The Real Effects of Investor Disagreement

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This version: November 30, 2025
Last Revised on: April 12, 2026

Abstract

This paper studies the impact of investor disagreement on the market feedback effect. We argue and show that disagreement contains useful private information for managerial learning, such that it is positively associated with investment-to-Q sensitivity. This impact is more pronounced when learning is more likely to occur, namely for R&D investment, for growth firms, and for firms that are less financially constrained. Our analysis based on a disagreement measure constructed from forecast revisions further substantiates this mechanism and helps mitigate reverse causality concerns. We also rule out the alternative explanation that disagreement merely reflects valuation uncertainty. Overall, the study provides evidence on the real effects of investor disagreement.

Keywords: Investor Disagreement, Market Feedback, Revelatory Price Efficiency
JEL Codes: G14 G31

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1 Introduction

A central function of financial markets is to aggregate dispersed information and incorporate it into prices, enabling managers to learn from market signals when making investment decisions[1]. The extent to which prices facilitate such learning hinges on the information environment in which they are formed (e.g., Chen et al., 2007). An important yet underexplored feature of this environment is investor disagreement. Existing studies have primarily examined disagreement through its asset-pricing implications, such as return predictability, volatility, and speculative trading. This study, instead, emphasizes its informational role in price formation and, consequently, in managerial learning. Disagreement arises because investors interpret firms' prospects using different private information sets, and their trading on these distinct signals contributes to the information incorporation into prices. This study therefore examines whether investor disagreement strengthens the relation between stock prices and corporate investment, providing new evidence on its real effects.

Our hypothesis is that investor disagreement, which reflects both diverse private information and heterogeneous interpretations, increases the information content in stock prices that is useful for investment decision making and enhances revelatory price efficiency. Such diversity of information can create strategic complementarities in trading, which amplify information aggregation and lead to more informative prices (Goldstein & Yang, 2015). To test this hypothesis, we examine how investor disagreement affects the sensitivity of investment to Tobin's Q, the specification commonly used to infer market feedback (e.g., Bakke & Whited, 2010; Chen et al., 2007). Our measure of disagreement is the standard deviation of analysts' earnings-per-share (EPS) forecasts, scaled by the stock price. We then regress investment on Tobin's Q, including both the disagreement measure and its interaction with Tobin's Q. We find investor disagreement enhances the investment-to-Q sensitivity, and this result is robust after including common control variables in this setting. Specifically, as disagreement increases from its 1st quartile to 3rd quartile, the investment-to-Q sensitivity increases by around 5%.

To substantiate the revelatory informational role of the disagreement, we conduct two more analyses based on our baseline. First, we include (the natural logarithm of) number of analyst coverage and its interaction with Tobin's Q as additional control variables. This helps disentangle whether the positive learning effect arises from the diversity of opinions or simply from greater analyst attention and information production. We find that analyst

[1] Bond et al. (2012) and Goldstein (2023), among others, provide insightful review on market feedback effect.

coverage also has an positive impact on the investment-to-Q sensitivity, consistent with Edmans et al. (2017). More importantly, the effect of disagreement remains positive and significant, suggesting it captures a distinct dimension of information heterogeneity beyond mere analyst coverage. Second, we restrict our sample to stocks that have larger number of analyst coverage, i.e., more than 7 or even 10. This, on the one hand, alleviates the measurement error concern and, on the other hand, strengthens the diverse information argument as more analysts increase the scope for private information. The slightly higher coefficient are observed for restricted samples. For instance, among stocks followed by at least 10 analysts, the investment-to-Q sensitivity increases by 7.36% as disagreement increases from its 1st quartile to 3rd quartile. Overall, these supplementary analyses reinforce that investor disagreement contains information useful for managerial learning.

To provide more rigorous evidence that disagreement conveys valuable external information, we next perform various cross-sectional tests. We posit that if disagreement truly reflects informative private signals, its impact on investment-to-Q sensitivity should be stronger in settings where managers are more likely to learn from market prices. The first two analyses are motivated by Goldstein et al. (2023), who propose that while managers are generally well-informed about assets-in-place, they are less informed about growth opportunities and thus rely more on the market for information about the latter. Specifically, we distinguish between investments in R&D, which represent uncertain growth opportunities, and capital expenditures, which largely expand existing assets (e.g., Peters & Taylor, 2017). Simultaneously, we separate growth firms, whose value is derived from future potential, from value firms, which are primarily valued on their assets-in-place. We should expect stronger learning, and hence stronger impact of disagreement, for R&D expenses and for growth firms. Our empirical evidence aligns with the prediction, suggesting that the role of disagreement is most pronounced precisely where the need for external market information is greatest. Our third test examines firm's financial conditions. Firms with less financial constraints are more flexible and hence more able to respond to market prices (Edmans et al., 2017), therefore disagreement should have stronger impact among less financial constrained firms. We find supporting evidence. In short, our cross-sectional analyses further strengthen our argument that disagreement contain useful external information to managers.

We next turn to provide causal evidence that disagreement contains useful external information that flow back to firm. We first examine the disagreement measured by their forecast revision around earnings announcement dates. This design provides a clear identification by capturing analyst revisions triggered directly by a fundamental news shock that managers already know. Therefore, for this disagreement to influence managerial learning, it cannot be a simple reflection of that public news, but must instead signal the novel, private information and heterogeneous interpretations generated by analysts outside the firm. Following Huang et al. (2024), for each quarterly earnings announcement, we calculate the standard deviation of analyst forecast revisions, defined as the difference between forecasts issued within 20 days after the announcement and those issued within 45 days before it[2]. We then average these quarterly values to match our annual sample, and repeat the baseline regression analysis. By construction, this revision-based disagreement should more directly reflect private information generated outside the firm triggered by public news, therefore we should expect a strong impact on investment-to-Q sensitivity. We find evidence consistent with our prediction, specifically, as revision-based disagreement increases from its 1st to 3rd quartile the investment-to-Q sensitivity increases by 10.63%, where the impact doubles relative to that of the baseline.

To substantiate that this revision-based disagreement contains valuable external information, we test whether its impact is significantly stronger when the public news causes analyst views to converge. This is because such convergence signals a setting where disagreement is more likely driven by the fundamental aggregation of private information as analysts rationally update their belief (e.g., Harris & Raviv, 1993; Kandel & Pearson, 1995), rather than by noise or behavioral biases. In our sample, 74% cases that they converge, that is, the post-EA disagreement is lower than pre-EA disagreement. Consistent with our conjecture, the impact of disagreement is significantly stronger in the convergence subsample, while it is insignificant in the divergence subsample, where revisions are more likely to reflect noise. Overall, this evidence confirms that revision-based disagreement captures external information revealed through market reactions to public news, and that such information meaningfully feeds back into firms' real decisions. The results strengthen our causal interpretation that disagreement enhances managerial learning rather than simply mirroring publicly known fundamentals.

Though we argue disagreement contain useful private information, one can also argue it is driven by or directly regarded as valuation uncertainty (e.g., Berkman et al., 2009). In our context, if disagreement is about valuation uncertainty, a positive impact on the investment-to-Q sensitivity is still plausible. This is because, when managers face high uncertainty, they are incentivized to rely on and gather all available sources of information in decision making. We then explore the feasibility of this mechanism through two tests.

[2] We exclude the fourth quarterly earnings announcement from our analysis because the pre- and post-earning announcement (EA) forecasts pertain to different fiscal years. Specifically, forecasts issued before the Q4 announcement are for the current fiscal year, while those issued afterward are for the upcoming fiscal year. This makes the revision between them non-comparable to revisions from other quarters.

First, we decompose disagreement measure into two components by regressing it on valuation uncertainty proxy variables, earning volatility and Loughran and McDonald (2024)'s firm complexity measure. If above mechanism works, we should expect a significantly positive impact of valuation uncertainty-driven disagreement on the investment-to-Q sensitivity. We do not find a significant impact when using either earnings volatility or firm complexity as proxies for valuation uncertainty, however, the residual disagreement orthogonal to valuation uncertainty remain highly significant. This suggests that it is the informational component of the disagreement, other than the valuation uncertainty component, leads to higher revelatory price efficiency.

In addition, we examine how firms respond to peers' prices, which constitutes another setting to identify managerial learning from the market (e.g., Foucault & Fresard, 2014). If disagreement merely reflects valuation uncertainty and managers rely on all available information, including information embedded in peers' prices, we should expect a positive coefficient on the interaction between our disagreement measure and peers' Q. We define peer firms based on two industry classifications: the conventional 2-digit Standard Industrial Classification (SIC) and the text-based industry classification of Hoberg and Phillips (2016) derived from product similarity in 10-K filings. We further construct aggregate peers' Q using three alternatives: equally weighted means, value-weighted means by firm size, and medians. We do not find significant evidence that disagreement strengthens the investment–to–peers' Q sensitivity, and in some cases, the effect is even negative. This rejects the interpretation of disagreement as purely valuation uncertainty and instead supports our information argument that when firms face higher disagreement, indicating more external information, managers rely more on their own price and less on peers' prices.

This paper contributes to literature in a number of ways. First, it contributes to the literature on market feedback effect. A long-standing and critical question in finance is that whether financial markets can affect the real economy or merely remain a sideshow. Theoretical models suggest that when informed traders impound their private signals into prices, managers can learn from these prices to guide real decisions (e.g., Goldstein et al., 2013; Subrahmanyam and Titman, 1999). Empirically, early work infers learning from the sensitivity of investment to Tobin's Q (e.g. Bakke & Whited, 2010; Chen et al., 2007), and event-study evidence shows that managers respond to market reactions. For example, Luo (2005) shows that managers are more likely to withdraw acquisition plans when the market reacts negatively to the announcement, while Zuo (2016) finds that recent stock price movements positively shape managers' beliefs about firm fundamentals. Building on this foundation, the empirical literature follows three main identification settings to test managerial learning. First, studies exploit settings in which the informativeness of stock prices varies exogenously, such as cross-listing events (Foucault & Frésard, 2012), staggered enforcement of insider-trading laws (Edmans et al., 2017), or changes in mandatory disclosure regulation (Bird et al., 2021; Goldstein et al., 2023; Jayaraman & Wu, 2019), to examine whether learning intensifies when prices embed more private information. Second, researchers study whether managers incorporate peers' stock prices when making investment decisions, reflecting the idea that managers learn from all available market signals (e.g. Foucault & Fresard, 2014; Yan, 2024). Third, a growing literature exploits non-fundamental shocks to prices, computed from extreme mutual-fund outflows, to identify the causal role of prices (Dessaint et al., 2019; Edmans et al., 2012; Jayaraman & Shuang Wu, 2020; Wardlaw, 2020). Because non-fundamental shocks should not directly affect real investment, a positive sensitivity of investment to the non-fundamental component of stock prices indicates active learning, provided that decision makers cannot distinguish whether price movements reflect fundamental information or non-fundamental noise.

Our study on disagreement fits naturally into this first setting. Disagreement, measured as the dispersion of analyst EPS forecasts, is generated outside the firm, as analysts update their beliefs based on earnings announcements, public disclosures, and their own information-processing. Because managers already know the information they disclose, the cross-sectional dispersion among analysts primarily reflects external information or interpretations not possessed by managers. As emphasized by Bond et al. (2012) and Edmans et al. (2017), it is this external private-information component of prices, rather than the overall amount of information in prices, that is relevant for real investment decisions. By showing that investment–to-Q sensitivity increases with investor disagreement, and that this relation is stronger both when disagreement more plausibly reflects informational heterogeneity rather than noise and when firms are in settings where learning is more likely, we provide evidence that prices reveal external useful information to managers.

Second, we contribute to the literature on the implications of investor disagreement. Previous literature largely focus on its impact on financial market outcomes, such as trading volume, return volatility, and expected returns. Most literature, both theoretical and empirical, agree on a positive relation between disagreement and trading volume, and volatility (e.g., Banerjee & Kremer, 2010; Fischer et al., 2022; Harris & Raviv, 1993; Kandel & Pearson, 1995). Regarding return predictability, many document a positive impact on expected return (e.g., Carlin et al., 2014; Fischer et al., 2022; Varian, 1985), while others report a negative impact (e.g., Diether et al., 2002; Hong & Sraer, 2016; Miller, 1977). We shift our focus to its informational role and its implication on revelatory price efficiency, since disagreement capture heterogeneous private beliefs from investors, which is valuable for real investment decision making. We argue and illustrate a positive impact of disagreement on revelatory price efficiency.

Two closely related studies that directly address the relation between disagreement and investment are Baker et al. (2016) and Garlappi et al. (2017). Baker et al. (2016) show theoretically that disagreement affects aggregate investment by altering equilibrium prices through speculative trading, but they do not examine whether disagreement changes the information embedded in prices or how managers respond to that information. Garlappi et al. (2017) focus on internal group disagreement and demonstrate that heterogeneous beliefs within a decision-making body lead to dynamic inconsistency and underinvestment, a mechanism unrelated to market information. In contrast, our study examines disagreement as an external information signal that financial markets incorporate into prices, and we investigate how this affects revelatory price efficiency and ultimately the strength of managerial learning from prices, thereby connecting disagreement to real corporate decisions through a channel absent in both papers.

This paper is organized as follows. Section 2 develops our main hypothesis. Section 3 describes our data and key variables. Section 4 empirically studies the impact of disagreement on managerial learning, i.e., investment-to-Q sensitivity, and provides cross-sectional analyses, and addresses endogeneity to substantiate our hypothesis. Section 5 explores alternative explanation. Section 6 concludes.

2 Hypothesis Development

Managers often rely on market prices to supplement their internal information when making investment decisions, particularly when prices reflect diverse and dispersed signals about future firm prospects, which is known as market feedback effect (Antoniou et al., 2023; Chen et al., 2007; Edmans et al., 2012; Foucault & Frésard, 2012, among others). Theories argue that while managers are generally well informed about assets in place, they are less informed about growth opportunities (Goldstein, 2023; Goldstein & Yang, 2019). In such contexts, prices that incorporate heterogeneous investor information can help managers update their beliefs and improve the efficiency of capital allocation. The mechanism relies on the aggregation of dispersed signals through trading, that is, when investors possess different pieces of information or interpret signals differently, their trading activity embeds these diverse insights into prices. When the market is particularly effective at aggregating information about the dimensions on which managers are relatively uninformed, such as future growth, the feedback from prices has stronger real effects (Goldstein & Yang, 2019). Managers can then learn from market prices that reflect a broader information set than their internal view alone, leading to stronger sensitivity of investment to Tobin's Q.

Investor disagreement captures the extent of heterogeneity in expectations about firm fundamentals and may arise from several theoretically distinct sources (e.g., Verardo, 2009). First, it can stem from differences in private signals, where investors hold diverse but partially informative views about future outcomes (Carlin et al., 2014; Harris & Raviv, 1993). Second, disagreement may result from differential interpretation of the same public information, as investors apply heterogeneous models or updating rules to identical signals (Bamber et al., 1999; Banerjee & Kremer, 2010; Kandel & Pearson, 1995). Third, it can arise from variation in beliefs about the precision or quality of available information, such as earnings quality or the reliability of disclosures (Huang et al., 2024). When these forms of disagreement lead investors to trade on heterogeneous yet informative beliefs, they increase both the volume and diversity of information-based trading and enhance the aggregation of dispersed information into prices, thereby increasing the value of prices as signals for managers seeking to learn about future fundamentals beyond their internal information. Moreover, belief heterogeneity can strengthen incentives for private information acquisition and information-based trading, as investors are more willing to act on their assessments when they perceive them as non-redundant (Goldstein & Yang, 2015). Such heterogeneity may also help sustain price informativeness, since excessively precise public disclosure can crowd out private information production, whereas moderately noisy signals preserve the market's role in aggregating dispersed beliefs (Goldstein & Yang, 2019).

While disagreement may also reflect valuation uncertainty or behavioral noise (Banerjee et al., 2025), these theoretical frameworks emphasize that belief heterogeneity, when grounded in information, can enhance the informational content of prices in a way that supports more informed corporate decision-making. If managers incorporate these signals into investment decisions, greater investor disagreement should be associated with stronger investment–Q sensitivity.

H1: Investor disagreement improves revelatory price efficiency, that is, it increases the investment-to-Q sensitivity.

3 Data

Our sample consists of common stocks listed on NYSE/AMEX/NASDAQ[3]. We start by obtaining accounting data from Compustat. Next, we merge this with stock prices, returns, and trading volumes from CRSP, and analyst coverage data from I/B/E/S. Following previous literature, we exclude financial and utility firms[4], and exclude observations of tiny firms with stock price lower than \$5 and total assets less than \$1 million (Antoniou et al., 2023; Kacperczyk et al., 2021, among others). Since our key variable of interest is investor disagreement, measured by I/B/E/S analyst dispersion in earnings per share (EPS) forecasts, we further exclude observations with fewer than two analysts covering the stock. After the merge and filter, the final dataset consists of 5,132 unique firms for a total of 35,563 firm-year observations, covering the sample period from 1975 to 2024.

3.1 Variables

Following previous literature (Antoniou et al., 2023; Chen et al., 2007; Goldstein et al., 2023, among others), we define corporate investment (INV) as the sum of capital expenditure and research and development (R&D) expenses scaled by lagged total assets. Tobin's Q is measured as the market value of equity plus the book value of assets minus book value of equity, scaled by total assets, and it implies firm's growth opportunity.

This study measures investor disagreement using analyst dispersion in EPS forecasts, defined as the standard deviation of analysts' EPS forecasts scaled by the stock price (e.g., Banerjee, 2011; Cheong and Thomas, 2011). In addition, we apply a $\log(1+\cdot)$ transformation to address the high skewness of the measure. This measure offers several advantages. Forecast dispersion is largely insulated from liquidity, trading cost, and size-related biases (Alexandridis et al., 2007), and analyst forecasts are issued frequently, providing a continuous flow of market-relevant information (Ajinkya et al., 1991). Moreover, dispersion is an appropriate proxy for disagreement when analysts reveal their unbiased expectations and investors incorporate these views into their beliefs (Garfinkel, 2009). In the literature, the standard deviation of analysts' EPS forecasts is often scaled by alternative denominators, such as mean absolute EPS (e.g., Diether et al., 2002), total assets (e.g., Golez and Goyenko,

[3]This corresponds to stocks with share code equal to 10 or 11, and primary exchange code equal to N, A, or Q, in the CRSP database

[4]Financial firms have a 1-digit SIC code of 6, while utility firms have a 2-digit SIC code of 49. Together, they account for only a small portion, approximately 2%, of our sample. Including them in the analysis yields nearly identical results.

2022), or book value of equity (e.g., Cen et al., 2017), to construct disagreement. A potential concern is that results may be sensitive to the choice of scaling factor. However, Cen et al. (2017) argue that disagreement measures are generally robust to such choices, as the variation in the numerator primarily captures the extent of disagreement. Consistent with this view, we adopt several alternative scaling factors in our analysis for robustness, and our results remain qualitatively unchanged.

Our control variable includes firm size ($SIZE$), cash flow (CF), number of analyst coverage ($ANALYST$), annualized cumulative returns over the next 3 years ($RET3Y$), and the inverse of total assets ($INVASSET$). $SIZE$ is computed as the natural logarithm of the total assets. CF is computed as the sum of the net income before extraordinary items, and depreciation and amortization expenses, and R&D expenses, scaled by lagged total assets. $ANALYST$ is measured as the natural logarithm of the number of analyst coverage. $RET3Y$ is measured as the value-weighted market adjusted three-year cumulative return, starting from the end of the investment year. Finally, $INVASSET$ is computed as the inverse of lagged total assets, and it is included to alleviate the concern of spurious correlation since both our dependent and independent variables are scaled by lagged total assets (Chen et al., 2007).

Table 1 reports the summary statistics for our variables. The means (standard deviations) of the investments, $CAPXRNDA$, $CAPXA$, and $RNDA$ are 0.137 (0.111), 0.069 (0.071), and 0.074 (0.095), respectively. This indicates that a typical firm makes annual investment equal to around 13.7% of its total assets, and this is distributed approximately evenly across capital expenditure and R&D expenses. The average Tobin's Q is 2.184. These statistics are close to typical values reported in this literature (See, e.g., Antoniou et al., 2023; Goldstein et al., 2023). Regarding disagreement, the sample firms are followed by an average of nine analysts, which generates a mean disagreement measure of about 0.004. In levels, this implies that the average standard deviation of EPS forecasts is roughly $0.07 per share.

[Insert Table 1 around here]

4 The Informational Role of Investor Disagreement

4.1 Empirical Results

To examine the impact of investor disagreement ($DISA_{it-1}$) on managerial learning, we follow standard specification in this literature and estimate the following panel regression,

$$INV_{it} = \beta_1 Q_{it-1} + \beta_2 DISA_{it-1} + \beta_3 Q_{it-1} \times DISA_{it-1} + \theta X_{it-1} + \alpha_t + \gamma_i + \epsilon_{it}, \quad (1)$$

where INV_{it} firm i's investment in year t, defined as the sum of capital expenditure and research and development (R&D) expenses scaled by lagged total assets. Q_{it-1} is firm i's Tobin's Q in year $t-1$. It is defined as the market value of equity plus the book value of assets minus book value of equity, scaled by total assets, and it implies firm's growth opportunity. These variables are defined following common practice in this literature (Antoniou et al., 2023; Chen et al., 2007; Goldstein et al., 2023, among others). $DISA_{it-1}$ is investor disagreement.

X_{it-1} is a set of control variables for firm characteristics. First, firm size correlates with its investment opportunities (Foucault & Fresard, 2014; Jayaraman & Wu, 2019), we control for size, both on its own and its interaction with Tobin's Q ($SIZE$ and $SIZE \times Q$). Second, to account for the impacts of financial constraints, we include cash flow (CF). The cash flow is well documented to affect investment (Fazzari et al., 1988), so we include it both separately and in interaction with disagreement variables (CF and $CF \times DISA$). Then, overvalued firms tend to invest more (Baker et al., 2003), so we include the annualized cumulative return over the future three years (RET). Last, since we scale both investments and Q by lagged total assets, we include the multiplicative inverse of assets ($INVASSET$) to ensure our result is not driven by the common deflator (Chen et al., 2007). Finally, we include both firm (γ_i) and time fixed effects (α_t) to account for any unobserved time-invariant firm-specific factors and variation in investment over time. The standard errors are clustered at both firm and time levels.

A positive β_1, which represents the average investment-to-Q sensitivity, is expected and implies a market feedback effect. The rationale is that if managers learn from market prices, or if prices contain useful information not already known by managers, and use this information to guide future investment decisions, then investment will be sensitive to stock prices (See, e.g., Chen et al., 2007; Edmans et al., 2012; Goldstein, 2023). The coefficient of interest, however, is β_3, which represents the coefficient on $Q_{it-1} \times DISA_{it-1}$. It captures the incremental impact of investor disagreement on the investment-to-Q sensitivity and hence managerial learning. Our hypothesis of the informational role of disagreement predicts a positive β_3.

Table 2 reports the baseline result. Column (1), without control variables, shows that investment is positively associated with Q, with the estimated coefficient of 0.016, significant at less than 1% level. This is consistent with the managerial learning theory. More importantly, the coefficient for interaction term, $Q_{it-1} \times DISA_{it-1}$, is positive as 0.569, significant at less than 1% level. This indicates that investor disagreement enhances managerial learning, consistent with our hypothesis. In Column (2), standard control variables are included, our result, though weaker, still remains. In our sample, the Q1 and Q3 of disagreement are 0.0005 and 0.004 respectively. Economically, the investment-to-Q sensitivity increases from 0.0212 to 0.0222, marking a 4.86% increase.

[Insert Table 2 around here]

We further include the natural logarithm of number of analyst coverage ($ANALYST_{it-1}$) and its interaction with Q ($ANALYST_{it-1} \times Q_{it-1}$) as control variable in Column (3). Since disagreement reflects dispersion in analysts' opinions, controlling for coverage helps disentangle whether the positive learning effect arises from the diversity of opinions or simply from greater analyst attention and information production. We find that analyst coverage has positive impact on investment-to-Q sensitivity (coefficient=0.003, significant at less than 1% level), consistent with findings in Edmans et al. (2017), who argue that greater analyst coverage enhances the RPE by improving information production and dissemination. More importantly, the coefficient for the interaction $Q_{it-1} \times DISA_{it-1}$ is slightly higher as 0.285 and more significant after controlling for impact of analyst coverage. This indicates that the informational value embedded in investor disagreement is not subsumed by analyst coverage. Rather, disagreement captures an additional dimension of information heterogeneity that independently strengthens managers' ability to extract useful signals from market prices.

To further substantiate our argument that disagreement carries useful outside information derived from dispersed private information among investors for managers to learn from, we repeat the baseline regression analysis in Column (3) of Table 2 by restricting the sample based on the number of analyst coverages. This approach helps alleviate concerns regarding measurement error in investor disagreement. Specifically, the disagreement measure can technically be computed with as few as two analyst forecasts; however, in such cases, the measure may capture estimation noise rather than genuine information dispersion, as the limited number of forecasts may not provide sufficient information content. The prediction is that disagreement should have at least an equivalent, if not stronger, impact. In other words, if disagreement indeed carries information, the coefficient on the interaction term $Q_{it-1} \times DISA_{it-1}$ should be no smaller, since higher analyst coverage is expected to enhance the accuracy and informational content of the measure. First, we restrict our sample to stock-year observations with at least seven analyst coverages, which is equivalent to being above the median level of coverage. The result is presented in Column (4). The coefficient for the interaction term is 0.31, significant at 5% level. Economically, as disagreement increases from its Q1 to Q3, the investment-to-Q sensitivity increases by 5.05%, from 0.0222 to 0.0233. Second, we further restrict sample to stocks covered by at least 10 analysts. The coefficient is greater at 0.536 and more significant at less than 1% level, additionally, the economical impact is more pronounced that as disagreement increases from its Q1 to Q3 the investment-to-Q sensitivity increases by 7.36%. To sum, we do not aim to claim a significantly stronger effect in the restricted samples, but the results at least suggest that disagreement reflects informative dispersion rather than measurement noise.

Overall, our baseline result is consistent with the hypothesis that disagreement provides useful information for managers when making investment decisions. Specifically, investment is more sensitive to growth opportunities revealed by stock prices for firms with higher levels of disagreement.

4.2 Cross-Sectional Analysis

Having established that investor disagreement enhances managerial learning, we next examine when such learning is more likely to be relevant. Managers are typically well informed about assets in place but less informed about future growth opportunities, demand conditions, and other forward-looking factors. Market prices, in contrast, aggregate dispersed private information from investors about these uncertain prospects (Goldstein, 2023; Goldstein & Yang, 2019). Thus, when disagreement, our proxy for the dispersion of private beliefs, is high, prices should convey more useful external information for managers. Guided by this logic, the cross-sectional analyses explore settings where reliance on market information is expected to vary, including 1) investment composition (CAPEX versus R&D), 2) firm valuation type (value versus growth), and 3) the degree of financial constraints.

First, we distinguish between capital expenditure and R&D investment. R&D-intensive investment is largely driven by uncertain, forward-looking growth opportunities, where markets aggregate dispersed private signals about demand, technology, and competition that managers may lack. In contrast, capital expenditure mainly augments assets in place, about which managers possess relatively superior internal information. Consistent with this distinction, prior studies show that R&D involves greater uncertainty, option-like payoffs, and distinct pricing by investors compared with tangible capital expenditure (Chan et al., 2001; Eberhart et al., 2004; Peters & Taylor, 2017, among others). Hence, if disagreement captures dispersed private information, the $Q \times DISA$ effect should be stronger for R&D than for capital expenditure, consistent with the managerial learning mechanism. We replace the dependent variable in the baseline regression with capital expenditure and R&D expenses (each scaled by total assets), and the results are reported in Table 3. As shown in Table 3, the coefficient on the interaction term $Q_{it-1} \times DISA_{it-1}$ is positive for both types of investment but substantially larger and more significant for R&D (0.210, t=2.77) than for capital expenditure (0.125, t=1.89). This finding indicates that disagreement exerts a stronger effect on the sensitivity of R&D investment to Q, consistent with the notion that markets provide more valuable information for decisions involving forward-looking, uncertain projects.

[Insert Table 3 around here]

Second, we distinguish value and growth firms. Growth firms derive a larger share of their value from intangible assets and uncertain future opportunities, leading to greater information asymmetry and reliance on external information compared with value firms, whose worth is primarily driven by assets in place (Fama & French, 1993; Farboodi et al., 2022, among others). Goldstein et al. (2023) show that when public access to firm disclosures (e.g., EDGAR) improves, the real effects of prices are stronger for firms whose value is tied to existing assets, whereas investment–price sensitivity declines for firms whose value is more forward-looking, indicating that these firms depend more on privately produced, growth-related information embedded in prices. Hence, if disagreement reflects dispersed private information, its informational contribution should be stronger among growth firms, where managers benefit more from learning about uncertain, forward-looking opportunities through market prices. We then split the sample into two groups based on the median beginning-of-year book-to-market (BM) ratio in each fiscal year, and within each subsample we repeat the baseline analysis for total investment (the sum of capital expenditure and R&D expenses), capital expenditure, and R&D expenses separately. The results are reported in Table 4. Comparing Columns (1) and (4), where the dependent variable is total investment, we find that the coefficient on the interaction term $Q_{it-1} \times DISP_{it-1}$ is significantly positive among growth firms (0.353, t = 2.71), but insignificant and slightly negative among value firms. This contrast indicates that disagreement enhances the sensitivity of investment to market valuations primarily for growth firms, consistent with the notion that dispersed private information embedded in prices provides more valuable external signals for firms whose value depends on future growth opportunities. Looking at Column (2) versus 5 and Column (3) versus (6), we confirm two observations that the disagreement's impact is more pronounced among growth firms, and within the growth subsample the impact is slightly stronger for R&D expenses.

[Insert Table 4 around here]

Finally, we investigate whether the effect of disagreement depends on firms' financial constraints. The RPE mechanism suggests that the ability to learn from prices depends not only on the information contained in the market but also on managers' capacity to respond to it. As shown in Edmans et al. (2017), when managers face fewer financing frictions, they can translate the informational content of prices more effectively into real investment decisions. In contrast, financially constrained firms may recognize informative prices but remain unable to act on them due to limited access to external funding. Therefore, if disagreement enhances the informational content of prices, its effect on investment–to-Q sensitivity should be stronger among less financially constrained firms, where managers can more readily adjust investment in response to the additional information revealed by market prices. We follow them and measure financial constraints as the difference between capital expenditures and cash flows scaled by capital expenditures, where higher (lower) values indicate industries with greater external (internal) financing and thus lower (higher) financial constraints. We then repeat the baseline analysis and report the results in Table 5. Consistent with our prediction, we find a positive and significant impact of disagreement on investment-to-Q sensitivity among firms that are less financially constrained, driven primarily by R&D expenses, while the impact among more financially constrained firms is insignificant.

[Insert Table 5 around here]

Overall, our cross-sectional evidence reinforces the view that disagreement reflects dispersed private information that enhances managerial learning from prices, with stronger effects observed in R&D-intensive, growth, and less financially constrained firms.

4.3 Identification

In this section, we conduct several analyses to substantiate that endogeneity is not driving our result. There are two endogeneity concerns with our baseline analysis. First, it is possible that our specification omits variables that affect the firm's investment-to-Q sensitivity and are correlated with analyst disagreement. One important factor is the number of analyst coverages, which influences both investor disagreement and investment-to-Q sensitivity. Since this variable is already included in our baseline regression, this crucial concern is largely mitigated, though not entirely eliminated. Second, reverse causality is present. The core of our hypothesis is that information flows from the market to the firm to guide investment, i.e., market feedback effect (Edmans et al., 2012; Goldstein, 2023). However, a simultaneous, reverse channel exists. A firm's complex investment decisions generate information that flows from the firm to the market, directly shaping the level of investor disagreement. This simultaneity in information flow creates a confounding loop that we must disentangle to establish causality.

4.3.1 Event Study Around Earning Announcement Dates

Our first analysis leverages analyst forecast revisions around earnings announcement (EA) dates. On each earnings announcement date, firm release information that managers are better informed, e.g., earnings and growth, and in response analysts revise their forecasts to update their belief upon receiving new information. This setting provides a powerful natural experiment for examining the market's informational role. When analysts update their forecasts following an earnings announcement, the resulting disagreement reflects both heterogeneous interpretations of the public news and the incorporation of their distinct private information. It is precisely this diversity of beliefs, this generation of new information, that, when aggregated into stock prices, creates a valuable information flow back to the firm. Managers can observe these price movements and learn from the novel insights they contain to guide investment decisions. Focusing on the earnings announcement window offers key advantages. First, it captures disagreement that is more likely to reflect genuine informational heterogeneity rather than noise or sentiment. Outside of announcements, revisions may be driven by speculation or stale information, whereas revisions around earnings announcements are directly triggered by a fundamental, firm-specific news shock. Second, by studying the period after managers have disclosed their information, we isolate the market's reciprocal information flow to the firm. Therefore, if post-EA disagreement enhances investment-to-Q sensitivity, it constitutes strong evidence that managers are learning from the external, private information revealed through the market's price-discovery process.

We follow Huang et al. (2024) to construct investor disagreement based on analysts' forecast revisions. For each earnings announcement date, we collect annual earnings forecasts issued by analysts within 45 days before the announcement and match them with forecasts made by the same analysts within 30 days after the announcement. The forecast revision is defined as the difference between the post-EA and pre-EA forecasts. Investor disagreement is measured as the cross-sectional standard deviation of these revisions, scaled by the stock price. Thus, by construction, this measure captures differences in analysts' interpretations of the same earnings news (Hong & Stein, 2007; Huang et al., 2024), reflecting heterogeneous information processing. It is well suited to our setting as it isolates disagreement that embodies new, market-generated information relevant for managerial learning.

We compute this measure for every quarterly earnings announcement, except for the final fiscal quarter, as forecasts before and after the announcement pertain to different fiscal years. To align with our annual data frequency, we take the average of the three quarterly observations within each fiscal year. We also merge the most recent fiscal quarter's disagreement measure into the annual dataset and re-estimate the regression using quarterly data. The results remain qualitatively similar. We then replace the disagreement measure in the baseline regression with the revision-based disagreement, $DISA^{rev}_{it-1}$, and re-estimate the model.

Table 6 reports the results. The coefficients on the interaction term, $Q_{it-1} \times DISA^{rev}_{it-1}$, remain statistically significant at the 1% level across all specifications. In Column (3), which includes the full set of control variables, the coefficient is 0.475, indicating a 10.63% increase in investment–Q sensitivity as revision-based disagreement increases from its Q1 to Q3. In Column (5), we further restrict the sample based on analyst coverage. Because the construction of revision-based disagreement requires each stock–quarter observation to have analysts issuing both pre- and post-EA forecasts, the number of observations and average analyst coverage are lower. To ensure sufficient coverage, we limit the sample to stocks followed by at least five analysts. The interaction coefficient is 0.625, corresponding to a 13.91% increase in investment–Q sensitivity as revision disagreement increases from its Q1 to Q3. Notably, the economic impact is larger when disagreement reflects differential interpretation of the same information than when it stems from heterogeneous prior beliefs.

[Insert Table 6 around here]

In addition, we study how the impact of revision disagreement differs conditional on whether the public earnings news causes analyst views to converge or diverge. We partition our sample based on whether analyst disagreement declines from the pre- to post-earnings announcement period. Drawing on the theoretical work of Harris and Raviv (1993) and Kandel and Pearson (1995), a decline in overall dispersion post-announcement is consistent with Bayesian learning, where the public signal helps resolve uncertainty. In this convergent setting, the revision-based disagreement ($DISA^{rev}_{it-1}$) is primarily driven by the rational incorporation of analysts' diverse private information into their forecasts. This makes the revision signal a potent and fundamental source of new information for managerial learning (Goldstein & Yang, 2015). Conversely, when overall dispersion increases post-announcement, it suggests the news was ambiguous and amplified differential interpretations. In this divergent setting, the revision-based disagreement is more likely contaminated by behavioral biases, such as overconfidence in one's own model (Daniel et al., 1998) or selective attention to information that confirms prior beliefs (Pouget et al., 2017). Under this view, the revision signal offers managers a noisier and less reliable guide for investment. We therefore predict that the positive effect of $DISA^{rev}$ on investment-Q sensitivity will be significantly stronger in the subsample where the earnings announcement leads to a convergence of analyst views.

We report the result in Columns (5) and (6) in Table 6. First, we find earning announcement reduces analysts' disagreement about future earning in general. In our sample, disagreement declines in roughly 74% of cases. Second, in the subsample where post-EA disagreement is lower than pre-EA, the interaction coefficient $Q_{it-1} \times DISA^{rev}_{it-1}$ is 0.452 and statistically significant at less than 1% level. By contrast, in the subsample where post-EA disagreement is higher, the coefficient is much lower as 0.143 and insignificant. This finding aligns with our prediction that the managerial learning effect is stronger when disagreement reflects genuine informational diversity rather than behavioral biases.

Overall, this analysis leverages the earnings announcement setting to construct a more compelling test of the market feedback channel. The design offers two key advantages. First, it focuses on information generated externally by market participants in response to firm disclosure, and it temporally sequences the information flow from the firm to the market and back, which helps mitigate reverse causality concerns. Second, our findings, particularly the stronger effect when disagreement converges, are more consistent with managers learning from the market's rational information processing, thereby strengthening the evidence for a specific informational role.

4.3.2 Instrumental Variable Method / DiD Method based on Analyst Broker Merger and Closure

Two potential shocks: broker closure and EDGAR implementation

5 Alternative Explanation

In this section, we explore an alternative explanation that investor disagreement may simply capture valuation uncertainty (VU). Higher valuation uncertainty can lead to greater disagreement, and in some studies, measures such as sales volatility are directly used as proxies for disagreement (e.g., Berkman et al., 2009). It can be argued that such uncertainty heightens RPE by increasing managers' incentive to scrutinize market prices for learning, as the marginal benefit of external information is greatest when internal uncertainty is high (Edmans et al., 2017). This mechanism, however, suggests a heightened reliance on prices due to uncertainty, whereas our main argument is that managers learn from the specific informational content of disagreement itself.

We conduct two tests. First, we decompose disagreement into two components: a valuation-uncertainty-driven component ($\widehat{DISA}_{it-1}$) and an orthogonal component ($DISA^{\perp}_{it-1}$). In doing so, we argue that disagreement carries useful private information, while also acknowledging that it partially reflects valuation uncertainty. The coefficient for the interaction between orthogonal and Tobin's Q ($Q_{it-1} \times DISA^{\perp}_{it-1}$) is expected to be significantly positive, consistent with our baseline result. If enhanced RPE also work through the channel that managers rely more on stock price due to heightened uncertainty, we should expect the coefficient for the interaction ($Q_{it-1} \times \widehat{DISA}_{it-1}$) to be significantly positive. Second, we examine how investor disagreement affects managerial learning from peer firms' stock prices. Prior studies document that managers actively extract information from peers' stock prices, particularly when those prices are more informative than their own (Antoniou et al., 2023; Foucault & Fresard, 2014). In our setting, the two channels, valuation uncertainty and informational disagreement, yield distinct predictions. If disagreement merely captures valuation uncertainty, managers facing higher uncertainty should rely more heavily on any external information source, including peer firms' prices. In this case, we would expect the interaction between disagreement and peers' Q ($PeerQ_{it-1} \times DISA_{it-1}$) to be significantly positive, reflecting broader reliance on market signals. Conversely, if disagreement represents the market's heterogeneous interpretation of firm-specific information rather than general uncertainty, its effect should be concentrated on learning from the firm's own stock price, with little or no impact on learning from peers' prices.

5.1 VU-driven disagreement versus Informational Disagreement

For this first test, we consider two VU proxies, historical earning volatility and firm complexity. First, historical earnings provide a key basis for forecasting future performance. When a firm's past earnings are more volatile, its future earnings become harder to predict, leading investors to disagree more about the firm's fundamental value (Berkman et al., 2009). We measure earnings volatility ($EarnVol$) as the standard deviation of earning (Income before extraordinary items available for common) to total assets ratio over the past 5 fiscal years. We require a minimum of 3-year in calculation. Second, we use Loughran and McDonald (2024)'s firm complexity as a proxy for valuation uncertainty[5]. They show that firms with more complex 10-K filings exhibit higher stock return volatility and analyst forecast dispersion, indicating greater difficulty in valuation. Such informational complexity naturally leads investors to interpret the same disclosures differently, generating disagreement that reflects valuation uncertainty rather than heterogeneous private information.

Next, we estimate a panel regression of investor disagreement ($DISA_{it}$) on each valuation uncertainty proxy separately, controlling for firm and year fixed effects. From this regression, we obtain the predicted component of disagreement ($\widehat{DISA}_{it-1}$) and the orthogonal residual component ($DISA^{\perp}_{it-1}$). We then re-estimate the baseline model by including these two components both individually and jointly. The results are reported in Table 7, where Columns (1)–(3) correspond to earnings volatility and Columns (4)–(6) correspond to firm complexity. The key focus in Column (1) is the coefficient for the interaction term $Q_{it-1} \times \widehat{DISA}_{it-1}$, which captures the impact of earnings-volatility-driven disagreement on RPE. It is positive at 0.228 but statistically insignificant, indicating that disagreement arising purely from valuation uncertainty does not significantly enhance managerial learning. In contrast, the coefficient for the interaction term between residual disagreement and Q, $Q_{it-1} \times DISA^{\perp}_{it-1}$, is positive at 0.605 and highly significant, reinforcing that the informational component of disagreement is the main driver of our results. In Column (3), both components are included jointly, and the results remain consistent. Together, these findings suggest that the portion of disagreement unrelated to valuation uncertainty continues to exert a strong positive influence on investment–Q sensitivity, supporting our interpretation

[5] Loughran and McDonald (2024) make their dataset publicly available at https://sraf.nd.edu/complexity/.

that disagreement reflects valuable private information rather than general uncertainty.

[Insert Table 7 around here]

Similar results are observed when using firm complexity as an alternative proxy for valuation uncertainty (Columns 4–6). The informational component of disagreement remains robustly positive and significant, while the valuation-uncertainty-driven component shows no significant effect, further confirming that our findings are not driven by uncertainty-related disagreement.

5.2 Disagreement and Investment-to-Peer's Q sensitivity

Our second test investigates how investor disagreement affects managerial learning from peer's price. Our second test investigates how investor disagreement affects managerial learning from peers' prices, where peers are defined using both traditional and text-based industry classifications. Specifically, we employ the Standard Industrial Classification (SIC) 2-digit system and the Fixed Industry Classification developed by Hoberg and Phillips (2016). The FIC-100 clusters firms into 100 text-based industries based on the cosine similarity of their 10-K product descriptions, providing a more economically grounded measure of product-market relatedness than SIC[6]. Unlike the administratively assigned and infrequently updated SIC codes, FIC-100 captures evolving product similarities while maintaining fixed industry definitions derived from 1997 clusters. Our analysis based on firm-level FIC-100 ranges from 1996 to 2015 due to data availability. When aggregating peers' Q, we consider three alternatives: the simple average, the value-weighted average based on firm size, and the median.

Table 8 reports the results. Across all specifications, the coefficient on peers' Q ($PeerQ_{it-1}$) is significantly positive, indicating that firms tend to increase investment when their peers exhibit higher market valuations. This finding is consistent with the notion that managers learn from peers' prices and interpret them as informative signals about industry-wide prospects. However, the interaction term $PeerQ_{it-1} \times DISA_{it-1}$ is statistically insignificant across all models, suggesting that investor disagreement does not amplify managerial learning from peers' valuations. This evidence supports our interpretation that disagreement reflects the informational heterogeneity embedded in a firm's own stock price rather than general valuation uncertainty. If disagreement merely captured valuation uncertainty, we would expect a

[6]Our results remain robust when using alternative FIC groupings such as FIC-25, FIC-50, and FIC-200.

significantly positive coefficient on $PeerQ_{it-1} \times DISA_{it-1}$, as managers facing higher uncertainty would rely more heavily on any available external information, including peers' prices. Instead, the lack of such an effect indicates that disagreement primarily enhances learning from a firm's own price rather than from peer firms' prices. The results remain robust across alternative measures of peers' Q—simple average, value-weighted average, and median—as well as under both FIC-100 and SIC-based industry classifications.

[Insert Table 8 around here]

6 Conclusion

In this paper, we argue that investor disagreement contains useful external private information that is not known to firm managers and therefore can enhance revelatory price efficiency and managerial learning. We provide evidence consistent with this hypothesis. Specifically, investor disagreement is positively associated with higher investment to Q sensitivity. This effect is more pronounced for R&D investment, for growth firms, and for firms with lower financial constraints, which are settings where managerial learning is more likely to occur. We also provide causal evidence and rule out the alternative explanation that disagreement simply reflects valuation uncertainty.

Our findings highlight the real effects of disagreement in financial markets. The results suggest that disagreement should not be viewed solely as noise or mispricing, but as a mechanism through which dispersed private information is incorporated into prices and ultimately guides investment decisions. This has managerial implications for how firms monitor and respond to market signals, as well as regulatory implications for policies that influence information production and analyst coverage in capital markets.

While this study documents robust evidence on the positive role of disagreement in strengthening investment-to-Q sensitivity, future research could further disentangle the sources of heterogeneous beliefs, such as differences in information precision versus belief updating, to clarify the economic mechanisms behind the learning channel. In addition, examining how corporate governance, managerial characteristics, or disclosure policies interact with disagreement would provide a richer understanding of how market feedback influences real decisions.

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Tables

Table 1: Descriptive Statistics

This table reports summary statistics for main variables used in the analysis. The definition of variables are presented in Table A1. The main sample period is from 1996 to 2011. Due to data availability, the sample period for disagreement calculated from unadjusted detailed I/B/E/S analyst forecasts is from 1982 to 2024, and the sample period for Loughran and McDonald (2024) firm complexity is from 1995 to 2021. All variables are winsorized at the 2.5% level in each tail.

Variable	count	mean	median	std	min	p25	p75	max
$CAPXRNDA$	35,563	0.137	0.104	0.111	0.009	0.058	0.179	0.724
$CAPXA$	54,548	0.069	0.047	0.071	0.001	0.023	0.089	0.501
$RNDA$	35,794	0.074	0.035	0.095	0.000	0.007	0.107	0.558
Q	63,264	2.184	1.636	1.654	0.665	1.198	2.521	20.348
$DISA$	63,264	0.004	0.001	0.009	0.000	0.001	0.004	0.121
$ANALYST$	63,264	1.911	1.946	0.767	0.693	1.386	2.485	3.526
$SIZE$	63,264	6.653	6.543	1.745	2.768	5.335	7.838	11.508
CF	54,917	0.083	0.099	0.131	-0.748	0.050	0.150	0.372
RET	58,406	0.040	0.057	0.236	-0.789	-0.094	0.188	0.745
$INVASSET$	63,264	0.004	0.001	0.007	0.000	0.000	0.005	0.063
BM	63,261	0.524	0.437	0.372	0.021	0.253	0.702	2.823
FC	62,996	-0.690	-0.182	2.437	-19.289	-1.195	0.458	7.120
$EarnVol$	45,426	0.042	0.027	0.044	0.001	0.014	0.051	0.282
$Complexity$	37,756	0.421	0.396	0.162	0.097	0.300	0.519	0.894
$DISA^{rev}$	31,600	0.005	0.002	0.008	0.000	0.001	0.006	0.079
$DISA^{pr}$	31,600	0.006	0.002	0.009	0.000	0.001	0.006	0.078
$DISA^{ps}$	31,600	0.004	0.002	0.008	0.000	0.001	0.005	0.086
$ANALYST^{rev}$	31,600	1.280	1.099	0.616	0.693	0.693	1.609	3.689

Table 2: Baseline Regression: Investment-Q Sensitivity and Investor Disagreement

This table reports estimates from panel regressions of capital investment on Tobin's Q, investor disagreement, and their interaction. The investment variable in the baseline specification is the sum of capital expenditure and R&D expenses scaled by lagged total assets ($CAPXRNDA$). Columns (1)–(3) use the full sample, while Columns (4)–(5) restrict the sample to firms followed by more analysts. T-statistics, based on standard errors clustered at both the firm and fiscal year levels, are reported in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

	Full Sample			No. of Analyst ≥ 7	No. of Analyst ≥ 10
	(1)	(2)	(3)	(4)	(5)
Q_{it-1}	0.016***	0.020***	0.021***	0.022***	0.026***
	(12.31)	(9.72)	(10.50)	(6.11)	(4.48)
$DISA_{it-1}$	-1.202***	-0.843***	-0.856***	-0.809***	-1.010***
	(-4.61)	(-5.09)	(-5.44)	(-3.82)	(-3.75)
$Q_{it-1} \times DISA_{it-1}$	0.569***	0.264**	0.285**	0.310**	0.536***
	(3.00)	(2.29)	(2.64)	(2.16)	(2.70)
$ANALYST_{it-1}$			-0.001	0.000	0.003
			(-0.35)	(0.04)	(0.54)
$Q_{it-1} \times ANALYST_{it-1}$			0.003***	0.002	-0.001
			(3.79)	(1.36)	(-0.28)
$SIZE_{it-1}$		-0.037***	-0.036***	-0.031***	-0.029***
		(-15.99)	(-14.88)	(-10.61)	(-8.18)
$SIZE_{it-1} \times Q_{it-1}$		-0.001***	-0.003***	-0.002***	-0.002***
		(-4.14)	(-6.19)	(-4.82)	(-3.58)
CF_{it}		-0.019	-0.086***	-0.098*	-0.149
		(-1.66)	(-3.73)	(-1.83)	(-1.57)
$CF_{it} \times DISA_{it-1}$		-1.539**	-1.232*	-0.400	0.512
		(-2.41)	(-1.95)	(-0.37)	(0.37)
$CF_{it} \times ANALYST_{it-1}$			0.035***	0.048**	0.067*
			(3.19)	(2.20)	(1.88)
RET_{it+3}		-0.004	-0.003	-0.010*	-0.008
		(-0.93)	(-0.78)	(-1.97)	(-1.36)
$INVASSET_{it-1}$		1.496***	1.685***	3.263***	3.634**
		(3.82)	(4.29)	(3.03)	(2.50)
Fixed Effects	Firm, Year	Firm, Year	Firm, Year	Firm, Year	Firm, Year
N	34,545	34,544	34,544	19,304	13,500
adj.R^2	0.749	0.779	0.781	0.800	0.796

Table 3: Cross-sectional Analysis: CAPEX v.s. R&D

This table reports the estimates from the panel regression of capital investment on Tobin's Q, investor disagreement, and their interaction. The investment variable is capital expenditure scaled by lagged total assets ($CAPNXA$) in Column (1), and R&D expenses scaled by lagged total assets ($RNDA$) in Column (2). This analysis examines whether investor disagreement has a differential impact on physical versus intangible investment. T-statistics, based on standard errors clustered at both the firm and fiscal year levels, are reported in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Dependent Variable is	CAPEX	R&D
	(1)	(2)
Q_{it-1}	0.008***	0.014***
	(6.66)	(8.87)
$DISA_{it-1}$	-0.776***	-0.280***
	(-5.41)	(-3.12)
$Q_{it-1} \times DISA_{it-1}$	0.125*	0.210***
	(1.89)	(2.77)
$ANALYST_{it-1}$	0.000	-0.001
	(0.28)	(-0.37)
$Q_{it-1} \times ANALYST_{it-1}$	0.001	0.002***
	(1.19)	(3.36)
$SIZE_{it-1}$	-0.015***	-0.022***
	(-10.12)	(-12.81)
$SIZE_{it-1} \times Q_{it-1}$	-0.001***	-0.002***
	(-2.85)	(-5.76)
CF_{it}	0.072***	-0.131***
	(5.46)	(-6.61)
$CF_{it} \times DISA_{it-1}$	-1.018***	0.203
	(-2.82)	(0.49)
$CF_{it} \times ANALYST_{it-1}$	0.009	0.025***
	(1.58)	(3.08)
RET_{it+3}	-0.017***	0.013***
	(-6.37)	(4.91)
$INVASSET_{it-1}$	0.657***	0.740**
	(3.82)	(2.68)
Fixed Effects	Firm, Year	Firm, Year
N	53,049	34,774
adj.R^2	0.690	0.883

Table 4: Cross-sectional Analysis: Growth v.s. Value Firms

This table reports estimates from panel regressions examining whether the impact of investor disagreement on the investment-to-Q sensitivity differs between value and growth firms. Firms are classified into growth (Columns (1)–(3)) and value (Columns (4)–(6)) subsamples based on whether their book-to-market (BM) ratios are below or above the sample median, respectively, in each fiscal year. For each subsample, we estimate three regressions, where the dependent variable is $CAPXRNDA$, $CAPXA$, and $RNDA$, respectively. T-statistics, based on standard errors clustered at both the firm and fiscal year levels, are reported in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

	Growth Firms (BM lower than sample median)			Value Firms (BM higher than sample median)		
	$CAPXRNDA$	$CAPXA$	$RNDA$	$CAPXRNDA$	$CAPXA$	$RNDA$
	(1)	(2)	(3)	(4)	(5)	(6)
Q_{it-1}	0.019***	0.008***	0.012***	0.067***	0.035***	0.025***
	(9.41)	(6.77)	(8.76)	(4.56)	(3.68)	(3.03)
$DISA_{it-1}$	-1.295***	-1.238***	-0.483**	-0.192	-0.739**	0.245
	(-4.07)	(-5.66)	(-2.37)	(-0.60)	(-2.55)	(1.19)
$Q_{it-1} \times DISA_{it-1}$	0.353***	0.191**	0.239**	-0.103	0.352	-0.258
	(2.71)	(2.45)	(2.48)	(-0.32)	(1.47)	(-1.23)
$ANALYST_{it-1}$	0.001	0.001	0.001	-0.005	-0.002	-0.000
	(0.15)	(0.31)	(0.55)	(-1.09)	(-0.57)	(-0.09)
$Q_{it-1} \times ANALYST_{it-1}$	0.003***	0.001	0.002***	0.004	0.002	0.000
	(3.16)	(1.12)	(2.99)	(1.35)	(0.71)	(0.06)
$SIZE_{it-1}$	-0.040***	-0.014***	-0.028***	-0.019***	-0.010***	-0.012***
	(-11.55)	(-7.44)	(-11.47)	(-5.80)	(-4.47)	(-5.61)
$SIZE_{it-1} \times Q_{it-1}$	-0.002***	-0.001***	-0.002***	-0.008***	-0.003*	-0.003**
	(-5.62)	(-3.49)	(-5.16)	(-3.48)	(-1.75)	(-2.49)
CF_{it}	-0.104***	0.065***	-0.149***	-0.050	0.063***	-0.074***
	(-3.61)	(4.08)	(-6.56)	(-1.67)	(3.31)	(-2.90)
$CF_{it} \times DISA_{it-1}$	-1.359*	-1.195***	0.035	-1.874**	-0.511	-1.079**
	(-1.73)	(-2.73)	(0.05)	(-2.23)	(-0.98)	(-2.49)
$CF_{it} \times ANALYST_{it-1}$	0.031**	0.001	0.028***	0.048***	0.020**	0.026***
	(2.29)	(0.14)	(2.85)	(3.82)	(2.33)	(2.74)
RET_{it+3}	0.004	-0.013***	0.016***	-0.011**	-0.013***	0.002
	(0.68)	(-4.34)	(4.41)	(-2.65)	(-3.92)	(0.98)
$INVASSET_{it-1}$	1.721***	0.530**	0.799**	2.022**	0.792*	0.992*
	(3.99)	(2.67)	(2.59)	(2.59)	(1.69)	(1.79)
Fixed Effects	Firm, Year	Firm, Year	Firm, Year	Firm, Year	Firm, Year	Firm, Year
N	19,145	26,249	19,254	14,288	25,207	14,406
adj.R^2	0.783	0.717	0.875	0.766	0.708	0.909

Table 5: Cross-sectional Analysis: Less v.s. More Financial Constraints

This table reports estimates from panel regressions examining whether the impact of investor disagreement on investment-to-Q sensitivity differs between firms facing low versus high financial constraints. Financial constraints (FC) are defined following Edmans et al. (2017) as the difference between capital expenditure and cash flow, scaled by total capital expenditure. Firms are classified into more financially constrained (Columns (1)–(3)) and less financially constrained (Columns (4)–(6)) subsamples based on whether their FC values are below or above the sample median in each fiscal year, respectively. For each subsample, we estimate three regressions, where the dependent variable is $CAPXRNDA$, $CAPXA$, and $RNDA$, respectively. T-statistics, based on standard errors clustered at both the firm and fiscal year levels, are reported in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

	More Financial Constraints			Less Financial Constraints		
	$CAPXRNDA$	$CAPXA$	$RNDA$	$CAPXRNDA$	$CAPXA$	$RNDA$
	(1)	(2)	(3)	(4)	(5)	(6)
Q_{it-1}	0.015***	0.010***	0.003	0.018***	0.004**	0.013***
	(5.54)	(5.50)	(1.47)	(6.64)	(2.62)	(6.89)
$DISA_{it-1}$	-0.280	-0.537***	-0.053	-0.988***	-0.895***	-0.273***
	(-0.81)	(-2.69)	(-0.25)	(-5.82)	(-5.39)	(-3.12)
$Q_{it-1} \times DISA_{it-1}$	-0.029	0.026	-0.025	0.267**	0.108	0.186**
	(-0.11)	(0.16)	(-0.15)	(2.59)	(1.52)	(2.61)
$ANALYST_{it-1}$	-0.002	0.000	-0.001	0.007**	0.003*	0.004**
	(-0.76)	(0.26)	(-0.39)	(2.54)	(1.86)	(2.24)
$Q_{it-1} \times ANALYST_{it-1}$	0.003**	0.001*	0.002*	0.002*	-0.001	0.002**
	(2.63)	(1.75)	(1.73)	(1.97)	(-0.91)	(2.22)
$SIZE_{it-1}$	-0.016***	-0.009***	-0.008***	-0.052***	-0.022***	-0.034***
	(-7.69)	(-6.53)	(-6.53)	(-14.42)	(-9.20)	(-13.86)
$SIZE_{it-1} \times Q_{it-1}$	-0.002***	-0.001***	-0.000	-0.002***	0.000	-0.001***
	(-4.05)	(-3.99)	(-1.09)	(-2.93)	(0.72)	(-3.50)
CF_{it}	0.049	0.088***	-0.026	-0.059**	0.098***	-0.121***
	(1.57)	(4.52)	(-1.06)	(-2.15)	(5.52)	(-5.39)
$CF_{it} \times DISA_{it-1}$	-0.525	0.143	0.938	-1.886***	-1.608***	-0.121
	(-0.38)	(0.17)	(1.16)	(-3.03)	(-3.76)	(-0.28)
$CF_{it} \times ANALYST_{it-1}$	-0.001	0.009	-0.008	0.028**	-0.001	0.026**
	(-0.04)	(1.03)	(-0.63)	(2.04)	(-0.12)	(2.57)
RET_{it+3}	-0.012***	-0.012***	0.002	-0.002	-0.019***	0.013***
	(-3.60)	(-6.33)	(1.02)	(-0.42)	(-5.34)	(3.97)
$INVASSET_{it-1}$	0.285	0.094	0.076	1.597***	0.593**	0.715**
	(0.83)	(0.41)	(0.35)	(3.42)	(2.65)	(2.28)
Fixed Effects	Firm, Year	Firm, Year	Firm, Year	Firm, Year	Firm, Year	Firm, Year
N	14,623	26,304	14,741	18,982	25,149	19,056
adj.R^2	0.706	0.655	0.821	0.751	0.706	0.866

Table 6: Revision around Earning Announcement Dates

This table reports the estimates from the panel regression of capital investment on Tobin's Q, revision-based disagreement, and their interaction. The investment variable is $CAPXRNDA$. Columns (1)–(3) use the full sample with valid revision-based disagreement measures. Column (4) restricts the sample to firms followed by at least five analysts who provide both pre- and post-earnings-announcement EPS forecasts to construct the disagreement measure. Columns (5) and (6) further separate the sample based on whether analysts' forecast revisions converge or diverge around earnings announcements. T-statistics, based on standard errors clustered at both the firm and fiscal year levels, are reported in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

	Full Sample			No. of Analyst ≥ 5	Converge	Diverge
	(1)	(2)	(3)	(4)	(5)	(6)
Q_{it-1}	0.014***	0.021***	0.021***	0.024***	0.020***	0.020***
	(9.55)	(7.49)	(7.59)	(3.77)	(6.09)	(4.15)
$DISA^{rev}_{it-1}$	-1.574***	-1.145***	-1.100***	-1.431***	-1.083***	-0.713*
	(-5.92)	(-5.12)	(-4.93)	(-3.94)	(-3.99)	(-1.96)
$Q_{it-1} \times DISA^{rev}_{it-1}$	0.841***	0.485***	0.475***	0.625***	0.452***	0.143
	(5.51)	(4.03)	(3.94)	(2.92)	(2.98)	(0.61)
$ANALYST^{rev}_{it-1}$			-0.006***	0.004	-0.007***	-0.001
			(-3.62)	(0.86)	(-3.62)	(-0.17)
$Q_{it-1} \times ANALYST^{rev}_{it-1}$			0.001	-0.000	0.001	0.000
			(1.35)	(-0.06)	(1.05)	(0.30)
$SIZE_{it-1}$		-0.032***	-0.031***	-0.028***	-0.032***	-0.028***
		(-12.54)	(-12.20)	(-6.51)	(-11.03)	(-7.00)
$SIZE_{it-1} \times Q_{it-1}$		-0.002***	-0.002***	-0.002**	-0.001***	-0.002**
		(-4.10)	(-4.52)	(-2.66)	(-3.63)	(-2.29)
CF_{it}		0.001	-0.043**	0.104	-0.032	-0.072*
		(0.09)	(-2.64)	(1.31)	(-1.55)	(-1.83)
$CF_{it} \times DISA^{rev}_{it-1}$		-0.232	-0.423	-1.746	-1.230	-0.043
		(-0.33)	(-0.59)	(-0.81)	(-1.41)	(-0.03)
$CF_{it} \times ANALYST^{rev}_{it-1}$			0.037***	-0.021	0.040***	0.037
			(3.37)	(-0.50)	(3.91)	(1.44)
RET_{it+3}		-0.007	-0.007	-0.012**	-0.007	-0.011
		(-1.33)	(-1.36)	(-2.22)	(-1.25)	(-1.55)
$INVASSET_{it-1}$		2.486***	2.465***	3.772	2.999***	2.837**
		(3.17)	(3.16)	(1.32)	(3.46)	(2.46)
Fixed Effects	Firm, Year	Firm, Year	Firm, Year	Firm, Year	Firm, Year	Firm, Year
N	18,148	18,148	18,148	5,196	12,626	4,498
adj.R^2	0.762	0.789	0.790	0.796	0.794	0.776

Table 7: Addressing Valuation Uncertainty

This table reports the estimates from the panel regression examining the impacts of valuation uncertainty (VU)-driven disagreement and the residual disagreement on the investment-to-Q sensitivity. The investment variable is $CAPXRNDA$. $\widehat{DISA}it-1$ represents the component of disagreement driven by valuation uncertainty (VU), obtained from regressing investor disagreement on one of two VU proxies, earnings volatility (Columns (1)-(3)) or Loughran and McDonald (2024)'s firm complexity (Columns (4)-(6)). $DISA^{\perp}it-1$ is the corresponding residual disagreement component orthogonal to these proxies. T-statistics, based on standard errors clustered at both the firm and fiscal year levels, are reported in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

	VU Proxy is Earnings Volatility			VU Proxy is Firm Complexity		
	(1)	(2)	(3)	(4)	(5)	(6)
Q_{it-1}	0.022***	0.025***	0.022***	0.018***	0.020***	0.019***
	(7.26)	(8.08)	(7.39)	(6.16)	(8.23)	(6.65)
$\widehat{DISA}_{it-1}$	-4.233***		-4.063***	-11.330***		-11.258***
	(-4.81)		(-4.42)	(-3.00)		(-2.96)
$Q_{it-1}\times\widehat{DISA}_{it-1}$	0.228		0.433	0.129		0.326
	(0.92)		(1.40)	(0.47)		(1.13)
$DISA^{\perp}_{it-1}$		-1.135***	-1.086***		-2.130***	-2.164***
		(-4.57)	(-4.48)		(-6.22)	(-6.35)
$Q_{it-1}\times DISA^{\perp}_{it-1}$		0.605***	0.598***		0.730***	0.762***
		(3.98)	(3.61)		(4.48)	(4.64)
$ANALYST_{it-1}$	0.000	-0.000	-0.000	0.000	-0.001	-0.001
	(0.12)	(-0.12)	(-0.21)	(0.03)	(-0.37)	(-0.45)
$Q_{it-1}\times ANALYST_{it-1}$	0.002**	0.002**	0.002**	0.002**	0.002***	0.003***
	(2.02)	(2.24)	(2.28)	(2.35)	(2.88)	(2.91)
$SIZE_{it-1}$	-0.035***	-0.032***	-0.034***	-0.038***	-0.038***	-0.038***
	(-13.49)	(-12.95)	(-13.16)	(-12.62)	(-12.76)	(-12.50)
$SIZE_{it-1}\times Q_{it-1}$	-0.002***	-0.003***	-0.002***	-0.002***	-0.002***	-0.002***
	(-4.36)	(-4.98)	(-4.52)	(-2.96)	(-3.64)	(-3.38)
CF_{it}	-0.066**	-0.066***	-0.060**	-0.077**	-0.092***	-0.073**
	(-2.66)	(-2.88)	(-2.51)	(-2.19)	(-3.02)	(-2.10)
$CF_{it}\times\widehat{DISA}_{it-1}$	-0.052		-0.872	-4.081*		-3.904*
	(-0.03)		(-0.51)	(-1.81)		(-1.75)
$CF_{it}\times DISA^{\perp}_{it-1}$		-1.411	-1.465		0.086	-0.041
		(-1.36)	(-1.55)		(0.09)	(-0.04)
$CF_{it}\times ANALYST_{it-1}$	0.030**	0.030**	0.028**	0.024	0.023	0.021
	(2.49)	(2.56)	(2.41)	(1.64)	(1.64)	(1.48)
RET_{it+3}	-0.010**	-0.009**	-0.008**	-0.001	0.001	0.000
	(-2.46)	(-2.19)	(-2.16)	(-0.22)	(0.15)	(0.10)
$INVASSET_{it-1}$	1.404**	1.297**	1.239*	2.943***	2.799***	2.833***
	(2.23)	(2.14)	(2.01)	(6.25)	(5.88)	(6.19)
Fixed Effects	Firm, Year	Firm, Year	Firm, Year	Firm, Year	Firm, Year	Firm, Year
N	25,604	25,604	25,604	21,720	21,720	21,720
adj.R^2	0.790	0.790	0.791	0.809	0.810	0.810

Table 8: Response to Peer's Q

This table reports the estimates from the panel regression examining the impact of investor disagreement on the sensitivity of investment to peer's Q. The investment variable is $CAPXRNDA$. Firms are classified into the same industry using one of two industry classification schemes, Hoberg and Phillips (2016) text-based Industrial Code (Column (1)-(3)) or 2-digit Standard Industrial Code (SIC) (Column (4)-(6)). When aggregating peer Q, we consider three alternatives: the equally weighted mean, the value-weighted mean based on firm size, and the industry median. T-statistics, based on standard errors clustered at both the firm and fiscal year levels, are reported in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

	Hoberg and Phillips (2016) FIC-100 Industry			SIC 2-digit Industry		
	EW Average	VW Average	Median	EW Average	VW Average	Median
	(1)	(2)	(3)	(4)	(5)	(6)
$PeerQ_{it-1}$	0.027***	0.028***	0.033***	0.046***	0.049***	0.065***
	(5.06)	(4.70)	(3.12)	(7.36)	(7.23)	(6.68)
$DISA_{it-1}$	-1.561***	-1.601***	-1.294**	-0.366*	-0.349*	-0.247
	(-3.57)	(-3.70)	(-2.80)	(-1.85)	(-1.76)	(-1.12)
$PeerQ_{it-1} \times DISA_{it-1}$	0.037	0.055	-0.077	-0.148	-0.162	-0.248*
	(0.24)	(0.36)	(-0.37)	(-1.44)	(-1.52)	(-1.71)
$ANALYST_{it-1}$	-0.014***	-0.014***	-0.017***	-0.009**	-0.009**	-0.013***
	(-3.61)	(-3.74)	(-4.21)	(-2.38)	(-2.42)	(-3.31)
$PeerQ_{it-1} \times ANALYST_{it-1}$	0.008***	0.008***	0.011***	0.007***	0.007***	0.010***
	(4.98)	(5.10)	(5.38)	(4.49)	(4.48)	(5.29)
$SIZE_{it-1}$	-0.044***	-0.044***	-0.043***	-0.034***	-0.034***	-0.032***
	(-8.97)	(-8.99)	(-8.61)	(-10.30)	(-10.02)	(-9.30)
$SIZE_{it-1} \times PeerQ_{it-1}$	-0.006***	-0.006***	-0.007***	-0.007***	-0.008***	-0.010***
	(-6.30)	(-6.18)	(-4.80)	(-6.16)	(-6.12)	(-6.73)
CF_{it}	-0.084**	-0.084**	-0.086**	-0.073***	-0.074***	-0.074***
	(-2.19)	(-2.18)	(-2.25)	(-2.89)	(-2.91)	(-2.92)
$CF_{it} \times DISA_{it-1}$	-1.503	-1.479	-1.650	-1.906***	-1.940***	-2.014***
	(-1.05)	(-1.02)	(-1.19)	(-2.80)	(-2.84)	(-2.91)
$CF_{it} \times ANALYST_{it-1}$	0.040**	0.040**	0.041**	0.044***	0.044***	0.044***
	(2.38)	(2.37)	(2.45)	(3.85)	(3.86)	(3.90)
RET_{it+3}	-0.031***	-0.031***	-0.032***	-0.024***	-0.024***	-0.024***
	(-4.70)	(-4.71)	(-4.74)	(-5.45)	(-5.42)	(-5.33)
$INVASSET_{it-1}$	3.359***	3.337***	3.356***	2.456***	2.481***	2.453***
	(6.32)	(6.30)	(6.18)	(6.32)	(6.38)	(6.28)
Fixed Effects	Firm, Year	Firm, Year	Firm, Year	Firm, Year	Firm, Year	Firm, Year
N	17,289	17,289	17,289	34,509	34,509	34,509
adj.R^2	0.783	0.783	0.783	0.770	0.770	0.770

Appendix A: Variable Definition

Table A1: Variable Definition

Variable	Definition
$CAPXRNDA$	the sum of capital expenditure and research & development expenses, scaled by lagged total assets
$CAPXA$	capital expenditure scaled by lagged total assets
$RNDA$	research & development expenses scaled by lagged total assets
Q	Tobin's Q, the market value of equity plus the book value of total assets minus the book value of debt, scaled by total assets
$DISA$	investor disagreement, measured as the standard deviation of the analysts' EPS forecasts, scaled by stock prices
$ANALYST$	(the natural logarithm) of the number of analyst coverage
$SIZE$	firm size, the natural logarithm of the total assets
CF	cash flow, the sum of the net income before extraordinary items, and depreciation and amortization expenses, and R&D expenses, scaled by lagged total assets
RET	the value-weighted market adjusted three-year cumulative return, starting from the end of the investment year
$INVASSET$	the inverse of total assets
BM	Book-to-Market ratio, the ratio of the book value to market value of equity
FC	financial constraints, measured as the difference between capital expenditures and cash flows scaled by capital expenditures
$EarnVol$	earnings volatility, the standard deviation of earning (Income before extraordinary items available for common) to total assets ratio over the past 5 fiscal years
$Complexity$	Loughran and McDonald (2024)'s firm complexity measure, constructed using a list of words that reflects the complexity of firm's business
$DISA^{rev}$	revision-based disagreement, defined as the average quarterly standard deviation of analysts' forecast revisions around earnings announcements
$ANALYST^{rev}$	the natural logarithm of the number of analysts who provide both pre- and post-earning announcement EPS forecasts