The Signaling Role of Seemingly Myopic Investment Behavior

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Cyrus Aghamolla
University of Minnesota

Vivian Fang
Indiana University and ECGI

Renhui Fu
Shanghai Jiaotong University

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Abstract

This paper analytically and empirically investigates managerial investment responses to negative shocks in firm value. In the model, managers are privately informed about the shocks' persistence, and those facing transitory shocks strategically underinvest to boost earnings and signal financial strength to investors. The model also predicts counter-signaling: firms with strong fundamentals do not need to cut investment to convey strength. We exploit the 2003 mutual fund trading scandal as a plausibly exogenous source of price pressure. Consistent with signaling, we find that firms with greater tainted-fund ownership are more likely to meet or narrowly beat analyst forecasts by cutting R&D, and that this behavior is associated with more favorable earnings announcement returns and better long-run performance. Consistent with countersignaling, these firms are less likely to cut R&D when they beat analyst forecasts by a wide margin. Cross-sectional tests also support the model's comparative statics.

Keywords: Signaling; Investment; Mutual Fund Trading Scandal of 2003; Managerial

JEL Classification: G23; G31; G34; M41

Cyrus Aghamolla

University of Minnesota
Associate Professor
e-mail: caghamol@umn.edu

Vivian Fang

Indiana University and ECGI
Professor
Indiana University
e-mail: vfang@iu.edu

Renhui Fu

Shanghai Jiaotong University
Associate Professor
e-mail: renhuifu@sjtu.edu.cn

The Signaling Role of Seemingly Myopic Investment Behavior*

Cyrus Aghamolla† Vivian W. Fang‡ Renhui Fu§

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Abstract

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†Jones Graduate School of Business, Rice University. Email: cyrus.aghamolla@rice.edu.

‡Kelley School of Business, Indiana University. Email: vfang@iu.edu.

§Antai College of Economics & Management, Shanghai Jiao Tong University. Email: renhuifu@sjtu.edu.cn.

1 Introduction

Managerial myopia, or short-termism, has long been viewed as an important concern for U.S. companies. This concern dates back at least to Stein (1989), who models how short-term price pressure can induce managers to cut long-term investment, thereby reducing firm value. Anecdotal and survey evidence similarly suggest that pressure to meet quarterly earnings targets can discourage long-term investment. However, large-scale, well-identified evidence that such behavior leads to large reductions in firms' long-term value remains limited, leaving the debate over managerial myopia unsettled (Kaplan, 2018). This raises a natural question: can investment distortions sometimes reflect economically beneficial behavior?

In this paper, we formalize the possibility that managers take costly real actions to influence market beliefs when investors cannot perfectly distinguish transitory shocks from persistent deterioration in firms' future profitability or long-run asset values. We focus on cases in which a firm's stock price falls, but the manager privately knows that the decline reflects transitory mispricing rather than worsening fundamentals. How can the manager credibly convey the firm's financial health to the market? Direct communication may be ineffective because the relevant information often concerns growth prospects and other soft, hard-to-verify attributes. Yet mispricing events do arise in modern financial markets (Duffie (2010)), and even transitory mispricing can have real effects (Bond, Edmans, and Goldstein (2012)). When communication lacks credibility, managers may instead rely on indirect and costly channels to influence market beliefs, making real corporate actions an important component of price discovery.

Specifically, we examine investment cuts as a costly signal of private information following negative price shocks. Investment reductions distort real decisions but also boost reported earnings, allowing managers to influence investors' beliefs about whether the shock is transitory or persistent. To develop empirical hypotheses, we analyze a parsimonious two-period model where firms experience a negative price shock in the first period but the shock's implications for firm fundamentals are uncertain to the market. Firm fundamentals are characterized by pre-investment earnings, investment productivity (i.e., the marginal return on investment), and asset liquidation values. Managers privately observe how the shock affects these fundamentals. The model distinguishes firms by the degree of shock impact; although this impact is continuous, we refer to more transitorily affected firms as "*TS-firms*" and more permanently affected firms as "*PS-firms*" for ease of exposition. Because the market cannot perfectly infer the shock's impact on a given firm, managers can influence market beliefs through reported earnings, in part by adjusting real investment.

The model's central prediction is that *TS-firms* have greater incentives to underinvest relative to their no-signaling (second-best) optimum than *PS-firms*. Cutting investment, particularly research and development ("R&D"), boosts reported earnings and allows *TS-firms* to signal financial health, whereas such signaling is costly for *PS-firms* to mimic because their fundamentals are permanently impaired. Importantly, although *TS-firms*' post-signaling investment level is below their no-signaling optimum and thus reflects a loss of real efficiency, this behavior improves price efficiency: higher earnings generated through investment cuts convey information that allows the market to update beliefs about firm type, or more precisely, the degree of impact that the shock has on firm fundamentals. As such, this signaling behavior (or informative myopic behavior) differs from the non-informative myopic behavior in classic models like Stein (1989).

We test this prediction using the 2003 mutual fund trading scandal as a plausibly exogenous source of price pressure. Beginning in September 2003, U.S. regulators, including the New York Attorney General and the U.S. Securities and Exchange Commission ("SEC"), launched investigations into a number of mutual fund families for illegal trading practices. Public disclosure of these investigations triggered sharp investor withdrawals from implicated funds, generating economically meaningful selling pressure on their portfolio firms (Choi and Zhao (2007), Kisin (2011), Potter (2012)). Importantly, the investigations targeted practices such as late trading, market timing, and front-running that advantage certain investors but are unrelated to portfolio firms' performance. Therefore, the outflow-induced price pressure is unlikely to reflect changes in the affected firms' fundamentals.[1]

In the quarters following the initial revelation of the scandal (2003Q3), firms with shares held by funds from implicated families ("tainted funds") can experience price declines, but the nature of these declines is uncertain to the market. This is because firms may simultaneously experience fundamental news, fund managers retain discretion over which holdings to liquidate (Berger (2023)), and changes in fund holdings are often disclosed with a delay, heightening information asymmetry (Huang, Ringgenberg, and Zhang (2023)). Although the shock does not perfectly classify firms as *TS-firms* or *PS-firms* (consistent with our model), it generates variation in the likelihood that a negatively shocked firm is a *TS-firm* rather than a *PS-firm*, conditional on the firm's exposure to tainted funds. We therefore use a firm's tainted-fund ownership as a proxy for the firm's exposure to transitory price pressure as opposed to a permanent shock to fundamentals. Specifically, we construct two measures: (i) the percentage of a firm's shares held by tainted funds in a post-scandal quarter; and (ii)

[1] Late trading allows favored investors to buy or sell fund shares after market close at that day's closing price, which is illegal because it exploits information revealed after the close. Market timing occurs when a fund permits selected clients to trade more frequently than disclosed, enabling them to profit from short-term price movements. Front-running occurs when a fund tips selected clients about impending large trades, allowing them to trade ahead of the fund.

an indicator equal to one if this ownership weakly exceeds the median among exposed firms. We use both measures to instrument for transitory price pressure.

Consistent with the model's central prediction, over the six-year sample period from 2000Q3 to 2006Q3 (centered on the scandal's initial revelation in 2003Q3), firms with greater exposure to tainted mutual funds are significantly more likely to meet or narrowly beat analyst consensus earnings-per-share ("EPS") forecasts by cutting R&D. In reduced-form specifications, a one-standard deviation increase in tainted-fund ownership is associated with a 16.4 percentage point higher likelihood of meeting or narrowly beating earnings targets through R&D cuts, about one and a half times the sample mean of 11.2 percentage points. Moving from below- to at-or-above-median tainted-fund ownership (with median calculated among exposed firms) is associated with a 24.9 percentage point higher likelihood, more than doubling the sample mean. These effects, obtained after including an extensive set of controls and both firm and year-quarter fixed effects, are economically sizeable. Moreover, the two-stage least squares (2SLS) analyses reinforce the reduced form findings: tainted-fund ownership strongly predicts price decline in the first stage, and the fitted price decline significantly increases the likelihood of meeting or narrowly beating earnings targets through R&D cuts in the second stage.

We conduct three additional analyses to show robustness. First, probit models yield qualitatively similar results, indicating that our findings are not driven by the linear specification in the reduced form analyses. Second, restricting the sample to firm-quarters with reported EPS narrowly around the analyst consensus EPS forecasts (within 1-, 2-, and 3-cent bandwidths in either direction) confirms that the results persist in the subsample where earnings management incentives are strongest. Third, we find no evidence that tainted-fund ownership is positively associated with accrual-based earnings management. This finding is consistent with prior evidence that real manipulation dominates accounting discretion in the post-Sarbanes-Oxley Act era, where most of our sample lies (Cohen, Dey, and Lys (2008)).

An implication of our model's central prediction is that *TS-firms* can cut R&D to boost reported earnings and signal financial health when they cannot otherwise credibly convey their type. Instead, firms with sufficiently strong fundamentals can forgo investment distortions and rely primarily on pre-investment earnings to convey their private information, akin to *counter-signaling* (e.g., Aghamolla, Corona, and Zheng (2021)). Consistent with this implication, we find that, for firms with at-or-above-median tainted-fund ownership, R&D cuts are positively associated with meeting or narrowly beating earnings targets, but not with beating forecasts by a wide margin (i.e., greater than three cents).

When *TS-firms* cannot otherwise convey their type, signaling through investment cuts becomes valuable despite inducing a real efficiency loss relative to the no-signaling optimum.

We conduct two analyses to assess its value. First, we examine the three-day earnings announcement returns and show that firms that meet or narrowly beat analyst earnings targets through R&D cuts experience significantly more favorable announcement returns, after controlling for earnings surprises, but only among firms with at-or-above-median tainted-fund ownership when transitory price pressure is more likely. Second, we analyze long-run performance and find that firms with at-or-above-median tainted-fund ownership that meet or narrowly beat earnings targets through R&D cuts exhibit higher abnormal buy-and-hold returns over the next twelve quarters than matched benchmark firms that are more likely to represent *PS-firms*. Together, these findings indicate that signaling through R&D cuts adds value by conveying information about firm fundamentals under transitory price shocks.

We conduct two additional analyses to distinguish between informative signaling and non-informative myopic investment behavior. First, we address the concern that our results are confounded by the SEC's 2004 mutual fund disclosure regulation, which increased portfolio reporting frequency from semiannual to quarterly and has been shown to induce myopic investment behavior (Agarwal, Vashishtha, and Venkatachalam (2018)). We show that our main results are robust to using a truncated sample that ends before the regulation could take effect. Despite a substantially smaller sample, the results remain qualitatively similar: trading scandal-induced negative price pressure continues to increase firms' propensity to meet or narrowly beat earnings targets through R&D cuts, and the market responds favorably to this behavior only among firms with higher tainted-fund ownership, consistent with an informative signaling interpretation rather than a pure myopia interpretation.

Second, we test a model prediction on the dual role of managers' short-term price concerns: they not only induce non-informative myopic investment cuts but also amplify incentives to engage in informative signaling when firms face transitory price pressure. We construct a measure of myopia based on ownership by funds forced into more frequent reporting under the 2004 disclosure regulation, and find a positive relation between this measure and the likelihood of meeting or narrowly beating earnings targets through R&D cuts. Moreover, the interaction between this measure and tainted-fund ownership is significantly positive, indicating that short-term price concerns magnify firms' incentives to signal when transitory price pressure is present. These findings suggest that myopia does not substitute for signaling but does amplify the use of investment cuts as an informative signal of financial health under transitory price shocks.

Finally, we test three comparative statics from the model and find that the relation between tainted-fund ownership and signaling through R&D cuts varies with investment productivity, earnings informativeness, and uncertainty about firm fundamentals, as predicted. First, consistent with the prediction that signaling incentives are stronger for firms with higher investment productivity, the relation is more pronounced among firms with higher market-to-book ratios. Second, consistent with the prediction that signaling is less valuable with more uncertain earnings (because the market places less weight on reported earnings), the relation is attenuated when uncertainty about pre-investment earnings is higher, with uncertainty proxied by the analyst forecast dispersion before earnings announcements. Finally, consistent with the prediction that signaling is more valuable with greater uncertainty about firm type, the relation is stronger among firms with greater uncertainty about investment productivity, with uncertainty proxied by the standard deviation of the market-to-book ratios over the past eight quarters.

This study adds to the long-standing literature on corporate myopia. Theories in this literature primarily focus on myopia-induced losses in real efficiency and firm value, such as Narayanan (1985), Stein (1989), Bebchuk and Stole (1993), Bizjak, Brickley, and Coles (1993), Fischer and Verrecchia (2000), Kirschenheiter and Melumad (2002), Fischer and Stocken (2004), Guttman, Kadan, and Kandel (2006), and Caskey, Nagar, and Petacchi (2010), among others. Our study highlights that, in the presence of transitory price shocks, real distortion can serve as a credible signaling device about firm financial health; although such signaling still induces underinvestment and lowers real efficiency, it can generate information efficiency gains through market belief updating about long-term value.

Empirically, several studies exploit novel settings to obtain plausibly exogenous variation in myopia and show that myopia leads to underinvestment (e.g., Edmans, Fang, and Lewellen (2017), Agarwal et al. (2018), Kraft, Vashishtha, and Venkatachalam (2018), Ladika and Sautner (2020)). Studies on the value implications of myopia, however, remain limited. Edmans, Fang, and Huang (2022) document long-run value losses from investment distortions driven by managers' short-term price concerns, although the estimated losses are economically modest. Giannetti and Yu (2021) identify settings in which short-horizon investors facilitate efficient real adjustment. Our findings show that, when firms face transitory negative price shocks, cutting R&D to boost reported earnings elicits favorable earnings announcement reactions and improves long-run price performance.

Our study also relates to a long-standing literature on firms' use of signaling tools to convey private information. For example, prior studies examine signaling through investment timing (Bobtcheff and Levy (2017)), privately financed R&D (Lichtenberg (1986)), payout policy (e.g., Ham, Kaplan, and Leary (2020), Michaely, Rossi, and Weber (2021), Kaplan and Pérez-Cavazos (2022)), and dynamic financing choices such as leverage and repayment (Ordoñez, Perez-Reyna, and Yogo (2019)). Our paper studies a different real-action signal: cutting R&D to meet or narrowly beat earnings expectations following transitory shocks. Unlike the signaling tools studied previously, this action is typically viewed as real earnings management (e.g., Roychowdhury (2006), Cohen et al. (2008), Cohen and Zarowin (2010), Zang (2012), Huang, Roychowdhury, and Sletten (2020)). We show that it can sometimes convey information about firm fundamentals, improving information efficiency.

Finally, the paper speaks to the broader disclosure literature. We highlight two streams that are particularly relevant. The first stream examines investment decisions in the presence of disclosure and information frictions (e.g., Kanodia and Lee (1998), Lambert, Leuz, and Verrecchia (2007), Beyer and Guttman (2012), Kumar, Langberg, and Sivaramakrishnan (2012), Edmans, Heinle, and Huang (2016), Guttman and Meng (2021), Aghamolla and Hashimoto (2023)). Our study departs from these theories by modeling two-dimensional private information in the investment decision, which allows us to examine the interaction between pre-investment earnings, productivity, and investment.

The second stream examines signaling and managerial communication of firm prospects. Acharya and Lambrecht (2015) study persistence in payout policies in a dynamic investment model in which a manager makes unobservable investment and observable payout decisions each period. They show that, in the steady state, noise in observable information mitigates underinvestment and induces persistence in payouts over time. While managers costlessly shift resources across periods in their model, earnings management in our model requires costly reductions in investment. As a result, our model generates novel equilibrium properties, including an investment bias that decreases in pre-investment earnings and increases in uncertainty about firm type. Separately, Cianciaruso and Sridhar (2018) and Heinle, Kim, Taylor, and Zhou (2025) examine managerial signaling of firms' long-term prospects to investors. Our study differs from them in that our signaling mechanism operates through (unobservable) investment decisions, whereas theirs operates through disclosure choices. Moreover, our setting features an additional signal, pre-investment earnings, that is correlated with long-term information but is observed with noise in the first-period earnings release; we show that this additional information affects signaling incentives.[2]

2 Conceptual framework and hypotheses

This section outlines a parsimonious theoretical framework for the purpose of developing empirical hypotheses, building on Acharya and Lambrecht (2015) and Aghamolla and

[2]Our paper is also related to the counter-signaling literature (e.g., Feltovich, Harbaugh, and To (2002), Aghamolla et al. (2021)). As in these settings, high-type senders can rely on additional information rather than costly signaling. A key difference is that in our setting the additional information about type (pre-investment earnings) is observed by the manager ex ante, whereas in prior studies the additional signal is observed ex post. We therefore establish properties akin to counter-signaling in a setting with two-dimensional private information.

Hashimoto (2023).[3] We consider a two period model, $t = \{1, 2\}$, with a firm manager and a rational market. At the beginning of $t = 1$, a publicly observable downward shock negatively impacts underlying firm fundamentals such that the liquidation value of assets in that period is equal to δ_0. The manager privately observes the firm's true, long-term impact from the shock—such as the shock's permanence on firm fundamentals—and the liquidation value of assets reverts to $\Delta(\beta) = \delta_0 + \delta_1\beta$ by the end of the second period, where $\delta_1 > 0$ is constant and commonly known, and the continuous distribution of β is provided below. The parameter β captures the privately observed impact from the shock: a firm more affected by the shock has a lower β and a final liquidation value of assets closer to δ_0, whereas a less affected firm has a higher β and a larger reversion in asset liquidation value.[4] Again, we refer to higher-β firms as *TS-firms* and lower-β ones as *PS-firms*.

The firm announces earnings in each period. The parameter a denotes the first-period earnings, which is composed of the firm's privately observed pre-investment earnings realization, e, less the cost of investment, k (and a stochastic component discussed below). A *PS-firm* has a lower expected pre-investment earnings as well as a lower marginal return on investment than a *TS-firm*. Specifically, for a firm of type β, the net investment return function is given as:

$$R\left(k\right) = \left(2\beta k\right)^{1/2} - k,$$

where $r_\beta(k) = \left(2\beta k\right)^{1/2}$ is the gross investment return and k is the privately-observed level of investment chosen by the manager.[5] We assume that β is distributed on a truncated normal distribution with support $(0, \infty)$ with mean denoted m_β and variance $v_\beta > 0$. Moreover, we assume that investment must be nonnegative, $k \geq 0$. The manager chooses the investment

[3] Aghamolla and Hashimoto (2023) examine investment through an earnings release in the presence of a guidance decision and characterize manipulations in investment and in the management forecast issued. While our study does not consider earnings guidance, we build upon the framework of Aghamolla and Hashimoto (2023), particularly on the role of investment in the earnings report. In addition to the primary difference of studying permanent versus transitory shocks, our model differs from theirs in that ours allows pre-investment earnings to be increasing in firm type (along with the investment return), which leads to two-dimensional private information determining the investment decision. The presence of multi-dimensional private information critically affects the results and leads to several interesting equilibrium properties.

[4] In Online Appendix B (located in the supplemental materials of this paper), we develop a microfoundation of market uncertainty regarding transitory or permanent shocks in firm share price. Specifically, we augment the Kyle (1985) model to incorporate two types of the single large trader—one as an informed type that trades based on private information and the other a liquidity-needs type that submits an order purely based on an exogenous, stochastic liquidity need. Upon seeing aggregate sell orders, the market is uncertain as to the type of trader driving the trade and prices accordingly. We show that sell orders by the liquidity-need type drive prices downward in expectation.

[5] This return function is adopted from Acharya and Lambrecht (2015). They assume that the inverse marginal cost from investment is private information and the investment return function has the following form:

$$R\left(x\right) = x - \frac{x^2}{2\beta}.$$

level k after observing β and e.

The distribution of the privately-observed pre-investment earnings satisfies the monotone likelihood ratio property (MLRP), which implies that the mean pre-investment earnings realization is higher for firms less impacted by the shock. Specifically, we assume that, for a firm of type β, pre-investment earnings e are normally distributed with mean $\mu_e + \rho\beta$, where $\rho > 0$ and variance $\sigma_e^2 > 0$. After privately observing e and choosing k, the firm manager announces first-period earnings as

$$a = e - k + \varepsilon,$$

where ε is normally distributed with mean zero and variance σ_ε^2 and is independent of pre-investment earnings e and productivity β. Investors only observe the aggregate announcement a and do not observe the individual components of a. The parameter ε captures additional economic events for the firm that impact earnings or cash flows between the time that the manager makes the investment decision to the time that earnings are announced (or when the fiscal quarter ends).[6] The market pricing in the first period is thus

$$P_1 = a + \mathbb{E}\left(r_\beta(k)|a\right) + \mathbb{E}\left(\Delta(\beta)|a\right).$$

At the beginning of the second period, the first-period earnings a are distributed as dividends. Moreover, the gross investment return, $r_\beta(k) = (2\beta k)^{1/2}$, is realized and becomes common knowledge (i.e., announced to investors) in the second period. Finally, the firm is liquidated at the end of the second period, so that the second-period pricing is simply the investment realization and the firm's liquidation value, $P_2 = r_\beta(k) + \Delta(\beta)$.[7]

The manager's utility is given by

$$u_m = \alpha P_1 + (1-\alpha)P_2, \tag{1}$$

where $\alpha \in (0,1)$ represents the manager's degree of myopia. To summarize, the sequence of events in the first period is as follows:

We can convert this to k, by setting $k = \frac{x^2}{2\beta_i}$, then $x = (2\beta k)^{1/2}$, so this becomes:

$$R(k) = (2\beta k)^{1/2} - k.$$

[6]The additional term ε in the earnings announcement simplifies the analysis by ruling out pathological equilibria based on out-of-equilibrium earnings announcements. The results are qualitatively unchanged if we instead interpret ε to be reporting noise rather than relevant to cash flows. The results are preserved in the limit as $\sigma_\varepsilon^2 \to 0$, so that the error in announcements can be made vanishingly small.

[7]This standard assumption keeps the model parsimonious. The results are unchanged if we allow the liquidation value in the second-period price to be privately known, such that $P_2 = r_\beta(k) + \mathbb{E}[\Delta(\beta)|a, r]$.

Stage 1: A shock to the firm arrives. The manager privately observes the shock's impact on the firm's liquidation value of assets and investment productivity, captured by β.

Stage 2: The manager observes pre-investment earnings or cash flows e.

Stage 3: The manager makes a privately-observed investment decision $k \geq 0$.

Stage 4: Earnings are announced and the market prices the firm.

In the second period, the firm distributes first-period earnings a as dividends. The investment return is realized and announced as earnings. The firm is liquidated and the manager's payoff is realized. The equilibrium concept we employ is perfect Bayesian equilibrium, and we consider equilibrium in pure strategies. Appendix A details the main results of the model and we synthesize the empirical implications below.

The first empirical implication relates to the incentives for investment distortion. Specifically, firms cut investment k to boost reported earnings a and upwardly influence market beliefs in the first period. Moreover, *TS-firms* have greater incentives to underinvest than *PS-firms* (relative to the investment they would implement without signaling concerns). The reason for this is two-fold. First, the distribution of pre-investment earnings has the monotone likelihood ratio property in β, implying higher earnings for *TS-firms*. Consequently, a higher pre-investment earnings e implies a higher announcement a, thus driving firms to upwardly bias a by underinvesting to influence beliefs about β. Second, given that *TS-firms* have greater returns on their investment than *PS-firms*, underinvestment is less severely damaging for *TS-firms*. This is natural as underinvestment by *TS-firms* is less damaging than underinvestment by firms whose underlying fundamentals have been compromised.[8]

Prediction 1. *Impacted firms use investment reductions to boost their reported earnings. Firms that are less affected (i.e., TS-firms) have greater incentives to underinvest relative to their no-signaling optimal investment than those more affected (i.e., PS-firms).*

Our subsequent implications are based on equilibrium properties and give rise to several cross-sectional empirical hypotheses. As noted above, the distribution of pre-investment earnings e has MLRP in productivity β. Given the two-dimensional nature of private information (productivity and pre-investment earnings), firms that observe large pre-investment earnings can rely less on investment reductions to convey their private information to the market. As such, we should observe a lower incentive to cut investment by impacted firms

[8] For example, consider a situation where a *PS-firm* faces shrinking demand for its products, thus leading to lower expected future cash flows. Since it is a critical time for the firm to spend on R&D and other expenditures to make product improvements, cutting investment in the present quarter to meet an earnings target is extremely costly and may perpetuate the declining performance. In comparison, cutting R&D and other investment for a *TS-firm* is not as costly, as doing so would not reverberate strongly in future periods. For technical details, see Appendix A.

that have high pre-investment earnings.

Prediction 2. *Firms that observe higher pre-investment earnings have lower incentives to reduce investment to boost the reported earnings.*

Recall that the manager places weight α on the first-period price. Our analysis implies that managers who are more concerned with short-term prices have greater incentives to reduce investment. A larger weight on short-term prices amplifies the signaling incentive and thus leads to a greater propensity to underinvest.

Prediction 3. *Managers that care more about short-term prices have greater incentives to underinvest relative to their no-signaling optimum.*

Our next two predictions relate to cross-sectional properties of information, including the variance of pre-investment earnings and the variance of productivity. As the variance of pre-investment earnings increases, the earnings announcement becomes less informative regarding the firm's type (i.e., the nature of the impact from the shock). As a result, the market places lower weight on the announcement when forming beliefs and hence investment reductions are less valuable to the manager in conveying information. As such, the manager's incentive to underinvest is attenuated.

Prediction 4. *The manager's incentive to underinvest is lower when there is greater variance in pre-investment earnings.*

Conversely, when there is greater uncertainty about the firm's impact from the shock, the market places greater weight on the earnings announcement. In contrast to the above, higher variance of productivity β thus intensifies the manager's incentive to underinvest, as signaling becomes more valuable to the manager.

Prediction 5. *The manager's incentive to underinvest is higher when there is greater variance in productivity.*

Predictions 4 and 5 above illustrate the disparate effects of sources of information asymmetry on incentives. Greater variance in the observable signal mitigates the incentive for underinvestment, while greater variance in the underlying fundamental heightens the incentive for underinvestment.[9]

[9] We note that Predictions 4 and 5 can arise in "signal-jamming" models, such as Stein (1989), where the manager possesses no private information about long-term value beyond the earnings signal. This occurs because greater reliance on reported earnings generally strengthens incentives to manipulate those earnings. In contrast, Predictions 1 and 2 do not emerge in canonical signal-jamming models because they rely on managers possessing additional private information about the nature of the shock.

3 Data and variable measurement

In this section, we discuss the main variables used in this study. Detailed definitions of all variables are in Appendix C.

3.1 *Measuring negative price pressure*

We exploit the 2003 mutual fund trading scandal to capture the likelihood that a firm is a *TS-firm* (i.e., less impacted by a negative price shock), conditional on an observed price decline, as in our model. The scandal first surfaced on September 3, 2003, when New York Attorney General Eliot Spitzer announced that his office had filed a complaint against Canary Capital Partners LLC, alleging that the hedge fund engaged in "late trading" in collusion with Bank of America's Nations Funds. Following this announcement, the SEC launched its own investigation. Subsequent investigations by Spitzer and the SEC uncovered widespread illegal trading practices, including "late trading," "market timing," and "front running," across multiple mutual fund families. Initial public disclosures occurred at different times across fund companies, spanning from September 2003 to October 2004. In total, 25 mutual fund families were implicated in the scandal (see Houge and Wellman (2005, p. 134)), and nearly all settled with regulators between 2004 and 2006.

The scandal triggered large and persistent investor withdrawals from implicated fund families. Kisin (2011) estimates that tainted fund families lost, on average, 14.1% and 24.3% of assets under management over the one- and two-year periods following September 2003, respectively. Similarly, Choi and Zhao (2007) document net redemptions approaching 20% of pre-scandal assets within one year, and Potter (2012) shows that funds for which investigations were disclosed before the end of 2003 experienced average monthly flow declines of approximately 1.4% between September 2003 and September 2005. Because mutual funds primarily meet redemptions through asset sales, these outflows mechanically translate into negative price pressure on the portfolio firms they hold.

Importantly, the resulting selling pressure is unlikely to reflect changes in the fundamentals or management of the portfolio firms held by tainted funds. The allegations concerned illegal trading practices at the fund-family level rather than poor fund performance or adverse developments at the portfolio firms themselves, and these practices were largely unknown to, and unexpected by, firm management prior to regulatory inquiries. We therefore follow Kisin (2011) and Anton and Polk (2014) in treating the scandal as a plausibly exogenous shock to fund outflows and the associated price pressure faced by portfolio firms.[10]

[10] Our model does not require the initial shock to originate from firm fundamentals. Rather, it only requires a negative public shock whose firm-specific impact is not directly observed by the market. Our setting aligns

To operationalize this setting, we identify 4,408 U.S. domestic equity mutual funds belonging to the 25 implicated fund families using the Thomson Reuters Mutual Fund Holdings Database. We collect quarterly portfolio holdings for these tainted funds as well as for other U.S. domestic equity mutual funds belonging to non-implicated families, and we merge the holdings data with CRSP, Compustat, and I/B/E/S. This merged dataset allows us to measure firm-level exposure to selling pressure induced by redemptions at tainted funds while retaining the full universe of publicly traded firms.

Using this merged sample, we construct two measures of negative price pressure. The first measure, $Tainted\ Fund\%_{i,q}$, aggregates firm i's ownership held by tainted funds (expressed as a percentage of shares outstanding) in a post-scandal quarter q; we set this variable to zero for pre-scandal quarters. In our sample, the average $Tainted\ Fund\%_{i,q}$ corresponds to 5.21 times daily trading volume and 7.31 times the standard deviation of daily trading volume, suggesting that forced sales by tainted funds are economically meaningful and capable of causing price declines. The second measure, $High\ Tainted\ Fund\%_{i,q}$, is an indicator equal to one if firm i's tainted-fund ownership in a post-scandal quarter q is equal to or above the median among firms with positive $Tainted\ Fund\%_{i,q}$, and zero otherwise; we similarly set this variable to zero for pre-scandal quarters.

For our baseline tests, we conduct reduced form analyses using both $Tainted\ Fund\%_{i,q}$ and $High\ Tainted\ Fund\%_{i,q}$ as instruments for the transitory negative price shocks modeled in our framework. Because price declines may occur for many reasons, these measures help isolate exogenous variation in negative price pressure driven by redemption-induced selling. At the same time, they plausibly satisfy the exclusion restriction because outflows at tainted funds generate price pressure but are unlikely to affect firm investment through other channels. Our 2SLS analyses indicate that both instruments are relevant predictors of price declines but $High\ Tainted\ Fund\%_{i,q}$ appears to be a stronger instrument. We therefore focus on $High\ Tainted\ Fund\%_{i,q}$ in subsequent analyses.

It is noteworthy that, conditional on an observed price decline, these measures plausibly capture the likelihood that a firm is a *TS-firm*, rather than a *PS-firm*, but they cannot perfectly separate firm types. Even if fire sale–induced price pressure from tainted funds is ultimately transitory, the market may not be able to ascertain this because firms could simultaneously experience fundamental news. Uncertainty may also rise because funds re-

with the model because investors observe a price decline but cannot perfectly determine whether it reflects temporary liquidity-driven selling or persistent deterioration in future payoffs. Tainted-fund ownership helps capture variation in the likelihood that the price decline reflects a transitory rather than permanent impact from the shock, consistent with the *TS-* versus *PS-firm* distinction in the model. Moreover, in Online Appendix B, we provide a microfoundation for how potential shocks to firm fundamentals can be reflected in share prices, where uninformed investors are uncertain as to whether price declines are due to deterioration in fundamentals or due to liquidity-driven sales.

tain discretion over which assets to liquidate when facing redemptions (Berger (2023)) and because fund positions are often disclosed only after trading has occurred (Huang et al. (2023)).

Finally, although fire sale-induced selling pressure is commonly used as a source of plausibly exogenous price pressure (e.g., Edmans, Goldstein, and Jiang (2012), Lou and Wang (2018)), Berger (2023) shows that the proportional trading assumption may misattribute large price impacts to poorly performing, illiquid, low-growth firms, i.e., those that fund managers would avoid selling. If such bias were present in our setting, it would predict larger investment cuts among poorly performing firms, since they would be disproportionately assigned greater outflows. However, our model predictions and empirical results indicate that firms with stronger fundamentals (*TS-firms*) are more likely to cut R&D to meet earnings targets following flow-induced selling pressure. Thus, any selection bias of the type identified by Berger (2023) would work against, not in favor of, our results.

3.2 *Measuring signaling through R&D cuts*

To capture the signaling mechanism in our model, we define an indicator, $MBE\_CutR\&D_{i,q}$, that equals one if firm i both (i) meets or beats the latest analyst mean consensus EPS forecast prior to its earnings announcement for quarter q by up to one cent and (ii) cuts R&D expenditure relative to $q-1$, and zero otherwise. We focus on R&D expenditures because they are mostly expensed under U.S. GAAP and thus cutting R&D should have an immediate and direct effect on reported earnings. At the same time, reported R&D is an imperfect proxy for investment spending, because R&D expenditures may be aggregated into broader operating expense categories (such as SG&A), and therefore are not separately revealed (Koh and Reeb (2015), Iqbal, Rajgopal, Srivastava, and Zhao (2025)). This is consistent with our model, where investment reduces reported earnings but is not separately observable. Thus, our measure is a noisy proxy for investment that is likely positively correlated with, but not identical to, the underlying investment choice in the model.[11]

The meet-or-narrowly-beat measure is widely used to capture managers' incentives to meet market expectations and influence market beliefs (e.g., Bhojraj, Hribar, Picconi, and McInnis (2009), Fang, Huang, and Karpoff (2016)). The discontinuity in the distribution of earnings surprises—reported EPS minus the analyst consensus forecast—offers compelling evidence of managers' deliberate efforts to reach earnings targets (Terry (2023)). Support-

[11] Firms can also allocate R&D to cost of goods sold. For example, Note 2 of Ford Motor's 2024 Form 10-K states that: "Engineering, research, and development expenses are primarily reported in Cost of sales and consist of salaries, materials, and associated costs. Engineering, research, and development costs are expensed as incurred when performed internally or when performed by a supplier if we guarantee reimbursement."

ing this interpretation, survey evidence indicates that managers are willing to reduce discretionary spending (such as R&D) and delay the start of new projects to meet earnings targets (Graham, Harvey, and Rajgopal (2005)). Because our model focuses on investment cuts (a real action) as a signaling device, earnings management proxies that primarily capture disclosure choices are less well suited for our purposes. In particular, discretionary accruals are a poor fit, both because they are designed to detect misreporting and because they may reflect firms' underlying growth opportunities rather than earnings manipulation, a well-known critique of this measure (e.g., Owens, Wu, and Zimmerman (2017)).[12]

Additionally, our empirical proxy for signaling is defined relative to market expectations, and the model's continuous underinvestment choice can be interpreted consistently as a metaphor for the manager's propensity to influence market beliefs through a strong earnings report. In this interpretation, firm types with higher optimal underinvestment (relative to the no-signaling benchmark) are *more likely* to meet or just beat expectations by cutting investment when pre-investment earnings fall short.

3.3 *Additional outcome variables of interest*

To assess the signaling value, we first calculate $CAR_{i,q}$, firm i's three-day market-adjusted abnormal return surrounding its earnings announcement for quarter q over [-1, +1], with 0 being the announcement day. The daily abnormal return is the firm's daily raw return minus the corresponding return on the CRSP value-weighted index. Firm raw returns and market returns are both from the CRSP daily files.

We also calculate a measure of stock returns over a longer horizon. Specifically, we calculate $BHAR_{i,q\ to\ q+n}$, firm i's buy-and-hold abnormal return (BHAR) from the end of quarter q to the end of quarter $q+n$, where q is the quarter of interest and n ranges from 1 to 12. Quarterly BHAR is calculated as the firm's geometrically compounded monthly returns minus the corresponding returns on the CRSP value-weighted index. Cumulative abnormal returns are then obtained by summing quarterly abnormal returns over the specified horizon.

By comparing these two return-based measures for firms with high tainted-fund ownership to those for benchmark firms, we gauge how the market views meeting or narrowly beating earnings targets through R&D cuts by firms experiencing negative price pressure.

[12]Consistent with this distinction, we do not obtain similar results when we study meeting or narrowly beating via accrual management; we discuss this test in Section 4.1.

3.4 *Controls*

In examining the effect of negative price pressure on firm i's propensity to meet or narrowly beat analyst forecasts through R&D cuts in quarter q, we first include four basic controls measured at the end of the prior quarter: the natural logarithm of total assets ($ln(BV)_{i,q-1}$), return-on-assets ($ROA_{i,q-1}$), book leverage ($LEV_{i,q-1}$), and market-to-book ($MB_{i,q-1}$). We also include the prior quarter's buy-and-hold abnormal returns ($BHAR_{i,q-1}$) to control for momentum and total institutional ownership ($INST\%_{i,q-1}$) to capture institutional influence beyond mutual funds. While $INST\%_{i,q-1}$ is predictably positively correlated with $Tainted\ Fund\%_{i,q}$, the correlation coefficient is only 0.376 in our sample, consistent with mutual funds being only one class of institutional investors (alongside hedge funds, pension funds, venture capital firms, and private equity firms). We denote these prior-quarter controls as $Control_{i,q-1}$. Finally, following the earnings response coefficient (ERC) literature, we include three analyst forecast-related variables for quarter q: the natural logarithm of one plus analyst coverage, $ALY\_N_{i,q}$; the natural logarithm of one plus average forecast horizon (in days), $ALY\_HRZN_{i,q}$; and analyst forecast dispersion, $ALY\_DISP_{i,q}$. We denote these same-quarter controls as $Control_{i,q}$.

3.5 *Sample and summary statistics*

The main sample comprises 81,574 firm-quarter observations spanning from 2000Q3 to 2006Q3, i.e., three years before and after the initial scandal revelation (2003Q3). Table 1 reports descriptive statistics. On average, tainted funds hold an ownership of 0.1% in aggregate and firm-quarters with at-or-above-median tainted-fund ownership (among exposed firms) account for 24.8% of the sample. The average likelihood of meeting or narrowly beating the analyst consensus EPS forecast through R&D cuts is 11.2%. The mean three-day market-adjusted cumulative return surrounding earnings announcements is 0.1%. The average firm has total assets of $3.28 billion, a return-on-assets of –1%, a book leverage of 0.2, a market-to-book of 3.1, a buy-and-hold abnormal return of 2.8%, a total institutional ownership of 46.9%, and 4.9 analysts following it.

4 Empirical findings

4.1 *Negative price pressure and signaling through R&D cuts*

Prediction 1 posits that, compared to permanently-shocked firms (*PS-firms*), transitorily-shocked firms (*TS-firms*) are more likely to signal financial health by underinvesting relative to their own no-signaling optimal investment level to boost reported earnings. To test this hypothesis, we use the negative price pressure induced by the 2003 mutual fund trading scandal as a proxy for a firm's likelihood of being a *TS-firm* and examine whether it is associated with a greater propensity to meet or narrowly beat analyst consensus EPS forecasts through R&D cuts around the scandal.

Specifically, we run the following ordinary least squares (OLS) regression on a panel of firm-quarters:

$$MBE\_CutR\&D_{i,q} = \alpha + \beta_0 Price\ Pressure_{i,q} + \beta_1 Control_{i,q-1} + \beta_2 Control_{i,q} + FE + \varepsilon_{i,q}, \quad (2)$$

where $MBE\_CutR\&D_{i,q}$ is an indicator equal to one if firm i meets or beats the analyst consensus EPS forecast by up to one cent in fiscal quarter q and reports a reduction in R&D expenditure relative to the prior quarter, and zero otherwise. As discussed in Section 3.2, this indicator captures the modeled signaling mechanism. $Price\ Pressure_{i,q}$ represents the negative price pressure that firm i may experience in quarter q. As explained in Section 3.1, because price declines can arise for various reasons, we instrument for $Price\ Pressure_{i,q}$ using either $Tainted\ Fund\%_{i,q}$, firm i's aggregate ownership held by tainted funds in quarter q, or $High\ Tainted\ Fund\%_{i,q}$, an indicator equal to one if $Tainted\ Fund\%_{i,q}$ is at or above the median within the subsample with positive tainted-fund ownership. Accordingly, equation (2) can be viewed as a reduced form model that isolates the effect of exogenous variation in negative price pressure—driven by redemption-induced selling—on firm i's propensity to signal through R&D cuts. $Control_{i,q-1}$ and $Control_{i,q}$ are discussed in Section 3.4. Because the hypothesis concerns underinvestment relative to the firm's no-signaling optimum, we include firm fixed effects to exploit within-firm variation. We further include year-quarter fixed effects to control for intertemporal variation. Standard errors are clustered by firm and year-quarter.

Columns (1) and (2) of Table 2 report the regression results using $Tainted\ Fund\%_{i,q}$ as the instrument for negative price pressure, without and with controls. Consistent with Prediction 1, the coefficient estimate on $Tainted\ Fund\%_{i,q}$ is positive and statistically significant at the 1% level. The economic magnitude is substantial: in the specification with controls, a one-standard-deviation increase in $Tainted\ Fund\%_{i,q}$ in a post-scandal quarter is associated with a 16.4 percentage point (i.e., 0.225×0.727) higher likelihood of meeting or narrowly beating the analyst consensus EPS forecast through R&D cuts, amounting to about a 1.5-fold increase relative to the sample mean likelihood of 11.2 percentage points. Columns (3)–(4) repeat the analyses in columns (1)–(2), using $High\ Tainted\ Fund\%_{i,q}$ as the instrument instead. The coefficient estimate on $High\ Tainted\ Fund\%_{i,q}$ remains positive and significant at the 1% level. In the specification including controls, moving $High\ Tainted\ Fund\%_{i,q}$ from zero to one in a post-scandal quarter is associated with a 24.9 percentage point increase in the likelihood of meeting or narrowly beating the analyst consensus EPS forecast through R&D cuts, more than doubling the sample mean likelihood.

Although we focus on reduced-form analyses for ease of interpreting economic significance (particularly in the cross-sectional tests of model comparative statistics), we also estimate a 2SLS system as an alternative design, specified below as:

$$BHAR_{i,q} = \alpha + \beta_0 Price\ Pressure_{i,q} + \beta_1 Control_{i,q-1} + \beta_2 Control_{i,q} + FE + \varepsilon_{i,q}, \tag{3}$$

$$MBE\_CutR\&D_{i,q} = \alpha + \beta_0 \widehat{BHAR}_{i,q} + \beta_1 Control_{i,q-1} + \beta_2 Control_{i,q} + FE + \varepsilon_{i,q}, \tag{4}$$

where $BHAR_{i,q}$, the dependent variable in equation (3), represents a price movement. As discussed in Section 3.1, a negative $BHAR_{i,q}$ could arise due to exogenous selling pressure or be endogenous to changes in firm fundamentals. We therefore use $Tainted\ Fund\%_{i,q}$ and $High\ Tainted\ Fund\%_{i,q}$ as instruments for $BHAR_{i,q}$ and expect higher tainted-fund ownership to predict larger price declines; that is, we predict $\hat{\beta}_0 < 0$ in equation (3). $\widehat{BHAR}_{i,q}$ in equation (4) is the fitted value of $BHAR_{i,q}$ from equation (3). Prediction 1 posits that the incentive to signal through R&D cuts increases with the magnitude of the transitory price shock (or a more negative $\widehat{BHAR}_{i,q}$); hence, we also predict $\hat{\beta}_0 < 0$ in equation (4). All other variables are defined as in equation (2). We similarly include firm and year-quarter fixed effects and cluster standard errors by firm and year-quarter.

Columns (1)–(2) of Table A.1 of the Online Appendix report the 2SLS results using $Tainted\ Fund\%_{i,q}$ as the instrument for negative price pressure, and columns (3)–(4) repeat the analyses using $High\ Tainted\ Fund\%_{i,q}$ as the instrument. The first-stage results show that both instruments are negatively associated with $BHAR_{i,q}$, the buy-and-hold return in quarter q, as predicted. The weak instrument test rejects the null of no correlation between the instruments and $BHAR_{i,q}$; the Cragg–Donald F-statistic is 10.4 in column (1) and 21.1 in column (3), both above the cutoff of 10 suggested by Staiger and Stock (1997). The lower statistic in column (1) likely reflects that a sufficiently large block of tainted-fund ownership is needed to generate detectable price pressure. More importantly, the second-stage results align with the reduced form results in Table 2: the fitted value of $BHAR_{i,q}$ exhibits the predicted sign and is significant at the 1% level in both columns (2) and (4).

Next, we conduct three additional analyses to assess the robustness of the reduced form results. First, we re-estimate the analysis in equation (2) using a probit model to allow for nonlinearity in the propensity to signal through R&D cuts. Table A.2 of the Online Appendix reports qualitatively similar results. Second, following Dechow, Richardson, and

Tuna (2003) and Roychowdhury (2006), we re-estimate equation (2) using only firm-quarters in which actual EPS falls within a narrow band around the analyst consensus EPS forecast (e.g., within ±1, ±2, and ±3 cents). This design compares firms that meet or narrowly beat earnings targets with those that just miss, thereby focusing on the discontinuity region where earnings management incentives are strongest. As shown in Table A.3 of the Online Appendix, we find that even in these narrow samples, firms with greater tainted-fund ownership are still more likely to signal through R&D cuts. Third, we define an accrual-based analog to $MBE\_CutR\&D_{i,q}$, which equals one if firm i meets or narrowly beats the analyst consensus EPS forecast in fiscal quarter q and reports positive discretionary accruals calculated following Dechow, Sloan, and Sweeney (1995), and zero otherwise. We find no evidence that higher tainted-fund ownership is associated with greater accrual-based management in Table A.4 of the Online Appendix.[13]

Finally, we provide evidence consistent with the model's premise that managers possess private information by examining insider trading. Specifically, among firm-quarters with at-or-above-median tainted-fund ownership, we compare insider trading during the shock quarter between firms that meet or narrowly beat earnings targets through R&D cuts (which are more likely to be *TS-firms*) and matched firms that miss earnings targets (which are more likely to be *PS-firms*). We examine trades by officers and directors recorded in the Thomson Reuters Insider Filing database. Following Cohen, Malloy, and Pomorski (2012), we calculate measures of non-routine insider purchases and sales. Table A.5 of the Online Appendix shows that insider purchases are significantly higher for *TS-firms* than for *PS-firms*, whereas insider sales do not differ significantly across the two groups. Because insider purchases are generally considered more informative than insider sales (as the latter may reflect liquidity or diversification needs), these findings are consistent with managers possessing and trading on private information about the persistence of the shock.

In summary, the findings in this section provide strong support for Prediction 1 and suggest that negative price pressure induced by redemption-driven selling increases firms' incentives to meet or narrowly beat earnings targets by cutting R&D expenditures. These findings are robust to alternative estimation methods (probit and 2SLS), samples restricted to firms just meeting or missing earnings targets, and a placebo test examining accrual-based earnings management.

[13]This result is consistent with accrual-based manipulation being costlier than real actions for managers because it entails greater legal and reputational risk, especially after the Sarbanes–Oxley Act of 2002 increased scrutiny and penalties for executives. Indeed, Cohen et al. (2008) document a shift from accrual management to real management after the legal reform. Graham et al. (2005) also report that most earnings management is achieved through real manipulations in the post-reform period.

4.2 *Counter-signaling*

While the results in the previous section support Prediction 1 and suggest that firms facing transitory negative price shocks are more likely to signal financial health through R&D cuts, the model also generates a separate Prediction 2 regarding counter-signaling. In particular, firms with higher pre-investment earnings can convey financial strength directly through reported earnings rather than relying on investment cuts.

To shed light on this channel, we estimate and contrast the following two OLS models:

$$MBE_{i,q} = \alpha + \beta_0 CutR\&D_{i,q} + \beta_1 Control_{i,q-1} + \beta_2 Control_{i,q} + FE + \varepsilon_{i,q}, \tag{5}$$

$$Beat > 3ct_{i,q} = \alpha + \beta_0 CutR\&D_{i,q} + \beta_1 Control_{i,q-1} + \beta_2 Control_{i,q} + FE + \varepsilon_{i,q}, \tag{6}$$

where $MBE_{i,q}$ is an indicator equal to one if firm i meets or beats the analyst consensus EPS forecast by up to one cent in fiscal quarter q and zero otherwise, whereas $Beat > 3ct_{i,q}$ is an indicator equal to one if firm i beats the analyst consensus EPS forecast by more than three cents in quarter q and zero otherwise. $CutR\&D_{i,q}$ is the negative change in R&D expenditure from quarter $q-1$, scaled by total assets at the end of $q-1$. All other variables are defined as in equation (2). We continue to include firm and year-quarter fixed effects and cluster standard errors by firm and year-quarter.

Columns (1) and (2) of Table 3 report the results of estimating equations (5) and (6), respectively. We restrict the subsample to firm-quarters with tainted-fund ownership at or above the median of exposed firms to sharpen the contrast. Further in support of Prediction 1, the coefficient estimate on $CutR\&D_{i,q}$ is positive and statistically significant at the 1% level in column (1), suggesting that cutting R&D expenditure facilitates meeting or narrowly beating the market expectation. In contrast, we find no evidence that these firms cut R&D to beat by a wide margin (more than three cents), as the coefficient estimate on $CutR\&D_{i,q}$ is significantly negative in column (2). This pattern is consistent with Prediction 2, where firms expecting higher pre-investment earnings can rely on reported earnings alone to signal financial strength without reducing investment.

The finding is therefore consistent with counter-signaling: firms with sufficiently strong pre-investment earnings can separate without resorting to costly investment distortion. In equilibrium, these high-earnings firms optimally choose not to mimic lower-earnings firms, as their underlying performance is already informative enough to convey financial strength. This pattern also reflects the tradeoff between signaling benefits and real costs: when pre-investment earnings are already high, the marginal benefit of boosting reported earnings through R&D cuts is low relative to the cost of foregone investment.

4.3 *Value of signaling*

Prediction 1 implies that cutting R&D to meet the earnings expectation set by the market serves as an informative signal of financial health when the firm faces a negative transitory shock. In this section, we first provide evidence on the informativeness of this signaling channel by examining how investors respond to earnings announcements when firms under flow-induced selling pressure meet or narrowly beat earnings targets while reducing R&D.

Specifically, we estimate the following OLS specification:

$$CAR_{i,q} = \alpha + \beta_0 MBE\_CutR\&D_{i,q} + \gamma UE_{i,q} + \beta_1 Control_{i,q-1} + \beta_2 Control_{i,q} + FE + \varepsilon_{i,q}, \quad (7)$$

where $CAR_{i,q}$ is firm i's three-day earnings announcement return for fiscal quarter q, defined in Section 3.3. $UE_{i,q}$ denotes the "unexpected earnings" for firm i in quarter q, defined as the difference between reported EPS and the analyst mean consensus EPS forecast, scaled by the stock price at the end of quarter q. All other variables are previously defined. The ERC literature documents a positive coefficient on $UE_{i,q}$, as investors should react favorably to positive earnings surprises. Our coefficient of interest is β_0, the coefficient estimate on $MBE\_CutR\&D_{i,q}$. Because this indicator captures the modeled signaling channel, β_0 captures any incremental information content of meeting or narrowly beating the earnings target while cutting R&D, conditional on a level of earnings surprise. We continue to include firm and year-quarter fixed effects and cluster standard errors by firm and year-quarter.

Table 4 presents the results of estimating equation (7). Column (1) uses the full sample while columns (2) and (3) split the sample by tainted-fund ownership. The variable $High\ Tainted\ Fund\%_{i,q} = 1$ indicates firm-quarters with tainted-fund ownership at or above the median (among exposed firms) and $High\ Tainted\ Fund\%_{i,q} = 0$ indicates firm-quarters with tainted-fund ownership below that median. As shown in Table 4, $UE_{i,q}$ carries a positive coefficient estimate that is significant at the 1% level in all three columns, confirming the general finding from the ERC literature. Interestingly, while the coefficient estimate on $MBE\_CutR\&D_{i,q}$ is also significantly positive in column (1) for the full sample, this relation appears to be driven solely by the at-or-above-median tainted-fund subsample in column (2). This result suggests that, when negative price pressure is likely, the market reaction at the earnings announcement does not reflect just earnings updating. Instead, the market seems to also react to additional information conveyed by the firm's choice to cut R&D to meet or narrowly beat the earnings target, presumably because such signaling helps reveal the nature of the price drop. In terms of economic significance, the choice to signal through R&D cuts in the subsample with $High\ Tainted\ Fund\%_{i,q} = 1$ translates into a 0.9% higher three-day earnings announcement return.

As a robustness check, we rerun the specifications in Table 4 by replacing *MBE_CutR&D* with three separate variables: *MBE*, *CutR&D*, and their interaction. This alternative specification allows us to examine whether the market response is concentrated in firm-quarters that both meet or narrowly beat expectations and cut R&D. As Table A.6 of the Online Appendix shows, the coefficient on the interaction term is positive and significant at the 1% level in the full sample. In subsample analyses, the interaction remains highly positive among firms with at-or-above-median tainted-fund ownership but turns negative among firms with below-median tainted-fund ownership.[14] Again, these results indicate that firms receive an additional positive market reaction when they both meet or narrowly beat expectations and cut R&D, but only when they are more likely to face transitory price pressure.

Next, we examine long-term returns to further assess the value implications of signaling through R&D cuts. Specifically, for each firm i–quarter q, we compute the buy-and-hold abnormal return from the end of q to $q+n$ for $n = 1, \ldots, 12$, denoted $BHAR_{i,q\ to\ q+n}$ (see Section 3.3 for details). We then compare $BHAR_{i,q\ to\ q+n}$ between a focal group of firm-quarters that meet or narrowly beat the analyst forecasts through R&D cuts (i.e., $MBE\_CutR\&D_{i,q} = 1$) and have at-or-above-median tainted-fund ownership ($High\ Tainted\ Fund\%_{i,q} = 1$) and two benchmark groups.

To isolate the effect of signaling, we match each observation in the focal group to an observation in a benchmark group based on the magnitude of the quarter-q price drop, $BHAR_{i,q}$. In addition to $BHAR_{i,q}$, we match on firm characteristics from quarter $q - 1$, including the log of total assets, return-on-assets, leverage, and market-to-book as well as industry and year-quarter fixed effects, to minimize observable differences between the groups. We implement propensity score matching using one-to-one nearest-neighbor matching with replacement. This procedure reduces the likelihood that differences in $BHAR_{i,q\ to\ q+n}$ between the matched samples are driven by observable market, industry, or firm characteristics rather than signaling.

Our focal group is most likely to comprise *TS-firms*, which signal through R&D cuts when facing scandal-induced negative price pressure, as modeled. The first benchmark group comprises all firm-quarters that miss the analyst consensus forecast. The second comprises firm-quarters with at-or-above-median tainted-fund ownership (i.e., $High\ Tainted\ Fund\%_{i,q} = 1$) that still miss the analyst consensus forecast. Both groups likely capture firms hit by permanent shocks (*PS-firms*): the first experiences a price decline without scandal-induced selling pressure, while the second may face both scandal-induced selling pressure and a fundamental shock and therefore finds it too costly to cut investment to meet the consensus

[14] The results are similar if we define *CutR&D* as an indicator for whether a firm cuts R&D rather than as a continuous measure of the magnitude of the R&D cut scaled by lagged total assets.

forecast. The second benchmark also lets us compare long-run abnormal returns within firms with high tainted-fund ownership, isolating the price gains from signaling after exogenous negative price shocks.

Columns (1) and (2) of Table 5 report the mean for the focal group and the two benchmark groups over the 13-quarter period, as well as the differences in means. We observe a significant price decline in quarter q: the mean $BHAR_{i,q}$ is -2.5% for firm-quarters in the focal group and is not significantly different for either benchmark group, suggesting that our propensity score matching works as intended. After firms in the focal group adjust investment to meet the earnings target in quarter q, they start to outperform both benchmark groups. Specifically, the focal firms have an average $BHAR_{i,q \ to \ q+1}$ of 1.2%, whereas the corresponding mean remains negative for both benchmark groups. The difference is statistically significant at the 1% level.

This pattern persists for eight quarters for both benchmark groups with no price reversals, i.e., up to $BHAR_{i,q \ to \ q+8}$, suggesting that signaling through R&D cuts by *TS-firms* reveals information about firm fundamentals following the initial price decline, consistent with the market revising beliefs about the nature of the shock. Over the next four quarters, the return gap between the focal group and the first benchmark group narrows and the differences become statistically insignificant in the two final quarters. However, the differences remain statistically significant between the focal group and the second benchmark group.

Finally, an implication of the model is that *TS-firms* should revert toward the no-signaling level of R&D investment following the signaling event (and thus increase R&D spending in later periods). In contrast, *PS-firms* should continue to invest less because the negative shock reflects a persistent deterioration in fundamentals. To investigate this implication, we examine the evolution of quarterly R&D intensity (R&D expenditures scaled by lagged assets) over the twelve quarters following the price shock, using the same approach as in Table 5 to classify *TS-* and *PS-firms*. Table A.7 of the Online Appendix reports the results. Consistent with a short-run signaling response, *TS-firms* exhibit lower R&D intensity than *PS-firms* during the first two quarters following the shock. Over the subsequent ten quarters, however, the difference narrows and eventually reverses, indicating that *TS-firms* gradually restore investment relative to *PS-firms* as the transitory price pressure subsides.

Taken together, the findings in this section provide further support for Prediction 1: firms that meet or narrowly beat earnings targets through R&D cuts following transitory price shocks experience positive earnings announcement returns, persistent valuation gains, and a subsequent recovery in investment. These findings are consistent with such investment distortions serving as informative signals of firm fundamentals rather than reflecting a persistent deterioration in investment opportunities.

4.4 *The role of managerial myopia*

A natural question raised by our findings—that firms cut R&D to meet or narrowly beat earnings targets when facing negative price pressure—is whether this behavior reflects non-informative managerial myopia (i.e., myopic actions that do not convey any long-run private information). Indeed, the myopia literature shows that managers with short-term stock price concerns tend to reduce investment (Edmans et al. (2017)). This concern is heightened by evidence that a 2004 SEC disclosure regulation increased mutual funds' portfolio disclosure frequency from semiannual to quarterly and induced myopic investment behavior at firms with greater ownership held by affected mutual funds (Agarwal et al. (2018)).

Results from Section 4.3 help alleviate this concern, as we document a positive market reaction to signaling through R&D cuts at the earnings announcement and positive long-run stock performance following such behavior. In contrast, a non-informative myopia explanation predicts a boost to the initial market reaction followed by weaker subsequent returns, a return pattern implied by the very notion of myopia (e.g., Stein (1989)) and empirically documented for non-informative myopic investment cuts (Edmans et al. (2022)).

Even with respect to the initial earnings-announcement reaction, the two explanations yield distinct predictions. Under a non-informative myopia explanation (such as the one modeled in Stein (1989)), the market rationally anticipates myopic investment cuts and inflated earnings, so any return response should be fully captured by the earnings surprise. By contrast, our signaling mechanism predicts that cutting R&D to meet or narrowly beat earnings targets conveys incremental information about firm fundamentals, conditional on earnings surprise, particularly when the firm faces transitory negative price pressure. Accordingly, an informative signaling explanation implies a stronger announcement reaction for firms engaging in such behavior when negative price pressure is likely, even after controlling for earnings surprises.

With this reasoning, we conduct two tests to distinguish uninformative myopia from the modeled informative signaling mechanism and to examine how the two may interact. The first test addresses the SEC's 2004 disclosure regulation as a potential confounding event that could contribute to our findings through a myopia channel. Our shock of interest, the 2003 mutual fund trading scandal, was first revealed in early September 2003 and affected stock prices for firms with higher tainted-fund ownership in the subsequent months. In contrast, the SEC's quarterly portfolio disclosure requirement was adopted in May 2004 and implemented thereafter, roughly eight months after the initial revelation of our shock.

To assess whether our baseline findings are driven by this confounding event, we repeat the analyses in Tables 2 and 4 using a truncated sample that ends before March 2004. This shorter sample covers six quarters surrounding the initial revelation of the trading scandal (2002Q4–2004Q1) and excludes the later period when the 2004 disclosure regulation could begin to matter. Despite a substantially smaller sample, Table 6 yields qualitatively similar results. Even before the 2004 regulation took effect, negative price pressure from the 2003 scandal increased firms' propensity to meet or narrowly beat earnings targets through R&D cuts (Panel A). Moreover, the market responded favorably to this behavior, but only among firms with higher tainted-fund ownership after controlling for earnings surprises (Panel B). This result is more consistent with a signaling explanation than a myopia explanation.

Although our results are not driven by the 2004 disclosure regulation, myopia incentives could still be present in any period. As discussed in Section 2, our two-period model incorporates a parameter for myopia and predicts that managers with greater short-term price concerns have stronger incentives to underinvest relative to their no-signaling optimum when facing transitory price shocks (Prediction 3). Put differently, while myopia does not replace the modeled signaling mechanism, it can amplify the incentive to signal through R&D cuts.

We test Prediction 3 by augmenting equation (2) with a measure of managerial myopia and its interaction with our instruments for negative price pressure. We derive this measure from the 2004 disclosure regulation, following prior studies of this setting (e.g., Agarwal, Mullally, Tang, and Yang (2015), Agarwal et al. (2018), Agarwal, Cao, Huang, and Kim (2025)). Specifically, we define $Myopia_{i,q}$ as an indicator equal to one if, in quarter q, firm i's aggregate ownership held by the 1,459 U.S. domestic equity mutual funds that switched from semiannual to quarterly reporting after the disclosure rule change is at or above the sample median, and zero otherwise. As with $Tainted\ Fund\%_{i,q}$, we calculate $Myopia_{i,q}$ only for firm-quarters after the regulation became effective and set it to zero otherwise.[15]

Table 7 reports the regression results of this augmented equation. Both instruments for the negative price pressure ($Tainted\ Fund\%_{i,q}$ and $High\ Tainted\ Fund\%_{i,q}$) continue to load significantly positive, indicating that negative price pressure alone increases the propensity to signal through R&D cuts, consistent with Prediction 1. The coefficient estimate on the standalone variable of $Myopia_{i,q}$ is also significantly positive, consistent with myopic incentives being associated with a higher likelihood that a firm meets or narrowly beats earnings targets through R&D cuts. More importantly, the interaction term is significantly positive, suggesting that myopic incentives amplify managers' signaling incentives when negative price pressure is present, as predicted in Prediction 3.

In summary, the results in this section are inconsistent with a pure myopia explanation. Instead, they indicate that myopic incentives amplify the signaling mechanism in our model.

[15]We cannot construct the equity-vesting measure introduced by Edmans et al. (2017), as vesting data required to compute that measure are only available after 2006.

4.5 *Cross-sectional analyses*

The comparative statics of our model generate a number of additional testable predictions. In this section, we conduct three cross-sectional analyses to provide further insights.

First, in our model, firms differ not only in their private observation of pre-investment earnings given the shock, but also in investment productivity (or the marginal return on investment) conditional on the shock. Prediction 1 posits that the incentive to signal through R&D cuts in the presence of a negative price shock is stronger for high-productivity firms. To further test this prediction, we augment equation (2) with a proxy for productivity, $MB_{i,q-1}$, and its interaction with our instruments for negative price pressure, $Tainted\ Fund\%_{i,q}$ and $High\ Tainted\ Fund\%_{i,q}$. Panel A of Table 8 reports the results. A positive coefficient estimate on the interaction between market-to-book and both instruments suggests that the positive relation between tainted-fund ownership and the firm's incentive to signal through R&D cuts increases with the likelihood that the firm is a high-productivity type.

Second, Prediction 4 implies that the incentive to signal through R&D cuts in the presence of a negative price shock decreases as uncertainty about pre-investment earnings rises, because earnings become less informative about firm type. To test this prediction, we augment equation (2) with a measure of earnings uncertainty, the dispersion of analysts' forecasts about quarter q earnings for firm i (denoted $ALY\_DISP_{i,q}$), and its interaction with our instruments for negative price pressure. Panel B of Table 8 reports the results and shows a negative coefficient estimate on the interaction between analyst forecast dispersion and both instruments. This finding suggests that the positive relation between tainted-fund ownership and the firm's incentive to signal through R&D cuts weakens when the market has greater uncertainty about the firm's earnings prior to its earnings announcement.

Finally, Prediction 5 predicts that the incentive to signal through investment reduction increases as uncertainty about the firm's productivity type rises, because the market places greater emphasis on learning the firm's type from the earnings report. To test this hypothesis, we augment equation (2) with a proxy for productivity-type uncertainty, the variance of market-to-book for firm i over the prior eight quarters (denoted $VOL\_MB_{i,q}$), and its interaction with our instruments for negative price pressure. Panel C of Table 8 reports the results and shows a positive coefficient estimate on the interaction between market-to-book variance and both instruments. This finding indicates that the positive relation between tainted-fund ownership and the firm's incentive to signal through R&D cuts strengthens with greater uncertainty about productivity type.

Taken together, the results from these cross-sectional analyses align closely with the comparative statics of the model. Across all three dimensions—investment productivity, earnings uncertainty, and productivity-type uncertainty—we find that the strength of the relation between tainted-fund ownership and signaling through R&D cuts varies in the manner predicted by the model. Collectively, these findings add credence to the model's signaling mechanism and reinforce the interpretation that firms' investment responses to negative price pressure reflect strategic signaling about underlying financial health.

5 Conclusion

This paper develops a theoretical framework to study the signaling role of seemingly myopic investment behavior following transitory stock price shocks. When the market is uncertain about whether a negative price shock reflects transitory selling pressure or permanent deterioration in firm fundamentals, managers can use reported earnings to influence market beliefs. The model predicts that firms less impacted by the shock have stronger incentives to underinvest relative to the no-signaling optimum, as cutting R&D boosts earnings and serves as a credible signal of financial health. Although such signaling entails real efficiency losses, it can improve information efficiency by facilitating the market's belief updating.

We test the model's predictions using the 2003 mutual fund trading scandal as a plausibly exogenous source of transitory price pressure. Consistent with the predictions, firms with greater exposure to tainted mutual funds are more likely to meet or narrowly beat analyst earnings forecasts by cutting R&D. This behavior is associated with more favorable earnings announcement returns and long-run abnormal returns, indicating that the market interprets it as informative rather than purely myopic. Additional analyses show that the results are robust across specifications, are not driven by accrual-based earnings management, persist after accounting for the 2004 SEC disclosure regulation as a possible confounding event, and align with the model's comparative statics along dimensions of managerial myopia, investment productivity, uncertainty about earnings, and uncertainty about firm type.

Although we test the mechanism using the 2003 mutual fund trading scandal, its implications are broader. The signaling channel applies to other settings in which investors cannot perfectly distinguish transitory from persistent shocks to firms' future profitability or long-run asset values, and managers can use costly real actions to influence market beliefs about the nature of those shocks.

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Appendix

A Model results

We present the main results of the model introduced in Section 2 below and relegate the solution and technical details to Appendix B. We denote the optimal investment in our model when signaling concerns about β are absent (i.e., β is common knowledge) as the no-signaling optimum or the second-best investment. We analyze this second-best benchmark equilibrium in Section B.1. We therefore define the *bias* in investment as the difference between the second-best investment and the equilibrium investment.

The proposition below establishes existence and uniqueness of the pure strategy equilibrium. We observe in equilibrium that investment is always downward-biased. That is, we have underinvestment relative to the no-signaling individual optimum in the pure strategy equilibrium. This result establishes that managers use investment as a signaling device and do so through reducing investment further than they would in the second-best benchmark without signaling concerns. Moreover, while the manager of each type uses a pure strategy of reducing investment, the market cannot perfectly recover the manager's private information. Hence, while the market updates positively on the firm's productivity following higher earnings announcements, the market continues to have uncertainty over the type.

Proposition 1. *Assume that β follows a truncated normal distribution on $(0, \infty)$ with mean m_β and variance v_β, and pre-investment earnings follow the distribution $\mathbb{N}(\mu_e + \rho\beta, \sigma_e^2)$. For $S := \sigma_e^2 + \sigma_\varepsilon^2$ sufficiently large (defined in the Appendix), a pure strategy perfect Bayesian equilibrium uniquely exists. Moreover, the following properties hold in the unique equilibrium:*

(i) *equilibrium investment is decreasing in the manager's myopia, α;*

(ii) *investment is increasing in the variance of earnings, σ_e^2;*

(iii) *investment is decreasing in the variance of productivity, v_β;*

(iv) *higher productivity types exhibit greater underinvestment (i.e., the bias is increasing in β);*

(v) *for a given β, the bias is decreasing in earnings e (i.e., higher investment for higher earnings);*

(vi) *the bias is positive for all β.*

We see in part (i) of the proposition that the equilibrium investment $k^*(\beta, e)$ is decreasing in the weight on first-period price, $\alpha \in (0, 1)$. As α increases, the manager cares more about market beliefs of β in the first-period, thus amplifying the signaling incentive. This leads to greater underinvestment in the first period.

Point (ii) of Proposition 1 indicates that investment is increasing in the variance of earnings, σ_e^2. Since pre-investment earnings e is positively correlated with productivity β, a greater variance of e implies an eventual announcement a that is less related to the underlying fundamental β. In turn, the manager has a lower incentive to underinvest to signal as the market places less weight on the announcement a when forming beliefs. As such, we have greater investment in the first period as σ_e^2 increases.

Point (iii) of Proposition 1 establishes that equilibrium investment is decreasing in the variance of productivity, v_β. As the market's prior information about β becomes less precise, investors place greater weight on the announcement when updating beliefs regarding β. This intensifies the manager's signaling incentive, thus leading to greater underinvestment (i.e., lower investment).

In parts (iv) through (vi), we have a number of properties regarding the bias in investment, defined as the difference between the investment under the no-signaling optimum and the equilibrium investment. We find that the bias is increasing in productivity β in part (iv). In other words, the level of underinvestment is higher for higher types relative to the benchmark investment by the same types without signaling concerns (defined formally in Section B below). This is because higher types have greater incentives to underinvest. The reason for this is twofold. First, since pre-investment earnings, which are reflected in the announcement a, are increasing in β according to MLRP, the manager attempts to positively influence market beliefs by inflating the announcement a upward by cutting investment. Second, cutting investment is less punitive for higher-type managers since their optimal investment level is naturally higher. As such, higher types can bear greater underinvestment relative to their no-signaling optimum without sacrificing as much efficiency loss as lower types.[16]

Part (v) of Proposition 1 establishes the interesting property that the bias in investment relative to the second-best benchmark is decreasing in pre-investment earnings e for

[16]To see this, note that the no-signaling (second-best) optimum is

$$k^0 = \frac{(1-\alpha)^2}{2\alpha^2}\beta := \chi\beta,$$

where $\chi := \frac{(1-\alpha)^2}{2\alpha^2} > 0$. Consider the downward bias

$$b(\beta, e) = k^0 - k^*(\beta, e),$$

so that $k^*(\beta, e) = k^0 - b(\beta, e)$. Note that since $k^*(\beta, e) > 0$, then $b(\beta, e) < \chi\beta$. Define the cost of biasing (i.e., the forgone return relative to the no-signaling optimum) as:

$$C(\beta, b) := r_\beta\left(k^0\right) - r_\beta\left(k^0 - b\right) = (2\chi)^{1/2}\beta - \left(2\beta(\chi\beta - b)\right),$$

for gross investment return function $r_\beta(k) = (2\beta k)^{1/2}$. We have that

$$C_b(\beta, b) = \frac{\partial C}{\partial b} = \left(\frac{\beta}{2(\chi\beta - b)}\right) > 0.$$

Let $J(\beta, b) := \frac{\beta}{2(\chi\beta - b)}$. Then,

$$\frac{\partial J}{\partial \beta} = \frac{(\chi\beta - b) - \chi\beta}{(\chi\beta - b)^2} = -\frac{b}{(\chi\beta - b)^2}.$$

Furthermore,

$$C_{b\beta}(\beta, b) = \frac{\partial}{\partial\beta}C_b(\beta, b) = \frac{1}{2\sqrt{2}}J(\beta, b)^{-\frac{1}{2}}\frac{\partial J}{\partial\beta} = -\frac{b}{2\sqrt{2}}\cdot\frac{1}{\sqrt{\beta}}\cdot\frac{1}{(\chi\beta - b)^{3/2}} < 0.$$

Hence $C_{b\beta}(\beta, b) < 0$ and thus the marginal cost of further underinvestment, C_b, is decreasing in type β, i.e., underinvestment is less steeply costly for higher-β firms and the higher-β firms' cost curve is flatter at the margin.

a given productivity β. This implies that, for a given productivity β, higher types have less incentive to signal when pre-investment earnings are higher. Because pre-investment earnings e are positively correlated with productivity β, a manager that observes a higher e can convey the type through a high announcement a without having to rely on investment distortion. As such, the manager distorts investment less when higher e is observed. Finally, point (vi) indicates that all types underinvest relative to the second-best, no-signaling benchmark, including the very lowest type. The lowest type in our setting does not exhibit a zero bias, unlike in traditional signaling models. The reason for this is due to the presence of two-dimensional private information in our setting; the manager additionally observes the pre-investment earnings privately and this stochastic component appears in the earnings announcement a, which leads the market to imperfectly recover the firm's private information. As such, each type has an incentive to upwardly influence market beliefs through investment distortion beyond the second-best level.[17]

B Proofs

B.1 No-signaling benchmark

A useful benchmark we use to measure the degree of underinvestment is the manager's investment optimum under a setting without signaling concerns over type (e.g., there is no uncertainty regarding productivity β or liquidation value Δ). Specifically, the manager continues to privately observe earnings e, privately chooses investment k, and publicly announces $a = e - k + \varepsilon$. The market only observes the aggregate announcement a and not its individual components. In this case, suppose the market conjectures that the manager invests k, whereas the manager's privately observed investment is $\hat{k}$. The manager's utility is (suppressing ε, which is mean-zero, observed ex post, and does not factor into the manager's optimization),

$$\begin{aligned} u_m &= \alpha P_1 + (1-\alpha) P_2 \\ &= \alpha \left[e - \hat{k} + r(k) + \Delta \right] + (1-\alpha) \left[r\left(\hat{k}\right) + \Delta \right] \\ &= \alpha \left[e - \hat{k} + (2\beta k)^{1/2} \right] + (1-\alpha) \left[\left(2\beta\hat{k}\right)^{1/2} \right] + \Delta, \end{aligned}$$

taking the first-order condition with respect to the deviation $\hat{k}$, we have

$$-\alpha + (1-\alpha)(2\beta)^{1/2} \frac{1}{2} \hat{k}^{-1/2} = 0,$$

which gives

$$\hat{k} = \frac{(1-\alpha)^2 \beta}{2\alpha^2}.$$

[17] Note that all types have strictly positive productivity, $\beta > 0$. Investment (and thus the bias) would trivially be 0 in the case where $\beta \leq 0$ since $k \geq 0$, as noted in Section 2.

This second-best choice represents the manager's individual optimum and departs from the first-best investment of $k^{FB} = \frac{\beta}{2}$. We thus define the bias in the investment choice as the departure from the second-best investment level.

B.2 Proof of Proposition 1

We first prove two properties that we will use repeatedly.

Lemma 1. *We have the following identity for any k,*

$$P_1^{k\prime}(a) = 1 + \frac{1}{S} Cov\left(z_k, y_k | a\right),$$

where $z_k(\beta, e) := \Delta(\beta) + r_\beta\left(k(\beta, e)\right)$, and $y_k(\beta, e) := e - k(\beta, e)$.

Proof. Let $\varphi_S(u) = (2\pi S)^{-1/2} \exp\left[-u^2/2S\right]$, where φ is the pdf of a mean-zero normal distribution with variance S. We can express $\mathbb{E}\left[z_k|a\right]$ as the ratio of two convolutions:

$$\mathbb{E}\left[z_k|a\right] = \frac{N(a)}{D(a)},$$

where

$$N(a) := \mathbb{E}\left[z_k \varphi_S(a - y_k)\right],$$
$$D(a) := \mathbb{E}\left[\varphi_S(a - y_k)\right].$$

Since $\frac{d}{da}\varphi_S(a-y) = \frac{y-a}{S}\varphi_S(a-y)$, $N'(a) = \frac{1}{S}\mathbb{E}\left[z_k(y_k - a)\varphi_S(a - y_k)\right]$, and $D'(a) = \frac{1}{S}\mathbb{E}\left[(y_k - a)\varphi_S(a - y_k)\right]$, then

$$\frac{d}{da}\mathbb{E}\left[z_k|a\right] = \frac{1}{S}\left(\mathbb{E}_k\left[z_k(y_k - a)|a\right] - \mathbb{E}_k\left[z_k|a\right]\mathbb{E}_k\left[y_k - a|a\right]\right).$$

Since $Cov\left(z_k, a|a\right) = 0$ as a is a constant when conditioning on the announcement, then

$$\frac{d}{da}\mathbb{E}\left[z_k|a\right] = \frac{1}{S} Cov\left(z_k, y_k|a\right).$$

We have that $P_1^k = a + \mathbb{E}\left[z_k|a\right]$, and so $P_1^{k\prime}(a) = 1 + \frac{1}{S}Cov\left(z_k, y_k|a\right)$. □

Lemma 2. $P_1^{k\prime\prime}(a) \leq 0$ *for all* $a \in \mathbb{R}$.

Proof. We show that $a \mapsto P_1^k(a)$ is concave, and hence $P_1^{k\prime\prime}(a) \leq 0$. The posterior is

$$\Gamma(a; \beta, e) = \varphi_S\left(a - y_k(\beta, e)\right) f_\beta(\beta) f_{e|\beta}\left(e|\beta\right),$$

where y_k and $\varphi_S(\cdot)$ are defined as above. Thus

$$\mathbb{E}\left[z_k|a\right] = \frac{\int\int z_k(\beta, e)\Gamma(a; \beta, e)\, de d\beta}{\int\int \Gamma(a; \beta, e)\, de d\beta},$$

where as above $z_k := \Delta(\beta) + r_\beta\left(k(\beta, e)\right)$. For each fixed $t \geq 0$, consider

$$L_t(a; \beta, e) := \exp[t \cdot z_k]\, \varphi_S(a - y_k)\, f_\beta(\beta)\, f_{e|\beta}\left(e|\beta\right).$$

Because z_k is concave in (β, e), the factor $\exp(t \cdot z_k)$ is log-concave in (β, e) for every $t \geq 0$. Moreover, the Gaussian density $\varphi_S(a - y_k)$ is log-concave in a. Hence, L_t is jointly log-concave in (a, β, e). By Prekopa's theorem, integration preserves log-concavity, so the marginal

$$G_t(a) := \int\int L_t(a; \beta, e)\, ded\beta$$

is log-concave in a for every $t \geq 0$. Therefore, $a \mapsto \log G_t(a)$ is concave. Define $H_t(a) := \log G_t(a)$. Differentiating at $t = 0$, we have

$$\frac{\partial}{\partial t} H_t(a)\,|_{t=0} = \frac{\frac{\partial}{\partial t} G_t(a)}{G_t(a)}|_{t=0} = \frac{\int\int z_k \exp[tz_k]\, \Gamma(a; \beta, e)\, ded\beta}{\int\int \exp[tz_k]\, \Gamma(a; \beta, e)\, ded\beta}|_{t=0} = \frac{\int\int z_k \Gamma(a; \beta, e)\, ded\beta}{\int\int \Gamma(a; \beta, e)\, ded\beta} = \mathbb{E}\left[z_k|a\right].$$

Because each $H_t(a)$ is concave in a and pointwise differentiation of a concave family preserves concavity, the map $a \mapsto \mathbb{E}\left[z_k|a\right]$ is concave. Since $P_1^k(a) = a + \mathbb{E}\left[z_k|a\right]$ is the sum of a linear function and a concave function, it is concave. □

Given a strategy $k(\beta, e) \geq 0$, as above we define

$$y_k(\beta, e) := e - k(\beta, e),$$

$$z_k(\beta, e) := \delta_1 \beta + \sqrt{2\beta\, k(\beta, e)}.$$

The constant term δ_0 in $\Delta(\beta) = \delta_0 + \delta_1\beta$ can be dropped from z_k since it vanishes in covariances. We thus suppress notation of δ_0.

The earnings announcement is thus $a = y_k + \varepsilon$. For each a, posterior beliefs under k satisfy

$$\pi_k^a(d\beta\, de) \;\propto\; f_\beta(\beta)\, f_{e|\beta}(e|\beta)\, \varphi_S(a - y_k(\beta, e))\, d\beta\, de,$$

where

$$\varphi_S(u) = (2\pi S)^{-1/2} e^{-u^2/(2S)}.$$

Denote the posterior expectation as $\mathbb{E}_k[\cdot \mid a]$ and the first-period price is

$$P_1^k(a) := a + \mathbb{E}_k[z_k \mid a],$$

Let $s_k(a) := P_1^{k\prime}(a)$. Define the weighted L^1-norm

$$\|h\|_{\beta,1} := \mathbb{E}[\beta|h(\beta, e)|] = \int_0^\infty \int_{\mathbb{R}} \beta\, |h(\beta, e)|\, f_\beta(\beta)\, f_{e|\beta}(e|\beta)\, de\, d\beta.$$

We denote by $m_{\beta,2}$ as the following, which will be used later:

$$m_{\beta,2} := \mathbb{E}[\beta^2] = m_\beta^2 + v_\beta < \infty.$$

To derive the best-response envelope, we first fix a conjectured strategy k and state (β, e).

For any radius $R > 0$, define the (radius-R) strategy ball

$$\mathcal{S}_R := \{k : \ 0 \le k(\beta, e) \le R\,\beta \text{ a.e.}\}.$$

Later we will work on the special ball $\mathcal{S}_\chi$, which is the case $R = \chi$. The manager chooses $x \ge 0$ to maximize

$$\Phi_k(x; \beta, e) = \alpha\, P_1^k(e - x) + (1 - \alpha)\left(\sqrt{2\beta x} + \delta_1 \beta\right).$$

Since P_1^k is concave (Lemma 2) and $\sqrt{2\beta x}$ is strictly concave, the maximizer is unique. The interior FOC is

$$(1 - \alpha)\, r_\beta'(x^*) = \alpha\, s_k(e - x^*), \tag{8}$$

where $r_\beta'(x) = \sqrt{\beta/2}\, x^{-1/2}$. By Lemma 4 below, $s_k(\cdot) := P_1^{k\prime}(a) \ge 1$, hence

$$(1 - \alpha)\sqrt{\frac{\beta}{2}}(x^*)^{-1/2} \ge \alpha.$$

Therefore

$$x^*(\beta, e; k) \le \chi\, \beta, \tag{9}$$

where $\chi := \frac{(1-\alpha)^2}{2\alpha^2}$. Define the strategy ball

$$\mathcal{S}_\chi := \mathcal{S}_R\big|_{R=\chi} = \{k : \ 0 \le k(\beta, e) \le \chi\,\beta \text{ a.e.}\}.$$

Then equation (9) implies that the best response operator satisfies

$$BR : \mathcal{S}_\chi \to \mathcal{S}_\chi.$$

For any $R > 0$, define

$$M_R := \delta_1 + \sqrt{2R}.$$

In particular, on $\mathcal{S}_\chi$,

$$M_\star := M_\chi = \delta_1 + \sqrt{2\chi} = \delta_1 + \frac{1 - \alpha}{\alpha}.$$

Moreover, if $k \in \mathcal{S}_R$, then $\sqrt{2\beta k} \le \sqrt{2R}\,\beta$, hence

$$|z_k(\beta, e)| \le (\delta_1 + \sqrt{2R})\beta = M_R\, \beta. \tag{10}$$

For the curvature constant for $\sqrt{2\beta x}$, since $r_\beta''(x) = -(1/2)\sqrt{\beta/2}\, x^{-3/2}$, then for any $\xi \in (0, \chi\beta]$,

$$-r_\beta''(\xi) = \frac{1}{2}\sqrt{\frac{\beta}{2}}\,\xi^{-3/2} \ge \frac{1}{2}\sqrt{\frac{\beta}{2}}\,(\chi\beta)^{-3/2} = \frac{1}{2\sqrt{2}\,\chi^{3/2}} \cdot \frac{1}{\beta} =: \frac{w_\alpha}{\beta}.$$

A direct calculation using $\chi = \frac{(1-\alpha)^2}{2\alpha^2}$ yields

$$w_\alpha = \frac{1}{2\sqrt{2}\,\chi^{3/2}} = \frac{\alpha^3}{(1-\alpha)^3}. \tag{11}$$

We next compare two best responses k and $\hat{k}$. Fix $k, \hat{k} \in \mathcal{S}_\chi$ and let

$$x := BR(k)(\beta, e),$$

and similarly for $\hat{k}$,

$$\hat{x} := BR(\hat{k})(\beta, e).$$

Their FOCs are

$$(1-\alpha)r'_\beta(x) = \alpha s_k(e-x),$$
$$(1-\alpha)r'_\beta(\hat{x}) = \alpha s_{\hat{k}}(e-\hat{x}).$$

Subtracting and using the fact that r'_β is decreasing and $s_k(\cdot)$ is nonincreasing gives

$$(1-\alpha)\big|r'_\beta(x) - r'_\beta(\hat{x})\big| \le \alpha\,\big|s_k(e-\hat{x}) - s_{\hat{k}}(e-\hat{x})\big| \le \alpha \sup_{a\in\mathbb{R}} |s_k(a) - s_{\hat{k}}(a)|.$$

By the mean value theorem, for some $\xi \in [\min\{x,\hat{x}\}, \max\{x,\hat{x}\}] \subset (0, \chi\beta]$,

$$|r'_\beta(x) - r'_\beta(\hat{x})| = |r''_\beta(\xi)|\,|x-\hat{x}| \ge \frac{w_\alpha}{\beta}|x-\hat{x}|.$$

Hence

$$(1-\alpha)w_\alpha \frac{|x-\hat{x}|}{\beta} \le \alpha \sup_a |s_k(a) - s_{\hat{k}}(a)|. \tag{12}$$

Multiplying by β^2 and integrating, we have:

$$(1-\alpha)w_\alpha \|BR(k) - BR(\hat{k})\|_{\beta,1} \le \alpha\,\mathbb{E}[\beta^2]\ \sup_a |s_k(a) - s_{\hat{k}}(a)| = \alpha\, m_{\beta,2}\ \sup_a |s_k(a) - s_{\hat{k}}(a)|.$$

Thus

$$\|BR(k) - BR(\hat{k})\|_{\beta,1} \le \frac{\alpha}{1-\alpha}\cdot\frac{m_{\beta,2}}{w_\alpha}\ \sup_a |s_k(a) - s_{\hat{k}}(a)|. \tag{13}$$

We next show the Gaussian Lipschitz bound for $P_1^{k\prime}(a)$ which will be used to show a contraction:

Lemma 3. *Fix $R > 0$ and let $k, \hat{k} \in \mathcal{S}_R$. Then, there exists a finite constant $C_\star(R)$ such that*

$$\sup_{a\in\mathbb{R}} \big|s_k(a) - s_{\hat{k}}(a)\big| \le \frac{C_\star(R)}{S}\, M_R\, \|k - \hat{k}\|_{\beta,1}, \tag{14}$$

where $M_R = \delta_1 + \sqrt{2R}$.

Proof. Let $\Delta k := \hat{k} - k$, and define $y_k = e - k$, $y_{\hat{k}} = e - \hat{k}$. By the score-covariance identity

(Lemma 1),

$$s_k(a) - s_{\hat{k}}(a) = \frac{1}{S}\Big(Cov_k(z_k, y_k \mid a) - Cov_{\hat{k}}(z_{\hat{k}}, y_{\hat{k}} \mid a)\Big) =: \frac{1}{S}\mathcal{D}(a).$$

Add and subtract the cross term $Cov_k(z_k, y_{\hat{k}} \mid a)$ to decompose

$$\mathcal{D}(a) = T_1(a) + T_2(a),$$

where

$$T_1(a) := Cov_k(z_k, y_k \mid a) - Cov_k(z_k, y_{\hat{k}} \mid a) = Cov_k(z_k, y_k - y_{\hat{k}} \mid a) = Cov_k(z_k, -\Delta k \mid a),$$

and

$$T_2(a) := Cov_k(z_k, y_{\hat{k}} \mid a) - Cov_{\hat{k}}(z_{\hat{k}}, y_{\hat{k}} \mid a).$$

By Cauchy–Schwarz,

$$|T_1(a)| \le sd_k(z_k \mid a)\, sd_k(\Delta k \mid a) \le sd_k(z_k \mid a)\, \mathbb{E}_k[|\Delta k| \mid a],$$

where $sd\,(\cdot)$ denotes standard deviation. Using (10), $|z_k| \le M_R \beta$ on $\mathcal{S}_R$, hence

$$sd_k(z_k \mid a) \le \mathbb{E}_k[|z_k| \mid a] \le M_R\, \mathbb{E}_k[\beta \mid a].$$

Next, on $\mathcal{S}_R$ we have $|\Delta k| \le R\beta$; in particular $|\Delta k|$ has the same linear envelope. Because $\beta > 0$ a.s. and posterior moments are continuous in a, there exists a compact interval $|a| \le A_0$ attaining the supremum in (14), and on this compact set we have

$$0 < \underline{m}_\beta(R) := \inf_{t\in[0,1],\, |a|\le A_0} \mathbb{E}_{k_t}[\beta \mid a] \le \sup_{t\in[0,1],\, |a|\le A_0} \mathbb{E}_{k_t}[\beta \mid a] =: \overline{m}_\beta(R) < \infty,$$

where $k_t := k + t\Delta k$. Therefore, for $|a| \le A_0$,

$$\mathbb{E}_k[|\Delta k| \mid a] \le \frac{1}{\underline{m}_\beta(R)}\, \mathbb{E}_k[\beta|\Delta k| \mid a].$$

Finally, since the likelihood $\varphi_S(a - y_k)$ is Gaussian and $|\Delta k| \le R\beta$, there exists a finite constant $C_0(R)$ such that for all $|a| \le A_0$,

$$\mathbb{E}_k[\beta|\Delta k| \mid a] \le C_0(R)\, \mathbb{E}[\beta|\Delta k|] = C_0(R)\, \|\Delta k\|_{\beta,1}.$$

Combining,

$$\sup_{|a|\le A_0} |T_1(a)| \le M_R\, \overline{m}_\beta(R)\, \frac{C_0(R)}{\underline{m}_\beta(R)}\, \|\Delta k\|_{\beta,1}.$$

For bound T_2, interpolate $k_t := k + t\Delta k$ and denote $\mathbb{E}_t[\cdot \mid a]$ for the posterior under k_t. Define the function

$$F(t,a) := Cov_{k_t}(z_k, y_{\hat{k}} \mid a).$$

A standard Gaussian score calculation by differentiating the posterior density in t gives

$$\partial_t \mathbb{E}_t[H \mid a] = \frac{1}{S} Cov_{k_t}\big(H,\, (y_t - a)\Delta k \;\big|\; a\big),$$

where $y_t = e - k_t$. We can apply this with $H = z_k y_{\hat{k}}$, $H = z_k$, and $H = y_{\hat{k}}$, and expanding $\partial_t F(t,a)$. Using Cauchy–Schwarz, the envelopes $|z_k| \le M_R \beta$ and $|y_{\hat{k}}| \le |e| + R\beta$, and the bound $|\Delta k| \le R\beta$, we obtain

$$|\partial_t F(t,a)| \le \frac{C_1(R)}{S}\, M_R\, \mathbb{E}_t[\beta|\Delta k| \mid a],$$

for some finite constant $C_1(R)$ absorbing uniformly bounded posterior moments on $|a| \le A_0$. Integrating $t \in [0,1]$ and using the same conditional-to-unconditional step as above yields

$$\sup_{|a|\le A_0} |T_2(a)| \le \frac{C_2(R)}{S}\, M_R\, \|\Delta k\|_{\beta,1},$$

for some finite $C_2(R)$.

Finally, since $\sup_a |s_k(a) - s_{\hat{k}}(a)|$ is attained on $|a| \le A_0$, combining the T_1 and T_2 bounds and dividing by S gives

$$\sup_{a\in\mathbb{R}} |s_k(a) - s_{\hat{k}}(a)| \le \frac{C_\star(R)}{S}\, M_R\, \|\Delta k\|_{\beta,1},$$

for a finite $C_\star(R)$. □

To show the contraction on $\mathcal{S}_\chi$, we apply Lemma 3 with $R = \chi$ so that $M_R = M_\star$. Then (13) and (14) yield

$$\|BR(k) - BR(\hat{k})\|_{\beta,1} \le \frac{\alpha}{1-\alpha} \cdot \frac{m_{\beta,2}}{w_\alpha} \cdot \frac{C_\star(\chi)}{S}\, M_\star\, \|k - \hat{k}\|_{\beta,1}.$$

Using $w_\alpha = \alpha^3/(1-\alpha)^3$ from (11), the prefactor simplifies to

$$\frac{\alpha}{1-\alpha} \cdot \frac{1}{w_\alpha} = \frac{\alpha}{1-\alpha} \cdot \frac{(1-\alpha)^3}{\alpha^3} = \frac{(1-\alpha)^2}{\alpha^2}.$$

Hence

$$\|BR(k) - BR(\hat{k})\|_{\beta,1} \le q\, \|k - \hat{k}\|_{\beta,1}, \tag{15}$$

where the contraction modulus is

$$q := \frac{(1-\alpha)^2}{\alpha^2} \cdot \frac{m_{\beta,2}\, C_\star(\chi)\, M_\star}{S}.$$

Therefore, for

$$S > \frac{(1-\alpha)^2}{\alpha^2}\, m_{\beta,2}\, C_\star(\chi)\, M_\star,$$

we have $q < 1$ and BR is a strict contraction on the complete metric space $(\mathcal{S}_\chi, \|\cdot\|_{\beta,1})$.

By Banach's fixed point theorem, there exists a unique $k^* \in \mathcal{S}_\chi$ such that $k^* = BR(k^*)$. Given k^*, define beliefs $\pi^a_{k^*}$ by Bayes' rule and prices $P_1^{k^*}(a) = a + \mathbb{E}_{k^*}[z_{k^*} \mid a]$. Sequential rationality holds by construction of BR, and beliefs are consistent. Thus $(k^*, P_1^{k^*}, \pi_{k^*})$ is a pure strategy PBE. Uniqueness follows from uniqueness of the fixed point.

B.3 Comparative statics

We next prove the comparative statics claims in Proposition 1. We begin with a preliminary lemma.

Lemma 4. $P_1^{k\prime}(a) \geq 1$ *for all* $a \in \mathbb{R}$*.*

Proof. Continuing with the earlier notation, suppressing the subscript and superscript k, let $z(\beta, e) := \Delta(\beta) + r_\beta\left(k^*(\beta, e)\right)$. We show that $G(a) := \mathbb{E}\left[z(\beta, e) \,|a\right]$ is nondecreasing in a. First, note that

$$\Phi(\beta, e; k) = \alpha P_1(e-k) + (1-\alpha) r_\beta(k) \tag{16}$$

has increasing differences in (β, k) since $\frac{\partial^2 r_\beta(k)}{\partial\beta\partial k} > 0$. Hence, by Topkis' theorem, the maximizer is nondecreasing in β, so we have that $\frac{\partial k^*(\beta,e)}{\partial\beta} \geq 0$. The FOC of (16) is $(1-\alpha) r'_\beta(k^*) = \alpha P'_1(e-k^*)$. Differentiating the FOC with respect to e, we have

$$\Big((1-\alpha) r''_\beta(k^*) \cdot k^*_e = \alpha P''_1(e-k^*)\Big)(1-k^*_e),$$

rearranging,

$$k^*_e = \frac{\alpha P''_1(a^*)}{(1-\alpha) r''_\beta(k^*) + \alpha P''_1(a^*)}$$

since $P''_1(a^*) \leq 0$ and $r''_\beta(k^*) < 0$, $k^*_e := \frac{\partial k^*}{\partial e} \geq 0$. Moreover, $k^*_e \in [0,1)$. Hence $e \mapsto y^*(\beta, e) := e - k^*(\beta, e)$ is strictly increasing with slope $1-k^*_e \in (0,1]$. Note also that $y^*(\beta, e)$ has increasing differences in (β, e). Define $F := (1-\alpha) r'_\beta(k) - \alpha P'(e-k)$. Differentiating $k^*_e = -F_e/F_k$ w.r.t. β,

$$k^*_{\beta e} = -\frac{F_{e\beta}F_k - F_e F_{\beta k}}{F_k^2} = \frac{F_e F_{k\beta}}{F_k^2}$$

because $F_{e\beta} = 0$. $F_e = -\alpha P''(e-k) \geq 0$, $F_{k\beta} = (1-\alpha)\left[-\frac{1}{4\sqrt{2}}\beta^{-\frac{1}{2}}k^{-\frac{3}{2}}\right] < 0$, and $F_k^2 > 0$, so $\frac{F_e F_{k\beta}}{F_k^2} \leq 0$. Hence, k^* has decreasing differences in (β, e) and $y^*(\beta, e) = e - k^*(\beta, e)$ has increasing differences in (β, e).

We next show that $z(\beta, e)$ is increasing in both arguments. In β, $\Delta(\beta) = \delta_0 + \delta_1\beta$ increases for $\delta_1 \geq 0$, while $r_\beta(k)$ has increasing differences in (β, k) and as shown above, $\frac{\partial k^*(\beta,e)}{\partial\beta} \geq 0$. Hence $\frac{\partial z(\beta,e)}{\partial\beta} \geq 0$. In e, $\frac{\partial k^*}{\partial e} \geq 0$, and since $r_\beta(k)$ is increasing in k, $\frac{\partial z(\beta,e)}{\partial e} \geq 0$. Hence, $z(\beta, e)$ is coordinate-wise increasing in (β, e).

We next employ properties of total positivity of order 2 (TP_2) functions. Note that a positive kernal $K(u, v)$ is TP_2 in (u, v) if and only if $\partial^2 \log K/\partial u\partial v \geq 0$. TP_2 implies MLRP: the ratios $K(u, v)/K(u', v)$ are increasing whenever $u > u'$. The conditional density

$f_{e|\beta}\left(e|\beta\right) \propto \exp\left[-\frac{\left(e-(\mu_e+\rho\beta)\right)^2}{2\sigma_e^2}\right]$ has cross derivative

$$\frac{\partial^2}{\partial e\partial\beta}\log f_{e|\beta}\left(e|\beta\right) = \frac{\rho}{\sigma_e^2} > 0,$$

which implies that $f_{e|\beta}$ is TP_2 in (e,β). Likewise, for the announcement kernel $K(a;y) := \varphi_{\sigma_\varepsilon}(a-y) \propto \exp\left[-\frac{(a-y)^2}{2\sigma_\varepsilon^2}\right]$,

$$\frac{\partial^2}{\partial a\partial y}\log K(a;y) = \frac{1}{\sigma_\varepsilon^2} > 0,$$

so K is TP_2 in (a,y). By the Karlin-Rinott composition theorem, for each fixed a, the composite $L_a(\beta,e) := K\left(a, y^*(\beta,e)\right)$ is TP_2 in (β,e) and the mixture

$$f_{a|\beta}\left(a|\beta\right) = \int L_a(\beta,e)\, f_{e|\beta}\left(e|\beta\right) de$$

is TP_2 in (a,β). As a result, $a|\beta$ has MLRP in β, and by the Karlin-Rubin monotonicity theorem, the posterior $\beta|a$ is FOSD-increasing in a. Likewise, for fixed a, $(e,\beta) \mapsto L_a(\beta,e) = \varphi_{\sigma_\varepsilon}\left(a-y^*(\beta,e)\right)$ is TP_2 in (β,e). Combining with the fact that $f_{e|\beta}$ is TP_2 in (e,β) (shown above), by Bayes,

$$f_{e|\beta,a}\left(e|\beta,a\right) \propto L_a(\beta,e)\, f_{e|\beta}\left(e|\beta\right),$$

which implies that the likelihood ratio in e between $\beta_2 > \beta_1$ is increasing, i.e., $e|(\beta,a)$ has MLRP in β, and hence for any increasing ϕ, $\mathbb{E}\left[\phi(e)|\beta_2,a\right] \geq \mathbb{E}\left[\phi(e)|\beta_1,a\right]$, so the posterior $e|(\beta,a=a)$ is FOSD-increasing in β. Finally, for each fixed β, since $a|(\beta,e)$ is normal with mean $y^*(\beta,e)$, which is increasing in e, the family $\left\{f_{a|\beta,e}\left(\cdot|\beta,e\right) : e \in \mathbb{R}\right\}$ has MLRP in e, so $e|(\beta,a=a)$ is FOSD-increasing in a.

Let

$$m(\beta,a) := \mathbb{E}\left[z(\beta,e)|\beta,a\right].$$

Since $z(\beta,e)$ is increasing in e and the FOSD increase of $e|(\beta,a)$ in a, for $a_2 > a_1$, we have that $m(\beta,a_2) \geq m(\beta,a_1)$. Since $z(\beta,e)$ is increasing in β and the FOSD increase of $e|(\beta,a)$ in β, for $\beta_2 > \beta_1$, $m(\beta_2,a) \geq m(\beta_1,a)$. Next, fix $a_2 > a_1$ and let

$$Q(a) = \mathbb{E}_{\beta|a}\left[m(\beta,a)\right].$$

We induce the change-of-measure weight

$$\omega(\beta) := \frac{f_{a|\beta}\left(a_2|\beta\right)}{f_{a|\beta}\left(a_1|\beta\right)} \cdot \frac{f_a(a_1)}{f_a(a_2)}.$$

Then $\mathbb{E}_{\beta|a_1}[\omega] = 1$ and

$$Q(a_2) - Q(a_1) = \mathbb{E}_{\beta|a_1}\left[\omega(\beta)\left(m(\beta,a_2) - m(\beta,a_1)\right)\right] + Cov_{\beta|a_1}\left[\omega(\beta), m(\beta,a_1)\right]. \quad (17)$$

The first term in the right-hand side of (17) is nonnegative since $\omega \geq 0$ and $m(\beta, \cdot)$ is nondecreasing. Moreover, $\omega(\beta)$ is increasing in β by MLRP of $a|\beta$ in β, and $m(\cdot, a_1)$ is increasing in β. Thus by Chebyshev-Hoeffding's covariance inequality, we have $Cov_{\beta|a_1}\left[\omega(\beta), m(\beta, a_1)\right] \geq 0$. Hence $Q(a_2) \geq Q(a_1)$ for any $a_2 > a_1$, i.e., Q is nondecreasing. As such, $Q'(a) \geq 0$, and thus $P_1'(a) = 1 + Q'(a) \geq 1$. □

For $\frac{\partial k^*}{\partial \alpha} \equiv k^*_\alpha$, differentiating the FOC w.r.t. α, where $a^* = e - k^*$, and let $s(a^*) := P_1'(a^*)$,

$$-r_\beta'(k^*) + (1-\alpha) r_\beta''(k^*) k^*_\alpha = s(a^*) + \alpha s'(a^*) \cdot (-k^*_\alpha).$$

Hence,

$$\Big((1-\alpha) r_\beta''(k^*) + \alpha s'(a^*)\Big) k^*_\alpha = r_\beta'(k^*) + s(a^*)\ .$$

The bracket in the left-hand side is strictly negative since $r_\beta''(k^*) < 0$ and $P_1''(a^*) \leq 0$, while the right-hand is positive, since $r_\beta'(k^*) > 0$ and $P_1'(a^*) \geq 1$. Hence, $k^*_\alpha < 0$.

For $\frac{\partial k^*}{\partial \sigma_\varepsilon^2}$ (equivalently $\frac{\partial k^*}{\partial S}$,where $S := \sigma_e^2 + \sigma_\varepsilon^2$), differentiating the FOC w.r.t. S, again letting $s(a^*) := P_1'(a^*)$,

$$(1-\alpha) r_\beta''(k^*) k^*_S = \alpha \left(s_S(a^*) + s'(a^*) \cdot (-k^*_S)\right),$$

which becomes

$$\Big((1-\alpha) r_\beta''(k^*) + \alpha s'(a^*)\Big) k^*_S = \alpha s_S(a^*)\ . \tag{18}$$

To see that $s_S(a^*) < 0$, let $S_2 > S_1$. The observation with noise S_2 can be generated by taking the S_1 observation and adding independent Gaussian noise $\eta \sim \mathbb{N}(0, S_2 - S_1)$. For any integrable function z of the underlying state ($z = \Delta(\beta) + r_\beta\left(k(\beta, e)\right)$), we have $m_S(a) := \mathbb{E}\left[z|a; S\right]$ and $m_{S_2} = m_{S_1} \cdot \varphi_{S_2 - S_1}$, where $\varphi_{S_2-S_1}$ is the pdf of a mean-zero normal distribution with variance $S_2 - S_1$. Because $\varphi_{S_2-S_1}$ is zero mean, convolution weakly preserves order;

$$s(\cdot; S_2) - 1 = m'_{S_1} \cdot \varphi_{S_2-S_1} \leq m'_{S_1} = s(\cdot; S_1) - 1$$

pointwise wherever m_{S_1} is concave, where $s(a) = P_1'(a) = 1 + m_S'(a)$. Since P_1 is concave, m_S is concave. Hence for $S_2 > S_1$, then $s(\cdot; S_2) \leq s(\cdot; S_1)$ pointwise. As such, the right-hand side of (18) is negative. The bracket in the left-hand side of (18) is negative since $r_\beta''(k^*) < 0$ and $s'(a^*) \leq 0$. Hence, $k^*_S > 0$ and thus $\frac{\partial k^*}{\partial \sigma_\varepsilon^2} > 0$ and also $\frac{\partial k^*}{\partial \sigma_e^2} > 0$.

For $\frac{\partial k^*}{\partial v_\beta} \equiv k^*_{v_\beta}$, differentiating the FOC with respect to v_β (where $s(a^*) := P_1'(a^*)$), we have

$$(1-\alpha) r_\beta''(k^*) k^*_{v_\beta} = \alpha \left(s_{v_\beta}(a^*) + s'(a^*) \left(-k^*_{v_\beta}\right)\right),$$

where $s_{v_\beta}(a) := \frac{\partial s(a)}{\partial v_\beta}$. Rearranging, we have

$$\Big((1-\alpha) r_\beta''(k^*) + \alpha s'(a^*)\Big) k^*_{v_\beta} = \alpha s_{v_\beta}(a^*). \tag{19}$$

To see that $s_{v_\beta}(a^*) > 0$, let $\pi^{(1)}$ and $\pi^{(2)}$ be two truncated-normal priors on $(0, \infty)$ with the same mean but variances $v_\beta^{(2)} > v_\beta^{(1)}$, so $\pi^{(2)}$ is more dispersed than $\pi^{(1)}$ in the convex order.

Let $\mathbb{E}^{(i)}$ denote the expectation under $\pi^{(i)}$. The price slope is

$$s^{(i)}(a) := P_1^{(i)\prime}(a) = 1 + \frac{d}{da} m^{(i)}(a),$$

where $m^{(i)}(a) := \mathbb{E}^{(i)}\left[g(\beta, e)\,|a\right]$. Using the score identity, we have

$$\frac{d}{da} m^{(i)}(a) = Cov^{(i)}\left(g(\beta, e), \psi(\beta, e; a)\,|a\right),$$

where $\psi(\beta, e; a) = \frac{\partial}{\partial a} \log f_{a|\beta,e}\left(a|\beta, e\right)$, which is TP_2 and thus increasing in β. The payoff kernel $g(\beta, e)$ is also increasing in β. Both functions are integrable and thus $\frac{d}{da} m^{(i)}(a)$ is the covariance of two increasing functions of β. Since $\pi^{(2)}$ is a mean-preserving spread of $\pi^{(1)}$, there is a monotone martingale coupling between the two posteriors at any announcement a (the posterior under $\pi^{(2)}$ is a mean-preserving spread of the posterior under $\pi^{(1)}$). The covariance of the comonotone pair g and ψ is therefore larger under the more dispersed prior. Concretely, for each a,

$$\frac{d}{da} m^{(2)}(a) = Cov^{(2)}\left(g, \psi|a\right) > Cov^{(1)}\left(g, \psi|a\right) = \frac{d}{da} m^{(1)}(a).$$

Hence,

$$s^{(2)}(a) - 1 = \frac{d}{da} m^{(2)}(a) > \frac{d}{da} m^{(1)}(a) = s^{(1)}(a) - 1.$$

Since $v_\beta^{(2)} > v_\beta^{(1)}$ is arbitrary, for any $v_2 > v_1$, $s(a; v_2) > s(a; v_1)$. Hence, $s_{v_\beta}(a) > 0$ and the right-hand side of (19) is positive. The bracket in the left-hand side of (19) is negative since $r_\beta''(k^*) < 0$ and $s'(a^*) \leq 0$. Hence, $k_{v_\beta}^* < 0$.

Recall that the bias in investment is defined as the departure from the second-best investment level, $b(\beta, e) = k^0 - k^*$, where $k^0(\beta, e) = \frac{(1-\alpha)^2}{2\alpha^2}\beta$ and $k^* = \frac{(1-\alpha)^2}{2\alpha^2}\frac{\beta}{s(a)^2}$. Since $s(a) \geq 1$ (i.e., $P_1'(a) \geq 1$) by Lemma 4, then $b(\beta, e) \geq 0$. For $\frac{\partial b(\beta, e)}{\partial \beta}$, let $g(\beta, e) := k^*(\beta, e)/\beta$, so $k^* = \beta g$. We have

$$r_\beta'(k) = \frac{\beta}{\sqrt{2\beta k}} = \frac{\beta}{\sqrt{2\beta(\beta g)}} = \frac{1}{\sqrt{2g}}.$$

And since $a^* = e - k^* = e - \beta g$, then the FOC becomes

$$(1-\alpha)\frac{1}{\sqrt{2g}} = \alpha \cdot s(e - \beta g).$$

Define $W(g, \beta; e) := (1-\alpha)(2g)^{-1/2} - \alpha s(e - \beta g)$. Then $W(g, \beta; e) = 0$. We have that

$$\frac{\partial W}{\partial g} = -\frac{1-\alpha}{(2g)^{3/2}} + \alpha\beta s'(a^*) < 0$$

since $s'(a^*) \leq 0$ and $-\frac{1-\alpha}{(2g)^{3/2}} < 0$, and

$$\frac{\partial W}{\partial \beta} = \alpha g s'(a^*) \leq 0.$$

By the implicit function theorem, $g_\beta = -\frac{W_\beta}{W_g} \leq 0$. Hence,

$$\begin{aligned}\frac{\partial b(\beta, e)}{\partial \beta} &= \frac{\partial}{\partial \beta}\left(k^0 - k^*\right) = \frac{\partial}{\partial \beta}\left[\frac{(1-\alpha)^2}{2\alpha^2}\beta - \beta g\right] \\ &= \frac{(1-\alpha)^2}{2\alpha^2} - g - \beta g_\beta\end{aligned}$$

Since $g_\beta \leq 0$, then $\frac{(1-\alpha)^2}{2\alpha^2} - g - \beta g_\beta \geq \frac{(1-\alpha)^2}{2\alpha^2} - g$. Since $g = \frac{(1-\alpha)^2}{2\alpha^2} \cdot \frac{1}{s(a)}$ and $s(a) \geq 1$ by Lemma 4, then $\frac{(1-\alpha)^2}{2\alpha^2} \geq g$ which implies that $\frac{\partial b(\beta,e)}{\partial \beta} \geq 0$. Hence the bias is increasing in productivity β.

Finally, as shown in Lemma 4, investment is increasing in earnings e, $\frac{\partial k^*}{\partial e} \geq 0$. Since k^0 does not depend on e, it follows that the bias is decreasing in e, hence $\frac{\partial b(\beta,e)}{\partial e} \leq 0$.

C Definitions of variables

Variable	Definition
Measures of negative price pressure	
$Tainted\ Fund\%_{i,q}$	The aggregate tainted-fund ownership of firm i in quarter q, measured as the percentage of the firm's shares outstanding held by the 4,408 U.S. domestic equity mutual funds belonging to the 25 implicated mutual fund families. For each firm i, this variable is calculated beginning in the quarter when the trading scandal was revealed, and set to zero in all prior quarters.
$High\ Tainted\ Fund\%_{i,q}$	An indicator variable that equals one if firm i's $Tainted\ Fund\%$ is at or above the sample median in quarter q and zero otherwise. The sample median is calculated among exposed firms, i.e., firms with positive tainted-fund ownership. For each firm i, this variable is calculated beginning in the quarter when the trading scandal was revealed, and set to zero in all prior quarters.
Outcome Variables of Interest	
$MBE\_CutR\&D_{i,q}$	An indicator variable that equals one if (i) firm i's reported EPS for quarter q falls between the latest mean analyst consensus EPS forecast prior to its earnings announcement date and that plus one cent and (ii) the firm reports a reduction in R&D expenditure (XRDQ) relative to $q-1$, and zero otherwise.
$CutR\&D_{i,q}$	The negative of firm i's change in R&D expenditures (XRDQ) from quarter $q-1$ to quarter q, scaled by total assets (ATQ) at the end of quarter $q-1$. Missing R&D expenditures are set to zero.
$MBE_{i,q}$	An indicator variable that equals one if firm i's reported EPS for quarter q falls between the latest mean analyst consensus EPS forecast prior to its earnings announcement date and that plus one cent, and zero otherwise.
$Beat > 3ct_{i,q}$	An indicator variable that equals one if firm i's reported EPS for quarter q exceeds the latest mean analyst consensus EPS forecast prior to its earnings announcement date by more than three cents, and zero otherwise.
$CAR_{i,q}$	The cumulative three-day market-adjusted abnormal return centered on the earnings announcement date of firm i-quarter q. The daily market-adjusted return is defined as the firm's daily raw return minus the corresponding return on the CRSP value-weighted index.
Control Variables	
$ln(BV)_{i,q-1}$	The natural logarithm of firm i's book value of assets (ATQ) at the end of quarter $q-1$.
$ROA_{i,q-1}$	Firm i's return-on-assets, defined as net income (NIQ) for quarter $q-1$ divided by the average of total assets (ATQ) at the beginning and end of that quarter.
$LEV_{i,q-1}$	Firm i's leverage ratio, defined as the firm's book value of debt (DLCQ + DLTTQ) divided by the sum of its book value of debt and total shareholders' equity (SEQQ) at the end of quarter $q-1$.
$MB_{i,q-1}$	Firm i's market-to-book ratio, defined as the firm's market value of equity (PRCCQ $\times$ CSHOQ) divided by its book value of equity (CEQQ) at the end of quarter $q-1$.
$INST\%_{i,q-1}$	Institutional ownership of firm i, measured as the percentage of the firm's shares outstanding at the end of quarter $q-1$. Ownership data are obtained from the Thomson Reuters Institutional Holdings (13F) database.
$BHAR\%_{i,q-1}$	Firm i's buy-and-hold abnormal return (BHAR) over quarter $q-1$, calculated as the firm's geometrically compounded monthly returns minus the corresponding returns on the CRSP value-weighted index.

$ALY\_N_{i,q}$	The natural logarithm of one plus the number of analysts following firm i during quarter q, obtained from the I/B/E/S database.
$ALY\_HRZN_{i,q}$	The natural logarithm of one plus the average analyst forecast horizon for firm i-quarter q, where each analyst's forecast horizon is defined as the number of days between the firm's earnings announcement date and the date of the analyst's latest forecast made prior to that.
$ALY\_DISP_{i,q}$	Analyst forecast dispersion for firm i-quarter q, defined as the standard deviation of individual analysts' latest forecasts made prior to the earnings announcement date divided by the stock price at the end of quarter q.
$UE_{i,q}$	Unexpected earnings, or earnings surprise, for firm i-quarter q, defined as the firm's reported EPS minus the latest mean analyst consensus EPS forecast prior to its earnings announcement date divided by the stock price at the end of quarter q.
$Miss_{i,q}$	An indicator variable that equals one if firm i's reported EPS for quarter q falls below the latest mean analyst consensus EPS forecast prior to its earnings announcement date, and zero otherwise.
$BHAR_{i,q\ to\ q+n}$	Firm i's buy-and-hold abnormal return (BHAR) from the end of quarter q to the end of $q+n$, where q is the quarter in which the firm experiences a price decline and n ranges from 1 to 12. Quarterly BHAR is calculated as the firm's geometrically compounded monthly returns minus the corresponding returns on the CRSP value-weighted index. Cumulative abnormal returns are then obtained by summing quarterly abnormal returns over the specified horizon.
Variables used in additional tests	
$Myopia_{i,q}$	An indicator variable that equals one if the aggregate ownership of firm i in quarter q, measured as the percentage of the firm's shares outstanding held by the 1,459 U.S. domestic equity mutual funds that switched from semi-annual to quarterly reporting following the May 2004 SEC disclosure rule change, is at or above the sample median, and zero otherwise. For each firm i, this variable is calculated beginning in the quarter when the rule became effective and set to zero in all prior quarters.
$Vol\_MB_{i,q}$	The standard deviation of MB in the past eight quarters (from $q-8$ to $q-1$), where MB is the firm's market-to-book ratio.

This appendix describes the calculation of variables used in all analyses. Underlined variables refer to variable names within Compustat. i indexes firms and q indexes fiscal quarters.

Table 1: Descriptive statistics

This table reports summary statistics of the variables used in the core analysis. Negative price pressure is measured using $Tainted\ Fund\%$, the tainted-fund ownership, and $High\ Tainted\ Fund\%$, an indicator equal to one if $Tainted\ Fund\%$ is at or above the median among positive observations. Dependent variables include $MBE\_CutR\&D$, an indicator equal to one if the firm meets or beats the analyst consensus forecast by up to one cent and reports a reduction in $R\&D$ expenditure, and CAR, the three-day earnings announcement return. Control variables include $ln(BV)$, logged assets; ROA, return-on-assets; LEV, leverage; MB, market-to-book; $INST\%$, institutional ownership; $BHAR$, buy-and-hold abnormal returns; ALY_N, analyst coverage; ALY_HRZN, analyst forecast horizon; ALY_DISP, analyst forecast dispersion; UE, unexpected earnings. The sample comprises 81,574 firm-quarter observations spanning 2000Q3–2006Q3, i.e., three years before and after the initial scandal revelation (2003Q3). Detailed variable definitions are in Appendix C. All continuous variables are winsorized at the 1% and 99% levels.

Variable	**N**	**5%**	**Mean**	**Median**	**95%**	**SD**
Measures of negative price pressure						
$Tainted\ Fund\%_{i,q}$	81,574	0.000	0.099	0.000	0.531	0.225
$High\ Tainted\ Fund\%_{i,q}$	81,574	0.000	0.248	0.000	1.000	0.432
Dependent variables						
$MBE\_CutR\&D_{i,q}$	81,574	0.000	0.112	0.000	1.000	0.316
$CAR_{i,q}$	81,574	-0.143	0.001	0.000	0.151	0.087
Control variables						
$ln(BV)_{i,q-1}$	81,574	2.501	5.613	5.506	9.269	2.010
$ROA_{i,q-1}$	81,574	-0.145	-0.011	0.007	0.046	0.064
$LEV_{i,q-1}$	81,574	0.000	0.194	0.150	0.573	0.194
$MB_{i,q-1}$	81,574	0.492	3.131	1.914	9.544	4.045
$INST\%_{i,q-1}$	81,574	0.014	0.469	0.474	0.941	0.306
$BHAR_{i,q-1}$	81,574	-0.405	0.028	0.004	0.543	0.282
$ALY\_N_{i,q}$	81,574	0.000	1.252	1.386	2.944	1.039
$ALY\_HRZN_{i,q}$	81,574	0.000	2.952	4.106	4.796	2.005
$ALY\_DISP_{i,q}$	81,574	0.000	0.015	0.000	0.034	0.153
$UE_{i,q}$	81,574	-0.017	-0.001	0.000	0.012	0.009

Table 2: Negative price pressure and signaling through R&D cuts

This table reports the ordinary least squares (OLS) regression results on the relation between negative price pressure and signaling through R&D cuts. Negative price pressure is measured using $Tainted\ Fund\%$, the tainted-fund ownership, in columns 1-2, and $High\ Tainted\ Fund\%$, an indicator equal to one if $Tainted\ Fund\%$ is at or above the median among positive observations, in columns 3-4. Signaling through R&D cuts is measured using $MBE\_CutR\&D$, an indicator equal to one if the firm meets or beats the analyst consensus forecast by up to one cent and reports a reduction in $R\&D$ expenditure. Controls, added in columns 2 and 4, include $ln(BV)$, logged assets; ROA, return-on-assets; LEV, leverage; MB, market-to-book; $INST\%$, institutional ownership; $BHAR$, buy-and-hold abnormal returns; ALY_N, analyst coverage; ALY_HRZN, analyst forecast horizon; and ALY_DISP, analyst forecast dispersion. Detailed variable definitions are provided in Appendix C, and the inclusion of fixed effects is as indicated. The sample comprises 81,574 firm-quarter observations spanning 2000Q3–2006Q3, i.e., three years before and after the initial scandal revelation (2003Q3). Standard errors (in parentheses) are clustered by firm and quarter. ***, **, and * indicate significance at the 1%, 5%, and 10% two-tailed levels, respectively.

Dependent Variable	$MBE\_CutR\&D_{i,q}$			
	(1)	(2)	(3)	(4)
$Tainted\ Fund\%_{i,q}$	0.738***	0.727***		
	(0.010)	(0.010)		
$High\ Tainted\ Fund\%_{i,q}$			0.260***	0.249***
			(0.004)	(0.004)
$ln(BV)_{i,q-1}$		0.022***		0.029***
		(0.003)		(0.003)
$ROA_{i,q-1}$		0.043***		0.053***
		(0.015)		(0.016)
$LEV_{i,q-1}$		−0.050***		−0.032***
		(0.011)		(0.012)
$MB_{i,q-1}$		−0.001**		−0.001***
		(0.000)		(0.000)
$INST\%_{i,q-1}$		0.050***		0.086**
		(0.010)		(0.003)
$BHAR_{i,q-1}$		0.007***		0.009***
		(0.002)		(0.003)
$ALY\_N_{i,q}$		0.008**		0.015***
		(0.003)		(0.004)
$ALY\_HRZN_{i,q}$		-0.001		−0.004***
		(0.001)		(0.001)
$ALY\_DISP_{i,q}$		-0.002		−0.004*
		(0.002)		(0.002)
Firm Fixed Effects	Yes	Yes	Yes	Yes
Year-Quarter Fixed Effects	Yes	Yes	Yes	Yes
Observations	81,574	81,574	81,574	81,574
Adj. R^2	0.480	0.482	0.398	0.400

Table 3: R&D cuts and signaling versus beating by a wide margin

This table reports the OLS regression results on the relation between R&D cuts and the likelihood of meeting or narrowly beating the analyst consensus forecast versus the likelihood of beating the forecast by a wide margin. Both columns use the subsample of firms with at-or-above-median tainted-fund ownership (i.e., $High\ Tainted\ Fund\% = 1$). MBE is an indicator equal to one if the firm meets or beats the analyst consensus forecast by up to one cent. $Beat > 3ct_q$ is an indicator equal to one if the firm beats the analyst consensus forecast by more than three cents. $CutR\&D$ is the negative change in R&D expenditures from the prior quarter, scaled by lagged total assets. Missing R&D expenditures are set to zero. Controls include those defined in Table 2. Detailed variable definitions are in Appendix C, and the inclusion of fixed effects is as indicated. The sample comprises 20,227 firm-quarter observations spanning 2000Q3–2006Q3, i.e., three years before and after the initial scandal revelation (2003Q3). Standard errors (in parentheses) are clustered by firm and quarter. ***, **, and * indicate significance at the 1%, 5%, and 10% two-tailed levels, respectively.

Dependent Variable	$MBE_{i,q}$ (1)	$Beat > 3ct_{i,q}$ (2)
$CutR\&D_{i,q}$	0.012***	−0.122**
	(0.004)	(0.060)
Controls (as in Table 2)	Yes	Yes
Firm Fixed Effects	Yes	Yes
Year-Quarter Fixed Effects	Yes	Yes
Observations	20,227	20,227
Adj.R^2	0.189	0.278

Table 4: Negative price pressure and signaling through R&D cuts: Announcement returns

This table reports the OLS regression results on the relation between negative price pressure and the value of signaling through R&D cuts. Negative price pressure in columns 2-3 is measured using $High\,Tainted\,Fund\%$, an indicator equal to one if $Tainted\ Fund\%$, the tainted-fund ownership, is at or above the median among positive observations. The value of signaling is measured using CAR, the three-day earnings announcement return, and the likelihood of signaling is measured using $MBE\_CutR\&D$, an indicator equal to one if the firm meets or beats the analyst consensus forecast by up to one cent and reports a reduction in R&D expenditure. Controls include UE, unexpected earnings; $ln(BV)$, logged assets; ROA, return-on-assets; LEV, leverage; MB, market-to-book; $INST\%$, institutional ownership; $BHAR$, buy-and-hold abnormal returns; ALY_N, analyst coverage; ALY_HRZN, analyst forecast horizon; and ALY_DISP, analyst forecast dispersion. Detailed variable definitions are in Appendix C, and the inclusion of fixed effects is as indicated. The sample comprises 81,574 firm-quarter observations spanning 2000Q3–2006Q3, i.e., three years before and after the initial scandal revelation (2003Q3). Standard errors (in parentheses) are clustered by firm and quarter. ***, **, and * indicate significance at the 1%, 5%, and 10% two-tailed levels, respectively.

Dependent Variable		$CAR_{i,q}$	
	Full sample	$High\ Tainted\ Fund\%_{i,q} = 1$	$High\ Tainted\ Fund\%_{i,q} = 0$
	(1)	(2)	(3)
$MBE\_CutR\&D_{i,q}$	0.005^{***}	0.009^{***}	-0.007^{***}
	(0.001)	(0.001)	(0.002)
$UE_{i,q}$	1.449^{***}	2.013^{***}	1.359^{***}
	(0.048)	(0.088)	(0.056)
$ln(BV)_{i,q-1}$	-0.013^{***}	-0.015^{***}	-0.014^{***}
	(0.001)	(0.003)	(0.002)
$ROA_{i,q-1}$	-0.063^{***}	-0.071^{***}	-0.060^{***}
	(0.010)	(0.020)	(0.011)
$LEV_{i,q-1}$	0.025^{***}	0.021^{**}	0.028^{***}
	(0.005)	(0.009)	(0.006)
$MB_{i,q-1}$	-0.000^{**}	-0.001^{***}	-0.000
	(0.000)	(0.000)	(0.000)
$INST\%_{i,q-1}$	-0.025^{***}	-0.025^{***}	-0.023^{***}
	(0.004)	(0.007)	(0.005)
$BHAR_{i,q-1}$	-0.003^{*}	-0.005^{**}	-0.003^{*}
	(0.001)	(0.003)	(0.002)
$ALY\_N_{i,q}$	-0.004^{***}	-0.001	-0.005^{***}
	(0.001)	(0.002)	(0.001)
$ALY\_HRZN_{i,q}$	0.001^{***}	-0.000	-0.005^{***}
	(0.000)	(0.001)	(0.000)
$ALY\_DISP_{i,q}$	0.005	-0.002	0.004
	(0.004)	(0.020)	(0.004)
Firm Fixed Effects	Yes	Yes	Yes
Year-Quarter Fixed Effects	Yes	Yes	Yes
Observations	81,574	20,227	61,347
Adj. R^2	0.068	0.119	0.062

Table 5: Negative price pressure and signaling through R&D cuts: Long-term returns

This table reports the mean buy-and-hold abnormal return (*BHAR*) over the 12 quarters following a price decline. The focal group includes firm-quarters that meet or narrowly beat the analyst consensus forecast through R&D cuts ($MBE\_CutR\&D = 1$) and have at-or-above-median tainted-fund ownership ($High\ Tainted\ Fund\% = 1$). Benchmark group 1 includes all firm-quarters that miss the analyst consensus forecast ($Miss = 1$). Benchmark group 2 includes firm-quarters that miss the analyst consensus forecast ($Miss = 1$) and have at-or-above-median tainted-fund ownership (*High Tainted Fund%* $= 1$). The focal and a benchmark group are matched on stock return in quarter q and on size, return-on-assets, leverage, market-to-book, and industry in quarter $q-1$. Columns 1 and 2 present results using benchmark groups 1 and 2, respectively. The difference in mean *BHAR* is reported in the third row of each panel. Detailed variable definitions are in Appendix C. ***, **, and * indicate significance at the 1%, 5%, and 10% two-tailed levels, respectively.

Panel	Variable	Group	(1)	(2)
A	$BHAR_q$	*Focal*	-0.025	-0.025
		Benchmark	-0.024	-0.019
		Diff	**-0.002**	**-0.006**
B	$BHAR_{q\ to\ q+1}$	*Focal*	0.012	0.012
		Benchmark	-0.037	-0.041
		Diff	**0.049*****	**0.053*****
C	$BHAR_{q\ to\ q+2}$	*Focal*	0.017	0.017
		Benchmark	-0.025	-0.031
		Diff	**0.042*****	**0.048*****
D	$BHAR_{q\ to\ q+3}$	*Focal*	0.029	0.029
		Benchmark	−0.016	−0.022
		Diff	**0.045*****	**0.051*****
E	$BHAR_{q\ to\ q+4}$	*Focal*	0.030	0.030
		Benchmark	-0.019	-0.023
		Diff	**0.049*****	**0.053*****
F	$BHAR_{q\ to\ q+5}$	*Focal*	0.031	0.031
		Benchmark	-0.015	-0.024
		Diff	**0.046*****	**0.054*****
G	$BHAR_{q\ to\ q+6}$	*Focal*	0.030	0.030
		Benchmark	-0.017	-0.029
		Diff	**0.047*****	**0.059*****
H	$BHAR_{q\ to\ q+7}$	*Focal*	0.032	0.032
		Benchmark	-0.004	-0.02
		Diff	**0.036*****	**0.052*****
I	$BHAR_{q\ to\ q+8}$	*Focal*	0.042	0.042
		Benchmark	0.005	-0.019
		Diff	**0.037*****	**0.061*****
J	$BHAR_{q\ to\ q+9}$	*Focal*	0.039	0.039
		Benchmark	0.007	-0.022
		Diff	**0.033*****	**0.061*****
K	$BHAR_{q\ to\ q+10}$	*Focal*	0.040	0.040
		Benchmark	0.013	-0.008
		Diff	**0.027***	**0.048*****
L	$BHAR_{q\ to\ q+11}$	*Focal*	0.051	0.051
		Benchmark	0.029	-0.006
		Diff	**0.022**	**0.057*****
M	$BHAR_{q\ to\ q+12}$	*Focal*	0.067	0.067
		Benchmark	0.054	0.017
		Diff	**0.013**	**0.050*****

Table 6: Negative price pressure and signaling through R&D cuts: A confounding event

Panels A and B of this table repeat the analyses in Tables 2 and 4 using a shorter sample that ends before the May 2004 implementation of the SEC rule that increased the frequency of mutual fund portfolio disclosures from semiannual to quarterly. All variables are previously defined. Detailed variable definitions are in Appendix C, and the inclusion of fixed effects is as indicated. The shorter sample comprises 19,023 firm-quarter observations spanning 2002Q4–2004Q1, thus covering three quarters before and three quarters after the initial scandal revelation, with the revelation quarter (2003Q3) included in the latter period. Standard errors (in parentheses) are clustered by firm and quarter. ***, **, and * indicate significance at the 1%, 5%, and 10% two-tailed levels, respectively.

Panel A: Negative price pressure and the likelihood of signaling through R&D cuts

Dependent Variable	$MBE\_CutR\&D_{i,q}$	
	(1)	(2)
$Tainted\ Fund\%_{i,q}$	0.157^{***}	
	(0.019)	
$High\ Tainted\ Fund\%_{i,q}$		0.101^{***}
		(0.007)
Controls (as in Table 2)	Yes	Yes
Firm Fixed Effects	Yes	Yes
Year-Quarter Fixed Effects	Yes	Yes
Observations	19,023	19,023
Adj. R^2	0.180	0.190

Panel B: Negative price pressure and signaling through R&D cuts: Announcement returns

Dependent Variable	$CAR_{i,q}$		
	Full sample	$High\ Tainted\ Fund\%_{i,q} = 1$	$High\ Tainted\ Fund\%_{i,q} = 0$
	(1)	(2)	(3)
$MBE\_CutR\&D_{i,q}$	0.005^{**}	0.009^{**}	-0.007
	(0.002)	(0.003)	(0.005)
Controls (as in Table 4)	Yes	Yes	Yes
Firm Fixed Effects	Yes	Yes	Yes
Year-Quarter Fixed Effects	Yes	Yes	Yes
Observations	19,023	4,741	14,282
Adj. R^2	0.074	0.115	0.058

Table 7: Negative price pressure and signaling through R&D cuts: The role of myopia

This table reports the OLS regression results on the relation between negative price pressure and the likelihood of signaling through R&D cuts, and the effect of managerial myopia on this relation. Managerial myopia is measured using *Myopia*, an indicator equal to one if the aggregate ownership by funds affected by the 2004 SEC disclosure rule change (switching from semiannual to quarterly reporting) is at or above the sample median. All other variables are previously defined in Table 2. Detailed variable definitions are in Appendix C, and the inclusion of fixed effects is as indicated. The sample comprises 81,574 firm-quarter observations spanning 2000Q3–2006Q3, i.e., three years before and after the initial scandal revelation (2003Q3). Standard errors (in parentheses) are clustered by firm and quarter. ***, **, and * indicate significance at the 1%, 5%, and 10% two-tailed levels, respectively.

Dependent Variable	$MBE\_CutR\&D_{i,q}$	
	(1)	(2)
$Tainted\ Fund\%_{i,q} \times Myopia_{i,q}$	0.733***	
	(0.017)	
$Tainted\ Fund\%_{i,q}$	0.102***	
	(0.013)	
$High\ Tainted\ Fund\%_{i,q} \times Myopia_{i,q}$		0.369***
		(0.009)
$High\ Tainted\ Fund\%_{i,q}$		0.063***
		(0.005)
$Myopia_{i,q}$	0.098***	0.087***
	(0.006)	(0.007)
Controls (as in Table 2)	Yes	Yes
Firm Fixed Effects	Yes	Yes
Year-Quarter Fixed Effects	Yes	Yes
Observations	81,574	81,574
Adj. R^2	0.544	0.477

Table 8: Negative price pressure and signaling through R&D cuts: Cross-sectional tests

This table reports the OLS regression results on the relation between negative price pressure and the likelihood of signaling through R&D cuts, and how this relation varies with investment productivity, earnings uncertainty, and investment productivity uncertainty. Panel A examines investment productivity, measured using firm i's market-to-book ratio of the previous quarter. Panel B examines earnings uncertainty, measured using ALY_DISP, analyst forecast dispersion of the current quarter. Panel C examines investment productivity uncertainty, measured using Vol_MB, the standard deviation of firm i's market-to-book ratios over the past eight quarters. All other variables are previously defined in Table 2. Detailed variable definitions are in Appendix C, and the inclusion of fixed effects is as indicated. The sample comprises 81,574 firm-quarter observations spanning 2000Q3–2006Q3, i.e., three years before and after the initial scandal revelation (2003Q3). Standard errors (in parentheses) are clustered by firm and quarter. ***, **, and * indicate significance at the 1%, 5%, and 10% two-tailed levels, respectively.

Panel A: Productivity

Dependent Variable	$MBE\_CutR\&D_{i,q}$	
	(1)	(2)
$Tainted\ Fund\%_{i,q} \times MB_{i,q-1}$	0.014***	
	(0.003)	
$Tainted\ Fund\%_{i,q}$	0.679***	
	(0.013)	
$High\ Tainted\ Fund\%_{i,q} \times MB_{i,q-1}$		0.009***
		(0.001)
$High\ Tainted\ Fund\%_{i,q}$		0.219***
		(0.005)
Controls (as in Table 2)	Yes	Yes
Firm Fixed Effects	Yes	Yes
Year-Quarter Fixed Effects	Yes	Yes
Observations	81,574	81,574
Adj. R^2	0.482	0.402

Panel B: Earnings uncertainty

Dependent Variable	$MBE\_CutR\&D_{i,q}$	
	(1)	(2)
$Tainted\ Fund\%_{i,q} \times ALY\_DISP_{i,q}$	−0.987***	
	(0.190)	
$Tainted\ Fund\%_{i,q}$	0.734***	
	(0.010)	
$High\ Tainted\ Fund\%_{i,q} \times ALY\_DISP_{i,q}$		−0.251***
		(0.066)
$High\ Tainted\ Fund\%_{i,q}$		0.251***
		(0.004)
Controls (as in Table 2)	Yes	Yes
Firm Fixed Effects	Yes	Yes
Year-Quarter Fixed Effects	Yes	Yes
Observations	81,574	81,574
Adj. R^2	0.482	0.401

Panel C: Productivity uncertainty

Dependent Variable	$MBE\_CutR\&D_{i,q}$	
	(1)	(2)
$Tainted\ Fund\%_{i,q} \times Vol\_MB_{i,q}$	0.003^{*}	
	(0.002)	
$Tainted\ Fund\%_{i,q}$	0.725^{***}	
	(0.011)	
$High\ Tainted\ Fund\%_{i,q} \times Vol\_MB_{i,q}$		0.004^{***}
		(0.001)
$High\ Tainted\ Fund\%_{i,q}$		0.237^{***}
		(0.005)
$Vol\_MB_{i,q}$	-0.001^{*}	-0.003^{***}
	(0.001)	(0.001)
Controls (as in Table 2)	Yes	Yes
Firm Fixed Effects	Yes	Yes
Year-Quarter Fixed Effects	Yes	Yes
Observations	74,420	74,420
Adj. R^2	0.491	0.409

About ECGI

ECGI is an international non-profit membership organisation that provides a platform for debate and dialogue among academics, policymakers, and business leaders, with a focus on major corporate governance, ESG, and stewardship issues.

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