

Learning about Discount Rates

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ABSTRACT

Using valuation reports disclosing managers' expectations of cashflow growth (g) and discount rates (k) in M&A transactions, we examine what they learn from target stock prices. Before correcting for endogeneity, both appear sensitive to prices—positively for g , negatively for k , and with equal magnitude—suggesting managers learn about both. However, using noise in prices as an instrument, only k reacts—with corrected estimates indicating that most of managers' information about k comes from prices. Thus, stock markets inform managers about risk and the compensation it requires, but contribute no detectable incremental information to their cash-flow expectations. Cross-sectional tests reinforce this conclusion.

Key words: Managerial Learning, Market Feedback Effects, Cash Flow Expectations, Return Expectations, Discount Rates, Capital Budgeting.

JEL classification: D84, G14, G17, M41

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“The manager of a biotechnology firm may have much better information than outside investors about the firm’s future cash flows, but may not know the rate at which the market will capitalize those cash flows. Thus, he might look at the stock price and, for example, pass up a scale-increasing project with very favorable expected cash flows because the firm’s low stock price indicates that the market puts a very high discount rate on those flows.”

Subrahmanyam and Titman (1999)

I Introduction

A long-standing question in financial economics is whether and how the stock market affects the real economy (Morck, Shleifer, and Vishny (1990)). A growing literature (surveyed by Bond, Edmans, and Goldstein (2012) and Goldstein (2023)) studies its potential informational role: stock prices provide real-time information about firms’ future prospects by aggregating the beliefs of myriad investors who trade on both public and private signals. As such, prices are a public good that can enrich economic agents’ information sets and guide their decisions. In particular, there is now compelling evidence that *firm managers* rely on stock prices to inform their investment choices—the so-called “feedback effect”. However, the specific nature of the information they extract remains an open question, especially since managers often have extensive firm- and industry-specific knowledge, potentially surpassing that of investors. In this paper, we attempt to make progress on this question.

Specifically, we investigate whether, and to what extent, managers learn about cash flows and discount rates from stock prices. A voluminous literature in asset pricing shows that stock prices incorporate information about both. Moreover, both are critical inputs for capital budgeting: to calculate the net present value (NPV) of an investment project or apply the internal rate of return (IRR), managers must assess future cash flows—represented by their expected growth rate g —and the return required by investors—represented by the discount rate k . But what information do managers extract from stock prices? Do they learn about g , k , or both? ¹

¹Our question builds on, but differs from, research in asset pricing (referenced below), which establishes that stock price variation arises from news about both cash flows and discount rates. That prices embed both

Addressing this question is important not only for future research but also for policy-making. Without an understanding of *what* managers learn from prices, it is difficult to devise disclosure rules, trading regulations, or market structures that improve their investment decisions (Goldstein and Yang (2019)).² Yet, most studies on the feedback from prices to investments remain silent on this question. They document that investment decisions respond to the information contained in stock prices in a way that is consistent with managerial learning. But because these decisions reflect managers’ beliefs about *both* g and k , this approach does not allow for disentangling what managers learn.

To bridge this gap, we directly examine managers’ expectations of cash flow growth g and discount rates k rather than inferring learning from investment decisions. Specifically, we employ valuation reports prepared by managers and their financial advisors to justify acquisition or merger prices.³ These reports describe the valuation methods used, including assumptions about the discount rate (k) and perpetual growth rate of future cash flows (g) for the target company. We collect this information and merge it with CRSP and Compustat for 1,231 US-listed firms between 2000 and 2022. On average, the expected k is 12.9%, and the expected g is 3.7%.⁴ Importantly, each (k, g) pair corresponds to the beliefs of the same

components does not necessarily imply that managers learn about both from stock prices. Indeed, managers may disregard price signals entirely if they already possess superior information about both components, or use them to extract insights about only one component. Thus, while prior evidence provides an important foundation, it serves only as a prerequisite for our inquiry.

²Goldstein and Yang (2019) show that real efficiency depends on which information is contained in the price, not only on how much. In their context, optimal mandatory disclosure depends on what managers seek to learn. More generally, improving Revelatory Price Efficiency (RPE)—the extent to which prices reveal information relevant for value-maximizing decisions, as distinct from Forecasting Price Efficiency (FPE), which measures how well prices aggregate all available information (Bond, Edmans, and Goldstein (2012))—requires identifying what decision makers ignore and seek to learn. While FPE is an unconditional criterion, RPE is conditional on what decision makers already know. Therefore, RPE can be optimally implemented only if the object of managerial learning is known, underscoring the importance of our research question.

³Throughout, we use the term “Managers” to refer to any agent involved in the M&A decision-making process, whether this decision is made internally or externalized to a third party (e.g., a financial advisor).

⁴Managers’ reported estimates are not mere noise. Cain and Denis (2013) show that the acquirer’s stock price reacts positively to the valuations reported in fairness opinions, both at the merger announcement and at the opinion’s disclosure. We further find that they are strongly correlated with the actual transaction price, with the expected signs—negative for k and positive for g . In addition, estimates of g and k align closely with, respectively, managers’ guidance on future sales and the hurdle rates discussed in earnings calls. That said, our analysis does *not* require fairness opinion valuations to be accurate. Rather, we focus on whether these valuations are informed by the target’s stock price, irrespective of whether this information

manager regarding the same target firm. We then investigate how these beliefs depend on the target’s stock price.

Beyond improving our understanding of what managers learn—our primary contribution, this approach allows for a more direct test of learning. Indeed, investment outcomes may reflect factors correlated with prices but unrelated to managers’ beliefs, such as credit rationing, adjustment costs, or agency frictions. By focusing on managers’ beliefs rather than on the *outcome* of these beliefs, we mitigate the concern that non-informational factors might confound our results, and thus achieve a higher level of proof for the managerial learning hypothesis—our secondary contribution.

To guide the empirical analysis and generate clear testable predictions, we first present a simple model in which a firm manager updates her expectations about g and k for a target firm based on two private signals—one about each variable—and a public signal—the target’s stock price. The stock price contains information about both g and k but also incorporates noise unrelated to either variable (e.g., due to liquidity or sentiment shocks), which the manager cannot fully filter out. The econometrician observes the manager’s expectations of g and k , the stock price, as well as some price noise (as explained below), but not the private signals. When the manager learns from the price, her expectations respond—positively for g and negatively for k . However, OLS regressions of expectations on prices cannot consistently recover these responses due to two sources of endogeneity.

The first source is an omitted-variable problem that is well-known in the learning literature. The econometrician cannot control for the manager’s own information. If this information is even partially embedded in stock prices—which is plausible—prices and managerial expectations will be correlated even in the absence of learning, biasing the *absolute* value of the OLS estimates *upward*. Thus, one cannot reject the null that managers do not learn from stock prices since prices may passively reflect information managers already possess. The second source of endogeneity is an errors-in-variables problem that arises be-

improves or reduces their accuracy.

cause managers use what they know to obtain better information from the price about what they seek to learn. For example, when forming an expectation of k , the manager uses her private signal about g to filter out price variation due to g , extracting a more precise signal about k from the price. Because the econometrician observes only prices—not the filtered signal actually used—measurement error arises, which attenuates the *absolute* value of OLS estimates and biases them *downward*.

To overcome these issues, we adopt an identification strategy inspired by Dessaint, Foucault, Frésard, and Matray (2019): noise in prices due to liquidity trading is plausibly exogenous to firm fundamentals and should therefore not affect managers’ beliefs about k and g *unless they use prices as a source of information*. If it does, then managers must be misled by stock prices, which paradoxically provides strong evidence of learning from them. We show that price noise can serve as an instrument for stock prices, yielding consistent estimates.

We identify price noise using monthly stock purchases and sales by mutual funds experiencing extreme flows in the 12 months preceding a deal announcement. Consistent with the literature (Coval and Stafford (2007)), we find that extreme inflows (outflows) generate large positive (negative) demand shocks for stocks, exerting upward (downward) pressure on prices for about 3 to 6 months.

To isolate price pressure mechanically induced by extreme flows and unrelated to stock fundamentals, we follow Edmans, Goldstein, and Jiang (2012) and use *hypothetical*, rather than actual, trades. We depart from their approach in two respects to address issues identified in the literature. First, we base hypothetical trades on the *market* portfolio—rather than funds’ disclosed portfolios—to avoid contamination from past trading decisions. Second, we do not normalize by dollar trading volume—which embeds stock returns and fundamental information—instead relying on variation in the fraction of a stock’s outstanding shares held by funds. We estimate its price impact using *stock-date fixed effects*, which absorb unobserved stock-level factors that influence all funds trading the same stock at the same time.

This procedure yields a measure of noise in stock prices that is orthogonal to time-varying fundamentals. To validate our approach, we exploit both tails of the flow distribution—not just outflows—and build separate measures of buying and selling pressure, which we use as distinct instruments. Reassuringly, both generate symmetric return patterns: price changes are immediate and in the expected direction, gradually revert over time, are stronger for smaller stocks, and exhibit no pre-trends.

Our main results are as follows. Before correcting for endogeneity (i.e., based on OLS regressions), managers’ beliefs about g and k (for the same firm) are sensitive to stock prices. The sensitivity is positive for g and negative for k —indicating that managers revise g upward and k downward when prices rise, and of similar economic magnitude. Taken at face value, these results suggest that market feedback about both g and k is equally important to managers when valuing future M&A investment opportunities.

However, after correcting for endogeneity, only k reacts to stock prices. Specifically, using noise as an instrument to filter out information already known to managers leads to an estimate of the sensitivity of g that is close to zero and statistically insignificant, consistent with managers obtaining no incremental information about g from stock prices. In contrast, the sensitivity of k remains significantly negative at -0.89 . It is larger in absolute value than the OLS estimate, as predicted by our model when managers know little about k and a lot about g . When mapped into the model, this estimate implies that managers obtain close to two-thirds (61%) of their information about k from stock prices. Thus, stock prices are managers’ primary source of information about k .

Our model offers additional predictions that are supported by the data. Most distinctively, it predicts how the effect of price noise on managers’ expectations of k depends on the precision of their signals. Specifically, this effect should (i) decrease with the precision of the manager’s private signal about k , (ii) increase with the precision of her private signal about g , and (iii) increase with the precision of price noise. Intuitively, as the private signal about k becomes more precise, the manager assigns *less* weight to the stock price when forming

her posterior expectation of k , making it less sensitive to price noise. Conversely, as the private signal about g becomes more precise or the price becomes less noisy, she places *more* weight on the price—since she can better filter out price variation unrelated to k —making her posterior expectation of k more responsive to the noise in the price. These are precisely the patterns we observe in the data, using the inverse of the reported ranges of estimates of g and k as proxies for posterior precisions, and the inverse of the range of price noise over the preceding twelve months as a proxy for the precision of stock price noise. This set of results reinforces our interpretation that managers learn about k from target stock prices. Any alternative explanation must account not only for our main finding but also for these cross-sectional results.

Overall, we find that managerial beliefs about k are sensitive to (noise in) prices, but beliefs about g are not, indicating that managers already know a lot about g , but little about k . We conclude that managers learn from stock prices about k , not about g —at least in the context of valuing M&A investment opportunities. What is more, they obtain the bulk of their information about k from prices.

Our main finding—that managers obtain most of their information about k , but none about g , from stock prices—is striking yet plausible given that information about g is available from multiple sources—ranging from customers and suppliers to employees, bankers, analysts and policy makers—whereas the primary source of information about k is the stock price itself. This is because determining a firm’s discount rate requires not only understanding its risk profile but also assessing the compensation that investors demand for bearing that risk. Unlike cash flow information, such information is not readily available to managers and is instead embedded in stock prices, as the epigraph on page 1 suggests. This scarcity of sources plausibly explains why managers’ estimates of discount rates are found to be highly imprecise (Gormsen and Huber (2024), Gormsen and Huber (2025)). In this context, stock prices play a crucial role in aggregating dispersed information about investors’ risk-bearing capacity.

The rest of the paper is organized as follows. Section II discusses the literature and our contribution. Section III develops the hypotheses. Section IV presents the data and identification strategy. Section V reports the results. Section VI assesses instrument validity. Section VII discusses limitations and alternative interpretations. Section VIII concludes.

II Related Literature

Our paper contributes to three strands of literature. First and foremost, it contributes to the literature on the real effects of financial markets—the so-called feedback effect from market prices to the real economy.⁵ While prior research documents that managers extract information from stock prices, much less is known about *what* managers actually learn from prices. The empirical literature is largely agnostic as to whether prices inform managers about cash flows, discount rates, or other factors, while the theoretical literature typically assumes learning about cash flows exclusively⁶. Our findings challenge this assumption, suggesting the need for a revised perspective.

Our key finding—that managers extract information about discount rates, but not cash flows, from stock prices—is consistent with two recent insights in the empirical literature. First, research in corporate finance shows that managers’ estimates of discount rates are highly imprecise (Gormsen and Huber (2024), Gormsen and Huber (2025)). In particular, managers lack information about investors’ risk appetite and portfolio holdings needed to determine the compensation investors require. Our results indicate that managers rely primarily on stock prices to obtain this information. Second, recent work in asset pricing suggests that valuation differences across firms are driven primarily by variations in discount rates or mispricing, rather than by differences in expected future cash flows (DeLaO, Han, and Myers (2024)).⁷ Relatedly, Campbell and Vuolteenaho (2004) show that discount-rate

⁵For example, see Antoniou, Weikai Li, Liu, Subrahmanyam, and Sun (2022), Bakke and Whited (2010), Chen, Goldstein, and Jiang (2007), Foucault and Fresard (2012), Foucault and Fresard (2014), Dessaint, Foucault, Frésard, and Matray (2019), Edmans, Jayaraman, and Schneemeier (2017), Yan (2024), among many others. Bond, Edmans, and Goldstein (2012) and Goldstein (2023) offer reviews of this literature.

⁶An exception is Banerjee, Breon-Drish, and Smith (2025), where managers learn about both g and k .

⁷Specifically, DeLaO, Han, and Myers (2024) estimate that over 70% of the cross-sectional variation in price-earnings ratios is attributable to differences in discount rates rather than anticipated earnings growth.

beta (“bad beta”) is priced in the cross-section, whereas cash-flow beta (“good beta”) is not. While the presence of discount-rate information in prices does not, by itself, imply learning, it does make such learning possible.

We make a secondary contribution to the literature on the feedback effect by strengthening the case for managerial learning from stock prices. Unlike prior work that infers learning from investment decisions, we directly examine managers’ beliefs—rather than the outcome of those beliefs. This approach provides more direct evidence that managers incorporate information from prices and is not confounded by external factors, such as financing or agency frictions that could simultaneously influence investments and prices. Moreover, it allows for a battery of ancillary predictions that we systematically test.

The second stream of research we contribute to concerns the theory and practice of capital budgeting and M&A. Although capital budgeting is among firms’ most fundamental decisions, field evidence on budgeting practices is scarce because project investments and their outcomes are typically unobservable. To address this challenge, scholars have surveyed managers (Graham and Harvey (2001), Graham (2022)), analyzed their conference calls (Gormsen and Huber (2024), Gormsen and Huber (2025)), or used observed investment choices to infer the discount rates managers apply to projects (Décaire (2026)). We bring novel data from M&A fairness opinions to this research question. Relative to survey data, they provide valuation inputs used in actual transactions rather than elicited responses, alleviating concerns about whether stated beliefs correspond to those used in actual decision-making. Relative to conference call data, they offer greater clarity about context and usage.⁸ We contribute two important facts to this literature. First, we empirically validate a key assumption in many capital budgeting models (e.g., Stein (2003)), namely that managers

In contrast, earlier papers (Fama and French (1995), Vuolteenaho (2002), Cohen, Polk, and Vuolteenaho (2003)) found the primary drivers of firm-level price-book ratios to be future profitability. DeLaO, Han, and Myers (2024) reconcile these findings by showing that earlier results depend critically on scaling prices by book values.

⁸It is often ambiguous whether discount rates discussed in conference calls apply to capital budgeting or M&A decisions, at the firm-wide or project-specific level, and whether they are actually used in decision-making. In contrast, rates reported in fairness opinions are explicitly used to discount cash flows in transaction valuations.

possess superior private information about future cash flows. Indeed, we show that managers do not update their beliefs about g based on stock prices, implying they are already well informed about future cash flows. Second, we document that managers’ primary source of information about k is the stock price.

Finally, we contribute to an emerging literature on the valuation practices of professional forecasters. Décaire and Graham (2024), Décaire, Sosyura, and Wittry (2024), Bastianello, Décaire, and Guenzel (2024), Bastianello, Décaire, and Guenzel (2025) study the models equity analysts use for valuation. Chaudhry (2025) documents that equity analysts use stock prices to forecast future cash flows, (erroneously) interpreting price movements driven by discount rates as cash-flow news. We extend this line of research by focusing on managers rather than sell-side analysts. Managers differ fundamentally from analysts in both objectives and information sets and, unlike analysts who issue recommendations, take real actions. Understanding how managers form expectations about both g and k is therefore important.

III Hypotheses Development

In this section, we model the manager’s learning process to guide the empirical analysis. As our contribution is not theoretical, we deliberately keep the model simple, relying solely on Bayesian updating and taking the firm’s valuation as given. Despite its simplicity, the model delivers a rich set of predictions—including some that are not straightforward—that differ sharply depending on whether the manager incorporates information from the stock price into her estimates.

A Theoretical framework

A.1 Setup

Firm value is determined using the Gordon growth model, which relates the next period cashflow C , the perpetual growth rate of cashflows G , and the discount rate K through the formula: $Q = \frac{C}{K-G}$. The manager is assumed to have complete knowledge of the next period cashflow C , but she is uncertain about the growth rate G and the discount rate K .

To estimate those, she relies on private signals, and potentially also on the stock price Q . For analytical tractability, we linearize the stock's price around a baseline corresponding to her prior (or last-period) beliefs about G and K . Specifically, we approximate: $G \approx g_0 + g$ and $K \approx k_0 + k$, where g and k represent small deviations from the baseline values g_0 and k_0 . A first-order Taylor approximation yields:

$$\begin{aligned} Q &= \frac{C}{K - G} = \frac{C}{k_0 + k - g_0 - g} = \frac{C}{k_0 - g_0} \frac{1}{1 + \frac{k-g}{k_0 - g_0}} \\ &\approx \frac{C}{k_0 - g_0} + \frac{C}{(k_0 - g_0)^2} (g - k) \equiv Q_0 + \Delta Q, \end{aligned} \tag{1}$$

where $Q_0 \equiv \frac{C}{k_0 - g_0}$ and $\Delta Q \equiv \frac{C}{(k_0 - g_0)^2} (g - k)$. Thus, the price change, $\Delta Q \equiv Q - Q_0$, provides a signal about $g - k$.

To provide some flexibility in matching the model to the data, we introduce random noise into the stock price: we assume that the price change ΔQ is a function of $q \equiv g - k + \theta$ where θ captures price fluctuations unrelated to the firm's fundamentals (that is, to g and k), which could stem from liquidity constraints or behavioral motivations.⁹ To sum up, the price reveals $q = g - k + \theta$ to the manager.

In addition, the manager receives two private signals. The first is about the growth rate of cash flows, $S_g = g + \varepsilon_g$, and the second about the discount rate, $S_k = k + \varepsilon_k$. We assume that g , k , θ , ε_g and ε_k are jointly normally distributed and mutually uncorrelated.¹⁰ They have mean zero and precisions (inverse variances) τ_g , τ_k , τ_θ , τ_{ε_g} and τ_{ε_k} , respectively.

⁹Our identification strategy does not strictly require θ to represent noise, although the proxy we employ (extreme mutual-fund flow shocks) is consistent with such an interpretation because its effect on prices is transitory. Rather, identification relies on the arguably weaker requirement that θ be unknown to the manager independently of the price. Hence, if θ enters the manager's expectations, she must have inferred it from the stock price. Our identification strategy—and the resulting interpretation—therefore continues to hold even if θ reflects a change in fundamentals, provided that the manager cannot learn about it other than through the stock price.

¹⁰The main prediction of the model regarding the IV coefficients, as well as their interpretation as the fraction of information extracted from prices continue to hold even when g and k are correlated (see Internet Appendix Section 13).

A.2 Manager's Posterior Beliefs

The following proposition and corollary characterize the manager's posterior beliefs about the growth rate g and the discount rate k depending on whether or not she incorporates information from the stock price in her estimates.¹¹

Proposition 1: *The manager's posterior beliefs about the growth rate g and the discount rate k are given by the following expressions.*

If the manager learns from the stock price:

$$\mathbb{E}(g|S_g, S_k, q) = \frac{\tau_{\varepsilon g}}{\tau_{g|S_g, S_k, q}} S_g + \frac{\tau_{qg}}{\tau_{g|S_g, S_k, q}} \frac{\tau_{\varepsilon k}}{\tau_k + \tau_{\varepsilon k}} S_k + \frac{\tau_{qg}}{\tau_{g|S_g, S_k, q}} q \quad (2)$$

$$\text{where } \text{Var}(g|S_g, S_k, q)^{-1} \equiv \tau_{g|S_g, S_k, q} = \tau_g + \tau_{\varepsilon g} + \tau_{qg} \quad (3)$$

$$\mathbb{E}(k|S_g, S_k, q) = \frac{\tau_{\varepsilon k}}{\tau_{k|S_g, S_k, q}} S_k + \frac{\tau_{qk}}{\tau_{k|S_g, S_k, q}} \frac{\tau_{\varepsilon g}}{\tau_g + \tau_{\varepsilon g}} S_g - \frac{\tau_{qk}}{\tau_{k|S_g, S_k, q}} q \quad (4)$$

$$\text{where } \text{Var}(k|S_g, S_k, q)^{-1} \equiv \tau_{k|S_g, S_k, q} = \tau_k + \tau_{\varepsilon k} + \tau_{qk} \quad (5)$$

$$\text{Cov}(k, g|S_g, S_k, q)^{-1} = \frac{1}{\tau_\theta} (\tau_g + \tau_{\varepsilon g} + \tau_\theta) \tau_{k|S_g, S_k, q} > 0. \quad (6)$$

Here $\tau_{qg} \equiv (\frac{1}{\tau_k + \tau_{\varepsilon k}} + \frac{1}{\tau_\theta})^{-1}$ and $\tau_{qk} \equiv (\frac{1}{\tau_g + \tau_{\varepsilon g}} + \frac{1}{\tau_\theta})^{-1}$ denote the precisions of the price signal q about g and k , respectively.

If the manager does not learn from the stock price:

$$E(g|S_g, S_k) = \frac{\tau_{\varepsilon g}}{\tau_g + \tau_{\varepsilon g}} S_g \quad \text{Var}(g|S_g, S_k)^{-1} = \tau_g + \tau_{\varepsilon g}$$

$$E(k|S_g, S_k) = \frac{\tau_{\varepsilon k}}{\tau_k + \tau_{\varepsilon k}} S_k \quad \text{Var}(k|S_g, S_k)^{-1} = \tau_k + \tau_{\varepsilon k}$$

$$\text{and } \text{Cov}(k, g|S_g, S_k) = 0.$$

These formulas can be interpreted as follows. When forming expectations about g , the total precision of the manager's information ($\tau_{g|S_g, S_k, q}$) is the sum of three components: the precision of her prior τ_g , the precision of her private signal $\tau_{\varepsilon g}$, and the precision of the price

¹¹The proofs of our propositions are in Appendix III.

signal about g , given by $\tau_{gg} = (\frac{1}{\tau_k + \tau_{\varepsilon_k}} + \frac{1}{\tau_\theta})^{-1}$. To interpret the third term, we can view the price as a signal about g with noise $-k + \theta$, which the manager can reduce using her private signal about k . The precision of $-k + \theta$, conditional on S_k is $\text{Var}(-k + \theta|S_k)^{-1} = (\text{Var}(k|S_k) + \text{Var}(\theta))^{-1} = (\frac{1}{\tau_k + \tau_{\varepsilon_k}} + \frac{1}{\tau_\theta})^{-1}$, since k and ε_k are uncorrelated with θ . This term reflects how much information about g the manager extracts from the stock price. Naturally, it is larger when the price is less noisy (higher τ_θ) and when she is better informed about k (larger $\tau_k + \tau_{\varepsilon_k}$). The manager's posterior expectation of g is the corresponding precision-weighted average of her sources of information: the prior, her private signal S_g about g , and the price signal q , filtered using S_k , her private signal about k .

A symmetric interpretation applies for the discount rate k . In particular, when inferring k , the manager treats the price as a signal about k with error $-(g + \theta)$. Conditional on the private signal S_g about g , this error has a precision of $\text{Var}(-(g + \theta)|S_g)^{-1} = (\frac{1}{\tau_g + \tau_{\varepsilon_g}} + \frac{1}{\tau_\theta})^{-1} \equiv \tau_{qk}$, which represents the precision to the manager of the price signal about k .

Conditional on the price, g and k are correlated, though they are unconditionally uncorrelated. This correlation is positive because the observed price pins down the difference between the variables, so a higher (lower) g must be matched by a higher (lower) k .

B Predictions

We consider two sets of regression analyses: OLS and IV. Those regressions are performed by an econometrician who observes the manager's posterior beliefs of g and k , the stock price q , and some variation in q unrelated to fundamentals due to noise θ .

B.1 OLS Regressions

Proposition 2 characterizes the coefficients in OLS regressions of the manager's posterior belief about g and k on the price q :

$$\mathbb{E}(g|S_g, S_k, q) = \alpha_g + b_g q + \varepsilon \tag{7}$$

$$\mathbb{E}(k|S_g, S_k, q) = \alpha_k + b_k q + \varepsilon'. \tag{8}$$

Proposition 2: *The coefficients in the regressions of the manager's expected growth rate g and discount rate k on the stock price q are given by the following expressions.*

If the manager learns from the stock price:

$$b_g^{OLS} = \frac{Cov(\mathbb{E}(g|S_g, S_k, q), q)}{Var(q)} = \frac{\frac{1}{\tau_g}}{\frac{1}{\tau_g} + \frac{1}{\tau_k} + \frac{1}{\tau_\theta}} > 0 \quad (9)$$

$$b_k^{OLS} = \frac{Cov(\mathbb{E}(k|S_g, S_k, q), q)}{Var(q)} = \frac{-\frac{1}{\tau_k}}{\frac{1}{\tau_g} + \frac{1}{\tau_k} + \frac{1}{\tau_\theta}} < 0 \quad (10)$$

If the manager does not learn from the stock price:

$$b_g^{*OLS} = \frac{Cov(\mathbb{E}(g|S_g, S_k), q)}{Var(q)} = \frac{\frac{1}{\tau_g}(1 - \frac{\tau_g}{\tau_{\varepsilon g} + \tau_g})}{\frac{1}{\tau_g} + \frac{1}{\tau_k} + \frac{1}{\tau_\theta}} > 0 \quad (11)$$

$$b_k^{*OLS} = \frac{Cov(\mathbb{E}(k|S_g, S_k), q)}{Var(q)} = -\frac{\frac{1}{\tau_k}(1 - \frac{\tau_k}{\tau_{\varepsilon k} + \tau_k})}{\frac{1}{\tau_g} + \frac{1}{\tau_k} + \frac{1}{\tau_\theta}} < 0 \quad (12)$$

The OLS coefficients are positive for g and negative for k , regardless of whether or not the manager learns from the price. Thus, OLS regressions alone cannot distinguish between active learning from the price and a passive correlation between the manager's expectations and the price (as would occur if, e.g., the manager already knows the information contained in the price). This difficulty arises because the private information of the manager (S_g and S_k) is not observed by the econometrician and hence cannot be controlled for in the regressions.

Prediction 1: *With learning from the price, the OLS regression coefficient is **positive** in the growth rate regression and **negative** in the discount rate regression. The sign of both coefficients is the **same** with and without learning from the price.*

B.2 IV Regressions

Next, we consider IV regressions using noise, θ , as an instrument for the stock price, q . We assume that θ is not observed by the manager—when observing q , she cannot distinguish

noise from information about g and k —but it is observed by the econometrician. Notably, it is not necessary for the econometrician to observe the *entire* noise term, nor is it needed that the manager be unable to *completely* filter it out.¹² Our predictions hold as long as the manager’s ability to identify noise is limited.

Proposition 3: *The coefficients in the regressions of the manager’s expected growth rate g and discount rate k on noise contained in stock price θ are given by the following expressions.*

If the manager learns from the stock price:

$$b_g^{IV} = \frac{Cov(E(g|S_g, S_k, q), \theta)}{Var(\theta)} = \frac{\tau_{qg}}{\tau_g + \tau_{\varepsilon g} + \tau_{qg}} > 0 \quad (13)$$

$$b_k^{IV} = \frac{Cov(E(k|S_g, S_k, q), \theta)}{Var(\theta)} = -\frac{\tau_{qk}}{\tau_k + \tau_{\varepsilon k} + \tau_{qk}} < 0 \quad (14)$$

If the manager does not learn from the stock price:

$$b_g^{*IV} = \frac{Cov(E(g|S_g, S_k), \theta)}{Var(\theta)} = 0 \quad (15)$$

$$b_k^{*IV} = \frac{Cov(E(k|S_g, S_k), \theta)}{Var(\theta)} = 0 \quad (16)$$

Unlike their OLS counterparts, IV regressions yield sharply contrasting results: the IV coefficients are non-zero *only* when the manager learns from the price. Moreover, they have a simple interpretation: they represent (in absolute value) the proportion of information about g or k that managers obtain from stock prices. For example, $|b_k^{IV}|$ measures the share (between 0 and 1) of managers’ posterior precision about k that is derived from information in stock prices (and used in combination with their private signal about g). We will utilize this interpretation to quantify the extent of managerial learning from stock prices.

¹²Assume θ comprises two components: noise observed by the econometrician, θ^{obs} (e.g., mutual fund fire sales), and unobserved noise, θ^{unobs} : $q = g - k + \theta^{obs} + \theta^{unobs}$. In this case, θ^{obs} is a valid instrument for q .

Prediction 2: *With learning from the price, the IV regression coefficient is **positive** in the growth rate regression and **negative** in the discount rate regression. They are **zero** in the absence of learning from the price. Moreover, they represent (in absolute value) the **proportion** of information about g or k that managers obtain from stock prices.*

B.3 Magnitudes of the OLS vs IV Regression Coefficients

Comparing the OLS and IV regression coefficients yields a third prediction. When the manager does not learn from the price, the IV coefficients are zero, so the OLS coefficients *exceed* them *in absolute value*. In this case, the IV method merely corrects for the endogeneity bias arising from the passive correlation between the manager’s posterior beliefs and the stock price, which *inflates* the OLS estimates.

However, when the manager does learn from the price, the comparison is less clear due to an additional, opposite, endogeneity bias. In the OLS regression of the manager’s expectation of g , k in the stock price acts as noise. The IV regressions, by removing the influence of k from the stock price, increase the coefficient. This bias is analogous to the well-known attenuation bias, where measurement errors in the independent variable tend to *reduce* OLS estimates relative to IV estimates in absolute value. Here, k introduces measurement error in the g regression while g injects measurement error in the k regression.

This attenuation bias is stronger in the g regression if the prior about g , the private signal about k or the price noise are more precise (i.e., τ_g , $\tau_{\varepsilon k}$ or τ_θ larger), or if the private signal about g is less precise (i.e., $\tau_{\varepsilon g}$ smaller), while the effect of τ_k is ambiguous. Similarly, in the k regression, the attenuation is stronger if the prior about k , the private signal about g or the price noise are more precise (i.e., τ_k , $\tau_{\varepsilon g}$ or τ_θ larger), or if the private signal about k is less precise (i.e., $\tau_{\varepsilon k}$ smaller), with the effect of τ_g being ambiguous.

An implication is that if the manager’s private signals are highly accurate for g but poor for k (i.e., $\tau_{\varepsilon g}$ large but $\tau_{\varepsilon k}$ small), then she learns a little or nothing about g from the price but learns a lot about k . In this case, the IV coefficient in the g regression will be *smaller in*

absolute value than the OLS coefficient.¹³ In contrast, the IV coefficient in the k regression will be *larger in absolute value* than the corresponding OLS coefficient. The IV coefficient will be even more negative because of a strong attenuation bias affecting the OLS estimate.

To summarise, whereas the IV coefficient is always lower than the OLS coefficient when there is no learning from the price, it can *exceed* the OLS coefficient when learning occurs. This effect is especially strong in the growth (respectively, discount) rate regression if the information about the discount (respectively, growth) rate is initially highly accurate.

Prediction 3: *With learning from the price, the IV regression coefficients can be larger (in absolute value) than the OLS regression coefficients. This is more likely to be the case in the growth (respectively, discount) rate regression if the manager’s private signal about the discount (respectively, growth) rate is more precise. In the absence of learning from the price, in contrast, the IV coefficients are always smaller (in absolute value).*

B.4 Cross-Sectional Variation

The IV regression coefficients exhibit distinct patterns in relation to signal precisions, allowing for further identification of learning effects in a cross-section of firms.

We start with the precisions of the non-price information (i.e., priors and private signals). For instance, in the discount rate regressions, the coefficient decreases with both τ_k and $\tau_{\varepsilon k}$, the precisions of the manager’s prior and private signal about k ; but it increases with both τ_g and $\tau_{\varepsilon g}$, the precisions of her prior and private signal about g . Intuitively, as τ_k or $\tau_{\varepsilon k}$ increase, the manager assigns *less* weight to the stock price when forming her posterior expectation of k , making it less sensitive to the noise in the price. On the other hand, as τ_g or $\tau_{\varepsilon g}$ increase, she places *more* weight on the stock price since she can better filter out the noise related to g , thereby making her posterior expectation of k more responsive to the noise in the stock price. In contrast, if the manager does not learn from the price, the IV coefficients remain zero and do not depend on the precision of private signals.

¹³In the extreme case where the manager learns nothing from the price about g , then the IV coefficient in the g regression will be zero.

Proposition 4: *With learning from the price, the IV regression coefficient in the growth rate (respectively, discount rate) regression decreases in absolute value with the precisions of the manager’s prior and private signal about g (respectively, k), but increases in absolute value with the precision of her prior and private signal about k (respectively, g).*

Our data do not provide proxies for the precisions of the non-price information (i.e., priors and private signals). However, they do offer a proxy for the manager’s posterior precisions, which reflect the combined precisions of price and non-price information. While both contribute positively to posterior precisions, their effect on IV regression coefficients are opposing. Recall that the IV regression coefficients reflect the share of information managers obtain from stock prices. For instance, in the discount rate regression, a more precise price signal (higher τ_{qk}) increases the absolute value of the IV coefficient, whereas more precise non-price signals (higher $\tau_{\varepsilon k}$ or τ_k) decrease it. This renders the relationship between posterior precisions and IV regression coefficients generally ambiguous.

To resolve this ambiguity, we perform a first-order linear approximation of the system that links together prior, private signal, and posterior precisions (see Internet Appendix Section 16). This approximation reveals that, for small changes in precisions, the prior and private signal precisions about k (g) are positively related to the posterior precisions about k (g), and negatively related to the posterior precisions about g (k). As a result, the implications presented in Proposition 4 for the prior and private signal precisions carry over to the posterior precisions. They are stated next:

Prediction 4: *With learning from the stock price, the IV regression coefficient in the growth rate (respectively, discount rate) regression decreases in absolute value with the manager’s posterior precisions about g (respectively, k), but increases in absolute value with her posterior precision about k (respectively, g). In contrast, without learning from the stock price, the IV coefficients remain unaffected by posterior precision.*

Another set of testable predictions can be derived when considering the precision of stock price noise. Less volatile stock price noise (higher τ_θ) makes the price signal more

informative, thereby raising the IV coefficients for both g and k , holding fixed the precisions of priors and private signals.

Prediction 5: *With learning from the stock price, the IV regression coefficient increases in absolute value with the precision of stock price noise. In contrast, without learning from the stock price, the IV coefficients remain unaffected by the precision of stock price noise.*

To illustrate Predictions 4 and 5, consider the case where the manager learns about k but not g from the stock price—in line with what we find in the data. In the model, this happens when the prior or the private signal about g are highly precise. In this case, the posterior precision about g is primarily driven by the precisions of the non-price signals: $\tau_{g|S_g, S_k, q} \approx \tau_g + \tau_{\varepsilon g}$. As a result, the precision of the price signal about k is approximately determined by the posterior precision about g : $\tau_{qk} \approx (\frac{1}{\tau_{g|S_g, S_k, q}} + \frac{1}{\tau_\theta})^{-1}$. These relationships imply $b_g^{IV} \approx 0$ and

$$|b_k^{IV}| = \frac{\tau_{qk}}{\tau_{k|S_g, S_k, q}} \approx \frac{(\frac{1}{\tau_{g|S_g, S_k, q}} + \frac{1}{\tau_\theta})^{-1}}{\tau_{k|S_g, S_k, q}}, \quad (17)$$

which decreases with the managers' posterior precision about k , $\tau_{k|S_g, S_k, q}$, and increases with both her posterior precision about g and the precision of price noise, $\tau_{g|S_g, S_k, q}$ and τ_θ .

IV Data and Methodology

To test our predictions, we need data on managers' expectations about g and k , stock prices, and stock price noise, as well as measures of the precision of the posteriors about g and k , and of price noise. This section describes our data sources and how we construct these measures. Appendix I provides a summary of the variables used in our tests and their definitions.

A Data and Variables

A.1 Expectations

We identify expectations about future cash flow growth and discount rates using M&A fairness opinions retrieved from LSEG (formerly Thomson Reuters—SDC Platinum). Fairness opinions are valuation reports prepared by investment bankers to assess whether the price

offered in a transaction is fair to target, seller, or acquirer shareholders. These reports describe the valuation methods used, including assumptions made by the management team(s) and their advisors about the discount rate (k) and perpetual growth rate of future cash flows (g) for the target company.

k is reported under items FO_DCF_RATE_LOW and FO_DCF_RATE_HI, which, respectively, provide the low and high end of the assumed range. Similarly, the range assumed for g is reported under items FO_DCF_PERP_LOW and FO_DCF_PERP_HI.¹⁴ We use the range mid-point as the estimate for k and g , and the inverse of the range width—the high–low difference denoted k Range and g Range—as the estimate of the precision of managers’ beliefs.¹⁵

Our initial sample contains all buy- and sell-side fairness opinions with non-missing information about k . We exclude non-US targets and years with incomplete data coverage (1999 and 2023), correct miscoded percentage entries (e.g., 12 for vs 0.12), eliminate observations where the high end of the range is lower than the low end, remove outliers ($k < 1\%$ or $g < 0\%$) and aggregate k , g , k Range, and g Range at the deal-level by averaging across opinions when multiples reports exist for the same target. We obtain a sample (before merging with CRSP and Compustat) of 3,205 M&A deals announced between 2000 and 2022 for 3,103 unique targets, with 3,205 non-missing observations on k and 1,632 on g .

[Insert Figure I about here]

On average, the expected discount rate k and growth rate g are 12.9% and 3.7%, respec-

¹⁴Sometimes, a multiple is used to compute terminal values instead of the Gordon Growth Model. In this case, we approximate the implicit range of values assumed for g using the formula, $g = (k \times MULT - 1) / (1 + MULT)$, where k is the mid-point of the assumed discount-rate range, and $MULT$ is the low or high end of the assumed terminal value multiple. The range for $MULT$ is reported under items FO_DCF_TERM_LOW and FO_DCF_TERM_HI. This conversion assumes that the reported multiple is defined using a cash-flow and timing convention consistent with the Gordon model, a convention that SDC does not document unambiguously. Importantly, our main results are robust to excluding all observations for which g is imputed from $MULT$ (see Internet Appendix Section 8.1 Table IA. 5)

¹⁵Occasionally, the low and high end of the reported range are identical because a single number (rather than a range) is reported in the fairness opinion letter. In this case, g Range and k Range are set to missing (although k and g are not).

tively. Figure I plots the average of k and g by year.

A.2 Price Pressure (Stock Price Noise)

We identify non-fundamental variation in stock prices (price noise) using monthly stock purchases and sales by mutual funds experiencing extreme flows in the 12 months preceding deal announcement. Consistent with the literature (Coval and Stafford (2007)), we show that extreme inflows (outflows) generate large positive (negative) demand shocks for stocks, creating upward (downward) price pressure that persists for 3 to 6 months before reversing.

Our price pressure measure follows Edmans, Goldstein, and Jiang (2012) but departs from their approach in two ways to address recognized limitations and adapt it to our setting. As in their framework, we use *hypothetical*, rather than actual, trades to isolate holdings changes mechanically induced by extreme flows, rather than by active trading. Our first departure is to base hypothetical trades on the market portfolio—common to all funds—rather than on funds’ previously disclosed portfolios. That is, we assume that, in response to extreme flows, funds adjust their holdings proportionally to each stock’s weight in the market portfolio at the beginning of the month. Doing so avoids capturing information about fundamentals embedded in fund managers’ past holdings. By removing information contained in trades made *before* the event, in addition to contemporaneous trades, we mitigate the concern raised by Berger (2023) that the measure reflects time-varying stock characteristics driving portfolio weights, thereby achieving a cleaner identification of mutual fund price pressure.

Our second departure concerns the inclusion of end-of-month (dollar) trading volume in the original price pressure formula to account for cross-stock differences in liquidity. Wardlaw (2020) shows that this adjustment is problematic because it inadvertently introduces (the inverse of) stock returns into the price pressure measure, along with stock-level fundamental information contained in trading volume. To address this concern, we (i) estimate the effect of a fund’s hypothetical *number* of shares purchased (sold) in response to extreme inflows (outflows) on the fraction of a stock’s outstanding shares held by the fund, *controlling for stock-date fixed effects*, (ii) aggregate these effects to the stock level by summing across

funds to identify, for each stock and date, the total change in the fraction of mutual-fund ownership induced by extreme flows, (iii) estimate the impact of extreme flows on stock returns by regressing monthly FF49-adjusted returns on the estimated ownership changes. By construction, our measure of stock return noise is immune to Wardlaw (2020)’s critique because it does not require normalizing for dollar volume, and it is orthogonal to (observed and unobserved) time-varying stock-level factors affecting all funds trading the same stock at the same time; such variation is absorbed by the stock-date fixed effects.¹⁶

Importantly, to verify that our approach yields coherent results, we exploit both tails of the flow distribution—not only outflows as in most of the literature—and build two separate measures: one capturing buying pressure and one capturing selling pressure. For that, we estimate the effect of hypothetical trades on changes in mutual fund ownership (ΔO) separately for extreme monthly inflows (exceeding 5% of fund assets) and outflows (exceeding 2%), denoted *High Inflow Induced ΔO* and *High Outflow Induced ΔO* , respectively. Then we isolate the effect of fire sales and purchases on stock returns by regressing monthly FF49-adjusted returns on leads and lags of *High Inflow Induced ΔO* and *High Outflow Induced ΔO* .

[Insert Figure II about here]

Figure II illustrates the two main effects from those regressions. An increase (decrease) in ownership following extreme inflows (outflows) positively (negatively) affects stock returns, and these effects are transient, consistent with both capturing non-fundamental variation in prices. The lower (upper) panel plots the cumulative FF49-adjusted return sensitivity to *High Outflow Induced ΔO* (*High Inflow Induced ΔO*), using $t = -1$ as the reference month. A 1% change in *High Outflow Induced ΔO* (*High Inflow Induced ΔO*) generates an immediate 0.24% drop (0.19% increase) in cumulative abnormal returns that persists for 2 months and then reverts 3 to 5 months after the initial flow shock. Section VI further discusses the results of each step in our procedure and confirms that the resulting measures

¹⁶Other papers addressing Wardlaw (2020)’s critique include Dessaint, Olivier, Otto, and Thesmar (2020) and Tubaldi (2024).

are reasonable.

We then infer monthly noise in prices by multiplying noise in stock returns by the beginning-of-month market capitalization, and noise in Tobin’s Q by scaling by total assets. *MF Buying Price Pressure* (*MF Selling Price Pressure*) is the average noise in Q in *absolute value* over the last 12 months induced by extreme monthly inflows (outflows).¹⁷ Appendix II details the procedure used to compute *MF Buying Price Pressure*, and *MF Selling Price Pressure*.

Finally, we use the distribution of monthly noise in Q induced by extreme fund flows to estimate the volatility of the noise. For each stock, we calculate *MF Noise Range* as the interquartile range of monthly noise in Q over the 12 months preceding the deal announcement, and use its inverse as a measure of the precision of the price signal.

A.3 Other Data

All M&A data are from LSEG. Data on market prices, trading volume, and number of shares outstanding are from CRSP. Financial accounting data are from Compustat North America. Mutual fund ownership data are from Thomson Reuters, and mutual fund flows data from CRSP. All variables are described in Appendix I.

A.4 Summary statistics

Our final sample includes all U.S. target firms from LSEG that (i) have non-missing information on g , k , Q , *MF Buying Pressure*, *MF Selling Pressure*, and (ii) can be merged with CRSP and COMPUSTAT.¹⁸ We further require that g , k , and Q be non-negative and that the change in Q is less than 10 in absolute value.

[Insert Table I about here]

Table I reports summary statistics. The main endogenous variables are g , k , Q , and ΔQ ,

¹⁷Typical M&A timeline from initial investment consideration to announcement ranges from 4 to 12 months. Results are robust to using windows of 6, 9, and 18 months.

¹⁸This requirement reduces the sample from 3,205 to 1,231 observations, mostly because g is missing for about half the valuation reports with non-missing k .

and the exogenous variables are *MF Buying Pressure* and *MF Selling Pressure*. All variables are defined in Appendix I. Continuous, non-log-transformed, non-well-behaved variables are winsorized at the 1% level in each tail to limit the influence of outliers.

B Methodology

B.1 OLS Regressions

We begin by testing whether prices affect beliefs using OLS. We estimate:

$$g_{i,t} = b_g \Delta Q_{i,t-1} + \gamma_g X_{i,t-1} + \phi_j + \eta_y + \varepsilon_{i,t} \quad (18)$$

$$k_{i,t} = b_k \Delta Q_{i,t-1} + \gamma_k X_{i,t-1} + \phi_j + \eta_y + \varepsilon'_{i,t}. \quad (19)$$

Here $g_{i,t}$ and $k_{i,t}$ are the expected growth and discount rate of target i at deal announcement t ; $\Delta Q_{i,t-1}$ is the change in Q over the last observable fiscal year prior to the announcement; $g_{i,t}$, $k_{i,t}$ and $\Delta Q_{i,t-1}$ are the empirical counterparts of g , k and q , where q and ΔQ are proportional in the model, with $\Delta Q \equiv \frac{C}{(k_0 - g_0)^2} q$ (see Eq. 1). The coefficients of interest are b_g and b_k . To ease interpretation and facilitate coefficient comparisons, we express each endogenous variable in units of its within-SDC-industry standard deviation.¹⁹ The learning hypothesis predicts $b_g > 0$, and $b_k < 0$.

We include industry (ϕ_j) and deal year (η_y) fixed effects as well as controls for known determinants of expected cash-flow growth (g) and firm-level returns (k), including firm size, the level of (and change in) realized cash flows, historical capital structure, and payout policy. Industry fixed effects absorb time-invariant industry characteristics, while year fixed effects absorb annual variation common to firms.

B.2 2SLS Regressions

Next, we use 2SLS regressions. Estimating b_g and b_k by OLS is problematic because Eq. 18 and Eq. 19 suffer from the endogeneity discussed in Section III: managers may possess private

¹⁹We apply this normalization to the variables in levels before constructing changes. Accordingly, g (k) is scaled by the within-industry standard deviation of g (k); and ΔQ is scaled by the within-industry standard deviation of Q .

information about the target that is also reflected in prices. As a result, finding $b_g > 0$ and $b_k < 0$ may simply reflect (passive) correlation between prices and unobserved managerial information rather than (active) learning from prices (cf. Prediction 1).

We address this problem by exploiting price variation driven noise, following Dessaint, Foucault, Frésard, and Matray (2019). They show that noise affects corporate investment through managerial learning because managers cannot easily distinguish informative price variations from those due to noise. In our setting, price noise unrelated to g and k should not affect managers' beliefs, unless managers use prices as a source of information about g or k and imperfectly filter out noise. Section III Part B.2 formalizes this intuition. Absent learning, managers ignore prices, so their beliefs do *not* depend on price variation due to noise or liquidity trading. Hence, if their beliefs respond to price noise, it must be because managers rely on prices for information (cf. Proposition 3). Therefore, reporting that managerial beliefs are sensitive to noise provides strong evidence of learning from prices (cf. Prediction 2).

We implement this strategy via 2SLS, instrumenting price changes ΔQ with both buying price pressure from extreme mutual funds inflows ($Z1$) and selling pressure from extreme outflows ($Z2$). The first-stage regression is

$$\Delta Q_{i,t-1} = \pi_1 Z1_{i,t-1} + \pi_2 Z2_{i,t-1} + \pi_3 X_{i,t-1} + \phi_j + \eta_y + \mu_{i,t}, \quad (20)$$

where $Z1_{i,t} \equiv MF \text{ Buying Pressure}_{i,t}$ is the average *over*-valuation of firm i due to mutual fund fire purchases, and $Z2_{i,t} \equiv MF \text{ Selling Pressure}_{i,t}$ is the average *under*-valuation due to fire sales, both computed over the 12-months preceding the deal announcement, expressed in dollar value and scaled by total assets.²⁰ Note that both instruments are positive or zero.

²⁰In our baseline specification, ΔQ is measured over the last available fiscal year, consistent with other annually observed accounting variables used as controls. Because this window may not perfectly overlap with the 12-month price-pressure window, the Internet Appendix directly aligns the two by defining ΔQ as the average (year-on-year) change in Q over the same 12-month period used to compute average price pressure. Our results are robust to this alternative specification (see Section IA.8.2).

The second-stage regressions are

$$g_{i,t} = b_g \widehat{\Delta Q_{i,t-1}} + \gamma_g X_{i,t-1} + \phi_j + \eta_y + e_{i,t} \quad (21)$$

$$k_{i,t} = b_k \widehat{\Delta Q_{i,t-1}} + \gamma_k X_{i,t-1} + \phi_j + \eta_y + e'_{i,t}, \quad (22)$$

where $\widehat{\Delta Q_{i,t-1}}$ is the fitted value from Eq. 20 measured over the last observable fiscal year before the deal announcement. Because Equations 18 and 19 share the same endogenous regressor ΔQ , the first stage is identical for estimating b_g and b_k . The learning hypothesis predicts $b_g > 0$ and $b_k < 0$.

B.3 Reduced form IV Regressions

An alternative to the 2SLS approach is to regress g and k directly on price noise, as in Section III, Part B.2 of the model. Beliefs about both g and k are sensitive to noise if, and only if, managers use prices as a signal (cf. Proposition 3). Accordingly, we estimate

$$g_{i,t} = \beta_{1,g} Z1_{i,t-1} + \beta_{2,g} Z2_{i,t-1} + \gamma_g X_{i,t-1} + \phi_j + \eta_y + \psi_{i,t} \quad (23)$$

$$k_{i,t} = \beta_{1,k} Z1_{i,t-1} + \beta_{2,k} Z2_{i,t-1} + \gamma_k X_{i,t-1} + \phi_j + \eta_y + \psi'_{i,t}, \quad (24)$$

where $Z1_{i,t}$ and $Z2_{i,t}$ measure target over-valuation (*MF Buying Pressure*_{*i,t*}) and under-valuation (*MF Selling Pressure*_{*i,t*}). The learning hypothesis predicts $\beta_{1,g} > 0$ and $\beta_{1,k} < 0$, but $\beta_{2,g} < 0$ and $\beta_{2,k} > 0$ (cf. Prediction 2).

These regressions are reduced-form IV regressions and provide the same identification as the 2SLS approach since they exploit the same source of price noise. We use them for three reasons: (i) consistency with the model—in which g and k are regressed directly on noise, (ii) convenience—to study cross-sectional heterogeneity and test Prediction 4 and Prediction 5, (iii) robustness—to verify that price increases and decreases induce beliefs' updates of opposite sign.

V Results

This section presents tests of our main predictions (Predictions 1, 2, and 3), and ancillary predictions (Predictions 4 and 5).

A Main Results

[Insert Table II about here]

Table II presents the tests of Predictions 1 to 3. All tests were performed on the same sample of firms, ensuring that differences in estimates cannot be due to sampling variation.

A.1 Learning about g

Columns (1) to (4) examine how prices affect beliefs about g . Column (1) displays OLS estimates of Eq. 18 and shows a positive and statistically significant relationship between beliefs about g and prices ($b_g > 0$), consistent with learning about g from prices.

However, this relationship does not survive instrumentation. Columns (2) and (3) instrument ΔQ with price noise generated by mutual fund liquidity trading. Column (2) reports the first-stage regression (Eq. 20) and shows that the relevance condition is satisfied: positive (negative) price pressure—captured by *MF Buying Price Pressure* (*MF Selling Price Pressure*)—leads to positive (negative) price changes. Column (3) reports the second-stage estimates (Eq. 21). The coefficient on $\widehat{\Delta Q}$ is economically small, statistically insignificant, and of the wrong sign, implying that beliefs about g do not respond to price variation plausibly unrelated to managers’ existing information ($b_g \approx 0$). Column (4) corroborates this conclusion using the reduced-form IV specification (Eq. 23): neither buying nor selling price pressure affects beliefs about g . These results indicate that, once endogeneity is addressed, we cannot reject the null that managers do not learn about g from stock prices.

A.2 Learning about k

Columns (5) to (8) examine how prices affect beliefs about k . Column (5) reports OLS estimates of Eq. 19 and shows a negative and statistically significant relationship between

prices and beliefs about k ($b_k < 0$), consistent with learning about discount rates from prices.

This relationship remains when prices are instrumented with liquidity-driven noise. Columns (6) and (7) report the 2SLS results. Column (6) presents the first-stage regression (Eq. 20), which is identical to Column (2) because the endogenous regressor is the same. Column (7) reports the second-stage estimates (Eq. 22) and shows that exogenous price variation affects beliefs about k : managers revise discount-rate expectations downward (upward) following positive (negative) price variation plausibly unrelated to their information ($b_k < 0$). Column (8) confirms this finding using the reduced-form IV specification (Eq. 24): buying (selling) price pressure lowers (raises) beliefs about k . These results reject the null that managers do not learn about discount rates from stock prices, even after correcting for endogeneity.

A.3 Interpreting OLS vs. IV coefficients

Before correcting for endogeneity, managers' beliefs about both g and k for the same set of firms are sensitive to prices. The sensitivity is positive for g (higher prices are associated with higher g) and negative for k (higher prices are associated with lower k), with similar economic magnitudes. In absolute value, a one standard-deviation (SD) in the price is associated with a 0.08 SD change in beliefs about both g and k . Taken at face value, these results suggest that market feedback about cash-flow growth and discount rates may be equally important for managers when valuing M&A opportunities.

However, after correcting for endogeneity—using price noise as instrument to filter out information about g and k already known to managers, the coefficient on g is indistinguishable from zero, consistent with managers being already well-informed about g , whereas the coefficient on k remains negative and increases in absolute value, consistent with managers having limited prior information about k . The amplification of b_k reflects an errors-in-variables problem in the OLS regression of k on prices. Since managers can use their private information about g to filter out g from prices, the signal about k that they extract differs from the prices observed by the econometrician. This mismatch attenuates the OLS estimate in Column (5). Instrumenting prices with variation unrelated to g eliminates this

attenuation, yielding a larger coefficient in Column (7).

To summarize, the nature of the endogeneity problem depends on whether managers know relatively more about g or k . When they know a lot about g and little about k , the OLS estimates suffer from an omitted-variable problem for g (Column (1)) and an errors-in-variables problem for k (Column (5)). In this case, the absolute value of the OLS coefficients are biased upward for g and downward for k .²¹

A.4 Interpreting Economic Magnitude

After correcting for endogeneity, we find $b_k = -0.89$. Because k and ΔQ are standardized, this estimate implies that an increase in ΔQ equal to one within-industry standard deviation of Q leads to a decrease in k of 0.89 within-industry standard deviations.

Alternatively, this estimate can be mapped into the model, where the IV coefficient from regressing the manager’s posterior on the price signal, $q = g - k + \theta$, represents the *share of information* she obtains from the price (Proposition 3). In the Internet Appendix, we show how to account for the standardization of the variables used in the regressions. Specifically, we establish that, when the Gordon-growth loading, $a \equiv Q_0/(k_0 - g_0)$, is constant, the empirical counterpart of our model-IV coefficient is:²²

$$b_k \times \frac{a s_k}{s_Q}, \quad (25)$$

The sample means in Table I imply $a = \bar{Q}/(\bar{k} - \bar{g}) \approx 20$ and $s_Q/s_k \approx 29$. Therefore, $b_k = -0.89$ implies that managers obtain close to two-thirds ($61\% = 0.89 \times 20/29$) of their information about k from the price.

Overall, Table II shows that managerial beliefs about k are highly sensitive to prices—with estimates implying that managers obtain close to two-thirds (61%) of their information about k from prices—whereas beliefs about g are not sensitive to prices. These results are in line with Predictions 1, 2, and 3 when managers are better informed about g than about

²¹These effects are formalized in Section III (see Proposition 3 and the discussion that follows).

²²see Internet Appendix, Section IA13

k .

B Cross-sectional Variation

This section reports tests of Predictions 4 and 5: if managers learn from prices, the sensitivity of g and k to price noise should vary systematically with managers' posterior precisions about g (τ_g) and k (τ_k), and with the precision of price noise (τ_θ).

B.1 Variation in k -to-noise sensitivity

Given our evidence that managers primarily learn about k from prices, we focus first on the sensitivity of beliefs about k to noise. The model predicts weaker sensitivity when managers are better informed about k , and stronger sensitivity when they can more easily extract information about k from prices—either because they are well informed about g or because prices are less noisy. Therefore, the *absolute value* of $\beta_{1,k}$ and $\beta_{2,k}$ in Eq.24 should decrease with τ_k and increase with τ_g and τ_θ .

[Insert Table III about here]

Table III presents reduced-form IV regressions (Eq. 24) in which price noise is interacted with (i) the inverse of the reported ranges for k and g (our proxies for their posterior precisions) and (ii) the inverse of *MF Noise Range* (our proxy for τ_θ). *MF Noise Range* is measured as the interquartile range of monthly equity misvaluation induced by trades of mutual funds subject to extreme inflows or outflows during the 12-month period preceding deal announcement. Quite remarkably, the sensitivity of k to price noise varies systematically in the direction predicted by the learning hypothesis. All interaction coefficients have the expected signs (Predictions 4 and 5) and are statistically significant or marginally so. Column (1) shows attenuated sensitivity when the inverse of the reported range for k is high: when managers are better informed about k (higher τ_k), they rely less on prices, weakening the impact of price noise. Column (2) shows amplified sensitivity when the inverse of the reported range for g is high: better information about g (τ_g is higher) allows managers to

more effectively filter out g -related price variation and rely more on prices to learn about k . Column (3) shows amplified sensitivity when prices are less noisy (lower *MF Noise Range*): more precise price noise (τ_θ) increases the weight managers place on prices—and hence on price noise. Column (4) confirms all three patterns when the interaction terms are included simultaneously.

Overall, these results provide strong support for the learning hypothesis about k .

B.2 Variation in g -to-noise sensitivity

Our evidence shows that beliefs about g are not sensitive to price noise. Nevertheless, for completeness, we repeat the cross-sectional analysis for the sensitivity of g to noise. In this case, the learning hypothesis predicts that the *absolute value* of $\beta_{1,g}$ and $\beta_{2,g}$ in Eq.23 should decrease with τ_g and increase with τ_k and τ_θ .

[Insert Table IV about here]

Table IV reports the results. In short, our finding that noise does not affect g unconditionally (Table II, Column 4) holds conditionally (Table IV). Columns (1) to (3) show no significant variation in the sensitivity of g to noise with respect to the precision of price or non-price information—contrary to Predictions 4 and 5 under learning about g .

Overall, these results provide little to no support for the hypothesis that managers learn about g from stock prices.

VI Instrument validity

In this section, we discuss the validity of the identifying conditions of our instrument.

A Relevance

Columns 2 and 6 of Table II show that the relevance condition is satisfied. Both *MF Buying Price Pressure* and *MF Selling Price Pressure* have a significant impact on price changes ΔQ with the expected opposite signs. These results are consistent with our premise that

those variables capture price pressure generated by liquidity trades of mutual funds forced to rebalance after large flows. Next, we provide additional supporting evidence.

A.1 Do extreme flows affect fund ownership?

First, we verify that mutual funds adjust their holdings after experiencing extreme flows.

[Insert Table V about here]

Table V reports the results of regressing changes in fund holdings on hypothetical purchases and sales, *controlling for stock-date fixed effects*. Hypothetical purchases (sales), denoted $HP_{i,j,t}$ ($HS_{i,j,t}$), measure the number of shares fund j would purchase (sell) if it responded to net inflows (outflows) at time t by adjusting its holding of stock i proportionally to the stock’s weight in the market portfolio at $t - 1$, scaled by the stock’s number of shares outstanding at $t - 1$. Scaling serves two purposes. First, it eases the interpretation: regression coefficients above (below) one imply that funds adjust holdings by more (less) than the stock’s weight in the market portfolio. Second and most importantly, it isolates the effect of flows by removing stock-specific influences beyond market weight. Indeed, as shown in Eq.31, $HP_{i,j,t}$ ($HS_{i,j,t}$) equals net flows to fund j divided by the value of the market portfolio at the beginning of the month—a ratio identical across stocks held by fund j . Hence $HP_{i,j,t}$ and $HS_{i,j,t}$ depend on stock i only at the *extensive margin*—that is, whether the stock is held prior to the flow shock.

Column (1) confirms that flow-induced trades generate stock ownership changes—positive for purchases and negative for sales. Column (2) shows that the magnitude of these changes increases with flow size: although not perfectly monotonic, larger flows tend to be associated with larger ownership adjustments. Consistent with the conjecture in Edmans, Goldstein, and Jiang (2012) on page 951 that only extreme flows are likely to trigger portfolio rebalancing while moderate flow shocks can be absorbed by internal cash, we observe no significant variation for small outflows representing less than 1% of AUM.

A.2 Do extreme flows generate price pressure?

From this point on, we focus on extreme inflows ($> 5\%$ of AUM) and outflows ($< -2\%$ of AUM). We verify next that the ownership changes they induce—reported in Table V and aggregated across all mutual funds—translate into price pressure followed by reversal.

[Insert Table VI about here]

Table VI shows that hypothetical purchases (sales) aggregated over all mutual funds experiencing extreme inflows (outflows) are associated with positive (negative) FF49-adjusted monthly returns (Column (1)). Returns do not react to ownership changes preceding the flow shock, and the flow-induced effect reverses within 3 to 6 months (Column (2)). This pattern is consistent with transitory price pressure (noise) rather than fundamental changes.

A.3 Does price pressure vary with market depth?

Finally, we examine whether the above fluctuations vary with market depth, proxied by firm size. Mispricing should be detected and arbitrated away more quickly for larger stocks, which are more closely followed by analysts and more liquid.

[Insert Figure III about here]

Figure III shows that price pressure is indeed economically smaller for larger stocks (top terciles by market capitalization). Nevertheless, even for large stocks, the mispricing remains statistically and economically significant.

To summarize, we find that (i) extreme flows induce changes in stock ownership, (ii) these ownership changes immediately affect prices, (iii) the resulting price changes are temporary, (iv) price pressure is stronger for small stocks, and (v) all effects hold symmetrically for inflows and outflows. Taken together, these findings support our premise that both *MF Buying Price Pressure* and *MF Selling Price Pressure* capture price noise and constitute plausible empirical counterparts to θ in the model.

B Exclusion Restriction

Establishing the plausibility of the exclusion restriction is inherently challenging as it requires evidence that *MF Buying Price Pressure* and *MF Selling Price Pressure* affect managers' beliefs about g and k only through their impact on prices, conditional on controls. While this assumption cannot be formally tested, we present five pieces of evidence suggesting that it cannot be easily rejected.

B.1 Are the instruments jointly exogenous?

We start by testing the *joint* exogeneity of *MF Buying Price Pressure* and *MF Selling Price Pressure* using a Sargan-Hansen test. The J -statistics, reported at the bottom of Table II (Columns (3) and (7)), are never significant at the 10% level. We therefore fail to reject the null that the instruments are jointly exogenous.

B.2 Do extreme flows exhibit any pre-trend?

Next, we confirm that extreme flows are infrequent events that do not exhibit any pre-trend, making them plausibly unanticipated by fund managers and unrelated to omitted economic forces already at play before the event. Supporting evidence is presented in the Internet Appendix (See sections IA.4 and IA.5).

B.3 Does the stock price reaction exhibit any pre-trend?

To further address the omitted variable concern, we also show that the stock prices do not display any pre-trend prior to extreme flows. Indeed, Column (2) of Table VI shows no significant price responses to *leads* of ownership changes induced by extreme flows.²³

B.4 Is the initial price reaction followed by a reversal?

Next, we verify that our instruments are also plausibly unrelated to economic forces inducing permanent changes in stock prices. As highlighted above, the price reaction indeed reverses within a few months. Both the absence of a pre-trend and the subsequent reversal are

²³Results are unchanged when extending the pre-event window to include more *leads* in the regression (See Internet Appendix, Section IA.8.3)

particularly clear in Figure II, which plots cumulative regression coefficients from Column (2) of Table VI, using the month preceding the extreme flow as the reference month. In the Internet Appendix, we show that this result is robust to using longer event windows and alternative models for calculating CARs. Extending the pre- and post-event windows reveals neither an early run-up preceding the extreme flow event nor a long-term drift following it (See IA. 8.3).

B.5 Do the instruments predict sample inclusion?

Our baseline estimates rely on a selected sample of deals with fairness opinions and non-missing information on k and g . When the valuation mandate predates the price pressure we measure, selection into the valuation process cannot mechanically explain our findings. When the mandate starts later, however, some sample-selection criteria may be realized after some of the price pressure we measure. We therefore examine whether our instruments predict selection into the estimation sample. We find that neither buying nor selling price pressure predicts fairness-opinion availability or the availability of k and g . We further find no relation between price pressure and deal completion. These results alleviate concerns that our findings are driven by instrument-induced sample selection.²⁴

C Summary and Comparison with Earlier Literature

Overall, our results corroborate and extend a large body of evidence documenting, in various settings and using different measurement approaches (including some designed to address the limitations of earlier approaches), that extreme mutual fund flows trigger immediate price changes followed by reversals, that corporate insiders trade against these shocks, and that such events represent transitory, non-fundamental, supply- or demand-driven shocks.²⁵

²⁴Results are reported in the Internet Appendix (see Section IA6).

²⁵For evidence on price drops followed by reversals, see Tubaldi (2024), Coval and Stafford (2007), Edmans, Goldstein, and Jiang (2012), Dessaint, Foucault, Frésard, and Matray (2019), or Honkanen and Schmidt (2021). For evidence on insider trading, see Dessaint, Foucault, Frésard, and Matray (2019), Ali, Wei, and Zhou (2011) or Khan, Kogan, and Serafeim (2012). For other papers using mutual fund flows as non-fundamental shocks, see Phillips and Zhdanov (2013), Acharya, Almeida, Ippolito, and Perez (2014), Eckbo, Makaew, and Thorburn (2018), Jayaraman and Shuang Wu (2019), Dessaint, Olivier, Otto, and Thesmar (2020), Gredil, Kapadia, and Lee (2022), Banerjee, Huang, Nanda, and Xiao (2023), Goldman (2023).

Together, these findings support the view that mutual fund-driven price pressure generates variation in stock prices that is plausibly exogenous to information about g and k .

VII Alternative Interpretations

In this section, we discuss possible alternative interpretations of our results.

A Learning by Managers or by Investment Bankers?

In our setting, we do not separately observe the beliefs of managers and those of the investment bankers advising them. Strictly speaking, our analysis therefore identifies whether—and what—agents involved in the transaction learn from stock prices. That said, we view the observed beliefs as the outcome of interactions between managers and their advisors, and throughout the paper, we treat these beliefs as shared.

Although fairness opinions are prepared by investment bankers (see Internet Appendix for examples), four considerations support the view that they also reflect management’s perspective. First, fairness opinions rely heavily on information—such as financial projections—provided by management. Second, the final version of the DCF is typically the result of multiple iterations between managers and bankers, involving detailed discussions of the target’s past, current, and expected future operations. These interactions make it unlikely that bankers’ views diverge materially from those of management. Third, valuation analyses are disclosed only when a deal is deemed fair. This truncation further supports our interpretation: estimates of k and g are observed only when managers and bankers agree on the valuation outcome. If they agree on this outcome, it is likely that they also agree on the underlying assumptions, including the estimates of g and k . Finally, the investment bank providing the fairness opinion is typically selected by management. Managers, therefore, have both the incentive and the discretion to hire bankers whose analytical frameworks and assumptions align with their own. Even before the iterative valuation process begins, this selection tilts the analysis toward management’s perspective, reinforcing our interpretation that the reported valuations reflect shared beliefs.

[Insert Table VII about here]

Table VII illustrates this alignment. The offer price—which ultimately reflects managers’ perception of k and g since it is the amount paid or received—is strongly correlated with beliefs about k and g . This correlation is significant across all measures of the price paid and has the expected sign—negative for k and positive for g . This indicates that the valuation analysis we observe makes explicit what is implicit in the price offered by the acquirer’s management and/or accepted by the target’s management. This evidence supports our premise that the reported values of k and g capture managers’ perceived k and g .

To further validate this premise, we show in the Internet Appendix that (i) our measure for k is closely related to managers’ hurdle rate, as extracted from earnings calls in Gormsen and Huber (2024); (ii) the reported values of g are positively related to managerial guidance about future sales growth; and (iii) variation in k (g) across banks issuing fairness opinions for the *same* deal is small relative to variation within a bank *across* deals, suggesting that manager fixed effects account for most of the variation in k (g).

B Learning or Reverse Engineering?

Another interpretation of our findings is strategic “reverse engineering.” Investment bankers seek to close deals while limiting reputation and litigation costs. Therefore, they may adjust reported DCF inputs to align valuations with market prices and support a fairness conclusion. Specifically, they may lower (raise) their reported k following increases (decreases) in the target’s share price, while not adjusting their reported g , perhaps because they perceive greater discretion over k .²⁶ This suggests a different form of market feedback, whereby agents rationalize prices ex post rather than learn from them. A compact framework that maps estimated coefficients into learning and strategic-reporting components is provided in Internet Appendix Section 14. We report three sets of evidence that help rule out this interpretation in favor of learning.

²⁶Consistent with this view, the cross-sectional standard deviation of g (2.6%) is smaller than that of k (4.1%); see Table I.

First, we exploit the OLS–IV wedge. Although the IV point estimates in Table II—zero for g , negative for k —are compatible with both learning and reverse engineering, their levels alone cannot distinguish between the two mechanisms. In the decomposition in Internet Appendix 14, additive strategic reporting shifts OLS and IV estimates in parallel, whereas learning generates a wedge between them. Intuitively, under reverse engineering, managers adjust estimates of g and k to align the implied valuation with the observed price regardless of the source of price variation. Thus, strategic reporting alone does not generate a systematic OLS–IV wedge. Empirically, moving from OLS to IV eliminates the effect on g while amplifying the effect on k by more than an order of magnitude. This contrasting pattern is difficult to reconcile with pure reverse engineering but arises naturally under learning.

Second, we draw on the ancillary predictions of learning. Under learning, the sensitivity of k to price noise should vary with information precision in the Bayesian direction: it should be weaker when managers are better informed about k , stronger when they are better informed about g , and stronger when prices are less noisy. These are precisely the patterns we document in Section V.B. For reverse engineering to explain all three patterns, the strength of strategic-reporting incentives would need to vary with information precision in a highly specific way.²⁷

Finally, we directly test three predictions specific to reverse engineering and show that the data lend no support to them.²⁸ Specifically, we find that the sensitivity of k to noise in prices (i) remains significant *even* when a large mismatch between the DCF-implied valuation reported in the fairness opinion and the market valuation of the target suggests that reverse engineering is unlikely,²⁹ (ii) does not strengthen when no alternative valuation methods,

²⁷In the Internet Appendix, we also rule out a variant based on reverse engineering the offer price rather than the target’s pre-announcement market price. Because offer prices typically include a premium and are not perfectly collinear with market prices, we can add them as separate controls in our regressions. Although this mechanically attenuates the IV estimate—since offer prices contain updated information about k —the IV estimate remains negative and marginally significant, suggesting that this form of reverse engineering cannot be the main explanation for our findings.

²⁸The results of these tests are reported in the Internet Appendix (see IA.9, IA.10, and IA.11).

²⁹Managers who “reverse engineer” adjust k to close the gap between the implied-DCF valuation of the target and its market valuation. We find that this gap is different from zero, which does not support reverse engineering, unless reverse engineering k is costly, with a wider gap indicating greater cost. However, if so,

such as multiples, complement the DCF valuation, even though managers attempting to reverse engineer valuations would then have fewer alternative margins to adjust and should therefore rely more on k to accommodate price noise, (iii) does not weaken when reported beliefs about k reflect opinions from both sell- and buy-side managers, whose incentives to adjust k operate in opposite directions.³⁰

Overall, these results suggest that while some managers may reverse engineer k , this behavior cannot be the main explanation for our findings.

C Learning about Short or Long Term Growth?

Our measure of g is the perpetual growth rate used to compute the terminal value, usually at the end of a 3 to 5 year business plan (see Dessaint, Foucault, and Frésard (2025)). Therefore, a more nuanced interpretation of our results is that managers do not learn from prices about *long-term* cash flows, while potentially still learning about *short-term* cash flows.

We do not observe the business plans underlying the DCF valuations—and, in particular, the associated short-term cash-flow projections. Therefore, we cannot formally test whether these projections are sensitive to price noise. Nevertheless, we offer suggestive evidence that learning about short-term cash flows is also limited. In the Internet Appendix, we show that the sensitivity of g to price noise does not vary significantly with the typical business plan horizon used in the targeted industry. Using the measure developed by Dessaint, Foucault, and Frésard (2025), we find that when business-plan horizons are shorter, the sign of the sensitivity of g to noise is consistent with learning, but it is never statistically significant at conventional levels. Hence, we find no clear evidence of managerial learning about cash flows, even at shorter horizons.

k should be less sensitive to noise when this cost increases, which it is not. The sensitivity of k to noise is unrelated to the gap between DCF-implied valuation and market valuation (see Internet Appendix, IA.9).

³⁰If the seller’s interest is to decrease k in order to provide evidence of fairness for her shareholders, the buyer’s interest is to do the opposite and increase it.

VIII Conclusion

Most existing research on market feedback effects posits that managers learn from stock prices about expected cash-flow growth g , and not about investors' required return k . We test this premise using direct measures of managers' beliefs about g and k . In OLS regressions, both beliefs are sensitive to stock prices—positively for g and negatively for k —and with similar magnitudes, suggesting, on the surface, that managers learn from markets about both cash flows and discount rates. However, after correcting for endogeneity by instrumenting prices with noise, only beliefs about k react to prices. We conclude that stock prices affect managers' perceptions of discount rates, but do not convey additional information to them about cash flows.

These findings underscore the role of stock prices as aggregators of dispersed information about stockholders' willingness to bear risk—a key input into firms' discount rates. For firms with diffuse ownership, managers have no clear alternative channel through which to access this information. In contrast to the emphasis in much of the theoretical feedback literature, our findings suggest that prices play a more important role in revealing discount rates than in providing insights into future cash flows—at least in the context of M&A valuation. Moreover, they imply that Bond, Edmans, and Goldstein (2012)'s concern—that stock prices, despite their predictive power, may be of limited real value because they incorporate information managers already know—is less severe than presumed. Stock prices embed critical information that no other source provides: the compensation investors require for bearing a project's risk. More work is needed to assess whether these conclusions extend beyond M&A—e.g., to capital budgeting—and beyond managers—to other economic agents such as investors, financial intermediaries, or regulators.

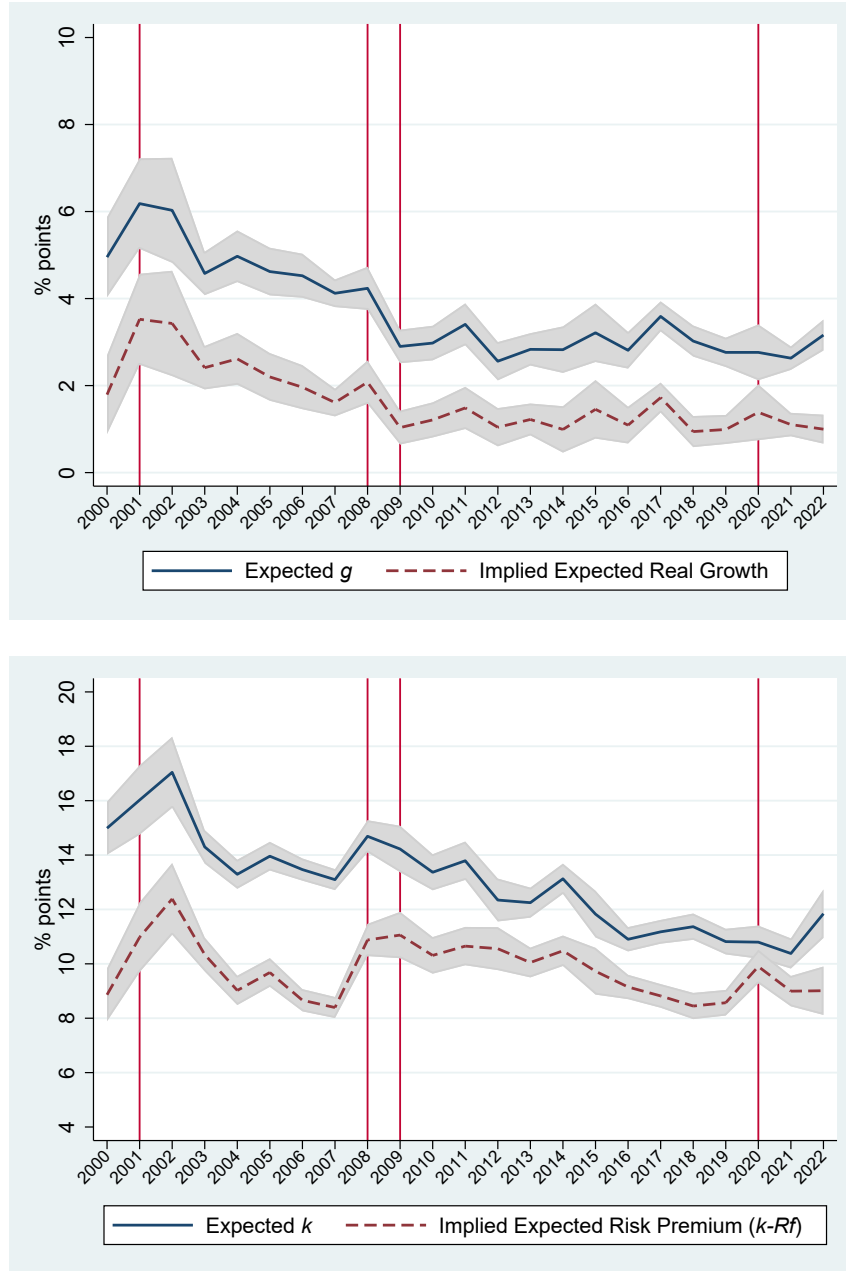
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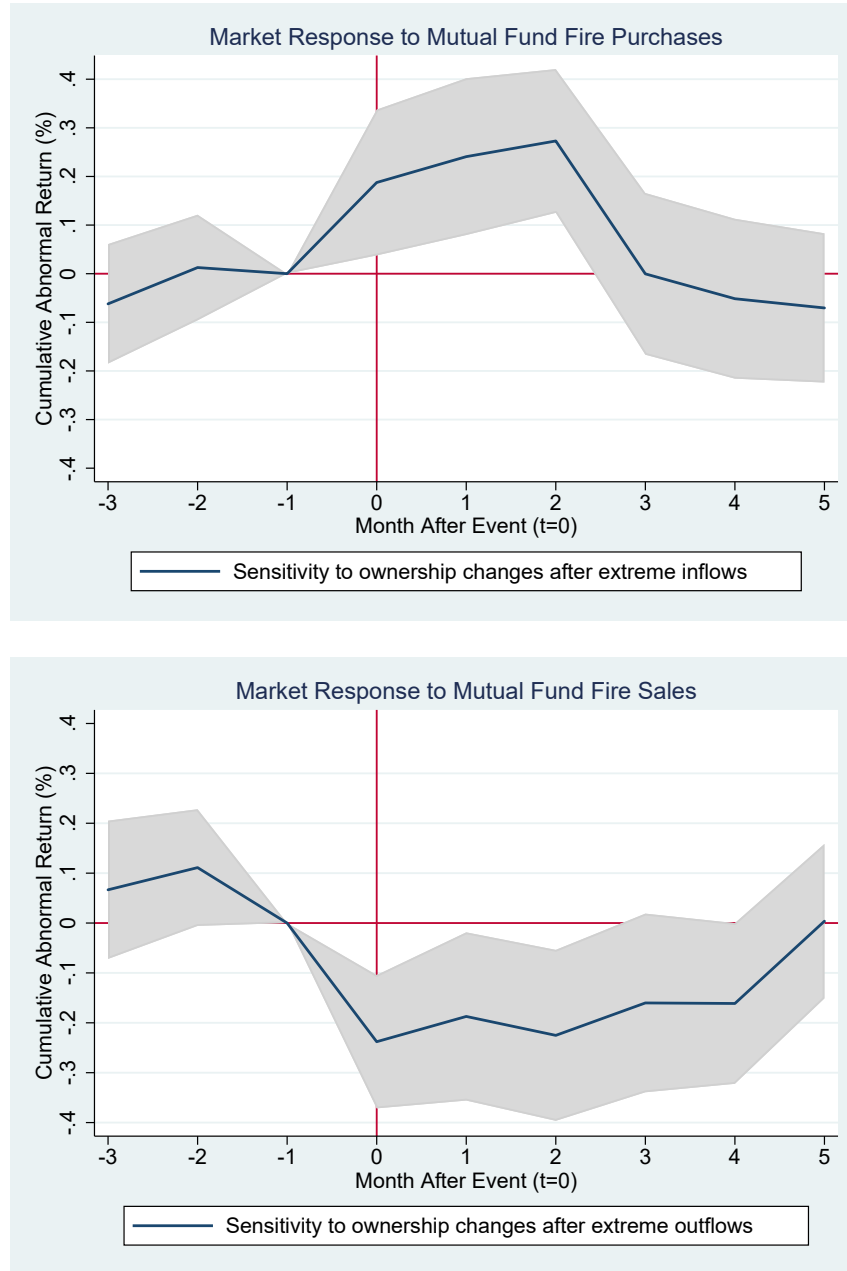
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Figure I: Expected g and k by year



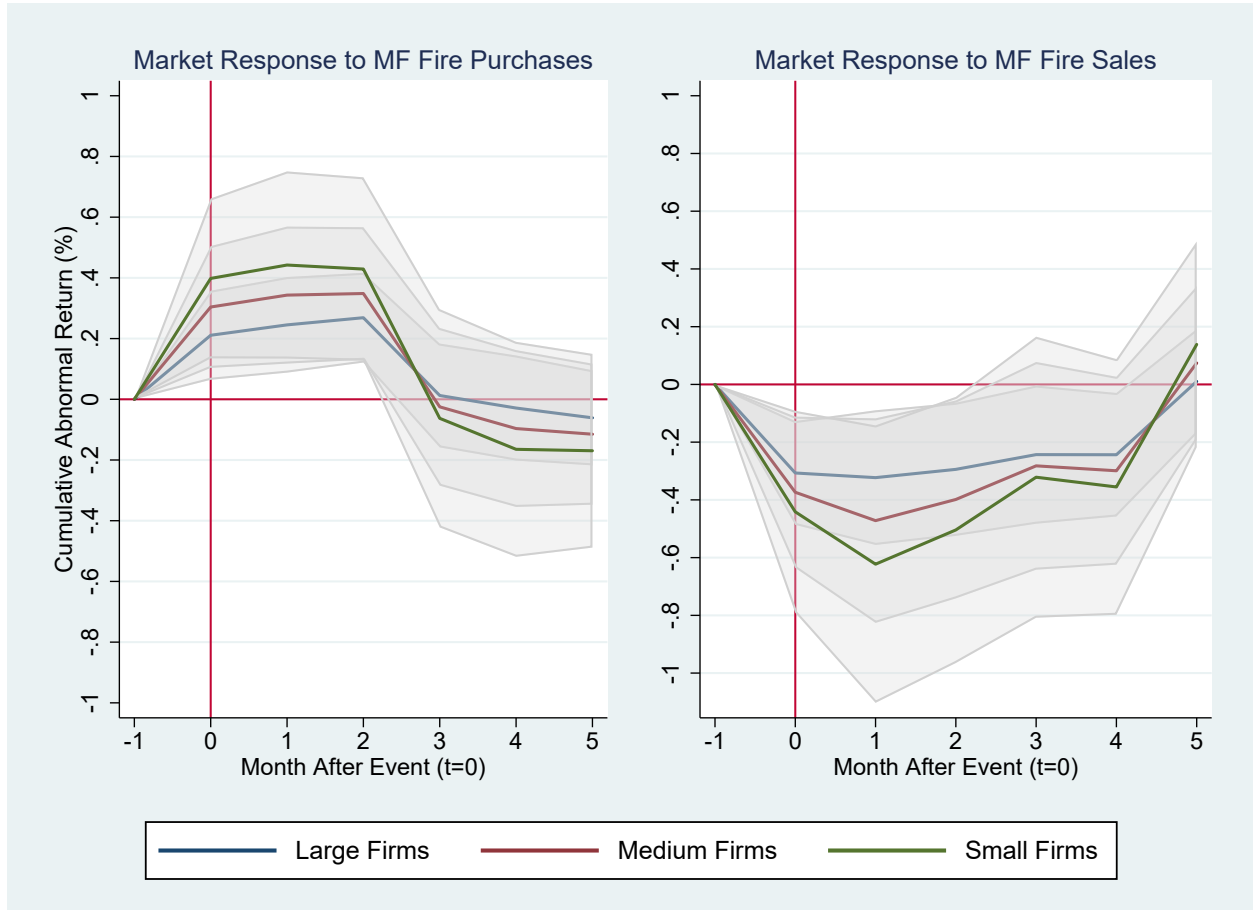
The top graph depicts the evolution of the expected growth rate g , both in nominal and real terms using the 10-year expected inflation rate as a benchmark for inflation. The bottom one displays the evolution of the annual average discount rate k and the implied risk premium using the yield on US 10-year treasury bond as a proxy for the contemporaneous risk free rate. Vertical lines indicate years with NBER recessions. Detailed variable definitions are in Appendix I. The sample includes all available observations for k ($N=3,250$) and g ($N=1,632$) before applying any filter. Reported confidence intervals are at 90% level.

Figure II: Extreme MFF Price Pressure Effects



This figure shows the average Cumulative Abnormal (FF49-industry adjusted) Return after a 1 percentage point variation in mutual fund ownership due to the underlying funds experiencing extreme inflows (upper graph) or extreme outflows (lower graph) at $t=0$. The graphs plot the cumulative sum of the regression coefficients reported in Table VI, starting from $t=0$. The sample includes all public target companies for which either k or g is not missing, and all monthly returns observed during the last 24 months before the month of deal announcement. Reported confidence intervals are at 90% level.

Figure III: Price Pressure Effects by Firm Size



This figure shows the average Cumulative Abnormal (FF49-industry adjusted) Return after a 1 percentage point variation in mutual fund ownership due to the underlying funds experiencing extreme inflows (left graph) or extreme outflows (right graph) at $t=0$ for three sub-samples of targets sorted by tercile of size. The sample includes all public target companies for which either k or g is not missing, and all monthly returns observed during the last 24 months before the month of deal announcement. Reported confidence intervals are at 90% level.

Table I: Summary Statistics

This table presents descriptive statistics for the variables we employ in our main analysis. The sample includes 1,231 deal observations between 2000 and 2022. Detailed variable definitions are in Appendix I.

	N	Mean	STDV	Min	P10	P25	P50	P75	P90	Max
<i>Main dependent variables</i>										
k	1,231	12.9%	4.1%	6.5%	8.8%	10.0%	12.0%	14.5%	18.0%	30.0%
k (Standardized)	1,231	3.97	2.24	1.15	1.90	2.33	3.23	4.73	8.11	10.10
k Range	1,221	2.7%	1.9%	0.0%	1.0%	1.5%	2.0%	4.0%	5.0%	10.0%
g	1,231	3.7%	2.6%	0.0%	1.0%	2.0%	3.0%	4.7%	6.8%	14.8%
g (Standardized)	1,231	1.53	1.05	0.00	0.44	0.76	1.27	2.04	3.09	5.04
g Range	1,128	1.9%	1.3%	0.0%	0.7%	1.0%	1.7%	2.2%	3.8%	7.1%
<i>Main explanatory variables</i>										
Q	1,231	1.80	1.17	0.64	0.98	1.07	1.38	2.08	3.17	7.08
ΔQ	1,231	-0.06	0.76	-3.08	-0.73	-0.23	-0.01	0.14	0.53	3.00
ΔQ (Standardized)	1,231	-0.06	0.67	-2.62	-0.78	-0.32	-0.02	0.24	0.62	1.94
MF Buying Price Pressure	1,231	0.018	0.030	0.000	0.000	0.001	0.008	0.022	0.044	0.293
MF Selling Price Pressure	1,231	0.024	0.046	0.000	0.000	0.001	0.009	0.028	0.061	0.541
MF Noise Range	1,231	0.013	0.024	0.000	0.000	0.001	0.006	0.015	0.031	0.457
<i>Other variables</i>										
Market Capitalization (M\$)	1,231	2,300	6,760	4	41	110	438	1,567	4,237	70,558
Assets (M\$)	1,231	4,454	32,625	3	63	167	568	2,004	5,792	1,020,050
Size (Log of Assets)	1,231	6.42	1.81	1.16	4.15	5.12	6.34	7.60	8.66	13.84
Cash Flow	1,231	0.06	0.16	-0.76	-0.04	0.02	0.08	0.14	0.20	0.41
Debt	1,231	0.23	0.23	0.00	0.00	0.02	0.17	0.36	0.53	1.00
Cash	1,231	0.19	0.20	0.00	0.01	0.03	0.10	0.28	0.51	0.84
Δ Sales	1,231	0.03	0.21	-0.94	-0.11	-0.01	0.02	0.11	0.21	0.73
Dividend	1,231	0.34	0.47	0.00	0.00	0.00	0.00	1.00	1.00	1.00

Table II: Main Results

This table presents the results of estimating Equation 18 (Column 1), Equation 20 (Column 2), Equation 21 (Column 3), Equation 23 (Column 4), Equation 19 (Column 5), Equation 20 (Column 6), Equation 22 (Column 7) and Equation 24 (Column 8). g is the perpetual growth rate of future cash flows assumed by the management team and their advisors for valuing the target company. k is the discount rate assumed by the management team and their advisors for valuing the target company. ΔQ is the change in Q of the target company during the last observable fiscal year before deal announcement. *MF Buying Price Pressure* is the average dollar amount of monthly equity overvaluation due to fire purchases by Mutual Funds subject to extreme inflows during the 12-month period preceding deal announcement, and scaled by total assets. *MF Selling Price Pressure* is the average dollar amount of monthly equity undervaluation due to fire sales by Mutual Funds subject to extreme outflows during the 12-month period preceding deal announcement, and scaled by total assets. All variables are defined in Appendix I. Explanatory variables that are absorbed by the fixed effects are omitted from the regression. t -statistics in parentheses are based on standard errors clustered by Target-SDC-industry. Symbols ***, **, and * denote statistical significance at the 1%, 5%, and 10% level, respectively.

Estimation Method	OLS				OLS			
Dep. Variable		Stage 1	IV	Reduced		Stage 1	IV	Reduced
Specification	g	ΔQ	g	g	k	ΔQ	k	k
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
ΔQ	0.08** (2.19)		-0.03 (-0.08)		-0.08** (-2.00)		-0.89** (-2.22)	
MF Buying Price Pressure		7.68*** (3.21)		0.31 (0.11)		7.68*** (3.21)		-8.06*** (-4.37)
MF Selling Price Pressure		-4.95*** (-3.24)		0.61 (0.29)		-4.95*** (-3.24)		3.35*** (2.99)
Size (Log)	-0.11*** (-6.82)	-0.02 (-1.17)	-0.11*** (-6.75)	-0.11*** (-7.15)	-0.23*** (-14.45)	-0.02 (-1.17)	-0.25*** (-12.26)	-0.21*** (-13.16)
Cash Flow	-0.64*** (-2.89)	-0.01 (-0.03)	-0.64*** (-2.87)	-0.69*** (-3.10)	-0.98*** (-6.24)	-0.01 (-0.03)	-0.97*** (-6.59)	-0.85*** (-5.02)
Debt	-0.06 (-0.35)	0.07 (0.80)	-0.06 (-0.32)	-0.05 (-0.27)	-0.01 (-0.07)	0.07 (0.80)	0.02 (0.12)	-0.08 (-0.54)
Cash	0.22 (1.18)	0.09 (0.60)	0.24 (1.15)	0.18 (0.95)	0.29* (1.66)	0.09 (0.60)	0.39** (2.05)	0.45*** (3.06)
Δ Sales	0.17 (1.10)	0 (-0.01)	0.17 (1.10)	0.16 (1.05)	-0.28** (-2.21)	0 (-0.01)	-0.29** (-1.97)	-0.28** (-2.21)
Dividend	-0.13** (-2.00)	0.01 (0.10)	-0.13* (-1.94)	-0.14* (-1.94)	-0.21*** (-4.37)	0.01 (0.10)	-0.20** (-2.52)	-0.19*** (-4.11)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
F-statistic		12.63				12.63		
Hansen J (statistic)			1.06				1.54	
Hansen J (p-value)			0.30				0.21	
N	1,231	1,231	1,231	1,231	1,231	1,231	1,231	1,231

Table III: Managerial Learning about k - Cross-Sectional Variation

This table presents the results of estimating Equation 24 when interacting all explanatory variables (including the fixed effects) with variables measuring the precision of managerial private information about k (Columns 1 and 4), g (Columns 2 and 4), and the noisiness of the price (Columns 3 and 4). k is the discount rate assumed by the management team and their advisors for valuing the target company. *MF Buying Price Pressure* is the average dollar amount of monthly equity overvaluation due to fire purchases by Mutual Funds subject to extreme inflows during the 12-month period preceding deal announcement, and scaled by total assets. *MF Selling Price Pressure* is the average dollar amount of monthly equity undervaluation due to fire sales by Mutual Funds subject to extreme outflows during the 12-month period preceding deal announcement, and scaled by total assets. k Range is the range reported for k . g Range is the range reported for g . *MF Noise Range* is the inter-quartile range of the net monthly equity misvaluation due to both fire purchases and sales by Mutual Funds subject to extreme inflows or outflows during the 12-month period preceding deal announcement. Control variables include *Size (Log)*, *Cash Flow*, *Debt*, *Cash*, Δ *Sales*, and *Dividend*. All variables are defined in Appendix I. Explanatory variables absorbed by the fixed effects or collinear with the slope fixed effects—resulting from the interaction of the fixed effects with the inverse of k Range (Columns 1 and 4), g Range (Columns 2 and 4), and *MF Noise Range* (Columns 3 and 4)—are omitted from the regression. t -statistics in parentheses are based on standard errors clustered by Target-SDC-industry. Symbols ***, **, and * denote statistical significance at the 1%, 5%, and 10% level, respectively.

Estimation Method Dep. variable: Specification	Reduced Form IV k			
	(1)	(2)	(3)	(4)
MF Buying Price Pressure $\times (k \text{ Range})^{-1}$	0.17*** (3.43)			0.22*** (3.31)
MF Selling Price Pressure $\times (k \text{ Range})^{-1}$	-0.08** (-2.28)			-0.12** (-2.48)
MF Buying Price Pressure $\times (g \text{ Range})^{-1}$		-0.07* (-1.93)		-0.11** (-2.28)
MF Selling Price Pressure $\times (g \text{ Range})^{-1}$		0.05*** (2.68)		0.08** (2.52)
MF Buying Price Pressure $\times (\text{MF Noise Range})^{-1}$			-0.10* (-1.88)	-0.10* (-1.67)
MF Selling Price Pressure $\times (\text{MF Noise Range})^{-1}$			0.06 (1.24)	0.05 (0.99)
MF Buying Price Pressure	-15.06*** (-3.64)	-3.27 (-1.15)	-5.59** (-2.08)	-7.01* (-1.74)
MF Selling Price Pressure	5.80*** (2.55)	0.28 (0.18)	2.11 (1.38)	2.06 (0.85)
Year FE (Interacted)	Yes	Yes	Yes	Yes
Industry FE (Interacted)	Yes	Yes	Yes	Yes
Controls (Interacted)	Yes	Yes	Yes	Yes
N	1,041	1,041	1,041	1,041

Table IV: Managerial Learning about g - Cross-Sectional Variation

This table presents the results of estimating Equation 23 when interacting all explanatory variables (including the fixed effects) with variables measuring the precision of managerial private information about k (Columns 1 and 4), g (Columns 2 and 4), and the noisiness of the price (Columns 3 and 4). g is the perpetual growth rate of future cash flows assumed by the management team and their advisors for valuing the target company. *MF Buying Price Pressure* is the average dollar amount of monthly equity overvaluation due to fire purchases by Mutual Funds subject to extreme inflows during the 12-month period preceding deal announcement, and scaled by total assets. *MF Selling Price Pressure* is the average dollar amount of monthly equity undervaluation due to fire sales by Mutual Funds subject to extreme outflows during the 12-month period preceding deal announcement, and scaled by total assets. k *Range* is the range reported for k . g *Range* is the range reported for g . *MF Noise Range* is the inter-quartile range of the net monthly equity misvaluation due to both fire purchases and sales by Mutual Funds subject to extreme inflows or outflows during the 12-month period preceding deal announcement. Control variables include *Size (Log)*, *Cash Flow*, *Debt*, *Cash*, Δ *Sales*, and *Dividend*. All variables are defined in Appendix I. Explanatory variables absorbed by the fixed effects or collinear with the slope fixed effects—resulting from the interaction of the fixed effects with the inverse of k *Range* (Columns 1 and 4), g *Range* (Columns 2 and 4), and *MF Noise Range* (Columns 3 and 4)—are omitted from the regression. t -statistics in parentheses are based on standard errors clustered by Target-SDC-industry. Symbols ***, **, and * denote statistical significance at the 1%, 5%, and 10% level, respectively.

Estimation Method Dep. variable: Specification	Reduced Form IV g			
	(1)	(2)	(3)	(4)
MF Buying Price Pressure $\times (k \text{ Range})^{-1}$	0.04 (0.58)			0.09 (1.11)
MF Selling Price Pressure $\times (k \text{ Range})^{-1}$	0.01 (0.24)			-0.05 (-0.93)
MF Buying Price Pressure $\times (g \text{ Range})^{-1}$		-0.06 (-0.95)		-0.06 (-0.83)
MF Selling Price Pressure $\times (g \text{ Range})^{-1}$		0.06 (1.42)		0.06 (1.23)
MF Buying Price Pressure $\times (\text{MF Noise Range})^{-1}$			-0.04 (-0.69)	-0.02 (-0.41)
MF Selling Price Pressure $\times (\text{MF Noise Range})^{-1}$			0.04 (0.73)	0.01 (0.19)
MF Buying Price Pressure	-0.22 (-0.04)	3.84 (0.66)	0.49 (0.13)	0.48 (0.06)
MF Selling Price Pressure	-1.55 (-0.38)	-3.53 (-0.95)	-0.1 (-0.04)	-2.34 (-0.53)
Year FE (Interacted)	Yes	Yes	Yes	Yes
Industry FE (Interacted)	Yes	Yes	Yes	Yes
Controls (Interacted)	Yes	Yes	Yes	Yes
N	1,041	1,041	1,041	1,041

Table V: Mutual Fund Flows and Ownership Changes

This table presents the results of estimating Equation 32. The estimation is at the fund-stock-month-year level. $\Delta O_{i,j,m,y}$ is the change in the percentage of ownership of stock i by fund j during month m of year y . $HP_{i,j,m,y}$ is the number of Hypothetical Purchases of stock i by fund j (scaled by the total number of shares of firm i), assuming the fund manager responds to the inflow by adjusting the holding of stock i according to its weight in the market portfolio at $m - 1$. $HS_{i,j,m,y}$ is the number of Hypothetical Sales of stock i by fund j (scaled by the total number of shares of firm i), assuming the fund manager responds to the outflow by adjusting the holding of stock i according to its weight in the market portfolio at $m - 1$. Flag $x\%$ -to- $y\%$ is a dummy variable equal to 1 if the *absolute value* of the net fund flow in percentage of assets under management (TNA) is between $x\%$ and $y\%$, and zero otherwise. Explanatory variables that are absorbed by the fixed effects are omitted from the regression. Stock $\times$ Date FE are fixed effects by stock i interacted with year and month ($i \times y \times m$). t -statistics in parentheses are based on standard errors clustered in three ways, by deal, by fund j , and by date ($y \times m$). Symbols ***, **, and * denote statistical significance at the 1%, 5%, and 10% level, respectively.

Dep. variable: Specification	$\Delta O_{i,j,m,y}$ (1)		$\Delta O_{i,j,m,y}$ (2)	
	Coef.	t-stat	Coef.	t-stat
$HP_{i,j,m,y}$	9.34***	(9.60)		
$HS_{i,j,m,y}$	-5.18***	(-6.53)		
$HP_{i,j,m,y} \times \text{Flag } 0\%\text{-to-}0.5\%$			6.61***	(2.83)
$HP_{i,j,m,y} \times \text{Flag } 0.5\%\text{-to-}1\%$			7.79***	(4.05)
$HP_{i,j,m,y} \times \text{Flag } 1\%\text{-to-}2\%$			8.55***	(6.73)
$HP_{i,j,m,y} \times \text{Flag } 2\%\text{-to-}3\%$			9.20***	(7.63)
$HP_{i,j,m,y} \times \text{Flag } 3\%\text{-to-}4\%$			6.79***	(3.03)
$HP_{i,j,m,y} \times \text{Flag } 4\%\text{-to-}5\%$			12.44***	(6.42)
$HP_{i,j,m,y} \times \text{Flag More than } 5\%$			11.20***	(9.37)
$HS_{i,j,m,y} \times \text{Flag } 0\%\text{-to-}0.5\%$			-1.52	(-0.46)
$HS_{i,j,m,y} \times \text{Flag } 0.5\%\text{-to-}1\%$			-0.53	(-0.29)
$HS_{i,j,m,y} \times \text{Flag } 1\%\text{-to-}2\%$			-2.23*	(-1.71)
$HS_{i,j,m,y} \times \text{Flag } 2\%\text{-to-}3\%$			-8.81***	(-4.28)
$HS_{i,j,m,y} \times \text{Flag } 3\%\text{-to-}4\%$			-8.33***	(-5.96)
$HS_{i,j,m,y} \times \text{Flag } 4\%\text{-to-}5\%$			-7.78***	(-4.81)
$HS_{i,j,m,y} \times \text{Flag More than } 5\%$			-8.16***	(-9.34)
Stock $\times$ Date FE	Yes		Yes	
N	5,844,344		5,844,344	

Table VI: Extreme Fund Flows and Stock Returns

This table presents the results of estimating Equation 37. Monthly abnormal return is the Fama-French 49 industry-adjusted return of target i in month t . *High Inflow Induced* $\Delta O_{i,t}$ is the absolute value of the total increase in mutual fund ownership associated with all hypothetical purchases by funds subject to extreme inflows in month t for target i . *High Outflow Induced* $\Delta O_{i,t}$ is the absolute value of the drop in mutual fund ownership associated with all hypothetical sales by funds subject to extreme outflows in month t for target i . The sample includes all monthly observations for all our targets during the 3-year period preceding deal-announcement. t -statistics in parentheses are based on standard errors clustered in two ways, by deal and by date ($y \times m$). Symbols ***, **, and * denote statistical significance at the 1%, 5%, and 10% level, respectively.

Dep. variable: Specification	Monthly Abnormal Return $_{i,t}$ (1)		Monthly Abnormal Return $_{i,t}$ (2)	
	Coef.	t-stat	Coef.	t-stat
High Inflow Induced $\Delta O_{i,t}$	0.18***	(3.47)		
High Outflow Induced $\Delta O_{i,t}$	-0.21***	(-4.42)		
High Inflow Induced $\Delta O_{i,t+3}$			0.07	(1.23)
High Inflow Induced $\Delta O_{i,t+2}$			-0.01	(-0.19)
High Inflow Induced $\Delta O_{i,t+0}$			0.19**	(2.06)
High Inflow Induced $\Delta O_{i,t-1}$			0.05	(0.58)
High Inflow Induced $\Delta O_{i,t-2}$			0.03	(0.50)
High Inflow Induced $\Delta O_{i,t-3}$			-0.27***	(-4.00)
High Inflow Induced $\Delta O_{i,t-4}$			-0.05	(-0.78)
High Inflow Induced $\Delta O_{i,t-5}$			-0.02	(-0.28)
High Outflow Induced $\Delta O_{i,t+3}$			0.04	(0.63)
High Outflow Induced $\Delta O_{i,t+2}$			-0.11	(-1.56)
High Outflow Induced $\Delta O_{i,t+0}$			-0.24***	(-2.93)
High Outflow Induced $\Delta O_{i,t-1}$			0.05	(0.61)
High Outflow Induced $\Delta O_{i,t-2}$			-0.04	(-0.51)
High Outflow Induced $\Delta O_{i,t-3}$			0.06	(0.94)
High Outflow Induced $\Delta O_{i,t-4}$			0.00	(-0.01)
High Outflow Induced $\Delta O_{i,t-5}$			0.16***	(2.56)
Constant	0.00	(1.61)	0.00	(1.20)
N	54,286		35,938	

Table VII: Transaction Value Determinants

This table presents the results of regressing the equity value paid for the target (Columns 1 to 2), the related implied enterprise value paid (Columns 3 to 4), and the deal value (Columns 5 to 6) on our data for g and k . *Equity Value Paid* is the value of equity implicitly paid for the target, calculated by multiplying the actual number of target shares outstanding by the offer price per share (SDC Item *EQVAL*). *Enterprise Value Paid* is the target enterprise value associated with the transaction, and obtained by multiplying the number of actual target shares outstanding (from the most recent balance sheet released prior to the announcement of the transaction) by the offer price and then by adding the cost to acquire convertible securities, plus short-term debt, straight debt, and preferred equity minus cash and marketable (SDC Item *ENTVAL*). *Deal Value* is the total value of consideration paid by the acquiring company, excluding fees and expenses (SDC Item *VALUE*). g is the perpetual growth rate of future cash flows assumed by the management team and their advisors for valuing the target company. k is the discount rate assumed by the management team and their advisors for valuing the target company. BV (*Assets*) is the book value of equity (assets) of the target from the most recent balance sheet before deal announcement. All variables are defined in Appendix I. Explanatory variables that are absorbed by the fixed effects are omitted from the regression. t -statistics in parentheses are based on standard errors clustered by Target-SDC-industry. Symbols ***, **, and * denote statistical significance at the 1%, 5%, and 10% level, respectively.

Estimation Method Dep. variable: Specification	OLS					
	Equity Value Paid / BV		Enterprise Value Paid / Assets		Deal Value (Log)	
	(1)	(2)	(3)	(4)	(5)	(6)
k	-18.19*** (-2.89)	-33.35*** (-4.14)	-9.87*** (-4.37)	-16.53*** (-5.17)	-26.35*** (-13.30)	-8.02*** (-5.75)
g	16.93** (2.06)	16.28* (1.95)	12.43*** (4.40)	11.70*** (3.82)	6.70** (2.22)	4.36*** (3.44)
Size (Log)		-0.45*** (-3.12)		-0.29*** (-4.16)		0.82*** (30.36)
Percentage Acquired		0.01** (2.24)		0.00 (0.94)		0.01*** (5.72)
Cash Flow		-4.48** (-2.06)		-0.76 (-0.91)		0.42 (1.45)
Δ Sales		2.31*** (2.97)		1.15*** (3.14)		0.37*** (3.26)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
N	1,208	1,202	1,264	1,258	1,261	1,255

IX Appendices

Appendix I – Variables’ Definition

Variable	Definition
Main variables	
g	Perpetual growth rate assumed for valuing the target company. g (<i>Standardized</i>) is g divided by the within-SDC-industry standard deviation of g .
g Range	Assumed range for the perpetual growth rate g .
k	Discount rate assumed for valuing the target company. k (<i>Standardized</i>) is k divided by the within-SDC-industry standard deviation of k .
k Range	Assumed range for the discount rate k .
Q	$(at - ceq + csho \times prccf)/at$ (from last financial statements in Compustat)
ΔQ	Change in Q during the last fiscal year available before deal announcement. ΔQ (<i>Standardized</i>) is ΔQ divided by the within-SDC-industry standard deviation of Q .
MF Buying Price Pressure	Average dollar amount of monthly equity overvaluation due to fire purchases by Mutual Funds subject to extreme inflows during the 12-month period preceding deal announcement, and scaled by total assets (from the last financial statement). MF Buying Price Pressure is always positive or zero.
MF Selling Price Pressure	Average dollar amount of monthly equity undervaluation due to fire sales by Mutual Funds subject to extreme outflows during the 12-month period preceding deal announcement, and scaled by total assets (from the last financial statement). MF Selling Price Pressure is always positive or zero.
Price Noisiness	The inter-quartile range of the net monthly equity misvaluation due to both fire purchases and sales by Mutual Funds subject to extreme inflows or outflows during the 12-month period preceding deal announcement.
Other variables used as controls and/or for cross-sectional analysis and/or in robustness tests	
$\Delta Sales$	Change in <i>sale</i> (over the last fiscal year in Compustat) / at (from last financial statements in Compustat).
Assets	at (from last financial statements in Compustat).
BP Horizon	Average business plan horizon by SIC2-industry from Dessaint, Foucault, and Frésard (2025)
Cash	che/at (from last financial statements in Compustat).
Cash Flow	$(ib + dp)/at$ (from last financial statements in Compustat).
Debt	$(dlc + dltd)/at$ (from last financial statements in Compustat).
Dividend	Dummy equal to 1 if <i>Div</i> is not zero (from last financial statements in Compustat).
Deal Value (log)	log of Deal Value, where Deal Value is the total value of consideration paid by the acquiring company, excluding fees and expenses (SDC Item <i>VALUE</i>).
Enterprise Value Paid / Assets	Implied target enterprise value (SDC Item <i>ENTVAL</i>) defined as the number of actual target shares outstanding times the offer price, plus the cost to acquire convertible securities, short-term debt, straight debt, and preferred equity minus cash and marketable divided by total assets (at from last available financial statements in Compustat).
Equity Value Paid / BV	Implied target equity value (SDC Item <i>EQVAL</i>) defined as the actual number of target shares outstanding times the offer price per share divided by shareholders’ equity (ceq from last available financial statements in Compustat)
Hurdle Rate	Hurdle rate used by managers extracted from earnings conference calls in Gormsen and Huber (2024) (Source: https://costofcapital.org/)
Percentage Acquired	Percentage of Shares Acquired in Transaction (SDC Item <i>PCTACQ</i>) defined as the number of common shares acquired in the transaction divided by the total number of shares outstanding.
Premium Paid	Offer Price to Target Stock Price Premium 4 Weeks Prior to Announcement (SDC Item <i>PPM4WK</i>)
RoA	Return on Assets ib/at (from last available financial statements in Compustat)
Sales Growth Guidance	(Managerial guidance of sales for the next fiscal year / <i>sale</i>) - 1 (from last financial statements in Compustat and last available guidance in I/B/E/S)
Size (log)	log of at (from last available financial statements in Compustat).

Appendix II – Mutual Fund Price Pressure Measure

We construct two variables, *MF Buying Price Pressure*_{*i,t*} and *MF Selling Price Pressure*_{*i,t*}, which measure the average over-valuation and under-valuation of stock *i* induced by extreme inflows and outflows, respectively, among mutual funds owning the stock during 12 months preceding the deal announcement at *t*. Our approach, which builds on Edmans, Goldstein, and Jiang (2012), proceeds in five steps.

Step 1 - Calculate fund flows

We estimate monthly mutual fund flows for all U.S. funds that are not specialized in a given industry using CRSP mutual fund data. For each fund, CRSP reports monthly returns and total net assets (TNA) by asset class. The average return of fund *j* during month *m* of year *y* is given by

$$RETURN_{j,m,y} = \frac{\sum_k (TNA_{k,j,m-1,y} \times RETURN_{k,j,m,y})}{TNA_{j,m-1,y}}, \quad (26)$$

where $TNA_{k,j,m,y}$ and $RETURN_{k,j,m,y}$ are fund *j*'s month-end total net asset value and monthly return in asset class *k*, and $TNA_{j,m,y} = \sum_k TNA_{k,j,m,y}$ is its month-end TNA.

The net flow experienced by fund *j* during month *m* of year *y* is estimated as

$$FLOW_{j,m,y} = TNA_{j,m,y} - TNA_{j,m-1,y} \times (1 + RETURN_{j,m,y}) - MGN_{j,m,y}, \quad (27)$$

where $MGN_{j,m,y}$ is the increase in TNA due to fund mergers.³¹ Thus, $FLOW_{j,m,y}$ measures the net flow (in dollars) experienced by fund *j* during month *m* of year *y*.

Step 2 - Calculate fund holdings

We retrieve each fund's portfolio composition from CDA Spectrum/Thomson, which reports U.S. mutual fund shareholdings at the end of each quarter along with changes since the previous reporting date. We combine this information with linear interpolation to estimate monthly fund holdings. We calculate the fraction of stock *i* held by fund's *j* at the end of month *m* of year *y* as

$$O_{j,i,m,y} = \frac{SHARES_{i,j,m,y}}{N_{i,m,y}}, \quad (28)$$

where $SHARES_{i,j,m,y}$ is the number of shares of stock *i* held by fund *j*, and $N_{i,m,y}$ is the number of shares outstanding of stock *i*, both measured at the end of month *m* of year *y*.

Step 3 - Calculate fund hypothetical trades

For each stock *i* in fund *j*'s portfolio $\mathbb{P}_{j,m,y}$, we compute the hypothetical trades under the assumption that funds respond to net flows by adjusting holdings proportionally to each stock's weight in the *market* portfolio, $W_{M_{i,m,y}} = \frac{P_{i,m,y} \times N_{i,m,y}}{\sum_k (P_{k,m,y} \times N_{k,m,y})}$, where *k* indexes stocks

³¹We follow Lou (2012) to estimate $MGN_{j,m,y}$ and use the last NAV report date of the target fund to approximate the date of fund mergers.

in the CRSP market portfolio, and $P_{i,m,y}$ and $N_{i,m,y}$ denote the price and number of shares outstanding of stock i at the end of month m of year y .

Accordingly, the dollar value of fund j 's hypothetical trades in stock i is $W_{M_{i,m-1,y}} \times FLOW_{j,m,y}$, implying a hypothetical number of shares traded of $\frac{W_{M_{i,m-1,y}} \times FLOW_{j,m,y}}{P_{i,m-1,y}}$. Our measure of hypothetical trades is this quantity scaled by the number of shares outstanding:

$$HT_{i,j,m,y} = \frac{W_{M_{i,m-1,y}} \times FLOW_{j,m,y}}{P_{i,m-1,y}} \times \frac{1}{N_{i,m-1,y}} \times \mathbb{1}_{[i \in \mathbb{P}_{j,m-1,y}]}, \quad (29)$$

where $\mathbb{1}_{[i \in \mathbb{P}_{j,m-1,y}]}$ is an indicator variable equal to one if fund j holds stock i at the end of month $m-1$ of year y and zero otherwise. Thus, $HT_{i,j,m,y}$ measures the fraction of a stock's outstanding shares traded by funds in response to flows.

Substituting the expression for market portfolio weights reveals that $HT_{i,j,m,y}$ does not depend on the price of stock i beyond its contribution to the value of market portfolio:

$$HT_{i,j,m,y} = \frac{P_{i,m-1,y} N_{i,m-1,y}}{\sum_k P_{k,m-1,y} N_{k,m-1,y}} \times \frac{FLOW_{j,m,y}}{P_{i,m-1,y} N_{i,m-1,y}} \times \mathbb{1}_{[i \in \mathbb{P}_{j,m-1,y}]} \quad (30)$$

$$HT_{i,j,m,y} = \frac{FLOW_{j,m,y}}{MKT\ PTF_{m-1,y}} \times \mathbb{1}_{[i \in \mathbb{P}_{j,m-1,y}]} \quad (31)$$

where $MKT\ PTF_{m-1,y}$ is the value of the CRSP market portfolio, which is common across all funds and stocks. In words, fund flows trigger a hypothetical portfolio rebalancing in which the same fraction of shares outstanding is traded for each stock. Note that only existing holdings are adjusted; no new positions are initiated.

Finally, we decompose hypothetical trades into purchases $HP_{i,j,m,y} = \max(HT_{i,j,m,y}, 0)$, and sales $HS_{i,j,m,y} = -\min(HT_{i,j,m,y}, 0)$.

Step 4 - Estimate and predict changes in fund holdings due to extreme flows

We estimate the effect of flow-induced hypothetical trades on fund holdings to verify that they correspond to actual portfolio changes. We further decompose this relationship by flow intensity to isolate the effect of extreme flows. To do so, we estimate the following regression

for changes in fund j 's ownership of stock i :

$$\begin{aligned}
\Delta O_{i,j,m,y} = & a_{i,m,y} \\
& + b_1 HP_{i,j,m,y} \times Flag_0\%_to_0.5\%_{j,m,y} + b_2 HP_{i,j,m,y} \times Flag_0.5\%_to_1\%_{j,m,y} \\
& + b_3 HP_{i,j,m,y} \times Flag_1\%_to_2\%_{j,m,y} + b_4 HP_{i,j,m,y} \times Flag_2\%_to_3\%_{j,m,y} \\
& + b_5 HP_{i,j,m,y} \times Flag_3\%_to_4\%_{j,m,y} + b_6 HP_{i,j,m,y} \times Flag_4\%_to_5\%_{j,m,y} \\
& + b_7 HP_{i,j,m,y} \times Flag_more_than_5\%_{j,m,y} \\
& + c_1 HS_{i,j,m,y} \times Flag_0\%_to_0.5\%_{j,m,y} + c_2 HS_{i,j,m,y} \times Flag_0.5\%_to_1\%_{j,m,y} \\
& + c_3 HS_{i,j,m,y} \times Flag_1\%_to_2\%_{j,m,y} + c_4 HS_{i,j,m,y} \times Flag_2\%_to_3\%_{j,m,y} \\
& + c_5 HS_{i,j,m,y} \times Flag_3\%_to_4\%_{j,m,y} + c_6 HS_{i,j,m,y} \times Flag_4\%_to_5\%_{j,m,y} \\
& + c_7 HS_{i,j,m,y} \times Flag_more_than_5\%_{j,m,y} \\
& + \epsilon_{i,j,m,y}
\end{aligned} \tag{32}$$

where $\Delta O_{i,j,m,y} = O_{i,j,m,y} - O_{i,j,m-1,y}$ is the monthly change in the fraction of stock i held by fund j , and $Flag_X\%_to_Y\%_{j,m,y}$ is an indicator variable equal to one if the absolute value of the fund j 's flow ($ABS(FLOW_{j,m,y})$), expressed as a fraction of beginning-of-month TNA ($TNA_{j,m-1,y}$) falls between $X\%$ and $Y\%$, and zero otherwise. $a_{i,m,y}$ denotes stock-date fixed effects.

Results from estimating Equation 32 are reported in Table V (see Section A.1 for a discussion). We use these estimates to predict ownership changes following extreme flows—defined as inflows exceeding 5% of assets and outflows exceeding 2%.³² Predicted changes in ownership due to extreme inflows are given by

$$High\ Inflow\ Induced\ \Delta O_{j,i,m,t} = 11.2 \times HP_{i,j,m,y} \times Flag_more_than_5\%_{j,m,y} \tag{33}$$

Predicted changes in ownership due to monthly outflows are given by

$$\begin{aligned}
High\ Outflow\ Induced\ \Delta O_{j,i,m,t} = & 8.81 \times HS_{i,j,m,y} \times Flag_2\%_to_3\%_{j,m,y} \\
& + 8.33 \times HS_{i,j,m,y} \times Flag_3\%_to_4\%_{j,m,y} \\
& + 7.78 \times HS_{i,j,m,y} \times Flag_4\%_to_5\%_{j,m,y} \\
& + 8.16 \times HS_{i,j,m,y} \times Flag_more_than_5\%_{j,m,y}
\end{aligned} \tag{34}$$

We obtain stock-level ownership changes by aggregating predicted fund-level changes across funds:

$$High\ Inflow\ Induced\ \Delta O_{i,m,y} = \sum_j (High\ Inflow\ Induced\ \Delta O_{j,i,m,y}), \tag{35}$$

³²The threshold we use to define extreme outflows is similar to Edmans, Goldstein, and Jiang (2012). They use 5% based on quarterly flows, whereas we use 2% based on monthly flows. We use a higher threshold for inflows because monthly net flows are highly positively skewed.

$$\text{High Outflow Induced } \Delta O_{i,m,y} = \sum_j (\text{High Outflow Induced } \Delta O_{j,i,m,y}), \quad (36)$$

Step 5 - Estimate and predict stock price changes due to extreme flows

We examine the dynamic effects of funds' hypothetical trades on stock returns by regressing the monthly returns of stock i on leads and lags of the predicted ownership changes:

$$\begin{aligned} \text{ARET}_{i,m,y} = & \text{Constant} \\ & + b_1 \text{High Inflow Induced } \Delta O_{i,m-3,y} + b_2 \text{High Inflow Induced } \Delta O_{i,m-2,y} \\ & + b_3 \text{High Inflow Induced } \Delta O_{i,m,y} + b_4 \text{High Inflow Induced } \Delta O_{i,m+1,y} \\ & + b_5 \text{High Inflow Induced } \Delta O_{i,m+2,y} + b_6 \text{High Inflow Induced } \Delta O_{i,m+3,y} \\ & + b_7 \text{High Inflow Induced } \Delta O_{i,m+4,y} + b_8 \text{High Inflow Induced } \Delta O_{i,m+5,y} \\ & + c_1 \text{High Outflow Induced } \Delta O_{i,m-3,y} + c_2 \text{High Outflow Induced } \Delta O_{i,m-2,y} \\ & + c_3 \text{High Outflow Induced } \Delta O_{i,m,y} + c_4 \text{High Outflow Induced } \Delta O_{i,m+1,y} \\ & + c_5 \text{High Outflow Induced } \Delta O_{i,m+2,y} + c_6 \text{High Outflow Induced } \Delta O_{i,m+3,y} \\ & + c_7 \text{High Outflow Induced } \Delta O_{i,m+4,y} + c_8 \text{High Outflow Induced } \Delta O_{i,m+5,y} \\ & + \epsilon_{j,i,m,y} \end{aligned} \quad (37)$$

where $\text{ARET}_{i,m,y}$ is the industry-adjusted return of stock i in month m of year y .³³

Results from estimating Equation 37 are reported in Table VI (see Section A.2 for a discussion). We use these estimates to predict stock return changes associated with ownership changes by mutual funds experiencing extreme flows.

Finally, we construct measures of price pressure in dollar terms by multiplying the predicted return effects by lagged market capitalization. Specifically, the dollar value of buying pressure is given by

$$\begin{aligned} \text{MF Buying Price Pressure}_{i,m,y}^{\text{DOLLAR}} = & \\ & + MV_{i,m-1,y} \times \text{High Inflow Induced } \Delta O_{i,m,y} \times 0.19 \\ & + MV_{i,m-2,y} \times \text{High Inflow Induced } \Delta O_{i,m-1,y} \times (0.19 + 0.05) \\ & + MV_{i,m-3,y} \times \text{High Inflow Induced } \Delta O_{i,m-2,y} \times (0.19 + 0.05 + 0.03), \end{aligned} \quad (38)$$

where $MV_{i,m,y}$ is the market capitalization of stock i in month m of year y . Likewise, the

³³Alternative measures of expected return lead to similar results (see Internet Appendix, Section 7).

dollar value of selling pressure is given by

$$\begin{aligned}
MF \text{ Selling Price Pressure}_{i,m,y}^{DOLLAR} = & \\
& + MV_{i,m-1,y} \times \text{High Outflow Induced } \Delta O_{i,m,y} \times 0.24 \\
& + MV_{i,m-2,y} \times \text{High Outflow Induced } \Delta O_{i,m-1,y} \times (0.24 - 0.05) \\
& + MV_{i,m-3,y} \times \text{High Outflow Induced } \Delta O_{i,m-2,y} \times (0.24 - 0.05 + 0.04) \\
& + MV_{i,m-4,y} \times \text{High Outflow Induced } \Delta O_{i,m-3,y} \times (0.24 - 0.05 + 0.04 - 0.06).
\end{aligned} \tag{39}$$

We define $MF \text{ Buying Price Pressure}_{i,t}$ as the average of $MF \text{ Selling Price Pressure}_{i,m,y}^{DOLLAR}$ over the 12 months preceding the deal announcement at t , divided by total assets from the most recent financial statement. Likewise, $MF \text{ Selling Price Pressure}_{i,t}$ is defined as the corresponding 12-month average of $MF \text{ Selling Price Pressure}_{i,m,y}^{DOLLAR}$, scaled by total assets.

Appendix III – Derivations in the Model

A Proof of proposition 1

The manager receives two private signals $S_g = g + \varepsilon_g$, $S_k = k + \varepsilon_k$ and a price signal $q = g - k + \theta$. Hence,

$$\begin{pmatrix} g \\ k \\ s_g \\ s_k \\ q \end{pmatrix} \sim N \left(\begin{pmatrix} 0 \\ 0 \\ 0 \\ 0 \\ 0 \end{pmatrix}, \begin{pmatrix} \frac{1}{\tau_g} & 0 & \frac{1}{\tau_g} & 0 & \frac{1}{\tau_g} \\ 0 & \frac{1}{\tau_k} & 0 & \frac{1}{\tau_k} & -\frac{1}{\tau_k} \\ \frac{1}{\tau_g} & 0 & \frac{1}{\tau_g} + \frac{1}{\tau_{\varepsilon g}} & 0 & \frac{1}{\tau_g} \\ 0 & \frac{1}{\tau_k} & 0 & \frac{1}{\tau_k} + \frac{1}{\tau_{\varepsilon k}} & -\frac{1}{\tau_k} \\ \frac{1}{\tau_g} & -\frac{1}{\tau_k} & \frac{1}{\tau_g} & -\frac{1}{\tau_k} & \frac{1}{\tau_g} + \frac{1}{\tau_k} + \frac{1}{\tau_{\theta}} \end{pmatrix} \right).$$

The projection theorem implies that

$$\begin{aligned} \mathbb{E}[g | \{s_g, s_k, q\}] &= \begin{pmatrix} \frac{1}{\tau_g} & 0 & \frac{1}{\tau_g} \end{pmatrix} \begin{pmatrix} \frac{1}{\tau_g} + \frac{1}{\tau_{\varepsilon g}} & 0 & \frac{1}{\tau_g} \\ 0 & \frac{1}{\tau_k} + \frac{1}{\tau_{\varepsilon k}} & -\frac{1}{\tau_k} \\ \frac{1}{\tau_g} & -\frac{1}{\tau_k} & \frac{1}{\tau_g} + \frac{1}{\tau_k} + \frac{1}{\tau_{\theta}} \end{pmatrix}^{-1} \begin{pmatrix} s_g \\ s_k \\ q \end{pmatrix} \\ \mathbb{V}[g | \{s_g, s_k, q\}] &= \frac{1}{\tau_g} - \begin{pmatrix} \frac{1}{\tau_g} & 0 & \frac{1}{\tau_g} \end{pmatrix} \begin{pmatrix} \frac{1}{\tau_g} + \frac{1}{\tau_{\varepsilon g}} & 0 & \frac{1}{\tau_g} \\ 0 & \frac{1}{\tau_k} + \frac{1}{\tau_{\varepsilon k}} & -\frac{1}{\tau_k} \\ \frac{1}{\tau_g} & -\frac{1}{\tau_k} & \frac{1}{\tau_g} + \frac{1}{\tau_k} + \frac{1}{\tau_{\theta}} \end{pmatrix}^{-1} \begin{pmatrix} \frac{1}{\tau_g} \\ 0 \\ \frac{1}{\tau_g} \end{pmatrix} \\ \mathbb{E}[k | \{s_g, s_k, q\}] &= \begin{pmatrix} 0 & \frac{1}{\tau_k} & -\frac{1}{\tau_k} \end{pmatrix} \begin{pmatrix} \frac{1}{\tau_g} + \frac{1}{\tau_{\varepsilon g}} & 0 & \frac{1}{\tau_g} \\ 0 & \frac{1}{\tau_k} + \frac{1}{\tau_{\varepsilon k}} & -\frac{1}{\tau_k} \\ \frac{1}{\tau_g} & -\frac{1}{\tau_k} & \frac{1}{\tau_g} + \frac{1}{\tau_k} + \frac{1}{\tau_{\theta}} \end{pmatrix}^{-1} \begin{pmatrix} s_g \\ s_k \\ q \end{pmatrix} \\ \mathbb{V}[k | \{s_g, s_k, q\}] &= \frac{1}{\tau_k} - \begin{pmatrix} 0 & \frac{1}{\tau_k} & -\frac{1}{\tau_k} \end{pmatrix} \begin{pmatrix} \frac{1}{\tau_g} + \frac{1}{\tau_{\varepsilon g}} & 0 & \frac{1}{\tau_g} \\ 0 & \frac{1}{\tau_k} + \frac{1}{\tau_{\varepsilon k}} & -\frac{1}{\tau_k} \\ \frac{1}{\tau_g} & -\frac{1}{\tau_k} & \frac{1}{\tau_g} + \frac{1}{\tau_k} + \frac{1}{\tau_{\theta}} \end{pmatrix}^{-1} \begin{pmatrix} 0 \\ \frac{1}{\tau_k} \\ -\frac{1}{\tau_k} \end{pmatrix} \\ \text{Cov}[g, k | \{s_g, s_k, q\}] &= - \begin{pmatrix} \frac{1}{\tau_g} & 0 & \frac{1}{\tau_g} \end{pmatrix} \begin{pmatrix} \frac{1}{\tau_g} + \frac{1}{\tau_{\varepsilon g}} & 0 & \frac{1}{\tau_g} \\ 0 & \frac{1}{\tau_k} + \frac{1}{\tau_{\varepsilon k}} & -\frac{1}{\tau_k} \\ \frac{1}{\tau_g} & -\frac{1}{\tau_k} & \frac{1}{\tau_g} + \frac{1}{\tau_k} + \frac{1}{\tau_{\theta}} \end{pmatrix}^{-1} \begin{pmatrix} 0 \\ \frac{1}{\tau_k} \\ -\frac{1}{\tau_k} \end{pmatrix} \end{aligned}$$

Simplifying these will get us the equations listed in Proposition 1.

B Proof of Proposition 2 and Proposition 3

Note that

$$\mathbb{E}(g | S_g, S_k, q) = \frac{\tau_{\varepsilon g}}{\tau_{g|S_g, S_k, q}} S_g + \frac{\tau_{qg}}{\tau_{g|S_g, S_k, q}} \frac{\tau_{\varepsilon k}}{\tau_k + \tau_{\varepsilon k}} S_k + \frac{\tau_{qg}}{\tau_{g|S_g, S_k, q}} q$$

which implies

$$Cov(\mathbb{E}(g|S_g, S_k, q), q) = \frac{\tau_{\varepsilon g}}{\tau_{g|S_g, S_k, q}} \frac{1}{\tau_g} - \frac{\tau_{qg}}{\tau_{g|S_g, S_k, q}} \frac{\tau_{\varepsilon k}}{\tau_k + \tau_{\varepsilon k}} \frac{1}{\tau_k} + \frac{\tau_{qg}}{\tau_{g|S_g, S_k, q}} \left(\frac{1}{\tau_g} + \frac{1}{\tau_k} + \frac{1}{\tau_\theta} \right) = \frac{1}{\tau_g}$$

$$Cov(\mathbb{E}(g|S_g, S_k, q), \theta) = \frac{\tau_{qg}}{\tau_{g|S_g, S_k, q}} \frac{1}{\tau_\theta}$$

which implies

$$b_g^{OLS} = \frac{Cov(\mathbb{E}(g|S_g, S_k, q), q)}{Var(q)} = \frac{\frac{1}{\tau_g}}{\frac{1}{\tau_g} + \frac{1}{\tau_k} + \frac{1}{\tau_\theta}}$$

$$b_g^{IV} = \frac{Cov(E(g|S_g, S_k, q), \theta)}{Var(\theta)} = \frac{\tau_{qg}}{\tau_g + \tau_{\varepsilon g} + \tau_{qg}}$$

Similarly,

$$\mathbb{E}(k|S_g, S_k, q) = \frac{\tau_{\varepsilon k}}{\tau_{k|S_g, S_k, q}} S_k + \frac{\tau_{qk}}{\tau_{k|S_g, S_k, q}} \frac{\tau_{\varepsilon g}}{\tau_g + \tau_{\varepsilon g}} S_g - \frac{\tau_{qk}}{\tau_{k|S_g, S_k, q}} q$$

which implies

$$Cov(\mathbb{E}(k|S_g, S_k, q), q) = -\frac{\tau_{\varepsilon k}}{\tau_{k|S_g, S_k, q}} \frac{1}{\tau_k} + \frac{\tau_{qk}}{\tau_{k|S_g, S_k, q}} \frac{\tau_{\varepsilon g}}{\tau_g + \tau_{\varepsilon g}} \frac{1}{\tau_g} - \frac{\tau_{qk}}{\tau_{k|S_g, S_k, q}} \left(\frac{1}{\tau_g} + \frac{1}{\tau_k} + \frac{1}{\tau_\theta} \right) = -\frac{1}{\tau_k}$$

$$Cov(\mathbb{E}(k|S_g, S_k, q), \theta) = -\frac{\tau_{qk}}{\tau_{k|S_g, S_k, q}} \frac{1}{\tau_\theta}$$

which implies

$$b_k^{OLS} = \frac{Cov(\mathbb{E}(k|S_g, S_k, q), q)}{Var(q)} = \frac{-\frac{1}{\tau_k}}{\frac{1}{\tau_g} + \frac{1}{\tau_k} + \frac{1}{\tau_\theta}}$$

$$b_k^{IV} = \frac{Cov(E(k|S_g, S_k, q), \theta)}{Var(\theta)} = -\frac{\tau_{qk}}{\tau_k + \tau_{\varepsilon k} + \tau_{qk}}$$

C Proof of Proposition 4

Note that

$$b_g^{IV} = \frac{\tau_{qg}}{\tau_g + \tau_{\varepsilon g} + \tau_{qg}}$$

decreases with the precisions of the manager's prior and private signal about g but increases in absolute value with the precision of her prior and private signal about k . Similarly,

$$b_k^{IV} = -\frac{\tau_{qk}}{\tau_k + \tau_{\varepsilon k} + \tau_{qk}}$$

decreases in absolute value with the precisions of the manager's prior and private signal about k , but increases with the precision of her prior and private signal about g .