Learning about Discount Rates

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ABSTRACT

Using valuation reports disclosing perceived cashflow growth (g) and discount rates (k) in M&A transactions, we examine what managers 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 89% of managers' information about k comes from prices. Therefore, stock markets provide insights into risk and the compensation it requires, but not cashflows, which managers already understand well. 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

"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 *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 (referenced below) 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]

[1]Our question builds on, but differs from, research in asset pricing which establishes that stock price variation arises from both cash flows and discount rates. Indeed, the fact that prices embed both components

Addressing this question is important for future research as well as policy-making (e.g., on financial disclosure or market design). Without an understanding of what managers learn from prices, it is difficult to devise optimal financial disclosure policies, trading rules, or market structures that enhance capital allocation efficiency (Goldstein and Yang (2019)). Yet, most studies on the feedback from prices to investments remain silent on this specific 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 their expectations of cash flow growth g and discount rates k rather than inferring managerial learning from investment decisions. Specifically, we employ valuation reports prepared by managers and their financial advisors to justify acquisition or merger prices.[2] These reports describe the valuation methods used, including assumptions about the discount rate (k) and 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%. Importantly, each (k,g) pair corresponds to the beliefs of the same 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 alternative approach allows for a more direct test of learning. Indeed, investment outcomes may reflect factors unrelated to managers' beliefs such as credit rationing or agency frictions. By focusing directly on managers' beliefs rather than on the *outcome* of these

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

[2] In this article, we use the term "Managers" to refer to any agent involved in the M&A decision-making process, regardless of whether this decision is made internally or externalized to a third party (e.g., a financial advisor).

beliefs, we mitigate the concern that non-information-related 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 g and the other about k—and a public signal—the target's stock price. The stock price contains information about both g and k, but it also incorporates noise unrelated to either variable (e.g., due to liquidity or sentiment shocks), which the manager cannot fully filter out. Ex-post, the econometrician observes the manager's expectations of g and k, the stock price, as well as some price variation due to noise (as explained below), but not the private signals the manager received. When the manager learns from the price, her expectations of g and k respond to it—positively for g and negatively for k. However, standard OLS regressions of g (or k) on the price cannot consistently estimate these relationships. As the model shows, two sources of endogeneity undermine the interpretation of OLS estimates.

The first issue is an omitted-variable problem that is well-known in the learning literature. The econometrician cannot control for what the manager already knows, namely, the private signal she uses to update her beliefs. If this signal contains information also embedded in the stock price—which is plausible—it simultaneously affects prices and managerial expectations, leading them to be correlated even if the manager does not learn from the price. That is, the *absolute* value of the OLS estimates is biased *upward*. Thus, one cannot reject the null that managers do not learn from stock prices and that prices passively reflect information managers already possess.

The second issue is an error-in-variable problem. Depending on what the manager wants to learn, one private signal is directly relevant, while the other is less so. However, the latter is still helpful for interpreting the stock price. For example, when forming an expectation of k, the manager can use her private signal about g to filter out price variations due to

g, thereby obtaining a more precise signal about k from the price. For the econometrician, however, this introduces measurement error as the price is only an imperfect proxy for the filtered public signal the manager actually uses. As the model shows, this approximation can generate attenuation and bias the *absolute* value of the OLS estimates *downward*.

To overcome these issues, we use an identification strategy inspired by Dessaint, Foucault, Frésard, and Matray (2019) who show that noise in stock prices influences investment via managerial learning. Noise due to liquidity trading is plausibly exogenous to firm fundamentals and should therefore not affect beliefs about k and g *unless managers rely on prices as a source of information*. If it does, managers are misguided by stock prices. Paradoxically, this provides strong evidence of learning from stock prices—since this misguidance cannot come from sources other than the price. We formalize this intuition and demonstrate that the econometrician can indeed exploit price variation due to noise trading to obtain consistent estimates using a 2SLS approach, with noise serving as an instrument for stock prices.

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

Like Edmans, Goldtsein, and Jiang (2012), we rely on *hypothetical* rather than actual trades to isolate the effect of the variation in fund size on prices; but unlike them, we calculate the *number* (rather than the dollar value) of shares traded assuming each fund responds to extreme flows by adjusting their holding of each stock according to its weight in the *market portfolio* (rather than relative to its previously disclosed portfolio). Then we (i) estimate the impact of a fund's hypothetical trades on its *percentage* of ownership of the stock *controlling for stock-date fixed effects*, (ii) take the sum across funds by stock-date, and (iii) estimate the aggregate impact of those changes in ownership on industry-adjusted returns.

Our motivation for this substantial revamping of the approach initially proposed by

Edmans, Goldtsein, and Jiang (2012) is to address recent concerns about their price pressure measure. In particular, we use *market portfolio* weights instead of fund-specific portfolio weights to mitigate selection bias, as highlighted by Berger (2023). Likewise, we use stock-date fixed effects to get around normalization issues and address the broader concern of Wardlaw (2020) regarding the need to control for fundamental information contained in contemporaneous price changes and total trading volume.[3] By construction, our measure is immune to this concern because it is independent of the stock's price and trading volume, as well as other unobserved time-varying stock-level variables that may influence all funds trading the same stock at the same time (whose variations are absorbed by the stock-date fixed effects in our revamped approach).

Moreover, to verify that our approach yields coherent results, we exploit both tails of the flow distribution—not just outflows—and build two separate measures: one capturing buying pressure and one capturing selling pressure, which we use as distinct instruments. Reassuringly, both measures are associated with symmetric return patterns. For both, the price change is immediate, goes in the expected direction, reverts gradually over time, is stronger (weaker) for small (large) stocks, and does not exhibit any pre-trend.

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

[3]The original price-pressure measure of Edmans, Goldtsein, and Jiang (2012) is defined as the dollar value of hypothetical sales by funds experiencing large outflows, normalized by dollar trading volume—calculated as the number of shares traded during the month multiplied by the end-of-month stock price. Wardlaw (2020) shows that this normalization is problematic because it introduces contemporaneous price variation into the measure, as well as information about stock fundamentals contained in trading volume.

to a statistically *insignificant* estimate for the sensitivity of g. Compared with the OLS, the corrected estimate is lower in absolute value, is no longer positive, and is economically close to zero, consistent with managers being already well-informed about g and hence not using stock prices to update their beliefs about it. 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. This estimate implies that a one-standard deviation increase in stock prices leads to a downward revision of expectations about k of 0.89 standard deviation. Together, these results imply that stock prices provide managers with nearly all (89%) of their information about k, but do not contribute at all to their understanding of g.

Our model offers several additional predictions which are supported in the data. More distinctively, it predicts how the effect of noise on k depends on the precision of the managers 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 the noise in the price. Conversely, as the private signal about g becomes more precise or the noise in the stock price becomes less volatile, she places *more* weight on the stock price—since she can better filter out sources of variation in the price that are unrelated to k—making her posterior expectation of k more responsive to the noise in the stock price. These are precisely the patterns we observe in the data, using the inverse of the range of estimates about g and k reported by managers as proxies for their signal precisions, and the inverse of the range for price noise over the preceding twelve months as a proxy for the precision of stock price noise. The sum of those cross-sectional patterns is important as it supports the idea that the sensitivity of k to noise is indeed due to managers' learning from target stock prices. Any alternative story must explain not only our main finding but also all of the cross-sectional results.

Overall, we find that managerial beliefs about k are sensitive to (noise in) prices, but beliefs about g are not, suggesting 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.

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 reviews the literature and discusses our contribution. In Section III, we develop our main hypothesis. Section IV presents the data and our identification strategy. In Section V, we report our findings. Section VI examines the validity of both the relevance condition and the exclusion restriction condition of our instrument. We discuss some limitations of our empirical setting and how those may affect the interpretation of our results in Section VII. 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.[4] Specifically, it examines how stock prices inform managerial

[4]For 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

investment decisions. While prior research has reported that managers use stock prices as a guide, much less is known about what managers actually learn from prices. Indeed, the empirical literature remains largely agnostic about the specific nature of the information extracted—whether it pertains to cash flows, discount rates, or other factors. Moreover, theoretical models typically assume that managers learn about cash flows rather than discount rates. 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 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 the information about investors' risk appetite and portfolio holdings needed to assess the compensation investors require. Our results indicate that managers rely almost entirely on stock prices to extract this information. Second, recent work in asset pricing suggests that valuation differences across firms are driven primarily by variations in discount rates or potential mispricing, rather than differences in expected future cash flows (DeLaO, Han, and Myers (2024)).[5] Relatedly, Campbell and Vuolteenaho (2004) show that only discount-rate beta ("bad beta") is priced in the cross-section of expected returns; cash-flow beta ("good beta") in contrast, is not. While the finding that stock prices embed a wealth of information about discount rates does not, by itself, imply that managers use that information, it does make such learning possible. Put differently, even if prices contained only a small amount of information about k, they could still serve as managers' primary source. Recent work by Chaudhry (2025) demonstrates that what appears to be analyst learning about cash flows is in fact driven by discount rate variation. Our findings complement this evidence: managers, when preparing M&A valuations, draw almost all of their information about discount rates

many others. Bond, Edmans, and Goldstein (2012) and Goldstein (2023) offer reviews of this literature.

[5]Specifically, 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. 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.

(k) from stock prices, while their expectations of cash flows (g) remain unchanged.

Our secondary contribution to the literature on the feedback effect is to strengthen 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 our paper contributes to is that concerned with the theory and practice of capital budgeting and mergers and acquisitions. While capital budgeting is one of the most fundamental corporate decisions, field evidence on firms' budgeting practices has been scarce because project investments and their outcomes are typically unobservable. To address this challenge, scholars have surveyed managers (Graham and Harvey (2001), Graham (2022)) and analyzed their conference calls (Gormsen and Huber (2024), Gormsen and Huber (2025)) in order to infer their discount rate and cost of capital. A key assumption in many capital budgeting models (e.g., Stein (2003)) is that managers possess superior private information about future cash flows. Our findings reinforce this assumption by showing that managers do not update their beliefs about g based on stock prices, implying they already have a good understanding of future cash flows.

Finally, we contribute to an emerging literature that examines the valuation practices of professional forecasters (Décaire (2024); Décaire, Sosyura, and Wittry (2024)). Décaire and Graham (2024) investigate the models professionals rely on to form subjective cash flow and discount rate estimates. They find that, for analysts, fluctuations in discount rates over time are primarily driven by movements in the risk-free rate and subjective betas. Taken together with our analysis, the results imply that professionals are using stock prices to infer either subjective betas or risk-free rates. Additionally, they show that terminal growth rates closely follow real macroeconomic variables, such as real GDP, but not inflation.

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 without incorporating utility maximization or market clearing. 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 benchmark based on her prior beliefs (or last periods 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:

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

where $Q_0 \equiv \frac{C}{k_0 - g_0}$ and $q \equiv \frac{C}{(k_0-g_0)^2}(g-k)$. Thus, the change in price $\Delta Q = Q - Q_0$ denoted q 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 is a function of $q \equiv g - k + \theta$ where θ is a noise term. Noise 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. In summary, 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. All variables have a mean of zero, with precisions (inverse variances) given by τ_g, τ_k, τ_θ, $\tau_{\varepsilon g}$ and $\tau_{\varepsilon k}$.

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.[6]

Proposition 1: *If the manager learns from the stock price, her posterior beliefs about the growth rate g and the discount rate k are given by*

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

$$\textit{where } \mathbb{V}ar(g|S_g, S_k, q)^{-1} \equiv \tau_{g|S_g,S_k,q} = \tau_g + \tau_{\varepsilon g} + \tau_{qg} \tag{3}$$

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

$$\textit{where } \mathbb{V}ar(k|S_g, S_k, q)^{-1} \equiv \tau_{k|S_g,S_k,q} = \tau_k + \tau_{\varepsilon k} + \tau_{qk} \tag{5}$$

$$\mathbb{C}ov(k, g|S_g, S_k, q)^{-1} = \frac{1}{\tau_\theta}(\tau_g + \tau_{\varepsilon g} + \tau_\theta)\tau_{k|S_g,S_k,q} > 0. \tag{6}$$

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.

These formulas can be interpreted as follows. When forming expectations about g, the

[6] The proofs of our propositions are in appendix III.

total precision of the manager's information (i.e., $\tau_{g|S_g,S_k,q}$) 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 signal about g, given by $\tau_{qg} = (\frac{1}{\tau_k+\tau_{\varepsilon k}} + \frac{1}{\tau_\theta})^{-1}$. To interpret the third term, we can view the price as a signal about g with noise $-k+\theta$. The manager can mitigate this noise using her private signal about k. The precision of $-k+\theta$, conditional on the private signal S_k, is given by $Var(-k+\theta|S_k)^{-1} = (Var(k|S_k) + Var(\theta))^{-1} = (\frac{1}{\tau_k+\tau_{\varepsilon k}} + \frac{1}{\tau_\theta})^{-1}$ since k and ε_k are uncorrelated with θ. This term represents the amount of information the manager can extract about g from the stock price. Naturally, it is larger when the price is less noisy (higher τ_θ) and when the manager is better informed about k (larger $\tau_k + \tau_{\varepsilon k}$). The manager's posterior expectation of g follows as a 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 $Var(-(g+\theta)|S_g)^{-1} = (\frac{1}{\tau_g+\tau_{\varepsilon g}} + \frac{1}{\tau_\theta})^{-1} \equiv \tau_{qk}$, which represents the precision to the manager of the price signal about k.

The manager's posterior expectations of g and k are positively correlated, though g and k are unconditionally uncorrelated. That is because the manager conditions on the price which contains both g and k.

The case in which the manager does not learn from the stock price can be derived from the general case by setting τ_θ to zero.

Corollary 1: *If the manager does not learn from the stock price, her posterior beliefs about the growth rate g and the discount rate k are given by:*

$$E(g|S_g, S_k) = \frac{\tau_{\varepsilon g}}{\tau_g + \tau_{\varepsilon g}} S_g$$

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

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

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

$$Cov(k, g|S_g, S_k) = 0$$

Here, her posterior expectation and precision reduce to the usual expressions based on a prior and a single private signal, as presented in Corollary 1.

B Predictions

We consider two sets of possible 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

We start with OLS regressions of the manager's posterior belief about g and k on the price q:

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

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

The following proposition characterizes the OLS regression coefficients.

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:

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

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

If the manager does not learn from the stock price:

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

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

Proposition 2 shows that OLS regression coefficients 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). It predicts a positive coefficient for g, and a negative coefficient for k, regardless of whether or not the manager learning from the price. This difficulty arises because the private information of the manager (S_g and S_k) is not observed by the econometrician and 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. In the base case, we assume that θ is not observed by the manager *ex-ante*—when observing q, she cannot distinguish noise from information about g and k—but it is observed by the econometrician *ex-post*. Notably, it is not necessary for the econometrician to observe the *entire* noise term.[7], nor is it needed that the manager be unable to *completely* filter it out. The same predictions hold as long as their ability to identify noise is only 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:*

[7] Assume θ is the sum of unexplained noise, $\theta^{unexplained}$, and noise due to liquidity trading (e.g., mutual fund fire sales observed by the econometrician ex-post), $\theta^{explained}$. Then $q = g - k + \theta^{explained} + \theta^{unexplained}$. In this case, $\theta^{explained}$ can be used to instrument q.

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

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

If the manager does not learn from the stock price:

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

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

Unlike their OLS counterparts, IV regressions yield sharply contrasting results: the IV regression 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 the information embedded in stock prices (and combined with their private signal about g). We will utilize this interpretation to quantify the extent of managerial learning from stock prices.

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 leads to an additional prediction. When the manager does not learn from the price, the IV coefficients are zero, making the OLS coefficients *larger in absolute value* than their IV counterparts. 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, and 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 coefficients. 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 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 *lower in absolute value* than the OLS coefficient. [8].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*

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

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 that allow to further identify learning effects when we consider 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.[9]

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

[9] In contrast, the OLS coefficients do not depend on the precision of the manager's private signals when she learns from the price. This is due to a counteracting effect: as the precision of her private signal increases, the manager places greater weight on it. Because the private signal is correlated with the price, it introduces an offsetting correlation that compensates for the reduced direct correlation with the price.

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 non-linear system that links together prior, private signal, and posterior precisions. This approximation reveals that the prior and private signal precisions about k (g) increase with the posterior precisions about k (g), and decrease with 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. When conditioning on posterior precisions, this prediction continues to hold (e.g., for $|b_k^{IV}|$) provided the prior and private signals (about g) are more precise than the price signal (about g).

Prediction 5: *With learning from the stock price, the IV regression coefficient increases in absolute value with the precision of stock price noise. This holds without controlling for posterior precisions, as well as with controls provided the prior and private signals are more precise than the price signals. 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 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

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

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 ($\tau_{g|S_g,S_k,q}$) and the precision of price noise (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. We also need measures for the precision of the posterior about g, the precision of the posterior about k, and the precision of stock price noise. This section describes our data sources and how we construct each measure we need. Appendix I provides a summary of all the variables used in our tests and their definition.

A Data

A.1 Expectations Data

We identify expectations about future cash flow growth g and firm discount rate k using M&A fairness opinions data from LSEG (formerly Thomson Reuters—SDC Platinum). Fairness opinions are valuation reports prepared by investment bankers to evaluate whether the price offered in a transaction is fair to the shareholders of the target, the seller, or the acquirer. These reports describe the valuation methods used, including assumptions made by the management team and their advisors about the discount rate (k) and perpetual growth rate of future cash flows (g) for the target company.

LSEG reports information about discount rate k under items FO_DCF_RATE_LOW and FO_DCF_RATE_HI. The two items respectively provide the low and high end of the range of values assumed for k. Similarly, the range assumed for the perpertual cash flow growth g is reported under items FO_DCF_PERP_LOW and FO_DCF_PERP_HI.[10] We use the range mid-point as the estimate for k and g, and the inverse of the range size as an estimate for the precision of managerial posterior beliefs about k and g. The size of the range is calculated as the difference between the high and low end of the range and is denoted k *Range* and g *Range* for k and g, respectively.[11]

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 data entry errors where k or g is not reported in percentage points (e.g. 12 for 12%) but was entered as a decimal number (0.12), eliminate observations where the high end of the range is lower than the low end, remove outliers (where $k < 1\%$ and where $g < 0\%$) and aggregate all variables k, g, k *Range*, g *Range* at the deal-level by taking the average across fairness opinions (when multiples opinions were provided on the price offered 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 with 3,205 non-missing observations about k and 1,632 non-missing observations about g expected for 3,103 unique targets.

[Insert Figure I about here]

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

[10]Sometimes, a multiple is used to compute terminal values instead of the Gordon Growth Model. In this case, we uncover the implicit range of values assumed for g using the following formula:

$$g = \frac{k \times MULT - 1}{1 + MULT} \tag{18}$$

where k is the mid-point of the range for the assumed discount rate, and $MULT$ is the low or high end of the range assumed for the terminal value multiple. The range assumed for $MULT$ is given by items FO_DCF_TERM_LOW and FO_DCF_TERM_HI.

[11]Occasionally, the low and high end of the reported range is the same 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).

spectively. Figure I plots the average of k and g by year. The Pearson correlation between between the two variables is positive (0.56), which is consistent with our model prediction when managers learn from prices: in our baseline model, managerial learning from prices indeed causes k and g to be positively correlated despite k and g being unconditionally uncorrelated. In the data, k and g may be related for other reasons than managerial learning (i.e., k and g may not be unconditionally uncorrelated). Thus, the positive correlation of 0.56 is only suggestive—not definitive—evidence of managerial learning from prices.

A.2 Price Pressure (Stock Price Noise) Data

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

An important feature of our price pressure measure is that it does not rely on actual fund trades. Like Edmans, Goldstein, and Jiang (2012), we use hypothetical, rather than actual, trades to isolate holdings changes mechanically induced by extreme flows, rather than by active trading decisions. However, unlike Edmans, Goldstein, and Jiang (2012), we do not base hypothetical trades on the fund's previously disclosed portfolio. Instead, we use the market portfolio (which is common to all funds), assuming that each fund adjusts its holdings in response to extreme flows proportionally to each stock's weight in the market portfolio at the beginning of the month. We do so to (i) ensure that our measure is not related to time-varying stock characteristics explaining fund portfolio weights (Berger (2023)), (ii) mitigate the concern that it captures information about fundamentals embedded in the fund manager's past trading decisions, (iii) better isolate the mechanical stock holding variations induced by the plausibly exogenous variations in fund size caused by extreme flows.

Moreover, we also depart from the original formula used to calculate price pressure, where the mispricing does not only depend on flows and portfolio weights, but also on market depth—measured as the dollar amount of trading volume, evaluated at the end of the month. Wardlaw (2020) shows that this approach is problematic because it inadvertently introduces the (inverse of the) stock return into the price pressure measure, along with stock-level information about fundamentals contained in trading volume. To address this problem, we (i) estimate the impact of a fund's hypothetical *number* of shares acquired (sold) in response to the extreme inflow (outflow) on its percentage of ownership at the fund-stock level, *controlling for stock-date fixed effects*, (ii) take the sum across funds by stock-date to obtain a stock-level estimate of change in Mutual Fund ownership *in percentage* induced by extreme flows, (iii) estimate the impact of extreme flows on returns at the stock-level by regressing monthly FF49-adjusted returns on the previously estimated changes in Mutual Fund ownership. By construction, the measure we obtain for noise in stock returns is immune to Wardlaw (2020)'s critic because it does not depend on dollar volume, and more fundamentally, because it is unrelated to any observed and unobserved time-varying stock-level variable that may affect all funds trading the same stock at the same time. Any such variation is fully absorbed by the stock-date fixed effects.[12]

Finally, to verify that our approach yields coherent results, we exploit both tails of the flow distribution—not just 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 mutul fund ownership (ΔO) separately for extreme monthly inflows (more than 5% of fund assets) and outflows (more than 2% of fund assets), which we denote *High Inflow Induced* ΔO and *High Outflow Induced* ΔO, respectively. Then we isolate the effect of both fire sales and fire purchases 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]

[12]Other papers discussing and proposing other ways to address Wardlaw (2020)'s critic include Dessaint, Olivier, Otto, and Thesmar (2020) and Tubaldi (2024)

Figure II provides a graphical illustration of the two main effects we uncover when running this regression. We find that an increase (decrease) in ownership following extreme inflows (outflows) positively (negatively) affects stock returns and that this effect is only transient, consistent with both capturing non-fundamental variation in prices only. The lower (upper) graph 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 abnormal return that persists for 2 months and then reverts 3 to 5 months after the initial change in mutual fund ownership induced by the extreme flow.

We use the above estimates to predict noise in stock returns. We then infer noise in prices every month by multiplying noise in monthly stock returns by the market capitalization at the beginning of the period, and noise in Q by scaling noise in prices 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).

Finally, we use the distribution of monthly noise in Q induced by extreme fund flows to obtain an estimate of the volatility of the noise. For each stock, we calculate *MF Noise Range* defined as the inter-quartile range of monthly noise in Q over the last 12 months before deal announcement, and use the inverse as an estimate of the precision of the price signal.

Appendix II describes in detail the procedure we use to compute *MF Buying Price Pressure*, *MF Selling Price Pressure*, and *MF Noise Range*.

A.3 Other Data

All M&A data are from LSEG. Data on market prices, volume and number of shares are from CRSP. Financial accounting data comes from Compustat North America. Mutual fund ownership data are from Thomson Reuters and data about mutual fund flows come 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. [13] We further require that g, k, and Q are not negative, and that the change in Q is less than 10 in absolute value. The sample starts in 2000 and ends in 2022.

[Insert Table I about here]

Table I shows summary statistics for all variables. The main endogenous variables we employ are g, k, Q, and ΔQ, and the two exogenous ones are *MF Buying Pressure*, *MF Selling Pressure*. We normalize the endogenous variables by the within-(SDC-)industry standard deviation to ease economic interpretation. All variables are defined in detail in Appendix I. Continuous, non-log-transformed, non-well-behaved variables are winsorized at the 1% level in each tail to reduce the effects of outliers.

B Methodology

B.1 OLS Regressions

We first test whether prices affect beliefs about g and k using OLS. The basic regressions we estimate are

$$g_{i,t} = b_g \Delta Q_{i,t-1} + \gamma_g X_{i,t-1} + \phi_j + \eta_y + \varepsilon_{i,t} \tag{19}$$

$$k_{i,t} = b_k \Delta Q_{i,t-1} + \gamma_k X_{i,t-1} + \phi_j + \eta_y + \varepsilon^{'}_{i,t} \tag{20}$$

where $g_{i,t}$ and $k_{i,t}$ are the expected growth and discount rate of target i at the time of deal announcement t; $\Delta Q_{i,t-1}$ is the change in Q over the last observable fiscal year of firm i before deal announcement. $g_{i,t}$ and $k_{i,t}$ are the empirical counterparts for g and k in our model. $\Delta Q_{i,t-1}$ is the empirical counterpart for q defined in the model as the change in price

[13] This requirement causes our sample to decrease from 3,205 to 1,231 observations, mostly because g is missing for half the valuation reports where k is not

$\Delta Q = Q - Q_0$ (see Eq. 1). The main coefficients of interest are b_g and b_k. 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 control variables for known determinants of expected free cash flow growth (g) and firm-level return (k). In particular, we control for size, level of (and change in) realized cash flows, historical capital structure, and payout policy. The industry fixed effects absorb time-invariant industry components, while year-fixed effects absorb annual variation common across firms.

B.2 2SLS Regressions

Next, we use 2SLS regressions. Estimating b_g and b_k by OLS is problematic because Eq. 19 and Eq. 20 are subject to a classic endogeneity problem discussed above.[14] Managers of the bidding firm and their advisors have access to various sources of information and already possess information themselves before observing the price of the target. Because the target price may also reflect this unobserved information, finding $b_g > 0$ and $b_k < 0$ does not imply prices contain new information to the manager (cf. Proposition 2). The same common unobserved information could jointly affect prices and managerial beliefs. Under this alternative interpretation, prices do not affect the beliefs of the manager of the bidding firm and its advisors, but simply passively reflect the private information she already has (cf. Prediction 1).

One possible identification strategy to overcome this problem is to exploit variation in prices due to noise. This strategy is inspired by Dessaint, Foucault, Frésard, and Matray (2019). They show that noise affects corporate investment via the learning channel because managers cannot easily detect price variations due to noise. In the context of our study, noise is plausibly unrelated to information about g and k. Therefore, it should not affect managers' beliefs, unless they are using prices to extract information and cannot easily separate noise from real information about g and k. Section III Part B.2 above formalizes this intuition. Without learning, managers do not look at prices or ignore them, so their

[14] See Section III, Part B.1

beliefs should *not* depend on price variation due to noise or liquidity trading. If, instead, noise in prices influences their beliefs, it must be that they are looking at them (cf. Proposition 3). Therefore, showing that managerial beliefs are sensitive to noise provides a higher level of proof for the learning hypothesis (cf. Prediction 2).

We implement this identification strategy with an instrumental variable approach. We estimate by 2SLS whether prices affect beliefs about g and k, using both buying price pressure caused by mutual funds subject to extreme inflows ($Z1$) and selling price pressure observed after mutual funds experience extreme outflows ($Z2$) as instruments for ΔQ.

The first-stage regression we estimate is

$$\Delta Q_{i,t-1} = \pi_1 Z1_{i,t-1} + \pi_2 Z2_{i,t-1} + \pi_3 X_{i,t-1} + \phi_j + \eta_y + \mu_{i,t} \tag{21}$$

where $Z1_{i,t} \equiv \mathit{MF\ Buying\ Pressure}_{i,t}$ is the average *over*-valuation of the target in dollar due to mutual funds fire purchases over the 12-month period before deal announcement scaled by total assets; and $Z2_{i,t} \equiv \mathit{MF\ Selling\ Pressure}_{i,t}$ the average *under*-valuation of the target in dollar due to mutual funds fire sales (also scaled by total assets).

The second-stage regressions are

$$g_{i,t} = b_g \widehat{\Delta Q_{i,t-1}} + \gamma_g X_{i,t-1} + \phi_j + \eta_y + e_{i,t} \tag{22}$$

$$k_{i,t} = b_k \widehat{\Delta Q_{i,t-1}} + \gamma_k X_{i,t-1} + \phi_j + \eta_y + e'_{i,t} \tag{23}$$

where $\widehat{\Delta Q_{i,t-1}}$ is the predicted change in Q over the last observable fiscal year of firm i before deal announcement from the first-stage regression (Eq. 21). Notice the first stage regression is the same whether we want to estimate b_g or b_k, because the endogenous regressor (ΔQ) in Eq. 19 and Eq. 20 is the same. The main coefficients of interest are again 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 noise in prices, as we do in the model.[15] Both g and k should be sensitive to noise if and only if managers are actually learning from the price (cf. Proposition 3). Hence, we also estimate

$$g_{i,t} = \beta_{1,g} Z1_{i,t-1} + \beta_{2,g} Z2_{i,t-1} + \gamma_g X_{i,t-1} + \phi_j + \eta_y + \psi_{i,t} \tag{24}$$

$$k_{i,t} = \beta_{1,k} Z1_{i,t-1} + \beta_{2,k} Z2_{i,t-1} + \gamma_k X_{i,t-1} + \phi_j + \eta_y + \psi'_{i,t} \tag{25}$$

where $Z1_{i,t}$ and $Z2_{i,t}$ measure target over-valuation ($\textit{MF Buying Pressure}_{i,t}$) and target under-valuation ($\textit{MF Selling Pressure}_{i,t}$) respectively, both in absolute dollar value scaled by total assets. 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).

The above regressions are sometimes referred to as reduced-form IV regressions and achieve the same level of proof as the 2SLS approach because they rely on the same source of noise in the price. We also use this approach despite being equally informative as the 2SLS for three reasons: (i) for consistency with our model—where g and k are directly regressed on noise, (ii) for convenience—to study cross-sectional variation and test Prediction 4 and Prediction 5, (iii) for robustness—to verify that both an increase and decrease in the price indeed lead to beliefs' updating of opposite sign.

V Results

This section presents the results of testing our main predictions (Predictions 1, 2, and 3), and the ancillary ones (Predictions 4 and 5).

A Main Results

[Insert Table II about here]

Table II presents our main results. We test Predictions 1, 2, and 3 by estimating Equa-

[15] See Section III, Part B.2.

tions 19 to 25. All tests were performed with the exact same sample of firms. Hence, differences in estimation results cannot be due to sampling variation.

A.1 Learning about g

In Columns (1) to (4), we study how prices affect beliefs about g. Column (1) displays OLS estimates for Eq. 19 and shows that beliefs about g are sensitive to prices. This sensitivity is positive ($b_g > 0$), suggesting manager could learn from prices about g. However, Columns (2) and (3) show that this sensitivity disappears (b_g decreases in absolute value, flips sign, and is no longer statistically significant) when using noise due to liquidity trading by mutual funds as instrument for ΔQ. In Column (2), we report the results from estimating Eq. 21. We find that the relevance condition is satisfied. Positive (Negative) price pressure captured by the variable *MF Buying Price Pressure* (*MF Selling Price Pressure*) generates positive (negative) change in price ΔQ. Column (3) reports the results from estimating Eq. 22 and shows that these price changes have no impact on g; that is, managers' beliefs about g are not sensitive to price variation plausibly unrelated to information already known to managers and their advisors ($b_g = 0$). Column (4) corroborates this result. We estimate Eq. 24 and find that neither buying price pressure, nor selling price pressure affects beliefs about g.

A.2 Learning about k

In Columns (5) to (8) we study how prices affect managers' beliefs about k. In Column (5), we report the results from estimating Eq. 20. We find that beliefs about k are sensitive to prices. This sensitivity is negative ($b_k < 0$), suggesting managers may learn from prices about k. In Columns (6) and (7), we find that this sensitivity is still negative when using noise due to liquidity trading by mutual funds as instrument for ΔQ. Column (6) estimates Eq. 21. Since the endogenous regressor in Column (5) is the same as in Column (1), the results are the same as in Column (2). In Column (7), we report the results from estimating Eq. 23 and find that independent price changes affect k; that is, beliefs about k are sensitive to price variation plausibly unrelated to information already known by the manager and her financial advisors ($b_k < 0$). Column (8) corroborates this result. We estimate Eq. 25 and find that beliefs about k are lower after the target's stock price experiences buying price pressure, and greater in case of selling price pressure in the 12-month period before deal announcement.

A.3 Interpreting OLS vs. IV coefficients

Before correcting for endogeneity, managers' beliefs about g and k for the same sample of firms are sensitive to prices. The sensitivity is positive for g (when the price increases, g is higher), negative for k (when the price increases, k is lower), and of similar economic magnitude. In absolute value, a one standard-deviation in the price is associated with a 0.08 standard deviation in g and k. Taken together at face value, these results suggest the market feedback about both g and k may be equally important to real decision makers when valuing future M&A investment opportunities.

However, after correcting for endogeneity, only k reacts to prices. When using noise as instrument to filter out the information about g and k already known to the manager, b_g decreases to zero as one would expect when managers are already well-informed about g, but b_k stays negative and even increases in absolute value as expected when managers know little about k and a lot about g. In this case, the information about g contained in the price creates a measurement error problem for the econometrician when regressing k on ΔQ. Since the manager can use her own private information about g to filter out g from ΔQ, the actual signal about k that she perceives is not the same as what the econometrician (who only observes the price) can measure. This measurement error generates attenuation bias in the OLS estimate (Column 5), that is removed when using price variation unrelated to g as instrument. Hence the greater coefficient we observe in Column (7).

To summarize, the nature of the endogeneity problem depends on whether managers know relatively more about g or k. If they know a lot about g and little about k, the endogeneity problem is an omitted variable problem in Column (1) and an error-in-variable problem in Column (5). In this case, the absolute value of the OLS coefficient will be upward biased in Column (1) and downward biased in Column (5). Those two effects are formalized in section III (see Proposition 3 and the discussion that follows) and summarized in Prediction 3. Table II provides empirical support for those.

A.4 Interpreting Economic Magnitude

After correcting for endogeneity, we find $b_g = -0.03$ and $b_k = -0.89$. When the price increases by one-standard deviation, expectation about k (g) decreases by 0.89 (0.03) standard deviation.

In our theoretical framework, the IV coefficients represent (in absolute value) the proportion of information about g or k that the manager obtains from observing the price. For example, b_k is the share (between 0 and 1) of the manager's posterior precision about k that is derived from the information contained in the price (and combined with observing a private signal about g). Therefore, a coefficient of 0.89 indicates that managers obtain 89% of their information about k from the price. Likewise, a statistically insignificant coefficient of -0.03 means they get no information at all about g from the price.

Overall, Table II shows that managerial beliefs about k are highly sensitive to prices—with estimates implying that managers obtain up to 90% of their information about k from stock prices—, but beliefs about g are not. These results are in line with Predictions 1, 2, and 3 when managers already know a lot about g, but little about k.

B Cross-sectional Variation

This section reports the results of testing Prediction 4 and 5. When managers learn from prices, theory predicts additional variation in the sensitivity of g and k to noise in prices, depending on the precision of the posterior of the manager about g (τ_{qg}) and k (τ_{qk}), and on the precision of the price signal (τ_θ).

B.1 Variation in k-to-noise sensitivity

Given prior evidence that managers learn more about k than g, we focus on k-to-noise sensitivity first. In this case, our model predicts weaker sensitivity when managers are better informed about k, and stronger sensitivity when they can better extract information about k from the price, either by removing information about g or because the price is less noisy to begin with. Therefore, the *absolute value* of $\beta_{1,k}$ and $\beta_{2,k}$ in Eq.25 should decrease with τ_{qk} and increase with τ_{qg} and τ_θ.

[Insert Table III about here]

Table III presents the results of interacting noise in prices in Eq. 25 with the inverse of the reported range for g and k (our empirical counterparts for τ_{qk} and τ_{qg}) and with the inverse of *MF Noise Range* (our empirical counterpart for τ_θ).

Quite remarkably, the sensitivity of k to noise in prices systematically varies in the expected direction when managers learn from the price about k. All coefficients on interaction terms have a sign in line with Predictions 4 and 5; and all are statistically significant or marginally so. Column (1) shows weaker sensitivity to noise when the inverse of the reported range for k is high. When managers are better informed about k (τ_{qk} is higher), the negative impact of *MF buying (selling) price pressure* is lower (higher). In Column (2), the sensitivity is greater when the inverse of the reported range for g is high. When managers are better informed about g (τ_{qg} is higher), managers can extract more information about k from the price by removing the information about g. As a result, they put more weight on prices and thus on noise. Hence, the more negative (positive) impact of *MF buying (selling) price pressure.* In Column (3), the sensitivity is greater when prices are less noisy to begin with (i.e., *MF Noise Range* is low). When prices are more informative (τ_θ is high), managers extract more information about k from the price and thus put more weight on noise. Column (4) provides similar evidence when testing simultaneously all three effects in the same regression.

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

B.2 Variation in g-to-noise sensitivity

Prior evidence shows that g is not sensitive to noise to begin with. Nevertheless, and for completeness, we report the results of performing the same analysis for the sensitivity of g

to noise in prices. In this case, the learning hypothesis predicts that the *absolute value* of $\beta_{1,g}$ and $\beta_{2,g}$ in Eq.24 should decrease with τ_{qg} and increase with τ_{qk} and τ_{θ}.

[Insert Table IV about here]

Results are in Table IV. In short, our finding that noise does not affect g unconditionally (Table II, Column 4) is also true conditionally (Table IV). Columns (1) to (4) show no significant variation by precision of non-price and price information—contrary to Predictions 4 and 5 when managers learn from prices about g.

Overall, these results provide little to no support for the learning hypothesis about g.

VI Instrument validity

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

A Relevance

Columns 2 and 6 from Table II show that the relevance condition is satisfied. Both *MF Buying Price Pressure* and *MF Selling Price Pressure* have a significant impact on ΔQ, and reassuringly, the sign of the correlation is the expected one—positive after buying pressure, negative after selling pressure.

This test is consistent with our premise, i.e., that both variables capture price pressure due to liquidity trading by Mutual Funds forced to either purchase or sell target's stock after a sudden change in size. Below, we provide additional evidence supporting this premise.

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 $HP_{i,j,t}$ ($HS_{i,j,t}$)—is the number of shares purchased (sold) assuming fund j responds to the net inflow (outflow) at t by adjusting their holding of stock i according to its weight in the market portfolio at $t-1$, scaled by the total number of shares i outstanding at $t-1$.

Scaling by the total number of shares outstanding serves two purposes. First, it eases the interpretation of the regression coefficient: If the coefficient is greater (less) than one, funds adjust their holdings by more (less) than the weight of stock i in the market portfolio. Second, it allows for better isolation of the effect of the flow by removing any unwanted influence of stock specific factors. Indeed, Eq. 31 shows that after scaling, $HP_{i,j,t}$ ($HS_{i,j,t}$) can be re-interpreted as the fund inflow (outflow) divided by the dollar value of the market portfolio at the beginning of the month, which does not depend on i such that $HP_{i,j,t}$ and $HS_{i,j,t}$ depend on i only at the *extensive margin* before the shock happens.

Column 1 confirms that purchases and sales induced by fund inflows and outflows lead to significant stock ownership variation—increasing for purchases, decreasing for sales. Column 2 shows that the magnitude of the change is related to the magnitude of the flow. The relation is not perfectly monotonic, but on average, the larger the flow, the higher the number of shares purchased or sold by the fund. Notice we observe no significant variation for small outflows representing less than 1% of AUM which supports the conjecture of Edmans, Goldtsein, and Jiang (2012) that only extreme flows matter while moderate flow shocks could be absorbed by internal cash.[16]Hence the importance of focusing on extreme flows only.

A.2 Do extreme flows generate price pressure?

Next, we focus on extreme inflows ($> 5\%$ of AUM) and outflows ($< -2\%$ of AUM), and verify that when those extreme events happen, changes in ownership reported in Table V generate changes in prices followed by a reversal.

[Insert Table VI about here]

Results are reported in Table VI. Column 1 of Table VI shows that hypothetical purchases

[16]See Edmans, Goldtsein, and Jiang (2012), page 951: *"only extreme outflows are likely to have an impact on pricing, while moderate flow shocks could be absorbed by internal cash or external liquidity providers"*

(sales) by mutual funds experiencing large inflows (outflows) positively (negatively) affect monthly FF49-adjusted returns. In Column 2, we study the dynamics of the change in price documented in Column 1 by introducing leads and lags of the main explanatory variable in the regression. We find that the initial effect on returns reverts after 3 to 6 months, consistent with our measure capturing noise only.

A.3 Does price pressure vary with market depth?

Finally, we examine whether the above fluctuations vary with market depth, measured by firm size. Intuitively, mis-pricing is more likely to be detected and arbitraged away for large stocks that are widely covered by analysts than for small, illiquid stocks.

[Insert FigureIII about here]

The results of this analysis are reported in FigureIII. We find that price pressure effects are indeed economically smaller for large than for small stocks. However, even for large firms, the mis-pricing is significant.

To summarize, we find that (i) extreme flows lead to changes in stock ownership, (ii) that those changes in ownership immediately affect returns, (iii) that changes in returns are only temporary, (iv) that price changes are higher (lower) in absolute value for small (large) stocks, and that reassuringly, all four effects are observed symmetrically for inflows and outflows. Taken together, we believe these findings are supportive of our premise, i.e., that both *MF Buying Price Pressure* and *MF Selling Price Pressure* represent noise in stock prices, and that both variables are plausible empirical counterparts for θ in our model.

B Exclusion Restriction

Showing that the exclusion restriction condition is likely satisfied is challenging because it requires providing evidence that *MF Buying Price Pressure* and *MF Selling Price Pressure* are exogenous to any variable other than ΔQ potentially affecting g and k after conditioning on the controls. This cannot formally be tested, but we show in this section that this assumption cannot easily be rejected.

B.1 Are the instruments jointly exogenous?

We start by testing whether *MF Buying Price Pressure* and *MF Selling Price Pressure* are *jointly* exogenous with a Sargan-Hansen test. The J-statistics (reported at the bottom of Table II, in Columns 3 and 7) are never significant at the 10% level, indicating that the exogeneity assumption cannot be rejected (assuming that at least one instrument is valid).

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

Second, we verify that extreme flows are infrequent events that do not exhibit any pre-trend and thus plausibly come as a surprise to fund managers. The result of this analysis is presented in the Internet Appendix (See sections IA.4 and IA.5).

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

Next, we also verify that the stock price reaction to extreme flows does not exhibit any trend before the event. Column 2 of Table VI shows that it is not the case. We find no significant abnormal variation in prices preceding the event, and thus no pre-trend (Leads of changes in ownership due to extreme flows are never significant).

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

As highlighted above, we also find a reversal after the initial reaction. Both patterns—the absence of pre-trend and the reversal—appear more clearly in Figure II, where we plot the cumulative regression coefficients reported in Column 2 of Table VI, using the month preceding the extreme flow as the reference month.

Overall, our results corroborate and provide further internal and external validity to the evidence already documented by many other papers, in various settings and using different measurement approaches (including some elaborated with the explicit objective to address the limitations of earlier approaches), that mutual fund fire sales or purchases trigger an immediate change in stock prices that is followed by a subsequent reversal,[17] that corporate insiders trade against these shocks,[18] and that these events represent temporary, non-fundamental supply or demand shocks, generating variation in prices plausibly exogenous to information about g and k.[19]

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. A strict interpretation of our analysis, therefore, is that it documents whether and what economic agents learn from stock prices. That said, we believe that our data for g (or k) reflect the outcome of interactions between managers with their advisors, and throughout the paper, we assume that both share the same beliefs.

To motivate this assumption, we report examples of fairness opinions (see Internet Appendix). Although prepared by investment bankers, four considerations indicate they were not produced in isolation. First, banks use information (e.g., financial projections) provided by the management. Second, the final version of the DCF is the outcome of multiple iterations between managers and bankers, involving discussions of the target's past, current, and expected operations. These interactions support our assumption that k and g represent the shared perceptions of managers and their advisors.

Third the valuation analysis supporting the fairness opinion is only available when the deal is deemed fair. This truncation in the distribution of possible opinions lends even

[17]For evidence on price drops followed by a reversal, see Coval and Stafford (2007), Edmans, Goldtsein, and Jiang (2012), Dessaint, Foucault, Frésard, and Matray (2019), Honkanen and Schmidt (2021)

[18]For evidence on insider trading, see Figure 3 in Dessaint, Foucault, Frésard, and Matray (2019), as well as Ali, Wei, and Zhou (2011) and Khan, Kogan, and Serafeim (2012)

[19]For other papers using mutual fund fire sales as non-fundamental shocks to prices or returns, 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), and Tubaldi (2024)

stronger support to our assumption because it implies that k and g are observed only when managers and bankers agree on the outcome of the valuation analysis. If they agree on this outcome, it is likely that they also agree on the underlying assumptions, and thus, on estimats g and k.

Finally, the investment bank providing the fairness opinion is typically hired by the firm's managers. This creates an additional channel through which managerial views are likely to be reflected in the final valuation. Managers have both the incentive and the discretion to selects bankers whose analytical frameworks and assumptions align with their own. Consequently, even before the iterative process of refining assumptions and projections begins, the mere choice of the bank tilts the analysis toward management's perspective. This further reinforces our assumption that the disclosed valuation analysis reflects a shared set of beliefs between managers and their advisors.

[Insert Table VII about here]

Table VII illustrates this imbrication. The offer price—which ultimately reflects managers' perception of k and g since it is the amount the firm pays or receives—is strongly correlated with our data for k and g. Regardless of how we measure the price paid, this correlation is highly significant and has the expected sign—negative for k and positive for g. This indicates that the valuation analysis we observe simply makes explicit what is implicit in the price offered by the acquirer's management and / or accepted by the target's management. This finding is important, because it supports our premise that the data we use for k and g can indeed serve as measures of 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 the hurdle rate used for k by managers, as extracted from earnings call in Gormsen and Huber (2024); (ii) our measure for g is positively related to managerial guidance about future sales growth; and (iii) the variation in k (g) across banks providing a fairness opinion on the *same* deal is small compared with the 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?

Investment bankers' objective is to close deals provided that the long-term reputation or litigation costs remain limited. Therefore, they may strategically decrease (increase) k when the target's share price rises (falls) in order to keep their DCF valuation in line with the publicly listed price and to conclude that the deal consideration is fair. This strategic "reverse engineering" of the DCF valuation suggests a different form of market feedback: whereby managers and bankers adjust k in response to price changes, but they do not learn about it.

The negative k-to-price sensitivity reported in Table II is consistent with the reverse engineering interpretation; but none of our other results are.

First, if k is "reverse-engineered", then so should g. In this case, our IV estimate in Column 3 of TableII would be positive and significant, which it is not.

Second, the learning interpretation predicts that the economic magnitude of our IV estimates should differ from their OLS counterparts because the extent to which managers learn about k and g *depends on what they already know* which is typically unobserved. In contrast, the strategic behavior implied by reverse engineering does *not* depend on what managers know. Therefore, using price noise as instrument to correct for the above omitted-variable problem should *not* affect the estimates. Specifically, the reverse engineering interpretation predicts that the difference between managers' reports of g and k should be equally sensitive to price and price noise. Hence, the gap between OLS coefficients for g and k should match the gap between the corresponding IV coefficients, which is also not what we find. [20]

Finally, the reverse engineering interpretation should explain all our cross-sectional results. For that, the incentive to behave strategically should systematically weaken with the

[20] To see this formally, denote $\hat{g}$ and $\hat{k}$ a manager's reports of g and k. Under reverse-engineering, $\hat{g}-\hat{k} = \rho q$ where $\rho > 0$ measures how closely the manager tracks the price. Importantly, we make no assumption on on how strongly the manager adjusts $\hat{g}$ or $\hat{k}$; they may adjust one more than the other, both similarly, or track prices loosely (ρ small) or excessively ($\rho > 1$). From this equation, it follows that $cov(\hat{g}, q) - cov(\hat{k}, q) = \rho var(q)$, implying $b_g^{OLS} - b_k^{OLS} = \rho$. Likewise, $cov(\hat{g}, \theta) - cov(\hat{k}, \theta) = cov(\rho(g - k + \theta), \theta) = \rho var(\theta)$, so $b_g^{IV} - b_k^{IV} = \rho$. Hence, under reverse engineering, the differences between the OLS and IV coefficients coincide.

precision of the posterior about k, strengthen with the precision of the posterior about g, and strengthen with the precision of price noise. While we cannot definitively rule out this possibility, it seems unlikely.[21]

C Learning about Short or Long Term Growth?

Our measure for g is the perpetual growth rate used in computing 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 the absence of learning about g is that managers do not learn from prices about *long-term* cash flows, leaving open the possibility that they could still learn about the *short-term* ones.[22]

We do not observe the business plans underlying the DCF valuations—and, in particular, the associated short-term cash flows projections. Therefore, we cannot formally test whether these projections are sensitive to noise in target prices. Nevertheless, we offer preliminary evidence suggesting that managers may not learn about short-term cash flows either. In the Internet Appendix, we show that the sensitivity of g to noise does not vary significantly with the horizon of the business plan typically used in the target firm's SIC2-industry. Using instead the SIC2-specific business plan horizon measure developed by Dessaint, Foucault, and Frésard (2025), we find that when the business plan horizon is short, the sensitivity of g to noise exhibits the expected sign and is economically stronger, but only marginally significant. Hence, we find no clear evidence of managerial learning about future cash flows, even at shorter horizons.

[21] In the Internet Appendix we further rule out a modified, yet more realistic version, of the reverse engineering interpretation, whereby managers and bankers reverse engineer the proposed offer price for the transaction rather than the target's publicly listed market price prior to the deal announcement. Unlike the latter, the former typically includes a premium. To rule out this possibility, we directly control for the offer price in our regressions. Doing so mechanically reduces the magnitude of the IV estimate because the offer price implicitly contains information about the updated k. Despite this over-controlling problem, the IV estimate remains negative and (marginally) significant, suggesting that this alternative form of reverse engineering cannot be the main explanation for our findings.

[22] This interpretation is consistent with a myopic view of financial markets, whereby market investors overweight information about short-term earnings in their trading decisions (e.g., Stein (1988), Stein (1989)). It also aligns with recent evidence that market participants have become better (worse) at producing information about short(long)-term earnings (Dessaint, Foucault, and Frésard (2024)).

VIII Conclusion

Most existing research on market feedback effects posits that managers learn about expected cash flow growth g, and not about the return expected by investors k. We test this premise using data on managers' beliefs about g and k. We find that both are sensitive to stock prices, positively for g, negatively for k, and with equal magnitude, suggesting, on the surface, that managers learn from financial markets about both cash flows and discount rates. However, after correcting for endogeneity using noise in prices as a plausible source of independent variation, we find that only beliefs about k reacts to prices. We conclude that stock prices affect managers' beliefs about discount rates, but do not convey additional information to them about cash flows.

These findings underscore the role of stock prices as aggregator of dispersed information about stockholders willingness to bear risk——a key input into the firm's discount rate. For firms with diffuse ownership, there is no clear alternative mechanism through which managers can 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 insight into future cash flows—at least in the context of valuing M&A investment opportunities. More work is needed to assess whether they extend beyond the M&A context (e.g., to capital budgeting) and to economic agents beyond managers (e.g., to investors, financial intermediaries, regulators).

References

Acharya, Viral, Heitor Almeida, Filippo Ippolito, and Ander Perez, 2014, Credit lines as monitored liquidity insurance: Theory and evidence, *Journal of Financial Economics* 112, 287–319.

Ali, Ashiq, Kelsey d. Wei, and Yibin Zhou, 2011, Insider trading and option grant timing in response to fire sales (and purchases) of stocks by mutual funds, *Journal of Accounting Research* 49, 595–632.

Antoniou, Constantinos, Frank Weikai Li, Xuewen Liu, Avanidhar Subrahmanyam, and Chengzhu Sun, 2022, Exchange-traded funds and real investment, *The Review of Financial Studies* 36, 1043–1093.

Bakke, Tor-Erik, and Toni Whited, 2010, Which firms follow the market? an analysis of corporate investment decisions, *The Review of Financial Studies* 23, 1941–1980.

Banerjee, Suman, Shiyang Huang, Vikram Nanda, and Steven Chong Xiao, 2023, Managerial overconfidence and market feedback effects, *Management Science* 69, 7285–7305.

Berger, Elizabeth A., 2023, Selection bias in mutual fund fire sales, *Journal of Financial and Quantitative Analysis* 58, 1039–1077.

Bond, Philip, Alex Edmans, and Itay Goldstein, 2012, The real effects of financial markets, *Annual Reviews of Financial Economics* 4, 339–360.

Chaudhry, Aditya, 2025, The impact of prices on analyst cash flow expectations: Reconciling subjective beliefs data with rational discount rate variation, *Journal of Financial Economics* 171, 104095.

Chen, Qi, Itay Goldstein, and Wei Jiang, 2007, Price informativeness and investment sensitivity to stock prices, *Review of Financial Studies* 20, 619–650.

Cohen, Randolph B., Christopher Polk, and Tuomo Vuolteenaho, 2003, The value spread, *Journal of Finance* 58, 609–641.

Coval, Joshua, and Erik Stafford, 2007, Asset fire sales (and purchases) in equity markets, *Journal of Financial Economics* 86, 479–512.

Décaire, Paul, 2024, Capital budgeting and idiosyncratic risk, Working Paper.

——— , and John R Graham, 2024, Valuation fundamentals, *John Robert, Valuation Fundamentals (September 09, 2024)*.

Décaire, Paul, Denis Sosyura, and Michael D Wittry, 2024, Resolving estimation ambiguity, Working Paper.

DeLaO, Ricardo, Xiao Han, and Sean Myers, 2024, The return of return dominance: Decomposing the cross-section of prices, *Journal of Financial Economics*.

Dessaint, Olivier, Thierry Foucault, and Laurent Frésard, 2024, Does alternative data improve financial forecasting? The horizon effect, Journal of Finance, Forthcoming.

——— , 2025, The horizon of investors' information and corporate investment, Working Paper.

Dessaint, Olivier, Thierry Foucault, Laurent Frésard, and Adrien Matray, 2019, Noisy stock prices and corporate investment, *Review of Financial Studies* 32, 2625–2672.

Dessaint, Olivier, Jacques Olivier, Clemens A Otto, and David Thesmar, 2020, Capm-based company (mis)valuations, *The Review of Financial Studies* 34, 1–66.

Eckbo, B. Espen, Tanakorn Makaew, and Karin S. Thorburn, 2018, Are stock-financed takeovers opportunistic?, *Journal of Financial Economics* 128, 443–465.

Edmans, Alex, Itay Goldtsein, and Wei Jiang, 2012, The real effects of financial markets: The impact of prices on takeovers, *Journal of Finance* 67, 933–971.

Edmans, Alex, Sudarshan Jayaraman, and Jan Schneemeier, 2017, The source of information in prices and investment-price sensitivity, *Journal of Financial Economics* 126, 74–96.

Fama, Eugene, and Kenneth French, 1995, Size and book-to-market factors in earnings and returns, *Journal of Finance* 50, 131–55.

Foucault, Thierry, and Laurent Fresard, 2012, Cross-listing, investment sensitivity to stock price and the learning hypothesis, *Review of Financial Studies* pp. 3305–3350.

——— , 2014, Learning from peers' stock prices and corporate investment, *Journal of Financial Economics* 111, 554–577.

Goldman, Jim, 2023, Do directors respond to stock mispricing? evidence from ceo turnovers, *Journal of Financial and Quantitative Analysis* 58, 2732–2751.

Goldstein, Itay, 2023, Information in Financial Markets and Its Real Effects, *Review of Finance* 27, 1–32.

——— , and Liyan Yang, 2019, Good disclosure, bad disclosure, *Journal of Financial Economics* 131, 118–138.

Gormsen, Niels Joachim, and Kilian Huber, 2024, Corporate discount rates, *American Economic Review*.

——— , 2025, Firms' perceived cost of capital, Working Paper.

Graham, John, 2022, Presidential address: Corporate finance and reality, *Journal of Finance* 77, 1975–2049.

Graham, John R., and Campbell Harvey, 2001, The theory and practice of corporate finance: evidence from the field, *Journal of Financial Economics* 60, 187–243.

Gredil, Oleg R., Nishad Kapadia, and Jung Hoon Lee, 2022, On the information content of credit ratings and market-based measures of default risk, *Journal of Financial Economics* 146, 172–204.

Honkanen, Pekka, and Daniel Schmidt, 2021, Learning from noise? price and liquidity spillovers around mutual fund fire sales, *The Review of Asset Pricing Studies* 12, 593–637.

Jayaraman, Sudarshan, and Joanna Shuang Wu, 2019, Should i stay or should i grow? using voluntary disclosure to elicit market feedback, *The Review of Financial Studies* 33, 3854–3888.

Khan, Mozaffar, Leonid Kogan, and George Serafeim, 2012, Mutual fund trading pressure: Firm-level stock price impact and timing of seos, *The Journal of Finance* 67, 1371–1395.

Lou, Dong, 2012, A flow-based explanation for return predictability, *Review of Financial Studies* 25, 3457–3489.

Morck, Randall, Andrei Shleifer, and Robert Vishny, 1990, The stock market and investment: Is the market a sideshow?, *Brookings Papers on Economic Activity* 21, 157–216.

Phillips, Gordon, and Alexei Zhdanov, 2013, R&D and the incentives from merger and acquisition activity, *Review of Financial Studies* 34-78, 189–238.

Stein, Jeremy, 2003, Agency, information and corporate investment, *Handbook of the Economics of Finance* pp. 110–63.

Stein, Jeremy C., 1988, Takeover threats and managerial myopia, *Journal of Political Economy* 96, 61–80.

——— , 1989, Efficient Capital Markets, Inefficient Firms: A Model of Myopic Corporate Behavior*, *The Quarterly Journal of Economics* 104, 655–669.

Subrahmanyam, Avanidhar, and Sheridan Titman, 1999, The going public decision and the development of financial markets, *Journal of Finance* 54, 1045–82.

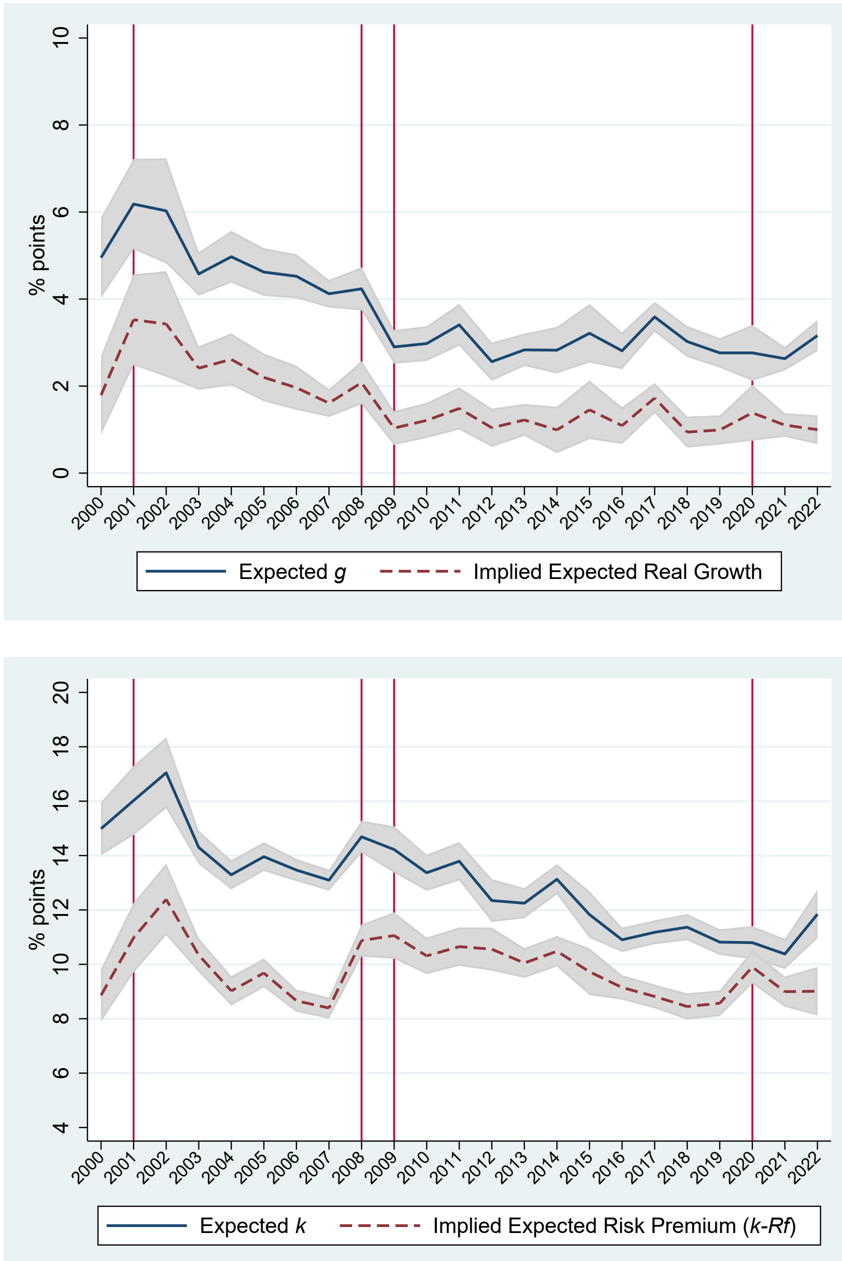
Tubaldi, Roberto, 2024, Mutual funds' fire sales and the real economy: Evidence from hurricanes, Working Paper.

Vuolteenaho, Tuomo, 2002, What drives firm-level stock returns?, *Journal of Finance* 57, 233–264.

Wardlaw, Malcom, 2020, Measuring mutual fund flow pressure as shock to stock returns, *Journal of Finance* 75, 3221–3243.

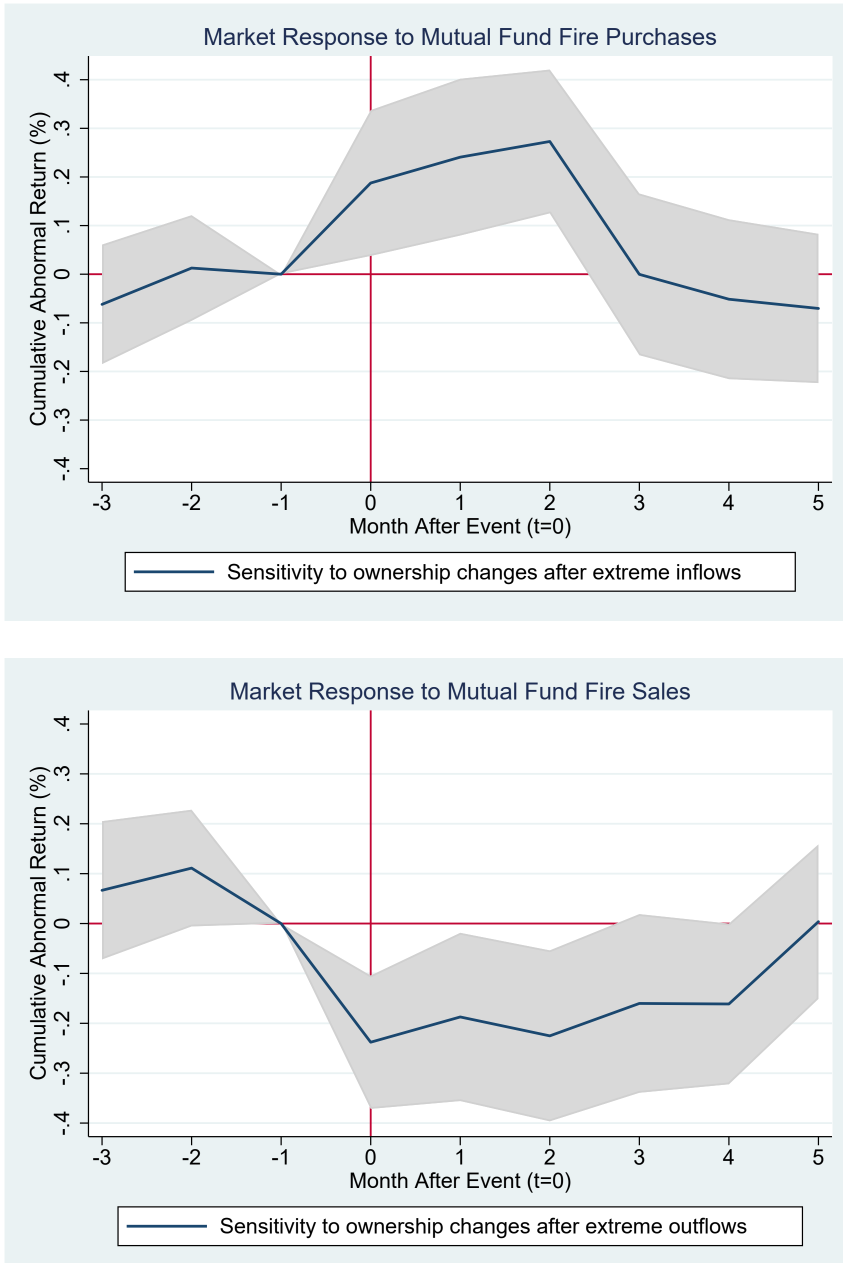
Yan, Dong, 2024, Do private firms (mis)learn from the stock market?, *Review of Finance* 28, 1483–1511.

Figure I: Expected g and k by year



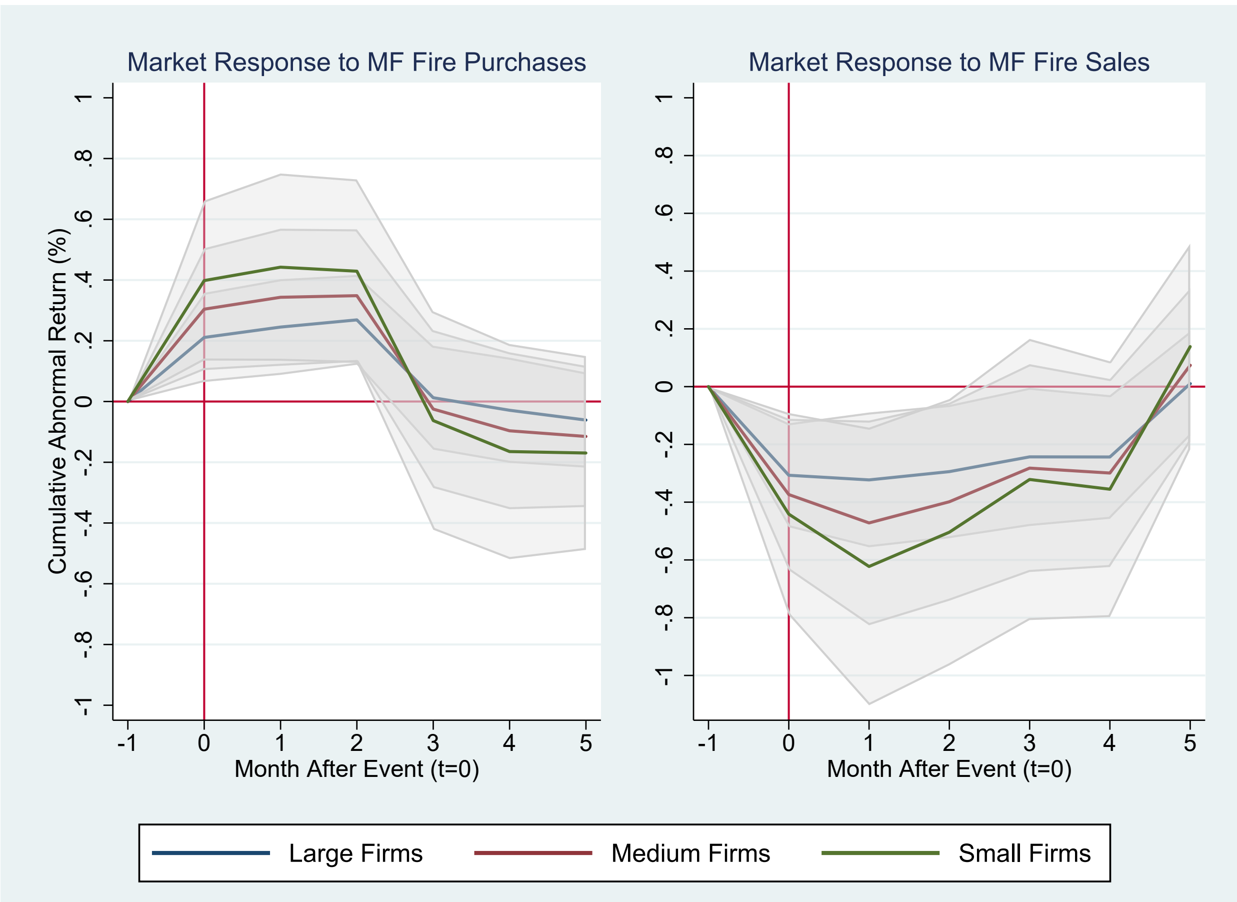
The top graph depicts the evolution of the expected growth rate g, both in nominal and real terms using the 10-year expected inflation rate as a benchmark for inflation. The bottom one displays the evolution of the annual average discount rate k and the implied risk premium using the yield on US 10-year 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 Target 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 cumulated 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
Main dependent variables										
k	1,231	12.9%	4.2%	1.5%	8.8%	10.0%	12.0%	14.5%	18.0%	44.0%
k (Standardized)	1,231	3.97	2.24	1.15	1.90	2.33	3.23	4.73	8.11	10.10
$ln(1+k)$	1,231	0.12	0.04	0.01	0.08	0.10	0.11	0.14	0.17	0.36
k Range	1,221	2.8%	2.4%	0.0%	1.0%	1.5%	2.0%	4.0%	5.0%	32.0%
g	1,231	3.7%	2.8%	0.0%	1.0%	2.0%	3.0%	4.7%	6.8%	26.1%
g (Standardized)	1,231	1.53	1.05	0.00	0.44	0.76	1.27	2.04	3.09	5.04
$ln(1+g)$	1,231	0.04	0.03	0.00	0.01	0.02	0.03	0.05	0.07	0.23
g Range	1,128	1.9%	1.4%	0.0%	0.7%	1.0%	1.7%	2.2%	3.8%	15.0%
Main explanatory variables										
Q	1,231	1.83	1.34	0.23	0.98	1.07	1.38	2.08	3.17	16.49
ΔQ	1,231	-0.07	0.92	-9.82	-0.73	-0.23	-0.01	0.14	0.53	6.44
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 Net Price Pressure	1,231	-0.006	0.022	-0.341	-0.019	-0.007	-0.001	0.000	0.004	0.106
MF Noise Range	1,231	0.013	0.024	0.000	0.000	0.001	0.006	0.015	0.031	0.457
Other variables										
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
ΔSales	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 19 (Column 1), Equation 21 (Column 2), Equation 22 (Column 3), Equation 24 (Column 4), Equation 20 (Column 5), Equation 21 (Column 6), Equation 23 (Column 7) and Equation 25 (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 (from the last available financial statement). *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 (from the last available financial statement). 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	IV			OLS	IV		
		Stage 1	Stage 2	Reduced		Stage 1	Stage 2	Reduced
Dep. Variable	g	ΔQ	g	g	k	ΔQ	k	k
Specification	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
ΔQ	0.08**		-0.03		-0.08**		-0.89**	
	(2.19)		(-0.08)		(-2.00)		(-2.22)	
MF Buying Price Pressure		7.68***		0.31		7.68***		-8.06***
		(3.21)		(0.11)		(3.21)		(-4.37)
MF Selling Price Pressure		-4.95***		0.61		-4.95***		3.35***
		(-3.24)		(0.29)		(-3.24)		(2.99)
Size (Log)	-0.11***	-0.02	-0.11***	-0.11***	-0.23***	-0.02	-0.25***	-0.21***
	(-6.82)	(-1.17)	(-6.75)	(-7.15)	(-14.45)	(-1.17)	(-12.26)	(-13.16)
Cash Flow	-0.64***	-0.01	-0.64***	-0.69***	-0.98***	-0.01	-0.97***	-0.85***
	(-2.89)	(-0.03)	(-2.87)	(-3.10)	(-6.24)	(-0.03)	(-6.59)	(-5.02)
Debt	-0.06	0.07	-0.06	-0.05	-0.01	0.07	0.02	-0.08
	(-0.35)	(0.80)	(-0.32)	(-0.27)	(-0.07)	(0.80)	(0.12)	(-0.54)
Cash	0.22	0.09	0.24	0.18	0.29*	0.09	0.39**	0.45***
	(1.18)	(0.60)	(1.15)	(0.95)	(1.66)	(0.60)	(2.05)	(3.06)
Δ Sales	0.17	0	0.17	0.16	-0.28**	0	-0.29**	-0.28**
	(1.10)	(-0.01)	(1.10)	(1.05)	(-2.21)	(-0.01)	(-1.97)	(-2.21)
Dividend	-0.13**	0.01	-0.13*	-0.14*	-0.21***	0.01	-0.20**	-0.19***
	(-2.00)	(0.10)	(-1.94)	(-1.94)	(-4.37)	(0.10)	(-2.52)	(-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 25 when interacting all explanatory variables 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. 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 (from the last available financial statement). *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 (from the last available financial statement). *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. Explanatory variables that are absorbed by the fixed effects (like the inverse of *k Range*, *g Range*, and *MF Noise Range*) are omitted from the regression. Control variables include *Size (Log)*, *Cash Flow*, *Debt*, *Cash*, Δ *Sales*, and *Dividend*. All variables are defined in Appendix I. 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	Reduced Form IV			
Dep. variable:	k			
Specification	(1)	(2)	(3)	(4)
MF Buying Price Pressure $\times(k \text{ Range})^{-1}$	0.17***			0.22***
	(3.43)			(3.31)
MF Selling Price Pressure $\times(k \text{ Range})^{-1}$	-0.08**			-0.12**
	(-2.28)			(-2.48)
MF Buying Price Pressure $\times(g \text{ Range})^{-1}$		-0.07*		-0.11**
		(-1.93)		(-2.28)
MF Selling Price Pressure $\times(g \text{ Range})^{-1}$		0.05***		0.08**
		(2.68)		(2.52)
MF Buying Price Pressure $\times(\text{MF Noise Range})^{-1}$			-0.10*	-0.10*
			(-1.88)	(-1.67)
MF Selling Price Pressure $\times(\text{MF Noise Range})^{-1}$			0.06	0.05
			(1.24)	(0.99)
MF Buying Price Pressure	-15.06***	-3.27	-5.59**	-7.01*
	(-3.64)	(-1.15)	(-2.08)	(-1.74)
MF Selling Price Pressure	5.80***	0.28	2.11	2.06
	(2.55)	(0.18)	(1.38)	(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 24 when interacting all explanatory variables 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. 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 (from the last available financial statement). *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 (from the last available financial statement). *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. Explanatory variables that are absorbed by the fixed effects (like the inverse of *k Range*, *g Range*, and *MF Noise Range*) are omitted from the regression. Control variables include *Size (Log)*, *Cash Flow*, *Debt*, *Cash*, *Δ Sales*, and *Dividend*. All variables are defined in Appendix I. 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	Reduced Form IV			
Dep. variable:	g			
Specification	(1)	(2)	(3)	(4)
MF Buying Price Pressure ×(k Range)$^{-1}$	0.04			0.09
	(0.58)			(1.11)
MF Selling Price Pressure ×(k Range)$^{-1}$	0.01			-0.05
	(0.24)			(-0.93)
MF Buying Price Pressure ×(g Range)$^{-1}$		-0.06		-0.06
		(-0.95)		(-0.83)
MF Selling Price Pressure ×(g Range)$^{-1}$		0.06		0.06
		(1.42)		(1.23)
MF Buying Price Pressure ×(MF Noise Range)$^{-1}$			-0.04	-0.02
			(-0.69)	(-0.41)
MF Selling Price Pressure ×(MF Noise Range)$^{-1}$			0.04	0.01
			(0.73)	(0.19)
MF Buying Price Pressure	-0.22	3.84	0.49	0.48
	(-0.04)	(0.66)	(0.13)	(0.06)
MF Selling Price Pressure	-1.55	-3.53	-0.1	-2.34
	(-0.38)	(-0.95)	(-0.04)	(-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 × 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:	$\Delta O_{i,j,m,y}$		$\Delta O_{i,j,m,y}$	
Specification	(1)		(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)		
$HP_{i,j,m,y}$ × Flag 0%-to-0.5%			6.61***	(2.83)
$HP_{i,j,m,y}$ × Flag 0.5%-to-1%			7.79***	(4.05)
$HP_{i,j,m,y}$ × Flag 1%-to-2%			8.55***	(6.73)
$HP_{i,j,m,y}$ × Flag 2%-to-3%			9.20***	(7.63)
$HP_{i,j,m,y}$ × Flag 3%-to-4%			6.79***	(3.03)
$HP_{i,j,m,y}$ × Flag 4%-to-5%			12.44***	(6.42)
$HP_{i,j,m,y}$ × Flag More than 5%			11.20***	(9.37)
$HS_{i,j,m,y}$ × Flag 0%-to-0.5%			-1.52	(-0.46)
$HS_{i,j,m,y}$ × Flag 0.5%-to-1%			-0.53	(-0.29)
$HS_{i,j,m,y}$ × Flag 1%-to-2%			-2.23*	(-1.71)
$HS_{i,j,m,y}$ × Flag 2%-to-3%			-8.81***	(-4.28)
$HS_{i,j,m,y}$ × Flag 3%-to-4%			-8.33***	(-5.96)
$HS_{i,j,m,y}$ × Flag 4%-to-5%			-7.78***	(-4.81)
$HS_{i,j,m,y}$ × Flag More than 5%			-8.16***	(-9.34)
Stock × 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:	Monthly Abnormal Return$_{i,t}$		Monthly Abnormal Return$_{i,t}$	
Specification	(1)		(1)	
	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	OLS					
Dep. variable:	Equity Value Paid / BV		Enterprise Value Paid / Assets		Ln(Deal Value)	
Specification	(1)	(2)	(3)	(4)	(5)	(6)
k	-18.19***	-33.35***	-9.87***	-16.53***	-26.35***	-8.02***
	(-2.89)	(-4.14)	(-4.37)	(-5.17)	(-13.30)	(-5.75)
g	16.93**	16.28*	12.43***	11.70***	6.70**	4.36***
	(2.06)	(1.95)	(4.40)	(3.82)	(2.22)	(3.44)
Size (Log)		-0.45***		-0.29***		0.82***
		(-3.12)		(-4.16)		(30.36)
Percentage Acquired		0.01**		0.00		0.01***
		(2.24)		(0.94)		(5.72)
Cash Flow		-4.48**		-0.76		0.42
		(-2.06)		(-0.91)		(1.45)
Δ Sales		2.31***		1.15***		0.37***
		(2.97)		(3.14)		(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 Range	Assumed range for the perpetual growth rate g.
k	Discount rate assumed for valuing the target company.
k Range	Assumed range for the discount rate k.
Q	$(at - ceq + csho \times prcc_f)/at$ (from last available financial statements in Compustat)
ΔQ	Change in Q during the last fiscal year available before deal announcement
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 available financial statement).
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 available financial statement).
MF Net Price Pressure	Average dollar amount of monthly equity misvaluation due to both fire purchases and sales by Mutual Funds during the 12-month period preceding deal announcement, and scaled by total assets (from the last available financial statement)
MF Noise Range	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, and scaled by total assets (from the last available financial statement)
Other variables used as controls and/or for cross-sectional analysis	
Size (log)	log of at from last available financial statements in Compustat
Assets	at (from last available financial statements in Compustat).
Debt	$(dlc + dltt)/at$ (from last available financial statements in Compustat).
Cash Flow	$(ib + dp)/at$ (from last available financial statements in Compustat).
Cash	che/at (from last available financial statements in Compustat).
$\Delta Sales$	Change in sales / at (from last available financial statements in Compustat).
Dividend	Dummy equal to 1 if Div is not zero (from last available financial statements in Compustat).

Appendix II – Mutual Fund Price Pressure Measure

For each firm i, we construct *MF Buying Price Pressure*$_{i,t}$ and *MF Selling Price Pressure*$_{i,t}$, respectively measuring the average over-valuation and under-valuation of firm i that are due to large inflows and outflows in mutual funds owning the stock of firm i during the last 12 months preceding deal announcement at t. Our approach builds on the approach of Edmans, Goldtsein, and Jiang (2012).

Step 1 - Calculate fund flows

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

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

where k indexes asset classes. We aggregate TNAs across asset classes to obtain the TNA of fund j at the end of every month in each year. An estimate of the net flow experienced by fund j during month m of year y is then given by

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

where $TNA_{j,m,y}$ is the total net asset value of fund j at the end of month m of year y, $RETURN_{j,m,y}$ is the return of fund j during month m of year y, and $MGN_{j,m,y}$ is the increase in TNA due to fund mergers in month m. Following prior studies (e.g., Lou (2012)), we use the last NAV report date of the target fund to approximate the merger date. $FLOW_{j,m,y}$ is an estimate of the net flow experienced by fund j during month m of year t.

Step 2 - Calculate fund holdings

Second, we estimate the composition of the portfolio of each fund and calculate $O_{j,i,m,y}$, the percentage of fund's j holdings of stock i at the end of every month m of year y using data from CDA Spectrum/Thomson. CDA Spectrum/Thomson provides the number of stocks held by all U.S. funds at the end of every quarter, and the change since the last reporting date. We use both information in combination with a linear interpolation approach to estimate the number of stocks of firm i held by fund j at the end of every month m of year y. $O_{j,i,m,y}$ is given by

$$O_{j,i,m,y} = \frac{SHARES_{i,j,m,y}}{N_{i,m,y}}, \tag{28}$$

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

Step 3 - Calculate fund hypothetical trades

For each stock i in the portfolio $\mathbb{P}$ of every fund j, we calculate the hypothetical number of shares bought or sold assuming funds respond to net flows by adjusting their holdings of each stock according to its weight in the *market* portfolio defined as $W_{M_{i,m,y}} = \frac{P_{i,m,y} \times N_{i,m,y}}{\sum_k (P_{k,m,y} \times N_{k,m,y})}$, where k indexes all stocks in the CRSP market portfolio, $P_{i,m,y}$ is the share price of firm i and $N_{i,m,y}$ its total number of shares outstanding at the end of month m in year y.

We estimate the value in dollar of the stake that is hypothetically purchased (or sold) as $W_{M_{i,m-1,y}} \times FLOW_{j,m,y}$, and the number of shares hypothetically purchased or sold as $\frac{W_{M_{i,m-1,y}} \times FLOW_{j,m,y}}{P_{i,m-1,y}}$. Our measure of hypothetical trades is the number of shares i hypothetically bought or sold, scaled by the total number of shares outstanding, and defined as

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

where i, j, m, y indexes firm, fund, month and year, respectively. Scaling by $N_{i,m-1,y}$ allows to better isolate the impact of the fund's flow by neutralizing the effect of firm-level characteristics on our measure of hypothetical trades, which can then be re-written as

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

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

where $MKT\ PTF_{m-1,y}$ is the total value in dollar of the CRSP market portfolio. Notice $MKT\ PTF_{m-1,y}$ does not depend on i or j because it is the same for all firms and funds. Finally, we separate hypothetical purchases (HP) and sales (HS) by computing $HP_{i,j,m,y} = \max(HT_{i,j,m,y}, 0)$ and $HS_{i,j,m,y} = -\min(HT_{i,j,m,y}, 0)$.

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

Next, we decompose changes in holdings of stock i by fund j and isolate changes due to hypothetical purchases (MP) and sales (HS) by estimating:

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

where $\Delta O_{i,j,m,y} = O_{i,j,m,y} - O_{i,j,m-1,y}$ is the monthly change in ownership of stock i by fund j, and $Flag\_X\%\_to\_Y\%_{j,m,y}$ is an indicator variable equal to 1 if the absolute value of the fund's flow ($ABS(FLOW_{j,m,y})$) expressed as a percentage of the asset under management at the beginning of the month ($TNA_{j,m-1,y}$) is between X% and Y%, and zero otherwise. $a_{i,m,y}$ are stock-date fixed effects (i.e., fixed effects by stock i, month m, and year y).

Results from estimating Equation 32 are displayed in Table V. We use these estimates to predict changes in ownership by fund j after experiencing extreme flows, i.e., more than 5% and 2% of assets for inflows and outflows, respectively.[23] Predicted changes in ownership due to extreme monthly outflows is 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 extreme monthly outflows is 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 estimate stock-level changes in ownership by taking the sum of predicted changes across funds j for a given stock i. The stock-level increase in mutual fund ownership associated with all hypothetical purchases by funds subject to extreme inflows is given by

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

Likewise, the total stock-level drop in mutual fund ownership is given by

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

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

We decompose monthly industry-adjusted returns of stock i and isolate the effect of funds' hypothetical purchases (HP) and sales (HS) in response to extreme flows by estimating:

[23] The threshold we use to define extreme outflows is similar to Edmans, Goldtsein, and Jiang (2012). They use 5% based on quarterly flows. We use 2% based on monthly flows. We use higher threshold to define extreme inflows because the distribution of monthly net flows is highly positively skewed.

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

where $ARET_{i,m,y}$ is the industry-adjusted return of stock i in month m and year y.

Results from estimating Equation 37 are displayed in Table VI. We use these estimates to predict changes in stock return due to changes in ownership by mutual funds subject to extreme inflows and outflows, and estimate price pressure in dollar value.

We compute the dollar amount of buying pressure in any given month as

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

where $MV_{i,m,y}$ is the market capitalization of stock i in month m and year y. Likewise, the dollar amount of selling pressure in dollar is given by

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

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

$MF\ Buying\ Price\ Pressure_{i,t}$ is the average of $MF\ Selling\ Price\ Pressure^{DOLLAR}_{i,m,y}$ for target i over the last 12 months before deal announcement at t divided by total assets (from last available financial statements). Likewise, $MF\ Selling\ Price\ Pressure_{i,t}$ is the average of $MF\ Selling\ Price\ Pressure^{DOLLAR}_{i,m,y}$ for target i over the last 12 month before deal announcement at t divided by total assets (from last available financial statements).

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,

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

The projection theorem implies that

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

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

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

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

$$\mathbb{C}ov[g,k|\{s_g,s_k,q\}] = -\begin{pmatrix} \frac{1}{\tau_g} & 0 & \frac{1}{\tau_g} \end{pmatrix} \begin{pmatrix} \frac{1}{\tau_g}+\frac{1}{\tau_{\epsilon g}} & 0 & \frac{1}{\tau_g} \\ 0 & \frac{1}{\tau_k}+\frac{1}{\tau_{\epsilon k}} & -\frac{1}{\tau_k} \\ \frac{1}{\tau_g} & -\frac{1}{\tau_k} & \frac{1}{\tau_g}+\frac{1}{\tau_k}+\frac{1}{\tau_\theta} \end{pmatrix}^{-1} \begin{pmatrix} 0 \\ -\frac{1}{\tau_k} \\ \frac{1}{\tau_k} \end{pmatrix}$$

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.