Does Soft Disagreement Matter?

Who, How much, When, and Its Economic Channels

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Abstract

This study investigates whether tonal disagreement in sentiments, a form of soft information, is priced in risk-adjusted stock returns. Leveraging a variety of speaker-level sentiment from earnings call transcripts, we identify four key channels through which tonal disagreement influences pricing: *who* disagree (managers versus analysts), *how much* they disagree (extreme versus moderate), *when* they disagree (early versus late in the call), and *how* investors process the contextual aspects of the disagreement (via credibility and information acquisition costs). We find that managerial disagreement commands a significant positive equity risk premium, particularly when the disagreement is extreme (measured by kurtosis) and occurs early in the call. In contrast, analyst disagreement exhibits a largely insignificant or negative risk premium, suggesting that it enhances the informativeness of the call rather than reflecting fundamental risk. The positive pricing effects are further amplified when information sources are highly credible but costly to process, consistent with the predictions of a Bayesian learning framework developed in this study. We further find that heightened managerial disagreement increases CEO turnover risk and introduces uncertainty in firm governance, factors the market prices as systematic risk. Our findings underscore that soft information influences asset prices through distinct, context-dependent channels, while also driving real economic consequences.

JEL classification: G11, G12, G14
Keywords: Disagreement, textual tone, soft information, earnings call, risk premium

1 Introduction

Financial markets have a remarkable ability to aggregate information through price discovery, a process driven by the swift movement of informed capital decisions. This fundamental mechanism has spurred extensive research into how information shapes investor behavior and market price outcomes. While the literature has traditionally focused on hard information—quantitative data directly tied to firm performance, market values, and capital allocation—our understanding of information's role in financial markets continues to evolve.

Early machine learning research initially reinforced the primacy of hard information. For instance, Gu, Kelly, and Xiu (2020) demonstrated that even shallow learning architectures could effectively predict risk premiums. However, their finding that non-linear models consistently outperform linear return predictions suggests the existence of deeper informational structures that traditional quantitative metrics may not fully capture. While hard information has traditionally dominated financial research, recent studies increasingly highlight the importance of soft information—qualitative data derived from sources such as text, speech, and facial characteristics. Soft information is inherently contextual and requires judgment to interpret (Liberti and Petersen (2019)). In this paper, we examine the extent to which soft information influences market outcomes.

Emerging research provides compelling empirical evidence that soft information significantly impacts financial markets. For instance, the volume of textual news flow explains a substantial portion of stock return jumps (Jeon, McCurdy, and Zhao (2022)), while pessimistic visual sentiment in news photos exhibits strong predictive power during periods of heightened market fear (Obaid and Pukthuanthong (2022)). These findings suggest that extreme forms of soft information can exert considerable pricing effects, sometimes independently and sometimes complementing traditional hard information metrics. However, disentangling the distinct effects of hard and soft information remains a key empirical challenge, as both types frequently co-occur in financial markets.

Earnings conference calls provide a unique and ideal setting to address this identification challenge. During these events, hard information—such as pre-announced earnings numbers—remains constant, while the soft information conveyed through verbal interactions varies considerably. This setting creates a natural experiment where the differential impact of soft information can be isolated and measured. Further, the dynamic nature of earnings calls creates a distinct information environment that extends well beyond quantitative metrics. During these calls, managers and analysts engage in real-time discussions, producing subtle insights through their interactions. The effectiveness of these exchanges varies with conversation tone, timing of disclosures, and speakers' roles, as managers share forward-looking insights while analysts seek clarifications through probing questions. Market participants, in turn, actively process this information flow through sophisticated filters. Investors carefully weigh various aspects of the discussion, from the perceived credibility of speakers to the complexity of the signals being conveyed.

In this study, we focus on disagreement as our central construct, as it remains one of the most elusive and imprecisely measured concepts in finance literature. While the use of analysts' forecast dispersion as a proxy for investor disagreement has a long history, Diether, Malloy, and Scherbina (2002) played a key role in formalizing its application within empirical asset pricing. Since then, a large body of research has relied on forecast dispersion as a measure of disagreement. However, this approach, though convenient, falls short of capturing the sentiment-driven, contextual nature of true disagreement. First, forecast dispersion is a hard-information measure, tied to quantitative expectations rather than the qualitative dimensions of disagreement. Second, it overlooks the dynamic and interactive nature of disagreement, particularly when it unfolds in real-time discussions such as earnings calls. This has led to a persistent empirical tension: disagreement has been linked both to mispricing—suggesting behavioral biases that impede arbitrage—and to a priced risk premium.[1]

By shifting our focus to soft and tonal disagreement in earnings calls, we propose a framework that aligns with the economic intuition behind disagreement and its impact on stock prices. Unlike hard information, which exerts a direct and one-dimensional influence on prices, soft disagreement operates through distinct contextual channels, reflecting the subjective and interpretive nature of sentiments. This contextual nature—where the same statement can carry different implications depending on who speaks, when they speak, and how they speak—naturally lends itself to a Bayesian learning framework. In this setting, hard information, such as pre-announced earnings, serves as the prior belief, while tonal signals from the call drive posterior updates. This framework allows us to disentangle the mechanisms through which disagreement influences asset prices, distinguishing between its generation (managers vs. analysts) and its interpretation by investors. By modeling how disagreement propagates through these channels, we provide new insights into the pricing

[1] The relationship between investor disagreement and stock returns remains debated. Miller (1977) argue that higher disagreement leads to overpricing and lower future returns due to short-sale constraints, a view supported by Diether et al. (2002), Chen, Hong, and Stein (2002), Yu (2011), Park (2005), and Hong and Sraer (2016). Conversely, other studies suggest that greater disagreement drives higher expected returns (Jiang and Sun (2014); Carlin, Longstaff, and Matoba (2014); Doukas, Kim, and Pantzalis (2006)).

dynamics of soft information and its role in financial markets.

We process approximately 11 million conversation paragraphs from earnings conference call transcripts (2006–2020), identifying about 139,600 individual speakers from both management and analyst sides. We calculate speaker-level tonal measures using dictionaries from Loughran and McDonald (2011), Rennekamp, Sethuraman, and Steenhoven (2022), and Comprix, Lopatta, and Tideman (2022). Our measure of tonal disagreement captures both moderate (standard deviation) and extreme (kurtosis) variations in sentiment across speakers.[2] The analysis spans two types of agents (managers and analysts) and five sentiment categories (positive, negative, litigious, uncertain, and forward-looking).

Our empirical analysis reveals that tonal disagreement influences asset prices through distinct soft channels, shaped by the source, degree, timing, and interpretation of disagreement. These findings challenge conventional wisdom and offer fresh perspectives on how soft information is priced in financial markets. First, we show that the pricing impact of soft information depends critically on its source (*Who* disagree). We find that managerial disagreement commands a positive and statistically significant risk premium, while analyst disagreement exhibits an insignificant and often negative risk premium. This stark contrast stems from the differing roles of managers and analysts in earnings calls. Managers share forward-looking views, and their disagreement signals uncertainty about the firm's future states, increasing perceived risk (Doukas et al. (2006); Savor and Wilson (2016)). In contrast, we find that analysts' disagreement, expressed through diverse and probing questions, enhances the informativeness of the call rather than reflecting fundamental risk.[3]

Second, we highlight the importance of the degree of disagreement in determining the managerial risk premium (*How much* they disagree). Using two metrics—standard dispersion (standard deviation of sentiments) and extreme dispersion (kurtosis)—we find that extreme disagreement generates a significantly higher risk premium, both statistically and economically, than moderate disagreement. This finding complements existing research that investors disproportionately focus on extreme news (Koester, Lundholm, and Soliman (2016)) and extends recent evidence on the pricing implications of extreme soft information (Jeon et al. (2022); Obaid and Pukthuanthong

[2]Our analysis focuses on these two moments as they align with our theoretical framework. We exclude skewness as it primarily captures information asymmetry and yields no significant results in our tests.

[3]In the Internet Appendix, we show that analyst disagreement increases both the overall word count and executive contributions during calls, supporting the view that it improves call informativeness.

(2022)).

Third, we examine when disagreement most impacts market pricing by analyzing its timing within earnings calls (*When* they disagree). We find that managerial disagreement in the first half of calls commands a significantly higher risk premium than disagreement in the second half. This timing effect suggests that investors anchor their beliefs on initial management interactions, contrasting with the recency effects documented for hard information (Bhootra and Hur (2013)).

Finally, we show that the managerial risk premium is amplified when investors perceive the information as highly credible but costly to process (*How* do investors interpret disagreement differently). These findings align with our Bayesian learning framework, where the credibility of the information source and its acquisition costs strengthen the positive pricing effects of disagreement.

We conduct a series of robustness tests to validate our findings. First, a beta test on the disagreement factor loadings confirms that only managerial disagreement exhibits significant pricing effects, reinforcing its role as a systematic risk factor. Second, using Fama and MacBeth (1973) regressions, we verify that the disagreement premium holds in the cross-section, with significant alpha estimates supporting its risk-adjusted return relevance. Third, to further assess the risk interpretation, we examine the relationship between disagreement and corporate bond credit spreads (Longstaff, Mithal, and Neis (2005); Nozawa (2017)), finding a positive association that aligns with the notion that managerial disagreement captures priced risk. Fourth, we perform a placebo test at the paragraph level to distinguish between true speaker-level disagreement and random extreme sentiment. While speaker-level disagreement commands a positive risk premium, paragraph-level sentiment does not exhibit a significant pricing effect, underscoring the importance of disagreement rather than extreme sentiment alone. Finally, we verify the robustness of our results using alternative sentiment measures, including Word2Vec (Mikolov, Sutskever, Chen, Corrado, and Dean (2013) and FinBERT (Huang, Wang, and Yang (2023)), both of which yield consistent findings.

Our study makes four key contributions to the literature. First, we advance the investor disagreement literature by shifting the focus from hard-information proxies to soft disagreement. While traditional measures capture quantitative divergence in expectations, we show that soft disagreement—shaped by speaker interactions, sentiment, and context—introduces a distinct pricing channel that carries systematic risk. Unlike forecast dispersion, tonal disagreement conveys subjective differences in tone and interpretation, offering a richer and more layered measure of disagreement.[4]

Second, we reconcile conflicting evidence on the pricing of disagreement through the lens of information source. While existing theories debate whether disagreement leads to mispricing or commands a risk premium, we find that managerial disagreement carries a positive risk premium, whereas analyst disagreement primarily enhances call informativeness.[5] This pricing effect is further amplified by information credibility and processing costs, consistent with the Bayesian learning models developed in our study.

Third, we demonstrate how the structure of tonal disagreement shapes market responses by analyzing both the intensity and timing of disagreement. Our findings on extreme disagreement align with broader evidence that investors react more strongly to extreme events.[6] Further, while studies on hard information document recency bias in investor reactions (Bhootra and Hur (2013)), our evidence suggests that soft information processing follows a different pattern, with investors anchoring their beliefs on initial management interactions (Tversky and Kahneman (1974); George and Hwang (2004)).

Finally, we provide novel insights into how executive team cohesion affects market perceptions of firm risk. Using earnings calls as a window into management interactions, we find that managerial disagreement intensifies CEO and CFOs turnover threat and also affects the systematic variance in topic subjectivity.[7] This finding suggests that markets interpret team discord as leadership uncertainty, pricing it as a significant risk factor. Importantly, our results demonstrate that soft information embedded in management communication offers a real-time lens into team dynamics, with meaningful implications for corporate governance and executive retention outcomes.

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[4]Prior studies have extensively used analyst forecast dispersion to measure investor disagreement. See Diether et al. (2002), Park (2005), Doukas et al. (2006), Yu (2011), and Hong and Sraer (2016). The literature also examines various forms of disagreement, including employee disagreement (Sheng (2024)), voting disagreement among mutual funds (Bena and Wang (2021)), and macroeconomic forecast survey disagreement (Li (2016)).

[5]See Miller (1977), Diether et al. (2002), Chen et al. (2002), and Yu (2011) for arguments linking disagreement to overpricing, and Carlin et al. (2014) and Doukas et al. (2006) for evidence of a positive risk premium.

[6]Prior studies document such overreaction across various contexts, including stock market anomalies (Song, Liu, Yang, Deane, and Datta (2015); Kwon and Tang (2020)), IPO markets (Leone, Rice, Weber, and Willenborg (2013)), and cultural events (Białkowski, Etebari, and Wisniewski (2012)). This consistent pattern of stronger market responses to extremes appears particularly pronounced in our soft information setting.

[7]Prior research shows that executive team dynamics significantly impact firm outcomes (Aggarwal and Samwick (2003); Jiang, Petroni, and Wang (2010)). Our earnings call setting provides unique insights into team cohesion, as both CEOs and CFOs regularly participate in these discussions (Feng, Ge, Luo, and Shevlin (2011); Klevak, Livnat, and Suslava (2024)), revealing how internal dynamics affect market perceptions of firm risk.

2 Theoretical Framework

We develop a parsiminous model to illustrate how *soft disagreement* in earnings calls affects both short-term price dynamics and long-run risk premiums. We build on a Bayesian framework in which investors update beliefs about firm fundamentals after observing (i) *hard information* (e.g., realized earnings) and (ii) *soft information* (e.g., managerial vs. analyst tones). We incorporate multiple *contextual layers*—the *who*, *how much*, *when*, and *credibility/cost* of the disagreement—into a single precision parameter that influences both prices and risk premiums.

2.1 Short-Term Price Formation Under Disagreement

We begin with a simplified version of the partial-equilibrium setting in Huang, Lunawat, and Wang (2024), focusing on the demand and market-clearing mechanism for short-run price formation. Let p_t denote the price at time $t = 2$ (the post-earnings-call window), and θ the underlying firm value. We assume a continuum of risk-averse investors with CARA utility, each facing a random supply shock s_t. Investors observe both hard- and soft-information signals before submitting their demands. Denote:

$$p_2 = a_2 + b_2\,\theta + c_2\,y + d_2\,p_1 - e_2\,s_2, \tag{1}$$

where p_1 is the pre-call price (reflecting the *hard information* prior), y is a public signal of hard earnings, and s_2 is the noise-trader supply. The parameter b_2 captures how strongly the new price reflects *fundamentals*, while c_2 measures the weight on hard-information disclosures. Critically, the sensitivity to *soft disagreement* enters through b_2 (and d_2), as disagreement about future firm states affects the total perceived risk.

Contextual Layers of Soft Disagreement. To capture the multifaceted nature of disagreement, we introduce a *layered* precision term,

$$\beta(\omega) \;=\; \beta_0 \;+\; \sum_{\ell=1}^{L} \Delta_\ell\big(\omega_\ell\big), \tag{2}$$

where β_0 is the *baseline precision* of soft information, and each $\Delta_\ell(\omega_\ell)$ represents a layer-specific adjustment. The vector $\omega = (\omega_1, \omega_2, \ldots, \omega_L)$ indexes *contextual channels* through which tonal signals may gain or lose credibility. In principle, L can be large, reflecting diverse layers such as *(i) Source*, *(ii) Magnitude*, *(iii) Timing*, or *(iv) Credibility/Cost*.

Layer Interpretation. Although the literature suggests many possible dimensions of soft disagreement, we adopt a *top-down* approach by focusing on four key layers that are both theoretically motivated and readily measurable:

- *Source* (Δ_{source}): Distinguishes which participants (managers vs. analysts) generate the disagreement, as managerial tones often signal uncertainty about future states while analysts' tones can enhance overall informativeness.
- *Magnitude* ($\Delta_{\text{magnitude}}$): Differentiates between *extreme* disagreement (e.g., heavy-tailed, high-kurtosis sentiment) and *moderate* disagreement (standard dispersion).
- *Timing* (Δ_{timing}): Accounts for whether disagreement occurs *early* in the call (where investors anchor on initial tone) or *later* in the discussion (potentially subject to recency bias).
- *Credibility/Cost* ($\Delta_{\text{cred/cost}}$): Reflects how signals from more credible sources (e.g., highly reputable managers) and/or information that is costly to process (due to complexity) affect perceived precision.

Each layer contributes an increment or decrement, $\Delta_\ell(\omega_\ell)$, to the overall precision in equation (2), thereby influencing how aggressively investors respond to tonal disagreement. Higher overall precision $\beta(\omega)$ implies that investors place greater weight on the soft-information signals in forming their posterior beliefs, thus leading to more aggressive trading on the observed disagreement. In equilibrium, short-term prices respond accordingly. Formally, returning to the linear pricing rule in (1), the *equilibrium* coefficients (b_2, c_2, d_2, e_2) endogenously adjust to clear the market, reflecting investors' heterogeneous posterior demands. As we show next, these contextual layers also influence long-run risk premiums when disagreement remains systematic.

2.2 Bayesian Updating With Contextual Layers

To formalize the role of soft disagreement, assume that prior to the earnings call, investors hold normally distributed beliefs on $\theta \sim \mathcal{N}(\bar{\theta}, \gamma^{-1})$. Hard information (e.g., realized earnings) arrives publicly, shifting beliefs to:

$$\theta \,|\, y \;\sim\; \mathcal{N}\Big(\mu_0,\, \sigma_0^2\Big).$$

Subsequently, each investor observes *soft signals* (e.g., managerial vs. analyst tones) with precision $\beta(\omega)$. We allow $\beta(\omega)$ to vary by *who* speaks, *how much* they disagree, *when* it occurs in the call, and *how* credibility and cost alter interpretation. Denote the soft-information signal for investor i by $x_i = \theta + \xi_i$, where $\xi_i \sim \mathcal{N}\big(0,\, \beta(\omega)^{-1}\big)$. Bayesian updating yields the posterior distribution:

$$\theta \,|\, y, \{x_i\} \;\sim\; \mathcal{N}\Big(\mu_1,\, \sigma_1^2\Big),$$

where

$$\mu_1 = \frac{\frac{1}{\sigma_0^2}\,\mu_0 \;+\; \beta(\omega)\,\bar{x}}{\frac{1}{\sigma_0^2} \;+\; \beta(\omega)}, \qquad \sigma_1^2 \;=\; \Big[\tfrac{1}{\sigma_0^2} + \beta(\omega)\Big]^{-1}, \tag{3}$$

and $\bar{x}$ is the average soft signal.

Crucially, *larger disagreement* (via higher variance or heavier tails of $\{x_i\}$) reduces the effective precision $\beta(\omega)$, driving up posterior uncertainty σ_1^2. Conversely, signals that are easier to interpret can *raise* $\beta(\omega)$ and lower posterior variance. These shifts feed back into the short-term price through market clearing, as in (1), and ultimately affect the cost of capital (long-term risk premium) if the additional uncertainty is systematic.

2.3 Long-Run Risk Premium and Hypotheses

In the longer run, persistent soft disagreement can become a priced risk factor if it correlates with the stochastic discount factor. Such systematic disagreement components affect marginal utility across states, leading to equilibrium risk premiums that cannot be diversified away. This is particularly relevant when disagreement signals correlate with economy-wide uncertainty or consumption growth volatility. Let r_{t+1} be the stock's realized return from $t = 2$ to $t = 3$ (payoff). If the posterior variance σ_1^2 (driven by disagreement) increases systematic uncertainty about future cash flows or discount rates, investors demand higher expected returns to compensate. Formally, in a one-factor setting with market price of risk λ, the required return includes a premium:

$$\text{Risk Premium} \;=\; \lambda\,\big(\sigma_1^2(\beta(\omega))\big), \tag{4}$$

where σ_1^2 is decreasing in $\beta(\omega)$. Thus, *lower-precision* soft information (i.e., higher disagreement) can amplify σ_1^2, raising required returns. The following hypotheses summarize the model's main predictions:

H1 (Source) *Disagreement among managers commands a positive risk premium, especially when it reflects uncertain future states. In contrast, analyst disagreement may improve information without necessarily increasing systematic risk.*

H2 (Magnitude & Timing) *Disagreement that is more extreme (heavier tails) or occurs earlier in the call (where investors anchor) exerts stronger pricing effects in both short-run price reactions and long-run returns.*

H3 (Credibility & Cost) *When information sources are highly credible but also costly to process, soft disagreement increases posterior variance more acutely, thereby enlarging the risk premium.*

These hypotheses directly connect our *contextual layers* of soft disagreement—*who, how much, when, how*—to asset-pricing outcomes. In the empirical analysis, we test these predictions by constructing speaker-level measures of tonal disagreement (both dispersion and kurtosis) within earnings calls, then relating them to cross-sectional variations in subsequent returns, controlling for hard-information fundamentals.

3 Data, Methodology, and Variable Construction

3.1 Sample

We constructed our sample using earnings conference call transcripts from Capital IQ over the 2006-2020 period. The transcripts' Q&A sections identify distinct executives and analysts participating in each firm-quarter call. We merged this data with Compustat Quarterly and CRSP to obtain firm-level financial and accounting variables. Data for the Fama and French (1995) factors are sourced from Kenneth R. French's website. Executive characteristics—including age, tenure, gender, and position—are obtained from Execucomp for S&P 1,500 firms and matched to our earnings call sample using executive names.[8] We complemented this dataset with analyst-level information from IBES, corporate bond transaction data from TRACE, and macroeconomic variables from FRED. For our cost of equity estimates, we merged IBES analysts' forecast data with CRSP price data following the ICC (Implied Cost of Capital) literature (Claus and Thomas (2001)). To identify founder- and heir-CEOs, we manually extended the founder-CEO datasets used in Fahlenbrach (2009) and Lee and Nanda (2025).[9] Lastly, for company's anti-takeover protection data, we followed the methodology in Bebchuk, Cohen, and Ferrell (2009).

The Q&A section of earnings calls offers distinct advantages over the scripted management presentation by capturing spontaneous and informal interactions (Lee (2016)). Matsumoto, Pronk, and Roelofsen (2011) document that these interactive sessions yield more informative content due to analysts' active participation. While executives' internal discussions remain largely unobservable, Q&A sessions provide a unique window into multiple executives' detailed perspectives about their firms through periodic interactions with external stakeholders. This setting enables us to measure management sentiment by analyzing executives' tone and language choices during their direct exchanges with analysts, revealing diverse viewpoints about firm fundamentals.

The Q&A format also provides a valuable context for measuring analyst sentiment dispersion. Unlike written reports, where analysts may face pressure to moderate critical opinions due to potential adverse consequences (Chen and Matsumoto (2006)), the interactive nature of Q&A sessions facilitates more immediate and unfiltered exchanges. This real-time dialogue often reveals more granular perspectives than those found in formal written analyses.

Our data sampling approach carefully preserves this structural integrity of the Q&A discussions. We analyze the textual content at multiple levels of granularity—sentence by sentence and paragraph by paragraph—following the chronological order of the dialogue. Our comprehensive sample comprises approximately 11 million paragraphs across all earnings calls. We first conducted a detailed textual analysis examining fundamental linguistic features, including word counts, numerical content, and speaker interaction patterns. Following Comprix et al. (2022), we measured various aspects of analyst-executive interactions, such as question directness, follow-up patterns,

[8] We implement fuzzy name-matching using the `stringdist` package in R to account for potential variations in executive name spellings across databases. Regarding further gender completion, in some cases for analysts' gender as well, we use the `gender` package in R. Our matching procedure covers approximately 82,035 unique executives and 57,582 unique analysts over the sample period.

[9] For missing cases, we complement these datasets with information from SEC filings, Bloomberg executive profiles, company websites, and news archives to identify heir-CEOs and verify founder and heir status.

negative questioning techniques, and preface structures. We then extended our analysis to capture semantic content using multiple approaches: the Loughran-McDonald dictionary-based method, Word2Vec embeddings, and the FinBERT language model. We then aggregate these measurements at the firm-quarter level, ensuring that our analysis captures the subtle layers of information embedded in these dynamic exchanges. This methodological precision allows us to extract rich insights from the soft information conveyed through Q&A interactions.

3.2 Measuring Soft Information Disagreement

We empirically define soft information disagreement (SID) for each sentiment category during conference calls as follows:

$$\mathrm{SID}^{g}_{d/\tau} : s \sim \mathcal{G}(S_{i,k,s,j,\tau} | \Omega_{\alpha,\theta}) \tag{5}$$

where g denotes the speaker group (executives or analysts); d represents the dispersion measure (moderate disagreement with standard deviation, σ, or extreme disagreement with kurtosis, κ); τ indicates the timing within the call (early or late); s represents the sentiment category where $s \in \{\mathrm{POS}, \mathrm{NEG}, \mathrm{LIT}, \mathrm{UNC}, \mathrm{FWD}\}$; and $S_{i,k,s,j,t}$ is the sentiment score for firm i, speaker k, sentiment category s, topic j, in quarter t for the call. $\mathcal{G}(\cdot|\Omega_{\alpha,\theta})$ is a grouping function conditional on information environment $\Omega_{\alpha,\theta}$, where α represents information acquisition costs and θ represents source credibility.

3.2.1 Sentiment Measures

We analyze five primary sentiment categories from earnings conference call transcripts: Positive (POS), Negative (NEG), Litigious (LIT), Uncertainty (UNC), and Forward-looking (FWD). For each sentiment category, we construct separate SID measures, denoted as $\mathrm{SID}^{g}_{d/\tau}$: POS, $\mathrm{SID}^{g}_{d/\tau}$: NEG, and so forth. The first four sentiment measures are calculated following Loughran and McDonald (2011), using their financial sentiment dictionaries specifically designed for financial texts. The Forward-looking measure captures future-oriented statements and is calculated following the methodology of Rennekamp et al. (2022).

For each conference call, we compute these sentiment measures at the individual speaker level. For example, if a call includes four executives, we measure each sentiment dimension separately for each executive based on their specific dialogue contributions throughout the call. This speaker-level approach allows us to capture variations in sentiment not only between executives and analysts but also within each group.

Additionally, we include an analyst-specific sentiment measure, Aggressiveness (AGG), following Comprix et al. (2022), denoted as $\text{SID}_{d/\tau}^{ANL}$: AGG. This composite metric encompasses four components: directness, follow-up, negative questions, and preface statements, all of which characterize the probing nature of analyst interactions.

For robustness, we also construct a composite SID measure using principal component analysis across all sentiment categories, denoted as $\text{SID}_{d/\tau}^{g}$: PCA.

3.2.2 Topic Classification

To examine how disagreement varies across discussion topics, we employ the topic dictionary developed by Fengler and Phan (2023). This dictionary identifies eleven prominent topics commonly discussed in financial contexts and uses the Word2Vec model (Mikolov et al. (2013)) to generate keywords for each topic category. We denote these topics as T_j.[10] This allows us to classify the content of each speaker's contribution according to the primary topic being discussed, enabling us to analyze how disagreement patterns vary across different subject matters.

3.2.3 Constructing Soft Information Disagreement Measures

Using the speaker-level sentiment measures, we construct our soft information disagreement (SID) metrics along four key dimensions:

Who disagrees: We calculate separate disagreement measures for executives ($\text{SID}_{d/\tau}^{EXE} : s$) and analysts ($\text{SID}_{d/\tau}^{ANL} : s$) by aggregating sentiment scores within each group. This speaker-group distinction forms the foundation of our analysis, as the source of disagreement fundamentally alters its economic interpretation and pricing implications.

How much they disagree: For both executive and analyst groups, we capture disagreement using two statistical measures that reflect different aspects of sentiment dispersion. The standard deviation measures moderate dispersion ($\text{SID}_{\sigma}^{EXE} : s$ and $\text{SID}_{\sigma}^{ANL} : s$), while kurtosis captures extreme dispersion ($\text{SID}_{\kappa}^{EXE} : s$ and $\text{SID}_{\kappa}^{ANL} : s$). For each firm i in quarter t and sentiment category s, we compute these measures as follows:

[10] The eleven topics included in our analysis are sales, cost, profit, operations, liquidity, investment, financing, litigation, employment, regulation, and accounting.

$$\mathrm{SID}^{g}_{\sigma,i,t} : s = \sqrt{\frac{1}{N^g_i - 1}\sum_{k=1}^{N^g_i}(S_{i,k,s,j,t} - \bar{S}^g_{i,s,j,t})^2} \tag{6}$$

$$\mathrm{SID}^{g}_{\kappa,i,t} : s = \frac{\frac{1}{N^g_i}\sum_{k=1}^{N^g_i}(S_{i,k,s,j,t} - \bar{S}^g_{i,s,j,t})^4}{\left(\frac{1}{N^g_i}\sum_{k=1}^{N^g_i}(S_{i,k,s,j,t} - \bar{S}^g_{i,s,j,t})^2\right)^2} \tag{7}$$

where g represents either EXE (executives) or ANL (analysts), N^g_i is the number of speakers in group g participating in firm i's call, and $\bar{S}^g_{i,s,j,t}$ is the mean sentiment score for that group.[11]

When they disagree: We divide each call into early (τ_E) and late (τ_L) segments, calculating separate disagreement measures for each section, i.e., ($\mathrm{SID}^{EXE}_{\kappa,\tau_E} : s$, $\mathrm{SID}^{EXE}_{\kappa,\tau_L} : s$). This temporal division allows us to test whether the timing of disagreement within the call affects its pricing implications.

How investors interpret disagreement differently: We condition our analysis on two contextual factors that influence information processing: information acquisition costs (α) and source credibility (θ). For each factor, we perform subsample analyses by partitioning our sample into high and low groups:

$$\mathrm{SID}^{g}_{d} : s|\alpha_{\text{High/Low}}, \theta_{\text{High/Low}} \tag{8}$$

This approach allows us to examine how the pricing of executive and analyst disagreement varies with the information environment, providing insights into why investors process soft information disagreement differently across firms.

3.3 Measuring Pricing Effects of Soft Information Disagreement

3.3.1 Measuring Risk Premium

To examine how markets price soft information disagreement (SID), we employ multiple complementary methodologies that capture different aspects of the pricing mechanisms. Our approach encompasses standard factor-based asset pricing tests (CAPM, FF3, FF5), and cross-sectional return analysis (Fama-MacBeth). Additionally, we explore direct measures of risk premiums through

[11] For our main analysis, we disregard the topic dimension j and focus on sentiment disagreement across all topics. We incorporate topic-specific disagreement analysis in our robustness tests in Section ??.

alternative channels, including the implied cost of equity (discount rates) and corporate bond yield spreads (default risk premium).

Formally, we specify the expected return-generating process as:

$$h(\mathbb{E}[R_{i,t+1}]) = \alpha + \gamma_{\text{SID}}\text{SID}_{i,t} + \mathbf{X}'_{i,t}\boldsymbol{\beta} + \delta_{FE} + \epsilon_{i,t+1}, \tag{9}$$

where $h(\cdot)$ represents the transformation implied by the estimation approach, $\mathbf{X}_{i,t}$ includes firm characteristics, and δ_{FE} captures standard fixed effects such as firm, industry, quarter, and year effects.

We estimate Equation (9) under three complementary methodologies:

Factor-Adjusted Long-Short Portfolio Returns To measure the risk premium associated with soft information disagreement, we form decile portfolios by sorting firms in ascending order of $\text{SID}_{i,t}$ from earnings calls that occurred in the previous month. If an earnings call occurs in month t, we use $\text{SID}_{i,t}$ to assign firms into deciles in period $t+1$, ensuring that portfolios are formed only in months following earnings calls. The sorting is conducted within Fama-French 5 industries to control for broader industry-specific factors that may influence our results. Given that most firms hold quarterly earnings calls, portfolios are rebalanced approximately four times per year.

We compute the value-weighted returns for each decile and construct a long-short portfolio by taking a long position in the highest-SID decile and a short position in the lowest-SID decile. The resulting portfolio returns are then adjusted for risk exposures using factor models:

$$R_{\text{LS},t} - R_{f,t} = \alpha_{\text{LS}} + \boldsymbol{\beta}'_{\text{LS}}\mathbf{F}_t + \epsilon_{\text{LS},t}, \tag{10}$$

where $R_{\text{LS},t}$ represents the return on the long-short portfolio, and $\mathbf{F}_t$ includes systematic risk factors. We employ three specifications ($\mathbf{F}_t^{\text{CAPM}}; \mathbf{F}_t^{\text{FF3}};$ and $\mathbf{F}_t^{\text{FF5}}$). The coefficient α_{LS} captures the abnormal return associated with soft information disagreement.[12]

Fama-MacBeth Regressions To test whether SID is systematically priced in the cross-section, we estimate the following sequence of Fama and MacBeth (1973) regressions:

$$R_{i,t+1} = \gamma_{0,t+1} + \gamma_{\text{SID},t+1}\text{SID}_{i,t} + \sum_m \gamma_{m,t+1}\hat{\beta}_{i,m} + \mathbf{Z}'_{i,t}\boldsymbol{\Gamma} + \nu_{i,t+1}, \tag{11}$$

[12]For robustness, we also construct quintile-based long-short portfolios and find that the risk premium remains statistically significant. The results are available upon request.

where factor betas $\hat{\beta}_{i,m}$ are estimated from first-stage time-series regressions of stock returns on standard risk factors. The time-series average $\overline{\gamma}_{\text{SID}}$ from the Fama and MacBeth (1973) regressions tests whether soft information disagreement in month t is associated with a systematic risk premium in the cross-section of stock returns in month $t+1$, controlling for firm characteristics and market factors included in $\mathbf{Z}_{i,t}$. Standard errors are clustered at the firm level.

3.3.2 Implied Cost of Equity

To establish a direct link between soft information disagreement and firms' discount rates, we estimate the implied cost of equity (CoE) using four established models from the accounting and finance literature. Following Claus and Thomas (2001), Gebhardt, Lee, and Swaminathan (2001), Ohlson and Juettner-Nauroth (2005), and Easton (2004), we compute the implied cost of equity as the internal rate of return that equates current stock prices with the present value of expected future cash flows.

For each firm-quarter, we calculate the implied cost of equity using each model and then take the average across all four models to obtain a more robust estimate. The models share a common theoretical foundation while differing in their specific assumptions about growth rates and forecast horizons. For instance, the Claus and Thomas (2001) model assumes clean surplus accounting with a five-year explicit forecast horizon, while the Gebhardt et al. (2001) model incorporates industry-specific mean reversion in profitability. We then examine the relationship between soft information disagreement and the implied cost of equity through panel regressions, controlling for established determinants of expected returns such as firm size, book-to-market ratio, leverage, and profitability.

3.3.3 Credit Spreads

As an additional validation of the risk premium channel, we analyze the relationship between soft information disagreement and corporate bond credit spreads. Using transaction-level data from TRACE, we compute firm-level credit spreads as:

$$CS_{i,t} = y_{i,t} - y^{m}_{TB,t} \tag{12}$$

where $y_{i,t}$ is the yield to maturity for firm i's bonds on date t, and $y^{m}_{TB,t}$ is the yield on a synthetic Treasury bond with the same maturity and coupon rate, constructed following Longstaff et al. (2005) and Nozawa (2017). For firms with multiple bonds, we compute the value-weighted average credit spread across all outstanding issues. This approach allows us to examine whether soft information disagreement affects the pricing of credit risk, providing additional evidence on whether disagreement reflects fundamental risk factors that are priced across different asset classes.

3.4 Measuring Short-term Market Reactions

3.4.1 Abnormal Trading Volume

Based on our Bayesian updating framework, we further examine how soft information disagreement influences abnormal trading volume following earnings calls, using this measure as a proxy for short-term market reactions. Following Pevzner, Xie, and Xin (2015), we measure abnormal trading volume as the ratio of event-period trading activity to normal trading levels. Specifically, for each firm i, we compute abnormal volume (AV_i) as:

$$AV_i = \frac{\frac{1}{2}\sum_{t=0}^{1} \frac{V_{i,t}}{SO_{i,t}}}{\frac{1}{100}\sum_{t=-120}^{-21} \frac{V_{i,t}}{SO_{i,t}}} \tag{13}$$

where $V_{i,t}$ is the number of shares of firm i traded on day t, and $SO_{i,t}$ is the total number of shares outstanding of firm i on day t. The numerator represents the average daily trading volume over the two-day event window [0,1] relative to the earnings call (day 0), while the denominator represents the average daily trading volume over the 100-day estimation window [-120,-21].

This measure captures the abnormal intensity of trading activity triggered by information released during earnings calls, with values greater than 1.0 indicating above-normal trading volume.

3.5 Measuring Real Economic Consequences of Soft Information Disagreement

To investigate whether soft information disagreement has real economic consequences beyond asset pricing effects, we examine its impact on corporate governance outcomes, specifically executive turnover risk. If managerial disagreement reflects underlying tensions within the executive team or signals potential leadership problems, it may increase the likelihood of CEO replacement, representing a tangible economic consequence of discord among firm leadership.

We estimate the relationship between managerial disagreement and CEO turnover using the following logit-regression specification for f:

$$\Pr(\text{CEO\_Turnover}_{i,t+1} = 1) = f(\beta_0 + \beta_{SID}\text{SID}^{EXE}_{\kappa,i,t} + \mathbf{X}'_{i,t}\boldsymbol{\gamma} + \delta_{FE} + \epsilon_{i,t}) \tag{14}$$

where $\text{CEO\_Turnover}_{i,t+1}$ is an indicator variable that equals one if the CEO of firm i is replaced in fiscal year $t+1$, and zero otherwise. The vector $\mathbf{X}_{i,t}$ includes control variables known to affect CEO turnover probability, and δ_{FE} represent firm and year-quarter fixed effects, respectively.[13]

A positive and significant coefficient on β_{SID} would indicate that higher managerial disagreement increases CEO turnover probability, suggesting that soft information disagreement has real governance implications.

3.6 Control Variables

We control for firm characteristics and risk factors that predict returns and influence firm risk.[14] To account for firm size and value effects, we include market capitalization and the market-to-book ratio. Profitability is controlled for using return on assets, financial risk is proxied by leverage, and growth opportunities are measured through R&D intensity. Systematic risk exposure is accounted for with market beta, and return persistence is controlled for using momentum. For implied cost of equity regressions, we include additional controls related to the information environment, such as analyst coverage and earnings forecast dispersion, as well as growth expectations through long-term analyst forecasts.

In the CEO turnover prediction models, we include controls addressing several dimensions that influence leadership change decisions. We control for firm performance and valuation metrics, as poor performance often drives forced CEO departures. We account for CEO-specific attributes such as power within the organization, proximity to retirement age, and tenure length. Our models also incorporate information environment factors, including earnings surprises, forecast accuracy, and analyst coverage. All specifications include industry or firm and year-quarter fixed effects to account for unobserved time-invariant firm characteristics and macroeconomic conditions that might affect turnover decisions.

[13] To complement our CEO turnover analysis as robustness tests, we also examine whether managerial disagreement affects other corporate outcomes such as CFO turnover, strategic decision-making (measured through changes in investment and financing policies), and organizational restructuring events.

[14] For complete variable definitions for our overall sections and measurement details, see Appendix A.

4 Empirical Results

4.1 Summary Statistics

Table 1 presents summary statistics for our soft information disagreement (SID) measures and control variables. Panel A reveals that earnings calls feature an average of 3.3 executives and 6.6 analysts, providing a rich environment to examine tonal disagreement across different information sources within the same event.

[Insert Table 1 here]

A particularly noteworthy finding is the systematic difference in persistence (ρ) between executive and analyst disagreement measures. Executive disagreement exhibits significantly higher autocorrelation coefficients across all sentiment categories, suggesting that managerial disagreement reflects persistent uncertainty about firm fundamentals. For instance, $\text{SID}_{\kappa}^{EXE}$: POS and $\text{SID}_{\kappa}^{EXE}$: NEG both show persistence coefficients of 0.286, while the corresponding analyst measures ($\text{SID}_{\kappa}^{ANL}$: POS and $\text{SID}_{\kappa}^{ANL}$: NEG) exhibit much lower persistence (0.049 and 0.064, respectively). This distinction in persistence patterns aligns with our theoretical framework, where executive disagreement commands a risk premium while analyst disagreement enhances call informativeness.

The persistence differential is particularly pronounced for forward-looking sentiment, where executive extreme disagreement ($\text{SID}_{\kappa}^{EXE}$: FWD) shows the highest persistence (0.311) among all sentiment categories. This finding suggests that disagreement about future prospects is especially difficult to resolve, consistent with our risk-based interpretation. In contrast, analyst forward-looking disagreement ($\text{SID}_{\kappa}^{ANL}$: FWD) exhibits low persistence (0.056), indicating that it primarily reflects transitory information-gathering rather than fundamental uncertainty.

Table 2 examines how executive disagreement influences analyst disagreement during earnings calls. The regressions use analyst SID measures as dependent variables and executive SID measures as independent variables, controlling for firm characteristics and fixed effects. This specification allows us to test whether management's tonal disagreement systematically affects how analysts respond during the same call. We find strong evidence that executive sentiment disagreement predicts analyst sentiment disagreement across all categories. We observe significant positive correlations across all sentiment categories with varying economic magnitudes. For moderate disagreement (standard deviation measures), Column (1) shows that executive positive sentiment disagreement

($\text{SID}_{\sigma}^{EXE}$: POS) significantly predicts analyst positive sentiment disagreement ($\text{SID}_{\sigma}^{ANL}$: POS). Similarly, Column (6) reveals that extreme disagreement (kurtosis) in positive sentiment among executives ($\text{SID}_{\kappa}^{EXE}$: POS) is significantly associated with the corresponding analyst measure ($\text{SID}_{\kappa}^{ANL}$: POS) with a coefficient of 0.06136 (t-statistic = 3.15).

[Insert Table 2 here]

The coefficient magnitudes vary meaningfully across sentiment categories. The strongest associations appear in litigious and uncertain sentiment categories, i.e., $\text{SID}_{\kappa}^{EXE}$: LIT with the largest coefficient of 0.15361 and t-statistic 4.09, and $\text{SID}_{\kappa}^{EXE}$: UNC with the coefficient of 0.09261 and t-statistic 4.63. These stronger effects for litigious and uncertainty sentiments suggest that legal and ambiguity concerns expressed by management particularly influence analyst questioning patterns. The explanatory power of these relationships also differs markedly across sentiment types. The specifications examining extreme disagreement (kurtosis) generally show higher adjusted R-squared values (ranging from 0.13 to 0.33) compared to those for moderate disagreement (standard deviation, ranging from 0.01 to 0.03).

These positive associations reflect the interactive nature of earnings calls, where sentiment expressions influence participants across roles. The correlation between executive and analyst disagreement suggests a dynamic feedback loop, where analyst questions may elicit diverse responses from management, and management's varied tones may prompt different lines of inquiry from analysts. However, despite these contemporaneous correlations, our subsequent analyses will demonstrate that executive and analyst disagreement exhibit fundamentally different pricing implications. This distinction underscores the contextual nature of soft information, where the source of disagreement—rather than merely its existence—determines its systematic risk implications.

4.2 Distinct Nature of Executive and Analyst Disagreement

To further explore the fundamental differences between executive and analyst disagreement, we examine how soft disagreement measures relate to firm characteristics. Figure 1 plots firm characteristics across quintile portfolios formed based on SID_{κ}, separately for executives (Panel B) and analysts (Panel A).

[Insert Figure 1 here]

The patterns revealed in Figure 1 provide striking evidence that executive and analyst disagreement capture fundamentally different information. Analyst sentiment dispersion (Panel A) exhibits strong monotonic relationships with firm characteristics. As analyst disagreement increases across quintiles, we observe a steady increase in market capitalization, profitability measures (both gross and operating margins), and capital intensity, alongside a consistent decrease in book-to-market ratios. These systematic patterns suggest that analyst disagreement largely reflects observable firm fundamentals and follows predictable patterns across the cross-section of firms.

In contrast, executive sentiment dispersion (Panel B) displays non-monotonic, often U-shaped or inverted U-shaped relationships with firm characteristics. The non-linear relationship between executive disagreement and firm characteristics helps explain why it represents a priced risk factor. The disruptive pattern in Q3 suggests that moderate levels of executive disagreement signal substantive uncertainties about firm prospects that are not fully reflected in standard financial metrics. This finding aligns with our theoretical framework, where executive disagreement reflects genuine uncertainty about future firm states rather than simply correlating with observable firm attributes.

Additionally, the sentiment-specific patterns further distinguish the two sources of disagreement. For executives, forward-looking sentiment dispersion (green line) typically shows the most pronounced non-monotonic pattern, particularly in capital intensity and book-to-market panels. This suggests that disagreement about future prospects—rather than current conditions—drives the distinctive executive patterns. In contrast, analyst sentiment measures (positive, negative, and forward-looking) exhibit largely parallel trends across firm characteristics, suggesting they capture similar underlying information.

These patterns complement our earlier findings on persistence differences. Executive disagreement not only persists longer but also relates to firm characteristics in ways that cannot be easily explained by standard risk factors. Analyst disagreement, meanwhile, shows both lower persistence and predictable relationships with firm fundamentals. Together, these findings provide compelling evidence that executive and analyst disagreement represent distinct information types—the former capturing fundamental uncertainty that commands a risk premium, and the latter reflecting information-gathering processes that enhance call informativeness.

4.3 Who Disagree: Executive versus Analyst Disagreement

To identify the economic significance of soft information disagreement (SID) as a risk factor, we sort firms into deciles at each time $t + 1$ based on the disagreement measures from earnings calls at time t. We rebalance portfolios with the same periodicity as earnings calls rather than monthly to avoid using stale information. We then form long-short portfolios that are long on the tenth decile and short on the first decile. The risk-adjusted returns from these portfolios reveal significant differences in how markets price disagreement based on its source.

[Insert Table 3 here]

Panel A of Table 3 shows that executive extreme disagreement ($\text{SID}_{\kappa}^{\text{EXE}}$) commands a significant positive risk premium across all sentiment categories. The five-factor alpha for positive sentiment extreme disagreement ($\text{SID}_{\kappa}^{\text{EXE}}$: POS) is 7.20% per annum (t-statistic = 1.78). Similarly, negative sentiment extreme disagreement ($\text{SID}_{\kappa}^{\text{EXE}}$: NEG) yields 7.68% ($t$-statistic = 1.70). The magnitudes remain economically and statistically significant across uncertainty, litigious, and forward-looking sentiments, with five-factor alphas ranging from 7.80% to 8.76% annually. Notably, uncertainty and forward-looking sentiment disagreement among executives ($\text{SID}_{\kappa}^{\text{EXE}}$: UNC and $\text{SID}_{\kappa}^{\text{EXE}}$: FWD) show the strongest effects, with alphas of 8.76% and 7.80% and t-statistics of 2.15 and 2.16, respectively.

In stark contrast, analyst extreme disagreement ($\text{SID}_{\kappa}^{\text{ANL}}$) exhibits either significantly negative or statistically insignificant pricing effects. For positive and negative sentiment categories, analyst disagreement is associated with negative five-factor alphas of -11.16% (t-statistic = -2.65) and -8.76% (t-statistic = -2.35), respectively. The analyst aggregate measure ($\text{SID}_{\kappa}^{\text{ANL}}$: AGG) also shows a negative premium of -8.28% (t-statistic = -2.02). For other sentiment categories (litigious, uncertainty, and forward-looking), analyst disagreement yields statistically insignificant alphas ranging from 0.00% to -2.88%.

This source-dependent pricing pattern aligns with our theoretical framework, where the role of the speaker critically determines how disagreement is priced. Executive disagreement reflects genuine uncertainty about future firm states, consistent with the findings of Doukas et al. (2006) and Savor and Wilson (2016), who document that fundamental uncertainty commands a risk premium. When multiple executives express divergent views about a firm's prospects, investors recognize this as a signal of heightened uncertainty, consistent with the notion that managerial disagreement reveals potentially systematic uncertainty about firm fundamentals.

Conversely, analyst disagreement appears to enhance the informativeness of the call rather than reflect fundamental risk. This finding echoes research by Huang, Liu, Wu, and Yang (2022), who show that analyst skepticism during calls predicts near-term returns. The negative alphas associated with analyst disagreement suggest that when analysts express diverse viewpoints, they effectively extract more information from management, reducing information asymmetry. This interpretation aligns with Comprix et al. (2022), who find that analyst aggressiveness during calls influences information flow and market responses. Supporting this interpretation, we document in the Internet Appendix a positive relationship between analyst disagreement and the volume of words spoken by executives during conference calls, suggesting that higher analyst disagreement leads to more comprehensive information disclosure.

Our results help reconcile the conflicting evidence on disagreement pricing in the literature. While some studies suggest that disagreement leads to overpricing and lower future returns (Diether et al. (2002); Yu (2011)), others find positive risk premiums (Carlin et al. (2014); Doukas et al. (2006)). Our findings suggest that these seemingly contradictory results may reflect differences in the sources of disagreement being measured.

4.4 How Much They Disagree: Moderate versus Extreme Disagreement

We next analyze how the magnitude of disagreement affects its pricing implications by comparing moderate disagreement (SID_{σ}^{g}) with extreme disagreement (SID_{κ}^{g}). Panels A and B of Table 3 reveal that extreme disagreement generally commands higher risk premiums than moderate disagreement, particularly among executives.

For executives, extreme disagreement measures ($\text{SID}_{\kappa}^{\text{EXE}}$) consistently generate significant positive alphas across all sentiment categories, as discussed earlier. In contrast, moderate disagreement measures ($\text{SID}_{\sigma}^{\text{EXE}}$) produce weaker and often insignificant pricing effects. For positive and negative sentiments, executive moderate disagreement yields insignificant five-factor alphas of 3.96% (t-statistic = 1.00) and 0.12% (t-statistic = 0.03), respectively. Only uncertainty and forward-looking sentiment disagreement show statistical significance, with five-factor alphas of 7.08% (t-statistic = 2.02) and 6.72% (t-statistic = 1.54), respectively.

This disparity in statistical and economic significance between extreme and moderate disagreement is consistent across all risk models (CAPM, FF3, and FF5). Under CAPM, for instance, executive extreme disagreement measures yield risk premiums ranging from 7.44% to 9.36% with t-statistics between 1.87 and 2.36, while moderate disagreement measures show weaker premiums ranging from 1.08% to 8.76% with many t-statistics below conventional significance thresholds.

For analysts, both extreme and moderate disagreement measures generally show negative or insignificant pricing effects. The stronger negative alphas for extreme analyst disagreement ($\text{SID}_{\kappa}^{\text{ANL}}$)

suggest that pronounced disagreement among analysts is particularly effective at reducing information asymmetry. Under the FF5 model, extreme analyst disagreement in positive and negative sentiment categories yields significant negative alphas of -11.16% and -8.76%, while moderate disagreement measures show weaker and insignificant negative alphas.

The stronger pricing of extreme versus moderate disagreement supports theoretical models where tail events drive risk premiums. As Harvey and Siddique (2000) suggest, investors generally dislike extreme patterns, which should be compensated with higher returns. Our findings are consistent with Song et al. (2015), Kwon and Tang (2020), and Koester et al. (2016), who document that investors give greater preference to tail events and extreme news. As Jia, Shen, and Zhang (2022) and Filip and Pochea (2023) note, extreme investor sentiments can have disproportionate pricing effects.

These results suggest that investors respond more strongly to extreme disagreement, particularly when it comes from executives. The kurtosis-based measure captures these tail scenarios where opinions diverge dramatically, which appears to be a more economically significant signal of fundamental uncertainty than standard dispersion. This finding extends recent research on the pricing of extreme soft information by demonstrating that both the source (*who*) and magnitude (*how much*) of disagreement jointly determine its pricing implications.

4.5 Short-Term Market Outcomes: Trading Volume Response to Disagreement

To further distinguish between risk-based and differences-of-opinion explanations for soft information disagreement, we examine trading volume responses around earnings calls. If executive disagreement reflects fundamental risk while analyst disagreement captures differences of opinion, we would expect to see distinct patterns in trading activity. This analysis provides a critical test of our framework, as theory suggests that disagreement-driven trading should lead to higher volume (Huang et al. (2024)). Additionally, we predict that higher information acquisition costs lead to lower trading volume due to reduced information processing. If executive soft information is indeed costlier to acquire than analyst information, we should observe differential volume responses to $\text{SID}_{\sigma}^{\text{EXE}}$ and $\text{SID}_{\kappa}^{\text{EXE}}$ versus $\text{SID}_{\sigma}^{\text{ANL}}$ and $\text{SID}_{\kappa}^{\text{ANL}}$.

[Insert Table 4 here]

Following Pevzner et al. (2015), we measure abnormal volume as the ratio of average trading volume during $[t, t+1]$ to $[t-21, t-120]$, where t is the earnings call date. Table 4 presents strong evidence supporting our framework's predictions. Executive disagreement ($\text{SID}_{\sigma}^{\text{EXE}}$ and $\text{SID}_{\kappa}^{\text{EXE}}$) exhibits predominantly negative and often insignificant associations with abnormal volume. For extreme disagreement measures ($\text{SID}_{\kappa}^{\text{EXE}}$), the coefficients for positive, negative, and forward-looking sentiment are -0.024, -0.027, and -0.027, respectively, with t-statistics of -1.86, -1.86, and -2.04. This muted or negative volume response aligns with our prediction that higher acquisition costs for executive information lead to less active information processing and trading.

In contrast, analyst extreme disagreement ($\text{SID}_{\kappa}^{\text{ANL}}$) consistently shows positive and highly significant associations with abnormal volume across all sentiment categories. The coefficients range from 0.014 to 0.028, with t-statistics consistently above 3.40. This consistency is particularly striking for uncertainty-related signals, where a one-unit increase in uncertainty kurtosis leads to a 0.022 increase in abnormal volume (t-statistic = 6.01), suggesting that extreme disagreement about uncertain aspects of firm performance drives trading activity. For moderate analyst disagreement ($\text{SID}_{\sigma}^{\text{ANL}}$), the results are more mixed, with significant negative coefficients for positive, litigious, and forward-looking sentiments.

These divergent volume responses align with theoretical models of disagreement and trading behavior. The negative volume response to executive disagreement suggests that investors perceive managerial discord as a signal of fundamental risk requiring greater information processing, leading to more cautious trading behavior. This interpretation is consistent with Hong and Sraer (2016), who find that when disagreement stems from fundamental uncertainty, some investors may withdraw from the market, reducing trading activity.

Conversely, the positive volume response to analyst extreme disagreement supports the view that it reflects differences of opinion rather than fundamental risk. This finding aligns with Kandel and Pearson (1995) and Atmaz and Basak (2018), who document that disagreement arising from heterogeneous interpretations of public information leads to increased trading volume. The particularly strong response to analyst uncertainty disagreement suggests that when analysts disagree about uncertain aspects of firm performance, it stimulates rather than deters trading.

These findings support our theoretical framework in two ways. First, they validate our assumption that executive information carries higher acquisition costs, as evidenced by the decreased volume response to $\text{SID}_{\sigma}^{\text{EXE}}$ and $\text{SID}_{\kappa}^{\text{EXE}}$. As Merton et al. (1987) and Easley and O'Hara (1992) argue, higher information acquisition costs typically lead to reduced trading activity as fewer investors process the costly information. Second, they suggest that analyst disagreement primarily reflects differences of opinion rather than fundamental risk, consistent with the findings of Diether et al. (2002) that diversity in opinions leads to return reversals under limits to arbitrage and Huang et al. (2024) that investor disagreement drives abnormal trading volume.

The stark contrast between executive and analyst effects on trading volume provides compelling evidence that these two sources of soft information disagreement operate through distinct economic channels—the former reflecting costly-to-process fundamental risk and the latter capturing differences of opinion that stimulate trading. These findings further validate our theoretical framework's prediction that the source of disagreement fundamentally alters its market impact.

4.6 When They Disagree: Temporal Patterns in Soft Information Disagreement

The timing of disagreement during earnings calls may significantly affect how investors process and price this information. To explore this dimension, we first examine temporal patterns in sentiment generation throughout conference calls, then analyze how disagreement at different stages affects risk premiums.

[Insert Figure 2 here]

[Insert Figure 3 here]

Figures 2 and 3 reveal distinctive temporal patterns in sentiment expression during earnings calls. We analyze these patterns using FinBERT (Huang et al. (2023)), a financial domain-specific BERT model, to quantify sentence-level sentiment across 30 normalized intervals within each call.

Panel A of Figure 2 shows that aggregate net sentiment across all participants follows a distinct U-shaped pattern, with strongly positive sentiment at the beginning of the call, a steady decline toward the middle, and a resurgence toward the end. Panel B, which separates executive and analyst sentiments, reveals that this pattern is primarily driven by executives, whose net sentiment exhibits a pronounced U-shape, while analyst sentiment remains relatively flat and near zero throughout the call.

The pattern in sentence volume shown in Figure 3 provides additional context. Panel C shows that the total number of sentences peaks early in the call before steadily declining, with a notable concentration of both positive and neutral statements in the initial segments. Panel D demonstrates that executives dominate the early discussion with substantially more sentences than analysts, consistent with the standard structure of earnings calls where management delivers prepared remarks before the Q&A session begins.

These temporal patterns suggest that earnings calls follow a predictable information flow: executives begin with prepared statements that contain highly positive sentiment, followed by more neutral Q&A interactions, and concluding with relatively positive closing remarks. This structure creates a natural experiment to examine how investors respond to disagreement at different stages of the information flow.

According to Tversky and Kahneman (1974) and George and Hwang (2004), investors exhibit anchoring bias, wherein they place disproportionate weight on initial information and under-react to subsequent news. In contrast, Bhootra and Hur (2013) proposes that investors display recency bias, giving greater weight to more recent information. Hao, Chu, Ho, and Ko (2016) find mixed evidence for these biases in Taiwanese markets.

To test for these biases, we divide each conference call into two halves: the first and second halves, defined by whether the text speech occurs before or after the median value of *componentorder*, a variable from the CapitalIQ transcripts database that indicates the chronological sequence of dialogues. We calculate $\text{SID}_{\kappa}^{\text{EXE}}$ for each half and measure its associated risk premium. If anchoring bias dominates, executive disagreement during the first half—when investors are processing the call with a fresh mind—should have a greater impact than disagreement during the second half, when investors may already be overwhelmed by information. Conversely, if recency bias dominates, disagreement during the second half should have a greater influence.

[Insert Table 5 here]

Table 5 reveals that executive disagreement in the first half of earnings calls generally commands a higher risk premium than disagreement in the second half. For positive sentiment extreme disagreement ($\text{SID}_{\kappa}^{\text{EXE}}$: POS), the CAPM alpha is 7.44% (t-statistic = 1.93) for the first half versus 5.16% (t-statistic = 1.50) for the second half. This pattern is even more pronounced for litigious sentiment, where first-half disagreement yields a 10.68% premium (t-statistic = 2.77) compared to just 4.32% (t-statistic = 1.59) for second-half disagreement. Similarly, uncertainty sentiment disagreement shows a marked difference: 7.32% (t-statistic = 1.83) for the first half versus 3.24% (t-statistic = 0.70) for the second half.

Our findings suggest that anchoring bias dominates investor actions. Across most model specifications and sentiment categories, the risk premium for $\text{SID}_{\kappa}^{\text{EXE}}$ is statistically and economically higher in the first half of the call. The only exception appears in negative sentiment, where second-half disagreement shows a slightly stronger premium (6.48%, t-statistic = 1.87) than first-half disagreement (5.40%, t-statistic = 1.53). This exception aligns with findings by Tetlock (2007) that negative information later in news reports carries heightened salience for investors, particularly when it contradicts earlier positive narratives.

These timing effects contrast with the recency bias documented for hard information (Bhootra and Hur (2013)), suggesting that the processing of soft information follows different cognitive patterns. When executives exhibit disagreement early in the call—during prepared remarks and initial Q&A exchanges—it appears to create a stronger signal of fundamental uncertainty than similar disagreement later in the call. This finding complements our earlier results on the differential pricing of executive versus analyst disagreement, indicating that both the source and timing of disagreement critically determine its market impact.

4.7 How Investors Process Disagreement: Credibility and Acquisition Costs

We hypothesize that if executive soft information disagreement is being priced, it should command a higher premium during periods when such information is considered more credible and when the cost of information acquisition is high. To test this prediction, we perform subsample analysis comparing the risk premium of long-short decile portfolios sorted on $\mathrm{SID}_{\kappa}^{\mathrm{EXE}}$ under varying conditions of information credibility and acquisition costs.

We examine three proxies of firm information credibility: governance quality (measured by e-index following Bebchuk et al. (2009)), size, and firms with family-CEOs (founders and heirs). We expect firms with high governance quality, large size, and non-family CEOs to provide more credible signals. These firms are expected to be more transparent in their disclosures and communications to outsiders. As pointed out by Ashbaugh-Skaife, Collins, and LaFond (2006) and Ravi and Hong (2014), by limiting their opportunistic behavior, executives of high governance quality firms can reduce information asymmetry between the firm and its external stakeholders. Further, Bhushan (1989) empirically demonstrates that firm size is positively associated with analyst following, which facilitates improved information availability and transmission to investors. Lastly, Anderson, Duru, and Reeb (2009) highlight that founder and heir-controlled firms show higher corporate opacity in terms of disclosure quality and low stock liquidity compared to professionally-led firms.

[Insert Table 6 here]

Consistent with our hypothesis, Table 6 Panel A shows that the risk premium for $\mathrm{SID}_{\kappa}^{\mathrm{EXE}}$ is concentrated in firms with high governance, larger size, and non-family CEOs. Columns (1) and

(2) indicate that for firms with high governance quality (*High Gov*), $\text{SID}_{\kappa}^{\text{EXE}}$: POS, $\text{SID}_{\kappa}^{\text{EXE}}$: NEG, $\text{SID}_{\kappa}^{\text{EXE}}$: LIT, $\text{SID}_{\kappa}^{\text{EXE}}$: UNC, and $\text{SID}_{\kappa}^{\text{EXE}}$: FWD exhibit statistically and economically significant risk premiums of 18.84%, 18.72%, 14.52%, 14.52%, and 16.44%, respectively, with robust t-values of 4.34, 4.29, 3.30, 3.21, and 3.44. In contrast, firms with low governance quality (*Low Gov*) show no significant risk premiums for any measure of $\text{SID}_{\kappa}^{\text{EXE}}$.

A similar pattern emerges from columns (3) and (4), which compare firms with high size (*High Size*) and low size (*Low Size*). For high-size firms, risk premiums for $\text{SID}_{\kappa}^{\text{EXE}}$: POS and $\text{SID}_{\kappa}^{\text{EXE}}$: NEG are 15.00% and 14.88%, both significant at the 1% level, whereas the corresponding risk premiums for low-size firms are negative and largely statistically insignificant. Finally, the executive disagreement risk premium is predominantly concentrated in non-family owned firms (*Non-family*). For instance, $\text{SID}_{\kappa}^{\text{EXE}}$: POS and $\text{SID}_{\kappa}^{\text{EXE}}$: NEG risk premiums for non-family firms are 9.96% and 6.72%, with t-values of 2.41 and 1.71, respectively, while the corresponding results for family-owned firms are economically and statistically insignificant. These findings underscore that credible signals provide more reliable information to investors and thus have a positive impact on the disagreement risk premium.

Table 6 Panel B presents subsample results for the cost of information acquisition, using two proxies: CEOs' equity-based compensation and firm-periods following shareholder class-action lawsuits. Higher equity-based compensation ties CEOs' wealth to stock price, which could lead to reduced transparency in order to boost stock price (Bergstresser and Philippon (2006); Burns and Kedia (2006)). Consequently, investors may have more difficulty obtaining complete information about firms led by managers with higher levels of equity-based compensation.

In addition, after a shareholder lawsuit, executives are expected to be more cautious in their statements and behavior, increasing the cost of acquiring information from managers. Following our hypothesis that higher acquisition costs should raise the risk premium, both these factors should, in turn, amplify the disagreement risk premium. These predictions are supported by the results in Table 6 Panel B. Columns (1) and (2) compare risk premiums in the high (*High Equity*) and low (*Low Equity*) equity-based compensation subsamples. Risk premiums are notably higher in the *High Equity* subsample, with $\text{SID}_{\kappa}^{\text{EXE}}$: POS, $\text{SID}_{\kappa}^{\text{EXE}}$: NEG, $\text{SID}_{\kappa}^{\text{EXE}}$: LIT, $\text{SID}_{\kappa}^{\text{EXE}}$: UNC, and $\text{SID}_{\kappa}^{\text{EXE}}$: FWD showing risk premiums of 6.48%, 7.68%, 7.08%, 5.64%, and 7.68%, respectively, with t-values of 1.51, 1.82, 1.95, 1.44, and 2.09. In contrast, the corresponding risk premiums in the *Low Equity* subsample are economically and statistically much lower.

A similar conclusion emerges from columns (3) and (4), which compare risk premiums in the period following a shareholder lawsuit (*Post-lawsuit*) and the period preceding it (*Pre-lawsuit*). The risk premium for executive disagreement is significantly higher in the post-lawsuit period, supporting our hypothesis that higher costs of information acquisition lead to higher disagreement risk premiums.

These findings align with rational asset pricing models where information frictions amplify risk premiums (Grossman and Stiglitz (1980); Verrecchia (1982)). When soft information is both credible and costly to process, investors require higher compensation for bearing the risk associated with executive disagreement. This result is consistent with our layered precision model where contextual factors—specifically information credibility and acquisition costs—modify the impact of soft disagreement on asset prices.

5 Economic Channels for Soft Information Risk Premium

5.1 Correlation with Macroeconomic Factors

After establishing that soft information disagreement commands a significant risk premium, we now investigate the economic sources of this premium. If executive disagreement represents a systematic risk factor, it should correlate with macroeconomic conditions in ways consistent with rational asset pricing theory (Chen, Roll, and Ross (1986)). To examine this relationship, we conduct time-series tests relating soft information disagreement to macroeconomic indicators. We aggregate $\mathrm{SID}_{\kappa}^{g}$ measures by taking the panel mean for each quarter, then regress these aggregate disagreement measures on quarterly macroeconomic factors. Our analysis includes Real GDP Growth from FRED, Service Personal Consumption Expenditure (SPCE) from the BEA, and Gross Output Growth from Fernald (2014).

[Insert Table 7 here]

Table 7 presents the results of these time-series regressions. Consistent with our theoretical framework, we find that executive extreme disagreement ($\mathrm{SID}_{\kappa}^{\mathrm{EXE}}$) exhibits a statistically significant pro-cyclical relationship with macroeconomic factors, while analyst extreme disagreement ($\mathrm{SID}_{\kappa}^{\mathrm{ANL}}$) shows predominantly counter-cyclical and insignificant associations.

For executive disagreement, several coefficients are statistically significant and economically meaningful. For example, positive sentiment extreme disagreement ($\mathrm{SID}_{\kappa}^{\mathrm{EXE}}$: POS) is significantly positively related to SPCE, RGDP, and GO, with coefficients of 95.79, 55.06, and 18.34, respectively (t-statistics of 1.82, 1.26, and 1.76). This pattern extends to other sentiment categories, with particularly strong relationships for uncertainty sentiment ($\text{SID}_{\kappa}^{\text{EXE}}$: UNC) and forward-looking sentiment ($\text{SID}_{\kappa}^{\text{EXE}}$: FWD). The latter shows the strongest associations, with coefficients of 134.88, 81.13, and 20.80 for SPCE, RGDP, and GO, respectively (t-statistics of 2.69, 1.92, and 2.07).

In contrast, analyst disagreement ($\text{SID}_{\kappa}^{\text{ANL}}$) generally exhibits negative or insignificant relationships with macroeconomic variables. For instance, positive sentiment analyst disagreement ($\text{SID}_{\kappa}^{\text{ANL}}$: POS) shows negative coefficients across SPCE, RGDP, and GO (-1.63, -1.62, and -0.085), though these relationships lack statistical significance.

These cyclical patterns align with our earlier findings on the pricing of executive versus analyst disagreement. Since pro-cyclical risk factors are typically associated with positive risk premiums while counter-cyclical factors command negative or insignificant premiums, the pro-cyclical nature of executive disagreement helps explain its positive risk premium. Similarly, the counter-cyclical tendency of analyst disagreement aligns with its negative or insignificant pricing effects documented in Table 3.

5.2 Cash Flow and Discount Rate Channels

To further understand the economic channels through which executive disagreement affects asset prices, we examine whether it is priced through cash flows or discount rates. Campbell (1993) and Campbell and Vuolteenaho (2004) suggest that risk factors can affect returns either by influencing expected future cash flows or by changing the rate at which these cash flows are discounted. Extending Savor and Wilson (2016), we test both channels by estimating:

$$\text{Aggregate Earning Growth/Discount Rate}_t = \alpha + \beta\text{High Portfolio Return}_t + \gamma\text{FF 5 Factors}_t + \varepsilon_t \tag{15}$$

Where the high portfolio returns are the value-weighted returns of stocks in the highest quintile sorted on $\text{SID}_{\kappa}^{\text{EXE}}$. We calculate aggregate earnings as the value-weighted gross margin within our sample and measure the discount rate using the primary credit rate (DR), which is the rate at which depository institutions can borrow on a short-term basis from the Federal Reserve.

[Insert Table 8 here]

Table 8 Panel A presents the results from these regressions. Columns (1) to (5) focus on aggregate gross profit growth and find that it is positively affected by executive extreme disagreement ($\text{SID}_{\kappa}^{\text{EXE}}$). Specifically, positive sentiment extreme disagreement ($\text{SID}_{\kappa}^{\text{EXE}}$: POS) in column (1) has a coefficient of 0.011 with a t-statistic of 2.04, significant at the 5% level. Similarly, negative sentiment extreme disagreement ($\text{SID}_{\kappa}^{\text{EXE}}$: NEG) has a coefficient of 0.010 with a t-statistic of 1.94. In column (3), litigious sentiment extreme disagreement ($\text{SID}_{\kappa}^{\text{EXE}}$: LIT) exhibits a coefficient of 0.008 with a t-statistic of 1.66. Similar results are observed for uncertainty and forward-looking sentiments. The positive association between executive disagreement and profitability growth aligns with the theoretical framework proposed by Campbell (1993), which posits that cash flow risk is a significant and highly compensated source of risk in asset pricing.

Columns (6) to (10) highlight the positive relationship between executive disagreement and the primary credit rate (DR). For instance, positive sentiment extreme disagreement ($\text{SID}_{\kappa}^{\text{EXE}}$: POS) in column (6) has a coefficient of 0.00043 with a t-statistic of 2.01, significant at the 5% level. In column (8), litigious sentiment extreme disagreement ($\text{SID}_{\kappa}^{\text{EXE}}$: LIT) has a coefficient of 0.00039 with a t-statistic of 1.90, while uncertainty sentiment extreme disagreement ($\text{SID}_{\kappa}^{\text{EXE}}$: UNC) shows a coefficient of 0.00036 with a t-statistic of 1.70. Finally, forward-looking sentiment extreme disagreement ($\text{SID}_{\kappa}^{\text{EXE}}$: FWD) in column (10) has a coefficient of 0.00049 with a t-statistic of 2.28. This indicates that market-wide discount rates serve as a channel through which executive disagreement risk is priced.

To further validate the firm-specific discount rate channel, we conduct an additional test using corporate bond yield spreads. We collected daily bond trading data from TRACE (Trade Reporting and Compliance Engine) and computed yield spreads of each corporate bond at the firm level, controlling for coupon rates, maturity, and benchmark Treasury bond yields. We then estimate the following cross-sectional regression:

$$\text{Credit Spread Change}_{i,t} = \alpha + \beta \text{SID}_{\kappa,i,t}^{\text{EXE}} + \gamma \text{Firm Controls}_{i,t} + \text{Fixed Effects} + \varepsilon_{i,t} \tag{16}$$

We use two measures of credit spread changes: (1) δ3moyld, calculated as the difference between yields three months after and one month before the earnings call ($\text{Yield}_{t+3} - \text{Yield}_{t-1}$), and (2) δLTyld, calculated as the difference between the average yield over five months after and five months before the earnings call ($\frac{1}{5}\sum_{j=1}^{5} \text{Yield}_{t+j} - \frac{1}{5}\sum_{j=1}^{5} \text{Yield}_{t-j}$).

Panel B of Table 8 presents these results and shows that across sentiment categories, executive extreme disagreement ($\text{SID}_{\kappa}^{\text{EXE}}$) is positively related to both δ3moyld and δLTyld. In Column (1), positive sentiment extreme disagreement ($\text{SID}_{\kappa}^{\text{EXE}}$: POS) shows a positive but statistically insignificant relationship with δ3moyld (0.00017, t-statistic = 1.34), while in Column (2), it has a positive and statistically significant association with δLTyld at the 5

In Columns (3) and (4), negative sentiment extreme disagreement ($\text{SID}_{\kappa}^{\text{EXE}}$: NEG) demonstrates a marginally significant positive relationship with δ3moyld (0.00026, t-statistic = 1.94) but no significant effect on δLTyld. Litigious sentiment extreme disagreement ($\text{SID}_{\kappa}^{\text{EXE}}$: LIT) in Columns (5) and (6) shows consistently significant positive relationships with both δ3moyld (0.00025, t-statistic = 1.99) and δLTyld (0.00024, t-statistic = 2.34).

These results on corporate credit spreads provide compelling firm-level evidence that executive disagreement influences the discount rates applied to firms' future cash flows. Combined with the aggregate-level findings in Panel A, our analysis demonstrates that executive disagreement is priced through both cash flow and discount rate channels, consistent with its status as a systematic risk factor that commands a positive risk premium.

6 Economic and Governance Related Consequences of Soft Information Disagreement

6.1 Determinants of Executive Disagreement

In this section, we examine the key determinants of executive disagreement and the topics on which executives most frequently disagree, providing insight into the underlying factors that drive the risk premium associated with this disagreement.

[Insert Table 9 here]

Panel A of Table 9 examines the firm and CEO characteristics that contribute to executive extreme disagreement ($\text{SID}_{\kappa}^{\text{EXE}}$). We find that the coefficient on *Market-To-Book* is negative and statistically significant across all sentiment categories, indicating that when firms have poor market performance, executives are more likely to exhibit higher disagreement. Notably, the coefficients on CEO power are negative and statistically significant, while the coefficients on CEO age (Old_CEOs) are positive and significant. This suggests that when CEOs become less powerful and older, disagreement among executives tends to increase.

Given that CEOs often exert significant power over CFOs, enabling them to pressure CFOs to bias performance measures (Feng et al. (2011); Friedman (2014); Florackis and Sainani (2021)), such pressure may also manifest in earnings calls in the form of strategic coordination of tones among executives. Our findings indicate that this strategic coordination with outsiders may exist, but it diminishes when CEOs lose power, along with weaker firm performance.

Additionally, we find that analyst forecast error and earnings surprise do not meaningfully load on executive disagreement ($\text{SID}_{\kappa}^{\text{EXE}}$). These are prominent indicators of hard information disagreement used in existing literature (e.g., Yu (2011)). The lack of meaningful association between soft information disagreement and hard information disagreement supports our claim that soft information is an important and distinct risk factor.

Panel B of Table 9 examines the topics on which managers mostly disagree. Using the topic dictionary provided by Fengler and Phan (2023), we classify discussions into eleven categories: sales, operations, employment, litigation, cost, profit, liquidity, financing, regulation, accounting, and investment. The results uncover an intriguing pattern in the relationship between specific topics and managerial disagreement.

Subjective topics like sales (T_sales), operations (T_operations), employment (T_employment), and litigation (T_litigation) are strongly associated with increased disagreement among executives. For instance, the coefficient for T_sales on $\text{SID}_{\kappa}^{\text{EXE}}$: POS is 2.541 (t = 4.61), while T_employment has an even larger effect, with a coefficient of 6.279 (t = 4.30). Similarly, T_operations and T_litigation also exhibit positive effects on executive disagreement, albeit to varying degrees of statistical significance. These findings suggest that subjective topics amplify managerial disagreement, likely because they involve qualitative judgments and diverging opinions.

In contrast, quantifiable topics such as cost (T_cost), profit (T_profit), liquidity (T_liquidity), and financing (T_financing) are associated with reduced executive disagreement. For example, T_profit, T_liquidity, and T_financing have significant negative coefficients on $\text{SID}_{\kappa}^{\text{EXE}}$: POS of -1.825 (t = -5.36), -3.873 (t = -2.39), and -1.449 (t = -1.70), respectively. These results indicate that when discussions are grounded in clear, quantifiable metrics, executives are more likely to reach a consensus, thereby reducing disagreement.

6.2 Executive Disagreement and CEO Turnover

Our final analysis examines the relationship between executive disagreement and CEO turnover. If our measure of soft information disagreement among executives captures fundamental firm-level risks, we expect shareholders or boards to respond with significant strategic and operational changes to address these challenges. In this context, CEO turnover could be a potential solution to drive rapid organizational transformation.

Prior research suggests that successors engage in operational restructuring, divesting underperforming assets and business divisions, and implementing changes to corporate policies (e.g., Pan, Wang, and Weisbach (2016); Denis and Denis (1995); Weisbach (1995)). Furthermore, our earlier findings indicate that executive disagreement is particularly heightened when CEOs are less powerful and firm performance is weaker, thereby facilitating the CEO turnover process. Taken together, we expect that increased executive disagreement may serve as a predictor of CEO turnover.

[Insert Table 10 here]

To test this hypothesis, we defined a CEO turnover event as occurring in fiscal year t if the CEO serving in year t is no longer in position in the subsequent fiscal year $t+1$. We excluded instances of interim CEO turnover, departures following mergers or acquisitions, cases where the company ceases to exist, and turnovers due to death or illness, as these cases are less likely associated with executive disagreement.

The results are presented in Table 10. We estimated a linear probability model using the same set of control variables and fixed effects as in Table 3. The coefficients for $\text{SID}_{\kappa}^{\text{EXE}}$: POS and $\text{SID}_{\kappa}^{\text{EXE}}$: NEG are both positive and statistically significant. Specifically, a one-standard-deviation increase in $\text{SID}_{\kappa}^{\text{EXE}}$: NEG is associated with a 1.8 percentage point increase in the probability of CEO turnover (t = 4.93). Similar results are observed for $\text{SID}_{\kappa}^{\text{EXE}}$: LIT, $\text{SID}_{\kappa}^{\text{EXE}}$: UNC, and $\text{SID}_{\kappa}^{\text{EXE}}$: FWD, with coefficients of 0.015, 0.019, and 0.020, respectively.

Overall, these findings indicate that executive disagreement is positively associated with CEO turnover, supporting our hypothesis that managerial disagreement, as captured in earnings calls, reflects fundamental firm-level risks recognized and priced by market participants. This real economic consequence further substantiates our findings that soft information disagreement represents a meaningful risk factor that affects firm governance decisions.

7 Robustness Tests

To validate the robustness of our main findings on the pricing of soft information disagreement, we conduct several additional tests. These tests verify that our results are robust to alternative specifications, measurement approaches, and economic interpretations.

First, we examine whether the risk premium associated with executive disagreement reflects a single unified factor or varies by sentiment category. Table A1 presents results for portfolios sorted on combined soft information disagreement measures constructed using principal component analysis (PCA). We find that extreme disagreement ($\mathrm{SID}_{\kappa}^{\mathrm{EXE}}$) formed through PCA yields significant and economically meaningful risk premiums of 11.28% to 12.96% annually, depending on the PCA specification. These magnitudes are consistent with or slightly larger than those for individual sentiment categories, suggesting that a common disagreement factor underlies the various sentiment dimensions. Importantly, combined analyst disagreement measures continue to show insignificant risk premiums, reinforcing the source-dependent nature of soft information pricing.

Second, we investigate whether the cross-sectional variation in disagreement that we document is related to differences in speech complexity between executives and analysts. Table A2 shows that executive speech is significantly more complex than analyst speech, with the coefficient on the executive indicator variable consistently positive and significant across all specifications. Following Loughran and McDonald (2024), this higher complexity increases information acquisition costs for market participants, which helps explain why executive disagreement commands a positive risk premium while analyst disagreement does not, consistent with our theoretical framework.

Third, we provide direct evidence that analyst disagreement enhances call informativeness rather than reflecting fundamental risk. Table A3 demonstrates that higher analyst disagreement is associated with significantly longer conference calls and more words spoken by executives. These results hold across all sentiment categories and are economically meaningful, with a one-standard-deviation increase in analyst extreme disagreement ($\mathrm{SID}_{\kappa}^{\mathrm{ANL}}$: AGG) associated with 184.60 more words in the total call and 116.80 more words from executives. This finding supports our hypothesis that analyst disagreement prompts more comprehensive information disclosure from management.

Fourth, to confirm that our long-short portfolio returns represent a priced risk factor rather than an anomaly, we conduct a test in the spirit of Fama and MacBeth (1973). Table A4 presents Fama-MacBeth regressions of stock returns on executive disagreement measures. We find that extreme disagreement ($\mathrm{SID}_{\kappa}^{\mathrm{EXE}}$) carries positive and significant coefficients across all sentiment categories, with magnitudes ranging from 3.12% to 5.40% annually. These coefficients remain significant even after controlling for firm characteristics and information environment variables, confirming that executive disagreement is priced in the cross-section of returns.

Fifth, we distinguish between speaker-level disagreement and general textual dispersion. Table A5 shows that when we measure disagreement at the dialogue level rather than the speaker level, the significant risk premium largely disappears. This suggests that the systematic risk stems from disagreement among executives rather than from general textual dispersion, further validating our speaker-level approach.

Finally, we examine the factor loadings of high and low disagreement portfolios to validate the systematic risk interpretation. Table A6 reveals that high disagreement portfolios consistently have positive and significant loadings on the disagreement factor (ranging from 6.60 to 7.80), while low disagreement portfolios have negative and significant loadings (ranging from -4.20 to -5.40). This clear separation in factor loadings, combined with significant intercepts in opposite directions, confirms that executive disagreement represents a systematic risk factor that cannot be explained by standard Fama-French factors.

Collectively, these tests substantiate our main findings that executive soft information disagreement commands a significant positive risk premium, while analyst disagreement primarily enhances information production. The results are robust to alternative measurement approaches and support our theoretical framework wherein the source, magnitude, timing, and processing of disagreement jointly determine its pricing implications.

8 Discussion and Conclusion

Soft information plays a critical role in capital markets. Unlike hard information, however, the effect of soft information on systematic risk depends on several factors that shape its context, magnitude, and processability by investors. Specifically, we identify the source, magnitude, timing, and ease of interpretability of soft information as key conditioning variables. Our findings show that when executives disagree during earnings calls, investors demand a significant risk premium. In contrast, analyst disagreement exhibits weaker or negative pricing effects, suggesting it enhances information production rather than reflecting fundamental risk. Moreover, the risk premium is positively influenced by the degree of disagreement, the early timing of disagreement, and the cost and credibility of the information. For each of these factors, we provide potential explanations supported by empirical evidence.

Our Bayesian learning framework provides a theoretical foundation for these empirical patterns. When information is scarce, as is often the case with executive communications about uncertain future states, extreme signals captured by kurtosis become the dominant factor in investors' belief updating process. The model demonstrates that this effect is amplified by both credibility and information acquisition costs, explaining why executive soft information disagreement commands higher risk premiums, particularly in firms with better governance (higher credibility) and more complex information environments (higher information acquisition costs). This theoretical prediction helps explain our empirical finding that extreme disagreement ($\text{SID}_{\kappa}^{\text{EXE}}$) measures generate more significant risk premiums than moderate disagreement ($\text{SID}_{\sigma}^{\text{EXE}}$), especially for executive information.

Supporting our framework's dual-channel prediction, we find that executive soft information disagreement affects asset prices through both cash flow and discount rate news. High-$\text{SID}_{\kappa}^{\text{EXE}}$ firms exhibit stronger predictability of future earnings growth, consistent with executive disagreement revealing uncertainty about future cash flows. Additionally, these firms face higher credit spreads and borrowing costs, indicating that the discount rate channel also plays a significant role. These findings align with recent work by Campbell and Vuolteenaho (2004) highlighting the importance of decomposing systematic risk into both cash flow and discount rate components.

The interaction between credibility and information acquisition costs generates rich cross-sectional implications. We observe that executive disagreement risk premiums are concentrated in firms characterized by high governance quality, larger size, and professional (non-family) CEOs - precisely the firms where executive signals are most credible. This pattern supports our model's prediction that credibility amplifies the pricing of soft information disagreement. Similarly, the stronger pricing effects observed in the context of equity-based compensation and shareholder lawsuits align with the model's predictions about the impact of costly information processing. Our robustness tests further confirm these findings, showing that the risk premium persists across alternative specifications and combined disagreement measures.

Our findings raise important questions for future research. The importance of soft information from an asset pricing perspective has been explored in many papers, including Engle, Giglio, Kelly, Lee, and Stroebel (2020), Chava, Du, Shah, and Zeng (2022), and Wu (2023). While we demonstrate that earnings call disagreement carries systematic risk information, other sources of soft information like news articles, social media, and corporate disclosures may exhibit different pricing patterns depending on their credibility and acquisition costs. This finding is further supported by our analysis of sentiment patterns over the course of calls, which reveals a distinctive U-shaped pattern in soft information generation. Understanding how such temporal dynamics in soft information processing affect asset prices across different communication channels and information environments remains an important area for investigation.

This paper leaves many unanswered questions and potentially opens up a new arena of future research. We demonstrate, empirically and theoretically, that the disagreement in soft information gleaned from earning calls is not just noise but could also carry systematic risk. A natural question that arises is: What about other sources of soft information such as news articles, firm reports versus analyst reports, blog posts, and social media content in video and audio formats? Does the soft information disagreement from these various sources influence investors and consequent market reactions? As alternative information sources proliferate, understanding the market impact of soft information disagreement across different mediums is an important area for future research. It would also be interesting to explore and compare the results in the context of varying levels of spontaneity (Lee (2016)) exhibited across soft-information mediums. Furthermore, our focus has been on within-group disagreement among executives and analysts, respectively. We do not study the cross-disagreement between analysts and executives. Various studies, including Comprix et al. (2022) and Brown, Francis, Hu, Shohfi, Zhang, and Xin (2023), have examined the interaction between analysts and executives, which could provide a foundation for this line of inquiry. We leave all these questions for future research.

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Appendix A: Variable Definitions

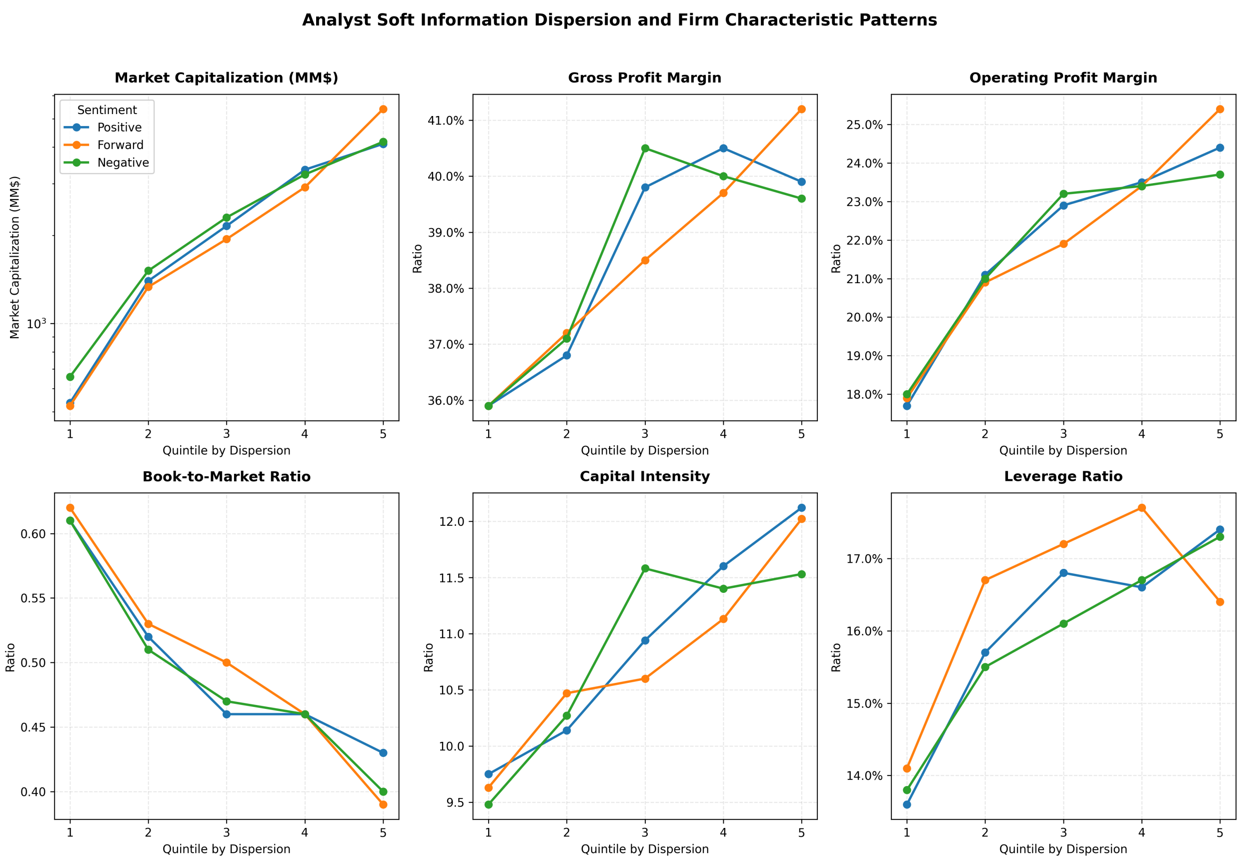
Variable	Definition
$\text{SID}^{g}_{d} : s$	General notation for soft information disagreement where g indicates the speaker group (EXE for executives, ANL for analysts, DIA for dialogue-level), d denotes the dispersion measure (kurtosis, κ, for extreme disagreement; standard deviation, σ, for moderate disagreement), and s indicates the sentiment category
$\text{SID}^{\text{EXE}}_{\kappa}$	Executive extreme disagreement (kurtosis) measured across sentiment categories following Loughran and McDonald (2011) for POS (positive), NEG (negative), LIT (litigious), UNC (uncertainty) sentiments, and Rennekamp, Sethuraman, and Steenhoven (2022) for FWD (forward-looking) statements
$\text{SID}^{\text{EXE}}_{\sigma}$	Executive moderate disagreement (standard deviation) measured across the same sentiment categories as above
$\text{SID}^{\text{ANL}}_{\kappa}$	Analyst extreme disagreement (kurtosis) measured across the same sentiment categories as executives, plus AGG (aggressiveness) following Comprix, Lopatta, and Tideman (2022)
$\text{SID}^{\text{ANL}}_{\sigma}$	Analyst moderate disagreement (standard deviation) measured across the same sentiment categories as above
$\text{SID}^{\text{DIA}}_{\kappa}$, $\text{SID}^{\text{DIA}}_{\sigma}$	Dialogue-level extreme and moderate disagreement measured at paragraph level rather than speaker level
complexity	Measure of speech complexity calculated using the methodology of Loughran and McDonald (2024)
$\mathcal{W}_{\text{T}}$, $\mathcal{W}_{\text{E}}$	Count of words spoken in a conference call in total and by executives, respectively
T_topic	Topic indices (where topic is one of: sales, operations, litigation, employment, cost, profit, liquidity, financing, regulation, accounting, investment) extracted using the dictionary from Fengler and Phan (2023)
ROA	Operating income (OIBDPQ) in quarter q divided by total assets (ATQ) in quarter $q-1$
Ln_MV	Natural logarithm of market value of equity (PRCCQ*CSHOQ)
R&D	R&D (XRDQ) in quarter q divided by total assets in quarter $q-1$, set to zero if missing
Leverage	Long-term debt (DLTTQ) divided by total asset (ATQ)
Market-To-Book	Market capitalization plus book value of total debt (DLTTQ + DLCQ), divided by total assets (ATQ)
OP	Operating Profitability: (revenue(REVT) - COGS - SG&A - XINT) divided by book equity
IF	Asset (AT) growth in the previous year

Appendix A. continued

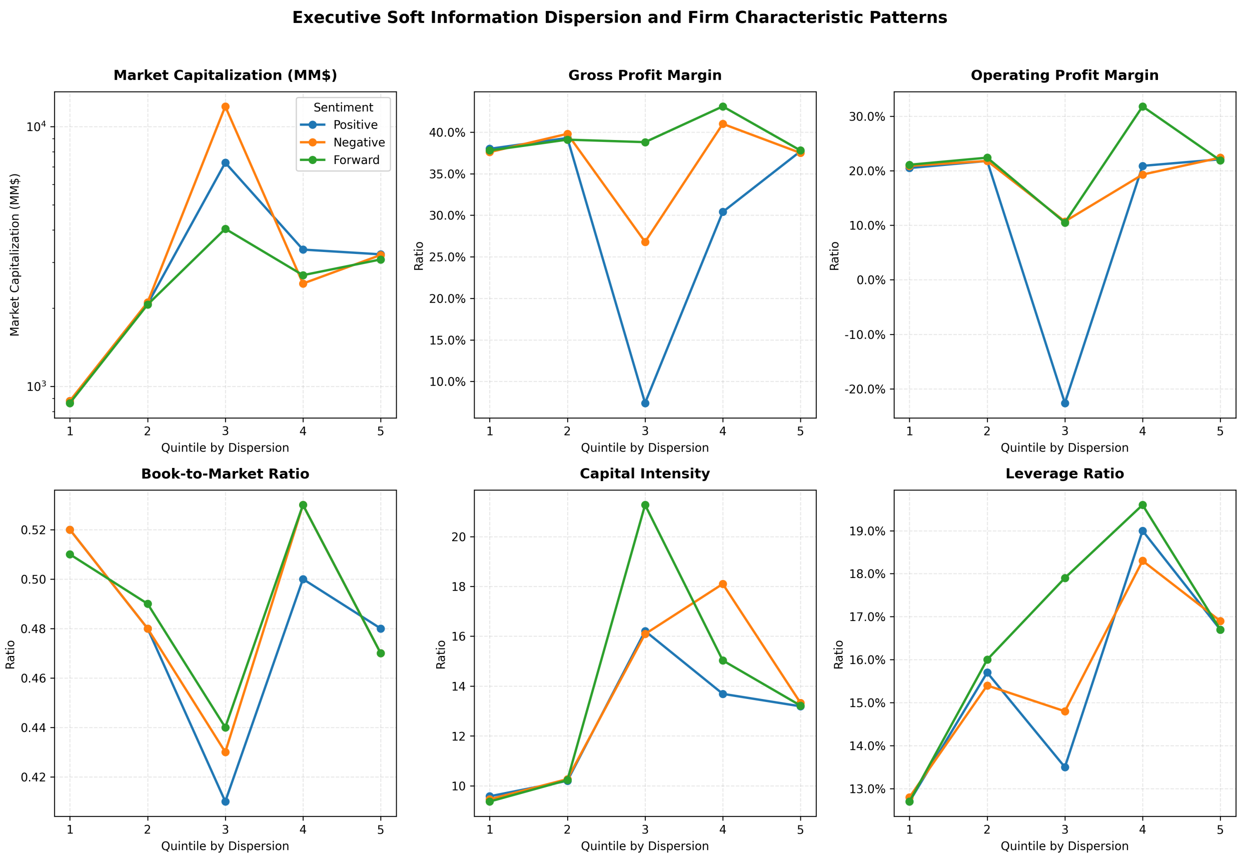
MktBeta	Market beta calculated from 3-year rolling regression of monthly excess stock returns on market excess returns
Momentum	Geometric sum of monthly returns from period $t-2$ to $t-12$
Size	Total Assets (AT)
AbVol	Ratio of average trading volume during $[t, t+1]$ to average volume during $[t-120, t-21]$ following Pevzner, Xie, and Xin (2015)
E-Index	Anti-takeover protection measure following Bebchuk, Cohen, and Ferrell (2009), calculated by tallying points across six provisions: staggered boards, restrictions on amending bylaws, poison pills, golden parachutes, supermajority requirements, and charter amendment constraints
Old_CEO	Indicator equal to one if CEO age is over 65
Family	Indicator equal to one if CEO is founder or descendant of founding family
Non-family	Indicator equal to one if firm has non-heir, non-founder professional CEO
CEOpower	Indicator equal to one if CEO is president or chairman of the board
Female	Indicator equal to one if CEO is female
Ln_CEOtenure	Natural logarithm of CEO's tenure in years
SUE	Standardized unexpected earnings based on median analyst forecast
Neg_SUE	Indicator equal to one if realized earnings fall below median analyst forecast
Forecast_Error	Standard deviation in analyst forecasts
Ln_Analysts	Natural logarithm of one plus maximum number of analysts following the stock for the year-quarter (0 if no I/B/E/S coverage)

Figure 1: Firm Characteristics Across Soft Information Disagreement Quintiles

This figure presents the relationship between firm characteristics and soft information disagreement (SID) measured from earnings conference calls during 2006-2020. Firms are sorted into quintiles based on extreme disagreement (SID_{κ}^{g}) expressed by analysts (Panel A) and executives (Panel B) during earnings calls. The portfolios are formed within Fama-French 5 industries, and firm-level characteristics are value-weighted within each quintile. For each information source, we plot three types of sentiment measures: positive (SID_{κ}^{g} : POS, blue line), negative (SID_{κ}^{g} : NEG, orange line), and forward-looking (SID_{κ}^{g} : FWD, green line) statements. The horizontal axis represents quintile portfolios (1-5), where quintile 5 contains firms with the highest sentiment extreme disagreement. Key firm characteristics shown include Market Capitalization (in millions of dollars), Gross Profit Margin, Operating Profit Margin, Book-to-Market Ratio, Capital Intensity, and Leverage Ratio.



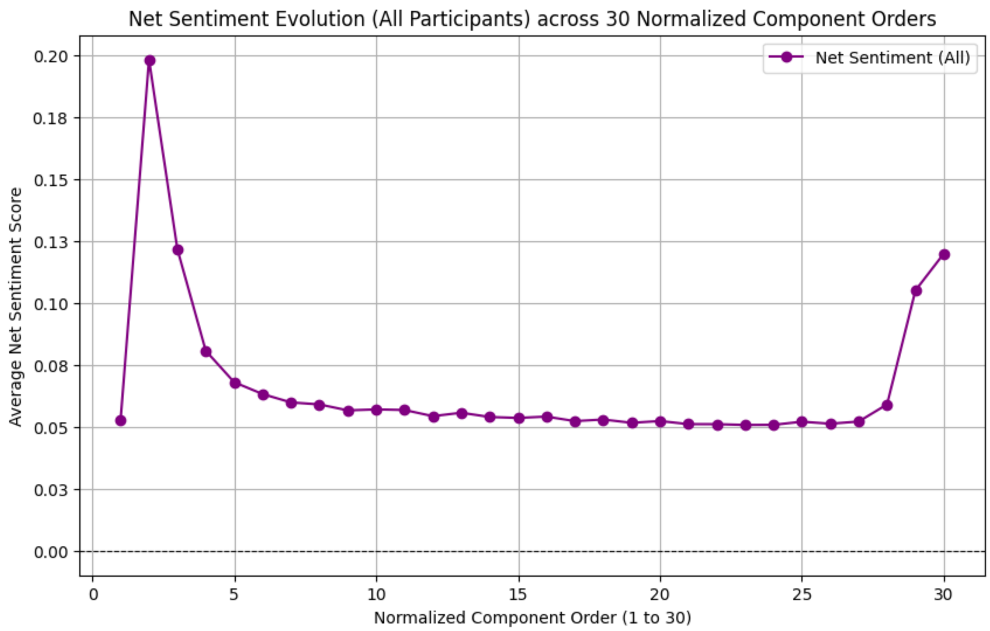
(a) Analyst Soft Information Disagreement Quintile ($\text{SID}_{\kappa}^{\text{ANL}}$)



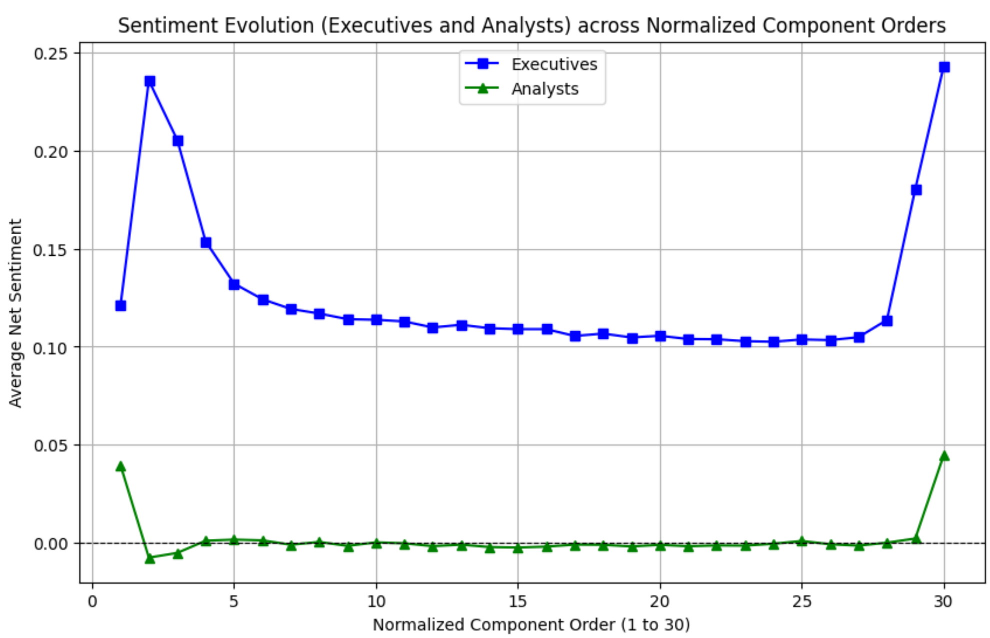
(b) Executive Soft Information Disagreement Quintile ($\mathrm{SID}_{\kappa}^{\mathrm{EXE}}$)

Figure 2: Sentiment Revolution in Conference Calls: Net Sentiment Score

This figure presents temporal patterns in sentiment generation during earnings conference calls from 2006 to 2020, analyzed using FinBERT, a financial domain-specific BERT model (Huang, Wang, and Yang (2023)). Panel A shows the aggregate pattern across all participants, while Panel B separates executive and analyst sentiments. Sentiment scores are calculated as the difference between positive and negative probabilities assigned by FinBERT to each speaker's sentence-level statements, then averaged and normalized across 30-component intervals within each conference call.

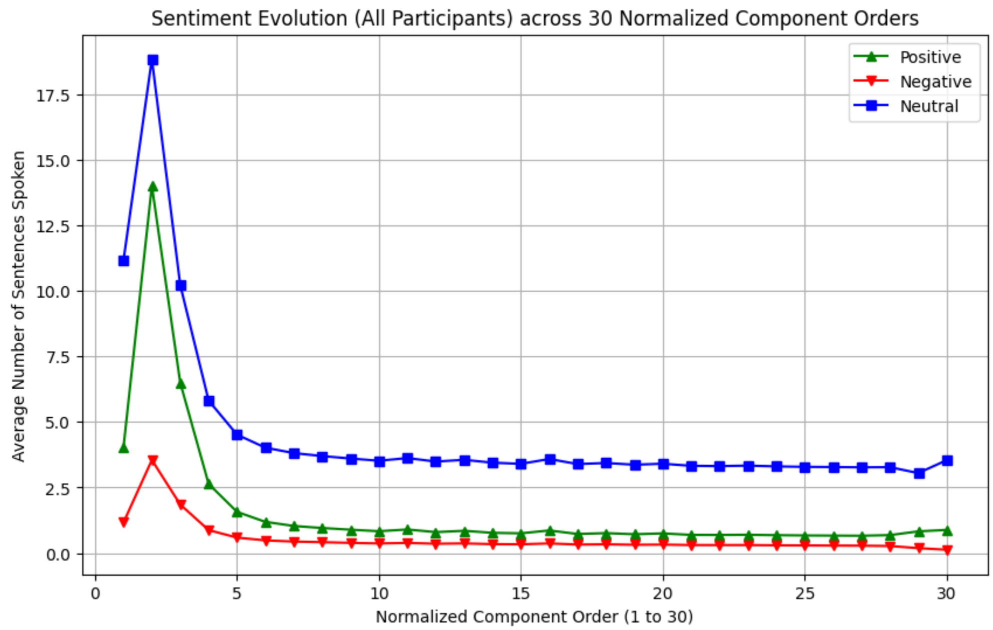


(a) All Participants

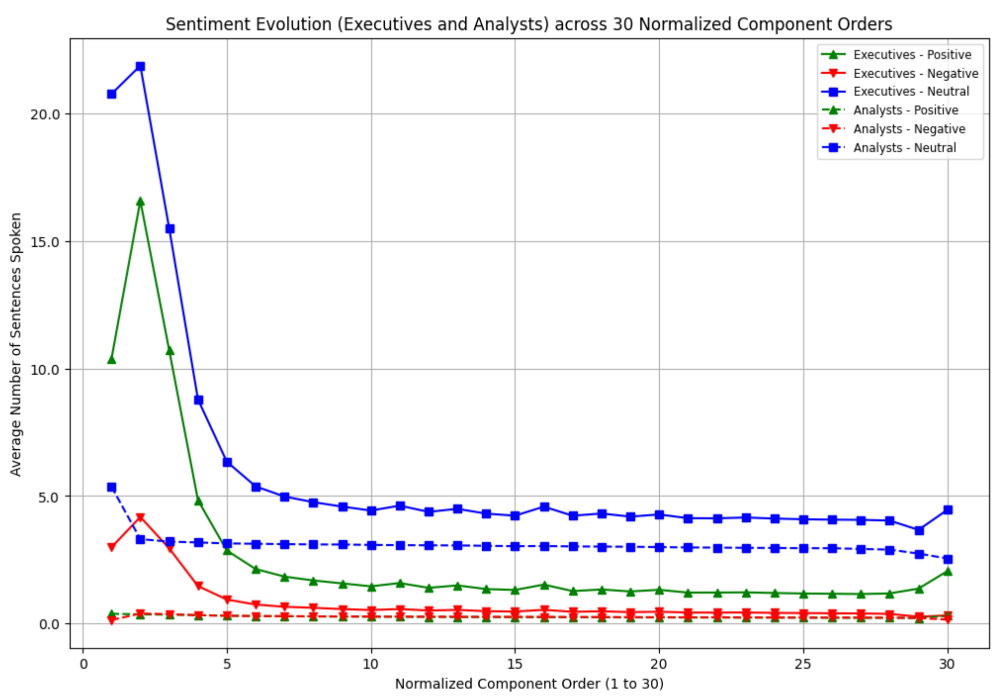


(b) Executives and Analysts

Figure 3: Sentiment Revolution in Conference Calls: Average Number of Sentences Spoken



(a) All Participants



(b) Executives and Analysts

Table 1: Summary statistics

This table provides summary statistics for soft information disagreement (SID) measures and control variables over the period 2006-2020. For each variable, we present the number of observations (N), mean, standard deviation (Std), quartiles (Q1, Q2, Q3), and persistence coefficient (ρ) estimated from AR(1) regressions. $\text{SID}_d^g : s$ represents soft information disagreement where g indicates the speaker group, d denotes the dispersion measure (kurtosis, κ, or standard deviation, σ), and s indicates the sentiment category. All variables are defined in Appendix A. Statistical significance is denoted by * p<0.1, ** p<0.05, and *** p<0.01.

	N	Mean	Std	Q1	Q2	Q3	ρ
Executive Disagreement Measures							
SID_κ^{EXE} : POS	88373	1.610	0.58	1.50	1.50	1.62	0.286
SID_κ^{EXE} : NEG	88374	1.613	0.58	1.50	1.50	1.63	0.286
SID_κ^{EXE} : LIT	88361	1.625	0.61	1.50	1.50	1.65	0.286
SID_κ^{EXE} : UNC	88374	1.613	0.58	1.50	1.50	1.63	0.274
SID_κ^{EXE} : FWD	88374	1.615	0.59	1.50	1.50	1.63	0.311
SID_σ^{EXE} : POS	88374	0.139	0.18	0.04	0.09	0.18	0.005
SID_σ^{EXE} : NEG	88374	0.094	0.19	0.02	0.05	0.11	0.027
SID_σ^{EXE} : LIT	88374	0.031	0.09	0.01	0.01	0.03	0.033
SID_σ^{EXE} : UNC	88374	0.076	0.13	0.02	0.04	0.09	0.011
SID_σ^{EXE} : FWD	88374	0.106	0.15	0.03	0.06	0.13	0.008
Analyst Disagreement Measures							
SID_κ^{ANL} : AGG	84163	2.295	1.19	1.50	2.00	2.69	0.066
SID_κ^{ANL} : POS	75624	2.847	1.72	1.52	2.33	3.53	0.049
SID_κ^{ANL} : NEG	77977	2.659	1.58	1.50	2.23	3.25	0.064
SID_κ^{ANL} : LIT	62187	4.380	2.99	2.13	3.47	6.14	0.095
SID_κ^{ANL} : UNC	84142	2.780	1.90	1.50	2.17	3.28	0.077
SID_κ^{ANL} : FWD	81563	3.183	2.20	1.50	2.38	4.10	0.056
SID_σ^{ANL} : AGG	84451	0.256	0.21	0.12	0.19	0.31	0.156
SID_σ^{ANL} : POS	84451	0.028	0.02	0.02	0.02	0.04	-0.031
SID_σ^{ANL} : NEG	84451	0.031	0.03	0.02	0.03	0.04	-0.011
SID_σ^{ANL} : LIT	84457	0.023	0.06	0.00	0.01	0.02	-0.0004
SID_σ^{ANL} : UNC	84457	0.106	0.14	0.04	0.07	0.11	0.009
SID_σ^{ANL} : FWD	84457	0.055	0.09	0.02	0.03	0.06	-0.029
Call Characteristics							
Executive Count	88374	3.3	1.1	3	3	4	0.439
Analyst Count	88374	6.6	3.8	4	6	9	0.353
Analyst Following	4317	5.251	5.160	1	4	8	0.053
Firm Characteristics							
ROA	84246	0.016	0.05	0.01	0.02	0.04	0.441
Ln_MV	85993	7.200	1.91	5.89	7.19	8.44	0.790
Market-to-Book	81728	1.820	1.68	0.84	1.28	2.15	0.715
R&D	86128	0.013	0.03	0.00	0.00	0.01	0.217
Leverage	81858	0.246	0.22	0.06	0.21	0.37	0.758
CEO Characteristics							
CEO Power	53634	0.873	0.33	1.00	1.00	1.00	0.524
CEO Tenure	52580	1.802	0.87	1.10	1.79	2.48	0.513
Old CEO	53619	0.089	0.28	0.00	0.00	0.00	0.125
Information Environment							
Negative SUE	3744	0.289	0.45	0.00	0.00	1.00	-0.008
Forecast Error	3056	0.086	0.21	0.02	0.04	0.08	-1.101
Cumulative Execess Return	86469	0.157	6.512	-3.629	0.169	4.026	-0.019

Table 2: Executive Soft Information Disagreement Impact on Analyst Soft Information Disagreement

This table provides evidence for the association between executive and analyst soft information disagreement (SID) measures. The dependent variable is analyst SID and the independent variable is executive SID. Controls include *Market_To_Book*, *ROA*, *Ln_MV*, *R&D*, and *Leverage*. $\text{SID}_d^g : s$ represents soft information disagreement where g indicates the speaker group (EXE for executives, ANL for analysts), d denotes the dispersion measure (kurtosis, κ, or standard deviation, σ), and s indicates the sentiment category: positive (POS), negative (NEG), litigious (LIT), uncertainty (UNC), and forward-looking (FWD) sentiments measured following Loughran and McDonald (2011) and Rennekamp, Sethuraman, and Steenhoven (2022). T-statistics are reported in parentheses. All variables are defined in Appendix A. Statistical significance is denoted by * p<0.1, ** p<0.05, and *** p<0.01.

	Analyst Soft Information Disagreement (SID^{ANL})									
Executive SID	(1) $\text{SID}_\sigma^{\text{ANL}}$: POS	(2) $\text{SID}_\sigma^{\text{ANL}}$: NEG	(3) $\text{SID}_\sigma^{\text{ANL}}$: LIT	(4) $\text{SID}_\sigma^{\text{ANL}}$: UNC	(5) $\text{SID}_\sigma^{\text{ANL}}$: FWD	(6) $\text{SID}_\kappa^{\text{ANL}}$: POS	(7) $\text{SID}_\kappa^{\text{ANL}}$: NEG	(8) $\text{SID}_\kappa^{\text{ANL}}$: LIT	(9) $\text{SID}_\kappa^{\text{ANL}}$: UNC	(10) $\text{SID}_\kappa^{\text{ANL}}$: FWD
$\text{SID}_\sigma^{\text{EXE}}$: POS	0.00468***									
	(6.20)									
$\text{SID}_\sigma^{\text{EXE}}$: NEG		0.00329***								
		(4.60)								
$\text{SID}_\sigma^{\text{EXE}}$: LIT			0.03310***							
			(3.64)							
$\text{SID}_\sigma^{\text{EXE}}$: UNC				0.04052***						
				(7.46)						
$\text{SID}_\sigma^{\text{EXE}}$: FWD					0.02612***					
					(10.12)					
$\text{SID}_\kappa^{\text{EXE}}$: POS						0.06136***				
						(3.15)				
$\text{SID}_\kappa^{\text{EXE}}$: NEG							0.02771*			
							(1.76)			
$\text{SID}_\kappa^{\text{EXE}}$: LIT								0.15361***		
								(4.09)		
$\text{SID}_\kappa^{\text{EXE}}$: UNC									0.09261***	
									(4.63)	
$\text{SID}_\kappa^{\text{EXE}}$: FWD										0.10933***
										(4.57)
YearQtr FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.02	0.02	0.03	0.01	0.02	0.14	0.13	0.33	0.20	0.25
Observations	76,096	76,096	76,102	76,102	76,102	68,355	70,333	56,039	75,834	73,580

Table 3: Long-Short Portfolio Annualized Alpha

This table provides annualized abnormal returns (alpha) of long-short portfolios formed on soft information disagreement (SID) measures. Firms are sorted into deciles within Fama-French 5 industries based on extreme disagreement (SID^g_κ - Panel A) and moderate disagreement (SID^g_σ - Panel B) measures. Returns are value-weighted, and portfolios are long the highest disagreement decile and short the lowest disagreement decile. Each SID measure is lagged by one month. $SID^g_d : s$ represents soft information disagreement where g indicates the speaker group (EXE for executives, ANL for analysts), d denotes the dispersion measure (kurtosis, κ, or standard deviation, σ), and s indicates the sentiment category: positive (POS), negative (NEG), litigious (LIT), uncertainty (UNC), forward-looking (FWD), and analyst aggressiveness (AGG). Sentiment measures follow Loughran and McDonald (2011), Rennekamp, Sethuraman, and Steenhoven (2022), and Comprix, Lopatta, and Tideman (2022). Columns (1)-(3) provide risk premiums for executive disagreement while columns (4)-(6) provide risk premiums for analyst disagreement. T-statistics are reported in parentheses. Statistical significance is denoted by * p<0.1, ** p<0.05, and *** p<0.01.

Panel A: *Extreme Disagreement (SID^g_κ)*

	Executive (SID^{EXE}_κ)			Analyst (SID^{ANL}_κ)		
	(1)	(2)	(3)	(4)	(5)	(6)
Sorting variables	CAPM alpha	FF3 alpha	FF5 alpha	CAPM alpha	FF3 alpha	FF5 alpha
SID^g_κ: POS	7.44**	7.56**	7.20**	-10.92***	-12.60***	-11.16***
	(1.87)	(1.90)	(1.78)	(-2.56)	(-3.05)	(-2.65)
SID^g_κ: NEG	8.76**	8.28**	7.68**	-7.20**	-9.12***	-8.76**
	(1.94)	(1.86)	(1.70)	(-1.87)	(-2.48)	(-2.35)
SID^g_κ: LIT	9.00**	8.76**	7.92**	-1.56	-2.16	-1.32
	(2.18)	(2.16)	(1.96)	(-0.54)	(-0.76)	(-0.44)
SID^g_κ: UNC	9.36**	9.12**	8.76**	-1.32	-3.48	-2.88
	(2.20)	(2.24)	(2.15)	(-0.33)	(-0.92)	(-0.76)
SID^g_κ: FWD	8.40**	7.80**	7.80**	-0.12	-1.56	0.00
	(2.36)	(2.18)	(2.16)	(-0.01)	(-0.34)	(0.00)
SID^{ANL}_κ: AGG				-7.80**	-9.72***	-8.28**
				(-1.86)	(-2.42)	(-2.02)

Panel B: *Moderate Disagreement (SID^g_σ)*

	Executive (SID^{EXE}_σ)			Analyst (SID^{ANL}_σ)		
	(1)	(2)	(3)	(4)	(5)	(6)
Sorting variables	CAPM alpha	FF3 alpha	FF5 alpha	CAPM alpha	FF3 alpha	FF5 alpha
SID^g_σ: POS	2.64	3.12	3.96	-5.64	-6.36	-5.76
	(0.70)	(0.78)	(1.00)	(-1.23)	(-1.38)	(-1.20)
SID^g_σ: NEG	1.08	1.56	0.12	-2.88	-3.72	-3.84
	(0.26)	(0.38)	(0.03)	(-0.71)	(-0.89)	(-0.90)
SID^g_σ: LIT	1.32	1.32	1.68	1.32	0.48	1.44
	(0.33)	(0.31)	(0.38)	(0.34)	(0.11)	(0.37)
SID^g_σ: UNC	6.48*	6.96**	7.08**	0.48	0.00	0.48
	(1.89)	(1.98)	(2.02)	(0.15)	(0.02)	(0.14)
SID^g_σ: FWD	8.76**	8.64**	6.72	-5.28	-5.76	-5.28
	(2.05)	(2.02)	(1.54)	(-1.48)	(-1.68)	(-1.53)
SID^{ANL}_σ: AGG				-4.44	-2.40	-3.84
				(-1.14)	(-0.65)	(-1.03)

Table 4: Soft Information Disagreement and Abnormal Trading Volume

This table presents the relationship between soft information disagreement (SID) and abnormal trading volume. Abnormal volume is measured as the ratio of average trading volume during $[t, t+1]$ to $[t-21, t-120]$ following Pevzner, Xie, and Xin (2015), where t is the earnings call date. $\text{SID}_d^g : s$ represents soft information disagreement where g indicates the speaker group (EXE for executives, ANL for analysts), d denotes the dispersion measure (kurtosis, κ, or standard deviation, σ), and s indicates the sentiment category. Controls include *Market_To_Book*, *ROA*, *Ln_MV*, *R&D*, *Leverage*, SUE, analyst forecast dispersion, and analyst coverage. T-statistics are reported in parentheses. All variables are defined in Appendix A. Standard errors are clustered at the firm level. Statistical significance is denoted by * p<0.1, ** p<0.05, and *** p<0.01.

	Abnormal Trading Volume			
	Executive (SID^{EXE})		Analyst (SID^{ANL})	
Sentiment Category	$\text{SID}_\sigma^{\text{EXE}}$	$\text{SID}_\kappa^{\text{EXE}}$	$\text{SID}_\sigma^{\text{ANL}}$	$\text{SID}_\kappa^{\text{ANL}}$
SID_d^g: POS	-0.055*	-0.024*	-0.911**	0.028***
	(-1.80)	(-1.86)	(-2.52)	(6.57)
SID_d^g: NEG	-0.021	-0.027*	0.518	0.014***
	(-0.87)	(-1.86)	(1.54)	(3.40)
SID_d^g: LIT	-0.017	-0.020	-0.157**	0.017***
	(-0.40)	(-1.57)	(-2.37)	(4.72)
SID_d^g: UNC	-0.040	-0.007	-0.047	0.022***
	(-0.81)	(-0.49)	(-0.72)	(6.01)
SID_d^g: FWD	0.000	-0.027**	-0.172**	0.018***
	(0.01)	(-2.04)	(-2.04)	(4.92)
Controls	Yes	Yes	Yes	Yes
YearQtr × Industry FE	Yes	Yes	Yes	Yes
Adjusted R^2	0.07	0.07	0.07	0.07
Observations	61,751	61,751	60,634	60,525

Table 5: Order of Speech and Risk Premium

This table reports the subsample abnormal returns of long-short decile portfolios sorted on executive soft information disagreement ($\text{SID}_{\kappa}^{\text{EXE}}$). 1^{st} half refers to the first-half period of the conference call, while 2^{nd} half refers to the second-half period. The two halves are measured for each conference call as before and after the median value of *componentorder* in the CapitalIQ transcripts database. Returns are value-weighted, and sorting variables are lagged by one month. T-statistics are reported in parentheses. All variables are defined in Appendix A. Statistical significance is denoted by * p<0.1, ** p<0.05, and *** p<0.01.

	CAPM Alpha		FF3 Alpha		FF5 Alpha	
Sorting Variable	1^{st} half	2^{nd} half	1^{st} half	2^{nd} half	1^{st} half	2^{nd} half
$\text{SID}_{\kappa}^{\text{EXE}}$: POS	7.44*	5.16	7.44*	4.44	6.72*	5.16
	(1.93)	(1.50)	(1.92)	(1.30)	(1.73)	(1.48)
$\text{SID}_{\kappa}^{\text{EXE}}$: NEG	5.40	6.48*	5.40	6.00*	5.64	6.36*
	(1.53)	(1.87)	(1.51)	(1.72)	(1.59)	(1.78)
$\text{SID}_{\kappa}^{\text{EXE}}$: LIT	10.68**	4.32	10.56*	3.36	10.44*	4.68
	(2.77)	(1.59)	(2.72)	(1.26)	(2.69)	(1.76)
$\text{SID}_{\kappa}^{\text{EXE}}$: UNC	7.32*	3.24	6.96*	3.00	7.08*	4.68
	(1.83)	(0.70)	(1.71)	(0.64)	(1.73)	(1.00)
$\text{SID}_{\kappa}^{\text{EXE}}$: FWD	9.12**	6.12*	9.00**	5.76*	8.40**	6.12*
	(2.24)	(1.80)	(2.21)	(1.68)	(2.06)	(1.74)

Table 6: Credibility and Acquisition Cost Impact on Risk Premium

This table reports the subsample CAPM abnormal returns of long-short decile portfolios sorted on executive soft information disagreement (SID_{κ}^{EXE}). In Panel A, High (Low) Gov subsamples refer to firm-months with e-index lower than (greater than or equal to) 4; High (Low) Size firms refer to firm-months with log market value above (below) the cross-sectional median; and *Family* refers to firms managed by founders or heirs, while *Non-family* refers to firms managed by a non-founder, non-heir professional CEO. E-index measures a company's anti-takeover protection (Bebchuk, Cohen, and Ferrell (2009)), calculated by tallying points across six anti-takeover measures. In Panel B, High (Low) Equity refers to firm-years when CEO's equity-based compensation is above (below) the cross-sectional median; and Post-lawsuit (Pre-lawsuit) refers to the period up to three years after (three years before) shareholders filed a class-action lawsuit against the company. Returns are value-weighted, and sorting variables are lagged by one month. T-statistics are reported in parentheses. Statistical significance is denoted by * p<0.1, ** p<0.05, and *** p<0.01.

Panel A: *Impact of Information Credibility on Risk Premium*

Sorting Variable	(1) High Gov	(2) Low Gov	(3) High Size	(4) Low Size	(5) Non-family	(6) Family
SID_{κ}^{EXE}: POS	18.84***	5.52	15.00***	-13.44*	9.96***	-0.24
	(4.34)	(1.21)	(2.76)	(-1.90)	(2.41)	(-0.03)
SID_{κ}^{EXE}: NEG	18.72***	3.60	14.88***	-8.04	6.72*	4.32
	(4.29)	(0.79)	(3.35)	(-1.00)	(1.71)	(0.55)
SID_{κ}^{EXE}: LIT	14.52***	6.24	15.12***	-16.68**	9.36***	0.12
	(3.30)	(1.41)	(2.90)	(-2.35)	(2.68)	(0.01)
SID_{κ}^{EXE}: UNC	14.52***	7.80	15.72***	-6.72	8.64**	0.60
	(3.21)	(1.73)	(2.96)	(-1.10)	(2.27)	(0.08)
SID_{κ}^{EXE}: FWD	16.44***	6.36	15.12***	-4.56	8.88***	-2.64
	(3.44)	(1.67)	(3.45)	(-0.60)	(3.05)	(-0.37)

Panel B: *Impact of Information Acquisition Cost on Risk Premium*

Sorting Variable	(1) High Equity	(2) Low Equity	(3) Post-lawsuit	(4) Pre-lawsuit
SID_{κ}^{EXE}: POS	6.48**	8.04**	9.00	-4.32
	(1.51)	(1.69)	(1.22)	(-0.43)
SID_{κ}^{EXE}: NEG	7.68**	3.12	9.96	-1.20
	(1.82)	(0.64)	(1.49)	(-0.11)
SID_{κ}^{EXE}: LIT	7.08**	2.76	9.60	-8.28
	(1.95)	(0.53)	(1.39)	(-0.89)
SID_{κ}^{EXE}: UNC	5.64*	3.48	10.92*	-7.32
	(1.44)	(0.79)	(1.68)	(-0.84)
SID_{κ}^{EXE}: FWD	7.68**	3.24	11.64	1.32
	(2.09)	(0.63)	(1.56)	(0.15)

Table 7: Macroeconomic Variables and Soft Information Disagreement

This table provides the coefficients from quarterly regressions of macroeconomic variables on the cross-sectional mean of soft information disagreement measures. $\text{SID}_{\kappa}^{g} : s$ represents the quarterly aggregated cross-sectional mean of extreme disagreement where g indicates the speaker group (EXE for executives, ANL for analysts) and s indicates the sentiment category. *SPCE* is the Real Services sector Personal Consumption Expenditure, *RGDP* is the growth in real Gross Domestic Product, and *GO* is the growth in gross output. T-statistics are reported in parentheses. All variables are defined in Appendix A. Statistical significance is denoted by * p<0.1, ** p<0.05, and *** p<0.01.

SID Measure	(1) SPCE	(2) RGDP	(3) GO	(4) SPCE	(5) RGDP	(6) GO	(7) SPCE	(8) RGDP	(9) GO	(10) SPCE	(11) RGDP	(12) GO	(13) SPCE	(14) RGDP	(15) GO
$\text{SID}_{\kappa}^{\text{ANL}}$: POS	-1.63	-1.62	-0.085												
	(-0.39)	(-0.47)	(-0.10)												
$\text{SID}_{\kappa}^{\text{EXE}}$: POS	95.79*	55.06	18.34*												
	(1.82)	(1.26)	(1.76)												
$\text{SID}_{\kappa}^{\text{ANL}}$: NEG				3.08	1.82	1.18									
				(0.49)	(0.36)	(0.97)									
$\text{SID}_{\kappa}^{\text{EXE}}$: NEG				88.72*	65.79*	18.99**									
				(1.96)	(1.77)	(2.16)									
$\text{SID}_{\kappa}^{\text{ANL}}$: LIT							-1.88	-0.08	0.36						
							(-0.41)	(-0.02)	(0.40)						
$\text{SID}_{\kappa}^{\text{EXE}}$: LIT							97.20	51.43	13.23						
							(1.67)	(1.07)	(1.15)						
$\text{SID}_{\kappa}^{\text{ANL}}$: UNC										-0.29	0.28	0.89			
										(-0.04)	(0.04)	(0.59)			
$\text{SID}_{\kappa}^{\text{EXE}}$: UNC										106.52**	76.30*	19.27*			
										(2.06)	(1.80)	(1.91)			
$\text{SID}_{\kappa}^{\text{ANL}}$: FWD													-2.68	-0.59	0.43
													(-0.43)	(-0.11)	(0.35)
$\text{SID}_{\kappa}^{\text{EXE}}$: FWD													134.88***	81.13*	20.80**
													(2.69)	(1.92)	(2.07)
Adjusted R^2	0.03	-0.00	0.02	0.04	0.03	0.08	0.03	-0.00	0.03	0.07	0.04	0.09	0.11	0.05	0.08

Table 8: Cash Flow and Discount Rate Channels

Panel A of this table provides the results of OLS regression of quarterly aggregate earning growth and discount rate on value-weighted quarterly returns of high quintile portfolio sorted on executive soft information disagreement ($\mathrm{SID}_{\kappa}^{\mathrm{EXE}}$). The dependent variables are average quarterly growth in aggregate gross profit (*GPgrth*) and primary credit rate (*DR*). The independent variable is the value-weighted return of highest quintile sorted on executive disagreement. Panel B provides the results of OLS regression of credit spread changes on executive sentiment disagreement. We use two measures of credit spread changes as dependent variables: δ3moyld is calculated as $\mathrm{Yield}_{t+3} - \mathrm{Yield}_{t-1}$, where t is in months; δLTyld is calculated as $\frac{1}{5}\sum_{j=1}^{5}\mathrm{Yield}_{t+j} - \frac{1}{5}\sum_{j=1}^{5}\mathrm{Yield}_{t-j}$. T-statistics are reported in parentheses. Statistical significance is denoted by * p<0.1, ** p<0.05, and *** p<0.01.

Panel A: *Aggregate Cash Flow and Market-Wide Discount Rate*

High quintile	(1) GPgrth	(2) GPgrth	(3) GPgrth	(4) GPgrth	(5) GPgrth	(6) DR	(7) DR	(8) DR	(9) DR	(10) DR
$\mathrm{SID}_{\kappa}^{\mathrm{EXE}}$: POS	0.011^{**}					0.00043^{**}				
	(2.04)					(2.01)				
$\mathrm{SID}_{\kappa}^{\mathrm{EXE}}$: NEG		0.010^{*}					0.00030			
		(1.94)					(1.37)			
$\mathrm{SID}_{\kappa}^{\mathrm{EXE}}$: LIT			0.008					0.00039^{*}		
			(1.66)					(1.90)		
$\mathrm{SID}_{\kappa}^{\mathrm{EXE}}$: UNC				0.010^{**}					0.00036^{*}	
				(2.02)					(1.70)	
$\mathrm{SID}_{\kappa}^{\mathrm{EXE}}$: FWD					0.011^{**}					0.00049^{**}
					(2.16)					(2.28)
mktrf	0.001	0.003	0.004	0.003	0.001	-0.00051^{*}	-0.00036	-0.00045^{*}	-0.00043	-0.00057^{**}
	(0.15)	(0.44)	(0.61)	(0.47)	(0.21)	(-1.90)	(-1.37)	(-1.77)	(-1.63)	(-2.13)
smb	0.013	0.014	0.013	0.015	0.015	-0.00029	-0.00029	-0.00027	-0.00025	-0.00023
	(1.29)	(1.38)	(1.30)	(1.42)	(1.48)	(-1.08)	(-1.05)	(-0.99)	(-0.93)	(-0.85)
hml	-0.003	-0.003	-0.003	-0.003	-0.003	-0.00019	-0.00017	-0.00017	-0.00016	-0.00017
	(-0.49)	(-0.45)	(-0.49)	(-0.53)	(-0.48)	(-0.81)	(-0.72)	(-0.71)	(-0.67)	(-0.70)
rmw	0.013	0.014	0.018	0.017	0.016	-0.00038	-0.00029	-0.00022	-0.00023	-0.00022
	(1.04)	(1.12)	(1.34)	(1.34)	(1.26)	(-1.10)	(-0.83)	(-0.64)	(-0.67)	(-0.66)
cma	-0.012	-0.011	-0.009	-0.009	-0.010	-0.00038	-0.00040	-0.00041	-0.00040	-0.00040
	(-0.75)	(-0.71)	(-0.56)	(-0.61)	(-0.65)	(-0.88)	(-0.90)	(-0.94)	(-0.92)	(-0.91)
Adjusted R^2	0.20	0.19	0.17	0.20	0.21	0.02	0.01	0.02	0.01	0.03
Observations	51	51	51	51	51	150	150	150	150	150

Panel B: *Credit Spread Changes on Executive Disagreement*

High quintile	(1) δ3moyld	(2) δLTyld	(3) δ3moyld	(4) δLTyld	(5) δ3moyld	(6) δLTyld	(7) δ3moyld	(8) δLTyld	(9) δ3moyld	(10) δLTyld
SID_{κ}^{EXE}: POS	0.00017	0.00023**								
	(1.34)	(2.19)								
SID_{κ}^{EXE}: NEG			0.00026*	0.00009						
			(1.94)	(0.94)						
SID_{κ}^{EXE}: LIT					0.00025**	0.00024**				
					(1.99)	(2.34)				
SID_{κ}^{EXE}: UNC							0.00022*	0.00013		
							(1.72)	(1.27)		
SID_{κ}^{EXE}: FWD									0.00008	0.00014
									(0.62)	(1.38)
Ln_MV	0.00**	0.00***	0.00***	0.00***	0.00**	0.00***	0.00**	0.00***	0.00**	0.00***
	(2.57)	(4.26)	(2.59)	(4.24)	(2.58)	(4.26)	(2.58)	(4.25)	(2.56)	(4.25)
Leverage	0.002***	0.001**	0.002***	0.001**	0.002***	0.001**	0.002***	0.001**	0.002***	0.001**
	(2.88)	(2.34)	(2.93)	(2.28)	(2.94)	(2.38)	(2.92)	(2.31)	(2.85)	(2.32)
GM	0.0004	0.0003	0.0004	0.0003	0.0004	0.0003	0.0004	0.0003	0.0004	0.0003
	(1.17)	(1.30)	(1.21)	(1.29)	(1.22)	(1.32)	(1.20)	(1.29)	(1.15)	(1.30)
YearQtr FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.26	0.49	0.26	0.49	0.26	0.49	0.26	0.49	0.26	0.49
Observations	7,793	9,343	7,793	9,343	7,793	9,343	7,793	9,343	7,793	9,343

Table 9: Determinants of Executive Soft Information Disagreement

This table examines the determinants of executive soft information disagreement ($\text{SID}_{\kappa}^{\text{EXE}}$). Panel A focuses on CEO and firm characteristics, while Panel B explores the topics discussed during conference calls. Eleven topics were derived from the conference call text using the topic dictionary provided by Fengler and Phan (2023). The dependent variable is executive extreme disagreement. $\text{SID}_{\kappa}^{\text{EXE}}$: s represents soft information disagreement where s indicates the sentiment category: positive (POS), negative (NEG), litigious (LIT), uncertainty (UNC), and forward-looking (FWD). T-statistics are reported in parentheses. All variables are defined in Appendix A. Standard errors are clustered at the firm level. Statistical significance is denoted by * p<0.1, ** p<0.05, and *** p<0.01.

Panel A: *CEO and Firm Characteristics*

	(1) $\text{SID}_{\kappa}^{\text{EXE}}$: POS	(2) $\text{SID}_{\kappa}^{\text{EXE}}$: NEG	(3) $\text{SID}_{\kappa}^{\text{EXE}}$: LIT	(4) $\text{SID}_{\kappa}^{\text{EXE}}$: UNC	(5) $\text{SID}_{\kappa}^{\text{EXE}}$: FWD
Market_To_Book	-0.013*	-0.017***	-0.020***	-0.018***	-0.017**
	(-1.88)	(-2.68)	(-2.79)	(-2.83)	(-2.39)
CEOpower	-0.038**	-0.047***	-0.050**	-0.045***	-0.034*
	(-2.11)	(-2.70)	(-2.51)	(-2.63)	(-1.96)
Old_CEO	0.072***	0.076***	0.080***	0.064***	0.075***
	(4.21)	(4.29)	(4.40)	(3.65)	(4.36)
Ln_CEOtenure	0.022***	0.015**	0.016**	0.020***	0.021***
	(3.64)	(2.35)	(2.53)	(3.22)	(3.40)
Neg_SUE	-0.002	0.004	0.004	0.002	0.005
	(-0.34)	(0.63)	(0.65)	(0.30)	(0.77)
Forecast_Error	0.031	0.026	0.082	0.078	-0.025
	(0.60)	(0.47)	(1.38)	(1.41)	(-0.49)
Ln_Analysts	0.010	0.007	0.020***	0.013	0.009
	(1.43)	(1.01)	(2.75)	(1.62)	(1.19)
ROA	-0.082	-0.113	-0.125	0.088	0.103
	(-0.50)	(-0.65)	(-0.66)	(0.52)	(0.62)
Ln_MV	0.034***	0.038***	0.046***	0.042***	0.038***
	(3.07)	(3.48)	(3.81)	(3.81)	(3.31)
R&D	0.065	0.566	-0.003	0.274	0.042
	(0.10)	(0.84)	(-0.00)	(0.45)	(0.07)
Leverage	0.040	0.013	0.041	0.025	0.031
	(0.91)	(0.30)	(0.86)	(0.55)	(0.67)
YearQtr FE	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.406	0.414	0.415	0.411	0.409
Observations	47,436	47,436	47,431	47,436	47,436

Panel B: *Topic-Specific Effects on Executive Disagreement*

Topic	(1) $\text{SID}_{\kappa}^{\text{EXE}}$: POS	(2) $\text{SID}_{\kappa}^{\text{EXE}}$: NEG	(3) $\text{SID}_{\kappa}^{\text{EXE}}$: LIT	(4) $\text{SID}_{\kappa}^{\text{EXE}}$: UNC	(5) $\text{SID}_{\kappa}^{\text{EXE}}$: FWD
T_sales	2.541***	2.019***	1.741***	1.863***	2.345***
	(4.61)	(3.79)	(3.16)	(3.48)	(4.24)
T_operations	1.276**	0.963*	0.857	0.716	0.991*
	(2.38)	(1.86)	(1.60)	(1.37)	(1.85)
T_employment	6.279***	5.947***	5.218***	5.641***	5.843***
	(4.30)	(4.21)	(3.58)	(3.96)	(4.00)
T_litigation	0.782	1.428***	1.985***	1.124**	0.846
	(1.45)	(2.73)	(3.67)	(2.13)	(1.57)
T_cost	-0.718	-0.526	-0.347	-0.624	-0.791
	(-1.25)	(-0.94)	(-0.60)	(-1.11)	(-1.37)
T_profit	-1.825***	-1.648***	-1.423***	-1.509***	-1.714***
	(-5.36)	(-5.00)	(-4.18)	(-4.54)	(-5.03)
T_liquidity	-3.873**	-3.041*	-2.673	-3.219*	-3.561**
	(-2.39)	(-1.93)	(-1.64)	(-2.03)	(-2.19)
T_financing	-1.449*	-1.264	-0.986	-1.079	-1.311
	(-1.70)	(-1.53)	(-1.15)	(-1.29)	(-1.53)
T_regulation	0.218	0.173	0.316	0.241	0.193
	(0.42)	(0.34)	(0.61)	(0.47)	(0.37)
T_accounting	-0.641	-0.518	-0.385	-0.549	-0.602
	(-1.15)	(-0.96)	(-0.69)	(-1.01)	(-1.08)
T_investment	0.324	0.276	0.215	0.293	0.305
	(0.59)	(0.52)	(0.39)	(0.54)	(0.56)
Controls	Yes	Yes	Yes	Yes	Yes
YearQtr FE	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.422	0.419	0.421	0.418	0.420
Observations	47,436	47,436	47,431	47,436	47,436

Table 10: Executive Soft Information Disagreement and CEO Turnover

This table explores the relationship between executive soft information disagreement ($\mathrm{SID}_{\kappa}^{\mathrm{EXE}}$) and the probability of CEO turnover. The dependent variable is one if the CEO is replaced in fiscal year t. $\mathrm{SID}_{\kappa}^{\mathrm{EXE}}$: s represents soft information disagreement where s indicates the sentiment category: positive (POS), negative (NEG), litigious (LIT), uncertainty (UNC), and forward-looking (FWD). T-statistics are reported in parentheses. All variables are defined in Appendix A. Standard errors are clustered at the firm level. Statistical significance is denoted by * p<0.1, ** p<0.05, and *** p<0.01.

	CEO Turnover (Dependent Variable)				
	(1)	(2)	(3)	(4)	(5)
$\mathrm{SID}_{\kappa}^{\mathrm{EXE}}$: POS	0.019***				
	(5.02)				
$\mathrm{SID}_{\kappa}^{\mathrm{EXE}}$: NEG		0.018***			
		(4.93)			
$\mathrm{SID}_{\kappa}^{\mathrm{EXE}}$: LIT			0.015***		
			(4.03)		
$\mathrm{SID}_{\kappa}^{\mathrm{EXE}}$: UNC				0.019***	
				(5.37)	
$\mathrm{SID}_{\kappa}^{\mathrm{EXE}}$: FWD					0.020***
					(5.41)
Market_To_Book	-0.006	-0.006	-0.006	-0.006	-0.006
	(-1.52)	(-1.50)	(-1.50)	(-1.49)	(-1.49)
CEOpower	-0.125***	-0.125***	-0.125***	-0.125***	-0.125***
	(-8.52)	(-8.51)	(-8.51)	(-8.51)	(-8.52)
Old_CEO	0.161***	0.161***	0.162***	0.162***	0.161***
	(11.90)	(11.90)	(11.90)	(11.91)	(11.89)
Ln_CEOtenure	0.119***	0.119***	0.119***	0.119***	0.119***
	(28.72)	(28.80)	(28.79)	(28.73)	(28.77)
Neg_SUE	0.013***	0.013***	0.013***	0.013***	0.013***
	(3.69)	(3.66)	(3.66)	(3.67)	(3.65)
Forecast_Error	0.045	0.045	0.044	0.044	0.046
	(1.56)	(1.56)	(1.54)	(1.52)	(1.60)
Ln_Analysts	0.009**	0.009**	0.008**	0.008**	0.009**
	(2.01)	(2.03)	(1.98)	(2.00)	(2.02)
ROA	-0.346***	-0.345***	-0.346***	-0.349***	-0.349***
	(-3.59)	(-3.59)	(-3.59)	(-3.63)	(-3.63)
Ln_MV	-0.024***	-0.024***	-0.024***	-0.024***	-0.024***
	(-3.34)	(-3.36)	(-3.35)	(-3.37)	(-3.36)
R&D	-0.094	-0.103	-0.092	-0.098	-0.093
	(-0.31)	(-0.34)	(-0.31)	(-0.33)	(-0.31)
Leverage	-0.048*	-0.048*	-0.048*	-0.048*	-0.048*
	(-1.76)	(-1.74)	(-1.76)	(-1.75)	(-1.76)
YearQtr FE	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.177	0.177	0.177	0.177	0.177
Observations	47,436	47,436	47,431	47,436	47,436

Internet Appendix Tables and Figures

Table A1: Decile Long-Short Annualized Alpha of Combined Soft Information Disagreement

This table presents the annualized abnormal returns (alpha) of long-short portfolio deciles sorted on disagreement variables constructed as combinations of sentiment measures. Panel A shows results for combined soft information disagreement formed using the first eigenvector from Principal Component Analysis (PCA) of sentiments in an expanding window panel manner, where at each month t, PCA was performed on the entire panel from 0 to $t-1$. Panel B shows results for combined soft information disagreement formed using the first eigenvector from PCA of sentiments in a cross-sectional manner, where at each month t, PCA was performed on the cross-section in period $t-1$. Panel C presents results for combined soft information disagreement formed using the mean of all sentiment dispersions from the previous month. The following sentiments were combined: positive (POS), negative (NEG), litigious (LIT), uncertainty (UNC), and forward-looking (FWD), for each of $\text{SID}_\kappa^{\text{EXE}}$, $\text{SID}_\sigma^{\text{EXE}}$, $\text{SID}_\kappa^{\text{ANL}}$ and $\text{SID}_\sigma^{\text{ANL}}$. The portfolios were formed within Fama-French 5 industries, and the returns were value-weighted. T-statistics are reported in parentheses. Statistical significance is denoted by * p<0.1, ** p<0.05, and *** p<0.01.

Panel A: *Expanding Window PCA*

	Executive (SID^{EXE})			Analyst (SID^{ANL})		
Dispersion Measure	CAPM alpha	FF3 alpha	FF5 alpha	CAPM alpha	FF3 alpha	FF5 alpha
SID_κ^g	12.96**	11.52**	11.28**	6.24	4.44	7.80
	(2.52)	(2.38)	(2.29)	(1.05)	(0.77)	(1.36)
SID_σ^g	0.72	0.00	-0.72	-3.60	-3.36	-1.80
	(0.19)	(0.01)	(-0.18)	(-0.86)	(-0.80)	(-0.44)

Panel B: *Cross-Sectional PCA*

	Executive (SID^{EXE})			Analyst (SID^{ANL})		
Dispersion Measure	CAPM alpha	FF3 alpha	FF5 alpha	CAPM alpha	FF3 alpha	FF5 alpha
SID_κ^g	11.40**	9.84**	10.20**	6.36	4.56	7.32
	(2.32)	(2.12)	(2.16)	(1.08)	(0.80)	(1.29)
SID_σ^g	1.08	0.48	1.20	-1.80	-1.20	-1.20
	(0.29)	(0.13)	(0.33)	(-0.47)	(-0.30)	(-0.31)

Panel C: *Simple Average*

	Executive (SID^{EXE})			Analyst (SID^{ANL})		
Dispersion Measure	CAPM alpha	FF3 alpha	FF5 alpha	CAPM alpha	FF3 alpha	FF5 alpha
SID_κ^g	12.48**	11.16**	10.92*	-0.72	-3.60	-1.20
	(2.46)	(2.33)	(2.23)	(-0.14)	(-0.76)	(-0.24)
SID_σ^g	1.80	1.68	1.32	-5.64	-4.68	-2.76
	(0.45)	(0.42)	(0.34)	(-1.23)	(-1.04)	(-0.61)

Table A2: Speech Complexity by Speaker Type

This table explores the relation between speaker type and speech complexity during earnings conference calls. The dependent variable is speech complexity measured following Loughran and McDonald (2024). *Executive* is an indicator variable that equals 1 if the speaker is an executive and 0 if the speaker is an analyst. All variables are defined in Appendix A. T-statistics are reported in parentheses. Standard errors are clustered by firm. Statistical significance is denoted by * p<0.1, ** p<0.05, and *** p<0.01.

	Speech Complexity		
	(1)	(2)	(3)
Executive	0.00036***	0.00027***	0.00034***
	(8.56)	(4.41)	(4.76)
Market_To_Book	-0.00000*	-0.00000*	-0.00000*
	(-1.83)	(-1.69)	(-1.95)
CEOpower		-0.00007	-0.00008
		(-0.51)	(-0.50)
Old_CEO		0.00028	-0.00009
		(0.57)	(-0.15)
Ln_CEOtenure		-0.00014***	-0.00009
		(-2.59)	(-1.29)
Neg_SUE			-0.00007
			(-0.99)
Forecast_Error			-0.00003***
			(-4.73)
Ln_Analysts			-0.00001
			(-0.70)
ROA	0.00002	-0.00546***	-0.00558***
	(0.03)	(-4.18)	(-3.20)
Ln_MV	0.00006**	0.00011***	0.00021***
	(2.39)	(2.68)	(3.63)
R&D	-0.00480*	-0.02162***	-0.02627***
	(-1.74)	(-6.51)	(-6.66)
Leverage	0.00150***	0.00157***	0.00149***
	(9.57)	(5.84)	(4.40)
YearQtr FE	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes
Adjusted R^2	0.01	0.01	0.01
Observations	6,497,331	3,567,816	2,226,365

Table A3: Analyst Soft Information Disagreement and Conference Call Word Count

This table examines the relationship between analyst soft information disagreement ($\text{SID}_{\kappa}^{\text{ANL}}$) and the word count of conference calls. The dependent variable is the word count, with $\mathcal{W}_{\text{T}}$ representing the total word count from the conference call, and $\mathcal{W}_{\text{E}}$ representing the count of words spoken by executives only. All variables are defined in Appendix A. T-statistics are reported in parentheses. Standard errors are clustered by firm. Statistical significance is denoted by * p<0.1, ** p<0.05, and *** p<0.01.

	(1) $\mathcal{W}_{\text{T}}$	(2) $\mathcal{W}_{\text{T}}$	(3) $\mathcal{W}_{\text{T}}$	(4) $\mathcal{W}_{\text{T}}$	(5) $\mathcal{W}_{\text{T}}$	(6) $\mathcal{W}_{\text{T}}$	(7) $\mathcal{W}_{\text{E}}$	(8) $\mathcal{W}_{\text{E}}$	(9) $\mathcal{W}_{\text{E}}$	(10) $\mathcal{W}_{\text{E}}$	(11) $\mathcal{W}_{\text{E}}$	(12) $\mathcal{W}_{\text{E}}$
$\text{SID}_{\kappa}^{\text{ANL}}$: AGG	184.60***						116.80***					
	(17.22)						(12.69)					
$\text{SID}_{\kappa}^{\text{ANL}}$: POS		116.70***						67.70***				
		(20.35)						(14.13)				
$\text{SID}_{\kappa}^{\text{ANL}}$: NEG			110.50***						62.50***			
			(19.73)						(13.26)			
$\text{SID}_{\kappa}^{\text{ANL}}$: LIT				116.40***						66.70***		
				(21.25)						(14.43)		
$\text{SID}_{\kappa}^{\text{ANL}}$: UNC					122.00***						72.80***	
					(19.75)						(13.78)	
$\text{SID}_{\kappa}^{\text{ANL}}$: FWD						113.70***						69.90***
						(20.02)						(14.31)
Market_To_Book	-70.00***	-75.70***	-69.00***	-55.10**	-67.80***	-72.70***	-71.80***	-75.80***	-70.60***	-61.70***	-70.60***	-73.50***
	(-3.15)	(-3.28)	(-3.01)	(-2.48)	(-3.06)	(-3.33)	(-3.63)	(-3.69)	(-3.45)	(-3.07)	(-3.56)	(-3.75)
ROA	-1988.70***	-2143.70***	-2045.80***	-2261.60***	-1965.90***	-1942.50***	-1842.80***	-2056.00***	-1917.20***	-2131.50***	-1822.90***	-1835.20***
	(-3.11)	(-3.23)	(-3.10)	(-3.06)	(-3.11)	(-3.03)	(-3.22)	(-3.48)	(-3.26)	(-3.14)	(-3.21)	(-3.18)
Ln_MV	388.10***	391.00***	380.80***	316.00***	383.80***	373.30***	300.90***	304.90***	296.60***	257.60***	298.70***	290.70***
	(8.88)	(8.60)	(8.63)	(6.78)	(8.77)	(8.56)	(7.63)	(7.50)	(7.44)	(6.12)	(7.55)	(7.36)
R&D	-448.00	-399.50	-632.90	-319.70	-467.90	-94.50	137.90	33.70	-91.70	73.00	122.60	245.90
	(-0.23)	(-0.19)	(-0.31)	(-0.15)	(-0.24)	(-0.05)	(0.08)	(0.02)	(-0.05)	(0.04)	(0.07)	(0.14)
Leverage	419.80**	364.20**	431.90**	430.70**	390.60**	413.20**	351.50**	300.10**	355.90**	338.00**	332.90**	343.10**
	(2.49)	(2.06)	(2.49)	(2.50)	(2.29)	(2.42)	(2.39)	(1.96)	(2.36)	(2.20)	(2.25)	(2.31)
CEOpower	-32.50	-40.20	-41.00	-23.70	-17.80	-25.00	-45.30	-50.10	-50.00	-32.70	-35.60	-40.50
	(-0.57)	(-0.68)	(-0.70)	(-0.40)	(-0.32)	(-0.44)	(-0.89)	(-0.95)	(-0.97)	(-0.61)	(-0.70)	(-0.80)
Old_CEO	-115.40**	-141.00**	-130.80**	-105.70*	-125.50**	-129.90**	-93.50*	-110.20**	-103.00**	-84.10	-101.40*	-105.10**
	(-2.03)	(-2.46)	(-2.29)	(-1.77)	(-2.18)	(-2.30)	(-1.83)	(-2.13)	(-1.99)	(-1.56)	(-1.95)	(-2.04)
Ln_CEOtenure	34.00	37.00	33.00	10.80	33.00	33.90	33.00	35.00	31.50	12.90	32.70	34.00
	(1.46)	(1.55)	(1.41)	(0.44)	(1.43)	(1.45)	(1.56)	(1.61)	(1.47)	(0.57)	(1.55)	(1.59)
Neg_SUE	38.10*	28.00	34.80*	24.20	39.90**	45.10**	31.20*	21.30	28.40	17.20	32.60*	36.50**
	(1.90)	(1.36)	(1.69)	(1.14)	(2.00)	(2.23)	(1.81)	(1.20)	(1.60)	(0.94)	(1.90)	(2.10)
Forecast_Error	506.60**	562.80**	544.80**	533.90**	579.00**	598.50**	533.60**	566.20**	548.90**	566.10**	575.10***	595.70***
	(2.18)	(2.27)	(2.27)	(1.97)	(2.48)	(2.53)	(2.55)	(2.54)	(2.55)	(2.35)	(2.72)	(2.80)
Ln_Analysts	469.50***	445.90***	456.80***	410.70***	459.20***	439.70***	327.90***	313.00***	318.90***	294.70***	323.10***	308.80***
	(16.32)	(15.21)	(16.04)	(13.72)	(16.13)	(15.55)	(13.25)	(12.41)	(12.99)	(11.21)	(13.14)	(12.63)
YearQtr FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.60	0.58	0.58	0.59	0.60	0.59	0.59	0.58	0.58	0.58	0.59	0.59
Observations	39,269	37,122	37,798	30,806	39,275	38,574	39,268	37,121	37,797	30,805	39,274	38,573

Table A4: Soft Information Disagreement and Stock Returns: Fama-MacBeth Regression

This table reports the results of Fama-MacBeth regressions of stock returns in month $t+1$ on executive soft information disagreement in month t and other control variables. $\mathrm{SID}_{\kappa}^{\mathrm{EXE}}$: s represents executive extreme disagreement where s indicates the sentiment category: positive (POS), negative (NEG), litigious (LIT), uncertainty (UNC), and forward-looking (FWD). All variables are defined in Appendix A. T-statistics are reported in parentheses. Statistical significance is denoted by * p<0.1, ** p<0.05, and *** p<0.01.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
$\mathrm{SID}_{\kappa}^{\mathrm{EXE}}$: POS	4.56***	-0.72								
	(1.89)	(-0.24)								
$\mathrm{SID}_{\kappa}^{\mathrm{EXE}}$: NEG			5.04***	3.48**						
			(2.29)	(2.38)						
$\mathrm{SID}_{\kappa}^{\mathrm{EXE}}$: LIT					4.68**	3.12*				
					(2.26)	(1.85)				
$\mathrm{SID}_{\kappa}^{\mathrm{EXE}}$: UNC							4.80**	3.84***		
							(2.06)	(2.47)		
$\mathrm{SID}_{\kappa}^{\mathrm{EXE}}$: FWD									5.40***	3.72**
									(2.52)	(2.35)
Market_To_Book	11.40	4.56	9.96	3.36	8.52	4.32	11.52	3.48	8.64	3.72
	(1.33)	(0.78)	(1.25)	(0.56)	(1.26)	(0.74)	(1.28)	(0.59)	(1.22)	(0.61)
OP	-18.00	2.16	-9.96	-1.56	-14.88	0.96	-17.52	-2.52	-18.00	-0.72
	(-0.86)	(0.37)	(-0.81)	(-0.44)	(-0.90)	(0.19)	(-0.90)	(-0.67)	(-0.93)	(-0.17)
IF	-2.28	2.40	-2.40	-0.24	-2.40	0.00	-1.80	0.48	-2.40	0.00
	(-0.38)	(0.36)	(-0.39)	(-0.04)	(-0.38)	(0.01)	(-0.29)	(0.08)	(-0.38)	(0.01)
Size	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	(-0.51)	(-0.95)	(-0.53)	(-0.97)	(-0.52)	(-0.97)	(-0.51)	(-0.96)	(-0.52)	(-0.97)
MktBeta	-6.72	3.48	-6.72	-0.24	-4.32	-0.48	-7.20	-0.72	-5.16	-0.96
	(-0.82)	(0.80)	(-0.86)	(-0.05)	(-0.67)	(-0.08)	(-0.85)	(-0.14)	(-0.80)	(-0.17)
Momentum	0.00	0.24**	0.00	0.24**	0.00	0.24**	0.00	0.24**	0.00	0.24**
	(0.56)	(2.09)	(0.63)	(2.36)	(0.61)	(2.35)	(0.63)	(2.27)	(0.53)	(2.22)
Forecast_Error		-34.44*		-36.36*		-33.96		-38.28		-36.12
		(-1.96)		(-2.09)		(-1.91)		(-2.05)		(-1.97)
Ln_Analysts		0.00		0.24		0.12		0.24		0.24
		(-0.03)		(0.39)		(0.33)		(0.44)		(0.41)

Table A5: Long-Short Portfolio Annualized Alpha - Dialogue Level

This table provides annualized abnormal returns (alpha) of long-short portfolio deciles constructed using extreme disagreement ($\text{SID}_{\kappa}^{\text{DIA}}$) and moderate disagreement ($\text{SID}_{\sigma}^{\text{DIA}}$) of various sentiments as sorting variables, with analysis performed at the dialogue level rather than speaker level. Thus, it does not measure disagreement among speakers and can only be interpreted as general textual disagreement. The portfolios were formed within Fama-French 5 industries, and returns were value-weighted. Each sorting variable was lagged by 1 month. $\text{SID}_{d}^{\text{DIA}}$: s represents dialogue-level soft information disagreement where d denotes the dispersion measure (kurtosis, κ, or standard deviation, σ) and s indicates the sentiment category: positive (POS), negative (NEG), litigious (LIT), uncertainty (UNC), and forward-looking (FWD). Columns (1)-(3) provide returns for extreme disagreement ($\text{SID}_{\kappa}^{\text{DIA}}$) while columns (4)-(6) provide returns for moderate disagreement ($\text{SID}_{\sigma}^{\text{DIA}}$). T-statistics are reported in parentheses. All variables are defined in Appendix A. Statistical significance is denoted by * p<0.1, ** p<0.05, and *** p<0.01.

	Extreme Disagreement ($\text{SID}_{\kappa}^{\text{DIA}}$)			Moderate Disagreement ($\text{SID}_{\sigma}^{\text{DIA}}$)		
Sentiment Category	CAPM alpha	FF3 alpha	FF5 alpha	CAPM alpha	FF3 alpha	FF5 alpha
POS	-2.52	-2.88	-2.52	-1.08	-0.96	-1.68
	(-0.68)	(-0.76)	(-0.63)	(-0.31)	(-0.29)	(-0.48)
NEG	2.64	2.16	3.36	2.16	2.04	2.76
	(0.71)	(0.56)	(0.88)	(0.68)	(0.64)	(0.88)
LIT	0.24	0.12	0.48	-4.44	-4.68	-6.48*
	(0.06)	(0.02)	(0.13)	(-1.23)	(-1.27)	(-1.76)
UNC	1.80	2.64	3.72	-3.96	-3.36	-2.64
	(0.46)	(0.64)	(0.91)	(-0.96)	(-0.82)	(-0.64)
FWD	4.80	4.08	4.08	3.36	4.20	5.16
	(1.31)	(1.13)	(1.08)	(0.78)	(1.00)	(1.18)

Table A6: Soft Information Disagreement Risk Premium Loadings on High and Low Portfolios

This table presents the coefficients from regressing the returns of the high and low decile portfolios on executive soft information disagreement (SID_{κ}^{EXE}) risk factors, alongside the Fama-French factors. The disagreement risk factor is calculated as the return of the long-short portfolio orthogonalized with respect to the Fama-French five factors. Both the risk factor and the high and low portfolios are constructed based on the same measure of executive extreme disagreement (SID_{κ}^{EXE}). SID_{κ}^{EXE} : s represents soft information disagreement where s indicates the sentiment category: positive (POS), negative (NEG), litigious (LIT), uncertainty (UNC), and forward-looking (FWD). All variables are defined in Appendix A. T-statistics are reported in parentheses. Statistical significance is denoted by * p<0.1, ** p<0.05, and *** p<0.01.

	Low					High				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
SID_{κ}^{EXE}: POS	-4.32***					7.68***				
	(-10.54)					(18.25)				
SID_{κ}^{EXE}: NEG		-4.20***					7.80***			
		(-8.11)					(15.09)			
SID_{κ}^{EXE}: LIT			-5.28***					6.72***		
			(-11.58)					(14.78)		
SID_{κ}^{EXE}: UNC				-5.40***					6.60***	
				(-12.05)					(14.65)	
SID_{κ}^{EXE}: FWD					-4.92***					7.08***
					(-8.71)					(12.66)
$mktrf$	12.24***	12.24***	12.48***	12.48***	12.24***	12.84***	12.00***	12.72***	12.84***	12.96***
	(26.61)	(23.70)	(27.07)	(27.78)	(24.53)	(27.08)	(22.87)	(27.37)	(27.96)	(25.76)
SMB	2.64***	2.16**	3.12***	3.00***	2.16**	-2.28**	-0.60	-1.68*	-3.60***	-2.40**
	(3.17)	(2.29)	(3.87)	(3.81)	(2.42)	(-2.76)	(-0.68)	(-2.05)	(-4.41)	(-2.75)
HML	0.00	0.36	-0.36	-0.72	0.48	0.72	2.04**	0.00	0.96	-0.36
	(0.06)	(0.40)	(-0.56)	(-1.02)	(0.59)	(1.04)	(2.44)	(0.05)	(1.31)	(-0.41)
RMW	2.40**	1.92	2.64***	2.04**	2.16**	0.48	0.72	-0.48	-2.76***	-1.56
	(2.33)	(1.62)	(2.61)	(2.07)	(1.90)	(0.51)	(0.65)	(-0.41)	(-2.64)	(-1.37)
CMA	-0.36	0.48	-1.20	-1.08	0.24	3.96***	2.88	5.16***	5.64***	3.84***
	(-0.30)	(0.32)	(-0.94)	(-0.82)	(0.16)	(2.91)	(1.90)	(3.94)	(4.27)	(2.72)
Intercept	-4.08**	-3.36	-4.68**	-4.68**	-3.12	3.72*	3.96	3.48	4.20**	4.68**
	(-2.19)	(-1.59)	(-2.52)	(-2.58)	(-1.58)	(1.96)	(1.90)	(1.84)	(2.28)	(2.33)