Learning about Discount Rates

Olivier Dessaint, Naveen Gondhi, and Joel Peress*

February 8, 2026

ABSTRACT

Using valuation reports disclosing managers' expectations of cashflow growth (g) and discount rates (k) in M&A transactions, we examine what they learn from target stock prices. Before correcting for endogeneity, both appear sensitive to prices—positively for g, negatively for k, and with equal magnitude—suggesting managers learn about both. However, using noise in prices as an instrument, only k reacts—with corrected estimates indicating that 89% of managers' information about k comes from prices. Therefore, stock markets inform managers about risk and the compensation it requires, but not cashflows, which they 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

*INSEAD. Dessaint can be reached at olivier.dessaint@insead.edu, Gondhi can be reached at naveen.gondhi@insead.edu, Peress can be reached at joel.peress@insead.edu. We thank Simona Abis, Matthieu Barouki, François Derrien, Pierre Mabille, Stephen Dimmock, Thierry Foucault, Laurent Frésard, Itay Goldstein, John Graham, Johan Hombert, Wei Jiang, Augustin Landier, Timothy Loughran, David Thesmar, Roberto Tubaldi, Dong Yan, and seminar participants at EFA 2025, INSEAD, LBS Finance Summer Symposium 2025, NUS, Tsinghua Theory and Finance Workshop, ISB Summer Research Conference 2025 for useful comments. All errors are the authors' alone.

> *"The manager of a biotechnology firm may have much better information than outside investors about the firm's future cash flows, but may not know the rate at which the market will capitalize those cash flows. Thus, he might look at the stock price and, for example, pass up a scale-increasing project with very favorable expected cash flows because the firm's low stock price indicates that the market puts a very high discount rate on those flows."*
>
> Subrahmanyam and Titman (1999)

I Introduction

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

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

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

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

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

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

[2]In Goldstein and Yang (2019), disclosure reduces traders' incentives to search for information. If disclosure pertains to a variable managers wish to learn about (e.g., project risk), then prices provide less valuable feedback. In their context, optimal mandatory disclosure depends on what managers seek to learn. More generally, policies aimed at enhancing the extent to which financial markets reveal information relevant for value-maximizing decisions—what Bond, Edmans, and Goldstein (2012) term Revelatory Price Efficiency (RPE), as distinct from Forecasting Price Efficiency (FPE), which measures how well prices aggregate all available information—require identifying what decision makers ignore and seek to learn. While FPE is an unconditional criterion, RPE is conditional on what decision makers already know. Therefore, RPE can be optimally implemented only if the object of managerial learning is known, underscoring the importance of our research question.

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

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

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

The first source is an omitted-variable problem that is well-known in the learning literature. The econometrician cannot control for the manager's private information. If this information is even partially embedded in stock prices—which is plausible—prices and managerial expectations will be correlated even in the absence of learning, biasing the *absolute* value of the OLS estimates *upward*. Thus, one cannot reject the null that managers do not learn from stock prices since prices may passively reflect information managers already possess. The second source of endogeneity is an errors-in-variables problem that arises because managers use what they know to obtain better information from the price about what they seek to learn. For example, when forming an expectation of k, the manager uses her private signal about g to filter out price variation due to g, extracting a more precise signal about k from the price. Because the econometrician observes only prices—not the filtered signal actually used—measurement error arises, which attenuates the *absolute* value of OLS estimates and biases them *downward*.

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

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

To isolate price pressure mechanically induced by extreme flows and unrelated to stock fundamentals, we follow Edmans, Goldstein, and Jiang (2012) and use *hypothetical*, rather than actual, trades. We depart from their approach in two respects to address issues identified in the literature. First, we base hypothetical trades on the *market* portfolio—rather than funds' disclosed portfolios—to avoid contamination from past trading decisions (Berger (2023)). Second, we do not normalize by dollar trading volume—which embeds stock returns and fundamental information (Wardlaw (2020))—instead relying on variation in the fraction of a stock's outstanding shares held by funds. We estimate its price impact using *stock-date fixed effects*, which absorb unobserved stock-level factors that influence all funds trading the same stock at the same time. This procedure yields a measure of noise in stock prices that is orthogonal to time-varying fundamentals. To validate our approach, we exploit both tails of the flow distribution—not just outflows—and build separate measures of buying and selling pressure, which we use as distinct instruments. Reassuringly, both generate symmetric return patterns: price changes are immediate and in the expected direction, gradually revert over time, are stronger for smaller stocks, and exhibit no pre-trends.

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

However, after correcting for endogeneity, *only k reacts to stock prices.* Specifically, using noise as an instrument to filter out information already known to managers leads to an estimate for the sensitivity of g that is close to zero and statistically *insignificant*, consistent with managers being already well-informed about g and hence not updating it using stock prices. In contrast, the sensitivity of k remains significantly negative at -0.89. It is larger in absolute value than the OLS estimate as predicted by our model when managers know little about k and a lot about g. 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 suggest 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 that are supported in the data. Most distinctively, it predicts how the effect of price 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 price becomes less noisy, she places *more* weight on the 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 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 those cross-sectional results.

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

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

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

II Related Literature

Our paper contributes to three strands of literature. First and foremost, it contributes to the literature on the real effects of financial markets—the so-called feedback effect from market prices to the real economy.[4] While prior research documents that managers extract information from stock prices, much less is known about *what* managers actually learn from prices. The empirical literature is largely agnostic as to whether prices inform managers about cash flows, discount rates, or other factors, while the theoretical literature typically assumes learning about cash flows exclusively; our findings challenge this assumption, suggesting the need for a revised perspective.

Our key finding—that managers extract information about discount rates, but not cash flows, from stock prices—is consistent with two recent insights in the empirical literature. First, research in corporate finance shows that managers' estimates of discount rates are highly imprecise (Gormsen and Huber (2024), Gormsen and Huber (2025)). In particular, managers lack information about investors' risk appetite and portfolio holdings needed to determine the compensation investors require. Our results indicate that managers rely almost entirely on stock prices to obtain this information. Second, recent work in asset pricing suggests that valuation differences across firms are driven primarily by variations in discount rates or mispricing, rather than by differences in expected future cash flows (DeLaO, Han, and Myers (2024)).[5] Relatedly, Campbell and Vuolteenaho (2004) show that discount-rate

[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 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.

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

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

The second stream of research we contribute to concerns the theory and practice of capital budgeting and M&A. Although capital budgeting is among firms' most fundamental decisions, field evidence on budgeting practices is scarce because project investments and their outcomes are typically unobservable. To address this challenge, scholars have surveyed managers (Graham and Harvey (2001), Graham (2022)) and analyzed their conference calls (Gormsen and Huber (2024), Gormsen and Huber (2025)) to infer their discount rate. We bring novel data from M&A fairness opinions to this research question. Relative to survey data, these are not subject to concerns about managerial misreporting. Relative to conference calls data, they offer greater clarity about context and usage.[6] We contribute two important facts to this literature. First, we empirically validate a key assumption in many capital budgeting models (e.g., Stein (2003)), namely that managers possess superior private information about future cash flows. Indeed, we show that managers do not update their beliefs about g based on stock prices, implying they are already well informed about future cash flows. Second, we document that managers' primary source of information about k is the stock price.

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

Finally, we contribute to an emerging literature on the valuation practices of professional forecasters (Décaire (2024); Décaire, Sosyura, and Wittry (2024)). Décaire and Graham (2024) study the models equity analysts use to estimate cash flows and discount rates. They find that variations in subjective betas derived from past stock returns drive much of the fluctuations in these estimates over time. Chaudhry (2025) documents that equity analysts use stock prices to forecast future cash flows, (erroneously) interpreting price movements driven by discount rates as cash-flow news. We extend this line of research focusing on managers rather than sell-side analysts. Managers differ fundamentally from analysts in both objectives and information sets, and unlike analysts who issue recommendations, managers take real actions. Hence the importance of understanding how managers form expectations about both g and k.

III Hypotheses Development

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

A Theoretical framework

A.1 Setup

Firm value is determined using the Gordon growth model, which relates the next period cashflow C, the perpetual growth rate of cashflows G, and the discount rate K through the formula: $Q = \frac{C}{K-G}$. The manager is assumed to have complete knowledge of the next period cashflow C, but she is uncertain about the growth rate G and the discount rate K. To estimate those, she relies on private signals, and potentially also on the stock price Q. For analytical tractability, we linearize the stock's price around a baseline corresponding to her prior (or last-period) beliefs about G and K. Specifically, we approximate: $G \approx g_0 + g$ and $K \approx k_0 + k$, where g and k represent small deviations from the baseline values g_0 and k_0. A first-order Taylor approximation yields:

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

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

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

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

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.[7]

Proposition 1: *If the manager learns from the stock price q, her posterior beliefs about the*

[7] The proofs of our propositions are in Appendix III.

growth rate g and the discount rate k are given by

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

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

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

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

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

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

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

The manager's posterior expectations of g and k are correlated, though g and k are unconditionally uncorrelated. This correlation arises because both expectations are formed conditional on the price. It is positive because the observed price pins down their difference, so a higher (lower) posterior expectation of g must be matched by a higher (lower) posterior expectation of 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. Her posterior expectation and precision reduce to the usual expressions based on a prior and a single private signal, as presented in Corollary 1.

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:*

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

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

and $\quad Cov(k, g|S_g, S_k) = 0.$

B Predictions

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

B.1 OLS Regressions

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

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

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

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

If the manager learns from the stock price:

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

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

If the manager does not learn from the stock price:

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

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

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

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

B.2 IV Regressions

Next, we consider IV regressions using noise, θ, as an instrument for the stock price, q. We assume that θ is not observed by the manager—when observing q, she cannot distinguish noise from information about g and k—but it is observed by the econometrician. Notably, it is not necessary for the econometrician to observe the *entire* noise term, nor is it needed that the manager be unable to *completely* filter it out.[8] Our predictions hold as long as the manager's ability to identify noise is limited.

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

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

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

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

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***

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

in the absence of learning from the price. Moreover, they represent (in absolute value) the ***proportion*** *of information about g or k that managers obtain from stock prices.*

B.3 Magnitudes of the OLS vs IV Regression Coefficients

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

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

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

An implication is that if the manager's private signals are highly accurate for g but poor for k (i.e., $\tau_{\varepsilon g}$ large but $\tau_{\varepsilon k}$ small), then she learns a little or nothing about g from the price but learns a lot about k. In this case, the IV coefficient in the g regression will be *smaller in absolute value* than the OLS coefficient.[9] In contrast, the IV coefficient in the k regression

[9] 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.

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

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

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

B.4 Cross-Sectional Variation

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

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

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

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

To resolve this ambiguity, we perform a first-order linear approximation of the system that links together prior, private signal, and posterior precisions. This approximation reveals that, for small changes in precisions, 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.

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

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

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

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 and the precision of price noise, $\tau_{g|S_g,S_k,q}$ and τ_θ.

IV Data and Methodology

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

A Data and Variables

A.1 Expectations

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

k is reported under items FO_DCF_RATE_LOW and FO_DCF_RATE_HI, which, respectively, provide the low and high end of the assumed range. Similarly, the range assumed for g is reported under items FO_DCF_PERP_LOW and FO_DCF_PERP_HI.[10] We use the range mid-point as the estimate for k and g, and the inverse of the range width-—-the high–low difference denoted *k Range* and *g Range*—as the estimate of the precision of managers' beliefs.[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 miscoded percentage entries (e.g., 12 for vs 0.12), eliminate observations where the high end of the range is lower than the low end, remove outliers ($k < 1\%$ or $g < 0\%$) and aggregate k, g, *k Range*, and *g Range* at the deal-level by averaging across opinions when multiples reports exist for the same target. We obtain a sample (before merging with CRSP and Compustat) of 3,205 M&A deals announced between 2000 and 2022 for 3,103 unique targets, with 3,205 non-missing observations on k and 1,632 on g.

[Insert Figure I about here]

On average, the expected discount rate k and growth rate g are 12.9% and 3.7%, respectively. Figure I plots the average of k and g by year. Their Pearson correlation is positive (0.56), which is consistent with our model when managers learn from prices: such learning induces a positive correlation between k and g even though they are unconditionally uncorrelated. However, this correlation is only suggestive of learning since k and g may be (unconditionally) correlated in the data for reasons unrelated to learning.

[10] Sometimes, a multiple is used to compute terminal values instead of the Gordon Growth Model. In this case, we approximate the implicit range of values assumed for g using the formula, $g = (k \times MULT - 1)/(1 + MULT)$, where k is the mid-point of the assumed discount-rate range, and $MULT$ is the low or high end of the assumed terminal value multiple. The range for $MULT$ is reported under items FO_DCF_TERM_LOW and FO_DCF_TERM_HI.

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

A.2 Price Pressure (Stock Price Noise)

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

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

Our second departure concerns the inclusion of end-of-month (dollar) trading volume in the original price pressure formula to account for cross-stock differences in liquidity. Wardlaw (2020) shows that this adjustment is problematic because it inadvertently introduces (the inverse of) stock returns into the price pressure measure, along with stock-level fundamental information contained in trading volume. To address this concern, we (i) estimate the effect of a fund's hypothetical *number* of shares purchased (sold) in response to extreme inflows (outflows) on the fraction of a stock's outstanding shares held by the fund, *controlling for stock-date fixed effects*, (ii) aggregate these effects to the stock level by summing across funds to identify, for each stock and date, the total change in the fraction of mutual-fund ownership induced by extreme flows , (iii) estimate the impact of extreme flows on stock returns by regressing monthly FF49-adjusted returns on the estimated ownership changes. By construction, our measure of stock return noise is immune to Wardlaw (2020)'s critique because it does not require normalizing for dollar volume, and it is orthogonal to (observed and unobserved) time-varying stock-level factors affecting all funds trading the same stock at the same time; such variation is absorbed by the stock-date fixed effects.[12]

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

[Insert Figure II about here]

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

We then infer monthly noise in prices by multiplying noise in stock returns by the

[12] Other papers addressing Wardlaw (2020)'s critique include Dessaint, Olivier, Otto, and Thesmar (2020) and Tubaldi (2024).

beginning-of-month market capitalization, and noise in Tobin's Q by scaling by total assets. *MF Buying Price Pressure* (*MF Selling Price Pressure*) is the average noise in Q in *absolute value* over the last 12 months induced by extreme monthly inflows (outflows).

Finally, we use the distribution of monthly noise in Q induced by extreme fund flows to estimate the volatility of the noise. For each stock, we calculate *MF Noise Range* as the interquartile range of monthly noise in Q over the 12 months preceding the deal announcement, and use its inverse as a measure of the precision of the price signal. Appendix II details the procedure used 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, trading volume, and number of shares outstanding are from CRSP. Financial accounting data are from Compustat North America. Mutual fund ownership data are from Thomson Reuters, and mutual fund flows data from CRSP. All variables are described in Appendix I.

A.4 Summary statistics

Our final sample includes all U.S. target firms from LSEG that (i) have non-missing information on g, k, Q, *MF Buying Pressure*, *MF Selling Pressure*, and (ii) can be merged with CRSP and COMPUSTAT. [13] We further require that g, k, and Q be non-negative and that the change in Q is less than 10 in absolute value.

[Insert Table I about here]

Table I reports summary statistics. The main endogenous variables are g, k, Q, and ΔQ, and the exogenous variables are *MF Buying Pressure* and *MF Selling Pressure*. We normalize endogenous variables by their within-(SDC-)industry standard deviation to ease economic interpretation. All variables are defined in Appendix I. Continuous, non-log-transformed,

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

non-well-behaved variables are winsorized at the 1% level in each tail to limit the influence of outliers.

B Methodology

B.1 OLS Regressions

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

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

$$k_{i,t} = b_k \Delta Q_{i,t-1} + \gamma_k X_{i,t-1} + \phi_j + \eta_y + \varepsilon_{i,t}^{'}. \tag{19}$$

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

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

B.2 2SLS Regressions

Next, we use 2SLS regressions. Estimating b_g and b_k by OLS is problematic because Eq. 18 and Eq. 19 suffer from the endogeneity discussed in Section III: managers may possess private information about the target that is also reflected in prices. As a result, finding $b_g > 0$ and $b_k < 0$ may simply reflect (passive) correlation between prices and unobserved managerial information rather than (active) learning from prices (cf. Prediction 1).

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

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

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

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

The second-stage regressions are

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

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

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

B.3 Reduced form IV Regressions

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

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

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

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

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

V Results

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

A Main Results

[Insert Table II about here]

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

A.1 Learning about g

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

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

A.2 Learning about k

Columns (5) to (8) examine how prices affect beliefs about k. Column (5) reports OLS estimates of Eq. 19 and shows a negative and statistically significant relationship between prices and beliefs about k ($b_k < 0$), consistent with learning about discount rates from prices.

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

A.3 Interpreting OLS vs. IV coefficients

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

However, after correcting for endogeneity—using price noise as instrument to filter out information about g and k already known to managers, the coefficient on g falls to zero, consistent with managers being already well-informed about g, whereas the coefficient on k remains negative and increases in absolute value, consistent with managers having limited prior information about k. The amplification of b_k reflects an errors-in-variables problem in the OLS regression of k on prices. Since managers can use their private information about g to filter out g from prices, the signal about k that they extract differs from the prices observed by the econometrician. This mismatch attenuates the OLS estimate in Column (5). Instrumenting prices with variation unrelated to g eliminates this attenuation, yielding a larger coefficient in Column (7).

To summarize, the nature of the endogeneity problem depends on whether managers know relatively more about g or k. When they know a lot about g and little about k, the OLS estimates suffer from an omitted-variable problem for g (Column (1)) and an errors-in-variables problem for k (Column (5)). In this case, the absolute value of the OLS coefficients are biased upward for g and downward for k.[14]

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

A.4 Interpreting Economic Magnitude

After correcting for endogeneity, we find $b_g = -0.03$ and $b_k = -0.89$. A one-SD increase in prices decreases expectation about k by 0.89 SD, while having a negligible effect on beliefs about g. In our theoretical framework, the IV coefficients measure (in absolute value) the share of information about g or k that managers obtain from observing prices. In particular, a coefficient of 0.89 for b_k implies that 89% of managers' posterior precision about k is derived from prices (combined with their private signal about g). By contrast, the statistically insignificant coefficient of -0.03 for b_g indicates that they get no incremental information about g from prices.

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 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 tests of Predictions 4 and 5. When managers learn from prices, the sensitivity of g and k to price noise should vary systematically with the precision of managers' posterior about g (τ_{qg}) and k (τ_{qk}), and with the precision of the price signal (τ_θ).

B.1 Variation in k-to-noise sensitivity

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

[Insert Table III about here]

Table III presents reduced form IV regressions (Eq. 24) in which price noise is interacted with (i) the inverse of the reported range for g and k (our proxies for τ_{qk} and τ_{qg}) and (ii) the inverse of *MF Noise Range* (our proxy for τ_{θ}). Quite remarkably, the sensitivity of k to price noise varies systematically in the direction predicted by the learning hypothesis. All interaction coefficients have the expected signs (Predictions 4 and 5) and are statistically significant or marginally so. Column (1) shows attenuated sensitivity when the inverse of the reported range for k is high: when managers are better informed about k (higher τ_{qk}), they rely less on prices, weakening the impact of price noise. Column (2) shows amplified sensitivity when the inverse of the reported range for g is high: better information about g (τ_{qg} is higher) allows managers to more effectively filter out g-related price variation and rely more on prices to learn about k. Column (3) shows amplified sensitivity when prices are less noisy (lower *MF Noise Range*), as higher price informativeness (τ_{θ}) increases the weight managers place on prices—and hence on noise. Column (4) confirms these patterns when all three interaction terms are included simultaneously.

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

B.2 Variation in g-to-noise sensitivity

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

[Insert Table IV about here]

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

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

VI Instrument validity

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

A Relevance

Columns 2 and 6 of Table II show that the relevance condition is satisfied. Both *MF Buying Price Pressure* and *MF Selling Price Pressure* have a significant impact on price changes ΔQ with the expected opposite signs. These results are consistent with our premise that those variables capture price pressure generated by liquidity trades of mutual funds forced to rebalance after large flows. Next, we provide additional supporting evidence.

A.1 Do extreme flows affect fund ownership?

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

[Insert Table V about here]

Table V reports the results of regressing changes in fund holdings on hypothetical purchases and sales, *controlling for stock-date fixed effects.* Hypothetical purchases (sales), denoted $HP_{i,j,t}$ ($HS_{i,j,t}$), measure the number of shares fund j would purchase (sell) if it responded to net inflows (outflows) at time t by adjusting its holding of stock i proportionally to the stock's weight in the market portfolio at $t-1$, scaled by the stock's number of shares outstanding at $t-1$. Scaling serves two purposes. First, it eases the interpretation: regression coefficients above (below) one imply that funds adjust holdings by more (less) than the stock's weight in the market portfolio. Second and most importantly, it isolates the effect of flows by removing stock-specific influences beyond market weight. Indeed, as shown in Eq.30, $HP_{i,j,t}$ ($HS_{i,j,t}$) equals net flows to fund j divided by the value of the market portfolio at the beginning of the month—a ratio identical across stocks held by fund j. Hence $HP_{i,j,t}$ and $HS_{i,j,t}$ depend on stock i only at the *extensive margin*—that is, whether the stock is held prior to the flow shock.

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

A.2 Do extreme flows generate price pressure?

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

[Insert Table VI about here]

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

A.3 Does price pressure vary with market depth?

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

[Insert Figure III about here]

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

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

B Exclusion Restriction

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

B.1 Are the instruments jointly exogenous?

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

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

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

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

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

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

Finally, we show that our instruments are also plausibly unrelated to economic forces inducing permanent changes in stock pries. As highlighted above, the price reaction indeed reverses within a few months. Both the absence of pre-trend and the subsequent reversal are particularly clear in Figure II, which plots cumulative regression coefficients from Column (2) of Table VI, using the month preceding the extreme flow as the reference month.

Overall, our results corroborate and extend a large body of evidence documenting, in various settings and using different measurement approaches (including some designed to address the limitations of earlier approaches), that extreme mutual fund flows trigger immediate price changes followed by reversals, that corporate insiders trade against these shocks, and that such events represent transitory, non-fundamental, supply- or demand-driven shocks.[15] Together, these findings provide strong support for the view that mutual fund–driven price pressure generates variation in stock prices that is exogenous to information about g and k.

VII Alternative Interpretations

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

A Learning by Managers or by Investment Bankers?

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

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

and throughout the paper, we treat these beliefs as shared.

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

[Insert Table VII about here]

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

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

B Learning or Reverse Engineering?

An alternative interpretation of our findings is strategic "reverse engineering." Investment bankers seek to close deals while limiting long-term reputation and litigation costs. Therefore, they may adjust their reported estimates to align DCF valuations with market prices and support a fairness conclusion. Specifically, they may lower (raise) their report of k following increases (decreases) in the target's share price. This suggests a different form of market feedback, whereby agents rationalize the price rather than learn from it.

While the negative k-to-price sensitivity reported in Table II is consistent with this interpretation, our other results are not. First, if k is "reverse-engineered", then so should g. In this case, the IV estimate for g in Column (3) of Table II should be positive and significant, which it is not. Second, reverse engineering does not explain why the IV estimate for k (Column (7)) differs from the OLS estimate (Column (5)). Indeed, reverse engineering implies that price sensitivity is independent of managers' information sets. By contrast, the learning interpretation predicts that OLS and IV coefficients differ because learning depends on what they already know, which is unobserved by the econometrician. Instrumenting prices with noise, by correcting this omitted-variable problem, therefore alters the estimates, but only under learning. Third, even if some other endogeneity problem predicted the same alteration of the k estimates under reverse engineering, then the gap between OLS coefficients for g and k should *match* the gap between the corresponding IV coefficients as reverse engineering predicts that the difference between managers' reports of g and k is *equally* sensitive to prices and to price noise. This is also not what we find.[16]

[16]Formally, let $\hat{g}$ and $\hat{k}$ denote reported beliefs which may differ from actual beliefs. Under reverse-engineering, suppose $\hat{g} - \hat{k} = \rho q$ where $\rho > 0$ measures how closely managers track prices. Importantly, we make no assumption on how managers adjust $\hat{g}$ or $\hat{k}$: they may adjust one more than the other or

Finally, reverse engineering would need to explain the full set of cross-sectional results. For that, the incentive to behave strategically should systematically weaken with the 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.[17]

C Learning about Short or Long Term Growth?

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

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

---

both similarly; moreover, they may track prices loosely (ρ small) or excessively ($\rho > 1$). It follows that $cov(\hat{g}, q) - cov(\hat{k}, q) = \rho var(q)$, implying $b_g^{OLS} - b_k^{OLS} = \rho$. Likewise, $cov(\hat{g}, \theta) - cov(\hat{k}, \theta) = cov(\rho q, \theta) = cov(\rho(g - k + \theta), \theta) = \rho var(\theta)$, so $b_g^{IV} - b_k^{IV} = \rho$. Hence, under reverse engineering, the difference between the OLS coefficients equals the difference between the IV coefficients.

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

VIII Conclusion

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

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

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, 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 Goldstein, 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.

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

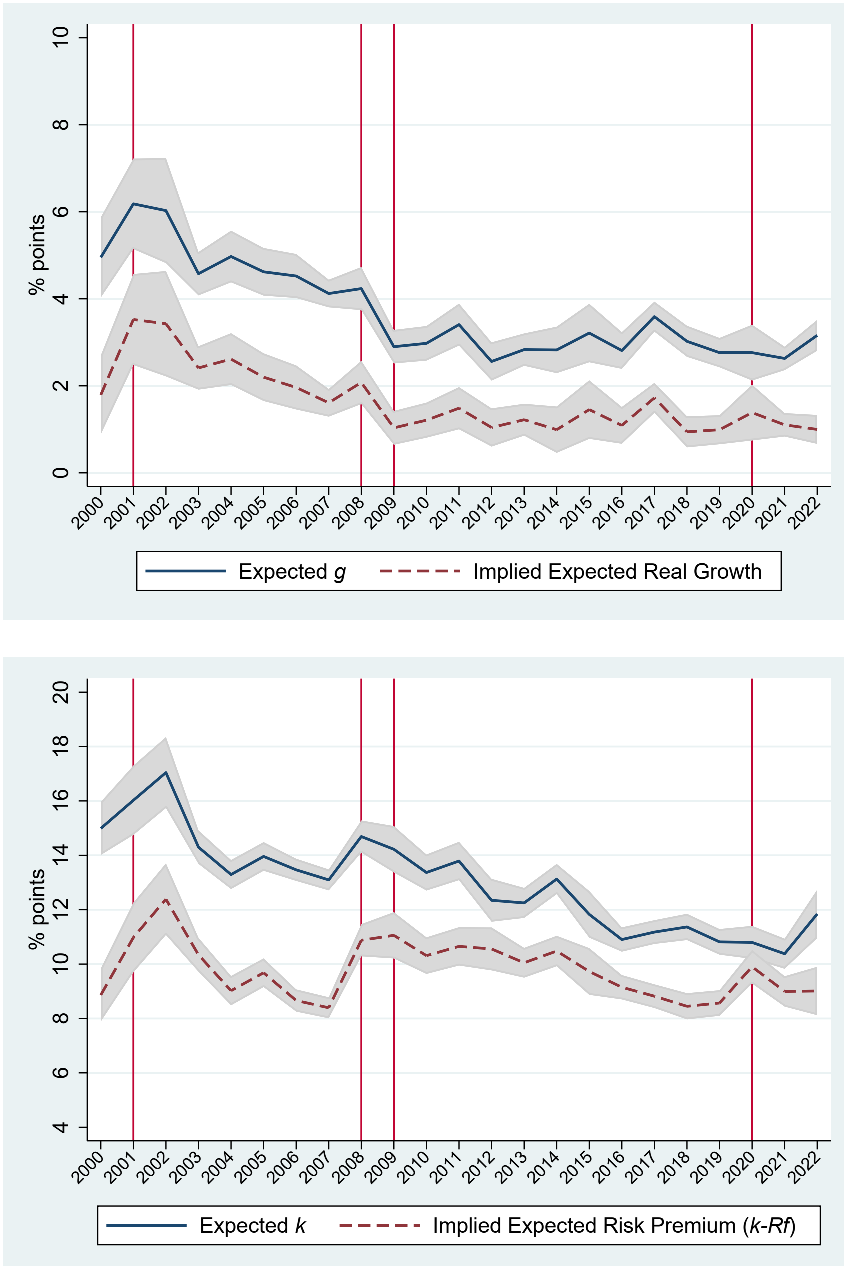
Tubaldi, Roberto, 2024, Mutual funds' fire sales and the real economy: Evidence from hurricanes, Working Paper.

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.

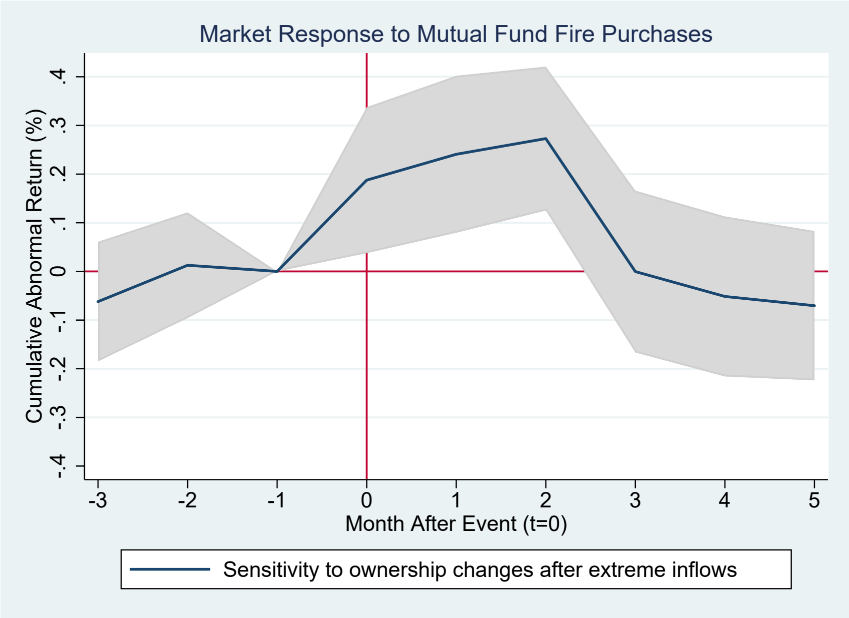
Yan, Dong, 2024, Do private firms (mis)learn from the stock market?, *Review of Finance* 28, 1483–1511.

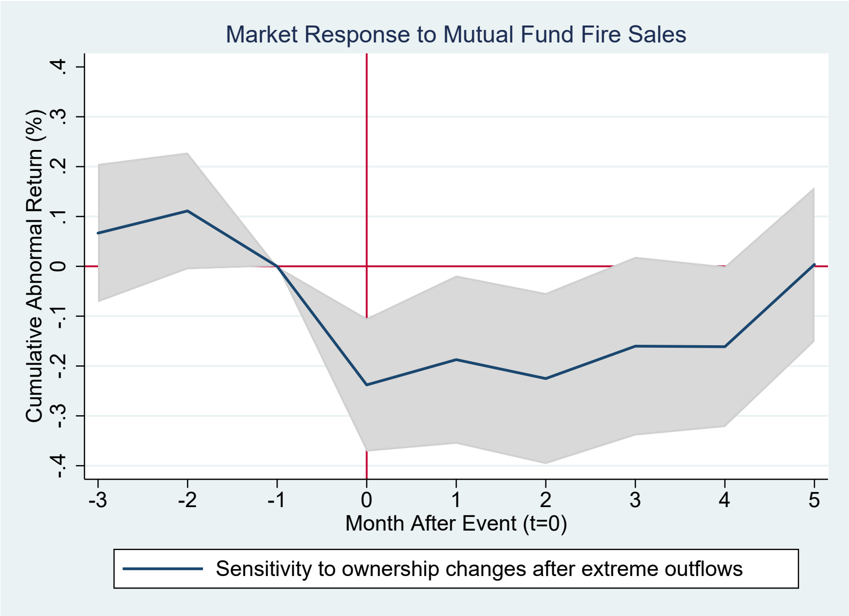
Figure I: Expected g and k by year



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.

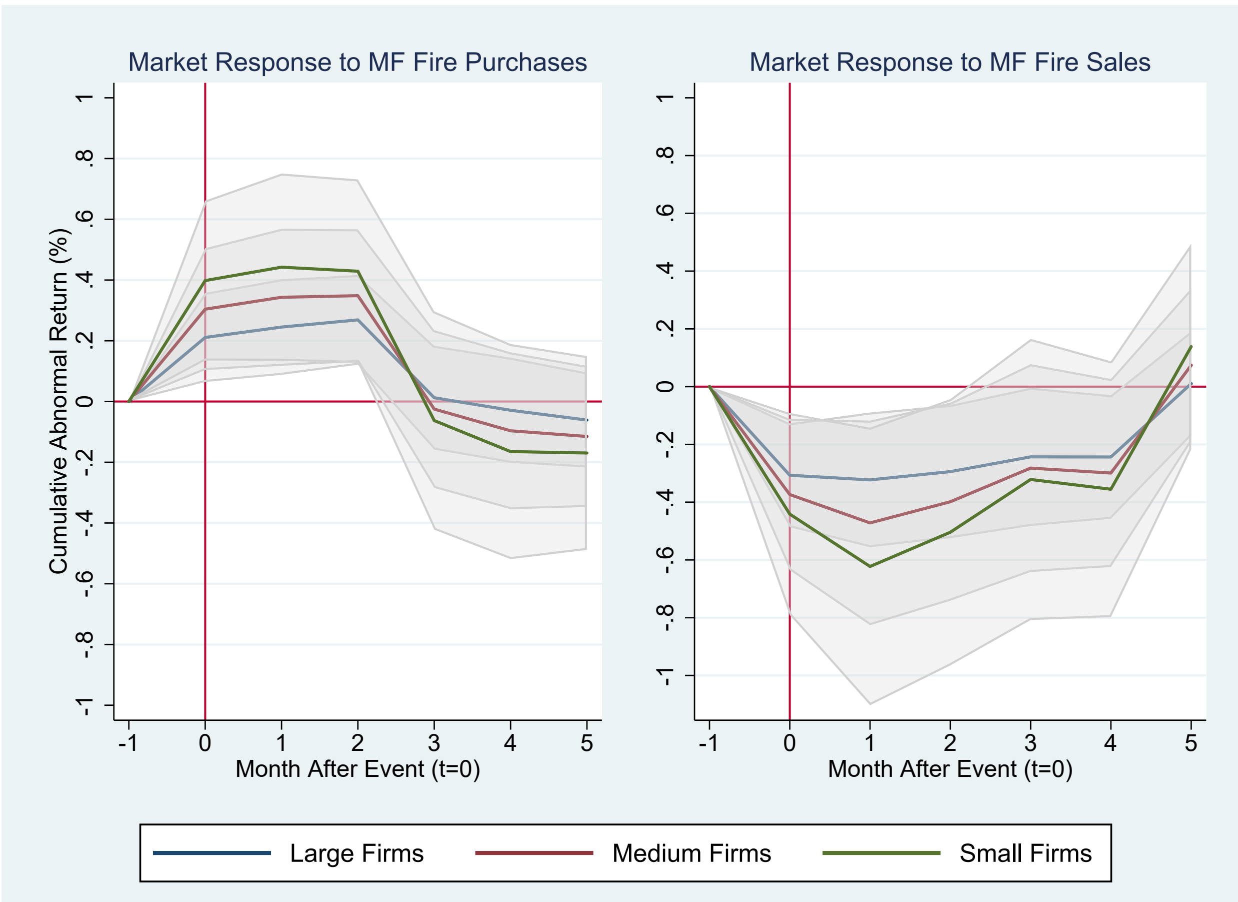
Figure II: Extreme MFF Price Pressure Effects





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

Figure III: Price Pressure Effects by Firm Size



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

Table I: Summary Statistics

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

	N	Mean	STDV	Min	P10	P25	P50	P75	P90	Max
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 18 (Column 1), Equation 20 (Column 2), Equation 21 (Column 3), Equation 23 (Column 4), Equation 19 (Column 5), Equation 20 (Column 6), Equation 22 (Column 7) and Equation 24 (Column 8). g is the perpetual growth rate of future cash flows assumed by the management team and their advisors for valuing the target company. k is the discount rate assumed by the management team and their advisors for valuing the target company. ΔQ is the change in Q of the target company during the last observable fiscal year before deal announcement. *MF Buying Price Pressure* is the average dollar amount of monthly equity overvaluation due to fire purchases by Mutual Funds subject to extreme inflows during the 12-month period preceding deal announcement, and scaled by total assets. *MF Selling Price Pressure* is the average dollar amount of monthly equity undervaluation due to fire sales by Mutual Funds subject to extreme outflows during the 12-month period preceding deal announcement, and scaled by total assets. All variables are defined in Appendix I. Explanatory variables that are absorbed by the fixed effects are omitted from the regression. t-statistics in parentheses are based on standard errors clustered by Target-SDC-industry. Symbols ***, **, and * denote statistical significance at the 1%, 5%, and 10% level, respectively.

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

Estimation Method	Reduced Form IV			
Dep. variable:	k			
Specification	(1)	(2)	(3)	(4)
MF Buying Price Pressure $\times$(k Range)$^{-1}$	0.17***			0.22***
	(3.43)			(3.31)
MF Selling Price Pressure $\times$(k Range)$^{-1}$	-0.08**			-0.12**
	(-2.28)			(-2.48)
MF Buying Price Pressure $\times$(g Range)$^{-1}$		-0.07*		-0.11**
		(-1.93)		(-2.28)
MF Selling Price Pressure $\times$(g Range)$^{-1}$		0.05***		0.08**
		(2.68)		(2.52)
MF Buying Price Pressure $\times$(MF Noise Range)$^{-1}$			-0.10*	-0.10*
			(-1.88)	(-1.67)
MF Selling Price Pressure $\times$(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 23 when interacting all explanatory variables (including the fixed effects) with variables measuring the precision of managerial private information about k (Columns 1 and 4), g (Columns 2 and 4), and the noisiness of the price (Columns 3 and 4). g is the perpetual growth rate of future cash flows assumed by the management team and their advisors for valuing the target company. *MF Buying Price Pressure* is the average dollar amount of monthly equity overvaluation due to fire purchases by Mutual Funds subject to extreme inflows during the 12-month period preceding deal announcement, and scaled by total assets. *MF Selling Price Pressure* is the average dollar amount of monthly equity undervaluation due to fire sales by Mutual Funds subject to extreme outflows during the 12-month period preceding deal announcement, and scaled by total assets. *k Range* is the range reported for k. *g Range* is the range reported for g. *MF Noise Range* is the inter-quartile range of the net monthly equity misvaluation due to both fire purchases and sales by Mutual Funds subject to extreme inflows or outflows during the 12-month period preceding deal announcement. Control variables include *Size (Log)*, *Cash Flow*, *Debt*, *Cash*, Δ *Sales*, and *Dividend*. All variables are defined in Appendix I. Explanatory variables absorbed by the fixed effects or collinear with the slope fixed effects—resulting from the interaction of the fixed effects with the inverse of *k Range* (Columns 1 and 4), *g Range* (Columns 2 and 4), and *MF Noise Range* (Columns 3 and 4)—are omitted from the regression. t-statistics in parentheses are based on standard errors clustered by Target-SDC-industry. Symbols ***, **, and * denote statistical significance at the 1%, 5%, and 10% level, respectively.

Estimation Method	Reduced Form IV			
Dep. variable:	g			
Specification	(1)	(2)	(3)	(4)
MF Buying Price Pressure $\times(k \text{ Range})^{-1}$	0.04			0.09
	(0.58)			(1.11)
MF Selling Price Pressure $\times(k \text{ Range})^{-1}$	0.01			-0.05
	(0.24)			(-0.93)
MF Buying Price Pressure $\times(g \text{ Range})^{-1}$		-0.06		-0.06
		(-0.95)		(-0.83)
MF Selling Price Pressure $\times(g \text{ Range})^{-1}$		0.06		0.06
		(1.42)		(1.23)
MF Buying Price Pressure $\times(\text{MF Noise Range})^{-1}$			-0.04	-0.02
			(-0.69)	(-0.41)
MF Selling Price Pressure $\times(\text{MF Noise Range})^{-1}$			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 31. 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 36. 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)		(2)	
	Coef.	t-stat	Coef.	t-stat
High Inflow Induced $\Delta O_{i,t}$	0.18***	(3.47)		
High Outflow Induced $\Delta O_{i,t}$	-0.21***	(-4.42)		
High Inflow Induced $\Delta O_{i,t+3}$			0.07	(1.23)
High Inflow Induced $\Delta O_{i,t+2}$			-0.01	(-0.19)
High Inflow Induced $\Delta O_{i,t+0}$			0.19**	(2.06)
High Inflow Induced $\Delta O_{i,t-1}$			0.05	(0.58)
High Inflow Induced $\Delta O_{i,t-2}$			0.03	(0.50)
High Inflow Induced $\Delta O_{i,t-3}$			-0.27***	(-4.00)
High Inflow Induced $\Delta O_{i,t-4}$			-0.05	(-0.78)
High Inflow Induced $\Delta O_{i,t-5}$			-0.02	(-0.28)
High Outflow Induced $\Delta O_{i,t+3}$			0.04	(0.63)
High Outflow Induced $\Delta O_{i,t+2}$			-0.11	(-1.56)
High Outflow Induced $\Delta O_{i,t+0}$			-0.24***	(-2.93)
High Outflow Induced $\Delta O_{i,t-1}$			0.05	(0.61)
High Outflow Induced $\Delta O_{i,t-2}$			-0.04	(-0.51)
High Outflow Induced $\Delta O_{i,t-3}$			0.06	(0.94)
High Outflow Induced $\Delta O_{i,t-4}$			0.00	(-0.01)
High Outflow Induced $\Delta O_{i,t-5}$			0.16***	(2.56)
Constant	0.00	(1.61)	0.00	(1.20)
N	54,286		35,938	

Table VII: Transaction Value Determinants

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

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

Appendix II – Mutual Fund Price Pressure Measure

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

Step 1 - Calculate fund flows

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

$$RETURN_{j,m,y} = \frac{\sum_k (TNA_{k,j,m-1,y} \times RETURN_{k,j,m,y})}{TNA_{j,m-1,y}}, \tag{25}$$

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

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

$$FLOW_{j,m,y} = TNA_{j,m,y} - TNA_{j,m-1,y} \times (1 + RETURN_{j,m,y}) - MGN_{j,m,y}, \tag{26}$$

where $MGN_{j,m,y}$ is the increase in TNA due to fund mergers.[18] Thus, $FLOW_{j,m,y}$ measures the net flow (in dollars) experienced by fund j during month m of year y.

Step 2 - Calculate fund holdings

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

$$O_{j,i,m,y} = \frac{SHARES_{i,j,m,y}}{N_{i,m,y}}, \tag{27}$$

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

Step 3 - Calculate fund hypothetical trades

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

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

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

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

$$HT_{i,j,m,y} = \frac{W_{M_{i,m-1,y}} \times FLOW_{j,m,y}}{P_{i,m-1,y}} \times \frac{1}{N_{i,m-1,y}} \times \mathbb{1}_{[i \in \mathbb{P}_{j,m-1,y}]}, \tag{28}$$

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

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

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

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

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

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

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

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

$$\begin{aligned}\Delta O_{i,j,m,y} = a_{i,m,y} \\ &+ b_1 HP_{i,j,m,y} \times Flag\_0\%\_to\_0.5\%_{j,m,y} + b_2 HP_{i,j,m,y} \times Flag\_0.5\%\_to\_1\%_{j,m,y} \\ &+ b_3 HP_{i,j,m,y} \times Flag\_1\%\_to\_2\%_{j,m,y} + b_4 HP_{i,j,m,y} \times Flag\_2\%\_to\_3\%_{j,m,y} \\ &+ b_5 HP_{i,j,m,y} \times Flag\_3\%\_to\_4\%_{j,m,y} + b_6 HP_{i,j,m,y} \times Flag\_4\%\_to\_5\%_{j,m,y} \\ &+ b_7 HP_{i,j,m,y} \times Flag\_more\_than\_5\%_{j,m,y} \\ &+ c_1 HS_{i,j,m,y} \times Flag\_0\%\_to\_0.5\%_{j,m,y} + c_2 HS_{i,j,m,y} \times Flag\_0.5\%\_to\_1\%_{j,m,y}, \\ &+ c_3 HS_{i,j,m,y} \times Flag\_1\%\_to\_2\%_{j,m,y} + c_4 HS_{i,j,m,y} \times Flag\_2\%\_to\_3\%_{j,m,y} \\ &+ c_5 HS_{i,j,m,y} \times Flag\_3\%\_to\_4\%_{j,m,y} + c_6 HS_{i,j,m,y} \times Flag\_4\%\_to\_5\%_{j,m,y} \\ &+ c_7 HS_{i,j,m,y} \times Flag\_more\_than\_5\%_{j,m,y} \\ &+ \epsilon_{i,j,m,y}\end{aligned} \quad (31)$$

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

Results from estimating Equation 31 are reported in Table V (see Section A.1 for a discussion). We use these estimates to predict ownership changes following extreme flows—defined as inflows exceeding 5% of assets and outflows exceeding 2%.[19] Predicted changes in ownership due to extreme inflows are given by

$$High\ Inflow\ Induced\ \Delta O_{j,i,m,t} = 11.2 \times HP_{i,j,m,y} \times Flag\_more\_than\_5\%_{j,m,y} \quad (32)$$

Predicted changes in ownership due to monthly outflows are given by

$$\begin{aligned}High\ Outflow\ Induced\ \Delta O_{j,i,m,t} &= 8.81 \times HS_{i,j,m,y} \times Flag\_2\%\_to\_3\%_{j,m,y} \\ &+ 8.33 \times HS_{i,j,m,y} \times Flag\_3\%\_to\_4\%_{j,m,y} \\ &+ 7.78 \times HS_{i,j,m,y} \times Flag\_4\%\_to\_5\%_{j,m,y} \\ &+ 8.16 \times HS_{i,j,m,y} \times Flag\_more\_than\_5\%_{j,m,y}\end{aligned} \quad (33)$$

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

$$High\ Inflow\ Induced\ \Delta O_{i,m,y} = \sum_j (High\ Inflow\ Induced\ \Delta O_{j,i,m,y}), \quad (34)$$

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

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

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

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

$$\begin{aligned} ARET_{i,m,y} = &\ Constant \\ &+ b_1 \textit{High Inflow Induced } \Delta O_{i,m-2,y} + b_2 \textit{High Inflow Induced } \Delta O_{i,m-1,y} \\ &+ b_3 \textit{High Inflow Induced } \Delta O_{i,m,y} + b_4 \textit{High Inflow Induced } \Delta O_{i,m+1,y} \\ &+ b_5 \textit{High Inflow Induced } \Delta O_{i,m+2,y} + b_6 \textit{High Inflow Induced } \Delta O_{i,m+3,y} \\ &+ b_7 \textit{High Inflow Induced } \Delta O_{i,m+4,y} + b_8 \textit{High Inflow Induced } \Delta O_{i,m+5,y} \\ &+ c_1 \textit{High Outflow Induced } \Delta O_{i,m-2,y} + c_2 \textit{High Outflow Induced } \Delta O_{i,m-1,y} \\ &+ c_3 \textit{High Outflow Induced } \Delta O_{i,m,y} + c_4 \textit{High Outflow Induced } \Delta O_{i,m+1,y} \\ &+ c_5 \textit{High Outflow Induced } \Delta O_{i,m+2,y} + c_6 \textit{High Outflow Induced } \Delta O_{i,m+3,y} \\ &+ c_7 \textit{High Outflow Induced } \Delta O_{i,m+4,y} + c_8 \textit{High Outflow Induced } \Delta O_{i,m+5,y} \\ &+ \epsilon_{j,i,m,y} \end{aligned} \tag{36}$$

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

Results from estimating Equation 36 are reported in Table VI (see Section A.2 for a discussion). We use these estimates to predict stock return changes associated with ownership changes by mutual funds experiencing extreme flows.

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

$$\begin{aligned} &\textit{MF Buying Price Pressure}^{DOLLAR}_{i,m,y} = \\ &+ MV_{i,m-1,y} \times \textit{High Inflow Induced } \Delta O_{i,m,t} \times 0.19 \\ &+ MV_{i,m-2,y} \times \textit{High Inflow Induced } \Delta O_{i,m-1,t} \times (0.19 + 0.05) \\ &+ MV_{i,m-3,y} \times \textit{High Inflow Induced } \Delta O_{i,m-2,t} \times (0.19 + 0.05 + 0.03), \end{aligned} \tag{37}$$

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

$$
\begin{aligned}
&\textit{MF Selling Price Pressure}^{DOLLAR}_{i,m,y} = \\
&+ MV_{i,m-1,y} \times \textit{High Outflow Induced } \Delta O_{i,m,t} \times 0.24 \\
&+ MV_{i,m-2,y} \times \textit{High Outflow Induced } \Delta O_{i,m-1,t} \times (0.24 - 0.05) \\
&+ MV_{i,m-3,y} \times \textit{High Outflow Induced } \Delta O_{i,m-2,t} \times (0.24 - 0.05 + 0.04) \\
&+ MV_{i,m-4,y} \times \textit{High Outflow Induced } \Delta O_{i,m-3,t} \times (0.24 - 0.05 + 0.04 - 0.06).
\end{aligned} \tag{38}
$$

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

Appendix III – Derivations in the Model

A Proof of proposition 1

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

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

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.

Internet Appendix for

Learning about Discount Rates

(not intended for publication)

February 8, 2026

Contents

1 Fairness Opinion Example

Figure IA.1 reproduces selected extracts of the fairness opinion letter issued by Qatalyst Partners about the price paid by Microsoft to take over LinkedIn in 2016. We highlight in yellow the data being extracted by our data provider (LSEG, formerly Thomson-SDC), and the source of information used by Qatalyst to carry out their valuation analysis. Financial projections prepared by the management of LinkedIn and discussions with the management team are explicitly acknowledged as critical sources, supporting our premise that the data we use for k and g capture the beliefs shared by both managers and their financial advisors.

2 Does k Reflect Managers' Perceived k?

Table IA1 shows that the measure we use for k is closely related to the hurdle rate used by managers (extracted from earnings conference calls in Gormsen and Huber (2024)). Both are positively correlated, and this correlation is economically large. When firms' hurdle rate increases by 1%, k increases by a similar magnitude, namely 1.28%.[1] This result supports our premise that k reflects managers' perceived k.

In unreported analysis, we also find that the standard deviation of k within deal when multiple fairness opinions are issued (the within-STDV) is low and significantly lower than the standard deviation across fairness opinions about different deals (the between-STDV). The within-STDV is only 0.76. It is much lower than the usual range reported for k and it is 6 times lower than the between-STDV. This result indicates that similar assumptions are used for k when advisors differ but managers are the same, which is consistent with the above premise.[2]

[1] Notice Gormsen and Huber (2024) do not publicly disclose the actual hurdle rate that managers use. Instead, they disclose the fitted value of a linear regression model where the outcome variable is the hurdle rate they privately observe. Because the hurdle rate they disclose is a predicted hurdle rate (and not the real one), we regress k on the hurdle rate (and not the opposite). Doing so eases the interpretation: In the extreme case where our data about discount rates were exactly the same, the regression coefficient should be one. If we were running the opposite regression (Hurdle Rate on k), it would be less than one, even if our data were the same, because of the attenuation effect induced by the use of a proxy for the true hurdle rate.

[2] If managers are the same, perceived k for the same deal should be similar. Hence, the low within standard deviation we observe, both in absolute terms and relative to the between standard deviation.

3 Does g Reflect Managers' Perceived g?

Table IA2 shows that the expected growth we observe g is related to managerial guidance about sales growth for the subsequent fiscal year. The correlation between both is positive and statistically significant, indicating that our measure for g captures variation that is systematically related to management's expectations about future cash flow growth.

In unreported analysis, we also find that the standard deviation of g within deal when multiple fairness opinions are issued (the within-STDV) is low and significantly lower than the standard deviation across opinions about different deals (the between-STDV). The within-STDV is 0.36. It is much lower than the usual range reported for g and it is 5 times smaller than the between-STDV. This result indicates that similar assumptions are used for g when advisors differ but managers are the same, which is consistent with our premise that g captures managers' perceived g.

4 Mutual Fund Flow Distribution

Figure IA.2 shows the distribution of monthly mutual fund flows. Extreme mutual fund flows are relatively infrequent events. Extreme inflows ($> 5\%$ of AUM) occur with 11% probability. Extreme outflows ($< -2\%$ of AUM) occur with 16% probability.

5 Trend in Mutual Fund Flow around Extreme Flows

Figure IA.3 examines the dynamics of flows in the periods leading up to extreme realizations. We find no evidence of systematic pre-trends. The absence of discernible buildup prior to the event suggests that such episodes are unlikely to be anticipated by fund managers, and that they are plausibly unrelated to omitted economic forces at play before they happen.

6 Controlling for Offer Prices

As mentioned in footnote 17 of Section VII.B, a more subtle "reverse engineering" explanation is that banks search for the value of k needed to justify the offer price, rather than the target stock price. Unlike the latter, the former typically includes a premium. However, Table IA3 shows that our results are robust to controlling for the offer price paid by the acquirer. Doing so mechanically attenuates the IV estimate—since offer prices contain updated information about k—, but the IV estimate remains negative and (marginally) significant, suggesting that this form of reverse engineering cannot be the main explanation for our findings.

7 Differential Effects by Business Plan Horizon

Table IA4 shows that the sensitivity of g to noise does not vary significantly with the average business plan horizon used in the target firm's SIC2-industry. Using the SIC2-specific horizon measure developed by Dessaint, Foucault, and Frésard (2025), we find that when horizons are shorter, the sensitivity of g to noise seems consistent with a learning behavior fading with horizon. The regression coefficient on the baseline variable *MF Buying Pressure* (*MF Selling Pressure*) is positive (negative)—consistent with managers updating g upward (downward) after buying (selling) pressure in the extreme case where the horizon is "zero"—, and the regression coefficient on the interaction with *BP Horizon* is negative (positive)—consistent with beliefs updating weakening as horizon increases. However, none of the coefficients is statistically significant at conventional level. Therefore, we cannot reject the null that managers are not learning about cash flows, even when the horizon is short.

References

Dessaint, Olivier, Thierry Foucault, and Laurent Frésard, 2025, The horizon of investors' information and corporate investment, Working Paper.

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

Figure IA 1: Fairness Opinion Example - 2016 LinkedIn takeover by Microsoft

"***Fairness Opinion of Qatalyst Partners***

LinkedIn retained Qatalyst Partners to act as its financial advisor to the LinkedIn Board (...) to evaluate whether the per share merger consideration to be received by the holders of shares (...) was fair, from a financial point of view (...). LinkedIn selected Qatalyst Partners to act as its financial advisor based on Qatalyst Partners' qualifications, expertise, reputation and knowledge of the business of LinkedIn and the industry in which it operates. (...). At the meeting of the LinkedIn Board on June 11, 2016, Qatalyst Partners rendered its oral opinion, subsequently confirmed in writing, that, as of such date and based upon and subject to the various assumptions, considerations, limitations and other matters set forth therein, the per share merger consideration to be received (...) was fair, from a financial point of view (...). Qatalyst Partners delivered its written opinion, dated June 11, 2016, to the LinkedIn Board following the meeting of the LinkedIn Board.

The full text of Qatalyst Partners' written opinion to the LinkedIn Board, dated June 11, 2016, is attached to this proxy statement as Annex B and is incorporated into this proxy statement by reference (...).

In arriving at its opinion, Qatalyst Partners reviewed the merger agreement, certain related documents, and certain publicly available financial statements and other business and financial information of LinkedIn. Qatalyst Partners also reviewed certain forward-looking information relating to LinkedIn prepared by the management of LinkedIn, including financial projections and operating data prepared by the management of LinkedIn, which we refer to as the "LinkedIn Projections," which are described in more detail below in the section of this proxy statement captioned "The Merger — Financial Forecasts." Additionally, Qatalyst Partners discussed the past and current operations and financial condition and the prospects of LinkedIn with senior executives of LinkedIn. Qatalyst Partners also reviewed the historical market prices and trading activity for the Class A common stock and compared the financial performance of LinkedIn and the prices and trading activity of the Class A common stock with that of certain other selected publicly-traded companies and their securities (...).

In arriving at its opinion, Qatalyst Partners assumed and relied upon, without independent verification, the accuracy and completeness of the information that was publicly available or supplied or otherwise made available to, or discussed with, Qatalyst Partners by LinkedIn. With respect to the LinkedIn Projections, Qatalyst Partners was advised by the management of LinkedIn, and Qatalyst Partners assumed, that the LinkedIn Projections had been reasonably prepared on bases reflecting the best currently available estimates and judgments of the management of LinkedIn of the future financial performance of LinkedIn and other matters covered thereby (...). Qatalyst Partners did not make any independent evaluation or appraisal of the assets or liabilities (contingent or otherwise) of LinkedIn, nor was Qatalyst Partners furnished with any such evaluation or appraisal. In addition, Qatalyst Partners relied, without independent verification, upon the assessment of LinkedIn management as to the existing and future technology and products of LinkedIn and the risks associated with such technology and products (...).

The following is a brief summary of the material analyses performed by Qatalyst Partners in connection with its opinion dated June 11, 2016 (...).

Illustrative Discounted Cash Flow Analysis

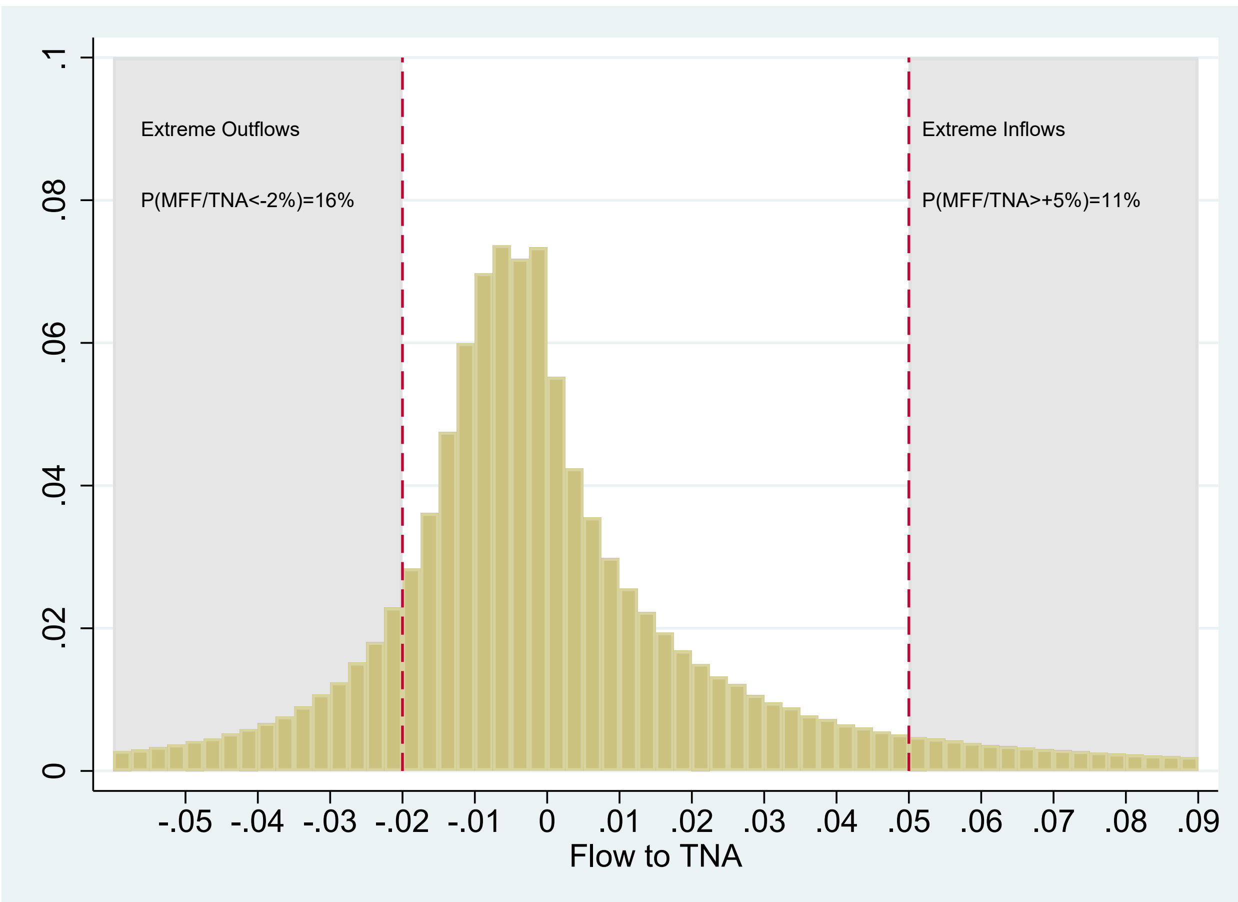
Qatalyst Partners performed an illustrative discounted cash flow analysis, which is designed to imply a potential, present value of share values for the Class A common stock as of March 31, 2016 by:

- *adding:*
  - *the implied net present value of the estimated future unlevered free cash flows of LinkedIn, based on the LinkedIn Projections, for the second through fourth quarters of calendar year 2016, and for calendar year 2017 through calendar year 2019 (which implied present value was calculated by using a range of discount rates of 10.0% to 13.0%, based on an estimated weighted average cost of capital for LinkedIn);*
  - *the implied net present value of a corresponding terminal value of LinkedIn, calculated by multiplying the estimated Adjusted EBITDA (...) by a range of multiples of fully-diluted enterprise value to next-twelve-months estimated Modified EBITDA of 12.0x to 18.0x and discounted to present value using the same range of discount rates (...);*
  - *the implied net present value of LinkedIn's forecasted tax attributes outstanding at the end of calendar year 2020, based on the LinkedIn Projections (which implied present value was calculated by using the same range of discount rates used in the first bullet above); and*
  - *LinkedIn's cash net of the face value of outstanding convertible notes and book value of minority interests, as provided by LinkedIn management as of March 31, 2016;*
- *applying a dilution factor of approximately 12%, as projected by LinkedIn management, to reflect the dilution to current stockholders (...)*
- *dividing the resulting amount by the number of fully-diluted shares of common stock outstanding (...) as provided by LinkedIn management.*

Based on the calculations set forth above, this analysis implied a range of values for the shares of common stock of $156.43 to $238.39 per share."

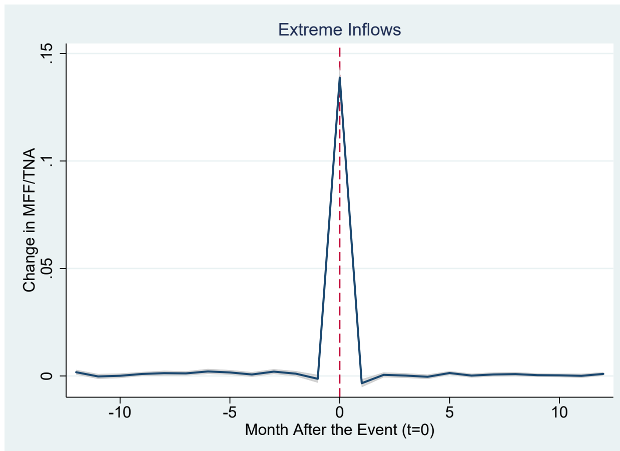
Selected extracts of LinkedIn preliminary proxy statement. Emphasis added by the authors. Source: https://www.sec.gov/Archives/edgar/data/1271024/000110465916130837/a16-14187_1prem14a.htm#FairnessOpinionofQatalystPartner_050648

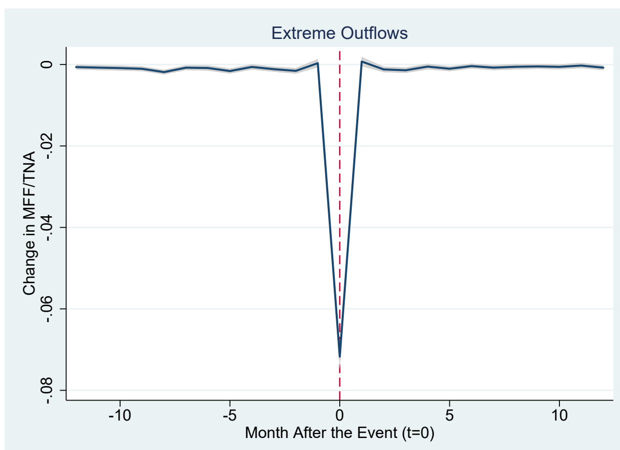
Figure IA 2: Monthly Mutual Fund Flow (MFF-to-AUM) Distribution



This figure shows the distribution of monthly net Mutual Fund Flows (MFF) expressed as a percentage of the Total Net Assets under management (TNA). We define extreme inflows (outflows) as positive (negative) MFF greater than 5% (2%) of TNA in absolute value. The unconditional probability of observing an extreme inflow (outflow) is 11% (16%). The sample includes all available observations *before* applying any filter (N=1,227,076).

Figure IA 3: Trend in MFF-to-AUM before and after an extreme flow





This figure shows the average change in monthly Mutual Fund Flow (MFF) expressed as percentage of TNA, before and after a fund experiences an extreme inflow (upper graph) or outflow (lower graph) at t=0. To estimate those changes, we regress MFF-to-TNA on leads and lags of variables indicating the occurrence of an extreme flow, controlling for fund and time fixed effects. We estimate the following equations at the fund-month-year level:

$$MFF\text{-}to\text{-}AUM_{j,m,y} = \alpha_j + \alpha_{m,y} + \sum_{k=-12}^{+12} b_{m-k} \mathbb{1}_{MFF\text{-}to\text{-}TNA_{j,m-k,y} > 5\%} + \epsilon_{j,m,y} \quad \text{(IA1)}$$

$$MFF\text{-}to\text{-}AUM_{j,m,y} = \alpha_j + \alpha_{m,y} + \sum_{k=-12}^{+12} b_{m-k} \mathbb{1}_{MFF\text{-}to\text{-}TNA_{j,m-k,y} < -2\%} + \epsilon_{j,m,y} \quad \text{(IA2)}$$

The upper (lower) graph plots the regression coefficients b_{m-k} obtained when estimating eq. IA1 (eq. IA2). The sample includes all available observations *before* applying any filter (N=1,227,076). Reported confidence intervals are at 90% level.

Table IA 1: k vs. Hurdle Rate in Earnings Conf. Calls

This table presents the results of regressing our measure for k on the Hurdle Rate extracted from earnings conference calls by Gormsen and Huber (2024). k is the discount rate assumed by the management team and their advisors for valuing the target company. 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:	k	
Specification	(1)	(2)
Hurdle Rate	1.45***	1.28***
	(13.85)	(9.15)
Constant	-0.05***	
	(-3.65)	
Year FE	No	Yes
Industry FE	No	Yes
N	686	686

Table IA 2: g vs. Managerial Sales Growth Guidance

This table presents the results of regressing the implied expected sales growth from managerial sales guidance for the coming year on our measure for g. g is the perpetual growth rate of future cash flows assumed by the management team and their advisors for valuing the target company. 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:	Sales Growth Guidance	
Specification	(1)	(2)
g	0.05***	0.04***
	(5.00)	(4.18)
Constant	0.03***	
	(18.61)	
Year FE	No	Yes
Industry FE	No	Yes
N	337	320

Table IA 3: Controlling for Offer Prices

This table presents the results of estimating Equation 22. 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. 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	IV - Stage 2		
Dep. Variable		k	
Specification	(1)	(2)	(3)
ΔQ	-0.62**	-0.89**	-0.42
	(-2.00)	(-2.23)	(-1.40)
Size (Log)	-0.06	-0.24***	-0.24***
	(-1.26)	(-12.12)	(-13.81)
Cash flow	-0.84***	-0.93***	-0.98***
	(-6.72)	(-6.44)	(-7.94)
Debt	-0.12	0	0.04
	(-0.91)	(-0.01)	(0.29)
Cash	0.67***	0.37**	0.56***
	(3.85)	(1.99)	(3.35)
Δ Sales	-0.16	-0.28*	-0.15
	(-1.19)	(-1.92)	(-0.98)
Dividend	-0.18***	-0.20**	-0.19***
	(-2.72)	(-2.46)	(-3.21)
Deal Value (Log)	-0.19***		
	(-4.21)		
Enterprise Value Paid / Assets		0.15**	
		(2.22)	
Premium Paid			-0.07**
			(-2.04)
Year FE	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes
N	1,228	1,231	1,231

Table IA 4: Differential Effects by Business Plan Horizon

This table presents the results of estimating Equation 23 when interacting all explanatory variables (including the fixed effects) with variables measuring the horizon of the business plan used in the target firm SIC2-industry. g is the perpetual growth rate of future cash flows assumed by the management team and their advisors for valuing the target company. *MF Buying Price Pressure* is the average dollar amount of monthly equity overvaluation due to fire purchases by Mutual Funds subject to extreme inflows during the 12-month period preceding deal announcement, and scaled by total assets. *MF Selling Price Pressure* is the average dollar amount of monthly equity undervaluation due to fire sales by Mutual Funds subject to extreme outflows during the 12-month period preceding deal announcement, and scaled by total assets. *BP Horizon* is the average business plan horizon by SIC2 industry from Dessaint, Foucault, and Frésard (2025) (before winsorizing in Column (1) and after winsorizing at the 1% level in each tail in Column (2)). Explanatory variables that are absorbed by the fixed effects or collinear with the slope fixed effects 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)
MF Buying Price Pressure × BP Horizon	-5.05	-4.35
	(-1.33)	(-1.13)
MF Selling Price Pressure × BP Horizon	4.07	3.71
	(1.55)	(1.37)
MF Buying Price Pressure	21.28	18.27
	(1.30)	(1.11)
MF Selling Price Pressure	-16.34	-14.8
	(-1.46)	(-1.29)
Year FE (Interacted)	Yes	Yes
Industry FE (Interacted)	Yes	Yes
Controls (Interacted)	Yes	Yes
N	1,196	1,196