Initial Green Innovation Intensity

This table reports firm-level 2SLS regression results for the interaction effects between import competition and lagged average green innovation intensity on subsequent green innovation outcomes from year $t+1$ to $t+5$. The dependent variable is (a) the log number of green patents filed, and (b) the log ratio of green patents to total patents in subsequent years. Panel A shows results for interactions with lagged average green innovation intensity normalized by detailed technology class (6-digit IPC/CPC subclass codes), where each patent is weighted by the inverse of total patents in its specific technology subclass-year. Panel B shows results for interactions with lagged average green innovation intensity normalized by broad technology class (4-digit IPC/CPC main class codes), where each patent is weighted by the inverse of total patents in its broader technology category-year. The interaction terms are constructed using the average normalized green innovation in the previous 5 years before the shock. Each cell reports the coefficient on the interaction term between direct import competition (IP) and the respective lagged normalized green innovation measure. All regressions include firm and industry-year fixed effects and control for log of total assets and firm age. Standard errors, reported in parentheses, are clustered at the 2-digit SIC industry-year level. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Dependent Variables	$t+1$	$t+2$	$t+3$	$t+4$	$t+5$
Panel A: Lagged Mean Green Innovation (Normalized by Detailed Technology Class) Interacted by IP					
a. Log Green Patents	0.294*	0.488***	0.554***	0.523***	0.458***
	(1.92)	(4.36)	(3.87)	(2.99)	(2.83)
b. Log Green Innovation Intensity	0.961	2.056***	2.028***	1.764**	1.523**
	(1.11)	(3.61)	(3.24)	(2.49)	(1.99)
Panel B: Lagged Mean Green Innovation (Normalized by Broad Technology Class) Interacted by IP					
a. Log Green Patents	0.300***	0.368***	0.404***	0.318**	0.205
	(2.75)	(3.23)	(3.35)	(2.32)	(1.32)
b. Log Green Innovation Intensity	2.941**	4.369***	3.696***	2.990**	2.254*
	(2.05)	(3.79)	(3.19)	(2.47)	(1.65)
Industry-Year FE	✓	✓	✓	✓	✓
Firm FE	✓	✓	✓	✓	✓

Table 11: Import Competition and the Strategic Nature of Green Innovation: Exploratory vs. Exploitative

This table reports firm-level 2SLS regression results for the interaction effects between import competition and lagged mean green innovation on subsequent innovation outcomes from year $t+1$ to $t+5$. Patents are classified as exploratory or exploitative based on citation patterns: patents are considered exploitative if at least 80% of their citations reference the firm's pre-existing knowledge base, and exploratory otherwise. Panel A presents results using lagged mean green innovation normalized by detailed technology class (6-digit IPC/CPC subclass codes), while Panel B presents results normalized by broad technology class (4-digit IPC/CPC main class codes). Dependent variables include the log number of exploratory patents, the log number of exploitative patents, and these measures scaled by firm assets. Each cell reports the coefficient on the interaction term between direct import competition (IP) and the respective lagged green innovation measure. All regressions include firm and industry-year fixed effects. Standard errors, reported in parentheses, are clustered at the 2-digit SIC industry-year level. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Dependent Variables	$t+1$	$t+2$	$t+3$	$t+4$	$t+5$
Panel A: Lagged Mean Green Innovation (Normalized by Detailed Technology Class) Interacted by IP					
a. Log Green Exploratory Patents	1.515***	2.111***	1.896***	1.536**	0.920
	(2.67)	(3.18)	(2.91)	(2.57)	(1.27)
b. Log Green Exploitative Patents	3.792***	4.569***	5.157***	5.255***	5.325***
	(6.35)	(5.84)	(6.10)	(5.63)	(5.48)
c. Log Green Exploratory Patents per Assets	−0.073	−0.123**	−0.130**	−0.075	−0.071
	(−1.13)	(−2.13)	(−1.98)	(−0.94)	(−0.82)
d. Log Green Exploitative Patents per Assets	0.094*	0.150**	0.180**	0.193**	0.259***
	(1.72)	(2.39)	(2.52)	(2.18)	(2.65)
Panel B: Lagged Mean Green Innovation (Normalized by Broad Technology Class) Interacted by IP					
a. Log Green Exploratory Patents	1.101	1.610	0.856	0.809	0.203
	(0.93)	(1.02)	(0.52)	(0.50)	(0.11)
b. Log Green Exploitative Patents	8.533***	9.952***	11.078***	10.701***	10.076***
	(5.83)	(5.39)	(6.12)	(5.41)	(4.86)
c. Log Green Exploratory Patents per Assets	−0.535***	−0.656***	−0.652***	−0.455**	−0.386
	(−3.03)	(−4.10)	(−3.72)	(−2.17)	(−1.59)
d. Log Green Exploitative Patents per Assets	−0.074	0.068	0.118	0.079	0.034
	(−0.47)	(0.41)	(0.78)	(0.46)	(0.16)
Industry-Year FE	✓	✓	✓	✓	✓
Firm FE	✓	✓	✓	✓	✓

Table 12: Import Competition and the Nature of Green Innovation: Process vs. Product

This table reports firm-level 2SLS regression results for the interaction effects between import competition and prior green innovation capacity (InitialRecord) on subsequent process and product innovation outcomes from year $t+1$ to $t+5$. InitialRecord is defined as the average number of green patents filed by the firm during the five-year period from $t-5$ to $t-1$, providing a stable measure of a firm's established technological base. Process versus product innovations are classified using the claim-level approach of Bena and Simintzi (2021), which identifies process patents as those containing one or more process-related claims, and product patents as those with none. Panel A presents results with green innovation normalized by detailed technology class (6-digit IPC/CPC subclass codes), while Panel B presents results normalized by broad technology class (4-digit IPC/CPC main class codes). Dependent variables include the log number of process and product patents, as well as their intensities scaled by firm assets. Each cell reports the coefficient on the interaction between import competition (IP) and lagged green innovation capacity. All regressions include firm and industry-year fixed effects. Standard errors, reported in parentheses, are clustered at the 2-digit SIC industry-year level. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Dependent Variables	$t+1$	$t+2$	$t+3$	$t+4$	$t+5$
Panel A: Lagged Mean Green Innovation (Normalized by Detailed Technology Class) Interacted by IP					
a. Log Green Process Patents	4.331***	4.359***	3.964***	3.967***	2.522*
	(7.11)	(7.30)	(6.04)	(6.88)	(1.76)
b. Log Green Product Patents	3.194***	4.082***	4.385***	4.473***	3.177**
	(5.61)	(6.69)	(6.37)	(7.27)	(2.25)
c. Log Green Process Patents per Assets	0.024	0.035	0.037	0.050*	0.025
	(0.60)	(1.07)	(1.22)	(1.83)	(0.75)
d. Log Green Product Patents per Assets	0.022	0.028	0.057**	0.068***	0.066**
	(0.86)	(1.16)	(2.19)	(2.88)	(2.27)
Panel B: Lagged Mean Green Innovation (Normalized by Broad Technology Class) Interacted by IP					
a. Log Green Process Patents	8.892***	8.955***	7.832***	6.885***	2.823
	(6.05)	(5.58)	(4.57)	(4.14)	(0.71)
b. Log Green Product Patents	6.998***	8.727***	9.124***	8.992***	4.838
	(5.25)	(5.83)	(6.00)	(4.59)	(1.16)
c. Log Green Process Patents per Assets	0.104	0.064	0.031	0.048	−0.026
	(1.13)	(0.80)	(0.46)	(0.80)	(−0.39)
d. Log Green Product Patents per Assets	0.077	0.064	0.104*	0.134**	0.097*
	(1.39)	(1.15)	(1.85)	(2.53)	(1.70)
Industry-Year FE	✓	✓	✓	✓	✓
Firm FE	✓	✓	✓	✓	✓