Managerial (In)Attention to Financial Markets

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Abstract

I develop a direct measure of managerial attention to financial markets using managers' own discussion on market conditions during earnings calls covering nearly all U.S. public firms from 2007–2023. Attention varies widely across firms, across industries, and within firms over time. Managers who pay greater attention to markets exhibit higher investment-price sensitivity. Attention also enhances managers' ability to access external capital when financing needs arise, at least through enabling them to respond more effectively to changing market conditions. These findings provide the first direct evidence, based on revealed managerial behavior, supporting price feedback theory and market-timing theory. I then develop and empirically show that a simple rational-inattention model explains why such heterogeneity in attention can arise rationally, completing the causal chain linking market informativeness, attention, and corporate decisions. Attention also offers a behavioral explanation for the large cross-sectional dispersion between true and perceived costs of capital documented by Gormsen and Huber (2024).

Keywords: Attention to Financial Markets, Earnings Calls, Machine Learning, Real Effects of Financial Markets, Rational Inattention

(JEL: G14, G32, G41)

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1. Introduction

Many foundational theories—including price feedback theory (Bond, Edmans, and Goldstein, 2012) and market-timing theory (Baker and Wurgler, 2002)—predict that when managers actively monitor financial markets, they can incorporate information embedded in prices into real corporate decisions. Stock prices may reveal information about investment opportunities, while conditions in equity and debt markets convey signals about firms' cost of capital and financing capacity. If managers attend to and process these signals, financial markets should exert real effects on corporate investment and financing policies.

A large empirical literature studies these predictions by examining correlations between market prices and corporate actions. Numerous studies document that investment is more sensitive to stock prices when prices are assumed to be more informative, such as when insider trading is constrained or when external information acquisition by investors intensifies (e.g., Chen, Goldstein, and Jiang, 2007; Edmans, Jayaraman, and Schneemeier, 2017). Related work shows that firms issue equity or debt more aggressively during favorable market conditions, consistent with market-timing behavior (Baker and Wurgler, 2002; Ma, 2019). However, as emphasized by Gelsomin and Hutton (2023), these studies typically *infer* the role of managerial learning—or, more broadly, the real effects of financial markets—from changes in investment–price sensitivity across settings where the information content of prices is presumed to vary, rather than from direct evidence on managers' engagement with market signals. As a result, the same empirical patterns are observationally consistent with alternative channels, including common unobserved factors influencing both prices and corporate policies, as well as investor influence that operates through private engagement with management while the same investors simultaneously affect stock prices through their trading activity. Similarly, correlations between security issuance and market conditions may reflect unobservable firm characteristics—such as governance quality, endogenous financing margins, or managerial biases—rather than managers actively timing the market (e.g., Jung, Kim, and Stulz, 1996; Hennessy and Whited, 2004; Malmendier, Tate, and Yan, 2011).

This challenge reflects a broader measurement problem. The real effects of financial markets operate through two jointly necessary channels: the usefulness of market signals and managers' attention to those signals. While existing research has devoted substantial effort to measuring and refining the first channel, the second has remained largely unobserved. Without a direct measure of managerial attention, empirical tests cannot disentangle learning from markets from correlations driven by omitted variables. This limitation is particularly important when attention is a scarce cognitive resource (Kahneman (1973)), and managers have limited attention (e.g., Yermack, 2014; Neyland, 2020; Ben-Rephael, Carlin, Da, and Israelsen, 2025). In such settings, the risk of false positive inference—misattributing observed correlations between market conditions and corporate policies to the real effects of financial markets—becomes especially pronounced.

In this paper, I address this missing behavioral channel by developing a novel and *direct measure* of managerial attention to financial markets—the *Index of Attention to Financial Markets* (IAFM)—constructed from managers' own discussions of market conditions during earnings calls. This measure allows me to examine whether managers who pay more attention to financial markets behave differently from those who pay less attention, and whether these behavioral differences align with theoretical predictions. The underlying idea is straightforward: if financial markets have real effects, managers should respond more strongly to market signals when they devote more attention to them.

Earnings calls provide an ideal setting for capturing such attention because these quarterly events combine structured presentations with spontaneous Q&A sessions, revealing both strategic priorities and top-of-mind concerns. Since earnings calls are time-constrained, managers must allocate their limited speaking time selectively. Greater discussion of financial market conditions therefore plausibly indicates higher attention allocation to such information—an assumption I validate through extensive testing. The near-universal use of earnings calls by public firms also enables a systematic and scalable measurement approach across a large panel (98,010 firm-year observations, 2007–2023).

Starting from a set of seed words that are unambiguously related to financial markets, I use machine learning keyword discovery techniques (Mikolov et al. 2013; specifically, *word2vec*) to construct a comprehensive dictionary capturing the language managers use to discuss market conditions. I then score transcripts with a tf-idf approach, producing firm-level measures of *equity* and *debt* market attention. Equity attention reflects the monitoring assumed by canonical theories such as price feedback and market timing, while debt attention captures monitoring of an important financing source that conveys distinct signals about investment and financing opportunities (e.g., Graham, Leary, and Roberts 2015; Ma 2019; Davis and Gondhi 2024).

I validate that the IAFM captures meaningful variation in attention, in line with economic intuition. For example, financial firms exhibit the highest attention to both equity and debt markets, consistent with their business models that inherently rely on continuous market monitoring. Firms led by finance-expert CEOs devote significantly greater attention to financial markets, consistent with the idea that specialized financial expertise enhances market awareness. Moreover, the two IAFM dimensions respond distinctly to relevant market movements: equity-market attention increases following positive firm-specific stock returns, whereas debt-market attention rises with changes in interest rates.

Beyond the validation exercises, a striking empirical finding is the substantial heterogeneity in how much managers attend to financial markets. Attention varies across firms (about 30% of total variation), across industries (roughly 40%), and even within firms over time (about 30%). This pattern challenges the long-standing implicit assumption in many theoretical models—that all managers should devote a homogeneous or fixed level of attention to market signals. Instead, it implies that differences in managerial attention are a first-order driver of why market prices affect real decisions more strongly for some firms than others. By documenting and quantifying this dispersion, the paper offers new behavioral micro-foundations for heterogeneity in the real effects of financial markets.

I then explore the implications of having a strong attention to financial markets on business outcomes. My empirical strategy is organized around testing the two fundamental roles that financial markets serve in corporate decision-making: (1) providing information about business opportunities to guide investment policy, and (2) conveying information about the cost of capital to guide financing policy. First, for investment policy, firms whose managers allocate greater attention to financial markets exhibit significantly greater investment-price sensitivity. A 10% increase in equity market attention enhances capital expenditure sensitivity to Tobin's Q by 1.85%, while a 10% increase in debt market attention increases this sensitivity by 2.58%. The effect is most pronounced in situations where the manager is particularly likely to learn from market signals: when insider trading is limited, when industry competition is high, when price is informative, when firms face financial constraints, and when attention carries a positive tone. These results provide the first *direct* evidence, based on revealed managerial behavior, for the feedback theory.

Second, for financing policy, I find that attention to financial markets serves as a critical organizational capability that enhances firms' ability to access external capital at the *extensive margin* when financing needs arise. A 10% increase in equity market attention is associated with a 1.66% higher likelihood of issuing equity in response to financing deficits, while a 10% increase in debt market attention corresponds to an 11.85% higher likelihood of issuing debt. Thus, managers who actively monitor financial market conditions appear to develop expertise in assessing cost of capital dynamics. Importantly, each form of attention also predicts issuance in the "other" market: a 10% increase in equity-market attention is associated with a 1.99% higher likelihood of issuing debt, while a 10% increase in debt-market attention corresponds to a 4.17% higher likelihood of issuing equity. These patterns cannot be explained by managers simply disclosing, or signaling, intended financing plans during calls; if that were the case, attention to the "other" market should exhibit no—or even negative—predictive power. Rather, the evidence is more consistent with the idea that attention captures distinct informational advantages that may help managers identify and seize financing opportunities across multiple markets.

To formally test this hypothesis, I examine whether attention alters the responsiveness of financing choices to *market-specific* conditions. I restrict the sample to firms that issue from a single source in a given year, thereby holding financing needs roughly constant and reducing concerns that attention merely proxies for capital demand. The results show that equity-market attention enhances responsiveness to equity conditions—firms are more likely to issue equity over debt when firm valuations or equity market sentiment are high—while debt-market attention sharpens responsiveness to debt conditions—firms are more likely to shift toward equity when interest rates rise. This dimension-specific responsiveness suggests that attention allows managers to time financing decisions more effectively by choosing the relatively cheaper source of capital. It provides the first *direct* empirical evidence from observed managerial attention in support of market-timing theory and Ma (2019), showing that firms' ability to exploit financing windows and cross-arbitrage their own securities hinges on how much attention managers actually devote to monitoring financial markets.[1]

Furthermore, since I have shown that attention enhances firms' financing capabilities, it becomes crucial now to disentangle two mechanisms that may drive the attention-induced investment-price sensitivity: (1) improved extraction of information about fundamental business opportunities (as predicted by price feedback theory), or/and (2) better assessment of financing conditions that enables more flexible investment responses when capital constraints are relaxed. To isolate the first channel, I examine firms that do not raise external funds during investment. Among these firms, equity market attention continues to strengthen investment-price sensitivity, consistent with managers learning about investment opportunities from stock prices. In contrast, the effect of debt market attention on investment-price sensitivity disappears without external financing, suggesting it primarily operates through easing financing constraints.

To further distinguish these mechanisms, I draw on Gormsen and Huber's (2024) earnings call–based measure of *perceived* cost of capital, which captures managers' subjective beliefs about their financing costs. Incorporating this measure into my analysis shows that equity-market attention continues to predict stronger investment–price sensitivity even after controlling for perceived cost of capital, consistent with attention operating through a business-opportunity channel. By contrast, the explanatory power of debt-market attention diminishes once perceived cost of capital is accounted for, indicating that it mainly affects investment by shaping how managers *perceive* financing conditions rather than by altering productivity of capital. Thus, this result shows that managerial attention not only reflects but also shapes perceptions of financing frictions—helping to explain why perceived and true costs of capital diverge, as documented by Gormsen and Huber (2024). More

[1] Because periods of strong equity performance often coincide with lower, time-varying adverse selection costs, my results may also be interpreted as consistent with managers *timing* such fluctuations—an interpretation also aligned with pecking order theory (Myers and Majluf 1984).

specifically, attentive managers learn from informative price signals and reduce uncertainty about financing conditions, whereas inattentive managers—processing fewer signals—tend to overestimate financing costs and underinvest even when capital is readily accessible.

Additional tests suggest that my findings are not driven by specific methodological choices in constructing the IAFM measures. Specifically, I start by separately analyzing attention derived from management presentations and Q&A sessions and show that both sources exhibit statistically significant effects on investment and financing decisions.[2] Furthermore, I find that results remain robust when using only term frequency without inverse document frequency weighting, addressing concerns that the tf-idf approach might introduce noise by overweighting infrequently used terms. Finally, the key findings remain both statistically and economically significant when I build the IAFM using only 25 seed words per dimension or replace the continuous IAFM measures with binary indicators.

A potential concern is that the observed link between managerial attention and corporate policies merely reflects a mechanical transmission of market conditions into firms' cost of capital or financing availability, rather than managers actively processing or learning from market information. In this "*attention-as-sideshow*" view, financial shocks influence firms *purely* through the primary-market channel while managerial attention merely tracks these shocks as a passive sideshow rather than influencing decision-making itself. If this were the case, attention should lose all explanatory power once market conditions such as Tobin's Q, bond yields, total implied cost of capital, sentiment, interest rates, and equity returns are directly controlled for. However, this prediction is not supported by the data: the interaction terms between attention and market variables remain positive and significant even after controlling for these market conditions, and the results are robust to additional controls for managers' attention to volatility and liquidity shock. Moreover, a key insight of this paper is

[2] I also find that the effects based on Q&A-derived measures are, on average, economically larger. This helps address an alternative explanation where managers have already formulated investment and financing decisions independent of financial market conditions but subsequently reference market conditions in earnings calls primarily to provide *post-hoc* rationalization to investors. For example, managers may do so to make their decisions appear more rational and externally validated to investors. If this "*post-hoc rationalization*" or "*reverse-causality*" explanation was driving the results, we would expect stronger effects in the more carefully scripted presentations, where managers exert greater control over the narrative. Instead, the larger effects are observed in the relatively unscripted Q&A discussions.

that even when a primary-market channel operates, attention exerts an incremental behavioral effect, echoing Song and Stern's (2025) finding that managerial inattention dampens firms' responses to monetary policy shocks. For example, for financing policies, managers who pay greater attention to debt markets are more likely to shift from debt to equity financing when interest rates rise, even after accounting for the direct effect of rate changes themselves. For investment policies, even after accounting for the direct effect of borrowing costs, managers with greater debt-market attention expand investment more when bond yields fall. Together, the results show that managerial attention shapes firms' responses to financial markets in ways that cannot be explained by a *purely* mechanical channel.

Another concern is that the documented relationship between managerial attention and corporate policies may reflect lifecycle, firm-stage characteristics, or investor pressure, rather than attention itself. For example, more mature firms may both appoint CEOs with stronger market orientation and pursue financing or investment strategies that are more sensitive to market conditions—possibly in response to investor pressure—creating endogenous matching between firm characteristics and managerial types. I address this concern in several ways. First, I control for firm and industry-by-year fixed effects, which addresses endogenous matching based on only time-invariant firm characteristics or common industry shocks. Second, I exploit within-firm variation around CEO turnovers and show that even around plausibly exogenous CEO transitions—specifically cases where predecessor CEOs retire at age 65 or older—firms led by high-attention successors tend to exhibit greater investment–price sensitivity and stronger responsiveness to financing needs. These findings suggest that, *at the very least*, managerial attention is a *necessary* mechanism for translating market signals into real corporate actions. In other words, even if a firm's industry, lifecycle stage, or investor pressure may determine that it should respond to market signals or time financing around market conditions, implementing those policies in practice requires managers who actually pay attention to markets. Without the informational role of financial markets—and managerial attention to those signals—firms would be unable to execute such optimal decisions. This is still in line with the causal role of financial markets operating through managers' active monitoring of market information. It is inconsistent with the alternative "*no-attention-needed*" or "*no-real-effects*" view, under which a firm would pursue exactly the same policies regardless of whether managers themselves are attentive to financial markets because market prices then contain no additional information beyond fundamentals already known to the firm.

To test whether managerial attention affects investment decisions through economically relevant information channels, I examine industry-specific responses to market signals using the energy sector as a natural comparison. Because energy firms are directly exposed to commodity price fluctuations, they rely more heavily on signals from commodity markets than on traditional equity or debt markets. I develop an *IAFM Other Assets* measure that captures attention to commodity, currency, and derivatives markets, and show that Energy firms consistently exhibit the highest levels of such attention. Consistent with the proposed mechanism, only Energy firms—those for whom commodity prices are informative—adjust their investment more sensitively to commodity price changes when attention is high, while traditional financial market signals matter more for non-Energy firms. This pattern supports the view that attention-induced investment responsiveness operates through channels relevant to firm-specific fundamentals—or, at the very least, provides an out-of-sample test (by studying a market setting different from my main analysis) showing that attention is a key channel through which market prices influence investment decisions.

Finally, I develop a simple rational inattention model to explain why some managers choose not to monitor financial markets despite the documented benefits for investment and financing decisions. Managers face a fixed cognitive budget that must be split between processing internal firm information and external price signals, so attention to markets can crowd out internal monitoring. Inattention becomes optimal when internal signals are more informative than prices. The model predicts that managers with lower cognitive costs—such as finance-expert CEOs—pay more attention, while those in industries characterized by greater information asymmetry tend to "look inward". I find empirical evidence supporting both predictions. Conceptually, this framework completes the causal chain necessary to establish the real effects of financial markets: managers have incentives to monitor markets precisely when market signals are relatively more informative, and they subsequently exploit the benefits of doing so when making investment and financing decisions. This rational allocation of attention contradicts the alternative hypothesis ("*no-attention-needed*" view), which implies that managers would have no reason to monitor markets—nor would doing so yield any benefit—if financial prices carried no information relevant to real decisions.

This paper revisits a fundamental but largely untested assumption underlying much of corporate finance theory: that managers actively pay attention to financial markets. The real effects of financial markets fundamentally depend on two necessary channels—(1) the usefulness of market signals and (2) managers' attention to financial markets. Foundational theories such as price feedback (as summarized in Bond, Edmans, and Goldstein 2012) and market timing (Baker and Wurgler 2002) have developed rich predictions about the first channel, while implicitly treating the second as given. Similarly, a large empirical literature has inferred the real effects of financial markets from correlations between prices and corporate policies, without direct evidence on whether managers actually monitor or process market information. This paper directly measures that missing behavioral channel—managerial attention to financial markets—and documents substantial heterogeneity in attention across firms, industries, and time.

Building on this behavioral foundation, the paper provides a new lens for testing and refining central theories of corporate finance. Bond, Edmans, and Goldstein argue that the real effects of financial markets originate from the informational role of prices.[3] Yet, while prior empirical studies have documented correlations between price informativeness and investment–price sensitivity, the causal mechanisms have remained largely theoretical because managerial attention—the necessary behavioral link—has been unobservable. This paper provides the first direct evidence, based on revealed managerial behavior, that market prices affect investment decisions specifically when managers pay attention to them. By decomposing attention into equity, debt, and other market dimensions (e.g., commodities,

[3] For theoretical papers, see, for example, Goldstein and Guembel (2008), Goldstein, Ozdenoren, and Yuan (2013), Hirshleifer, Subrahmanyam, and Titman (2006), Sockin and Xiong (2015), Goldstein and Yang (2019), and Goldstein and Yang (2022), among many others. For empirical papers, see, for example, Luo (2005), Chen, Goldstein, and Jiang (2007), Bakke and Whited (2010), Foucault and Fresard (2012), Edmans, Jayaraman, and Schneemeier (2017), and Dessaint, Foucault, Fresard, and Matray (2019), Ye, Zheng, and Zhu (2023), Kwan, Lin, and Liu (2024), and Cao, Goldstein, He, and Zhao (2025) among many others.

volatility, liquidity), I also show that managers extract and act on distinct information from different market signals, each shaping corporate decisions through different mechanisms.

This revealed-behavior approach also complements recent survey-based and Bloomberg-based evidence. Goldstein, Liu, and Yang (2025) survey Chinese listed firms on whether they monitor financial markets, but their responses largely come from non-decision-makers—board secretaries and investor-relations staff—rather than CEOs or CFOs who actually shape corporate policies. Moreover, their binary survey measure cannot capture the intensity, multidimensionality, or dynamics of managerial attention, nor the interaction between managers' and analysts' attention.[4] In contrast, my text-based measure—constructed from earnings-call transcripts—captures actual managerial behavior as it unfolds in real time, reflecting both how managers allocate attention across multiple financial market dimensions (equity, debt, liquidity and volatility shocks, commodities, and others) and how they interact with analysts' questions during Q&A sessions. Spanning sixteen years of longitudinal variation, this approach enables a richer and more causal identification of how managerial attention mediates the link between market signals and real corporate decisions.

This paper also refines the empirical foundations of market-timing and capital-structure research (e.g., Baker and Wurgler 2002; Henderson, Jegadeesh, and Weisbach 2006; Huang and Ritter 2009). Previous studies inferred timing behavior from issuance outcomes relative to valuation proxies, which are easily confounded by unobservable factors such as governance quality, endogenous financing margin, or managerial bias (e.g., Jung, Kim, and Stulz, 1996; Hennessy and Whited, 2004; Malmendier, Tate, and Yan, 2011). By directly observing whether managers monitor market conditions, I isolate the behavioral precondition for market timing: recognizing and acting on financing windows. In doing so, I complement the pioneering survey evidence of Graham and Harvey (2001), showing that managers not

[4] For example, the study uses managers' 2022 survey responses to explain firm behaviors from 2012–2021, even though managerial attitudes and personnel may have changed over time. This design potentially introduces survivorship bias, as only firms still active in 2022 are observed, and causal interpretation becomes problematic. Moreover, firms may ex post justify past strategies—after seeing their investments align with stock-price movements, managers might claim they had been "learning from markets," making survey responses endogenous to past outcomes rather than true ex-ante attention.

only claim to consider market timing, but that variation in their actual attention to financial markets systematically explains when and how they exploit financing opportunities.

In addition, the paper extends rational inattention theory to the domain of corporate finance for the first time. Existing studies have primarily focused on investors or macroeconomic decision-making (e.g., Sims 2003; Kacperczyk, Van Nieuwerburgh, and Veldkamp 2016). The managerial-learning setting provides a uniquely clean environment to empirically test rational inattention, as the informativeness of a key decision-relevant signal—the market price—can be directly observed and quantified.

Finally, the paper contributes to the behavioral finance literature by providing the first comprehensive documentation of managerial attention to financial markets. Decades of research have examined how investors allocate attention and how it shapes asset pricing outcomes (e.g., Peng and Xiong 2006; Barber and Odean 2008; Engelberg, and Gao 2011; Chen, Tang, Yao, and Zhou 2022), yet the attention patterns of managers—the decision-makers who ultimately translate market signals into corporate policies—have remained unmeasured and largely theoretical.

My paper is organized as follows. Section 2 describes the data. Section 3 outlines the methodology for constructing the IAFM measure. Section 4 validates the IAFM. Sections 5 and 6 examine the implications of IAFM for investment and financing policies, respectively. Section 7 presents robustness checks. Section 8 develops and tests a simple rational inattention model. Section 9 concludes.

2. Data

I retrieve yearly fundamentals data from Compustat Annual, and stock market data from CRSP. I obtain CEO's scaled wealth-performance sensitivity (WPS) data from http://alexedmans.com/data/ and managerial stock ownership from ExecuComp. I collect M&A from SDC Platinum database, and insider trading data from Thomson Reuters Insider Filing database. Bond yield data is obtained from WRDS Bond Returns.

I construct firm-level IAFM measures by analyzing transcripts of quarterly earnings calls conducted by U.S. publicly listed companies. All transcripts are sourced from the

Capital IQ database, covering the complete set of 327,328 English-language calls from 2007 through 2023.[5] Since most of the accompanying data are annual, I aggregate the quarterly IAFM measures to the firm-year level unless otherwise noted. The earnings call transcript dataset consists of 98,010 firm-year observations across 14,582 distinct firms. Conditioning on the availability of firm fundamentals data, the final sample comprises 60,820 firm-year observations across 7,673 firms with non-missing fundamentals data.

3. Quantifying Attention to the Financial Market

3.1 Word Embedding and *word2vec*

To quantify firm-level attention to financial markets, I employ the machine learning keyword discovery method developed by Li, Mai, Shen, and Yan (2021). This approach offers significant advantages over conventional methods such as pre-specified word lists, which traditionally require manual expert categorization of common contextual terminology. For example, financial market discussions employ nuanced terminology that is difficult to classify manually. Unlike general sentiment analysis, financial market attention utilizes specialized phrases and idioms like "watermark clause" (a specialized contract provision in investment management) that are challenging to systematically identify without computational tools. Furthermore, financial market attention is inherently multidimensional. Human experts struggle to consistently categorize terms across multiple dimensions (e.g., my IAFM dimensions: equity market and debt market). Additionally, financial vocabulary evolves rapidly with market innovations. Static dictionaries quickly become outdated as financial practices transform. Terms like "ETF", "credit risk transfer bond", "curve control", and "LIBOR/SOFR" emerged as significant financial concepts after the 2000s—developments that traditional dictionaries could not anticipate.

My measurement of firm-level attention to financial markets begins with carefully selected seed words that unambiguously relate to specific IAFM dimensions. Using these seed words as anchors, I implement a word embedding model that learns semantic meanings

[5] Out of 327,328 earnings calls, 316,805 include both the manager presentation and Q&A sections, 10,301 include only the manager presentation, and 222 include only the Q&A section.

based on contextual relationships, thereby identifying additional financial market-related words (phrases) directly from earnings call transcripts.[6]

The word embedding model operationalizes a fundamental linguistic principle: words appearing in similar contexts likely carry similar meanings (Harris, 1954). The model represents semantic content through numeric vectors, enabling relationship quantification through vector arithmetic. Specifically, I utilize cosine similarity between word vectors to determine synonymic relationships. This approach allows for the identification of a comprehensive lexicon describing particular financial market dimensions, which then serves as the basis for firm-level scoring.

To address dimensionality challenges when identifying semantically similar words, I implement *word2vec* (Mikolov et al., 2013), which employs neural networks to efficiently generate dense, low-dimensional vectors representing word meanings.[7] As Levy and Goldberg (2014) demonstrate, *word2vec* vectorization effectively performs a singular value decomposition on the neighboring word count matrix. In the implementation, I utilize the *gensim* library in Python, configuring word vectors at 300 dimensions.[8] Two words are considered contextual neighbors when they appear within five words of each other in a sentence, and terms appearing fewer than five times in the corpus are excluded to ensure statistical reliability.

3.2 IAFM Dimensions and Seed Words

The starting point to measure how much attention earnings call participants pay to financial markets is to construct a two-dimensional IAFM framework. I choose to measure the attention to two distinct aspects of the financial market: equity market and debt market.

[6] The method captures the meanings of both individual words and multi-word phrases. For simplicity, the term "word" will be used throughout the discussion to refer to either a single word or a phrase.
[7] Ideally, identifying semantically similar words requires constructing word-word co-occurrence matrices that track contextual proximity. However, this approach faces severe computational limitations due to the "curse of dimensionality": vocabularies with thousands of terms generate billions of potential word-pair combinations, rendering direct matrix methods impractical.
[8] The *gensim* library is an open-sourced NLP Python package that I use for training the word2vec model. I use version 4.3.3, which is available at https://github.com/RaRe-Technologies/gensim

I measure equity-market attention because, as discussed earlier, several theories including feedback effect (Bond et al., 2012) and market timing theory (Baker and Wurgler, 2002) primarily rely on managerial attention to equity markets. Then, I measure attention to the debt market as the second IAFM dimension, focusing on bond markets, interest rates, and credit market conditions, because debt represents a key financing source (e.g., Graham, Leary, and Roberts 2015) and contains information relevant for investment decisions (e.g., Davis and Gondhi, 2024)

[Insert Table 1 about here]

Table 1 Panel A displays the seed words for each IAFM dimension. Each dimension contains 25 seed words that unambiguously relate to aspects of financial markets. The equity dimension focuses on stock valuation concepts (e.g., "market_valuation," "overvalued"), while the debt dimension encompasses bond market terminology and interest rate concepts (e.g., "bond_yield," "credit_spread"). These two dimensions collectively provide a comprehensive framework for understanding the complex ways in which firms attend to financial markets.

3.3 Preprocessing and Parsing, and Learning Phrases

Prior to the application of seed words for the identification of financial market-related terminology in earnings call transcripts, I follow Li, Mai, Shen, and Yan (2021) by using the Stanford CoreNLP to prepare the textual corpus for subsequent analysis.[9] This preprocessing stage is important for improving the accuracy and reliability of subsequent word embedding models by standardizing linguistic features and capturing multi-word expressions that carry unified meanings.

First, I segment all earnings call transcripts into their constituent sentences and discrete lexical tokens. Second, to reduce inflectional forms and derivationally related forms of words to a common base form, I apply lemmatization. This process converts various word forms to their lemma, ensuring that semantic relationships are identified regardless of grammatical variations. Third, I implement Named Entity Recognition (NER) algorithms to

[9] The CoreNLP package is an open-source Natural Language Processing (NLP) toolkit for a variety of tasks (Manning et al. 2014). I use version 4.5.8 which is available at https://stanfordnlp.github.io/CoreNLP.

identify and systematically replace specific named entities such as geographical locations, temporal references, individuals, and corporate entities with predetermined taxonomic classifications. This standardization procedure prevents the model from interpreting different proper nouns as semantically distinct entities when their underlying functional roles are equivalent.

Fourth, I employ two steps to recognize multi-word expressions (i.e., phrases or collocations) that contain critical semantic information during earnings calls that cannot be adequately captured through single-word analytical approaches. In the first step, I employ the dependency parser within the Stanford CoreNLP architecture to identify two distinct categories of multi-word expressions that tend to be part of general English vocabulary: fixed expressions (e.g., "compared to," "as well as"), and compound items (e.g., "break_down," "spin_off"). In the second step, to identify domain-specific terminology unique to earnings calls, I implement the *phraser* module from the *gensim* library. This approach facilitates the identification of bi-gram and tri-gram expressions that exhibit statistically significant co-occurrence patterns within the transcript corpus. Examples of such corpus-specific phrases include "ipo_discount" and "credit_default_protection". All identified multi-word expressions are normalized through underscore concatenation, preserving their semantic integrity while enabling their computational treatment as unified lexical units in the embedding model.

3.4 Constructing the IAFM Dictionary

After preprocessing and parsing earnings call transcripts, I train the *word2vec* model to generate 300-dimensional vector representations for each word in the corpus, including my predefined seed words. These word vectors serve as the foundation for constructing an expanded, context-specific dictionary that measures attention to financial markets. As an example, for the equity-market attention dimension of the IAFM, there are twenty seed words. To illustrate the approach mathematically, let the vector representation for the first seed word "closing_price" be $V^1 = [x_1^1, x_2^1, \dots, x_{300}^1]$, the vector for the second seed word "equity_market" be $V^2 = [x_1^2, x_2^2, \dots, x_{300}^2]$, and so forth, with the vector for the 25th seed word represented as $V^{25} = [x_1^{25}, x_2^{25}, \dots, x_{300}^{25}]$. I computed the centroid vector by averaging all seed word vectors within the dimension $\bar{V}^{equity} = \frac{1}{25}\sum_{i=1}^{25}\left[x_1^i, x_2^i, \ldots, x_{300}^i\right]$. Next, I calculate the cosine similarity between this centroid vector and each unique word in the earnings call corpus. From these calculations, I selected the top 500 words with the highest positive cosine similarity to $\bar{V}^{equity}$ as candidates for the equity market attention dictionary, while excluding named entities automatically recognized by the CoreNLP package. For words that appeared in dictionaries for multiple IAFM dimensions, I assigned the word only in the dimension where it demonstrated the highest cosine similarity to the average seed word vector.

Table 1 Panel B lists the top 50 most representative words for each IAFM dimension. The high similarity scores across both dimensions—ranging from 0.86 for "share_price" in the Equity dimension to 0.83 for "credit_spread" in the Debt dimension—indicate strong semantic coherence within each IAFM dimension. The minimal semantic overlap between dimensions suggests that the *word2vec* methodology effectively identifies contextually relevant terminology while maintaining distinct theoretical constructs for each aspect of firm attention to financial markets.

3.5 Generating Firm-Level IAFM Measures

After constructing the IAFM across the two dimensions (Equity and Debt), I measure attention to financial markets at the firm-year level for each dimension. I treat each earnings call's management presentation section and the Q&A session with analysts as separate documents and score each document independently. To compute the final earnings call-level score, I use an equal-weighted average of scores from both the management's prepared statements and the analyst Q&A segments. This equal-weighting approach ensures balanced representation of both the strategic, prepared communications of management and their spontaneous responses to analyst inquiries, regardless of their relative lengths. If one of these sections is missing from a particular call, I use only the available portion.

To calculate the firm-year level IAFM for each dimension, I employ the term frequency-inverse document frequency (tf-idf) approach, which accounts for both the frequency of dictionary terms and their specificity across the corpus. The calculation proceeds through three steps. First, for each word w in dimension dim appearing in document d, I calculate the term frequency $tf(w, d) = count(w, d)$, which represents the number of occurrences of word w in document d. I also calculate the inverse document frequency $idf(w) = log\,(N/df(w))$, where N is the total number of documents in the document corpus and $df(w)$ is the number of documents containing word w. Second, the document-level IAFM score for dimension dim is calculated as: $IAFM(d, dim) = \sum_{w \in \{dim \cap d\}} tf(w, d) \times idf(w)$. This approach gives higher weight to terms that are both frequently used in a particular document and relatively rare across the entire corpus, thereby capturing the distinctive attention patterns of each firm to specific financial market dimensions. Finally, for firms with multiple earnings calls within a fiscal year, I average the call-level IAFM scores to produce a firm-year measure.

Table 1 Panel C shows distinctive patterns in the frequency of financial market-related terminology across the two IAFM dimensions. In the Equity dimension, "equity" (20.36%) and "valuation" (10.86%) dominate the discourse, reflecting firms' primary focus on equity valuation concepts. The Debt dimension vocabulary is concentrated around interest rate and bond-related terminology, with "interest_rate" (20.24%) and "bond" (13.17%) commanding the highest contributions, followed by "interest_rate_environment" (4.67%) and "treasury" (4.44%), highlighting firms' attention to borrowing costs and fixed income markets.

[Insert Table 2 about here]

Table 2 Panel A demonstrates significant heterogeneity in firm-level attention to financial markets across the sample of 7,673 U.S. public firms from 2007 to 2023. The IAFM Equity measure exhibits significant variation (mean of 3.05 with standard deviation of 4.44), while IAFM Debt shows even greater relative dispersion (mean of 2.29 with standard deviation of 5.04). The presence of zero values at the 25th percentile for Debt markets suggests that a large portion of firms do not discuss this aspect at all during earnings calls. Panel B presents statistics after excluding financial firms and utilities, which is methodologically important as these firms naturally exhibit different baseline attention to financial markets. After this exclusion, the mean IAFM Equity score drops significantly from 3.05 to 1.93 (a 37% decrease), and IAFM Debt declines even more dramatically from 2.29 to 0.81 (a 65% decrease), reflecting the outsized attention that financial firms and utilities pay to both equity and debt markets. This pronounced variation in IAFM measures across the restricted sample provides a rich foundation for investigating how differential attention to financial markets relates to corporate policies and outcomes.

3.6 Variance Decomposition of IAFM Measures

Table 3 presents the incremental R^2 (%) from adding specific fixed effects to firm-year level regressions of IAFM Equity and IAFM Debt. This variance decomposition reveals the relative importance of different sources of variation in firms' attention to financial markets. For IAFM Equity, industry fixed effects account for the largest portion of variation (38.12%), followed by firm fixed effects (30.4%), and residual firm-year variation (28%). Year fixed effects and industry-by-year interaction effects contribute relatively little (0.28% and 3.2%, respectively). The pattern is similar for IAFM Debt, with industry fixed effects explaining 44.77% of variation, firm fixed effects accounting for 33.9%, and residual firm-year variation representing 17.79%. Again, year fixed effects (0.64%) and industry-by-year interaction effects (2.9%) contribute minimally.

[Insert Table 3 about here]

These results indicate that managerial attention to financial markets is primarily determined by persistent industry and firm characteristics rather than time-specific factors. The industry component suggests that firms within the same industry tend to exhibit similar patterns of attention to financial markets, likely reflecting shared business models, competitive environments, and regulatory frameworks. The large firm-fixed component points to stable firm-specific characteristics that influence attention allocation, such as corporate culture, governance structures, or business strategies. The residual firm-year component (28% for Equity and 17.79% for Debt) represents time-varying, firm-specific factors that affect attention allocation, potentially including changes in leadership, strategic initiatives, or idiosyncratic events.

The pronounced dispersion in IAFM measures shows that managerial attention to financial markets is far from homogeneous. Whereas canonical corporate-finance and price-feedback models assume that all managers monitor market signals with equal intensity, the evidence reveals highly uneven attention shaped by persistent firm- and industry-level factors.

This challenges the conventional “representative-manager” assumption and highlights heterogeneous managerial attention as a fundamental micro-foundation explaining why even seemingly identical market signals could produce divergent real responses across firms. The variance decomposition thus provides important context for interpreting the economic implications of IAFM in subsequent sections.

4. Validation of the IAFM Measure

4.1 Industry Variation in Attention to Financial Markets

Table 4 presents the industry distribution of IAFM measures, providing the first validation of the index by demonstrating patterns consistent with economic intuition. The results reveal significant heterogeneity across industries in how managers allocate their scarce attention to financial markets, with variations that align with industry-specific sensitivities and business models.

[Insert Table 4 about here]

Panel A shows that managers in Finance (Fama-French Industry 11) exhibit the highest attention to equity markets (mean IAFM Equity = 7.67), more than twice the overall sample average of 3.05 reported in Table 2. This pronounced attention is expected given these firms' core business of facilitating market transactions and equity investments. Utilities (Fama-French Industry 8) also demonstrate high equity market attention (mean = 4.61), reflecting their investor focus as dividend-paying stocks and their regulatory frameworks that often tie returns to equity capital. Management at Energy firms (Oil, Gas, and Coal Extraction and Products) shows the third-highest equity market attention (mean = 3.38), likely due to these firms' sensitivity to market valuation in a capital-intensive industry with volatile commodity exposure. In contrast, Healthcare, Medical Equipment, and Drugs (Industry 10) exhibit the lowest attention to equity markets (mean = 1.22), alongside Business Equipment (Industry 6) at 1.41 and Consumer Nondurables (Industry 1) at 1.66. This pattern suggests these industries may be less sensitive to short-term equity market conditions, potentially due to longer product development cycles or more stable consumer demand patterns.

Panel B reveals that Finance (Industry 11) also leads in debt market attention (mean IAFM Debt = 8.77), nearly four times the sample average of 2.29. This heightened focus reflects financial firms' core business in lending, borrowing, and interest rate management. Utilities rank second (mean = 2.03), consistent with their typically high leverage and sensitivity to interest rate movements given their capital structure. The “Other” category (Industry 12), which includes transportation and construction firms, shows the third-highest debt market attention (mean = 1.46), possibly reflecting their capital-intensive business models and reliance on debt financing.

At the lower end, Healthcare (Industry 10) shows minimal debt market attention (mean = 0.32), with Business Equipment (Industry 6) similarly low at 0.52. This pattern may reflect these sectors' traditionally lower leverage and greater reliance on equity financing, particularly for growth firms in these industries.

[Insert Fig 1 about here]

Figure 1 reveals that IAFM measures respond distinctively to major economic events, with industries reacting based on their exposure to specific market conditions. During the 2008 financial crisis, Finance firms predictably increased equity market attention, but more notably, Manufacturing and Business Equipment firms doubled their debt market attention, reflecting heightened concerns about credit availability. The 2015 oil price collapse triggered targeted responses, with Utilities and Chemicals exhibiting pronounced spikes in equity market attention due to their energy price sensitivity. The 2018 US-China trade war sparked widespread increases in equity market attention, particularly in sectors directly affected by trade tensions—Chemicals (69%), Business Equipment (26%), and Consumer Non-Durables (50%)—as firms monitored market reactions to supply chain disruptions. The COVID-19 pandemic produced a more bifurcated pattern: sectors facing operational challenges (Manufacturing, Chemicals, Healthcare) decreased equity market attention by 20-30% to focus on immediate business concerns, while simultaneously increasing debt market attention by 18-32% due to liquidity concerns. Throughout all periods, Finance firms maintained consistently higher attention to both markets, with Utilities ranking second, validating that the IAFM measures effectively capture industry-specific economic exposures and priorities.

4.2 Managerial Ownership

This subsection examines the relationship between managerial incentives and financial market attention as a validation test of the IAFM measure. Agency theory suggests that managers' equity stakes and compensation structures should influence their attentiveness to financial markets, as these align managerial interests with share price performance (e.g., Morck, Shleifer, and Vishny, 1988). If the IAFM truly captures meaningful variation in firm-level attention to financial markets, we would expect systematic relationships between managerial incentives and IAFM scores that reflect theoretical predictions about incentive alignment and agency conflicts.

To test this hypothesis, I employ two complementary measures of managerial incentives. First, I use the scaled wealth-performance sensitivity (WPS) developed by Edmans, Gabaix, and Landier (2009), which measures the dollar change in CEO wealth for a 100 percentage point change in stock price, scaled by annual pay.[10] This comprehensive measure captures the sensitivity of a manager's total wealth—including direct ownership and stock options—to firm performance. Second, I examine simple managerial ownership percentages to provide a more straightforward measure of skin in the game. I regress log-transformed IAFM measures on these incentive variables and their squared terms, controlling for year-end Tobin's Q (Year-End Q), firm size (Ln(Total Assets)), cash holdings, leverage, past sales growth, dividend yield, and institutional ownership. All independent variables are lagged by one year to mitigate reverse causality concerns. I also account for both firm- and year-fixed effects. In this validation test as well as the rest of regressions in this paper, I remove all financial firms (SIC code 6000-6999) and utilities (4900-4999). It is because financial firms naturally exhibit higher baseline attention to financial markets as an inherent part of their operations rather than as a discretionary choice, as demonstrated in Table 3. Similarly, utilities face extensive regulatory constraints that may suppress the financial market attention. Definitions of variables can be found in Table A1.

[Insert Table 5 about here]

[10] As the yearly WPS database from http://alexedmans.com/data/ only extends to the fiscal year 2018, the most recent fiscal year with WPS data in our regressions (as I lag WPS by one year) would be 2019.

Table 5 shows that both incentive measures exhibit inverted U-shaped relationships with management's attention to financial markets. For WPS (Columns (1)-(2)), a one-standard deviation increase in WPS ($\times 10^3$) is associated with a 5.94% increase in equity market attention, with this effect attenuated at higher levels. However, WPS shows no significant relationship with debt market attention, suggesting that equity-linked compensation specifically heightens managers' focus on equity markets. For managerial ownership (Columns (3)-(4)), a one-standard deviation increase is associated with approximately an 8.32% increase in attention to equity markets and a 5.34% increase in debt market attention, with both effects attenuated at higher ownership levels.

The consistent inverted U-shaped relationship across both measures suggests that as managers acquire initial incentive alignment through either equity-linked compensation or direct ownership, their attention to financial markets increases, consistent with greater alignment between manager and shareholder interests. However, at higher incentive levels, financial market attention begins to decline, potentially reflecting entrenchment effects or reduced reliance on market signals when managers possess significant control rights.

Among control variables, firm size shows a consistently positive relationship with both IAFM dimensions. Larger firms allocate more of their limited attention to financial markets possibly because these markets play a more critical role in their operations—they face more complex financing needs, greater investor scrutiny, and larger absolute impacts from market conditions. Leverage is negatively related to equity market attention but positively related to debt market attention, indicating that highly leveraged firms strategically focus their scarce attention more on debt market conditions and less on equity markets based on their capital structure needs. Cash holdings are positively associated with debt market attention but show no significant relationship with equity market attention.

These findings provide strong support for the validity of the IAFM measures, as they align with agency theory's prediction that managerial incentives serve as a key mechanism for aligning managerial attention with shareholder interests.

4.3 Finance-expert CEOs

This subsection examines whether firms led by CEOs with financial expertise exhibit greater attention to financial markets, providing another validation test for the IAFM measures. Custódio and Metzger (2014) demonstrate that finance-expert CEOs are more financially sophisticated, managing financial resources more actively and making better communications about firm prospects with outside investors. If the IAFM measures truly capture meaningful variation in attention to financial markets, we would expect firms with finance-expert CEOs to exhibit systematically higher IAFM scores.

Following Custódio and Metzger (2014), I define a finance-expert CEO as one who has prior experience in either Financials sectors, in a finance-related executive role such as accountant, chief financial officer (CFO), treasurer, or vice president of finance, or in a large auditing firm. I restrict to firms governed by a single CEO in a year. As shown in Table 2, about 33% of CEOs are finance experts in my sample.[11] I regress log-transformed IAFM measures on the finance-expert CEO indicator, controlling for other CEO characteristics including gender, tenure, age, and age squared, as well as the standard firm-level control variables used in previous analyses.

[Insert Table 6 about here]

Table 6 provides strong support for the validity of the IAFM measures. Across all specifications, firms with finance-expert CEOs exhibit significantly higher attention to both equity and debt markets. In the basic specification (Columns (1)-(2)), the finance-expert CEO indicator is associated with an 8.78% increase in equity market attention and a 3.85% increase in debt market attention. These effects remain robust when controlling for additional CEO characteristics (Columns (3)-(4)), with coefficients of 8.75% and 4.17% for equity and debt market attention, respectively. When including firm fixed effects (Columns (5)-(6)), the coefficients become smaller but remain statistically significant. The results suggest that

[11] The proportion of finance-expert CEOs in my sample is slightly lower than the 41% reported by Custódio and Metzger (2014). This discrepancy partly stems from differences in sample coverage: my sample spans the full BoardEx-COMPUSTAT universe, while theirs is restricted to firms matched with ExecuComp, which focuses on the S&P 1500. Time trends also plays a role: my sample covers the period from 2007 to 2023, whereas theirs spans 1993 to 2007.

replacing a non-finance-expert CEO with a finance-expert CEO is associated with a 5.65% increase in equity market attention and a 3.31% increase in debt market attention.

Among the CEO control variables. I find that female CEOs, on average, exhibit lower attention to both equity and debt markets in the cross-sectional specifications, though this effect is less significant for equity market attention with firm fixed effects. Firms governed by CEO with longer tenure are associated with higher debt market attention.

These findings provide an external validity check for my IAFM measures, as they align with theoretical expectations that financial expertise should translate into greater attention to financial market conditions. The fact that this relationship holds both cross-sectionally and within firms over time strengthens confidence that the IAFM measures capture genuine variation in managerial attention to financial markets.

4.4 Performance of the Equity Market and Debt Market

I further validate the IAFM measures by examining how firms dynamically adjust their attention to financial markets in response to changing market conditions. If the IAFM effectively captures variation in financial market attention, we would expect firms to exhibit systematic shifts in attention allocation across different dimensions in response to various market movements.

[Insert Table 7 about here]

I show that firm-specific equity returns significantly predict attention to financial markets. Specifically, I regress the log-transformed IAFM measures (Ln(1 + IAFM)) on firm-level equity returns and return volatility realized over the prior calendar year, using the same set of control variables and sample used in previous tables. Table 7 Panel A shows that a 10-percentage point increase in firm-level annual returns is associated with a 0.29% rise in equity market attention, suggesting that strong stock performance prompts firms to devote more attention to equity valuation discussions. Interestingly, firm-level returns also show a marginal positive relationship with debt market attention (0.13%), suggesting that positive equity performance may lead firms to discuss broader financial market conditions.

Furthermore, firm-level equity volatility exhibits a significant negative relationship with equity market attention. A 10-percentage point increase in firm-specific volatility decreases equity market attention by 1.95%. This pattern suggests that during turbulent periods for a specific firm, managers may be less inclined to discuss equity valuations, possibly because higher volatility makes equity prices less reliable as signals.

Next, I examine the relationship between the IAFM measures and market-wide equity performance. Table 7 Panel B shows a contrasting pattern: a 10-percentage point increase in market-wide annual returns is associated with a 0.54% decrease in equity market attention. This negative relationship stands in stark contrast to the positive relationship observed with firm-level returns. Besides, market-wide equity returns show no significant relationship with debt market attention, while market-wide volatility exhibits a strong positive relationship with debt market attention but a negative relationship with equity market attention. This suggests that attention is scarce even across different sub-markets within financial markets, leading managers to reallocate their limited cognitive resources toward the market dimension that provides more precise signals during turbulent periods.

This contrasting pattern between market-wide and firm-level equity returns provides insights into when and why firms allocate attention to financial markets. The negative relationship between market-wide returns and equity market attention suggests that managers tend to devote more attention to equity markets during market-wide downturns. This is consistent with a defensive posture where management increases monitoring of financial markets when external conditions deteriorate, potentially to address investor concerns about broader market risks. Conversely, the positive relationship between firm-level returns and equity market attention suggests that managers are more likely to discuss equity valuations when their firm outperforms. This could reflect strategic communication where managers emphasize positive performance drivers to highlight their managerial capabilities and justify equity valuations. When firms outperform their peers, managers may seize the opportunity to elaborate on how market conditions validate their strategic decisions.

Table 7 Panel C examines how interest rate movements affect attention to financial markets. I choose the 7-year U.S. Treasury yield to be the representative interest rate because it aligns with the maturity pattern of publicly traded corporate bonds: the median firm-level time to maturity in the sample is 6.5 years, and the mean is 7.8 years.[12] I find that, after controlling for firm fixed effects, changes in interest rates significantly predict firms' attention to debt markets but not equity markets. Specifically, one standard deviation increase in interest rates (0.668) is associated with a 3.2% increase in debt market attention in the following year.[13] This relationship aligns with economic intuition, as rising rates directly impact firms' borrowing costs, prompting increased discussion of debt financing terms and strategies. The absence of a significant relationship with equity market attention suggests that interest rate changes primarily affect how firms discuss debt market conditions rather than equity valuations. I also find that attention paid to debt and equity markets decreases when the prior year's interest rate movements were volatile. In Table IA1, I document the relationship between attention to financial markets and Treasury yields with four alternative maturities (6-month, 1-year, 5-year, and 10-year), and the conclusion holds.

Finally, I examine whether cross-sectional differences in firms' cost of debt predict their attention to equity and debt markets. I proxy firm-level cost of debt using each firm's latest average monthly closing yield from the prior calendar year, expressed in real terms and weighted by outstanding bond amounts across all publicly traded bonds. Table 7 Panel D presents regressions of firms' financial market attention against prior-year firm-level bond yields and yield volatility, controlling for industry-by-year fixed effects. The results show that firms with higher bond yields devote greater attention to debt markets and less attention to equity markets compared to firms with lower yields. Thus, the IAFM measures capture economically rational attention allocation, where firms focus their scarce cognitive resources on the financial market dimensions most relevant to their current financing challenges.

Taken together, this subsection provides validation for the IAFM framework by demonstrating dimension-specific responses to relevant market conditions. Firm-specific equity returns primarily drive attention to equity markets, while interest rate changes

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[12] Firm-level time to maturity is measured as the latest weighted-average (weighted by outstanding amount) time to maturity across all bonds for a firm in a given calendar year.

[13] Note that the average annual rate of change in the 7-year U.S. Treasury bill yield between 2007 and 2023 is 0.15 (=15%).

significantly impact debt market attention. These findings support that the IAFM measures effectively capture meaningful variation in how firms allocate attention across different financial market dimensions in response to changing market conditions.

More importantly, while the IAFM measures do covary with relevant market conditions as expected, they capture a fundamentally different construct—managerial attention—that has previously been an unobservable firm-level characteristic in the literature. Rather than simply reflecting market conditions themselves, the IAFM measures quantify the extent to which managers actively process, discuss, and incorporate market information into their strategic communications. This direct measurement of attention provides a novel lens through which to examine how firms filter and respond to financial market signals.

5. Role of Attention in Shaping Investment Policies

Having established the validity of the IAFM measures, I now investigate their economic implications for corporate decision-making. In this section, I examine how firm-level attention to financial markets influences investment-price sensitivity.

5.1 Unconditional Effect of Attention on Investment-Price Sensitivity

A fundamental question in corporate finance is whether managers learn from stock prices when making investment decisions. The "feedback effect" theory suggests that stock prices aggregate diverse information from market participants, providing signals that managers can use when allocating capital (Bond, Edmans, and Goldstein, 2012). If this effect exists, investment-price sensitivity should be stronger when managers pay more attention to financial markets. I test this hypothesis using the following equation:

$$I_{i,t} = \alpha_{t,j} + \eta_i + \beta_1 Q_{i,t-1} + \beta_2 Ln\left(1 + IAFM_{i,t-1}\right) + \beta_3 Ln\left(1 + IAFM_{i,t-1}\right) \times Q_{i,t-1} + \gamma CONTROL_{i,t-1} + \epsilon_{i,t} \quad 1)$$

where $I_{i,t}$ is one of two investment measures: capital expenditures (CAPX and total investment (INVT) for firm i in year t, where the first measure equals 100 × the capital expenditure (Compustat CAPX) divided by lagged total assets (Compustat AT), and the second measure equals 100 × the changes in gross property, plant, and equipment (Compustat PPEGT) plus changes in inventory (Compustat INVT), divided by lagged total assets

(Compustat AT). Compared to the first measure, the second measure additionally captures the sales of fixed assets, and changes in inventory. $\alpha_{t,j}$ and η_i represent industry-by-year and firm fixed effects, respectively. $Q_{i,t-1}$ is the (normalized) price and is measured by firm i in year $t-1$. $Ln(1+IAFM_{i,t-1})$ indicates the log-transformed IAFM measure for either IAFM Equity or IAFM Debt, for firm i in year $t-1$. I also control for firm size (Ln(Total Assets)), cash holdings, leverage, past sales growth, dividend yield, and institutional ownership.[14] The presence of the price feedback effect requires both $\beta_1 > 0$ and $\beta_3 > 0$ to hold. Put differently, a firm's investment should be positively correlated with $Q_{i,t-1}$, and such correlation should be greater when managers allocate more attention to financial markets.

[Insert Table 8 about here]

Table 8 Panel A shows that attention to financial markets significantly enhances the sensitivity of capital expenditures to Tobin's Q. In the specifications with both industry-by-year and firm fixed effects (Columns (3)-(4)), which represent my primary focus, the interaction coefficient between IAFM Equity and Tobin's Q is positive and statistically significant (0.0633). This effect is economically significant: firms whose managers devote 10% more attention to equity markets exhibit investment decisions that are 1.85% more responsive to Tobin's Q, relative to the baseline sensitivity of 0.343. Similarly, Column (4), which focuses on debt market attention, shows an even stronger positive interaction coefficient (0.0938), which translates to a 2.58% increase over the baseline sensitivity of 0.363 for a 10% increase in IAFM Debt. These findings support that firms paying greater attention to financial

[14] It is worth noting that I intentionally do not control for market conditions (e.g., stock returns or volatility) in the baseline investment–price-sensitivity regressions because the goal in Section 5 is to estimate the *total effect* of financial markets *operating through managerial attention*. Conceptually, the estimand is a treatment-on-the-treated effect: the difference in investment–price sensitivity between managers who pay attention to financial markets and those who do not. If market conditions influence investment–price sensitivity through shaping managers' attention, then controlling for those market variables would introduce a classic "bad-control" problem: it would partial out precisely the channel through which financial markets are supposed to operate in my framework, thereby underestimating the true total effect of financial markets. Section 7.1 then decomposes this total effect into the primary-market channel and the secondary-market (managerial learning) channel. Omitting market conditions would only be problematic if those variables *directly* affect investment–price sensitivity through affecting financing capacity with managerial attention being a *pure* passive sideshow. I address this alternative "attention-as-sideshow" view in Section 7.6, and show that this view is unlikely to explain the results.

markets are significantly more responsive to price signals when making investments, consistent with the feedback theory of market prices.

The cross-sectional results with only industry-by-year fixed effects (Columns (1)-(2)) show a slightly different pattern. While the interaction between IAFM Debt and Tobin's Q remains positive and significant (0.131), representing a 4.15% increase over the baseline sensitivity of 0.316 for a 10% increase in IAFM Debt, the interaction between IAFM Equity and Tobin's Q is positive yet statistically insignificant. Thus, the relationship between equity market attention and investment-price sensitivity may be driven more by within-firm variation compared to cross-sectional differences.

Panel B extends this analysis to broader measures of investment (INVT). For total investment, in the specifications with both industry-by-year and firm fixed effects (Columns (3)-(4)), the interaction between IAFM Equity and Tobin's Q (0.247) represents a 2.95% increase over the baseline sensitivity for a 10% increase in equity market attention. Similarly, the interaction between IAFM Debt and Tobin's Q (0.269) represents a 2.89% increase over the baseline sensitivity of for a 10% increase in debt market attention. These effects are even more pronounced than those observed for capital expenditures, suggesting that broader investment decisions are particularly responsive to market signals when managers are attentive to financial markets. Besides, in the cross-sectional specifications (Columns (1)-(2)), both IAFM Equity and IAFM Debt show positive and significant interactions with Tobin's Q, although the magnitude is smaller than in the fixed effects models. Specifically, the interaction coefficients represent increases of 2.06% and 3.04% over the baseline sensitivity for a 10% increase in IAFM Equity and IAFM Debt, respectively.

Overall, these results provide *direct* evidence for the feedback effect theory, with firms exhibiting significantly higher investment-price sensitivity when they have higher attention to financial markets. This effect applies to both equity and debt market attention, suggesting that managers who monitor both segments of financial markets develop more sophisticated frameworks for interpreting and responding to price signals.

5.2 Heterogeneity Across Firm Groups

I expect the strength of the relation between IAFM and investment-price sensitivity to vary depending on firm characteristics. I examine five key dimensions of heterogeneity: insider trading intensity, competitive pressure, price informativeness, financial constraints, and manager sentiment.

First, Bond, Edmans, and Goldstein (2012) argue that the usefulness of secondary markets hinges on the extent to which prices convey information beyond what decision makers already know. Building on this, Edmans, Jayaraman, and Schneemeier (2017) demonstrate theoretically that stricter insider-trading enforcement—by discouraging insiders from trading—lowers competitive trading pressure, thereby incentivizing outside investors to gather additional information and enriching price signals with knowledge unavailable to managers. Therefore, I hypothesize that the influence of IAFM on the investment-price sensitivity will be most pronounced in firms characterized by low insider-trading intensity.

To test this hypothesis, I measure insider-trading intensity as the ratio of shares traded by insiders to total shares traded within a calendar year, focusing exclusively on open market transactions initiated by key executives (CEO, CFO, COO, President, and Chairman of the Board). I then partition the sample into three distinct categories: firms with zero insider trading, firms with below-median insider trading intensity, and firms with above-median insider trading intensity, subsequently estimating regressions separately for each subsample.

Table A2 supports this prediction. For firms with no insider trading, the interaction between IAFM and Tobin's Q is positive and significant for both capital expenditures and total investment. This effect becomes insignificant for firms with higher insider trading intensity. For example, a 10% increase in equity market attention enhances CAPX-price sensitivity by 2.05% (=10%×0.0702/0.342) in firms without insider trading but shows no significant effect in firms with insider trading. This pattern supports the theory that market signals provide less unique information when managers already trade extensively on their private knowledge.

Second, firms that operate in more competitive environments have stronger incentives to make the best use of their resources, as they operate with little slack (e.g., Hart, 1983). I hypothesize that the influence of IAFM on the investment-price sensitivity will be most pronounced in firms operating in highly competitive markets. Table A3 shows that the effect of IAFM on investment-price sensitivity is significant only in highly competitive industries. For capital expenditures, firms in high-competition industries (based on SIC 3-digit HHI) show a positive interaction between IAFM Equity and Tobin's Q (0.0688), while firms in low-competition industries show no significant effect. This pattern is consistent across both IAFM measures and both investment types. Table IA2 suggests these findings using an alternative product market competition measure from Hoberg and Phillips (2016). The results suggest that competitive pressure enhances firms' incentives to incorporate market signals into investment decisions, as failing to do so could result in competitive disadvantage.

Third, I examine how the informativeness of price signals conditions the relationship between attention and investment-price sensitivity. Chen, Goldstein, and Jiang (2007) establish that managers learn more from stock prices when those prices contain more private information, as measured by the probability of informed trading (PIN). Building on this insight, I test whether the effect of managerial attention on investment-price sensitivity varies with the information content of market prices. I measure price informativeness using industry-level PIN, calculated as the equally-weighted average across firms within each SIC 3-digit industry. This industry-level approach captures the common information environment that shapes price discovery for firms operating in similar markets, facing comparable regulatory frameworks, and subject to parallel economic shocks.

Third, I examine whether the value of managerial attention varies with the informativeness of price signals themselves. The probability of informed trading (PIN), developed by Easley and O'Hara (1992) and Easley, Kiefer, and O'Hara (1996), provides a structural measure of price informativeness based on a market microstructure model that estimates the probability that a trade is information-based. Chen, Goldstein, and Jiang (2007) establish that investment-price sensitivity is stronger when prices contain more information that managers do not already possess. Building on this insight, I hypothesize that managerial attention to financial markets should be particularly valuable when price signals are rich in information. To test this prediction, I calculate industry-level PIN measures by averaging firm-level estimates within each three-digit SIC industry, capturing the typical information environment that firms face in their competitive landscape—reflecting common factors such as disclosure requirements, analyst coverage patterns, and business model complexity that affect information production across industry peers.

Table A4 confirms that attention to financial markets enhances investment-price sensitivity primarily in high-PIN industries. When industry-level price informativeness is high, a 10% increase in equity market attention enhances CAPX-price sensitivity by 2.03% (=10%×0.0604/0.297), while the effect is statistically insignificant in low-PIN industries. Similarly, debt market attention shows significant effects only in high-PIN environments, with a 10% increase enhancing CAPX-price sensitivity by 3.85% (=10%×0.120/0.312). These patterns hold for total investment as well. Table IA3 corroborates these findings using product-market PIN measures from Hoberg and Phillips (2016), showing that the value of attention depends on the information content of the price signals managers observe. These results indicate that the benefits of paying attention to financial markets are contingent on the quality of information those markets provide—when prices are less informative, even high levels of managerial attention fail to enhance investment-price sensitivity.

Fourth, economic theory suggests that the incentives of firms to use stock price information depend on their financial situation and the environment they are in. Financially constrained firms have strong incentives to allocate resources efficiently to relax their financial constraints, but these constraints may prevent them from implementing changes that require funding. Consequently, whether financially constrained firms make more use of stock price discovery is an empirical matter.

I employ Linn and Weagley's (2024) (LW) machine-learning-based measure of equity constraint to proxy a firm's financial constraint severity.[15] Firms with an LW constraint measure above the median are classified as financially constrained, while those below the median are considered unconstrained. Table A5 shows that the effect of IAFM on

[15] This measure captures firms' differential access to equity financing without relying on traditional proxies that have been criticized in literature (Bodnaruk, Loughran and McDonald 2015; Farre-Mensa and Ljungqvist, 2016). I focus on firms that are constrained in equity financing, as prior research suggests that financial constraints tend to have a more pronounced impact on these firms compared to those that rely primarily on debt financing (e.g., Linn and Weagley, 2024; Hoberg and Maksimovic, 2015).

investment-price sensitivity is strongest among financially constrained firms. For these firms, a 10% increase in equity market attention enhances CAPX-price sensitivity by 2.16%, compared to no significant effect for unconstrained firms. For debt market attention, the effect is even more pronounced (3.22% increase). The conclusion remains robust when I use a composite indicator of financial constraint, which is constructed based on five traditional proxies of financial constraints: dividend, credit ratings, the Kaplan and Zingales (1997) index, the Hadlock and Pierce (2010) index, and Whited and Wu (2006) index. The regression results that utilize this composite indicator are reported in Table IA4.

These results suggest that constrained firms derive greater benefits from attending to financial markets, as market signals help them identify and prioritize the most valuable opportunities when resources are limited. The heightened sensitivity of constrained firms to market information reflects the higher opportunity cost of misallocating scarce capital.

Fifth, I exploit the sentiment polarity embedded in financial-market discussions. Table A6 distinguishes between positive-sentiment and negative-sentiment attention—defined as the proportion of sentences in an earnings call that simultaneously reference financial-market terms and contain the positive or negative words identified by Loughran and McDonald (2011). The results show that investment–price sensitivity is significantly stronger when attention carries a positive sentiment. For example, the interaction between equity-market attention and Tobin's Q becomes more pronounced when such attention is expressed in a positive tone, whereas the corresponding coefficient under negative sentiment is economically smaller and statistically insignificant. Moreover, sentiment plays no statistically significant role for debt-market attention, suggesting that managers' reactions to debt-market information are less influenced by tone or affect. These findings provide suggestive evidence that attentive managers not only monitor financial markets more closely but also interpret equity-market signals more constructively when conditions are favorable—consistent with the view that attention functions as an information-processing channel that amplifies the responsiveness of real decisions to market signals rather than a passive disclosure mechanism.

Collectively, these heterogeneity analyses show that the relationship between attention to financial markets and investment-price sensitivity is most pronounced when: (1)

insider trading is limited, providing more unique information in prices; (2) competitive pressure is high, creating stronger incentives for efficient resource use; (3) price informativeness is high, enhancing the quality of external signals available to managers; (4) financial constraints are binding, increasing the value of market signals for optimal resource allocation, and (5) such attention is expressed in a positive tone, indicating a more constructive interpretation of market conditions.

5.3 Why Does Debt Market Attention Facilitate Investment-Price Sensitivity?

Previous subsections demonstrate that attention to financial markets plays a crucial mediating role in corporate decision-making where both equity and debt market attention enhance investment-stock price sensitivity. I focused on the sensitivity of investment to stock prices in previous subsections for two key reasons. First, compared to bond prices, stock prices are more capable of capturing the upside potential of the firm, thereby being more able to incorporate information related to investments. Second, in the literature on the real effects of financial markets on investments (e.g., Chen, Goldstein, and Jiang (2007)), the majority of empirical papers use stock prices as a proxy for the signal source from which managers extract information from financial markets regarding future business opportunities.

In this subsection, I examine why debt market attention facilitates the sensitivity of investment to stock prices. There are two potential channels. First, debt market attention might be highly correlated with equity market attention, essentially capturing the same underlying construct. Second, debt-market attention may convey distinct yet complementary information that helps managers better interpret or act upon stock-price signals. This information does not necessarily have to be associated with business opportunities, which may arise more from firms' own traded bond prices (Davis and Gondhi 2024); it may also reflect insights about firms' own financing conditions—such as changes in the cost of debt capital—or broader macro-financial developments, including interest rate trends or monetary policy shifts, that shape firms' capacity to fund new investments when opportunities arise.

I start by analyzing how attention to both equity and debt markets simultaneously affects investment-price sensitivity, and whether this relationship varies with firms' leverage levels. The extent to which the coefficient of debt market attention on investment-price sensitivity is reduced after controlling for equity market attention reflects the percentage of results documented in Section 5.1 that can be explained by the first channel—correlation between debt and equity market attention. The remaining effect likely represents the second channel's contribution.

Table A7 Panel A presents these results. In Column (1), which includes the full sample, both interaction terms between IAFM measures and Tobin's Q are positive and statistically significant for capital expenditures (Panel A.1) and total investment (Panel A.2). Comparing these coefficients with those in Table 8, we can quantify the channels' relative importance. For IAFM Debt, the coefficient decreases from 0.0938 in Table 8 Column (4) to 0.0831 in Table A7 Panel A.1 Column (1), indicating that approximately 11.4% of the original debt market attention effect can be attributed to its correlation with equity market attention. The remaining 88.6% supports the complementary information hypothesis.

Furthermore, if debt market attention primarily helps firms react to equity market signals more effectively, this complementary information should be particularly valuable for firms with greater exposure to debt markets. Leverage provides a natural proxy for a firm's stake in debt market conditions, as highly leveraged firms face greater exposure to interest rate fluctuations, refinancing risks, and debt market pricing efficiency. These firms likely develop more specialized expertise in interpreting debt market signals and have stronger incentives to monitor debt market conditions. Consequently, debt market attention should enhance investment-price sensitivity more significantly for highly leveraged firms.

I find that for firms with low leverage (Panel A Column (2)), only equity market attention significantly enhances investment-price sensitivity (0.0842 for CAPX and 0.192 for INVT), while debt market attention shows no significant effect. In contrast, for highly leveraged firms (Column (3)), debt market attention significantly enhances investment-price sensitivity (0.0701 for CAPX and 0.230 for INVT), while equity attention remains statistically significant only for total investment. This pattern strongly supports mechanism (2), suggesting that debt market information becomes increasingly valuable as firms' exposure to financing conditions increases.

Panel B excludes firms with traded bonds to control for the possibility that the observed effects might stem directly from bond price signals rather than general attention to debt markets. The results remain qualitatively similar, supporting that the complementary value of debt market attention is not driven solely by information contained in a firm's own traded bonds but rather by broader awareness of debt market conditions.

Additionally, I examine in Table IA5 whether debt market attention influences firms' responsiveness to their own bond yields when making investment decisions, using a sample of firms with publicly traded bonds. If debt market attention helps firms interpret information from their debt pricing (either about business opportunities or cost of capital), we expect IAFM Debt to enhance the investment-bond yield sensitivity.

The results show that for total investment (Column (2)), the interaction between IAFM Debt and bond yield is negative and significant (-21.27), indicating that firms with 10% higher debt market attention increase their investment sensitivity to bond yields by 5.73%. This suggests that debt market attention also provides unique information that influences how firms respond to their debt financing costs, supporting mechanism (3). For capital expenditures (Column (1)), although the coefficient on the interaction between IAFM Debt and bond yield (-2.922) is not statistically significant, its negative sign is consistent with the pattern observed for total investment. The lower statistical significance for capital expenditures likely reflects that CAPX captures only fixed asset expenditures (which typically follow longer-term plans), while INVT also includes fixed asset sales and inventory changes that can be adjusted more readily in response to financing conditions.

Table IA6 further decomposes bond yields into (1) firm-level credit spread, (2) firm-level term spread, and (3) treasury yield, demonstrating that the results in Table IA5 are at least driven by information contained in firm-level credit spreads, supporting the idea that debt market attention can help firms extract firm-specific information from their bond pricing.

Overall, this subsection demonstrates that debt market attention provides *complementary* information value for investment decisions beyond what is captured by equity market attention. This complementary effect is particularly pronounced for highly leveraged firms, where debt market signals likely provide more incremental information for investment decisions. Furthermore, debt market attention uniquely influences how firms respond to their own bond yields, supporting the paper's overarching hypothesis that market-specific managerial attention enhances firms' responsiveness to information embedded in that particular market. These findings together support the view that debt markets contain investment-relevant information through mechanisms *distinct* from equity markets. In Section 7.1, I further unpack this mechanism by examining whether this distinct information reflects improved interpretation of business opportunities or of firms' cost of capital.

6. Role of Attention in Shaping Financing Policies

6.1 Does Attention Facilitate Firms' Ability to Raise Capital?

While Section 5 demonstrates that financial markets provide valuable information about investment opportunities, this section examines the second fundamental role of financial markets: facilitating access to capital. Theoretical and empirical research suggests that managers who better understand market conditions should be more effective at accessing external financing when capital needs arise. Baker and Wurgler (2002) show that firms issue more equity when market valuations are temporarily high, while Ma (2019) demonstrates that firms substitute between debt and equity in response to relative valuation changes across these markets. Begenau and Salomao (2019) document cyclical patterns in debt and equity issuance that reflect differences in funding needs and exposures to financial frictions.

If managers who pay greater attention to financial markets develop superior understanding of market conditions and timing, they should be better positioned to access external financing when capital needs arise. To test this hypothesis, I examine whether firms with higher IAFM measures are more likely to tap external financing at the extensive margin when facing financing deficits. I estimate the following specification:

$$\begin{aligned} &Net\ Issue\ Indicator_{i,t} \\ &\quad = \alpha_{t,j} + \eta_i + \omega_1 NFD_{i,t} + \omega_2 Ln\left(1 + IAFM_{i,t-1}\right) \\ &\quad + \omega_3 Ln\left(1 + IAFM_{i,t-1}\right) \times NFD_{i,t} + \gamma CONTROL_{i,t-1} + \epsilon_{i,t} \end{aligned} \quad 2)$$

where $Net\ Issue\ Indicator_{i,t}$ denotes either the net equity issue indicator or the net debt issue indicator for firm i in year t in industry *j*. The net *equity* issue indicator equals one if there is a positive difference between sales of common stock and stock buybacks, scaled by lagged total assets, and zero otherwise. The net *debt* issue indicator equals one if long-term debt issues minus long-term debt reduction, scaled by lagged total assets, and zero otherwise. $NFD_{i,t}$ represent the net financing deficit (NFD), which equals the sum of cash dividends, net investment, change in working capital, and minus cash flow after interest and tax, scaled by lagged total assets. I control for year-end Tobin's Q, firm size (Ln(Total Assets)), cash holdings, leverage, past sales growth, dividend yield, and institutional ownership. $\alpha_{t,j}$ and η_i denote industry-by-year and firm fixed effects, respectively. ω_3 captures the extent to which attention to financial markets enhances firms' ability to access external financing when capital needs arise. If attention to financial markets helps firms better manage their cost of capital and timing of market access, we should observe $\omega_3 > 0$ for both equity and debt financing, indicating that high-attention firms are more responsive to financing needs and better able to tap external markets.

[Insert Table 9 about here]

Table 9 demonstrates that attention to financial markets enhances firms' responsiveness to financing needs by facilitating access to capital. I begin by examining the cross-sectional patterns in Columns (1)-(3), which include only industry-by-year fixed effects and reveal how differences in attention across firms relate to financing behavior.

Panel A shows that firms with higher attention to equity markets are significantly more responsive in accessing equity financing when needs arise. In Column (1), the interaction coefficient between IAFM Equity and NFD (0.0553) indicates that firms with 10% higher equity market attention show a 1.66% increase in equity financing responsiveness relative to the baseline NFD effect (0.333). Column (2) shows an even stronger pattern for debt market attention, with a 10% increase in IAFM Debt associated with a 4.17% increase in responsiveness (=10%×0.143/0.343). Panel B provides parallel evidence for debt financing. In Column (1), a 10% increase in equity-market attention raises responsiveness by 1.99%. In Column (2), a 10% increase in debt-market attention leads to an 11.85% (=10%×0.507/0.428) increase in debt-financing responsiveness relative to baseline.

When both attention measures are included simultaneously in Column (3) of each panel, both remain statistically significant. The fact that debt (equity) attention also predicts equity (debt) issuance indicates that the effect cannot be explained solely by managers disclosing intended financing plans during calls; if that were the case, attention to the “other” market would exhibit no—or even negative—predictive power. Instead, it is more consistent with the idea that equity- and debt-market attention capture distinct informational advantages, enabling managers to more accurately gauge the *relative* cost of capital and assess conditions in each market. I formally test this mechanism hypothesis in Section 6.2. Columns (4)–(6), which add firm fixed effects, reveal qualitatively similar patterns with somewhat smaller magnitudes, suggesting that the results are not driven by time-invariant firm characteristics.

6.2 Attention as a Driver of Market Timing

Building on the evidence in Section 6.1, I now test whether equity- and debt-market attention capture distinct informational advantages by shaping firms’ responsiveness to market-specific conditions. To minimize the concern that attention simply reflects capital demand, rather than reflecting a capability that reduces financing frictions (e.g., search frictions, timing frictions) in a given market, I restrict the sample to firm-year observations in which firms raised external funds from a single source—issuing either net equity or net debt, but not both. By holding total external financing needs roughly constant, this restriction allows the financing source to be interpreted primarily as a managerial choice.

Accordingly, equity-market attention should amplify responsiveness to equity-market conditions, while debt-market attention should amplify responsiveness to debt-market conditions. Evidence of such dimension-specific responsiveness would provide more granular support for the mechanism through which attention facilitates access to financial markets—specifically, by enhancing managers’ ability to time financing decisions more effectively. To test this prediction, I estimate the following:

$$
\begin{aligned}
&Equity\ vs\ Debt_{i,t} \\
&\quad = \alpha_{t,j} + \eta_i + \omega_1 NFD_{i,t} + \omega_2 Ln(1 + IAFM_{i,t-1}) \qquad 3) \\
&\quad + \omega_3 Ln(1 + IAFM_{i,t-1}) \times NFD_{i,t} \\
&\quad + \omega_4 Ln(1 + IAFM_{i,t-1}) \times Market\ Condition_{i,t} \\
&\quad + \omega_5 NFD_{i,t} \times Market\ Condition_{i,t} \\
&\quad + \omega_6 Ln(1 + IAFM_{i,t-1}) \times NFD_{i,t} \times Market\ Condition_{i,t} \\
&\quad + \gamma CONTROL_{i,t-1} + \epsilon_{i,t}
\end{aligned}
$$

where the dependent variable, $Equity\ vs\ Debt_{i,t}$, equals one for equity financing and zero for debt financing. Compared to Equation (2), I add a market-conditional term $Market\ Condition_{i,t}$, which captures episodes when equity markets are temporarily more favorable than debt markets (proxies include firm-specific valuation (Tobin's Q), equity market sentiment, or interest rate changes). I also include interactions among $Ln(1 + IAFM_{i,t-1})$, $NFD_{i,t}$, and $Market\ Condition_{i,t}$. The focus is on ω_6 , which reflects how attention alters the responsiveness of financing choices to equity-favorable conditions.

[Insert Table 10 about here]

Panel A of Table 10 examines how equity market attention interacts with two key equity market conditions: firm-specific valuation (measured by Tobin's Q) and market-wide equity sentiment, proxied using Baker and Wurgler (2006) index (orthogonalized to six macroeconomic conditions).[16] These two conditions are chosen because they directly capture episodes when equity financing is temporarily advantageous relative to debt. Baker and Wurgler (2002), for example, find that firms are more likely to issue equity when their market values, relative to book values, are high. Lowry (2003) and Lamont and Stein (2006) show that firms react to waves of high sentiment by issuing more equity. I employ two different specifications for market sentiment. Column (1) uses the annual percentage change in equity market sentiment to capture dynamic shifts in investor optimism, while Column (2) employs the level of equity market sentiment to reflect absolute market conditions.

[16] I thank Jeffrey Wurgler for sharing the data via https://pages.stern.nyu.edu/~jwurgler/.

Consistent with the market timing view, ω_6 is positive and significant across both specifications. The three-way interaction between IAFM Equity, NFD, and Tobin's Q yields positive and significant coefficients of 0.0171 and 0.0180, while the interactions with equity market sentiment yield coefficients of 0.0154 (for changes in sentiment) and 0.0990 (for sentiment levels). These results show that attentive firms are disproportionately likely to switch toward equity issuance when firm valuations are high or when sentiment is buoyant, precisely when equity financing windows open. Thus, attention facilitates market timing by allowing firms to reallocate issuance to the relatively cheaper source of capital. In this sense, attention acts as a capability that enables managers to more effectively recognize and exploit financing opportunities when they arise.

Panel B examines how debt market attention influences financing choices in response to interest rate conditions, employing two specifications: Column (1) uses annual changes in interest rates, while Column (2) uses interest rate levels. As discussed in Section 4.4, I use 7-year Treasury yield to proxy interest rate, though the results remain qualitatively the same if I use alternative maturities, including 6 months, 1 year, 5 years, or 10 years. In Column (1), the three-way interaction between IAFM Debt, NFD, and *changes* in interest rates shows a positive and statistically significant coefficient (0.111), indicating that firms with higher debt-market attention are more likely to shift from debt to equity issuance when interest rates rise. In Column (2), the corresponding interaction with interest rate *levels* is also positive albeit statistically insignificant. Together, these results suggest that debt-market attention enhances firms' ability to time financing by reallocating issuance toward the cheaper source of funds when borrowing costs shift.[17]

Overall, these results indicate that attention to equity and debt markets facilitates firms' access to external capital *at least* through enabling managers to better identify and exploit market-specific opportunities. They provide the first *direct* empirical evidence based on observed managerial attention in support of the market-timing theory and Ma (2019),

[17] Although reacting to changes in interest rates is not exactly the same as the market timing described in Baker and Wurgler (2002), which refers to firms' response to equity overvaluation episodes, I interpret it as a form of market timing. The rationale is that interest rate changes are generally temporary, so managers must still "time" their financing by issuing equity—the relatively cheaper source—when debt becomes more expensive due to rising rates.

showing that managers' ability to time issuance windows and cross-arbitrage their own securities is strengthened when they genuinely monitor financial markets. To the extent that periods of strong equity performance often coincide with lower, time-varying adverse selection cost, my results can also be viewed as consistent with pecking order theory (Myers and Majluf 1984). As an additional exercise, Table IA7 explores whether firms' financing choices respond to changes in firm-specific bond yields. While the sign of coefficient estimates suggests that firms with greater attention to the debt market favor equity over debt following rising bond yields, these coefficients are not statistically significant.

7. Robustness Checks

7.1 Is Attention-Induced Investment-Price Sensitivity Driven More by Information on Business Opportunities or Costs of Capital?

In Section 5, I presented evidence that higher managerial attention to financial markets facilitates firms' sensitivity of investments to market signals, particularly among firms with high attention to market signals. However, this enhanced sensitivity could operate through two distinct channels: (1) improved extraction of information about fundamental business opportunities (the core prediction of price feedback theory), or/and (2) better assessment of financing conditions that enables more flexible investment responses when capital constraints are relaxed. Since Section 6 establishes that attention to financial markets enhances firms' financing capabilities, it becomes crucial to disentangle these mechanisms to understand the precise role of managerial attention in mediating market information.

To isolate the business opportunities channel, I employ a sample-splitting approach that controls for the financing mechanism. Specifically, I restrict the analysis to firms that do not tap external financing (defined as having non-positive net external financing) in the year of investment decision. The underlying logic is straightforward: if the investment-price sensitivity effects were driven purely by improved financing capabilities, they should disappear when firms are not actively accessing external capital markets. Conversely, significant effects that persist among non-financing firms would indicate genuine information extraction about business fundamentals. This approach provides a conservative test of the business opportunities channel, as it excludes firms most actively integrating financial market information across both investment and financing decisions.

Table A8 shows differences between equity and debt market attention in terms of the mechanisms driving investment-price sensitivity. Panel A shows that for equity market attention, the interaction coefficients remain positive and statistically significant even among firms with non-positive net external financing: 0.0662 for capital expenditures (significant at the 5% level) and 0.166 for total investment (significant at the 10% level). This supports the price feedback mechanism, indicating that equity market attention indeed facilitates managers' ability to extract information about fundamental business opportunities.

In contrast, debt market attention shows a different pattern. As shown in Panel B, among firms with non-positive net external financing, the interaction coefficients become statistically insignificant, and they are only significant for firms with positive net external financing (0.189 for CAPX and 0.447 for INVT). This indicates that debt market attention operates primarily through the cost of capital channel—enhancing managers' ability to respond to investment opportunities by improving their access to financing.

Panel C provides additional corroborating evidence by examining how firms' investment responds to their own bond yields. If debt-market attention enhances investment–bond price sensitivity by prompting managers to expand investment most readily when debt financing costs are lower, such sensitivity should appear only among firms that access external debt markets in the investment year and should disappear when the sample is restricted to firms that do not raise external funds. Consistent with this prediction, that is precisely what I find among firms with publicly traded bonds.

I next provide another test of this mechanism using Gormsen and Huber's (2024) *perceived* cost of capital, which captures managers' own stated beliefs about their financing costs as expressed in earnings calls (e.g., "our WACC is 9%"). This variable offers a unique opportunity to distinguish between the two channels because it reflects managerial *perceptions* of financing conditions independent of realized financing actions. If debt-market attention primarily affects investment by altering *perceived* financing costs, its explanatory power should diminish once perceived cost of capital is controlled for. Conversely, if equity-market attention captures information about real business opportunities, its effect should remain robust.

Table A9 first establishes that IAFM measures are, if anything, negatively correlated with perceived cost of capital in the cross-section and uncorrelated within firms over time. This relationship remains even after controlling for two proxies of the firm's true financing costs: the implied cost of capital and the implied cost of debt, constructed following Gormsen and Huber (2024) and Eskildsen, Ibert, Jensen, and Pedersen (2024). The implied cost of capital is computed as the average of four standard accounting-based estimates—the residual income models of Gebhardt, Lee, and Swaminathan (2001) and Claus and Thomas (2001), and the dividend discount models of Easton (2004) and Ohlson and Juettner-Nauroth (2005). The implied cost of debt is proxied by the ratio of total interest expense to total debt from Compustat. This indicates that attention does not merely proxy for high financing costs or tighter constraints. Instead, more attentive managers appear to *perceive* lower costs of capital, consistent with their being better informed about market conditions.

Next, I include perceived cost of capital directly in the investment–price sensitivity regressions (Table IA8, Panel A). Controlling for this variable leaves the coefficient on Equity Attention × Tobin's Q largely unchanged and still highly significant, supporting that equity-market attention operates at least through the information channel. In contrast, the coefficient on Debt Attention × Tobin's Q becomes statistically insignificant once perceived cost of capital is added, indicating that debt-market attention influences investment mainly by altering managers' financing perceptions and cost-management ability. Panel B shows that roughly half of the decline in the debt-attention coefficient arises from the larger-firm sample used by Gormsen and Huber (2024)—which is intuitive since larger firms rely more on internal cash flows and less on external capital, where debt-market attention is most valuable—while the remaining half is explained by controlling for perceived cost of capital.

Additional evidence in Table IA8 Panel C shows that both equity- and debt-market attention remain significant predictors of investment–price sensitivity when only *true* costs of capital are controlled for. The distinct result when controlling for *perceived*, rather than *true*, financial constraints implies that debt-market attention reflects a behavioral channel through which attentive managers internalize financing conditions more effectively, enabling them to act on profitable investment opportunities when funding costs are favorable.

Taken together, these results provide a coherent interpretation of how managerial attention affects investment. Equity-market attention strengthens the link between prices and real investment primarily because attentive managers extract decision-relevant information about fundamentals from stock prices. Debt-market attention, in contrast, affects investment mainly by shaping managers' perceptions and management of financing costs, enabling more flexible investment responses when funding conditions change. The joint use of real financing activity and *perceived cost of capital* measures therefore allows me to disentangle these two mechanisms empirically.

Moreover, at a conceptual level, the overlap between the effects of debt attention and perceived cost of capital suggests that my attention measure does not merely proxy for existing financing constraints but instead shapes how managers *perceive and interpret* those frictions. Gormsen and Huber (2024) show that only about 20% of the cross-sectional variation in perceived cost of capital corresponds to firms' true cost of capital, with the remaining 80% driven by differences in perception. My findings offer a behavioral explanation for this gap: heterogeneity in managerial attention to financial markets. Managers who allocate more attention to market signals are better informed about financing conditions and therefore perceive lower costs of capital. In this sense, attention acts as an interpretive filter through which objective market information becomes subjectively processed. Within the rational-inattention framework developed in Section 8, such heterogeneity can naturally arise when managers optimally allocate limited cognitive resources between internal and external signals. Attentive managers learn from informative price signals and reduce uncertainty about financing conditions, while inattentive managers—processing fewer signals—tend to overestimate financing costs and underinvest even when capital is accessible.

7.2 Management Presentation versus Q&A

Understanding the distinct roles of management presentations and Q&A sessions in earnings calls provides insights into different forms of managerial attention to financial markets. The management presentation represents the *supply side* of information, reflecting managers' deliberate, strategic communication choices about which financial market dimensions to emphasize. When managers discuss financial markets in prepared remarks, it signals their proactive assessment of which market signals are most relevant for their business strategy.

In contrast, the Q&A session reflects the demand side of information, where analysts steer the discussion toward topics they deem most relevant. Unlike managerial speeches—which Cao, Jiang, Yang, and Zhang (2023) show are more strategically scripted when firms expect higher machine readership—managers' references to financial markets during Q&A arise more organically and spontaneously. These relatively unscripted responses offer a clearer window into how managers process market information in real time and respond to investor concerns about prevailing market conditions.

Tables IA9 and IA10 present the economic implications of IAFM measures constructed separately from management presentations and Q&A sessions, respectively. The results demonstrate that both sources of attention yield statistically significant effects across most specifications, supporting the robustness of the main findings.

For investment-price sensitivity (Panel A), both presentation-based and Q&A-based measures show positive and statistically significant interactions with Tobin's Q. Q&A-based measures consistently demonstrate larger economic magnitudes—for example, Q&A-based equity attention shows a coefficient of 0.0435 for capital expenditures compared to 0.0315 for presentation-based attention, both statistically significant.

The financing decisions (Panel B) demonstrate that both forms of attention significantly influence firms' propensity to tap external financing. For equity financing, Q&A-based equity attention shows a coefficient of 0.0538 compared to 0.0418 for presentation-based attention, both statistically significant at the 1% level. The pattern is similar for debt financing, where Q&A-based debt attention yields a coefficient of 0.137 (significant at the 1% level) compared to 0.0348 for presentation-based attention (significant at the 10% level).

The market timing and interest rate sensitivity results (Panels C and D) show consistent patterns across both approaches. For market timing behavior, Q&A-based equity market sentiment interactions demonstrate larger and more statistically significant effects:

coefficients of 0.0223 for sentiment changes (significant at the 1% level) and 0.108 for sentiment levels (significant at the 1% level), compared to presentation-based coefficients of 0.00584 (statistically insignificant) and 0.0784 (significant at the 5% level), respectively. For interest rate sensitivity, the Q&A-based measure yields a coefficient of 0.0838 (though statistically insignificant), while the presentation-based measure shows 0.0826 (significant at the 10% level). Furthermore, for market timing behavior based on firm-level valuation (Tobin's Q), both forms of attention significantly predict firms' likelihood of issuing equity over debt, with coefficients of similar economic magnitude and statistical significance.

This subsection provides evidence that both management presentations and Q&A sessions significantly predict firms' investment and financing decisions. The finding that attention measured using Q&A sessions tends to be, on average, both statistically and economically more significant may reflect two factors. First, the interactive, unscripted nature of analyst questioning reduces managers' ability to strategically script their responses. Second, managers may pay closer attention to topics raised by analysts because these topics signal what shareholders and analysts consider important.

Furthermore, the economically larger effect of Q&As-based measures mitigates the concern that my results are driven by an alternative explanation where managers might *post hoc* reference current financial market conditions to rationalize decisions they have already formulated independently of market signals. Managers have incentives to engage in such performative behavior because it enhances the perceived legitimacy and external validation of their choices. If this explanation were driving my results, we would expect stronger effects from management presentations, where managers have greater control over content and more opportunity to craft justifications. However, we do not find such a pattern.

Another concern is that the attention captured in the Q&A section might partly reflect investors' attention rather than managers' own monitoring of financial markets. If analysts steer the conversation toward market conditions, one may worry that the IAFM is picking up investor pressure rather than managerial cognition. The significant results obtained when using attention constructed solely from the management presentation—where executives speak in their own words—help alleviate this concern. Moreover, even if from investors' perspective it may be optimal for the firm to respond to financial markets, such responses can only materialize if managers themselves attend to and operationalize the information conveyed. This is inconsistent with a "*no-attention-needed*" or "*no-real-effects*" view, under which managers would adopt identical policies regardless of their own attention to market prices because prices would contain no additional information beyond fundamentals already known inside the firm. I also address this alternative explanation in Section 7.7.

7.3 Using the Term Frequency (TF) Approach

A potential concern with the TF-IDF methodology is that the inverse document frequency (IDF) component may introduce noise by overweighting terms that appear infrequently across the corpus, potentially due to measurement error or idiosyncratic usage patterns. More specifically, when applying IDF, the weighting is based on the frequency of terms that appear in the entire corpus of earnings calls, which covers the entire sample period and all firms across different industries. This weighting may induce issues such as temporal bias, where terms that were rare in early sample years but became common later (or vice versa) receive inappropriate weights, and industry bias, where terms that are common within specific industries but rare across the full sample receive artificially high weights even when used by firms in those industries where such terminology represents routine discussion rather than exceptional attention. [18]

To address this concern, I test the robustness of my findings using only the term frequency (TF) component, which measures the raw frequency of financial market-related terms within each firm's earnings calls without adjusting for their rarity across the entire sample. This approach eliminates potential cross-sectional and temporal contamination in the weighting scheme while providing a more transparent measure of attention intensity. Figure

[18] For example, terms like "enterprise_value" (which falls into IAFM Equity) might be relatively rare before 2010 but increasingly common in recent years as this valuation metric became more standardized in corporate discourse, leading to inflated IDF weights even in periods when such discussions represent standard valuation commentary rather than exceptional attention. Similarly, mortgage-related terms such as "agency_mbs," "cmbs_market," or "mortgage_spread" (which fall into IFAM Debt) might be routine vocabulary for financial services firms but rare across the full sample, resulting in artificially high weights that overstate the significance of such discussions for banks and REITs where these terms represent normal business operations rather than heightened financial market focus. That said, the latter concern is likely mitigated by the exclusion of financial sector firms from our main analysis.

IA1 shows the time-series variation in industry-level TF-only measures, which display a similar pattern to those constructed using the TF-IDF method. Table IA11 presents the regression results. The findings support the robustness of the main results.

7.4 Using Seed Words Only

The *word2vec* expansion methodology, while providing comprehensive coverage of financial market terminology, raises the question of whether the machine learning-based dictionary expansion is necessary for the main results. To address this concern, I test the robustness of findings using only the original 25 seed words per dimension, without any algorithmic expansion.

This robustness check is important for several reasons. First, it ensures that the results are not dependent on the specific *word2vec* algorithm or the particular corpus used for training, which could introduce systematic biases in word selection. Second, it tests whether the core economic relationships can be detected using only the most unambiguous, manually selected financial market terms. Third, it provides a more transparent and replicable approach that relies entirely on ex-ante term selection rather than machine learning-derived associations.

Table IA12 presents regression results using only the original seed words. The findings continue to support the main conclusions, though with somewhat attenuated magnitudes. Therefore, the *word2vec* expansion appears to enhance statistical power by providing more comprehensive coverage of financial market terminology, but the fundamental economic relationships are detectable even with a more conservative, manually curated approach. Additionally, Figure IA2 illustrates the time-series variation in industry-level IAFM measures constructed using seed words. These measures follow a pattern similar to those based on an expanded dictionary, though they show a smaller disparity between the financial sector and other sectors. Also, since 2021, energy firms have increasingly focused on the equity market.

7.5 Constructing IAFM Using Binary Indicators

Throughout this paper, I have employed log-transformed, continuous measures of IAFM to facilitate interpretation of percentage changes in attention allocation. To ensure robustness, I examine whether results persist using binary indicators that equal one if the corresponding IAFM measure falls within the top two quintiles of the sample distribution in a given year, and zero otherwise.[19] This approach addresses concerns about functional form assumptions and extreme values while providing more intuitive interpretation. Table IA13 shows that my key findings remain intact under this alternative specification.

7.6 Could Attention Be Merely a Passive Sideshow?

An alternative interpretation of the findings is that the observed relationship between managerial attention and corporate policies reflects a purely *mechanical* transmission of market conditions—such as changes in Tobin's Q, sentiment, or interest rates—into firms' cost of capital or financing access, rather than managers actively processing market information. In this alternative "*attention-as-sideshow*" view, financial shocks affect firms through the primary-market channel *alone*, and managerial attention co-moves with those shocks as a *pure* passive by-product.

However, this mechanical explanation implies an empirical prediction that is not supported by the data. If attention merely passively reflected cost-of-capital fluctuations, its interaction with financial-market proxies should be insignificant once those market conditions are directly controlled for in the regression, because it would have no independent predictive power. Specifically, Tobin's Q (for investment) and sentiment, Tobin's Q, or the interest rate (for financing) should alone explain corporate investment and financing policies. In contrast, I find the opposite: interaction terms between attention and these market variables remain positive and statistically significant, indicating that attention actively shapes how managers interpret and act on market signals rather than merely co-moving with them.

For investment policies in particular, this concern is further mitigated when I simultaneously include both equity-market and debt-market attention—together with their respective interactions with Tobin's Q and the firm's bond yield—in the regression, as shown

[19] The main conclusions hold if I use other split points, including sample median, terciles, or quartiles.

in Section 5.3 and Table IA5. If one believes that attention to the debt market more likely captures variation in firms' financing capability—especially since bond yield directly reflects the firm's cost of debt—then controlling for debt-market attention and its interaction with bond yield should help absorb the mechanical financing-channel effects. Yet, the coefficient on the equity-market-attention interaction remains positive and significant, indicating that equity-market attention contains incremental informational value beyond financing capacity. Main results hold when I control for the total implied cost of capital, as in Table IA8 Panel C.

A related concern is that past stock returns—omitted from my baseline regressions and shown in Table 7 to positively predict future attention—may be driving the main results. However, omitting past returns is problematic only if they *directly* affect investment–price sensitivity while attention serves purely as a passive sideshow. If instead market conditions influence corporate policies *through* attention, then controlling for past returns would introduce a "bad-control" problem by partialing out the very channel through which financial markets operate. Section 7.1 addresses this concern more directly by restricting the sample to firms that do not tap external capital markets, thereby shutting down the primary-market channel through which past returns might mechanically affect investment. The persistence of equity attention effects among these non-financing firms supports an information channel distinct from financing capacity. Nevertheless, Table IA14 explicitly controls for past stock returns, and the main results continue to hold.

One might still worry that the results capture higher-order movements in financial markets—particularly volatility or liquidity conditions—that directly affect corporate policies while attention passively co-moves with them. For example, Table 7 shows that stock return volatility indeed correlates with attention to financial markets. To address this possibility, I construct a direct measure—IAFM Vol. & Liq.—that captures attention to financial-market volatility and liquidity conditions. The intuition is that when firms extensively discuss liquidity strains, volatility spikes, or broader market disruptions, this language likely reflects heightened awareness of turbulent conditions, which could directly affect corporate policies. By explicitly controlling for this volatility-and-liquidity dimension of attention, I isolate the incremental, information-driven component of managerial market monitoring from the more passive variation that arises when managers respond mechanically to market turmoil.

Table IA15 Panel A presents the seed words for this dimension, including terms like "market_volatility," "trading_volume," "liquidity_risk," and "market_turmoil." Panel C documents meaningful industry variation: Financial firms exhibit the highest mean attention to volatility and liquidity conditions (2.98), followed by Utilities (1.31) and Chemicals (1.10), consistent with these sectors' greater exposure to financial-market fluctuations. Panel D further shows that managerial attention to volatility and liquidity events increases following years of higher market volatility, but is not significantly correlated with the level of market returns, indicating that the measure captures sensitivity to at least the second moment of market conditions, rather than general optimism or pessimism. Figure IA3 supports this interpretation by showing that firms' discussions of market volatility respond intuitively to major economic disruptions, including the 2008 financial crisis and the COVID-19 pandemic.

Table IA16 examines how controlling for this passive, turbulence-driven component of attention affects the main results. I include both a High IAFM Vol. & Liq. Indicator (equal to one for firms within the top two sample quintiles in a given year and zero otherwise) and the specific IAFM Equity/Debt measures, allowing me to distinguish attention driven by general market stress from deliberate, targeted attention to particular financial market segments.[20]

Panel A shows that both firms' attention to market shocks and their targeted financial-market attention independently affect investment-price sensitivity. The interaction between the vulnerability indicator and Tobin's Q is positive and significant for both capital expenditures (0.0744) and total investment (0.297), indicating that firms more exposed to volatile or illiquid markets are indeed more responsive to price signals. Importantly, the interactions between IAFM Equity/Debt and Tobin's Q remain positive and significant (0.0601 and 0.0865 for CAPX; 0.234 and 0.239 for INVT). This suggests that targeted attention to equity and debt markets exerts incremental, information-driven effects beyond what can be explained by firms' underlying exposure to disruptive market conditions.

[20] Main conclusions remain intact when using other split points, including sample median, terciles, or quartiles.

Panel B demonstrates similar patterns for financing decisions. Firms that devote greater attention to volatility and liquidity conditions exhibit a stronger tendency to tap external capital markets—issuing equity (0.107) or debt (0.104) when financing deficits arise. This reflects that managers in more turbulent or liquidity-sensitive environments are more alert to funding constraints and react more decisively when market access becomes available. After accounting for this turbulence-driven responsiveness, the effects of IAFM Equity and IAFM Debt attention remain robust and significant, suggesting that targeted attention to specific financial-market segments provides additional, information-based explanatory power beyond firms' general sensitivity to volatile financing conditions. Panels C and D extend this robustness check to the market timing results from Section 6.2, and the key interactions between specific market attention and market conditions maintain their significance. Results remain robust when the Equity and Debt IAFM measures are also coded as binary indicators, as reported in Table IA17.

In sum, the evidence is inconsistent with the view that managerial attention *purely* serves as a passive marker for firms' mechanical exposure to cost-of-capital shocks or market turbulence. While attention or exposure to market disruptions naturally affects investment and financing behavior, targeted attention to equity and debt markets exerts distinct, incremental effects beyond those exposures.

Furthermore, a key insight of this paper is to show that even when a primary-market channel operates, attention contributes an independent behavioral channel—consistent with Song and Stern (2025), who show that managerial inattention dampens firms' responses to monetary-policy shocks. For instance, as shown in Section 6.2, debt-market attention continues to predict managers' tendency to issue equity rather than debt when interest rates rise, beyond the direct effect of rate changes themselves. Similarly, for investment policies, Section 5.3 and Table IA5 show that when both equity- and debt-market attention, along with their respective interactions with Tobin's Q and bond yields, are included in the specification, the coefficient on bond yield captures the direct effect of financing conditions, while the negative debt-market-attention × bond-yield interaction implies that attentive managers adjust investment more promptly to changing borrowing costs. Table A8, Panel C supports this interpretation, showing that debt-market attention indeed translates into greater investment expansion precisely by enabling managers to capitalize on lower borrowing costs. Together, these findings show that attention shapes firms' real responses to financial markets in ways that cannot be explained by a *purely* mechanical channel.

7.7 CEO Effects and Evidence of "Exogenous" Turnovers

A natural follow-up question in interpreting my findings is the extent to which attention to financial markets reflects individual managerial styles. I start by investigating whether individual CEOs exhibit consistent attention patterns across their tenures. Table IA18 presents a variance decomposition analysis that includes manager fixed effects in addition to the firm and industry-by-year fixed effects examined in Table 3. Manager-specific factors contribute an incremental 5.7% and 3.2% of the variation in attention to equity and debt markets, respectively, beyond what is explained by firm and industry-by-year effects. This suggests that individual executives do bring distinctive styles to monitoring financial markets.

Next, I examine whether changes in firm-level attention around CEO turnovers affect corporate policies. To measure CEO-specific attention patterns, I calculate each CEO's tenure-specific attention as the equally-weighted average of IAFM scores across their entire tenure period. It provides a practical proxy for the attention level that characterizes each CEO's leadership period, assuming some persistence in managerial approach over time.

One concern of this approach is that tenure-specific attention patterns may be endogenously determined by factors such as endogenous matching between firms and CEOs, firm lifecycle effects, industry, or competitive positions.[21] I address this concern in two ways. First, I include firm and industry-by-year fixed effects in all specifications, which addresses mitigates endogenous matching based only on firm-specific characteristics or common industry shocks. Second, I focus on CEO turnovers where the transition timing is more likely to be exogenous to strategic considerations about attention patterns: cases where the incumbent CEO retires (defined as departing at age 65 or older). Following Custódio and

[21] For example, a CEO who begins their tenure during a crisis period may exhibit systematically different attention patterns compared to one who assumes leadership during stable conditions, making it difficult to disentangle manager-specific effects from circumstantial factors.

Metzger (2014) and Jenter and Lewellen (2015), I argue that such turnovers are less likely to be driven by strategic considerations about optimal attention allocation, as the timing is largely determined by the outgoing CEO's age rather than firm's lifecycle-specific needs. For example, when a CEO reaches retirement age, the firm may not have access to the ideal successor in terms of attention to financial markets. This approach provides a cleaner test of whether changes in managerial attention to financial markets influence corporate policies.

Table IA19 examines the economic implications of CEO tenure-specific attention patterns for the full sample of CEO turnovers. Panel A shows that firms led by CEOs with higher tenure-average attention to financial markets exhibit greater investment-price sensitivity. The interaction coefficients of 0.0837 for CAPX and 0.400 for total investment when examining equity market attention suggest that changes in manager-specific attention can influence how firms respond to market signals. Panel B demonstrates that high-attention CEOs enhance firms' responsiveness to financing needs in terms of accessing more external capital, with significant effects for both equity and debt financing decisions. Panels C and D examine market timing behavior, showing that high-attention CEOs make firms more responsive to equity market sentiment and firm-specific valuations, though the effects on interest rate sensitivity are not significant.

Table IA20 presents results restricted to cases where the predecessor CEO retires at age 65 or older. Several key results remain significant. High-attention successors continue to enhance investment-price sensitivity, with particularly large effects for capital expenditures (0.197 for CAPX and 0.611 for INVT when examining equity market attention, and 0.212 for CAPX and 1.016 for INVT when examining debt market attention). The effect of attention on the likelihood of tapping external capital markets remains positive and significant. However, the market timing results, except for responsiveness for firm-specific valuations, become statistically insignificant in this restricted sample, likely due to reduced statistical power.

Another limitation of measuring attention using tenure-averages is the look-ahead bias: future attention patterns may be influenced by outcomes that have not yet occurred when CEOs make their decisions in their early tenure. To address this concern, I conduct an additional robustness check in Table IA21 using a CEO's pre-tenure attention level, measured as the equally-weighted average of IAFM scores during their prior C-suite positions (across both current and prior firms) before assuming their current CEO role. This approach eliminates look-ahead bias but comes with severe data limitations, as it requires observing (both incumbent and incoming) managers in multiple high-level positions with measurable IAFM data (beginning only in 2007). The results show that, around "exogenous" turnovers, CEOs with higher attention backgrounds continue to enhance investment-price sensitivity. However, the financing and market timing results become largely insignificant.

Several important caveats apply to the analysis of this subsection. First, while the timing of a retiring CEO's departure may be plausibly exogenous, the board's choice of successor is not. Boards may strategically select CEOs whose attention patterns align with desired policy changes, creating a matching explanation for the observed relationships. Second, the severe sample restrictions required for clean identification limit the generalizability of findings to the broader population of CEO transitions.

However, *at the very least* the persistence of CEO tenure-specific effects even in the restricted retirement sample suggests that managerial attention serves as a *necessary* implementation mechanism. While a firm's industry and lifecycle may determine that it should respond to market signals or time financing decisions around market conditions, actually executing these strategies requires managers who actively monitor market information. Without adequate attention to financial markets, firms may struggle to implement otherwise value-maximizing policies, creating a gap between optimal and realized strategies. These results are inconsistent with the alternative "*no-attention-needed*" or "*no-real-effects*" view, under which managers would pursue identical policies regardless of whether they attend to market prices, because financial markets play no real role in the decision-making process (e.g., prices merely reflect fundamentals already known to the firm).

7.8 IAFM Other Assets and Investment Decisions in the Energy Sector

The information channel predicts that attention to financial markets should enhance investment sensitivity only when those markets convey relevant signals about business fundamentals. This section tests this prediction by exploiting natural variation in which market signals are most informative across industries.

For energy firms, commodity prices—particularly oil and gas prices—provide more immediate and relevant information about investment opportunities than traditional equity market signals, given these firms' direct exposure to commodity price fluctuations (Gilje and Taillard, 2017; Shi and Zhang, 2024). Conversely, for non-energy firms, commodity price movements contain minimal information about core business fundamentals, even if such firms occasionally discuss commodity markets due to input costs or macroeconomic exposure. This asymmetry yields a clear prediction: if attention operates through information acquisition, energy firms should respond to commodity price signals when they attend to commodity markets, while non-energy firms should show little responsiveness regardless of their attention.

To examine this industry-specific information usage, I develop the IAFM Other Assets measure using the same methodology as previous IAFM dimensions. This measure captures firms' attention to commodity, currency, and derivatives markets through 25 seed words (as shown in Table IA22 Panel A) including “commodity_price,” “oil_price,” and “future_market.”[22] Panel B shows that the most representative words demonstrate strong semantic coherence, with “commodity_market” (0.75) and “future_market” (0.74) exhibiting high similarity scores. The most frequent terms include “hedge” (18.44%), “commodity” (8.63%), and “oil_price” (8.35%), in line with the measure's focus on commodity markets.

The IAFM Other Assets measure displays substantial industry variation consistent with economic intuition (Table IA22 Panel C). Energy firms exhibit the highest attention to commodity markets (mean = 12.77), followed by Utilities (8.15) and Chemicals (5.02). The measure also responds appropriately to market conditions: on average, a 10% increase in fuel prices predicts a 0.42% increase in commodity market attention the following year (Panel D). Figure IA3 provides further temporal validation. During the 2008 financial crisis, energy

[22] A critical design choice involves constructing this measure to encompass broader discussions of commodity, currency, and derivatives markets rather than focusing exclusively on oil price attention. This approach is pivotal for two reasons. First, constructing an index purely focused on oil price discussions would result in most non-Energy firms scoring zero, creating a mechanical relationship where only Energy firms have meaningful variation in the measure. Second, the broader measure captures the important insight that even non-Energy firms discuss commodity markets to varying degrees—through input cost concerns, hedging activities, or macroeconomic exposure—but this attention should interact meaningfully with commodity price movements only for firms where these prices predominately reflect future business opportunities.

firms' attention rose from 12.41 to 14.61; amid the 2015 oil-price collapse, it climbed from 11.04 to 17.49; and following the COVID-19 shock in 2020, it increased from 10.42 to 14.47. Throughout 2007–2023, energy firms maintain attention levels three to four times higher than most other industries, consistent with their fundamental reliance on commodity signals.

Table IA23 tests whether Energy and non-Energy firms respond differently to various price signals when making investment decisions. For non-Energy firms, traditional equity and debt market attention significantly enhance investment-price sensitivity, consistent with the main results. However, Energy firms show no significant relationship between equity/debt market attention and investment-price sensitivity, suggesting these traditional financial market signals may be less relevant for their investment decisions. Instead, Energy firms demonstrate significant responsiveness to commodity price signals when they pay attention to commodity markets. The interaction between IAFM Other Assets and fuel price changes is positive and significant for Energy firms (1.50 for CAPX and 2.54 for INVT) but statistically insignificant for non-Energy firms.

These findings support the interpretation that firms respond to market signals only when those signals contain relevant information about their business opportunities. One caveat is that firms may rationally self-select to focus their limited attention on the most the market signals most informative for their specific business context. Although it is difficult to design a natural experiment that fully rules out this self-selection, the results nonetheless offer an out-of-sample test: by examining a market setting distinct from the main analysis, the evidence shows that attention serves as an important channel through which commodity prices affect producers' investment decisions. More broadly, these findings are inconsistent with a "*no-attention-needed*" view, under which managers would pursue identical policies regardless of whether they monitor market (or energy) prices because financial markets play no meaningful role in the decision-making process. Instead, the evidence suggests that without adequate attention to relevant price signals, firms may fail to implement otherwise value-maximizing responses to market conditions.

8. Why Do Some Managers Not Pay Attention? A Rational Inattention Framework

The previous sections demonstrate that financial markets serve two primary roles for corporate decision-making: providing information about business opportunities and facilitating access to capital. Yet substantial heterogeneity exists in managerial attention to financial markets across industries and firms as documented in Table 3's variance decomposition. This variation raises a fundamental question: *why do some managers rationally choose not to pay attention to financial markets?* The fact that as shown in Table 4, certain industries have low attention across a large number of firms suggests that this heterogeneity cannot be explained solely by idiosyncratic behavioral biases.

I argue that this cross-sectional heterogeneity in attention reflects a *rational inattention* equilibrium. Managers optimally allocate their limited attention between processing internal information about their firms and external market prices. Industries with fundamentally opaque or idiosyncratic business environments (e.g., R&D-intensive sectors) generate internal information that is far more precise than what prices can reveal, lowering the relative informativeness of market signals. In these settings, managers rationally "focus inward" and devote less attention to markets. Conversely, industries with tangible assets and transparent business models present rich price signals and lower internal informational advantages, inducing managers to allocate more attention to markets.

To formalize this logic, I develop a simple model. Consider a firm with assets $\theta = \theta_1 + \theta_2$. The firm's securities are traded by risk-neutral outsiders ("she") and liquidity traders ("they"). There are three periods. At $t = 1$, traders may acquire information and trade. Outsiders can pay a fixed cost F to observe a noisy signal s_i of total assets in place. Conditional on incurring this cost, she privately observes the signal $s_i = \theta_1 + \theta_2 + \eta_i$; if not, she remains uninformed and does not trade. I use "speculator" to denote an outsider who chooses to become informed, a denote the number of speculators, and x_i the trade of speculators i.

The manager is an insider ("he") who costlessly and privately observes the signal θ_1 at $t = 1$. He also has a fixed time endowment of one unit, a fraction τ (where $0 < \tau < 1$) of which can be allocated to observing the security price at $t = 2$, which aggregates the information contained in speculators' trade. He will allocate the remaining time to privately observe an internal signal about assets in place $s_m = \theta_1 + \theta_2 + \epsilon$, which will be realized in $t = 2$. Alternatively, he can choose to allocate the entirety of his time to observe the internal signal, in which case the precision of ϵ is h_ϵ. If he decides to also observe security price, the time spent in processing price crowds out part of his time that would be used in collecting the internal signal, reducing the precision of ϵ from h_ϵ to $(1-\tau)h_\epsilon$. I denote by s_m^{att} (with precision of $\epsilon\ being\ (1-\tau)h_\epsilon$) the internal signal the manager receives if he allocates time to observe security price, and by s_m^{int} (with precision of $\epsilon\ being\ h_\epsilon$) the internal signal the manager receives if he does not allocates time to observe price. His time allocation decision is represented by $O \in \{0,1\}$, where $O = 0$ indicates exclusive focus on the internal signal, and $O = 1$ indicates that he processes the security price in addition to the internal signal. This setup captures the core tradeoff: acquiring and interpreting price signals consumes managerial cognitive and temporal resources, crowding out attention to internal information sources. When mapping the model to reality, one may view τ as manager-specific cost of attention diversion (i.e., the minimum share of attention that must be diverted to processing price signals, away from internal sources) and h_ϵ as firm- or industry-specific informativeness of internal sources.

The random variables $\{\theta_1, \theta_2, \eta_i, \epsilon\}$ are mutually independent and normally distributed with zero means and precision $\{h_\theta, h_\theta, h_\eta, h_\epsilon\}$.[23] Outsiders' signal is imprecise due to noise term η_i, and so they are less informed about θ_1 than the insider. The manager, while having perfect knowledge of θ_1, can further improve his information by deciding how to allocate his limited time at $t = 2$: he may either devote all of it to gathering and processing the internal signal s_m, which is noisy due to ϵ, or split his time between collecting this internal signal and additionally observing the security price (modeled next), which aggregates outsiders' signals.

I assume exogenous and price-dependent liquidity traders' demands. I denote this demand by $L = z - \frac{1}{\lambda}p$, where z is normally distributed with mean zero and precision h_z, and

[23] This information structure, as in Edmans, Jayaraman, and Schneemeier (2017), highlights the difference in the scope of information available to insiders versus outsiders.

independent of all other random variables. The component $-\frac{1}{\lambda}p$, where $\lambda > 0$ gives a downward-sloping demand curve consistent with Hellwig, Mukherji, and Tsyvinski (2006) and Goldstein, Ozdenoren, and Yuan (2013). The total demand from all traders is therefore $d = \sum_{i=1}^{a} x_i + z - \frac{1}{\lambda}p$. The market clearing stock price can be obtained by setting $d = 0$.

At $t = 2$, the manager rationally invests K units in a growth opportunity at cost $\frac{1}{2}cK^2$ where $c > 0$. The profitability of such opportunity equally correlates with both θ_1 and θ_2; relaxing this assumption does not change the results. He chooses K and time allocation Z and O to maximize expected firm value, which includes assets in place, plus the growth opportunity, minus the investment cost, based on his signals (i.e., θ_1 and s_m^{int} if he does not pay attention to stock price and θ_1, s_m^{att} and p if he does).

If he does not pay attention to stock price (i.e.,$O = 0$):

$$V\left(\theta_1, s_m^{int}\right) = Max_K E\left[\theta_1 + \theta_2 + (\theta_1 + \theta_2)K - \frac{1}{2}cK^2 \middle| \theta_1, s_m^{int}\right]$$

If he pays attention (i.e., $O = 1$):

$$V(\theta_1, s_m^{att}, p) = Max_K E\left[\theta_1 + \theta_2 + (\theta_1 + \theta_2)K - \frac{1}{2}cK^2 \middle| \theta_1, s_m^{att}, p\right]$$

where $(\theta_1 + \theta_2)K$ captures the growth opportunity. At $t = 3$, all payoffs are realized. As in Subrahmanyam and Titman (1999), Foucault and Gehrig (2008) and Edmans, Jayaraman, and Schneemeier (2017), I model securities as a claim only to assets in place θ, rather than the sum of assets in place and growth projects. If securities instead paid out on the sum of assets in place and the growth project, each informed trader's first-order condition would include an additional term capturing how his trade changes the manager's subsequent choice of K; traders could then trade not only to exploit information but also to influence investment, which materially complicates equilibrium characterization in the normal Gaussian environment. This simplification does not alter my main results, which center on the relative informativeness of the security price versus the internal source (as I will show in Lemma 2).[24]

[24] Incorporating the feedback effect only amplifies the role of this relative informativeness in shaping the manager's incentive to attend to the price. Specifically, when relative informativeness is high—already implying

The equilibrium in this model consists of: (i) A trading strategy x_i mapping each speculator's private signal to an order that maximizes expected trading profits $E[x_i(\theta - p)|s_i]$ given the price function; (ii) A price function that clears the security market, given traders' signals; iii) An investment decision K by the manager that maximize expected firm value given manager's information set ($I \in \{I^{int}, I^{att}\} = \{\{\theta_1, s_m^{int}\}, \{\theta_1, s_m^{att}, p\}\}$) and time allocation decision; iv) Time allocation decision $O \in \{0,1\}$ by the manager that maximize the period 1's expected firm value conditional on θ_1 before observing internal signal or/and security price; and (v) All agents correctly anticipate the strategies of others.

I show the manager's optimal time allocation decision O, which maximize the period 1's expected firm value given θ_1 in Position 1. I defer the proof to Internet Appendix II.

Proposition 1: *The manager chooses to attend to the price ($O = 1$) if and only if the price precision exceeds the internal-precision loss:*

$$O = 1 \Leftrightarrow \Omega \coloneqq \frac{h_p}{h_\epsilon} - \tau > 0$$

where $h_p = \frac{a^2 h_\eta^2 h_z}{a h_z h_\eta + \lambda^2 \left(h_\eta (a+1) + h_\theta\right)^2}$ *denotes the precision of the price signal (i.e., price informativeness) to the manager.*

The time-allocation condition in Proposition 1 presents a fundamental attention trade-off: the manager pays attention to the market price precisely when the price's relative precision exceeds the attention/crowding cost—in symbols, attend if and only if $\frac{h_p}{h_\epsilon} - \tau > 0$. This compact inequality packages two economically intuitive objects: $\frac{h_p}{h_\epsilon}$ measures the *relative* informativeness of the price signal versus the internal source, and τ captures how

a strong incentive to attend—the fact that speculators' trades become more profitable as managers learn from prices induces them to trade more aggressively. This, in turn, makes the price even more informative and further strengthens the manager's incentive. Conversely, when relative informativeness is low—already implying a weak incentive to attend—speculators know that their trades have little impact on profitability through managerial learning. They therefore trade less aggressively, reducing price informativeness and further weakening the manager's incentive.

costly (in units of internal-signal precision) it is to divert time to reading prices.[25] Thus, a larger $\frac{h_p}{h_\epsilon}$ says that each "unit" of attention spent on price buys you more reduction in uncertainty than the same unit spent on internal investigation; the optimal investment rule then weights the price heavily because it meaningfully tightens the manager's posterior. Then, larger τ means the crowding cost is bigger (or the manager is less efficient at processing price and internal signals simultaneously), so the price must offer a proportionately larger precision advantage to justify attention.

These theoretical insights generate two complementary testable hypotheses. The *Attention Cost Hypothesis* (ACH) posits that managers with lower effective attention costs τ should be more likely to process market signals. This prediction finds strong support in the empirical evidence showing that managers with financial expertise—acquired through prior employment in the financial industry or finance-focused roles—demonstrate significantly higher attention to market prices, as documented in Section 4.3.

The *Information Asymmetry Hypothesis* (IAH) predicts that when the *relative* informativeness (of the price signal versus the internal signal) ratio $\frac{h_p}{h_\epsilon}$ is low, managers rationally rely more on internal information and less on price signals for investment and financing decisions. I test the Information-Asymmetry Hypothesis (IAH) by examining two empirical implications. The first concerns the informativeness of market prices, and the second concerns the informativeness of internal signals, proxied by firms' R&D intensity.

For the first implication, I evaluate how managerial attention varies with the informativeness of equity and debt market prices. As discussed in Section 5.2, equity price informativeness is measured using the probability of informed trading (PIN), as developed by Easley and O'Hara (1992) and Easley, Kiefer, and O'Hara (1996). I measure bond price informativeness using bond price non-synchronicity (i.e., $(1\text{-}R^2)$) from regressions of

[25] An alternative interpretation of τ is that it parameterizes the degree of substitutability between market and internal information in the manager's overall information-production technology. When $\tau > 0$, price- and firm-specific information are substitutes in producing managerial knowledge. By contrast, if τ is allowed to be negative, the two sources are *complementary*: processing market signals enhances the value of internal information, for instance by helping managers interpret firm-specific shocks or benchmark internal forecasts against external expectations. In this complementary regime, manager always pays attention to financial market.

individual bond returns on market bond indices. A PIN-style model is unsuitable in the bond setting because corporate bond trading occurs primarily in over-the-counter markets with limited liquidity and irregular trade frequency, making parameter estimates highly unstable.[26] This price non-synchronicity approach, originally proposed in an equity-market setting by Roll (1988) and extended by studies including Morck, Yeung, and Yu (2000), captures the firm-specific component of price variation. When a firm's bond return is highly correlated with the market return, the bond price conveys little firm-specific information; conversely, higher non-synchronicity indicates greater informational content about firm fundamentals.

Figure 2 provides evidence supporting the IAH by plotting industry-average IAFM measures against price informativeness (orthogonalized with respect to firm size) across eleven of the twelve Fama–French industries (excluding Finance). The positive association between industry-level managerial attention and both equity and bond price informativeness indicates that managers devote more attention to financial markets precisely when prices are more informative about fundamentals.

[Insert Figure 2 about here]

To examine the second implication, I analyze how managerial attention relates to the informativeness of internal signals, proxied by firms' R&D intensity (orthogonalized with respect to firm size). Figure 3 shows a pronounced negative relationship between industry-average IAFM measures and R&D intensity. This pattern is consistent with the IAH. The inherently uncertain, long-horizon, and proprietary nature of R&D projects makes them difficult for outside investors to evaluate (Aboody and Lev 2000). Managers in these environments, by contrast, have access to detailed, project-specific information—such as prototype performance, experimental outcomes, and early customer feedback—that is unavailable to outsiders and highly informative for internal decision-making. Consequently, managers in these settings rationally allocate less attention to financial markets.

[Insert Figure 3 about here]

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[26] As an illustration, between 2007 and 2023, firms in my sample have trading activity on an average of 167 days per year. On an average trading day, the number of executed buy (sell) orders is only 2.8 (1.8).

Table A10 formalizes these relationships by regressing firm-level attention measures on proxies for external and internal signal precision while controlling for firm characteristics and industry-by-year effects. This specification is intended to capture cross-sectional equilibrium patterns linking managerial attention to the prevailing information environment. The results support the theoretical predictions of the rational-inattention framework. The coefficients on equity PIN and bond price non-synchronicity are positive and statistically significant, indicating that higher external signal precision is associated with greater managerial attention to financial markets. Conversely, the coefficients on R&D intensity are negative and significant across both IAFM Equity and IAFM Debt regressions, showing that higher internal signal precision reduces managerial attention. As a robustness check, I also estimate complementary specifications using equity price non-synchronicity as an alternative measure of equity-market informativeness and a bond-market PIN estimated from TRACE data as an alternative measure of debt-market informativeness. I continue to find positive correlations between attention and price informativeness. Results are reported in Table IA24.

In sum, this section explains why managers sometimes choose not to monitor financial markets: doing so is cognitively costly, as it diverts limited resources from processing firm-specific information. The rational inattention framework provides at least one plausible explanation for the cross-sectional variation in managerial attention documented throughout the paper. This evidence also challenges the long-standing theoretical assumption that all managers actively attend to market signals.

Conceptually, this framework completes the causal chain driving the real effects of financial markets: managers choose to monitor markets precisely when external price signals are relatively more informative, and they subsequently act on signals in their investment and financing decisions. This rational allocation of attention stands in contrast to the alternative hypothesis ("*no-attention-needed*" view), which holds that managers would have neither the incentive nor the payoff to monitor markets if financial prices contained no information relevant to real corporate decisions. Besides, the model also provides a behavioral foundation for the large dispersion between true and perceived costs of capital documented by Gormsen and Huber (2024). In my framework, such dispersion can arise endogenously from heterogeneity in managers' optimal attention allocation—reflecting differences in how effectively they manage their cost of capital, for example through better market timing—rather than from biases or mistakes as mainly argued in their analysis.

9. Conclusion

This paper introduces a novel approach to quantifying firm-level attention to financial markets by developing the *Index of Attention to the Financial Market* (IAFM). By analyzing the content of 98,010 earnings call transcripts across 7,673 firms from 2007-2023, I provide the first comprehensive measurement of how managers allocate attention to equity and debt markets. A key empirical finding is the substantial heterogeneity in managerial attention across firms, industries, and over time. This dispersion reveals that the link between financial markets and corporate policies is not uniform but mediated by the degree of managerial attentiveness. As such, heterogeneity in attention itself becomes a first-order source of heterogeneity in the real effects of financial markets—explaining why even seemingly identical market signals can elicit vastly different corporate responses across firms.

I then show that attention indeed serves as an important behavioral channel through which market information influences corporate decisions. Firms whose managers pay higher attention to financial markets exhibit greater investment-price sensitivity, the first *direct* evidence based on revealed behavior for the feedback theory of market prices (Bond, Edmans, and Goldstein, 2012). Moreover, attention shapes financing decisions. Attentive managers are more likely to tap external capital when financing needs arise, and—conditional on issuing—allocate across debt and equity in a manner that reflects prevailing market conditions. This yields the first *direct* empirical evidence from observed managerial attention in support of market timing theory (Baker and Wurgler 2002; Ma 2019).

Finally, I develop a rational inattention model in which managers optimally allocate scarce cognitive resources between internal and external signals. The model explains why some managers rationally remain inattentive to financial markets and provides a theoretical foundation for the observed heterogeneity in attention. Together, the empirical evidence and theoretical framework complete the causal chain necessary to establish the real effects of financial markets. Recognizing attention as a scarce and heterogeneous resource opens new avenues for modeling corporate decision-making and for understanding when—and for whom—financial markets exert real effects on the real economy.

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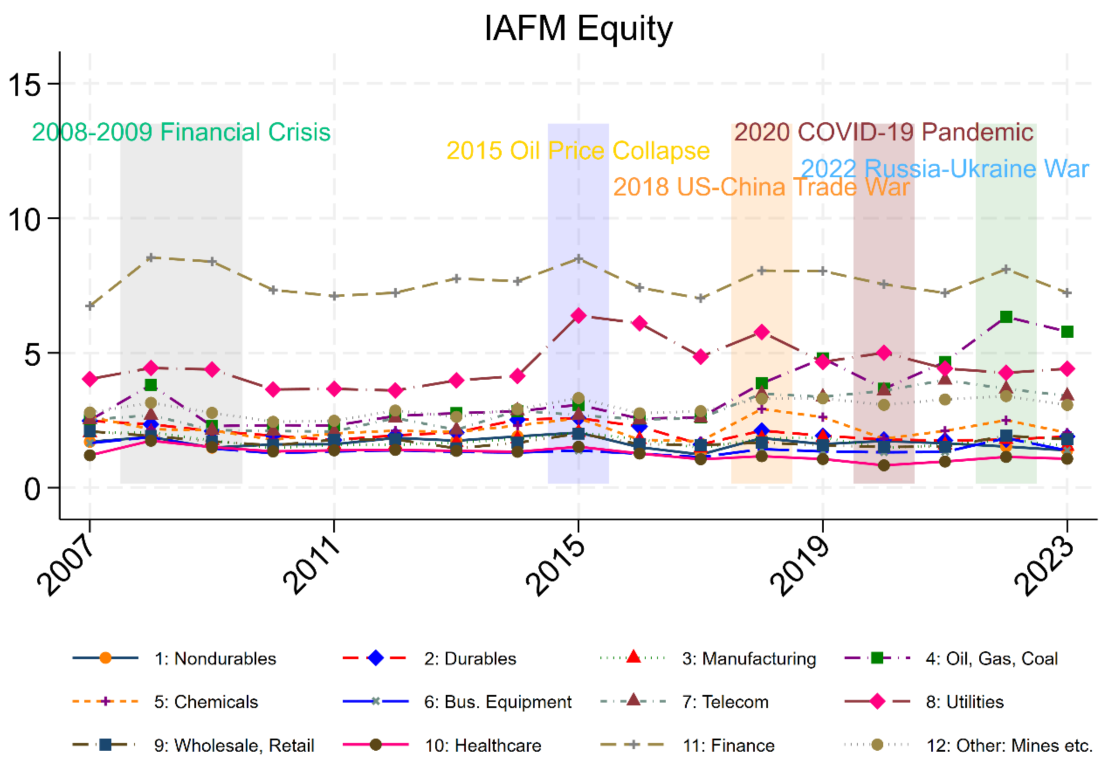

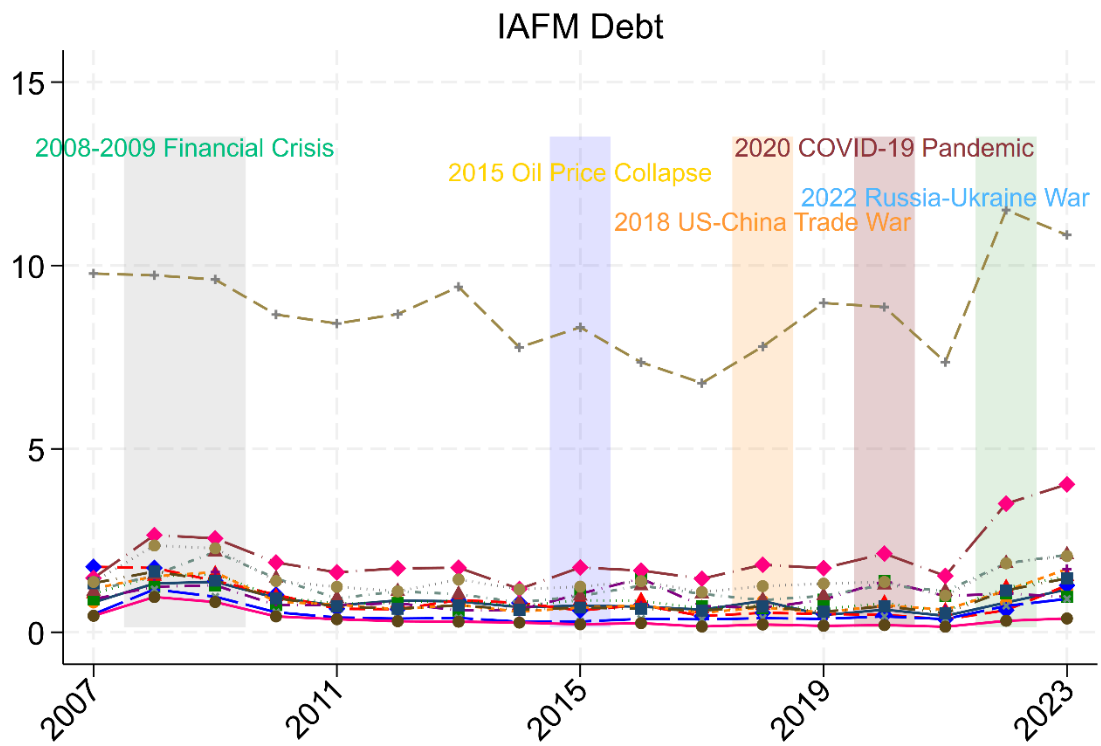

Fig 1: IAFM Measures Across 12 Fama-French Industries Over Time. This figure shows the two tf-idf IAFM measures (IAFM Equity and IAFM Debt) over time for the 12 Fama-French industries. The y-axis indicates the average IAFM measure across firms within each industry, while the x-axis represents the years from 2007 to 2023.

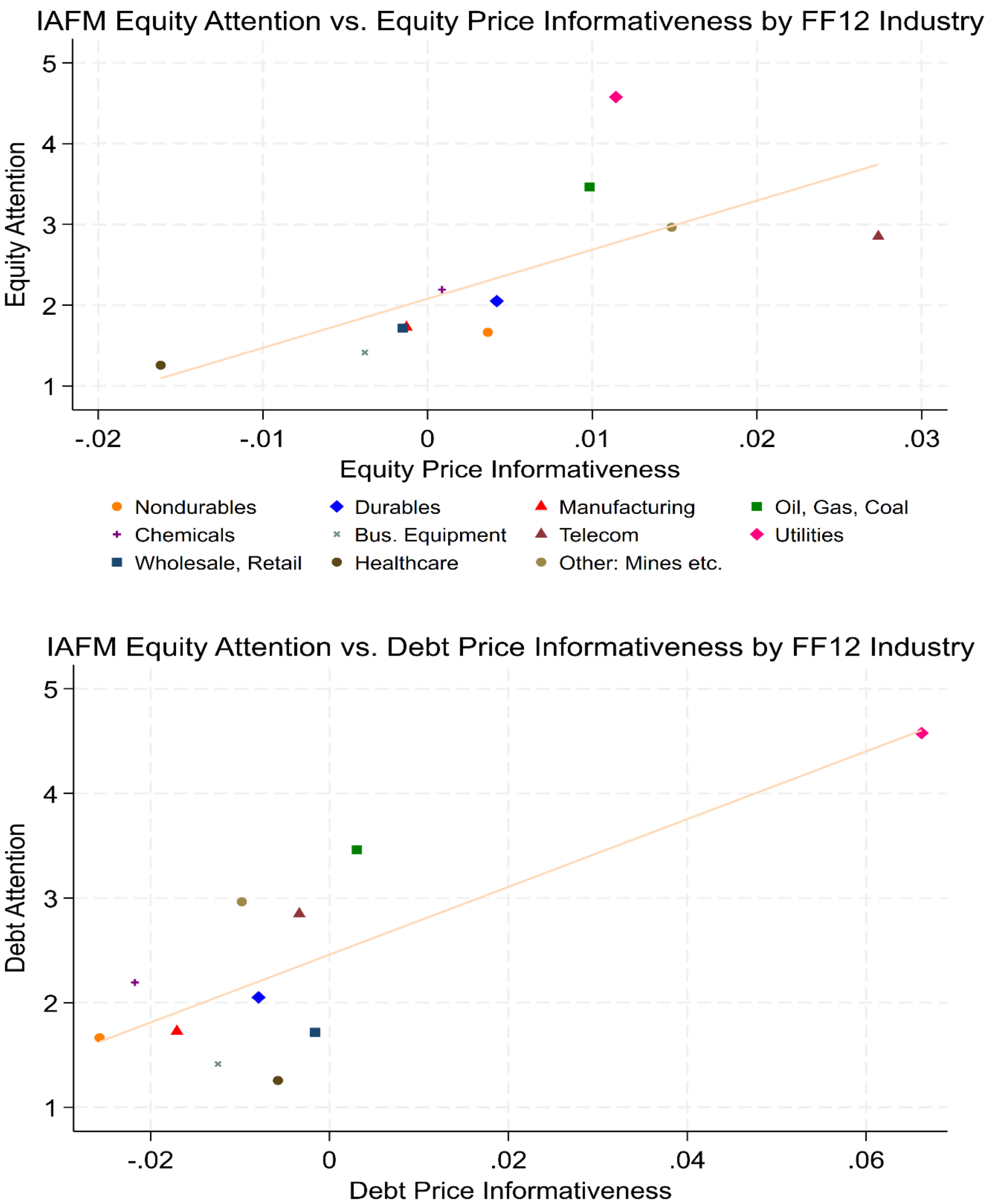

Figure 2: IAFM Measures Versus Price Informativeness. This figure plots the relationship between industry-average IAFM measures—IAFM Equity and IAFM Debt—and price informativeness across 11 of the 12 Fama–French industries over 2007–2023 (excluding the Finance industry). The y-axis reports average IAFM values by industry, while the x-axis shows industry-level average price informativeness. In the top panel, IAFM Equity is plotted against equity price informativeness, proxied by the probability of informed trading (PIN). In the bottom panel, IAFM Debt is plotted against debt price informativeness, proxied by bond price non-synchronicity ((1-R^2)). All firm-level price informativeness measures are averaged within industries after orthogonalizing against log asset size.

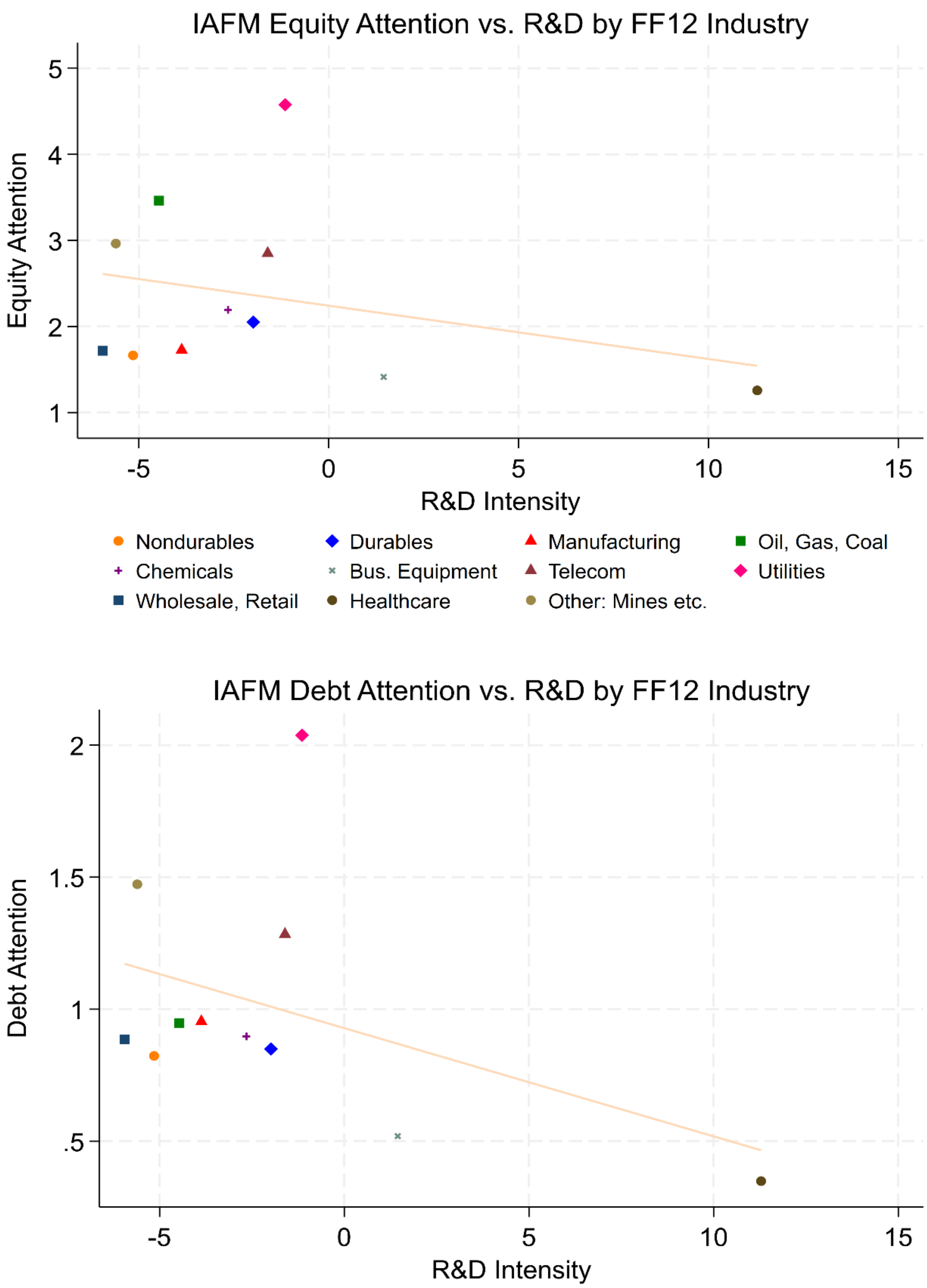

Figure 3: IAFM Measures Versus R&D Intensity. This figure plots the relationship between industry-average IAFM measures (IAFM Equity and IAFM Debt) and R&D across 11 of the 12 Fama-French industries, 2007-2023 (Finance industry excluded). The y-axis shows average IAFM measures by industry, while the x-axis shows average R&D expenditure by industry. Industry-level R&D intensity is calculated as the equally-weighted average of firm-level R&D intensity, measured using research and development expenses (Compustat XRD) as a percentage of total assets (Compustat AT). Firm-level R&D intensity is averaged within industries after orthogonalizing against log asset size.

Table 1. Seed Words and Expanded Dictionary

Panel A presents the seed words used to construct the expanded dictionaries for each dimension of the IAFM framework. Each dimension contains 25 seed words. IAFM Equity focuses on equity market-related phrases in earnings calls. IAFM Debt focuses on debt market-related phrases in earnings calls. Panel B lists the 50 most representative words for each IAFM dimension, ranked by descending similarity to the corresponding seed words. Panel C reports top 50 most frequent words per dimension ranked by tf-idf, with percentages showing each word's contribution to dimension's total tf-idf score across all transcripts.

Panel A: Seed words

Equity	Debt
closing_price	bond_market
equity_market	bond_price
equity_performance	bond_yield
equity_price	borrowing_cost
equity_return	corporate_bond
equity_valuation	credit_market
equity_value	credit_spread
market_cap	credit_yield
market_reaction	debt_market
market_valuation	gilt_market
market_value	gilt_yield
mispriced	government_bond
overvalued	interest_rate
price_-_to_-_book_ratio	interest_rate_risk
price_target	investment_-_grade_bond
share_valuation	loan_market
share_price	municipal_bond
shareholder_return	sovereign_bond
shareholder_value	t_-_bill
stock_market	treasury_bill
stock_performance	treasury_bond
stock_price	treasury_rate
stock_return	treasury_yield
stock_valuation	yield_curve
undervalued	yield_spread

Panel B: Fifty most representative words for each IAFM dimension in the IAFM dictionary

Equity				Debt			
Word	Sim	Word	Sim	Word	Sim	Word	Sim
share_price	0.86	stock_price_performance	0.67	credit_spread	0.83	investment_-_grade_spread	0.69
stock_price	0.84	unit_price_trading	0.67	bond_yield	0.81	income_portfolio_valuation	0.69
equity_valuation	0.75	equity_market	0.66	government_bond	0.79	market_interest_rate	0.69
equity_price	0.75	dividend_yield	0.66	treasury_yield	0.77	bond_rate	0.69
market_valuation	0.75	unit_price_trade	0.66	bond_market	0.77	treasury_bond	0.69
stock_market	0.72	stock_trade	0.66	yield_curve	0.74	spread_widening	0.69
valuation	0.72	undervalue	0.66	interest_rate	0.74	year_maturity_treasury_bond	0.69
price_-_to_-_book_ratio	0.71	trading_price	0.66	swap_rate	0.74	government_yield	0.69
stock_valuation	0.70	price_-_to_-_book_multiple	0.66	bond_portfolio	0.74	loan_credit_spread	0.69
market_capitalization	0.70	stock_price_trade	0.66	year_treasury	0.73	agency_mbs_price	0.69
valuation_level	0.69	calculated_intrinsic	0.66	term_interest_rate	0.72	swap_interest_rate	0.69
market_timberland_value	0.69	stock_value	0.66	swap_yield	0.72	interest_rate_type	0.69
market_cap	0.69	unit_trading_price	0.65	treasury_rate	0.72	term_rate	0.69
stock_price_trading	0.69	nav_valuation	0.65	spread_widen	0.71	agency_mortgage_valuation	0.69
share_value	0.69	nav_standpoint	0.65	t_-_bill	0.71	agency_mortgage_security	0.69
equity_value	0.69	monster_stock	0.65	treasury_bill	0.70	aa_bond	0.68
dryships_share	0.68	languish_down	0.65	bond_price	0.70	credit_spread_environment	0.68
share_price_trade	0.68	price_-_to_-_earnings_multiple	0.65	agency_rmbs_price	0.70	repo	0.68
book_value_multiple	0.68	company_share_price	0.65	mortgage_spread	0.70	agency_mbs	0.68
intrinsic_value	0.68	business_and_growth_trajectory	0.65	income_instrument	0.70	government_bond_side	0.68
share_price_performance	0.68	stock_performance	0.64	government_security	0.70	interest_rate_environment	0.68
price_-_to_-_book_value_ratio	0.67	stock_price_valuation	0.64	sovereign_bond	0.70	bond_spread	0.68
share_price_level	0.67	point_trading	0.64	risk_bond	0.69	income_market	0.68
price_-_to_-_book_basis	0.67	asset_value	0.64	flatten_yield_curve	0.69	duration_u.s._treasury	0.68
market_equity_value	0.67	market_stock_price	0.64	widening_credit_spread	0.69	steep_yield_curve	0.68

Panel C: Fifty most frequently occurring words by tf-idf contribution for each IAFM dimension in the IAFM dictionary

Equity				Debt			
Word	%	Word	%	Word	%	Word	%
equity	20.36%	market_reaction	0.33%	interest_rate	20.24%	loan_market	0.70%
valuation	10.86%	trading_price	0.32%	bond	13.17%	income_market	0.65%
shareholder_value	6.88%	share_price_performance	0.31%	interest_rate_environment	4.67%	year_treasury	0.61%
book_value	7.36%	stock_undervalue	0.29%	treasury	4.44%	agency_mbs	0.66%
share_price	5.54%	stock_performance	0.29%	rate_environment	4.17%	bond_yield	0.59%
nav	5.65%	stock_trading	0.28%	funding_cost	3.38%	yield_market	0.56%
stock_price	4.70%	valuation_multiple	0.27%	credit_market	2.64%	risk_asset	0.56%
shareholder_return	3.79%	stock_trade	0.25%	repo	2.20%	year_bond	0.54%
asset_value	3.72%	trading_level	0.25%	yield_curve	2.07%	interest_rate_level	0.46%
market_value	3.40%	equity_valuation	0.25%	debt_market	1.81%	yield_bond	0.46%
equity_market	3.16%	valuation_perspective	0.24%	credit_spread	1.70%	interest_rate_volatility	0.45%
market_cap	2.11%	equity_price	0.23%	term_rate	1.61%	interest_rate_movement	0.44%
stock_market	1.73%	undervalued	0.22%	bond_market	1.62%	income_security	0.44%
dividend_yield	1.51%	valuation_level	0.22%	borrowing_cost	1.51%	covered_bond	0.46%
undervalue	1.43%	market_multiple	0.19%	cmbs	1.41%	benchmark_rate	0.44%
enterprise_value	1.44%	valuation_gap	0.18%	bond_portfolio	1.33%	municipal_bond	0.43%
intrinsic_value	1.16%	trading_value	0.16%	asset_yield	1.23%	reference_rate	0.42%
market_capitalization	0.95%	equity_performance	0.15%	term_interest_rate	1.17%	swap_rate	0.38%
equity_value	0.85%	stock_price_performance	0.15%	interest_rate_risk	1.14%	reinvestment_yield	0.37%
market_valuation	0.67%	stock_value	0.14%	income_portfolio	1.02%	cmbs_market	0.31%
asset_price	0.66%	price_target	0.14%	spread_widen	1.00%	agency_rmbs	0.32%
closing_price	0.63%	share_price_appreciation	0.14%	government_bond	0.87%	income_investment	0.28%
cash_flow_yield	0.55%	share_market	0.13%	money_market_fund	0.80%	term_bond	0.28%
equity_return	0.38%	stock_valuation	0.13%	debt_security	0.76%	government_security	0.28%
share_value	0.37%	p_/_e	0.13%	market_interest_rate	0.71%	loan_spread	0.27%

Table 2. Summary Statistics

This table reports summary statistics for firm-level IAFM measures and other characteristics. IAFM Equity and IAFM Debt are TF-IDF-based measures that capture the frequency of equity-related and debt-related phrases, respectively, in earnings call transcripts. All measures are averaged across all quarterly earnings calls within each calendar year. The sample for Panel A includes 7,673 unique U.S. public firms over the period 2007 to 2023, whereas the sample for Panel B exclude financial firms and utilities. Panel C reports summary statistics of non-IAFM firm characteristics, calculated for firms that have non-missing IAFM measures and are not financial firms or utilities. Table A1 provides detailed variable definitions.

	Mean	STD	25%	Median	75%	N
Panel A: IAFM Measures for All U.S. Public Firms						
IAFM Equity	3.05	4.44	0.35	1.41	3.71	60820
IAFM Debt	2.29	5.04	0	0.34	1.93	60820
Panel B: IAFM Measures for U.S. Public Firms Excluding Financial Firms and Utilities						
IAFM Equity	1.93	2.86	0.22	1.01	2.47	47812
IAFM Debt	0.81	1.74	0	0	0.94	47812
Panel C: Non-IAFM Firm Characteristics, Excluding Financial Firms and Utilities						
Year-End Tobin's Q	2.38	2.31	1.17	1.64	2.62	45344
Total Assets ($'mil)	6889.39	19466.22	263.9	1034.43	3986.85	43627
Cash (%)	22.85	24.10	4.88	13.43	32.82	43626
Leverage (%)	25.1	22.44	4.72	21.69	38.52	43435
Sales Growth (%)	14.47	49.00	-3.03	6.82	19.75	52129
Dividend Yield (%)	1.92	8.50	0	0	2.07	60820
Inst. Ownership (%)	51.2	37.61	3.67	60.87	86.26	60820
WPS (X 10^3)	0.03	0.10	0	0	0.01	15666
Mgr. Ownership	0.02	0.05	0	0	0.01	19909
Finance-Expert CEO	0.33	0.47	0	0	1	39963
Bond Yield	0.05	0.04	0.03	0.05	0.06	7573
CAPX (%)	4.98	6.54	1.34	2.9	5.89	43576
INVT (%)	4.91	13.12	0	2.49	7.38	43613
Net Equity Issue Indicator	0.42	0.49	0	0	1	40394
Net Debt Issue Indicator	0.34	0.47	0	0	1	42266
Equity Issue vs Debt Issue	0.59	0.49	0	1	1	19672
NFD	0.08	0.30	-0.04	0	0.07	55519
R&Ds (%)	5.87	11.33	0	0.15	6.76	47812
HHI(SIC 3-digit Industry Sales)	0.19	0.18	0.06	0.13	0.25	47807
Insider Trading Indicator	0.5	0.50	0	1	1	46305
Insider Trading Intensity	2.56	11.38	0.14	0.53	1.77	23304
LW (2024) Financial Constraint	-0.1	0.58	-0.46	-0.19	0.16	38986
PIN (SIC 3-digit)	0.17	0.03	0.15	0.17	0.19	44596

Table 3. Variance Decomposition of IAFM Measures

This table presents the *incremental* R^2 (%) from adding a specific set of fixed effects to firm-year level regressions. IAFM Equity (Column (1)) and IAFM Debt (Column (2)) are TF-IDF-based measures that capture the frequency of equity-related and debt-related phrases, respectively, in earnings call transcripts. All measures are averaged across all quarterly earnings calls within each calendar year. The sample period is 2007-2023.

Dep. Var.: IAFM Dimension:	(1) Equity	(2) Debt
Year FE	0.28%	0.64%
Industry FE	38.12%	44.77%
Industry × Year FE	3.2%	2.9%
Firm FE	30.4%	33.9%
Residual Firm × Year Variation	28%	17.79%
Sum	100%	100%

Table 4. Industry Distribution of IAFM Equity and IAFM Debt

This table presents firm-level IAFM measures across the 12 Fama-French Industries, classified using four-digit SIC codes. Industries are ranked by the average firm-year IAFM score, which is based on a TF-IDF approach capturing the frequency of financial-market-related phrases in earnings calls. IAFM Equity (Panel A) and IAFM Debt (Panel B), respectively, measures the frequency of phrases related to equity and debt. All IAFM measures are computed at the firm-year level by averaging across all quarterly earnings calls within each calendar year. The sample period is 2007-2023. Variable definitions are provided in Table A.1.

Panel A: IAFM Equity				
Industry (12 Fama-French Industries)	Mean	STD	Median	N
11 (Finance)	7.67	6.55	5.76	10992
8 (Utilities)	4.61	4.31	3.47	1671
4 (Oil, Gas, and Coal Extraction and Products)	3.38	3.98	2.10	3074
12 (Other: Mines, Construction, Building Materials, Trans, Hotels, Bus Serv, Entertainment)	2.98	4.09	1.59	8257
7 (Telephone and Television Transmission)	2.80	3.51	1.74	1800
5 (Chemicals and Allied Products)	2.18	2.63	1.39	1501
2 (Consumer Durables: Cars, TVs, Furniture, Household Appliances)	2.02	2.64	1.26	1410
3 (Manufacturing: Machinery, Trucks, Planes, Off Furn, Paper, Com Printing)	1.71	2.26	1.04	5107
9 (Wholesale, Retail, and Some Services (Laundries, Repair Shops))	1.71	2.41	0.95	5155
1 (Consumer Nondurables: Food, Tobacco, Textiles, Apparel, Leather, Toys)	1.66	2.08	1.03	2405
6 (Business Equipment: Computers, Software, and Electronic Equipment)	1.41	2.06	0.70	11517
10 (Healthcare, Medical Equipment, and Drugs)	1.22	2.00	0.48	7931
Panel B: IAFM Debt				
Industry (12 Fama-French Industries)	Mean	STD	Median	N
11 (Finance)	8.77	8.62	5.88	10992
8 (Utilities)	2.03	2.89	1.04	1671
12 (Other: Mines, Construction, Building Materials, Trans, Hotels, Bus Serv, Entertainment)	1.46	2.70	0.55	8257
7 (Telephone and Television Transmission)	1.26	1.82	0.57	1800
3 (Manufacturing: Machinery, Trucks, Planes, Off Furn, Paper, Com Printing)	0.94	1.61	0.34	5107
4 (Oil, Gas, and Coal Extraction and Products)	0.92	1.60	0.34	3074
5 (Chemicals and Allied Products)	0.87	1.33	0.34	1501
9 (Wholesale, Retail, and Some Services (Laundries, Repair Shops))	0.87	1.66	0.23	5155
1 (Consumer Nondurables: Food, Tobacco, Textiles, Apparel, Leather, Toys)	0.82	1.64	0.23	2405
2 (Consumer Durables: Cars, TVs, Furniture, Household Appliances)	0.80	1.39	0.23	1410
6 (Business Equipment: Computers, Software, and Electronic Equipment)	0.52	1.42	0.00	11517
10 (Healthcare, Medical Equipment, and Drugs)	0.32	0.85	0.00	7931

Table 5. Managerial Equity Ownership

This table reports regression results investigating whether managerial ownership predicts firm-level attention to financial markets. The dependent variable is the tf-idf measure of IAFM Equity for Columns (1) and (3), and IAFM Debt for Columns (2) and (4). In Columns (1) and (2), the main independent variables are the scaled wealth–performance sensitivity (WPS (X 10^3)) and its squared term (WPS (X $10^3)^2$). WPS measures dollar change in CEO wealth for a one percentage point change in firm value, divided by annual pay as in Edmans, Gabaix, and Landier (2009). In Columns (3) and (4), the main independent variables are managerial ownership (Mgr. Ownership) and its squared term (Mgr. Ownership^2). Control variables include end-of-year Tobin's Q, firm size (ln(Assets)), cash holdings, leverage, sales growth, dividend yield, and institutional ownership. Firm and 3-digit industry-by-year fixed effects are included. All independent variables are lagged by one year. The sample period is 2007-2023. Standard errors are clustered at the 3-digit industry-by-year level. T-statistics are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Dep. Var.: Ln(1+IAFM)	(1)	(2)	(3)	(4)
Dimension:	Equity	Debt	Equity	Debt
WPS (× 10^3)	0.594**	-0.166		
	(2.362)	(-0.815)		
WPS (× $10^3)^2$	-0.757***	0.103		
	(-2.593)	(0.424)		
Mgr. Ownership			1.664***	1.067**
			(3.342)	(2.530)
Mgr. Ownership^2			-5.202***	-4.269***
			(-2.700)	(-2.822)
Year-End Q	-0.0153**	0.0100**	-0.0187***	0.000220
	(-2.512)	(2.253)	(-3.468)	(0.0780)
Ln(Total Assets)	0.0382**	0.0545***	0.0501***	0.0498***
	(2.220)	(4.206)	(3.791)	(4.932)
Cash	0.000382	0.00116**	0.000402	0.00104**
	(0.576)	(2.342)	(0.733)	(2.478)
Leverage	-0.00137**	0.00295***	-0.00119***	0.00258***
	(-2.556)	(6.627)	(-2.926)	(6.953)
Sales Growth	0.000219	-0.000191	0.000212	-0.000169*
	(1.079)	(-1.470)	(1.524)	(-1.663)
Dividend Yield	0.000319	0.000540	-0.000439	0.000600
	(0.267)	(0.449)	(-0.296)	(0.468)
Inst. Ownership	0.000205	-0.000340	-0.000136	-9.40e-05
	(0.627)	(-1.343)	(-0.526)	(-0.460)
Observations	14,647	14,647	18,411	18,411
Adj. R^2	0.327	0.442	0.350	0.449
Firm FE	Yes	Yes	Yes	Yes
Industry-by-Year FE	Yes	Yes	Yes	Yes

Table 6. Finance-Expert CEOs

This table reports regression results investigating whether having a finance-expert CEO predicts firm-level attention to financial markets. The dependent variable is the tf-idf measure of IAFM Equity for Columns (1), (3), and (5), and IAFM Debt for Columns (2), (4) and (6). The main independent variables are the finance-expert CEO indicator. Control variables include end-of-year Tobin's Q, firm size (ln(Assets)), cash holdings, leverage, sales growth, dividend yield, and institutional ownership. I additionally control for the gender, tenure, age, and squared age of the CEO. 3-digit industry-by-year fixed effects are included for Columns (1)-(6), and Columns (5) and (6) additionally include firm effects. All independent variables are lagged by one year. The sample period is 2007-2023. Standard errors are clustered at the 3-digit industry-by-year level. T-statistics are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Dep. Var.: Ln(1+IAFM)	(1)	(2)	(3)	(4)	(5)	(6)
Dimension:	Equity	Debt	Equity	Debt	Equity	Debt
Finance-Expert CEO	0.0878***	0.0385***	0.0875***	0.0417***	0.0565***	0.0331***
	(10.82)	(6.273)	(10.59)	(6.749)	(4.695)	(3.607)
Female CEO			-0.0352**	-0.0330***	-0.00722	-0.0622***
			(-2.264)	(-2.843)	(-0.296)	(-3.360)
CEO Tenure			-5.78e-05	0.00180***	0.000728	0.000549
			(-0.0916)	(3.998)	(0.757)	(0.754)
CEO Age			-0.00116	0.00552	0.00339	0.00589
			(-0.224)	(1.539)	(0.458)	(1.055)
CEO Age Squared			9.84e-06	-4.51e-05	-2.90e-05	-4.97e-05
			(0.218)	(-1.436)	(-0.455)	(-1.022)
Observations	33,453	33,453	33,416	33,416	32,705	32,705
Adj. R^2	0.147	0.276	0.147	0.277	0.382	0.460
Firm FE	No	No	No	No	Yes	Yes
Industry-by-Year FE	Yes	Yes	Yes	Yes	Yes	Yes

Table 7. Equity and Debt Markets Performance

This table reports regression results investigating whether equity and debt markets performance predict firm-level attention to financial markets. The dependent variable is IAFM Equity for Column (1), and IAFM Debt for Column (2). For Panel A, the main independent variables are the firm-level equity return over the past calendar year and the annualized volatility of daily firm-level return. For Panel B, they are the market-wide equity return over the past calendar year and the annualized volatility of daily market-wide returns. For Panel C, the main independent variables include the annual rate of change and volatility in the 7-year U.S. Treasury yield over the past calendar year. The annual rate of change is the annual change in the yield divided by the previous year end's yield. Annual volatility in yield is the standard deviation of daily rate of change in yield. For Panel D, the main independent variables include the firm-level bond yield and its volatility over the past calendar year. Analysis in Panel D restricts to observations with at least one publicly tradable bond. Control variables include end-of-year Tobin's Q, firm size (log of assets), cash holdings, leverage, sales growth, dividend yield, and institutional ownership. Returns, return volatility, interest rate change, interest rate change volatility, bond yield and bond yield volatility are all expressed in actual number (e.g., 1 unit = 100% change) for easier interpretability, not in percentage form. All explanatory variables are lagged by one year. Firm fixed effects are included across Panels A, B, and C, whereas Panel A additionally includes 3-digit industry-by-year fixed effects. Panel D includes 3-digit industry-by-year fixed effects only. The sample period is 2007-2023. Standard errors are clustered at the 3-digit industry-by-year level. T-statistics are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Dep. Var.: Ln(1+IAFM)	(1)	(2)
Dimension:	Equity	Debt
Panel A: Firm-Level Equity Performance		
Firm-Level 1-Year Equity Return	0.0292***	0.0134*
	(3.214)	(1.771)
Firm-Level Equity Return Volatility	-1.945***	-0.324
	(-3.910)	(-0.826)
Observations	26,851	26,851
Adj. R^2	0.424	0.450
Firm FE	Yes	Yes
Industry-by-Year FE	Yes	Yes
Panel B: Market-Wide Equity Performance		
Market-Wide 1-Year Equity Return	-0.0535***	-0.00135
	(-2.861)	(-0.0840)
Market-Wide Return Volatility	-1.176*	7.811***
	(-1.837)	(10.01)
Observations	39,349	39,349
Adj. R^2	0.401	0.410
Firm FE	Yes	Yes
Industry-by-Year FE	No	No

Dep. Var.: Ln(1+IAFM)	(1)	(2)
Dimension:	Equity	Debt
Panel C: Interest Rate Movements		
Δ in Interest Rate	0.00452	0.0480***
	(0.628)	(7.207)
Volatility(Δ in Interest Rate)	-0.381***	-0.420***
	(-3.728)	(-4.228)
Observations	39,349	39,349
Adj. R^2	0.401	0.406
Firm FE	Yes	Yes
Industry-by-Year FE	No	No
Panel D: Credit Spread		
Bond Yield	-0.915***	1.159***
	(-2.623)	(3.102)
Volatility(Bond Yield)	95.07	64.44
	(0.809)	(0.638)
Observations	6,322	6,322
Adj. R^2	0.160	0.258
Firm FE	No	No
Industry-by-Year FE	Yes	Yes

Table 8. Investment-Price Sensitivity

This table presents regression results examining the effect of IAFM on investment-price sensitivity. The dependent variable is CAPX for Panel A and INVT for Panel B. The main independent variable is the interaction term between log-transformed IAFM measures and year-end Tobin's Q. Columns (1) and (3) use the tf-idf measure of IAFM Equity. Columns (2) and (4) use the tf-idf measure of IAFM Debt. Control variables include end-of-year Tobin's Q, firm size (log of assets), cash holdings, leverage, sales growth, dividend yield, and institutional ownership. 3-digit industry-by-year fixed effects are included for Columns (1)-(4), and Columns (3) and (4) additionally include firm effects. The sample period is 2008-2023. Standard errors are clustered at the 3-digit industry-by-year level. T-statistics are reported in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$

	(1)	(2)	(3)	(4)
Proxy for IAFM:	Equity	Debt	Equity	Debt
Panel A: Dep. Var.: CAPX (%)				
Ln(1+IAFM) × Year-End Q	0.0275	0.131***	0.0633***	0.0938***
	(0.968)	(2.964)	(2.891)	(2.670)
Ln(1+IAFM)	-0.275***	-0.528***	-0.164**	-0.307***
	(-3.748)	(-4.616)	(-2.507)	(-3.256)
Year-End Q	0.327***	0.316***	0.343***	0.363***
	(10.54)	(12.95)	(10.45)	(11.20)
Observations	36,754	36,754	35,885	35,885
Adj. R^2	0.409	0.409	0.680	0.680
Firm FE	No	No	Yes	Yes
Industry-by-Year FE	Yes	Yes	Yes	Yes
Panel B: Dep. Var.: INVT (%)				
Ln(1+IAFM) × Year-End Q	0.129**	0.201**	0.247***	0.269**
	(2.034)	(2.121)	(3.624)	(2.455)
Ln(1+IAFM)	-0.422**	-0.438*	-0.456**	-0.832***
	(-2.458)	(-1.693)	(-2.357)	(-2.677)
Year-End Q	0.626***	0.662***	0.838***	0.930***
	(10.03)	(12.09)	(10.38)	(11.23)
Observations	36,785	36,785	35,919	35,919
Adj. R^2	0.162	0.162	0.290	0.289
Firm FE	No	No	Yes	Yes
Industry-by-Year FE	Yes	Yes	Yes	Yes

Table 9. Financing Policies: Whether Tapping External Financing by Source

This table presents regression results examining the effect of IAFM on decisions to tap external financing or not. The dependent variable is whether tapping equity financing (i.e., equal to one if positive net equity issuance and zero otherwise) for Panel A and whether tapping debt financing (i.e., equal to one if positive net debt issuance and zero otherwise) for Panel B. The main independent variable is the interaction term between log-transformed IAFM measures and NFD. Control variables include end-of-year Tobin's Q, firm size (log of assets), cash holdings, leverage, sales growth, dividend yield, and institutional ownership. Across both panels, 3-digit industry-by-year fixed effects are included for Columns (1)-(3), and Columns (4)-(6) additionally include firm effects. All independent variables are lagged by one year. The sample period is 2008-2023. Standard errors are clustered at the 3-digit industry-by-year level. T-statistics are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Panel A: Effect of IAFM on Whether Tapping Equity Financing

Dep. Var.: Net Equity Issue Indicator	(1)	(2)	(3)	(4)	(5)	(6)
Ln(1+IAFM Equity) × NFD	0.0553***		0.0399***	0.0641***		0.0522***
	(3.760)		(2.844)	(4.663)		(3.834)
Ln(1+IAFM Equity)	-0.0448***		-0.0439***	-0.0208***		-0.0208***
	(-10.81)		(-10.56)	(-4.695)		(-4.701)
Ln(1+IAFM Debt) × NFD		0.143***	0.130***		0.116***	0.0976***
		(4.762)	(4.415)		(3.960)	(3.330)
Ln(1+IAFM Debt)		-0.0145***	-0.00527		0.000993	0.00368
		(-2.682)	(-0.984)		(0.166)	(0.613)
NFD	0.333***	0.343***	0.319***	0.204***	0.224***	0.192***
	(14.20)	(16.25)	(13.42)	(10.05)	(11.51)	(9.416)
Observations	33,981	33,981	33,981	33,073	33,073	33,073
Adj. R^2	0.223	0.221	0.224	0.428	0.427	0.428
Firm FE	No	No	No	Yes	Yes	Yes
Industry-by-Year FE	Yes	Yes	Yes	Yes	Yes	Yes

Panel B: Effect of IAFM on Whether Tapping Debt Financing

Dep. Var.: Net Debt Issue Indicator	(1)	(2)	(3)	(4)	(5)	(6)
Ln(1+IAFM Equity) × NFD	0.0906***		0.0383**	0.104***		0.0541**
	(4.492)		(2.034)	(4.657)		(2.534)
Ln(1+IAFM Equity)	0.00774*		0.0101**	0.00221		0.00456
	(1.848)		(2.441)	(0.435)		(0.904)
Ln(1+IAFM Debt) × NFD		0.507***	0.493***		0.487***	0.468***
		(10.62)	(10.37)		(10.27)	(10.11)
Ln(1+IAFM Debt)		-0.00601	-0.00806		-0.00906	-0.00907
		(-1.147)	(-1.528)		(-1.418)	(-1.418)
NFD	0.456***	0.428***	0.404***	0.477***	0.455***	0.422***
	(12.84)	(14.40)	(11.90)	(11.69)	(13.70)	(10.94)
Observations	35,534	35,534	35,534	34,651	34,651	34,651
Adj. R^2	0.191	0.202	0.202	0.261	0.269	0.270
Firm FE	No	No	No	Yes	Yes	Yes
Industry-by-Year FE	Yes	Yes	Yes	Yes	Yes	Yes

Table 10. Financing Policies: External Financing Intensity by Source, Conditional on Firm-Level Valuation, Equity Market Sentiment, and Interest Rates

This table examines how financial market attention (IAFM) affects firms' choice between equity and debt financing, conditional on market conditions and firm characteristics. The sample includes firm-year observations where firms raised external financing from a single source (either equity or debt only). The dependent variable equals one if the firm issued net equity with non-positive net debt issuance, and zero if the firm issued net debt with non-positive net equity issuance. Panel A tests whether equity market attention interacts with equity market sentiment (Baker and Wurgler (2006) index, orthogonalized to six macroeconomic conditions) and firm valuation level (Tobin's Q) to predict financing choice. Panel B examines whether debt market attention interacts with Treasury yields, while equity market attention interacts with Tobin's Q. The main independent variables are interaction terms between log-transformed IAFM indices, NFD, and the respective market condition variables. Annual changes in Treasury yield are measured using annual changes in the yield divided by the previous year end's yield, and are expressed in real units, instead of percent changes (e.g., 1 unit = 100% change). Control variables include end-of-year Tobin's Q, firm size (log of assets), cash holdings, leverage, sales growth, dividend yield, and institutional ownership. 3-digit industry-by-year fixed effects and firm effects are included. All independent variables are lagged by one year. The sample period is 2008-2023. Standard errors are clustered at the 3-digit industry-by-year level. T-statistics are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Panel A: Choice of Financing Source in Response to Changes in Equity Market Sentiment

Dep. Var.: Equity Issue vs Debt Issue	(1)	(2)
Ln(1+IAFM Equity) × NFD × Δ in Equity Market Sentiment	0.0154**	
	(2.152)	
Ln(1+IAFM Equity) × Δ in Equity Market Sentiment	0.00157	
	(0.630)	
NFD × Δ in Equity Market Sentiment	-0.00474	
	(-0.606)	
Ln(1+IAFM Equity) × NFD × Equity Market Sentiment		0.0990***
		(3.426)
Ln(1+IAFM Equity) × Equity Market Sentiment		-0.00674
		(-0.740)
NFD × Equity Market Sentiment		-0.0472*
		(-1.667)
Ln(1+IAFM Equity) × NFD × Year-End Q	0.0171***	0.0180***
	(3.173)	(3.411)
Ln(1+IAFM Equity) × NFD	-0.0873***	-0.0981***
	(-3.132)	(-3.423)
Ln(1+IAFM Equity) × Year-End Q	-0.000349	-4.63e-05
	(-0.102)	(-0.0136)
NFD × Year-End Q	0.0122***	0.0120***
	(3.757)	(3.641)
Ln(1+IAFM Equity)	-0.0120	-0.0139
	(-1.091)	(-1.278)
NFD	-0.242***	-0.240***
	(-6.792)	(-6.610)
Year-End Q	-0.00211	-0.00236
	(-0.816)	(-0.912)
Observations	14,586	14,586
Adj. R^2	0.579	0.579
Firm FE	Yes	Yes
Industry-by-Year FE	Yes	Yes

Panel B: Choice of Financing Source in Response to Changes in Interest Rates

Dep. Var.: Equity Issue vs Debt Issue	(1)	(2)
Ln(1+IAFM Debt) × NFD × Δ in Interest Rate	0.111*	
	(1.890)	
Ln(1+IAFM Debt) × Δ in Interest Rate	-2.09e-05	
	(-0.00185)	
NFD × Δ in Interest Rate	-0.0365*	
	(-1.880)	
Ln(1+IAFM Debt) × NFD × Interest Rate		4.013
		(0.757)
Ln(1+IAFM Debt) × Interest Rate		0.473
		(0.540)
NFD × Interest Rate		-1.186
		(-0.772)
Ln(1+IAFM Equity) × NFD × Year-End Q	0.0138**	0.0136**
	(2.542)	(2.572)
Ln(1+IAFM Debt) × NFD	-0.313***	-0.390***
	(-6.726)	(-3.149)
Ln(1+IAFM Equity) × NFD	-0.0555**	-0.0516*
	(-1.963)	(-1.847)
Ln(1+IAFM Equity) × Year-End Q	6.24e-05	-1.09e-05
	(0.0184)	(-0.00324)
NFD × Year-End Q	0.0102***	0.0105***
	(3.143)	(3.234)
Ln(1+IAFM Debt)	0.0101	-0.000207
	(1.133)	(-0.00979)
Ln(1+IAFM Equity)	-0.0154	-0.0155
	(-1.442)	(-1.445)
NFD	-0.199***	-0.178***
	(-6.110)	(-4.069)
Year-End Q	-0.00201	-0.00204
	(-0.777)	(-0.787)
Observations	14,586	14,586
Adj. R^2	0.582	0.582
Firm FE	Yes	Yes
Industry-by-Year FE	Yes	Yes

Appendix

Table A1. Definitions of Variables

Variable	Definition
IAFM Equity	IAFM Equity is a TF-IDF-based measure that focuses specifically on equity market-related phrases in earnings calls.
IAFM Debt	IAFM Debt is a TF-IDF-based measure that focuses specifically on debt market-related phrases in earnings calls.
IAFM Vol. & Liq.	IAFM Vol. & Liq. is a TF-IDF-based measure that captures terms associated with financial market volatility and liquidity.
IAFM Other Assets	IAFM Other Assets is a TF-IDF-based measure that captures phrases related to commodity, currency, and derivatives markets.
Year-End Q	The year-end market value of equity over year t-1 (the closing price at year-end × shares outstanding from CRSP) plus book value of assets minus the book value of equity (Compustat AT–CEQ).
Ln(Total Assets)	Log of total assets (Compustat AT), lagged by one year.
Cash (%)	100 × cash and Short-term investment (Compustat CHE) scaled by assets (Compustat AT), lagged by one year.
Leverage (%)	100 × long-term debt (Compustat DLTT) plus debt in current liabilities (Compustat DLC) scaled by total assets (Compustat AT), lagged by one year.
Sales Growth (%)	100 × ($SALE_{t-1} - SALE_{t-2}$)/ $SALE_{t-2}$) where $SALE_{t-1}$ denotes the Compustat SALE in year t-1.
Dividend Yield (%)	100 × the sum of total dividends paid to common shares (Compustat DVC) and preferred shares (Compustat DVP), scaled by the sum of the market value of common equity (year-end closing price × shares outstanding from CRSP) and the book value of preferred stock (Compustat PSTK), lagged by one year.
Inst. Ownership (%)	100 × total shares held by all institutional investors scaled by total shares outstanding.
CAPX (%)	100 × the capital expenditure (Compustat CAPX) divided by lagged total assets (Compustat AT).
INVT (%)	100 × the changes in gross property, plant, and equipment (Compustat PPEGT) plus changes in inventory (Compustat INVT), divided by lagged total assets (Compustat AT).
WPS (X 10^3)	The scaled wealth-performance sensitivity measure of Edmans, Gabaix, and Landier (2009): The dollar change in the CEO's wealth for a 100 percentage point change in the stock price, scaled by annual pay.
Mgr. Ownership	Total number of shares held by CEO (Execucomp CEO_SHROWN) scaled by the total number of shares outstanding (Compustat CSHO)
Finance-Expert CEO	A CEO who has prior experience in either banking or investment firms, in a finance-related executive role such as accountant, chief financial officer (CFO), treasurer, or vice

	president of finance, or in a large auditing firm. It is defined following Custódio and Metzger (2014).
Interest Rate	The 7-year U.S. Treasury yield as of the end of the previous calendar year is used to capture U.S. firms' general exposure to interest rate fluctuations. This maturity is chosen because it aligns with the maturity pattern of publicly traded corporate bonds in my sample: the median firm-level time to maturity of bonds in the sample is 6.5 years, and the mean is 7.8 years.
Bond Yield	The firm's most recent monthly close yield (expressed in real terms) as of the prior calendar year, averaged across all publicly traded bonds (weighted by outstanding amount).
Net Equity Issue Indicator	Equity issuance is 100 × the difference between sales of common stock (Compustat SSTK) and stock repurchases (Compustat PRSTKC), scaled by lagged total assets (Compustat AT).
Net Debt Issue Indicator	Debt issuance is 100 × the difference between long-term debt issuance (Compustat DLTIS) and long-term debt reduction (Compustat DLTR), scaled by lagged total assets (Compustat AT).
NFD	Net financing deficit is the sum of cash dividends, net investment, change in working capital, and minus cash flow after interest and tax, scaled by lagged total assets (Compustat AT). For firms reporting format codes 1 to 3, net investment is CAPX + IVCH + AQC + FUSEO – SPPE – SIV; for firms reporting format code 7, it is CAPX + IVCH + AQC – SPPE – SIV – IVSTCH – IVACO. When items are missing or combined with other items, I code them as 0. To compute change in working capital, for format code 1, it is WCAPC + CHECH + DLCCH; for codes 2 and 3, – WCAPC + CHECH – DLCCH; for code 7, – RECCH – INVCH – APALCH – TXACH – AOLOCH + CHECH – FIAO – DLCCH. All items, excluding CHECH, are replaced with 0 when missing or combined with other items. To calculate cash after interest and tax, for codes 1 to 3, it is IBC + XIDOC + DPC + TXDC + ESUBC + SPPIV + FOPO + FSRCO. For code 7, this is items IBC + XIDOC + DPC + TXDC + ESUBC + SPPIV + FOPO + EXRE. Items are coded as 0 when missing or combined with other items.
Equity Market Sentiment	Sentiment index in Baker and Wurgler (2006); based on first principal component of FIVE (standardized) sentiment proxies where each of the proxies has first been orthogonalized with respect to a set of six macroeconomic indicators
R&D Investment (%)	100 × research and development expenses (Compustat XRD) scaled by lagged total assets (Compustat AT). Missing observations are replaced with zero.
Insider Trading Intensity	1000 × number of shares traded by insiders in a given calendar year (Thomson Reuters Insider Filing SHARES) scaled by the total number of shares traded (sum of daily trading volume (CRSP CSHTRD) over the year). I only consider open market

	stock transactions initiated by the top five executives (CEO, CFO, COO, President, and Chairman of theBoard).
HHI(SIC 3-Digit Industry Sales)	Sales-based Herfindahl–Hirschman index of the SIC 3-digit industry to which a firm belongs.
HHI(Product Market Sales)	Sales-based Herfindahl–Hirschman index of the product market to which a firm belongs, where product market peers are defined in Hoberg and Phillips (2016).
LW (2024) Financial Constraint	Linn and Weagley's (2024) continuous equity constraint measure, which is computed using full firm characteristics.
Equity Price Informativeness	The probability of informed trading (PIN) measure is estimated based on a structural market microstructure model, in which trades can come from noise traders or from informed traders, as developed in Easley and O'Hara (1992) and Easley, Kiefer, O'Hara, and Paperman (1996). I estimate it using intra-day transaction data from Trade And Quote (TAQ) for each firm and year. To construct industry-level measure, I compute the equally weighted average of firm-level PINs within each three-digit SIC industry and year. For the product-market-level measure, I follow the product market definitions in Hoberg and Phillips (2016) and take the equally weighted average of firm-level PINs within each product market and year.
Bond Price Informativeness	The bond price non-synchronicity measure, ($1-R^2$), captures the extent of firm-specific information embedded in bond prices. To construct the firm-level measure, I proceed in two steps. First, for each bond and year, I estimate R^2 from a regression of monthly bond returns on the monthly market return, where the market return is proxied by the value-weighted average return of all bonds in the WRDS Bond Sample (weights based on amounts outstanding). A minimum of six non-missing monthly observations per bond-year is required to compute the measure. Second, I aggregate bond-level R^2 values into a firm-level measure by taking an amount-weighted average across all bonds issued by the firm. To construct industry-level measure, I compute the equally weighted average of firm-level ($1-R^2$) within each industry and year.

Table A2. Role of Insider Information

This table presents regression results examining the effect of IAFM on investment-price sensitivity, conditional the level of insider trading. The dependent variable is CAPX for Panel and INVT for Panel B. The main independent variable is the interaction term between log-transformed IAFM measures and year-end Tobin's Q. Columns (1)-(3) use the tf-idf measure of IAFM Equity. Columns (4)-(6) use the tf-idf measure of IAFM Debt. In Columns (1) and (4), I focus on firms without any insider trading in a year. In Columns (2) and (5), I focus on firms with a below-median insider trading intensity in a year, conditional on non-zero insider trading. In Columns (3) and (6), I focus on firms with an above-median insider trading intensity in a year, conditional on non-zero insider trading. Control variables include end-of-year Tobin's Q, firm size (log of assets), cash holdings, leverage, sales growth, dividend yield, and institutional ownership. 3-digit industry-by-year fixed effects and firm effects are included. sample period is 2008-2023. Standard errors are clustered at the 3-digit industry-by-year level. T-statistics are reported in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$

Proxy for IAFM:	Equity			Debt		
	(1)	(2)	(3)	(4)	(5)	(6)
Insider Trading Level:	No Insid. Trad.	Low Insid. Trad.	High Insid. Trad.	No Insid. Trad.	Low Insid. Trad.	High Insid. Trad.
Panel A: Dep. Var.: CAPX (%)						
Ln(1+IAFM) × Year-End Q	0.0702**	0.0222	0.0496	0.177***	0.0262	-0.0462
	(2.172)	(0.597)	(1.155)	(3.217)	(0.426)	(-0.780)
Ln(1+IAFM)	-0.226**	0.0238	-0.0140	-0.397**	-0.0190	-0.0224
	(-2.084)	(0.203)	(-0.107)	(-2.304)	(-0.108)	(-0.126)
Year-End Q	0.342***	0.318***	0.244***	0.353***	0.324***	0.277***
	(6.781)	(7.437)	(5.048)	(7.704)	(7.654)	(5.744)
Observations	15,669	8,564	7,112	15,669	8,564	7,112
Adj. R^2	0.646	0.761	0.728	0.647	0.761	0.728
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry-by-Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Panel B: Dep. Var.: INVT (%)						
Ln(1+IAFM) × Year-End Q	0.311***	0.0958	0.0806	0.246*	0.471**	0.0822
	(3.187)	(0.822)	(0.560)	(1.907)	(2.396)	(0.417)
Ln(1+IAFM)	-0.417	-0.468	0.0493	-0.810*	-1.247**	-0.381
	(-1.387)	(-1.233)	(0.114)	(-1.704)	(-2.319)	(-0.574)
Year-End Q	0.747***	0.795***	0.733***	0.311***	0.0958	0.0806
	(5.790)	(5.960)	(6.504)	(3.187)	(0.822)	(0.560)
Observations	15,693	8,569	7,118	15,693	8,569	7,118
Adj. R^2	0.227	0.369	0.387	0.227	0.370	0.386
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry-by-Year FE	Yes	Yes	Yes	Yes	Yes	Yes

Table A3. Role of SIC 3-Digit Industry Competition

This table presents regression results examining the effect of IAFM on investment-price sensitivity, conditional on different levels of industry competition. The dependent variable is CAPX for Panel A and INVT for Panel B. The main independent variable is the interaction term between log-transformed IAFM measures and year-end Tobin's Q across all model specifications. Columns (1) and (2) use the tf-idf measure of IAFM Equity. Columns (3) and (4) use the tf-idf measure of IAFM Debt. Control variables include end-of-year Tobin's Q, firm size (log of assets), cash holdings, leverage, sales growth, dividend yield, and institutional ownership. In Columns (1) and (3), I focus on firms falling into the 3-digit industry with a below-median sales-based HHI. In Columns (2) and (4), I focus on firms falling into the 3-digit industry with an above-median sales-based HHI. 3-digit industry-by-year fixed effects and firm effects are included. sample period is 2008-2023. Standard errors are clustered at the 3-digit industry-by-year level. T-statistics are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Proxy for IAFM:	Equity		Debt	
	(1)	(2)	(3)	(4)
SIC 3-Digit Industry Competition Level:	Low	High	Low	High
Panel A: Dep. Var.: CAPX (%)				
Ln(1+IAFM) × Year-End Q	0.0408	0.0688***	-0.0813	0.109***
	(0.579)	(3.028)	(-0.656)	(3.022)
Ln(1+IAFM)	0.0618	-0.187***	0.196	-0.340***
	(0.426)	(-2.624)	(0.853)	(-3.314)
Year-End Q	0.757***	0.318***	0.794***	0.339***
	(5.510)	(9.791)	(5.206)	(10.54)
Observations	4,731	30,963	4,731	30,963
Adj. R^2	0.598	0.690	0.597	0.690
Firm FE	Yes	Yes	Yes	Yes
Industry-by-Year FE	Yes	Yes	Yes	Yes
Panel B: Dep. Var.: INVT (%)				
Ln(1+IAFM) × Year-End Q	0.380	0.253***	0.483	0.257**
	(1.543)	(3.581)	(1.389)	(2.304)
Ln(1+IAFM)	-0.445	-0.479**	-0.546	-0.835**
	(-0.792)	(-2.307)	(-0.714)	(-2.505)
Year-End Q	2.182***	0.763***	2.275***	0.861***
	(6.536)	(9.552)	(6.774)	(10.43)
Observations	4,727	31,002	4,727	31,002
Adj. R^2	0.280	0.296	0.280	0.296
Firm FE	Yes	Yes	Yes	Yes
Industry-by-Year FE	Yes	Yes	Yes	Yes

Table A4. Role of SIC 3-Digit Industry Price Informativeness

This table presents regression results examining the effect of IAFM on investment-price sensitivity, conditional on different levels of industry price informativeness. The dependent variable is CAPX for Panel A and INVT for Panel B. The main independent variable is the interaction term between log-transformed IAFM measures and year-end Tobin's Q across all model specifications. Columns (1) and (2) use the tf-idf measure of IAFM Equity. Columns (3) and (4) use the tf-idf measure of IAFM Debt. Control variables include end-of-year Tobin's Q, firm size (log of assets), cash holdings, leverage, sales growth, dividend yield, and institutional ownership. In Columns (1) and (3), I focus on firms falling into the 3-digit industry with a below-median PIN. In Columns (2) and (4), I focus on firms falling into the 3-digit industry with an above-median PIN. 3-digit industry-by-year fixed effects and firm effects are included. sample period is 2008-2023. Standard errors are clustered at the 3-digit industry-by-year level. T-statistics are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Proxy for IAFM:	Equity		Debt	
	(1)	(2)	(3)	(4)
SIC 3-Digit Industry Price Informativeness:	Low	High	Low	High
Panel A: Dep. Var.: CAPX (%)				
Ln(1+IAFM) × Year-End Q	0.0117	0.0604**	-0.0526	0.120**
	(0.209)	(2.560)	(-0.870)	(2.310)
Ln(1+IAFM)	0.0244	-0.169**	-0.0418	-0.330**
	(0.172)	(-2.269)	(-0.278)	(-2.573)
Year-End Q	0.798***	0.297***	0.828***	0.312***
	(7.974)	(8.988)	(8.460)	(9.796)
Observations	9,770	22,907	9,770	22,907
Adj. R^2	0.755	0.627	0.755	0.627
Firm FE	Yes	Yes	Yes	Yes
Industry-by-Year FE	Yes	Yes	Yes	Yes
Panel B: Dep. Var.: INVT (%)				
Ln(1+IAFM) × Year-End Q	0.205	0.188**	-0.0368	0.269**
	(1.062)	(2.530)	(-0.151)	(2.223)
Ln(1+IAFM)	-0.0912	-0.314	-0.157	-0.872**
	(-0.196)	(-1.340)	(-0.278)	(-2.283)
Year-End Q	2.132***	0.738***	2.296***	0.799***
	(7.164)	(9.389)	(8.495)	(10.39)
Observations	9,775	22,933	9,775	22,933
Adj. R^2	0.356	0.267	0.356	0.267
Firm FE	Yes	Yes	Yes	Yes
Industry-by-Year FE	Yes	Yes	Yes	Yes

Table A5. Role of Financial Constraints

This table presents regression results examining the effect of IAFM on investment-price sensitivity, conditional on whether the firm is financially constrained. The dependent variable is CAPX for Panel A and INVT for Panel B. The main independent variable is the interaction term between log-transformed IAFM measures and year-end Tobin's Q across all model specifications. Columns (1) and (2) use the tf-idf measure of IAFM Equity. Columns (3) and (4) use the tf-idf measure of IAFM Debt. Control variables include end-of-year Tobin's Q, firm size (log of assets), cash holdings, leverage, sales growth, dividend yield, and institutional ownership. Columns (1) and (3) present results for firms classified as financially unconstrained (below-median Linn and Weagley's (2024) equity constraint measure), while Columns (2) and (4) focus on financially constrained firms (above-median constraint measure). 3-digit industry-by-year fixed effects and firm effects are included. sample period is 2008-2023. Standard errors are clustered at the 3-digit industry-by-year level. T-statistics are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Proxy for IAFM:	Equity		Debt	
	(1)	(2)	(3)	(4)
Financial Constraints:	Uncon.	Con.	Uncon.	Con.
Panel A: Dep. Var.: CAPX (%)				
Ln(1+IAFM) × Year-End Q	0.0269	0.0668*	0.0463	0.166**
	(0.778)	(1.871)	(0.946)	(2.235)
Ln(1+IAFM)	-0.127	-0.0703	-0.0964	-0.673***
	(-1.584)	(-0.506)	(-0.822)	(-2.816)
Year-End Q	0.455***	0.250***	0.463***	0.263***
	(8.511)	(6.504)	(9.981)	(6.992)
Observations	16,829	11,914	16,829	11,914
Adj. R^2	0.703	0.679	0.703	0.680
Firm FE	Yes	Yes	Yes	Yes
Industry-by-Year FE	Yes	Yes	Yes	Yes
Panel B: Dep. Var.: INVT (%)				
Ln(1+IAFM) × Year-End Q	0.115	0.334***	0.160	0.361*
	(1.061)	(3.006)	(1.005)	(1.939)
Ln(1+IAFM)	-0.292	-0.514	-0.308	-1.896***
	(-1.050)	(-1.379)	(-0.781)	(-2.828)
Year-End Q	1.119***	0.599***	1.159***	0.730***
	(7.969)	(6.123)	(8.938)	(7.077)
Observations	16,839	11,936	16,839	11,936
Adj. R^2	0.297	0.321	0.297	0.321
Firm FE	Yes	Yes	Yes	Yes
Industry-by-Year FE	Yes	Yes	Yes	Yes

Table A6. Role of Sentiment

This table reports regressions examining how managerial attention to financial markets (IAFM) affects investment–price sensitivity, conditional on the sentiment associated with that attention. The dependent variable is CAPX in Columns (1) and (3), and INVT in Columns (2) and (4). The key independent variables are interaction terms between the log-transformed IAFM measures and year-end Tobin's Q, separately interacted with Positive-Sentiment Attention and Negative-Sentiment Attention. Positive (Negative)-Sentiment Attention captures the likelihood that managerial attention carries positive (negative) sentiment, measured as the proportion of sentences in an earnings call that simultaneously mention financial-market keywords and contain positive (negative) words as defined by Loughran and McDonald (2011). Columns (1)–(2) use the tf-idf measure of IAFM Equity, while Columns (3)–(4) use the tf-idf measure of IAFM Debt. Control variables include year-end Tobin's Q, firm size (log of assets), cash holdings, leverage, sales growth, dividend yield, and institutional ownership. 3-digit industry-by-year fixed effects and firm fixed effects are included across all specifications. The sample period covers 2008–2023. Standard errors are clustered at the 3-digit industry-by-year level, and t-statistics are reported in parentheses. Statistical significance is denoted by *** p<0.01, ** p<0.05, and * p<0.1.

Proxy for IAFM:	Equity		Debt	
	(1)	(2)	(3)	(4)
Dep. Var.:	CAPX (%)	INVT (%)	CAPX (%)	INVT (%)
Positive-Sentiment Attention				
× Ln(1+IAFM) × Year-End Q	22.39**	83.17**	-22.18	-79.10
	(1.969)	(2.229)	(-1.122)	(-1.101)
Negative-Sentiment Attention				
× Ln(1+IAFM) × Year-End Q	-5.248	56.28	17.84	47.07
	(-0.275)	(0.814)	(0.928)	(0.652)
Observations	35,885	35,919	35,885	35,919
Adj. R^2	0.680	0.291	0.680	0.290
Firm FE	Yes	Yes	Yes	Yes
Industry-by-Year FE	Yes	Yes	Yes	Yes

Table A7. Complementary Role of Debt Market Attention for Investment-Price Sensitivity

This table presents regression results examining the complementary role of IAFM Debt in shaping investment-price sensitivity. Panels A uses the full sample, regardless of whether a firm had at least one publicly traded bond in the prior calendar year, while Panel B focuses exclusively on firms with such bonds. The dependent variable is CAPX in Panels A.1 and B.1, and INVT in Panels A.2 and B.2. In each panel, the key independent variables are the interactions between year-end Tobin's Q and the log of (1) IAFM Equity and (2) IAFM Debt. Control variables include lagged Tobin's Q, firm size (log of assets), cash holdings, leverage, sales growth, dividend yield, and institutional ownership. Across panels, Column (1) includes all firms, while Columns (2) and (3) split the sample by median leverage—Column (2) includes low-leverage firms, and Column (3) includes high-leverage firms. All regressions include 3-digit industry-by-year and firm fixed effects. The sample period is 2008–2023. Standard errors are clustered at the 3-digit industry-by-year level, and t-statistics are reported in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$

Panel A: Full Sample, including firms with and without publicly traded bonds

	(1)	(2)	(3)
	Full Sample	Low Leverage	High Leverage
Panel A.1: Dep. Var.: CAPX (%)			
Ln(1+IAFM Equity) × Year-End Q	0.0557**	0.0842***	0.0340
	(2.553)	(3.320)	(0.929)
Ln(1+IAFM Debt) × Year-End Q	0.0831**	0.0385	0.0701*
	(2.368)	(0.685)	(1.701)
Ln(1+IAFM Equity)	-0.140**	-0.226***	-0.0439
	(-2.115)	(-2.596)	(-0.440)
Ln(1+IAFM Debt)	-0.282***	-0.227	-0.242**
	(-2.964)	(-1.488)	(-2.033)
Year-End Q	0.333***	0.285***	0.360***
	(10.19)	(9.049)	(6.439)
Observations	35,885	14,555	19,588
Adj. R^2	0.680	0.689	0.691
Firm FE	Yes	Yes	Yes
Industry-by-Year FE	Yes	Yes	Yes

Panel A.2: Dep. Var.: INVT (%)			
Ln(1+IAFM Equity) × Year-End Q	0.226***	0.192**	0.293***
	(3.365)	(2.437)	(2.608)
Ln(1+IAFM Debt) × Year-End Q	0.225**	-0.00452	0.230*
	(2.071)	(-0.0336)	(1.898)
Ln(1+IAFM Equity)	-0.391**	-0.371	-0.523*
	(-1.999)	(-1.345)	(-1.733)
Ln(1+IAFM Debt)	-0.750**	0.0164	-0.782**
	(-2.386)	(0.0348)	(-2.192)
Year-End Q	0.812***	0.793***	0.719***
	(10.08)	(8.783)	(5.324)
Observations	35,919	14,583	19,600
Adj. R^2	0.290	0.368	0.258
Firm FE	Yes	Yes	Yes
Industry-by-Year FE	Yes	Yes	Yes

Panel B: Sample only including firms without publicly traded bonds

	(1)	(2)	(3)
	Unconditional	Low Leverage	High Leverage
Panel B.1: Dep. Var.: CAPX (%)			
Ln(1+IAFM Equity) × Year-End Q	0.0617***	0.0942***	0.0223
	(2.662)	(3.394)	(0.554)
Ln(1+IAFM Debt) × Year-End Q	0.0975**	0.0160	0.148***
	(2.526)	(0.219)	(2.708)
Ln(1+IAFM Equity)	-0.156**	-0.303***	0.0137
	(-2.039)	(-2.982)	(0.124)
Ln(1+IAFM Debt)	-0.288***	-0.137	-0.370***
	(-2.790)	(-0.699)	(-2.730)
Year-End Q	0.317***	0.277***	0.336***
	(9.767)	(8.376)	(5.856)
Observations	28,973	11,757	15,443
Adj. R^2	0.654	0.672	0.658
Firm FE	Yes	Yes	Yes
Industry-by-Year FE	Yes	Yes	Yes

Panel B.2: Dep. Var.: INVT (%)			
Ln(1+IAFM Equity) × Year-End Q	0.218***	0.224***	0.254**
	(2.993)	(2.694)	(2.096)
Ln(1+IAFM Debt) × Year-End Q	0.227*	-0.0332	0.261*
	(1.880)	(-0.236)	(1.854)
Ln(1+IAFM Equity)	-0.320	-0.444	-0.367
	(-1.434)	(-1.434)	(-1.125)
Ln(1+IAFM Debt)	-0.658*	0.336	-0.709*
	(-1.926)	(0.657)	(-1.742)
Year-End Q	0.798***	0.760***	0.711***
	(9.593)	(7.910)	(5.352)
Observations	29,004	11,777	15,454
Adj. R^2	0.289	0.368	0.255
Firm FE	Yes	Yes	Yes
Industry-by-Year FE	Yes	Yes	Yes

Table A8. Isolating the Channel of Information on Business Opportunities for Attention-Induced Investment-Price Sensitivity

This table presents regression results isolating the channel of information on business opportunities through which IAFM affects investment-price sensitivity. Panel A focuses on equity market attention, examining how the sensitivity of investment to stock prices varies with firms' contemporaneous external financing activity. Panel B shifts to debt market attention, using the same investment-stock price sensitivity framework. Panel C also centers on debt market attention, but investigates investment sensitivity to bond yields instead. Across all panels, the dependent variable is CAPX in Columns (1) and (3), and INVT in Columns (2) and (4). The key independent variable is the interaction between the log-transformed IAFM measure and a price-based signal: year-end Tobin's Q in Panels A and B, and year-end bond yield in Panel C. Control variables include end-of-year Tobin's Q, firm size (log of assets), cash holdings, leverage, sales growth, dividend yield, and institutional ownership. Columns (1) and (2) report results for firms with non-positive net external financing—defined as the sum of net equity and net debt financing—in the year of investment. In contrast, Columns (3) and (4) focus on firms with positive net external financing during the same period. 3-digit industry-by-year fixed effects and firm effects are included. sample period is 2008-2023. Standard errors are clustered at the 3-digit industry-by-year level. T-statistics are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Panel A: Isolating the Equity Market Attention's Information Channel

Net External Financing:	Non-Positive		Positive	
	(1)	(2)	(3)	(4)
Dep. Var.:	CAPX (%)	INVT (%)	CAPX (%)	INVT (%)
Ln(1+IAFM Equity) × Year-End Q	0.0662**	0.166*	0.0777*	0.303**
	(2.337)	(1.653)	(1.834)	(2.291)
Ln(1+IAFM Equity)	-0.195***	-0.181	-0.104	-0.588
	(-2.760)	(-0.742)	(-0.788)	(-1.420)
Year-End Q	0.304***	0.719***	0.335***	0.847***
	(7.892)	(7.543)	(8.310)	(7.903)
Observations	19,438	19,443	13,925	13,922
Adj. R^2	0.682	0.286	0.714	0.329
Firm FE	Yes	Yes	Yes	Yes
Industry-by-Year FE	Yes	Yes	Yes	Yes

Panel B: Isolating the Debt Market Attention's Information Channel, Based on Investment-Stock Price Sensitivity

Net External Financing:	Non-Positive		Positive	
	(1)	(2)	(3)	(4)
Dep. Var.:	CAPX (%)	INVT (%)	CAPX (%)	INVT (%)
Ln(1+IAFM Debt) × Year-End Q	0.0610	0.123	0.189***	0.447***
	(1.294)	(0.749)	(3.280)	(2.818)
Ln(1+IAFM Debt)	-0.137	-0.442	-0.657***	-1.624***
	(-1.354)	(-1.220)	(-3.544)	(-2.626)
Year-End Q	0.334***	0.799***	0.349***	0.937***
	(9.097)	(8.097)	(8.436)	(8.473)
Observations	19,438	19,443	13,925	13,922
Adj. R^2	0.682	0.285	0.715	0.330
Firm FE	Yes	Yes	Yes	Yes
Industry-by-Year FE	Yes	Yes	Yes	Yes

Panel C: Isolating the Debt Market Attention's Information Channel, Based on Investment-Bond Price Sensitivity

Net External Financing:	Non-Positive		Positive	
	(1)	(2)	(3)	(4)
Dep. Var.:	CAPX (%)	INVT (%)	CAPX (%)	INVT (%)
Ln(1+IAFM Debt) × Bond Yield	-0.195	-16.59	-15.65*	-55.95**
	(-0.0427)	(-1.044)	(-1.666)	(-2.063)
Ln(1+IAFM Debt)	-0.000848	0.0921	0.463	1.934
	(-0.00393)	(0.128)	(0.766)	(0.990)
Bond Yield	-3.307	-13.03	-25.10***	-31.52
	(-0.661)	(-0.711)	(-2.604)	(-0.872)
Observations	3,528	3,529	1,312	1,313
Adj. R^2	0.793	0.229	0.783	0.247
Firm FE	Yes	Yes	Yes	Yes
Industry-by-Year FE	Yes	Yes	Yes	Yes

Table A9. Does IAFM Correlate with Perceived Cost of Capital?

This table presents regression results examining the relationship between perceived cost of capital (Gormsen and Huber 2024) and IAFM. Across panels, the dependent variable is log-transformed IAFM measures. IAFM the tf-idf measure of IAFM Equity for Columns (1) and (3), and the tf-idf measure of IAFM Debt for Columns (2) and (4). The key independent variable is the perceived cost of capital, which was measured and made publicly available by Gormsen and Huber (2024). Control variables include end-of-year Tobin's Q, firm size (log of assets), cash holdings, leverage, sales growth, dividend yield, and institutional ownership. Across panels, Columns (2) and (4) additionally control for two proxies of the true cost of capital. The first is the implied cost of equity, constructed as the average of four accounting-based estimates commonly used in the literature: the residual income models of Gebhardt, Lee, and Swaminathan (2001) and Claus and Thomas (2001), and the dividend discount models of Easton (2004) and Ohlson and Juettner-Nauroth (2005). The second is the implied cost of debt, proxied by the ratio of total interest expense to total debt from Compustat, which reflects the firm's effective borrowing cost. 3-digit-by-year fixed effects are included in Panel A, and Panel B additionally include firm fixed effects. All independent variables are lagged by one year. The sample period is 2007-2023. Standard errors are clustered at the 3-digit industry-by-year level. T-statistics are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Panel A: Cross-Sectional Correlation Between Perceived Cost of Capital and Attention

Dep. Var.: Ln(1+IAFM)	(1)	(2)	(3)	(4)
Proxy for IAFM:	Equity	Debt	Equity	Debt
Perceived Cost of Capital	-6.095***	-1.552***	-5.305***	-1.712**
	(-7.716)	(-2.801)	(-5.638)	(-2.318)
Implied Cost of Capital			1.029***	0.271**
			(7.229)	(2.239)
Interest Expense			0.0249	0.0445**
			(1.233)	(2.257)
Observations	25,539	25,539	18,759	18,759
Adj. R^2	0.154	0.282	0.169	0.258
Firm FE	No	No	No	No
Industry-by-Year FE	Yes	Yes	Yes	Yes

Panel B: Within-Firm Correlation Between Perceived Cost of Capital and Attention

Dep. Var.: Ln(1+IAFM)	(1)	(2)	(3)	(4)
Proxy for IAFM:	Equity	Debt	Equity	Debt
Perceived Cost of Capital	-0.814	0.582	-1.531	1.117
	(-0.807)	(0.746)	(-1.136)	(1.048)
Implied Cost of Capital			0.483***	-0.128
			(3.013)	(-0.927)
Interest Expense			-0.0120	0.00508
			(-0.578)	(0.281)
Observations	25,087	25,087	18,327	18,327
Adj. R^2	0.391	0.458	0.398	0.434
Firm FE	Yes	Yes	Yes	Yes
Industry-by-Year FE	Yes	Yes	Yes	Yes

Table A10. Price Informativeness and Internal Informativeness

This table reports regressions examining whether equity price informativeness, bond price informativeness, and internal informativeness predict firm-level attention to financial markets. The dependent variable is the tf-idf measure of IAFM Equity for Columns (1) and (3), and IAFM Debt for Columns (2) and (4). I proxy equity informativeness using PIN, capturing the probability of informed trading. Bond informativeness is measured by bond price non-synchronicity, i.e., Bond ($1-R^2$). Internal informativeness is proxied by R&D intensity, which equals 100 × research and development expenses scaled by total assets with missing observations replaced with zero. Control variables include end-of-year Tobin's Q, firm size (ln(Assets)), cash holdings, leverage, sales growth, dividend yield, and institutional ownership. All independent variables are lagged by one year. The sample period is 2007-2023. 3-digit industry-by-year fixed effects are included for Columns (3) and (4). All independent variables are lagged by one year. Standard errors are clustered at the 3-digit industry-by-year level. T-statistics are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Dep. Var.: Ln(1+IAFM)	(1)	(2)	(3)	(4)
Dimension:	Equity	Debt	Equity	Debt
Proxy for Equity Informativeness:				
Equity Price Informativeness	0.471***		0.401***	
	(5.758)		(4.922)	
Proxy for Bond Informativeness:				
Bond Price Informativeness		0.0990**		0.117***
		(2.388)		(2.729)
Proxy for Internal Informativeness:				
R&D Intensity (%)	-0.00452***	-0.0235***	-0.00369***	-0.0193***
	(-5.549)	(-9.050)	(-4.922)	(-8.287)
Observations	33,242	6,824	32,765	6,015
Adj. R^2	0.084	0.069	0.169	0.267
Firm FE	No	No	No	No
Industry-by-Year FE	No	No	Yes	Yes