Discount Rates vs. Cash Flows: What Do Managers Actually Learn from Stock Prices?

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ABSTRACT

Using new data on firm managers' beliefs about cash flow growth (g) and discount rates (k) in the context of M&A transactions, we examine what they learn from the target's stock prices. Initially, beliefs about g and k appear sensitive to stock price movements, suggesting that managers may learn about both. However, after correcting for endogeneity using noise in prices as an instrument, we find that only k reacts to price changes. This implies managers do not extract information about g from stock prices but do about k—with estimates indicating that they obtain up to 90% of their information about k from stock prices. Overall, these findings support the notion that stock markets provide managers with valuable insights about risk and the compensation investors require for bearing it, but not about cashflows, which managers already understand well.

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

JEL classification: D84, G14, G17, M41

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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)) studies its potential informational role: stock prices provide real-time information about firms' future prospects by aggregating the beliefs of myriad investors who trade on both public and private signals. As such, prices are a public good that can enrich economic agents' information sets and guide their decisions. In particular, there is now compelling evidence that *managers* rely on stock prices to inform their investment choices—the so-called "feedback effect".[1] 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 empirically investigate whether, and to what extent, managers learn about cash flows and discount rates from stock prices. A voluminous literature in asset pricing (referenced below) shows that stock prices incorporate information about both. Moreover, both are critical inputs for capital budgeting: to calculate the net present value (NPV) of an investment project or apply the internal rate of return (IRR), managers must assess future cash flows-—represented by their expected growth rate g—and the return required by investors—represented by the discount rate k. But what information do managers extract from stock prices? Do they learn about g, k, or both?

Addressing this question is important for future research as well as policy-making (e.g., on financial disclosure or market design). Without an understanding of what managers learn from prices, it is difficult to devise optimal financial disclosure policies, trading rules, or market structures that enhance capital allocation efficiency. Yet, most studies on the feedback from prices to investments remain silent on this specific question. They merely document that investment decisions respond to the information contained in stock prices,

[1] See Goldstein (2023) for a survey.

implying managerial learning.[2] But because these decisions reflect managers' beliefs about *both* g and k, this approach does not allow to disentangle what managers learn.

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

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

To guide the empirical analysis and generate clear testable predictions, we first present a simple model in which a firm manager updates her expectations about g and k for a target firm based on two private signals—one about g and the other about k—and a public signal—the target's stock price. The stock price contains information about both g and k, but it also incorporates noise unrelated to either variable (e.g., due to liquidity or sentiment shocks), which the manager cannot fully filter out. Ex-post, the econometrician observes the manager's expectations of g and k, the stock price, as well as some price variation due

[2] e.g., Chen, Goldstein, and Jiang (2007), Foucault and Fresard (2012), Foucault and Fresard (2014), Yan (2024), among many others (See survey by Goldstein (2023)).

to noise (as explained below), but not the private signals the manager received. When the manager learns from the price, her expectations of g and k respond to it—positively for g and negatively for k. However, standard OLS regressions of g (or k) on the price cannot consistently estimate these relationships. As the model shows, two sources of endogeneity undermine the interpretation of OLS estimates.

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

The second issue is an error-in-variable problem. Depending on what the manager wants to learn, one private signal is directly relevant, while the other is less so. However, the latter is still helpful for interpreting the stock price. For example, when forming an expectation of k, the manager can use her private signal about g to filter out price variations due to g, thereby obtaining a more precise signal about k from the price. For the econometrician, however, this introduces measurement error as the price is only an imperfect proxy for the filtered public signal the manager actually uses. As the model shows, this approximation can generate attenuation and bias the *absolute* value of the OLS estimates *downward*.

To overcome these issues, we use an identification strategy inspired by Dessaint, Foucault, Frésard, and Matray (2019) who show that noise in stock prices influences investment via managerial learning. Noise due to liquidity trading is plausibly exogenous to firm fundamentals and should therefore not affect beliefs about k and g *unless managers rely on prices as a source of information*. If it does, managers are misguided by stock prices. Paradoxically, this provides strong evidence of learning from stock prices—since this misguidance cannot come

from sources other than the price. We formalize this intuition and demonstrate that the econometrician can indeed exploit price variation due to noise trading to obtain consistent estimates using a 2SLS approach, with noise serving as an instrument for stock prices.

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

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

Our motivation for this substantial revamping of the approach initially proposed by Edmans, Goldtsein, and Jiang (2012) is to address recent concerns about the validity of their price pressure measure. In particular, we use *market portfolio* weights instead of fund-specific portfolio weights to mitigate selection bias, as highlighted by Berger (2023). Likewise, we use stock-date fixed effects to get around normalization issues and address the broader concern of Wardlaw (2020) regarding the need to control for fundamental information contained in contemporaneous price changes and total trading volume.[3] By construction, our measure is immune to this concern because it does not rely on any normalization, and is independent

[3]Wardlaw (2020) shows that normalizing the dollar amount of hypothetical trades for dollar volume - calculated as end-of-period stock price multiplied by trading volume - is problematic because it incidentally reintroduces the inverse of the stock return in the price pressure measure as well as information about fundamentals contained in trading volume at the stock level.

of the stock's price and trading volume, as well as other unobserved time-varying stock-level variables that may influence all funds trading the same stock at the same time.

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

Our main results are as follows. Before correcting for endogeneity (i.e., based on OLS regressions), managers' beliefs about g and k (for the same firm) are sensitive to stock prices. The sensitivity is positive for g and negative for k—indicating that managers revise g upward and k downward when prices rise, and of similar economic magnitude. Taken at face value, these results suggest that market feedback about both g and k is equally important to managers when valuing future 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 a statistically insignificant estimate of -0.03 for beliefs about g. This estimate is consistent with managers being already well-informed about g and hence not using stock prices to update their beliefs about it. In contrast, the sensitivity of k remains significantly negative at -0.89. It is larger in absolute value than the OLS estimate as predicted by our model when managers know little about k and a lot about g. This estimate implies that a one-standard deviation increase in stock prices leads to a downward revision of expectations about k of 0.89 standard deviation. Together, these results imply that stock prices provide managers with nearly all (89%) of their information about k, but do not contribute at all to their understanding of g.

Our model offers several additional predictions which are supported in the data. More distinctively, it predicts how the IV coefficient in the discount rate regressions depends on

the precision of the managers signals. Specifically, the IV coefficient should (i) decrease with the precision of the manager's private signal about k, (ii) increase with the precision of her private signal about g, and (iii) increase with the precision of price noise. Intuitively, as the private signal about k becomes more precise, the manager assigns *less* weight to the stock price when forming her posterior expectation of k, making it less sensitive to the noise in the price. Conversely, as the private signal about g becomes more precise or the noise in the stock price becomes less volatile, she places *more* weight on the stock price—since she can better filter out the noise related to k—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 signal precisions. 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.

It is worth noting that our conclusion—that managers extract information about discount rates from stock prices—aligns with recent findings in the asset pricing literature on the cross-sectional determinants of stock prices, though we do not contribute to this literature—rather than explaining stock prices, we take as given their information content. This literature documents that differences in valuation ratios across firms are driven more by differences in discount rates or potential mispricing than by differences in future profitability (i.e., cash flows), implying that individual stock prices embed a wealth of information about discount rates. 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.[4]

Overall, we find that managerial beliefs about k are sensitive to (noise in) prices, but be-

[4]In contrast, earlier papers (Fama and French (1995), Vuolteenaho (2002) (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.

liefs about g are not, suggesting that managers already know a lot about g, but little about k. We conclude that stock prices affect managers' beliefs about discount rates, but do not convey additional information to them about future cash flows. In short, they learn from prices about k, not about g—at least in the context of valuing M&A investment opportunities.

A common counterargument to the idea that managers learn from stock prices is that, as key decision-makers with privileged access to first-hand information, they possess superior knowledge of the firm's fundamentals. Our response is twofold. First, while a manager may be more informed than any individual trader, financial markets excel at aggregating dispersed information from numerous participants. The manager is not likely to already know *everything* the price conveys. For example, Hutton, Lee, and Shu (2012) document that analysts often have an informational edge over managers in assessing the impact of macroeconomic conditions on a firm. Second, determining a firm's discount rate requires not only understanding the firm's risk profile but also assessing the compensation that investors demand for bearing that risk. Unlike firm-specific fundamentals, such information is not readily available to managers but is instead embedded in stock prices.[5] In light of these arguments, our findings —that stock prices influence managers' beliefs about discount rates but not about cash flows—suggest that financial markets aggregate and convey to managers valuable insights about risk and its compensation, but do not provide additional information about cashflows which managers may already possess.

The rest of the paper is organized as follows. In Section II, we develop our main hypothesis. Section III presents the data and our identification strategy. In Section IV, we report our findings. Section V examines the validity of both the relevance condition and the exclusion restriction condition of our instrument. Section VI concludes. All definitions for the variables used in our tests are reported in the Appendix.

[5]As Subrahmanyam and Titman (1999) note: "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."

II 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 as simple as possible. Our objective is simply to derive clear and sharply contrasting testable predictions depending on whether or not the manager incorporates information from the stock price in her estimates.

A Theoretical framework

A.1 Setup

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

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

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

To provide some flexibility in matching the model to the data, we introduce random noise into the stock price: we assume that the price is a function of $q \equiv g - k + \theta$ where θ is a noise term. Noise θ captures price fluctuations unrelated to the firm's fundamentals (that

is, to g and k), which could stem from liquidity constraints or behavioral motivations. In summary, the price reveals $q = g - k + \theta$ to the manager.

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

A.2 Manager's Posterior Beliefs

The following proposition and corollary characterize the manager's posterior beliefs about the growth rate g and the discount rate k depending on whether or not she incorporates information from the stock price in her estimates.[6]

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

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

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

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

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

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

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 (i.e., $\tau_{g|S_g,S_k,q}$) is the sum of three components: the precision of her prior τ_g, the precision of her private signal $\tau_{\varepsilon g}$, and the precision of the

[6] The proofs of our propositions are omitted for brevity.

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

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

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

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

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

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

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

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

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

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

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

B Predictions

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

B.1 OLS Regressions

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

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

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

The following proposition characterizes the OLS regression coefficients.

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

If the manager learns from the stock price:

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

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

If the manager does not learn from the stock price:

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

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

Proposition 2 shows that OLS regression coefficients alone cannot distinguish between active learning from the price and a passive correlation between the manager's expectations and the price (as would occur if, e.g., the manager already knows the information contained in the price). It predicts a positive coefficient for g, and a negative coefficient for k, regardless of whether or not the manager learning from the price. This difficulty arises because the private information of the manager (S_g and S_k) is not observed by the econometrician and cannot be controlled for in the regressions.

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

B.2 IV Regressions

Next, we consider IV regressions using noise, θ, as an instrument for the stock price, q. In the base case, we assume that θ is not observed by the manager *ex-ante*—when observing q, she cannot distinguish noise from information about g and k—but it is observed by the econometrician *ex-post*. Notably, it is not necessary for the econometrician to observe the *entire* noise term.[7], nor is it needed that the manager be unable to *completely* filter it out. The same predictions hold as long as their ability to identify noise is only limited.

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

If the manager learns from the stock price:

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

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

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

If the manager does not learn from the stock price:

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

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

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

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

B.3 Cross-Sectional Predictions

Effect of the precisions of priors and private signals

The IV regression coefficients exhibit distinct patterns in relation to the precisions of the non-price information (i.e., priors and private signals) that allow to further identify learning effects when we consider a cross-section of firms. 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. [8]

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 non-linear system that links together prior, private signal, and posterior precisions. This approximation reveals that the prior and private signal precisions about k (g) increase with the posterior

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

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 3: *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 noise. Less volatile stock noise (higher τ_θ) makes the price signal more informative, thereby raising the IV coefficients for both g and k, holding fixed the precisions of priors and private signals. When conditioning on posterior precisions, this prediction continues to hold (e.g., for $|b_k^{IV}|$) provided the prior and private signals (about g) are more precise than the price signal (about g).

Prediction 4: *With learning from the stock price, the IV regression coefficient increases in absolute value with the precision of stock price noise. This holds without controlling for posterior precisions, as well as with controls provided the prior and private signals are more precise than the price signals. In contrast, without learning from the stock price, the IV coefficients remain unaffected by the precision of stock price noise.*

To illustrate Predictions 3 and 4, consider the case where the manager learns about k but not g from the stock price—in line with what we find in the data. In the model, this happens when prior or the private signal about g are highly precise. In this case, the posterior precision about g is primarily driven by the precisions of the non-price signals: $\tau_{g|S_g,S_k,q} \approx \tau_g + \tau_{\varepsilon g}$. As a result, the precision of the price signal about k is approximately determined by the posterior precision about g: $\tau_{qk} \approx (\frac{1}{\tau_{g|S_g,S_k,q}} + \frac{1}{\tau_\theta})^{-1}$. These relationships imply $b_g^{IV} \approx 0$ and

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

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

Magnitudes of OLS and IV coefficients

Comparing the OLS and IV regression coefficients leads to an additional prediction. When the manager does not learn from the price, the IV coefficients are zero, making the OLS coefficients clearly larger (in absolute value) than their IV counterparts. This conforms to the general intuition that the IV method corrects for endogeneity bias, which inflates OLS estimates. In our context, the bias arises from the passive correlation between the manager's posterior beliefs and the stock price.

However, when the manager does learn from the price, the comparison is less clear due to an additional effect. In the OLS regression of the manager's expectation of g, k in the stock price acts as noise. Indeed, it contributes to price variations, but it is only weakly correlated with the manager's expectation of g since it provides her with indirect information about g. The IV regressions, by removing the influence of k from the stock price, increase the coefficients. This effect is analogous to the well-known attenuation bias, where measurement errors in the independent variable tend to reduce OLS estimates relative to IV estimates. Here, k introduces measurement error in the g regression while g injects measurement error in the k regression.

This attenuation effect is stronger in the growth rate 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 accurate (i.e., $\tau_{\varepsilon g}$ smaller), while the effect of τ_k is ambiguous. Similarly, in the discount rate regression, the attenuation effect 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 accurate (i.e., $\tau_{\varepsilon k}$ smaller), with the effect of τ_g being ambiguous.

An implication is that if the manager private signals are highly accurate for g but poor for k (i.e., $\tau_{\varepsilon g}$ large but $\tau_{\varepsilon k}$ small), then she learns a little or nothing about g from the price

but learns a lot about k. As noted, this is the pattern we uncover in the data. In this case, the OLS coefficients will be large (in absolute value) in both regressions since those regressions do not distinguish active learning from a passive correlation. In contrast, the IV coefficients—which isolate active learning—will be low to zero in the g regression and large (very negative) in the k regression; moreover the IV coefficient for k will be larger (in absolute value) than the corresponding OLS coefficient because of a powerful attenuation effect.

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 5: *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 accurate. In the absence of learning from the price, in contrast, the IV coefficients are always smaller (in absolute value).*

III Data and Methodology

To test our predictions, we need data on managers' expectations, stock prices, as well as measures of mispricing. This section describes our data sources and how we construct mispricing measures (Appendix I provides a summary of all the variables used in our tests and their definition).

A Data

A.1 Expectations Data

We identify expectations about future cash flow growth g and firm discount rate k using M&A fairness opinions data from Thomson SDC. Fairness opinions are valuation reports prepared by investment bankers to evaluate whether the price offered in a transaction is

fair to the shareholders of the target, the seller, or the acquirer. These reports describe the valuation methods used, including assumptions made by the management team and their advisors about the discount rate (k) and perpetual growth rate of future cash flows (g) for the target company. Whenever a range (rather than a single number) is reported in the fairness opinion letter, we use the range mid-point as the estimate for k and g, and the inverse of the range size as an estimate for the precision of managerial posterior beliefs about k and g.

Thomson SDC reports information about discount rate k under the items FO_DCF_RATE_LOW and FO_DCF_RATE_HI representing the low and high end of the reported range, respectively. Similarly, the range assumed for cash flow growth g is reported under items FO_DCF_PERP_LOW and FO_DCF_PERP_HI.

[Insert Figure I about here]

Figure I shows presents statistics for k and g before applying any filters. The sample includes all buy- and sell-side fairness opinions reported in SDC. It includes 3,250 observations about k and 1,632 observations about g across US and Non-US targets between 1999 and 2022. On average, the expected discount rate k and growth rate g are 12.9% and 3.7%, respectively. The Pearson correlation between both is positive (0.57), which is consistent with our model prediction when managers learn from prices (despite k and g being assumed unconditionally uncorrelated).

A.2 Price Pressure Data

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

An important feature of our price pressure measure is that it does not rely on actual fund

trades. Like Edmans, Goldstein, and Jiang (2012), we use hypothetical, rather than actual, trades to isolate holdings changes mechanically induced by extreme flows, rather than by active trading decisions. However, unlike Edmans, Goldstein, and Jiang (2012), we do not base hypothetical trades on the fund's previously disclosed portfolio. Instead, we use the market portfolio (which is common to all funds), assuming that each fund adjusts its holdings in response to extreme flows proportionally to each stock's weight in the market portfolio at the beginning of the month. We do so to further mitigate the concern that our measure captures private information embedded in the fund manager's past trading decisions, and to better isolate the mechanical stock holding variations induced by the plausibly exogenous variations in fund size caused by extreme flows.

Another departure from the approach initially proposed by Edmans, Goldstein, and Jiang (2012) is that our price pressure measure does *not* require any normalization for trading volume. We do not need this normalization because we do not use hypothetical trades in *dollar value* but in *volume*. which we use to decompose (i) changes in stock holding by fund and (ii) monthly stock return by stock. Specifically, we proceed in three steps. First, we estimate by OLS the impact of a fund's hypothetical tradeing volume on its percentage ownership of a stock at the fund-stock level, *controlling for stock-date fixed effects*. Second, we aggregate this impact across funds to obtain a stock-level estimate of change in Mutual Fund ownership (in percentage) induced by extreme flows. Finally, we estimate the impact of extreme flows on prices by regressing monthly abnormal (industry-adjusted) returns on the previously estimated changes in ownership.

We use this alternative decomposition to address Wardlaw (2019) concern that normalizing for dollar volume—calculated as end-of-period stock price multiplied by trading volume—is problematic because it inadvertently reintroduces the inverse of stock returns into the price pressure measure along with fundamental information contained in trading volume. By construction, our measure is immune to this critic because it is unrelated to the price and trading volume, as well as any other unobserved time-varying stock-level variable that may affect all funds trading the same stock at the same time. Any such variation is

fully absorbed by the stock-date fixed effects.

Finally, we exploit both tails of the flow distribution and build two separate instruments (instead of only one, based on outflows, as is customary). For that, we estimate the effect of hypothetical trades on changes in ownership separately for extreme monthly inflows (more than 5% of fund assets) and outflows (more than 2% of fund assets), and then isolate the effect of both fire sales and fire purchases on prices by regressing monthly abnormal (industry-adjusted) returns on the previously estimated changes in ownership. We find that an increase (decrease) in ownership following extreme inflows (outflows) positively (negatively) affects stock returns and that this effect is only transient, consistent with both capturing non-fundamental variation in prices only.

Once noise in returns by firm is isolated, we estimate noise in prices by multiplying noise in monthly stock returns by the market capitalization at the beginning of the period, and noise in Q by scaling noise in prices by total assets. *MF Buying Price Pressure* (*MF Selling Price Pressure*) is the average noise in Q over the last 12 months induced by extreme monthly inflows (outflows).

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

A.3 Other Data

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

A.4 Summary statistics

Our final sample includes all U.S. target firms from SDC 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. We further require that g, k, Q are not negative, and that the

change in Q is less than 10 in absolute value. The sample starts in 1999 and ends in 2022.

[Insert Table I about here]

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

B Methodology

B.1 OLS Regressions

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

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

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

where $g_{i,t}$ and $k_{i,t}$ are the expected growth and discount rate (both standardized by the within-industry j standard deviation) of target i at the time of deal announcement t; $\Delta Q_{i,t-1}$ is the change in Q over the last observable fiscal year of firm i before deal announcement. The main coefficients of interest are b_g and b_k. The learning hypothesis predicts $b_g > 0$, and $b_k < 0$.

We include industry (ϕ_j) and deal year (η_y) fixed effects as well as control variables for known determinants of expected free cash flow growth (g) and firm-level return (k). In particular, we control for size, level of (and change in) realized cash flows, historical capital structure and payout policy. The industry fixed effects absorb time-invariant industry component, while year fixed effects absorb annual variation common across firms.

B.2 2SLS Regressions

Next we use 2SLS regressions. Estimating b_g and b_k by OLS is problematic because equations 18 and 19 are subject to a classic endogeneity problem (see section B.1). Managers of the bidding firm and their advisors have access to various sources of information and already possess information themselves before observing the price of the target. Because the target price may also reflect this unobserved information, finding $b_g > 0$ and $b_k < 0$ does not imply prices contain new information to the manager. The same common information could jointly affect prices and managerial beliefs. Under this alternative interpretation, prices do not affect the beliefs of the manager of the bidding firm and its advisors, but simply passively reflect the private information she already has.

To provide evidence of active learning, one would like to control for the information known by the manager before observing ΔQ in equations 18 and 19, but this information cannot be controlled for because we, as econometricians, do not know what managers know. Hence, $b_g > 0$ and $b_k < 0$ even in the absence of learning (see Proposition 2 and Prediction 1).

To overcome this omitted variable problem, we adopt an identification strategy similar to Dessaint, Foucault, Frésard, and Matray (2019). This strategy relies on the observation that prices are noisy signals about cash flow and discount rate news. Dessaint, Foucault, Frésard, and Matray (2019) shows that another prediction of the learning hypothesis is that managers should react to the noise contained in the price, provided they cannot easily separate noise from real information about g and k.

Section B.2 above formalizes this prediction. Without learning, managers do not look at prices or ignore them, so their beliefs should *not* depend on price variation due to noise or liquidity trading. If, instead, noise in prices influences their beliefs, it must be that they are looking at them. Showing that managerial beliefs are sensitive to noise provides a higher level of proof for the learning hypothesis because noise is plausibly unrelated to managerial private information about g and k.

We implement this identification strategy with an instrumental variable approach. We

estimate by 2SLS whether prices affect beliefs about g and k, using both buying price pressure caused by mutual funds subject to extreme inflows ($Z1$) and selling price pressure following extreme outflows ($Z2$) as instruments for $\Delta Q_{i,t-1}$.

The first-stage regression we estimate is

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

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

The second-stage regressions are

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

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

where $\widehat{\Delta Q_{i,t-1}}$ is the predicted change in Q over the last observable fiscal year of firm i before deal announcement from the first-stage regression. Notice the first stage regression is the same whether we want to estimate b_g or b_k, because the endogenous regressor in equations 18 and 19 (ΔQ) is the same. The main coefficients of interest are again b_g and b_k. The learning hypothesis predicts $b_g > 0$ and $b_k < 0$.

B.3 Reduced form IV Regressions

An alternative to the 2SLS approach is to regress g and k directly on noise in prices, as we do in the theory section (see section B.2). As discussed in section B.2, the learning hypothesis predicts that both g and k should be sensitive to noise if and only if managers are actually learning from the price (See Prediction 2). Hence, we also estimate

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

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

Because $Z1_{i,t}$ (hereafter *MF Buying Pressure*) measures target over-valuation in dollar scaled by total assets, the learning hypothesis predicts $\beta_{1,g} > 0$ and $\beta_{1,k} < 0$. However, $Z2_{i,t}$ (hereafter *MF Selling Pressure*) measures target under-valuation in dollar scaled by total assets (in *absolute* value). Hence, the learning hypothesis predicts $\beta_{2,g} < 0$ and $\beta_{1,k} > 0$.

The above regressions are sometimes referred to as reduced form IV regressions. These regressions achieve the same level of proof as the 2SLS approach because they rely on the same source of noise in the price. We use this alternative approach despite being equally informative as the 2SLS for three reasons: (i) for consistency with Proposition 3 - where g and k are directly regressed on noise, (ii) for convenience - to study cross-sectional variation and test our ancillary predictions (e.g., Prediction 3), (iii) for robustness - to verify that both an increase and decrease in the price indeed lead to beliefs' updating of opposite sign.

IV Results

This section tests the learning hypothesis about g and the learning hypothesis about k. We first study how expectations about changes in cash flows (the perpetual growth rate g) and future returns (the discount rate k) relate to the same realized changes in market prices. Then we establish causality using plausibly exogenous variation in prices, not directly observed by managers nor their financial advisors.

A Main Results

[Insert Table II about here]

Table II presents our main results. All tests were performed with the exact same sample of firms. Hence, differences in estimation results cannot be due to sampling variation.

A.1 Learning about g

In Columns (1) to (4), we study how prices affect beliefs about g. Column (1) displays estimates from OLS regressions (Equation 18) and shows that beliefs about g are sensitive to prices. This sensitivity is positive ($b_g > 0$), suggesting manager could learn from prices about g. However, Columns (2) and (3) show that this sensitivity disappears (b_g decreases in absolute value, flips sign, and is no longer statistically significant) when using noise due to liquidity trading by mutual funds as instrument for ΔQ. Column (2) estimates equation 20 and shows that the relevance condition is satisfied. Positive (Negative) price pressure captured by the variable *MF Buying Price Pressure* (*MF Selling Price Pressure*) generates positive (negative) change in price, ΔQ. Column (3) estimates Equation 21 and shows that these price changes have no impact on g; that is, managers' beliefs about g are not sensitive to price variation plausibly unrelated to information already known to managers and their financial advisors ($b_g = 0$). Column (4) corroborates this result. We estimate Equation 23 and find that neither buying price pressure, nor selling price pressure affects beliefs about g.

A.2 Learning about k

In Columns (5) to (8) we study how prices affect managers' beliefs about k. In Column (5), we report the results from estimating Equation 19. We find that beliefs about k are sensitive to prices. This sensitivity is negative ($b_k < 0$), suggesting managers may learn from prices about k. In Columns (6) and (7), we find that this sensitivity is still negative when using noise due to liquidity trading by mutual funds as instrument for ΔQ. Column (6) estimates Equation 20. Since the endogenous regressor in Column (5) is the same as in Column (1), the results are the same as in Column (2). In Column (7), we report the results from estimating Equation 22 and find that independent price changes affect k; that is, beliefs about k are sensitive to price variation plausibly unrelated to information already known by the manager and her financial advisors ($b_k < 0$). Column (8) corroborates this result. We estimate Equation 24 and find that beliefs about k are lower after the target price experiences buying price pressure, and greater in case of selling price pressure in the

12-month period before deal announcement.

A.3 Interpreting OLS vs. IV coefficients

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

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

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

Overall, Table II shows that managerial beliefs about k are sensitive to prices, but beliefs about g are not, suggesting that managers already know a lot about g, but little about k. We conclude that stock prices affect managers' beliefs about discount rates, but do not convey additional information to them about future cash flows. In short, they learn from prices about k, not about g - at least in the context of valuing M&A investment opportunities.

A.4 Interpreting Economic Magnitude

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

In our theoretical framework, the IV coefficients represent (in absolute value) the proportion of information about g or k that the manager obtains from observing the price. For example, b_k is the share (between 0 and 1) of the manager's posterior precision about k that is derived from the information contained in the price (and combined with observing a private signal about g).

Therefore, a coefficient of 0.89 indicates that managers obtain 89% of their information about k from the price. Likewise, a statistically insignificant coefficient of -0.03 means they get no information at all about g from the price.

B Cross-sectional Variation

Theory predicts variation in b_g and b_k depending on the precision of managerial private information about g ($\tau_{\varepsilon g}$) and k ($\tau_{\varepsilon k}$) (see Prediction 3), and on price informativeness τ_θ (see Prediction 4). We test those predictions in this section.

To test prediction Prediction 3, we exploit data on reported ranges for g and k to measure precision τ. Ideally, we would like to observe this range before managers observe the price—not after, but we expect both to be highly positively correlated, especially across firms. A larger posterior estimation range (ex-post) is arguably more likely to be observed when prior information (ex-ante) was less precise to begin with. Hence, we use the inverse of

the reported range for g (k) as an approximation for the precision $\tau_{\varepsilon g}$ ($\tau_{\varepsilon k}$) of the private information of the manager and her advisors about g (k).

To test prediction Prediction 4, we exploit the distribution of the noise introduced by mutual funds subject to extreme flows. Specifically, we calculate the inter-quartile range of the net monthly mis-valuation introduced by Mutual Funds subject to both, extreme inflows and extreme outflows during the 12-month period preceding deal announcement (hereafter *MF Noise Range*), and take the inverse as approximation for τ_θ.

[Insert Table III about here]

Table III presents the results of interacting noise in prices in Equations 23 and 24 with the inverse of the reported range for g and k (our empirical counterparts for $\tau_{\varepsilon g}$ and $\tau_{\varepsilon k}$) and with the inverse of the inter-quartile range of mis-valuation due to mutual funds (our empirical counterpart for τ_θ)

Prediction 3 predicts weaker sensitivity to noise when managers are better informed to begin with, and stronger sensitivity when they can better extract information from the price by removing the information unrelated to what they wish to learn.

Prediction 4 predicts stronger sensitivity to noise in absolute value when prices are more informative (*MF Noise Range* is low).

B.1 Variation in *g*-to-noise sensitivity

In Columns (1) to (4), we focus on the sensitivity of g to noise in prices, and find no significant variation across firms. This absence of variation is hardly surprising given prior evidence that noise does not affect g to begin with. Our evidence that noise has no effect on g unconditionally (Table II, Column 4) is also true conditionally (Table III, Columns 1 to 4).

B.2 Variation in *k*-to-noise sensitivity

In Columns (5) to (8), we focus on the sensitivity of k to noise in prices. Quite remarkably this sensitivity systematically varies in the expected direction when managers learn from the

price about k. All coefficients on interaction terms have a sign in line with Prediction 3 and 4; and almost all of them are statistically significant, or marginally so.

Column (5) shows weaker sensitivity to noise when the inverse of the reported range for k is high. When managers are better informed about k ($\tau_{\varepsilon k}$ is higher), the negative impact of *MF buying (selling) price pressure* is lower (higher). In Column (6), the sensitivity is greater when the inverse of the reported range for g is high. When managers are better informed about g ($\tau_{\varepsilon g}$ is higher), managers can extract more information about k from the price, by removing the information about g. As a result, they put more weight on prices, and thus on noise. Hence the lower (higher) negative impact of *MF buying (selling) price pressure*. In Column (7), the sensitivity is greater when prices are less noisy to begin with (i.e., *MF Noise Range* is low). When prices are more informative (τ_θ is high) managers can extract more information about k from the price and thus put more weight on noise. Hence the lower (higher) negative impact of *MF buying (selling) price pressure*. Column (8) provides similar evidence when testing simultaneously all three effects in the same regression.

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

V Instrument validity

In this section, we investigate whether the conditions for our instrument validity are satisfied.

A Relevance

A first identifying assumption for using hypothetical trades as instrument is that they indeed affect the fund position, and that changes in stock ownership affect prices.

We first test whether hypothetical purchases and sales indeed lead to a change in ownership. Results are reported in Table IV.

[Insert Table IV about here]

We find that purchases and sales induced by fund inflows and outflows indeed lead to significant changes in percentage of stock ownership, and that this change goes in the expected

direction (increasing for purchases, decreasing for sales)

Next, we test whether hypothetical purchases and sales affect prices. Results are reported in Table V.

[Insert Table V about here]

We find that hypothetical purchases (sales) by mutual funds experiencing large inflows (outflows) positively (negatively) affect returns.

B Exclusion Restriction

The exclusion restriction cannot be formally tested, but it can be falsified.

[Insert graph III and graph IV about here]

We show that extreme flows are isolated events (see graph III), and most importantly that the effect on prices reverts overtime (see graph IV), which is consistent with our measure of price pressure capturing noise only.

VI Conclusion

Most existing research on market feed-back effects posits that managers learn about expected cash flow growth g, and not about expected return by investors k. We investigate whether this premise is correct using new data about g and k.

We find that both are sensitive to prices. This sensitivity is positive for g, negative for k, and of equal magnitude, suggesting managers could learn from financial markets about both cash flows and discount-rate. However, after correcting for endogeneity using noise in prices as a plausible source of independent variation, we find that only k reacts to prices.

We conclude that stock prices affect managers' beliefs about discount rate, but do not convey additional information to them about cash flows.

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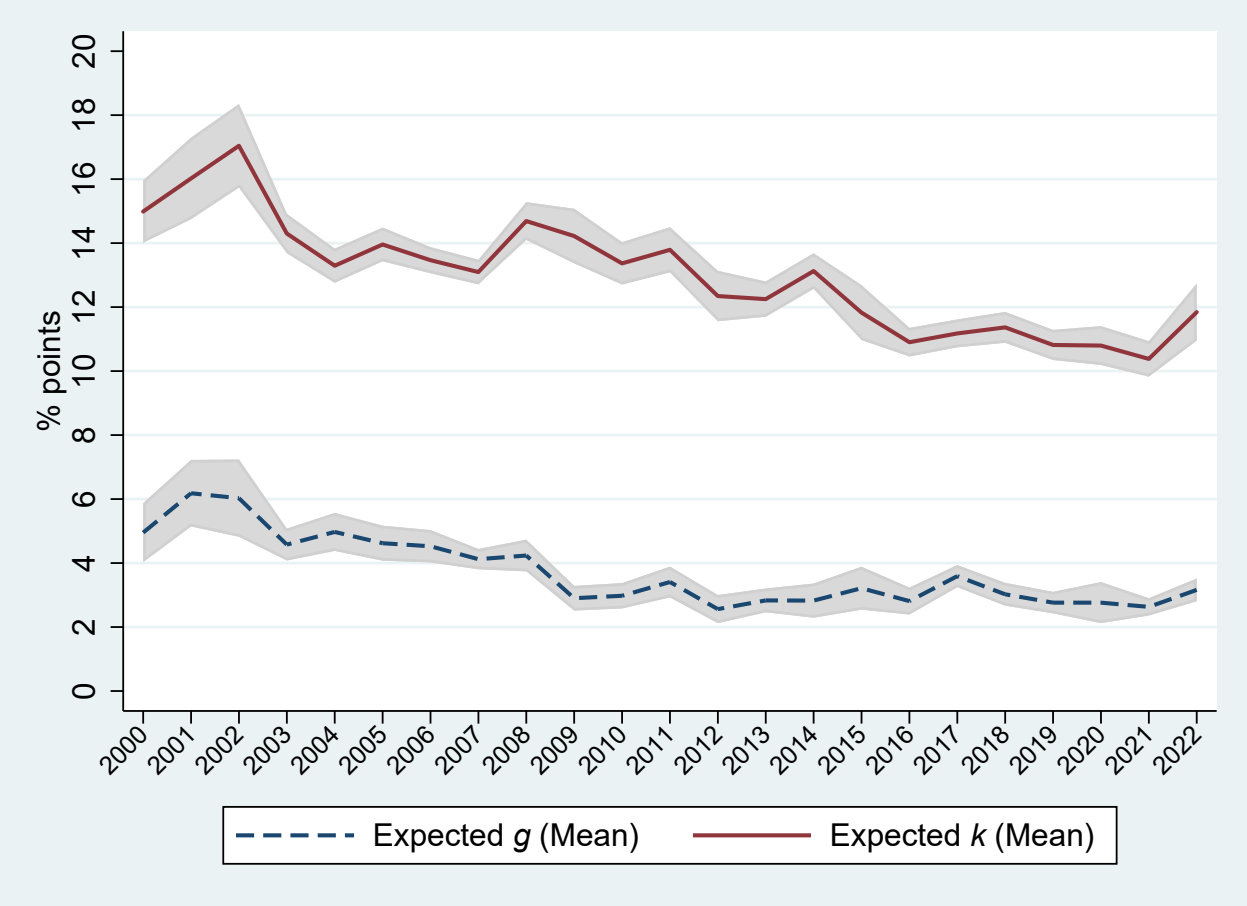
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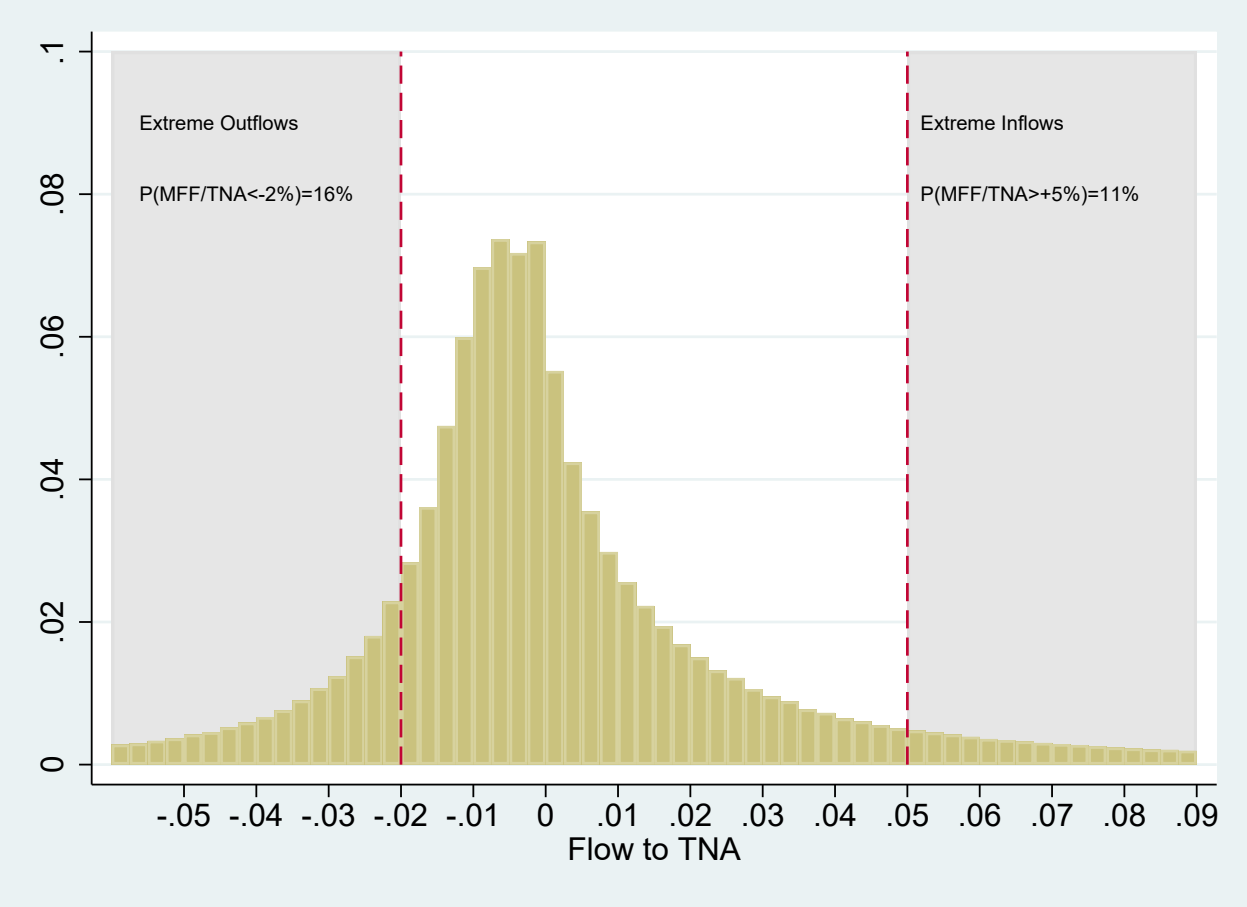
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Figure I: Expected g and k by year



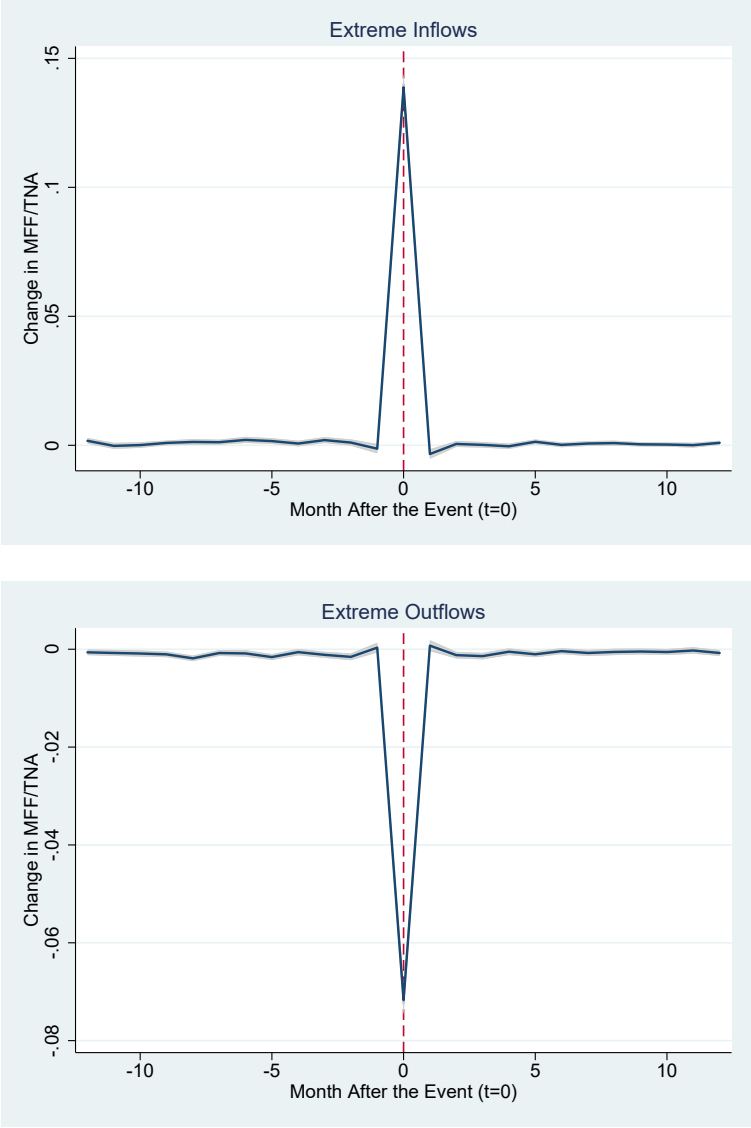
This figure plots the annual average expected growth rate g and discount rate k used by managers and their financial advisors for valuing M&A investment opportunities. Detailed variable definitions are in Appendix I. The sample includes all available observations for k (N=3,250) and g (N=1,632) *before* applying any filter. Reported confidence intervals are at 90% level.

Figure II: 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 III: Trend in MFF-to-AUM before and after an extreme flow



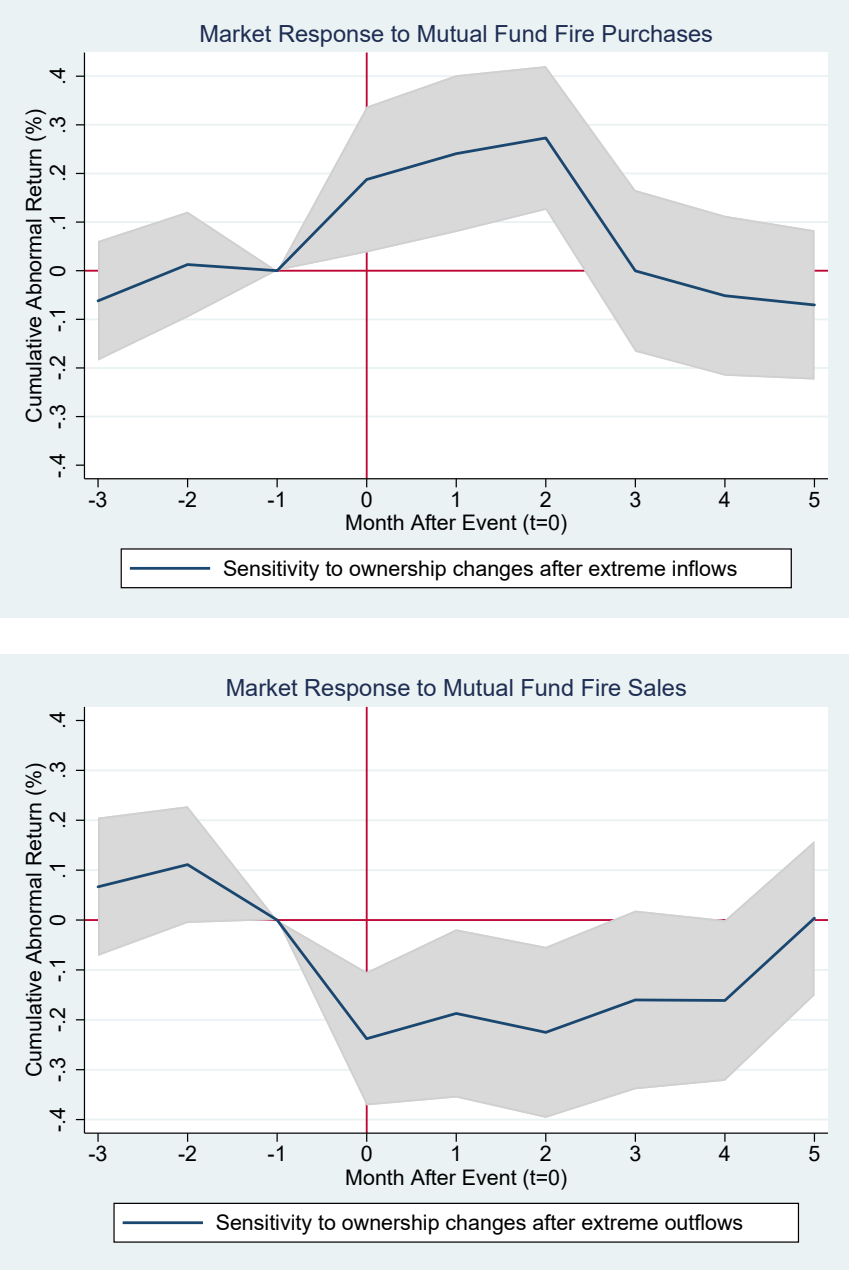
This figure shows the average change in monthly Mutual Fund Flow (MFF) expressed as percentage of TNA, before and after a fund experiences an extreme inflow (upper graph) or outflow (lower graph) at t=0. To estimate those changes, we regress MFF-to-TNA on leads and lags of variables indicating the occurrence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

$$\textit{MFF-to-AUM}_{j,m,y} = \alpha_j + \alpha_{m,y} + \sum_{k=-12}^{+12} b_{m-k} \mathbb{1}_{\textit{MFF-to-TNA}_{j,m-k,y} > 5\%} + \epsilon_{j,m,y} \tag{25}$$

$$\textit{MFF-to-AUM}_{j,m,y} = \alpha_j + \alpha_{m,y} + \sum_{k=-12}^{+12} b_{m-k} \mathbb{1}_{\textit{MFF-to-TNA}_{j,m-k,y} < -2\%} + \epsilon_{j,m,y} \tag{26}$$

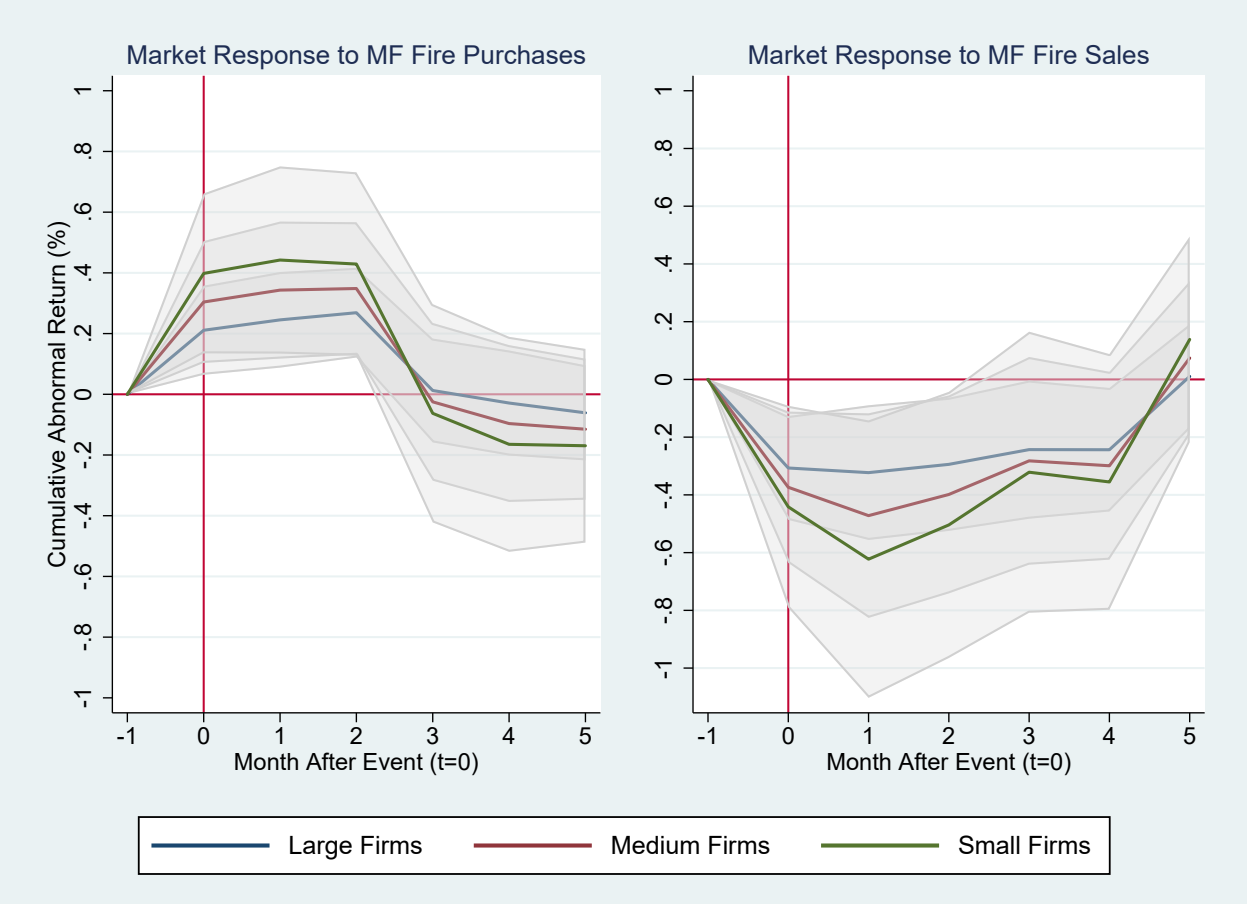
The upper (lower) graph plots the regression coefficients b_{m-k} obtained when estimating eq. 25 (eq. 26). The sample includes all available observations *before* applying any filter (N=1,227,076). Reported confidence intervals are at 90% level.

Figure IV: Extreme MFF Price Pressure Effects



This figure shows the average Target Cumulative Abnormal (FF49-industry adjusted) Return after a 1 percentage point variation in mutual fund ownership due to the underlying funds experiencing extreme inflows (upper graph) or extreme outflows (lower graph) at t=0. The graphs plot the cumulated sum of the regression coefficients reported in Table V, 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 V: 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 (upper graph) or extreme outflows (lower 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 main variables employed 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 expected 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. $MFBuyingPricePressure$ is the average dollar amount of monthly overvaluation introduced by Mutual Funds subject to extreme inflows during the 12-month period preceding deal announcement, and scaled by total assets (from the last available financial statement). $MFSellingPricePressure$ is the average dollar amount of monthly undervaluation introduced by Mutual Funds subject to extreme outflows during the 12-month period preceding deal announcement, and scaled by total assets (from the last available financial statement). All variables are defined in Appendix I. Explanatory variables that are absorbed by the fixed effects are omitted from the regression. t-statistics in parentheses are based on standard errors clustered by Target SDC industry. Symbols ***, **, and * denote statistical significance at the 1%, 5%, and 10% level, respectively.

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

Table III: Cross-Sectional Variation

This table presents the results of estimating Equation 23 and Equation 24 when interacting all explanatory variables with variables measuring the precision of managerial private information about k (Columns 1, 4, 5 and 8), g (Columns 2, 4, 6, and 8), and the noisiness of the price (Columns 3, 4, 7 and 8). g (k)is the perpetual growth rate of future cash flows (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. $MFBuyingPricePressure$ is the average dollar amount of monthly overvaluation introduced by Mutual Funds subject to extreme inflows during the 12-month period preceding deal announcement, and scaled by total assets (from the last available financial statement). $MFSellingPricePressure$ is the average dollar amount of monthly undervaluation introduced by Mutual Funds subject to extreme outflows during the 12-month period preceding deal announcement, and scaled by total assets (from the last available financial statement). *k Range* is the range reported for k. *g Range* is the range reported for g.*MF Noise Range* is the inter-quartile range of the net monthly mis-valuation introduced by Mutual Funds subject to both, extreme inflows and extreme outflows during the 12-month period preceding deal announcement. Explanatory variables that are absorbed by the fixed effects (like the inverse of *k Range*, *g Range*, and *MF Noise Range*) are omitted from the regression. 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				k			
Specification	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
MF Buying Price Pressure $\times(k$ Range$)^{-1}$	0.04			0.09	0.17***			0.22***
	(0.58)			(1.11)	(3.43)			(3.31)
MF Selling Price Pressure $\times(k$ Range$)^{-1}$	0.01			-0.05	-0.08**			-0.12**
	(0.24)			(-0.93)	(-2.28)			(-2.48)
MF Buying Price Pressure $\times(g$ Range$)^{-1}$		-0.06		-0.06		-0.07*		-0.11**
		(-0.95)		(-0.83)		(-1.93)		(-2.28)
MF Selling Price Pressure $\times(g$ Range$)^{-1}$		0.06		0.06		0.05***		0.08**
		(1.42)		(1.23)		(2.68)		(2.52)
MF Buying Price Pressure $\times$(MF Noise Range$)^{-1}$			-0.04	-0.02			-0.10*	-0.10*
			(-0.69)	(-0.41)			(-1.88)	(-1.67)
MF Selling Price Pressure $\times$(MF Noise Range$)^{-1}$			0.04	0.01			0.06	0.05
			(0.73)	(0.19)			(1.24)	(0.99)
MF Buying Price Pressure	-0.22	3.84	0.49	0.48	-15.06***	-3.27	-5.59**	-7.01*
	(-0.04)	(0.66)	(0.13)	(0.06)	(-3.64)	(-1.15)	(-2.08)	(-1.74)
MF Selling Price Pressure	-1.55	-3.53	-0.1	-2.34	5.80***	0.28	2.11	2.06
	(-0.38)	(-0.95)	(-0.04)	(-0.53)	(2.55)	(0.18)	(1.38)	(0.85)
Year FE (Interacted)	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE (Interacted)	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls (Interacted)	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	1,041	1,041	1,041	1,041	1,041	1,041	1,041	1,041

Table IV: Mutual Fund Flows and Ownership Changes

This table presents the results of estimating Equation 35. The estimation is at the fund-stock-month-year level. $\Delta O_{j,i,m,y}$ is the change in the percentage of ownership of stock i by fund j during month m of year y. $HP_{j,i,m,y}$ is the number of Hypothetical Purchases of stock i by fund j (expressed as a percentage of 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. $HS_{j,i,m,y}$ is the number of Hypothetical Sales of stock i by fund j (expressed as a percentage of 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. Flag x%-to-y% is a dummy variable equal to 1 if the *absolute value* of the net fund flow expressed as a percentage of TNA is between x% and y%. Explanatory variables that are absorbed by the fixed effects are omitted from the regression. Stock $\times$ Date FE are fixed effects by stock i interacted with year and month ($i \times y \times m$). t-statistics in parentheses are based on standard errors clustered in three ways, by deal, by fund j, and by date ($y \times m$). Symbols ***, **, and * denote statistical significance at the 1%, 5%, and 10% level, respectively.

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

Table V: Extreme Fund Flows and Price Changes

This table presents the results of estimating Equation 40. 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. All variables are defined in Appendix II. t-statistics in parentheses are based on standard errors clustered in two ways, by deal and by date ($y \times m$). Symbols ***, **, and * denote statistical significance at the 1%, 5%, and 10% level, respectively.

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

VII Appendices

Appendix I – Variables' Definition

Variable	Definition
Main variables	
g	Perpetual growth rate assumed for valuing the target company
k	Discount rate (WACC) assumed for valuing the target company
Q	$(at - ceq + csho \times prcc_f)/at$ (from last available financial statements in Compustat)
ΔQ	Change in Q during the last fiscal year available before deal announcement
Other variables used as controls and/or for cross-sectional analysis	
Size (log)	log of at from last available financial statements in Compustat
Assets	at (from last available financial statements in Compustat).
Debt	$(dlc + dltt)/at$ (from last available financial statements in Compustat).
Cash Flow	$(ib + dp)/at$ (from last available financial statements in Compustat).
Cash	che/at (from last available financial statements in Compustat).
$\Delta Sales$	Change in sales / at (from last available financial statements in Compustat).
Dividend	Dummy equal to 1 if Div is not zero (from last available financial statements in Compustat).

Appendix II – Mutual Fund Price Pressure Measure

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

Step 1 - Calculate fund flows

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

$$RETURN_{j,m,y} = \frac{\sum_k (TNA_{k,j,m-1,y} \times RETURN_{k,j,m,y})}{\sum_k TNA_{k,j,m-1,y}}, \tag{27}$$

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

$$FLOW_{j,m,y} = TNA_{j,m,y} - TNA_{j,m-1,y} \times (1 + RETURN_{j,m,y}) - MGN_{j,m,y}, \tag{28}$$

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

Step 2 - Calculate fund holdings

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

$$O_{j,i,m,y} = \frac{SHARES_{i,j,m,y}}{N_{i,m,y}}, \tag{29}$$

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

Step 3 - Calculate market portfolio weights

Third, we calculate $W_{M_{i,m,y}}$, the weight of stock i in the market portfolio at the end of every month using monthly CRSP data. This weight is given by

$$W_{M_{i,m,y}} = \frac{P_{i,m,y} \times N_{i,m,y}}{\sum_k (P_{k,m,y} \times N_{k,m,y})}, \tag{30}$$

where k indexes all stocks in the CRSP market portfolio, $P_{,i,m,y}$ is the price of stock i, and $N_{i,m,y}$ is its total number of outstanding shares.

Step 4 - Calculate fund hypothetical purchases and hypothetical sales

Fourth, we compute hypothetical trades (denoted HT) as

$$HT_{i,j,m,y} = \frac{W_{M_{i,m-1,y}} \times FLOW_{j,m,y}}{P_{i,m-1,y}} \times \frac{1}{N_{i,m-1,y}} \tag{31}$$

This variable corresponds to the hypothetical net buying of stock i, in percentage, assuming each fund j responds to net flows by adjusting its holding of stock i according to its weight in the *market* portfolio.[9] It is also equal to

$$HT_{i,j,m,y} = \frac{P_{i,m-1,y} N_{i,m-1,y}}{\sum_k P_{k,m-1,y} N_{k,m-1,y}} \times \frac{FLOW_{j,m,y}}{P_{i,m-1,y} N_{i,m-1,y}} = \frac{FLOW_{j,m,y}}{MKT\ PTF_{m-1,y}}, \tag{32}$$

where $MKT\ PTF_{m-1,y}$ is the total value of the CRSP market portfolio, defined as $\sum_k P_{k,m-1,y} \times N_{k,m-1,y}$, where k indexes all stocks in the CRSP market portfolio, $P_{k,m,y}$ is the price of stock k, and $N_{k,m,y}$ is its total number of shares outstanding.

Then we compute hypothetical purchases (HP) and hypothetical sales (HS) as

$$HP_{i,j,m,y} = \max(HT_{i,j,m,y}, 0) \tag{33}$$

$$HS_{i,j,m,y} = -\min(HT_{i,j,m,y}, 0) \tag{34}$$

Step 5 - Decompose changes in fund holdings

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

[9] Notice $W_{M_{i,m-1,y}} \times FLOW_{j,m,y}$ is the value in dollar of the stake that is hypothetically purchased (or sold), and that $\frac{W_{M_{i,m-1,y}} \times FLOW_{j,m,y}}{P_{i,m-1,y}}$ is thus the hypothetical volume of net buying of i.

$$
\begin{aligned}
\Delta O_{j,i,m,y} = & \, a_{i,m,y} \\
& + b_1 HP_{j,i,m,y} \mathbb{1}_{0\% \leq \frac{FLOW}{TNA} < 0.5\% bp} + b_2 HP_{j,i,m,y} \mathbb{1}_{0.5\% \leq \frac{FLOW}{TNA} < 1\%} \\
& + b_3 HP_{j,i,m,y} \mathbb{1}_{1\% \leq \frac{FLOW}{TNA} < 2\%} + b_4 HP_{j,i,m,y} \mathbb{1}_{2\% \leq \frac{FLOW}{TNA} < 3\%} \\
& + b_5 HP_{j,i,m,y} \mathbb{1}_{3\% \leq \frac{FLOW}{TNA} < 4\%} + b_6 HP_{j,i,m,y} \mathbb{1}_{4\% \leq \frac{FLOW}{TNA} < 5\%} \\
& + b_7 HP_{j,i,m,y} \mathbb{1}_{\frac{FLOW}{TNA} \geq 5\%} \\
& + c_1 HS_{j,i,m,y} \mathbb{1}_{0 \geq \frac{FLOW}{TNA} > -0.5\%} + c_2 HS_{j,i,m,y} \mathbb{1}_{-0.5\% \geq \frac{FLOW}{TNA} > -1\%} \\
& + c_3 HS_{j,i,m,y} \mathbb{1}_{-1\% \geq \frac{FLOW}{TNA} > -2\%} + c_4 HS_{j,i,m,y} \mathbb{1}_{-2\% \geq \frac{FLOW}{TNA} > -3\% bp} \\
& + c_5 HS_{j,i,m,y} \mathbb{1}_{-3\% \geq \frac{FLOW}{TNA} > -4\%} + c_6 HS_{j,i,m,y} \mathbb{1}_{-4\% \geq \frac{FLOW}{TNA} > -5\%} \\
& + c_7 HS_{j,i,m,y} \mathbb{1}_{\frac{FLOW}{TNA} \leq -5\%} \\
& + \epsilon_{j,i,m,y}
\end{aligned}
\tag{35}
$$

where $\Delta O_{j,i,m,y} = O_{j,i,m,y} - O_{j,i,m-1,y}$ and $a_{i,m,y}$ are stock-date fixed effects (i.e., fixed effects by stock i, month m, and year y).

Results from estimating Equation 35 are displayed in Table IV. We use these estimates to predict changes in ownership by fund j associated with both hypothetical purchases (HP) and hypothetical sales (HS), focusing on extreme flows only.

$$
\textit{High Inflow Induced}\Delta O_{j,i,m,t} = b_7 \times HP_{i,j,m,y} \times \mathbb{1}_{\frac{FLOW}{TNA} \geq 5\%}, \tag{36}
$$

$$
\begin{aligned}
\textit{High Outflow Induced}\Delta O_{j,i,m,t} = & \, HS_{i,j,m,y} \times c_4 \times \mathbb{1}_{-2\% \geq \frac{FLOW}{TNA} > -3\% bp} \\
& + HS_{i,j,m,y} \times c_5 \times \mathbb{1}_{-3\% \geq \frac{FLOW}{TNA} > -4\%} \\
& + HS_{i,j,m,y} \times c_6 \times \mathbb{1}_{-4\% \geq \frac{FLOW}{TNA} > -5\%} \\
& + HS_{i,j,m,y} \times c_7 \times \mathbb{1}_{\frac{FLOW}{TNA} \leq -5\%}
\end{aligned}
\tag{37}
$$

Stock-level changes in mutual fund ownership due to extreme flows are obtained by taking the sum of predicted changes across funds j for a given stock i.

$$
\textit{High Inflow Induced } \Delta O_{i,m,t} = \sum_j (\textit{High Inflow Induced } \Delta O_{j,i,m,t}), \tag{38}
$$

$$
\textit{High Outflow Induced } \Delta O_{i,m,t} = \sum_j (\textit{High Outflow Induced } \Delta O_{j,i,m,t}), \tag{39}
$$

High Inflow Induced $\Delta O_{i,m,t}$ represents the total increase in mutual fund ownership associated with all hypothetical purchases by funds subject to extreme inflows. Likewise, *High Outflow Induced* $\Delta O_{i,m,t}$ represents the total drop in mutual fund ownership associated with all hypothetical sales by funds subject to extreme outflows.

Step 6 - Decompose stock returns and calculate price pressure

Next, we decompose monthly industry-adjusted returns of stock i and isolate the effect of all hypothetical purchases (MP) and hypothetical sales (HS) by funds experiencing extreme flows by estimating the following equation:

$$\begin{aligned} ARET_{i,m,y} = & \, Constant \\ & + b_1 High\ Inflow\ Induced\ \Delta O_{i,m-2,y} \\ & + b_2 High\ Inflow\ Induced\ \Delta O_{i,m-1,y} \\ & + b_3 High\ Inflow\ Induced\ \Delta O_{i,m,y} \\ & + b_4 High\ Inflow\ Induced\ \Delta O_{i,m+1,y} \\ & + b_5 High\ Inflow\ Induced\ \Delta O_{i,m+2,y} \\ & + b_6 High\ Inflow\ Induced\ \Delta O_{i,m+3,y} \\ & + b_7 High\ Inflow\ Induced\ \Delta O_{i,m+4,y} \\ & + b_8 High\ Inflow\ Induced\ \Delta O_{i,m+5,y} \\ & + c_1 High\ Outflow\ Induced\ \Delta O_{i,m-2,y} \\ & + c_2 High\ Outflow\ Induced\ \Delta O_{i,m-1,y} \\ & + c_3 High\ Outflow\ Induced\ \Delta O_{i,m,y} \\ & + c_4 High\ Outflow\ Induced\ \Delta O_{i,m+1,y} \\ & + c_5 High\ Outflow\ Induced\ \Delta O_{i,m+2,y} \\ & + c_6 High\ Outflow\ Induced\ \Delta O_{i,m+3,y} \\ & + c_7 High\ Outflow\ Induced\ \Delta O_{i,m+4,y} \\ & + c_8 High\ Outflow\ Induced\ \Delta O_{i,m+5,y} \\ & + \epsilon_{j,i,m,y} \end{aligned} \tag{40}$$

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

Results from estimating Equation 40 are displayed in Table V. We use these estimates to predict changes in stock return due to changes in ownership by mutual funds subject to extreme inflows and extreme outflows, and estimate price pressure in dollar.

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

$$
\begin{aligned}
&\textit{MF Buying Price Pressure}^{DOLLAR}_{i,m,y} = \\
&+ MV_{i,m-1,y} \times \textit{High Inflow Induced } \Delta O_{i,m,t} \times b_4 \\
&+ MV_{i,m-2,y} \times \textit{High Inflow Induced } \Delta O_{i,m-1,t} \times (b_4 + b_5) \\
&+ MV_{i,m-3,y} \times \textit{High Inflow Induced } \Delta O_{i,m-2,t} \times (b_4 + b_5 + b_6),
\end{aligned} \tag{41}
$$

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

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

$$
\begin{aligned}
&\textit{MF Selling Price Pressure}^{DOLLAR}_{i,m,y} = \\
&+ MV_{i,m-1,y} \times \textit{High Outflow Induced } \Delta O_{i,m,t} \times b_4 \\
&+ MV_{i,m-2,y} \times \textit{High Outflow Induced } \Delta O_{i,m-1,t} \times (b_4 + b_5) \\
&+ MV_{i,m-3,y} \times \textit{High Outflow Induced } \Delta O_{i,m-2,t} \times (b_4 + b_5 + b_6) \\
&+ MV_{i,m-4,y} \times \textit{High Outflow Induced } \Delta O_{i,m-3,t} \times (b_4 + b_5 + b_6 + b_7),
\end{aligned} \tag{42}
$$

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

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