Real Misvaluation Externalities

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ABSTRACT

We show that the misvaluation of a firm affects the investment of related firms, which we call real misvaluation externalities. We estimate that firms significantly reduce investment when their peers' stock prices fall due to exogenous fire sales triggered by mutual funds redemptions, as predicted by a model in which managers rely on stock prices a source of information but cannot perfectly filter out noise in prices. The model also implies that the investment-to-noise sensitivity should be stronger when peers' prices are more informative, and weaker when managers are better informed. We also find support for these predictions. Overall, our results provide a new channel through which non-fundamental shocks to stock prices influence the real economy.

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I Introduction

It has long been established that stock prices can deviate from their fundamental value for prolonged period of times (see Duffie (2010) for examples). Such distortions are important as they can influence the real economy. In particular, existing research indicates that firms alter their investment decisions when their own stock prices deviate from fundamentals.[1] In this paper, we ask whether deviations from fundamentals can trigger real externalities affecting the investment decisions of other firms. The existence of such externalities can have important implications for our understanding of the real effect of financial markets, as well as the origins of macroeconomic fluctuations.

We argue that the misvaluation of a particular firm can influence the investment of related firms – a mechanism we call real misvaluation externalities – when corporate managers rely on the stock prices of peer firms as a source of information about investment opportunities (e.g. Foucault and Frésard (2014)). Deviations from fundamentals can thus trigger real externalities if managers condition their decisions on stock prices but cannot perfectly separate the fundamental from the non-fundamental components (the noise). In this context, peers' stock prices act as "faulty informant" (Morck, Shleifer, and Vishny (1990)), which lead firms' investment to be affected by noise.

We formalize the above idea using a simple model where a manager must choose the scale of his investment in a growth opportunity. His private information on the marginal return of this opportunity is imperfect and, therefore, he relies on his own stock price and the stock price of a peer firm as additional sources of information. In line with the above intuition, we show that in equilibrium the noise in his peer (and own) stock price has a strictly positive causal effect on the manager's investment decision, except if the manager is perfectly informed, either on the marginal return of his growth opportunity or on the noise in its peer stock price.

We further show that one can obtain a theoretically unbiased estimate of this real

[1] See for instance Baker, Shleifer, and Wurgler (2003), Hau and Lai (2012), Campello and Graham (2013).

externality regressing the firm investment on the noise in its peer stock price that the econometrician can observe, and the component of its peer stock price that is orthogonal to this noise.[2] This observation forms the backbone of our empirical tests and we refer to the sensitivity of a firm investment to the noise in its peer stock price as the *investment-to-noise* sensitivity.

In the model, estimating a positive investment-to-noise sensitivity is sufficient to identify the presence real externalities originating from managers' imperfect learning from prices. In reality, of course, other mechanisms (unaccounted for by the theory) may also affect this sensitivity. In particular, existing research suggests that a firm's stock price can influence its investment through its effect on access to external financing (e.g. Baker, Stein, and Wurgler (2003)) as well as career concerns (e.g. Stein (1989)). Yet, while these "financing" and "pressure" channels may explain why a firm's investment is sensitive to the noise in its *own* stock price, there is little reason to believe that they should be related to the investment-to-noise sensitivity. In other words, focusing on peers allows us to limit the scope for alternative explanations.[3].

We estimate the investment-to-noise sensitivity on a panel of U.S. firms over the period 1996-2011. For each firm in our sample, we identify a set of product market peers using the Text-based Network Industry Classification (TNIC) developed by Hoberg and Phillips (2015).[4] As suggested by our theory, we first decompose the annual stock price (Tobin Q) of each peer firm into a non-fundamental component and a component (the "fundamental" component) orthogonal to the non fundamental component.[5] As in Edmans, Goldstein, and Jiang (2012), the non-fundamental component of a peer stock

[2]In this regression, one does not need to control for the manager's private information. In contrast, even in the theory, one cannot obtain an unbiased estimate of the causal effect of the fundamental components in a firm's peer and own stock price without controlling for the manager's private information. In practice, this problem has been a stumbling block for tests of the active informant hypothesis since a manager's private information cannot be observed.

[3]We provide empirical evidence supporting this claim below

[4]This classification is based on textual analysis of the product description sections of firms' 10-K (Item 1 or Item 1A) filed every year with the Securities and Exchange Commission (SEC). The classification covers the 1996 to 2011 period because TNIC industries require the availability of 10-K annual filings in electronically readable format.

[5]We refer to the second component as the 'fundamental" component for brevity. However, this does not imply that this second component does not itself contains noise. Our tests only require the fundamental and non-fundamental components to be orthogonal.

price is the predicted value of a regression of this price on its *hypothetical* sale by mutual funds experiencing large redemptions. Indeed, Coval and Stafford (2007) show that sales of mutual funds hit by large outflows exert large negative price pressures on stocks held by these funds. These pressures last for long but eventually disappear, which suggest that they are not driven by information about fundamentals. One might still be concerned that fund managers selectively sell stocks for which they have bad information. To alleviate this problem, Edmans, Goldstein, and Jiang (2012) propose to use hypothetical (i.e., assuming that mutual funds rkeep the distribution of stocks in their portfolio constant) rather than effective sales of stocks held by mutual funds experiencing large redemptions as an instrument for non fundamental price shocks. We follow this approach.

In a second step, we estimate the investment-to-noise sensitivity by regressing a firm's investment on the average (across its peers in each year) non-fundamental and fundamental components of its peers' stock prices and additional control variables, including a firm's own stock price (decomposed, in the same way as peer stock prices, in a non-fundamental component and a fundamental component). Consistent with the presence of real misvaluation externalities, we find that the investment-to-noise sensitivity is significantly positive. The economic size of this sensitivity is significant. Indeed, our estimates imply that a one standard deviation drop in a peers' stock price, due to a non-fundamental shock, leads the average firm in our sample to cut its investment in fixed capital by 1.8% percent (a 5% decrease relative to the mean).

The model further enables us to predict which firms' characteristics should affect the investment-to-noise sensitivity when managers have imperfect information. First, this sensitivity should increase with the firm's peer stock price informativeness because the manager's forecast of his investment payoff should be more influenced by his peer stock price if he expects it to be more informative. Second, the investment-to-noise sensitivity should decrease when the manager is better privately informed, either about the payoff of his investment or the noise in his peer's stock price. We find supporting evidence for these predictions in the data. Namely, a firm's investment is significantly *more* sensitive to the non-fundamental component of its peers' stock prices when (i) these prices are more informative (as proxied for instance by the forecasting ability of prices or earnings forecasts errors of financial analysts) and (ii) when firms' managers are less likely to be informed (as measured for instance using the profitability of insiders' trades or previous exposure to severe misvaluation).

Overall, we show that our findings are hard to reconcile with alternative explanations. First, we find no evidence that firms' financing costs increase when their peers experience large fund-driven downward price pressure. Thus, the financing channel is unlikely to explain why firms' investment is sensitive to the noise in their peer stock prices.[6] Second, noise in peers' stock prices does not affect the likelihood that a firm becomes a takeover target, nor the likelihood of observing CEO departure, suggesting that the pressure channel does not explain our findings. Third, we show that the investment-to-noise sensitivity is not reflecting mimetic behaviors, whereby firms' investment is related to the noise in peers' stock prices solely because peers' reduce investment when they stocks are undervalued.

Further supporting our interpretation, we find that the non-fundamental component of peers' stock prices influences capital allocation decisions *within* firms. Using data on multi-division firms from Compustat segment files, we estimate that investment in a division is sensitive to the noise in the stock prices of that division's peers.[7] Thus, conglomerate firms reduce the capital allocated to one division relative to others when the product market peers of that division experience negative non-fundamental shocks to their stock prices. This finding is consistent with the presence of externalities, and is particularly hard to explain with the financing and pressure channels. Indeed, these channels may explain variations in investment across firms but *not* across divisions for a given firm since financing constraints and CEO incentives should play out at the firm, not division, level.

[6] In contrast, Hau and Lai (2013) find that the causal effect of the noise in a firm's own stock price on investment is stronger for financially constrained firms. This is consistent with the fact that the sensitivity of a firm investment to the noise in its own stock price can, in theory, stem from the three channels through which stock prices can affect investment.

[7] For these tests, we use Fama French 48 industry classification to identify the peers of a given division.

Our analysis contributes on two fronts. First, our findings add to literature examining how firms' investment respond to non-fundamental shocks to their stock price. The novel aspect of our paper is our focus on a firm's product market peers, and the resulting learning externalities. A few related studies also suggest the presence of misvaluation externalities, but focus on externalities *between* sectors or real asset markets, and arising because of financing frictions. For instance, Campello and Graham (2013) report that the economy-wide stock prices overvaluation during the 1990s technology boom affected the investment in non-tech sectors by relaxing financing constraints. Other studies indicate that deviations from fundamentals in the real estate market spillover to corporate investment through a financing channel (e.g. Chaney, Sraer, and Thesmar (2012), Chakraborty, Goldstein, and MacKinlay (2014)). In contrast, we show that stock price deviations from fundamentals generate real externalities *within* sectors, and because of informational frictions. Our findings suggest that managers' reliance on the stock market as a source of information can exacerbate the impact of misvaluation on the real economy, and particularly so when managers' ability to filter out the noise in prices is limited. These real misvaluation externalities can potentially trigger amplification effects, and magnify variations in aggregate investment.

Second, our analysis adds to the literature that studies how information contained in asset prices guide corporate managers for their investment decisions (See Bond, Edmans, and Goldstein (2012) for a detailed survey). Testing the so-called "active informant" hypothesis has been challenging because of the impossibility to measure the amount of *new* information that managers learn from observing stock prices. Existing studies typically assume that managers can perfectly isolate the information about fundamentals in prices, and examine whether investment is more sensitive to prices when prices are overall more informative (e.g. Chen, Goldstein, and Jiang (2006), Bakke and Whited (2010), or Foucault and Frésard (2012)). By assuming that managers cannot always perfectly isolate the fundamental information in stock prices, our model predicts that if managers rely on stock market information for investment but cannot perfectly filter out the noise, firms' investment should (perhaps paradoxically) be sensitive to noise. Our results thus provide novel evidence supporting the active informant hypothesis.

The rest of the paper is organized as follows. In the next section, we describe the model and detail the empirical predictions derived from the model and how to test them. We present the implementation of our main test and describe the sample in section III. Section IV reports the empirical findings and interpretation, and Section V presents our conclusions.

II Theory and Predictions

A Investment When Managers Learn From Stock Prices

In this section, we present the model of investment that guides our empirical tests. As in Subrahmanyam and Titman (1999), we assume that firm i has a growth opportunity whose payoff at date 3 is:

$$G(K_i, \theta) = ((K_{i0} + \theta)K_i - \frac{K_i^2}{2}), \tag{1}$$

where θ represents the marginal productivity of investment (i.e., the "fundamental") and K_i is the size of the investment of firm i in its growth opportunity. We assume that θ has a normal distribution with mean zero and variance σ_θ^2. The manager of firm i chooses investment K_i at date 2 to maximize the expected value of the growth opportunity. When doing so, he has access to three information signals:

1. *Private information about the fundamental, θ*: A private signal $s_m = \theta + \chi$ where the error χ has mean zero and variance σ_χ^2. The larger is σ_χ^2, the lower is the quality of signal s_m.

2. *Firm i's stock price.* We denote the signal contained the stock price of firm i by $P_i = \theta + u_i$ where the noise (or non fundamental) component u_i has a normal distribution with mean zero and variance $\sigma_{u_i}^2$.

3. *Private managerial information about the non fundamental component of its stock price, u_i:* a signal $s_{u_i} = u_i + \eta_i$ where η_i has a normal distribution with mean zero and variance $\sigma_{\eta_i}^2$.

Errors in the manager's signals (χ, u_i,η_i) are independent from each other and θ. The stock price of firm i is realized at date 1, i.e., prior to the investment decision of firm i. For brevity, we do not explicitly model price formation in the stock market at date 1.[8] Rather, we directly assume that the stock price of firm i can be decomposed in two components: (i) one component that is informative about the fundamental θ of its growth opportunity and (ii) one component that is uninformative about this component. This decomposition is standard in finance. In models of informed trading (e.g., Grossman and Stiglitz (1985) or Kyle (1985)), the first component stems from informed investors' signals about θ and the second component (the noise in prices) is due to (a) uninformative trades from noise traders and (b) errors in informed investors' signals. The variance of the noise in prices ($\sigma^2_{u_i}$) is endogenous in these models (e.g., it will be smaller if there are more informed investors or if the variance of noise traders' supply shock is smaller).[9] However, this feature is not important for our tests.

For greater generality, we assume that the manager of firm i might have some information (s_{u_i}) about the noise in his own stock price. As explained below, the faulty informant hypothesis requires that $\sigma^2_{\eta_i} > 0$: The manager cannot perfectly identify whether stock price changes are due to fundamentals or noise.

We use the following notations

$$\phi_i = \frac{\sigma^2_{u_i}}{\sigma^2_{u_i} + \sigma^2_{\eta_i}},\ \kappa_i = \frac{\sigma^2_{\theta}}{\sigma^2_{u_i} + \sigma^2_{\theta}},\ \psi = \frac{\sigma^2_{\theta}}{\sigma^2_{\theta} + \sigma^2_{\chi}}.$$

These parameters are the signal-to-noise ratio of each signal received by the manager. For instance, when κ_i increases, the signal conveyed by the stock price about θ becomes

[8] This could be done as in Subrahmanyam and Titman (1999). In this case, for technical reasons, one needs to assume that the firm has assets in place whose payoff is θ and that the firm existing shares are claims on the asset in place only, rather than the whole firm (assets in place and the growth opportunity). In Subrahmanyam and Titman (1999), the second assumption allows to compute equilibrium prices in closed form because otherwise cash-flows would be non linear in θ.

[9] For instance, in Grossman and Stiglitz (1980), observing the equilibrium stock prices is informationally equivalent to observing a variable $w_\lambda = \theta - \frac{\alpha^2\sigma^2_\epsilon}{\lambda}(x - E(x^*))$ where θ is the asset payoff, x is the asset random supply, λ the fraction of informed investors, σ^2_ϵ the variance of the error in informed investors' signals, and α is investors' risk aversion (see Grossman and Stiglitz (1980), Theorem 1). The noisy supply x is independent from θ and prevents prices from fully revealing the asset payoff. Thus, observing the equilibrium price is equivalent to observing $\theta + u$ where $u = -\frac{\alpha^2\sigma^2_\epsilon}{\lambda}(x - E(x^*))$. Thus, u is independent from θ. Moreover, the probability distribution of u is normal in Grossman and Stiglitz (1980) with mean zero and variance $\sigma^2_u = \frac{\alpha^4\sigma^4_\epsilon\sigma^4_u}{\lambda^2}$.

more accurate and is perfect if $\kappa_i = 1$. Similarly, an increase in ϕ_i means that the manager is better able to identify deviations of its stock price from fundamentals. In what follows, we normalize σ_θ^2 to one and we use ϕ_i, κ_i, and ψ as parameters. Thus, holding κ_i constant (i.e., $\sigma_{u_i}^2$), an increase in ϕ_i (resp., ψ) means that s_{u_i} (resp., s_m) is more informative, i.e., σ_η^2 (resp., σ_χ^2) is smaller since $\sigma_{\eta_i}^2 = \frac{(1-\phi_{-i})}{\phi_{-i}}\sigma_{u_{-i}}^2$. We assume that $\sigma_{u_i}^2 > 0$ (i.e., $\kappa_i < 1$; firm i's stock price is never fully revealing), as otherwise $\phi_i = 0$ for all $\sigma_{\eta_i}^2$ and, therefore, cannot be treated as a parameter.

Let $\Omega_2 = \{s_m, P_i, s_{u_i}\}$ be the manager's information set at date 2. The manager chooses K_i^* to maximize the expected value of his growth opportunity conditional on his information, Ω_2. Thus, K_i^* solves:

$$Max_{K_i}\ E(G(K_i,\theta)\,|\Omega_2) = (K_{i0} + E(\theta\,|\Omega_1))K_i - \frac{K_i^2}{2} \tag{2}$$

The first order condition of this problem yields the optimal investment at date 1:

$$K_i^*(\Omega_2) = K_{i0} + E(\theta\,|\Omega_2) \tag{3}$$

Thus, $K_{i0} = \mathrm{E}(K_i^*(\Omega_2))$ is the average level of the investment since $E(E(\theta\,|\Omega_2)) = E(\theta) = 0$. To simplify notations, we set $K_{i0} = 0$ and interpret $K_i^*(\Omega_2)$ as the optimal deviation of the investment from its mean value.

As θ, s_m, P, and $s_{u_{-i}}$ are normally distributed, we deduce that:[10]

$$K_i^*(\Omega_2) = E(\theta\,|\Omega_2) = a \times s_m + b \times P_i + c \times s_{u_i}, \tag{4}$$

where:

$$a = \frac{\sigma_\theta^2\sigma_{u_i}^2(1-\phi_i)}{\sigma_{u_i}^2(1-\phi_i)(\sigma_\theta^2+\sigma_\chi^2)+\sigma_\theta^2\sigma_\chi^2} = \frac{\psi(1-\phi_i)(1-\kappa_i)}{(1-\phi_i)(1-\kappa_i)+(1-\psi)\kappa_i}, \tag{5}$$

$$b = \frac{\sigma_\theta^2\sigma_\chi^2}{(\sigma_{u_i}^2(1-\phi_i)(\sigma_\theta^2+\sigma_\chi^2)+\sigma_\theta^2\sigma_\chi^2)} = \frac{(1-\psi)\kappa_i}{(1-\phi_i)(1-\kappa_i)+(1-\psi)\kappa_i}, \tag{6}$$

$$c = -\frac{\sigma_\theta^2\sigma_\chi^2\phi_i}{\sigma_{u_i}^2(1-\phi_i)(\sigma_\theta^2+\sigma_\chi^2)+\sigma_\theta^2\sigma_\chi^2\sigma_{u_i}^2} = -\frac{(1-\psi)\phi_{-i}\kappa_i}{(1-\phi_i)(1-\kappa_i)+(1-\psi)\kappa_i}, \tag{7}$$

[10]If Y is normally distributed and X is a vector with a multivariate normal distribution then $E(Y\,|X) = E(Y) + Cov(Y,X)^t\Omega^{-1}X$ where Ω^{-1} is the inverse of the variance-covariance matrix between X and Y and $Cov(Y,X)^t$ is the transpose of the vector giving the covariance between Y and each component of X. We use this property at various places for the results in this section.

Equation (4) describes how the manager's information at date 2 affects his investment decision. If $\psi = 1$ (i.e., $\sigma_\chi^2 = 0$), the manager's private information is perfect and therefore he has no information to learn from his stock price. Hence, in this case, $a > 0$ and $b = c = 0$. If $\psi < 1$, the manager can complement his own private information by using information from his own stock price if the latter is informative ($\kappa_i > 0$). Thus, $b > 0$ when $\kappa_i > 0$ and $\psi < 1$. In addition, in this case, $c < 0$ if $\phi_i > 0$. Indeed, in this case, the manager uses his information about u_i to filter out part of the noise in his stock price. Thus, his investment depends on his signal about the non-fundamental component of his stock price, s_{u_i}, even though this signal is, in isolation, uninformative about θ. Coefficient c is negative because when the manager observes $s_{u_i} > 0$ ($s_{u_i} < 0$), he expects his stock price to exceed (be smaller than) the fundamental, θ. Hence, the manager corrects downward (upward) the positive (negative) effect of the stock price on his estimate of θ. In the polar case $\phi_i = 1$, the manager ignores his own private signal, i.e., $a = 0$ if $\psi < 1$. Indeed, he perfectly observes u_i. Thus, observing $\{P_i, u_i\}$ is equivalent to observing θ and in this case $K_i^* = bP_i + cs_{u_i} = P_i - u_i = \theta$.

B The Faulty Informant Channel

The "active informant" hypothesis states that stock prices influence investment because they contain information new to managers (Morck, Shleifer and Vishny (1990)). In the terminology of our model, the hypothesis is that $\psi < 1$ and $\kappa_i > 0$ so that $b > 0$. This raises the possibility that investment decisions are driven by non-fundamental variations in a firm's stock price if managers cannot perfectly distinguish fundamental from non-fundamental shocks. Morck, Shleifer, and Vishny calls this implication of the active informant hypothesis, the "faulty informant" hypothesis. This hypothesis is satsified in our model when $\psi < 1$ and $0 < \kappa_i$ and $\phi_i < 1$.

To see this, observe that equation (4) implies that:

$$K_i^* = (a + b) \times \theta + (b + c) \times u_i + (a\chi + b\eta). \tag{8}$$

Thus, investment is influenced by the non-fundamental component of firm i's stock price if and only if $(b + c) \neq 0$. Using the expressions for a, b, and c in equations (5), (6), and (7), we get:

$$\rho_i \stackrel{def}{=} b + c = \frac{(1-\psi)\kappa_i(1-\phi_i)}{(1-\phi_i)(1-\kappa_i) + (1-\psi)\kappa_i} \geq 0. \tag{9}$$

Thus, $(b+c) \neq 0$ if and only if $\psi < 1$, $\phi_i < 1$ and $\kappa_i > 0$. This is intuitive: The noise in firm i's stock price can influence its investment if and only if its manager relies on his stock price as a source of information ($\psi < 1$ and $\kappa_i > 0$) and cannot perfectly identify non fundamental shocks (i.e., $\phi_i < 1$). Moreover, in this case, $b+c > 0$: An increase in the non-fundamental component of firm i's stock price, u_i, leads its manager to invest more because the manager cannot tell whether the resulting increase in his stock price is due to a fundamental or a non-fundamental shock.

The model suggests that one can test the faulty informant hypothesis by examining whether $b+c > 0$. A rejection indicates that either managers have perfect information on θ ($\psi = 1$) or perfect information on the noise in the stock price ($\phi_i = 1$). Note that investment might be sensitive to noise in the stock price even if (i) the manager forms its beliefs rationally, and (ii) the investment decision is optimal. In our model, the manager of firm i forms his belief about θ through bayesian updating. Hence, his investment decision depends on his stock price because this price is informative about θ. Ignoring this information would be suboptimal.[11] This signal, however, is noisy and the manager has limited information on the noise in the price. As a result, his optimal investment policy can be driven by non-fundamental component of his stock price.[12]

An empirical test of the faulty informant hypothesis requires an estimate of $b + c$. Such an estimate is *a priori* difficult to obtain because the econometrician cannot easily observe the manager's private information about θ (s_m) and about the non-fundamental component of the stock price u_i (s_{u_i}). Yet, we show that it in fact suffices to obtain information on u_i to correctly estimate $b+c$. To see this, let $u_i = u_i^o + u_i^{no}$ where u_i^o is the component of the noise in firm i's stock price that the econometrician can measure, whereas u_i^{no} is unobserved. We assume that both u_i^o and u_i^{no} are independent and

[11]It is straightforward to show that firm i's ex-ante expected value is higher if its manager follows the investment policy $K^*(\Omega_2)$ rather than a policy that only depends on his private signal s_m.

[12]Similarly, as equation (8) shows, the manager's investment decision is also driven by the noise χ in his private signal, s_m.

normally distributed with mean zero and variances $\lambda_i\sigma^2_{u_i}$ and $(1-\lambda_i)\sigma^2_{u_i}$, respectively. Using equation (4), we have

$$\mathrm{E}(K_i^* \,|P_i, u_i^o) = a\mathrm{E}(s_m \,|P_i, u_i^o) + b \times P_i + c \times \mathrm{E}(u_i \,|P_i, u_i^o)\,. \tag{10}$$

Now, using the fact that all variables have a normal distribution, we deduce that:

$$\mathrm{E}(s_m \left|P_i, u_{-i}^o\right.) = \alpha_i(P_i - u_i^o), \tag{11}$$

where:

$$\alpha_i = \frac{\sigma^2_\theta}{(1-\lambda)\sigma^2_{u_i} + \sigma^2_\theta} \tag{12}$$

and

$$\mathrm{E}(u_i \,|P_i, u_i^o) = (1-\alpha_i)P_i + \alpha_i u_i^o. \tag{13}$$

Substituting eq.(11) and (13) in (10) and simplifying, we obtain:

$$\mathrm{E}(K_i^* \,|P_i, u_i^o) = (a\alpha_i + (1-\alpha_i)c + b)P_i + \alpha_i(c-a)u_i^o = \beta_i P_i^* + \rho_i u_i^o,$$

where $P_i^* = \theta + u_i^{no} = P_i - \mathrm{E}(P_i \,|u_i^o)$ and $\beta_i = \alpha_i(a-c) + \rho$. Hence:

$$K_i^* = \mathrm{E}(K_i^* \,|P_i, u_i^o) + \epsilon = \beta_i P_i^* + \rho_i u_i^o + \epsilon, \tag{14}$$

where ϵ is orthogonal to P_i^* and u_i^o (i.e., $\mathrm{E}(\epsilon \,|P_i^*, u_i^o) = E(\epsilon \,|u_i^o) = E(\epsilon \,|P_i^*) = E(\epsilon) = 0$). Hence, eq.(14) indicates that the optimal investment K_i^* is a linear function of P_i^* and u_i^o. We can thus obtain theoretically unbiased estimates of β_i and ρ_i by estimating equation (14) via ordinary least squares, using the residual of a regression of P_i on u_i^o as a proxy for P_i^* (since $P_i^* = P_i - \mathrm{E}(P_i \,|u_i^o)$). Therefore, our model of investment yields an unbiased estimate of $\rho = b + c$ that can be estimated with time-series data on investment, stock prices, and a measure of noise in stock prices.[13]

[13] Testing the faulty informant hypothesis is not equivalent to testing the hypothesis that managers learn information from prices. Indeed, rejecting the faulty informant hypothesis is not sufficient to conclude that managers do not learn information from stock prices because $b + c = 0$ (no faulty learning) does not imply that $b = 0$ (no learning). Estimating b is challenging. Indeed, even if our model of investment is well specified, regressions of investment on stock prices would yield a biased estimate of b.

C Testing the Faulty Informant Channel

Within the boundaries of the model, we can formulate a direct test of the faulty informant hypothesis ($\rho = b + c > 0$). Yet, although the model delineates a minimal discipline for testing the faulty informant channel, corporate investment might arguably be related to the observed non-fundamental component of the stock price u_i^o through channels that are not explicitly included in our model. If this is the case in reality, a positive coefficient on u_i^o ($\rho_i > 0$) may not uniquely identify the faulty informant channel, but may partly reflect these unmodelled channels.

In fact, the literature has proposed two other reasons for why stock prices may influence corporate investment (e.g., Morck, Shleifer, and Vishny (1990)). First, noise in the stock price can influence investment through its effect on financing (the "financing" channel). According to this view, the manager can detect deviations of prices from fundamentals ($\phi_i > 0$) and opportunistically issue stocks when the price is overvalued ($P_i > \theta$ or equivalently $u_i > 0$) and repurchase undervalued stocks ($u_i < 0$). When the firm is financially constrained, investment might be below the optimal level, holding θ constant. For instance, an increase in their stock price for non-fundamental reasons (an increase in u_i) reduces their cost of capital and thereby relaxes the financial constraint. In this case, the observed investment is correlated with u_i even if the manager does not extract from the stock price information about fundamentals (e.g., Baker, Wurgler, and Stein (2003) or Hau and Lai (2013)). Second, noise in the firm stock price can influence investment through its effect on the managers' incentives (the "pressure" channel). In this scenario, the manager can also detect deviations of its stock price from fundamentals ($\phi_i > 0$) and fear from his employment. A drop in stock price due to non-fundamental reasons ($P_i < \theta$ or equivalently $u_i < 0$) may increase the risk that the firm is taken over and the manager removed (e.g Stein (1988)). In this case, the manager may reduce its firm's investment to boost short-term profits and enhance its stock price (e.g. Stein (1988, 1989), or Bhojraj, Hribar, Picconi, and McInnis (2009)).

In order to attenuate the potential impact of these alternative channels, we focus on the influence on a firm's investment of the non-fundamental component of its *peers*' stock prices. We argue that while the financing and pressure channels could explain why a firm's investment is sensitive to the noise in its own stock price, these channels do *not* predict that the investment of a firm should be related to the noise in its peers' stock price, especially if we control for the noise in the firm's own stock price. Indeed, by construction, a firm cannot take advantage of the misvaluation of its peers to issue stocks at a cheap cost. Similarly, there is little reason to believe that the misvaluation of peers affect a manager's incentives, through a higher risk of takeover or its compensation contract. We thus extend our model to account for the possibility that the manager of firm i might also learn information from its peers' stock prices, as suggested by empirical findings in Foucault and Fresard (2014). We show below that the sensitivity of firm i's investment to a proxy for the noise in its peers' stock price (u_{-i}) is strictly positive if and only if the faulty informant hypothesis is valid, i.e., if the firm cannot fully separate fundamental from non-fundamental shocks in the stock price of its peers.

To derive the implications of faulty informant hypothesis that are based on peers' stock price, we introduce a peer in our model and index all variables referring to this peer of firm i by $-i$. Let $P_{-i} = \theta + u_{-i}$ be the signal contained in peer stock price about θ where u_{-i} and θ are independent. Let $s_{u_{-i}} = u_{-i} + \eta_{-i}$ be the signal that the manager of firm i has about u_{-i}. We assume that u_{-i} and η_{-i} are normally distributed with mean zero and variance $\sigma^2_{u_{-i}}$ and $\sigma^2_{\eta_{-i}}$.[14] They are independent from each other and u_i, η_i, and χ.[15] Moreover, to simplify the exposition, we assume that the manager of firm

[14] We do not need to assume that the fundamentals of firm i and its peer are identical. For instance, suppose that the fundamental of firm $-i$ is $\theta_{-i} = \theta + \epsilon$ where ϵ and θ are independent. The correlation between θ_{-i} and θ is less than one and decreases with the variance of ϵ. The stock price of firm $-i$ reveals a signal about θ_{-i}. Let $P_{-i} = \theta_{-i} + \widehat{u}_{-i}$ be this signal. One can always write it: $P_{-i} = \theta + u_{-i}$ where $u_{-i} = \widehat{u}_{-i} + \epsilon$. In this interpretation, the manager of firm i's signal about u_{-i} might come from the fact that the manager has information about ϵ (the component of its peer fundamental unrelated to the manager's own firm fundamental), $\widehat{u}_{-i}$, or both. This does not matter for our results.

[15] We assume that the price of stock i is not a sufficient statistic for the information about the growth opportunity of firm i contained in its peer stock price. There are various scenarios under which this will happen even if investors account for the information contained in trades of each market. One reason is that firms are portfolios of projects. Their stock price will therefore convey information about the payoff of the portfolio rather than the payoff of a specific project in this portfolio. If a firm has a growth opportunity in one particular project, it will therefore find useful to obtain information about the payoff of this project by learning from the stock prices of firms that are specialized in this type of project. For instance, suppose that firm i has assets in place whose payoff is $\theta_{iA} + \theta_{iB}$ (projects

i has no information on the noise in his own stock price ($\sigma^2_{\eta_i} = \infty$). This assumption can be easily relaxed without affecting the results below. The proofs of the results in this section are in the appendix. We define $a_i^* = \frac{\psi(1-\kappa_i)}{(1-\kappa_i)+(1-\psi)\kappa_i}$, $b_i^* = \frac{(1-\psi)\kappa_i}{(1-\kappa_i)+(1-\psi)\kappa_i}$, $\sigma^2_{\chi^*} = \left(\frac{a_i^*}{a_i^*+b_i^*}\right)^2 \sigma^2_\chi + \left(\frac{b_i^*}{a_i^*+b_i^*}\right)^2 \sigma^2_{u_i}$ and $\psi^* = \frac{\sigma^2_\theta}{\sigma^2_\theta+\sigma^2_{\chi^*}}$.

Lemma 1. *Let $\Omega_2 = \{s_m, P_i, P_{-i}, s_{u_{-i}}\}$. The optimal investment policy at date 2 is:*

$$K_i^*(\Omega_2) = E(\theta\,|\Omega_2) = a_i \times s_m + b_i \times P_i + b_{-i} \times P_{-i} + c_{-i} \times s_{u_{-i}}, \tag{15}$$

where:

$$\begin{aligned} a_i &= a_i^*(1-b_{-i}), & (16)\\ b_i &= b_i^*(1-b_{-i}) & (17)\\ b_{-i} &= \frac{\sigma^2_\theta\sigma^2_{\chi^*}}{(\sigma^2_{u_{-i}}(1-\phi_{-i})(\sigma^2_\theta+\sigma^2_{\chi^*})+\sigma^2_\theta\sigma^2_{\chi^*})} = \frac{(1-\psi^*)\kappa_{-i}}{(1-\phi_{-i})(1-\kappa_{-i})+(1-\psi^*)\kappa_{-i}}, & (18)\\ c_{-i} &= -\frac{\sigma^2_\theta\sigma^2_{\chi^*}\phi_{-i}}{\sigma_{u_{-i}}(1-\phi_i)(\sigma^2_\theta+\sigma^2_{\chi^*})+\sigma^2_\theta\sigma^2_{\chi^*}\sigma^2_{u_{-i}}} = -\frac{(1-\psi^*)\phi_{-i}\kappa_{-i}}{(1-\phi_i)(1-\kappa_{-i})+(1-\psi^*)\kappa_{-i}} & (19)\end{aligned}$$

To understand this result, observe that the optimal investment policy of firm i (given by eq.(15)) can be rewritten:

$$K_i^*(\Omega_2) = E(\theta\,|\Omega_2) = (1-b_{-i})a^* \times s_m^* + b_{-i} \times P_{-i} + c_{-i} \times s_{u_{-i}}, \tag{20}$$

where $s_m^* = \frac{(a\times s_m + b_i \times P_i)}{(a+b)(1-b_{-i})} = \theta + \chi^*$ with $\chi^* = \left(\frac{a_i^*}{a_i^*+b_i^*}\right)\theta + \left(\frac{b_i^*}{a_i^*+b_i^*}\right)^2 u_i$. Thus, the optimal investment policy for firm i is identical to that it would have if its manager had three signals: s_m^*, P_{-i}, and $s_{u_{-i}}$. Intuitively, s_m^* (which is a linear combination of s_m and P_i) is the sufficient statistic that the manager extracts from his own private signal and his stock price about the fundamental of firm i.[16] The variance of the error term in this signal is $\sigma^2_{\chi^*}$ and $\psi^* = \frac{\sigma^2_\theta}{\sigma^2_\theta+\sigma^2_{\chi^*}}$ measures the informativeness of s_m^* about θ, i.e., the informativeness of the joint observation of s_m and P_i about θ. It is easily shown that ψ^* increases with both ψ (the informativeness of s_m, the manager's private signal about θ) and κ_i (the informativeness of the firm i stock price).

A and B) and that the payoff of firm A's growth opportunity only depends on θ_{iB}. Moreover suppose that there is another firm $-i$ whose payoff is $\theta_{-i} = \theta_{iB}$. Take the extreme case in which stock prices fully reveal the value of assets in place. Thus, the stock price of firm A reveals $\theta_{iA} + \theta_{iB}$ while that of stock B reveals θ_{iB}. In this case, observing the stock price of firms i *and* $-i$ reveal θ_{iB} while observing the stock price of firm A only does not, even though prices reflect all available information.

[16] It can be shown that the distribution of θ conditional on (i) Ω_2 or (ii) $\{s_m^*, P_{-i}, u_{-i}\}$ are identical. Thus, s_m^* has the same informational content as $\{s_m, P_i\}$.

Equation (20) shows that the case in which firm i learns from its peer stock price is isomorphic to the case in which it learns only from its own stock price. The role of s_m in the baseline model is now played by s_m^* and the role of ϕ_i, κ_i, and ψ is now played by ϕ_{-i}, κ_{-i}, and ψ^*. This explains why the expressions for b_{-i} and c_{-i} are similar to the expressions for b and c in the baseline model.

From (15), we deduce that:

$$K_i^*(\Omega_2) = (a + b_i + b_{-i})\theta + b_i u_i + (b_{-i} + c_{-i})u_{-i} + (a\chi + b_i\eta_i + b_{-i}\eta_{-i}).$$

Thus, firm i's investment policy is driven by the noise in their peer stock price if and only if $\rho_{-i} = b_{-i} + c_{-i} \neq 0$, i.e., if and only if $\psi^* < 1$, $\kappa_{-i} > 0$ and $\phi_{-i} < 1$. Hence, we can test whether firms react to noise in stock prices because they learn imperfectly from stock prices (the faulty informant hypothesis) by estimating $b_{-i} + c_{-i}$. The next proposition shows that we can do so following the procedure described in the baseline case. Let $u_{-i} = u_{-i}^o + u_{-i}^{no}$ where u_{-i}^o is the component of the noise in peer stock price that can be measured by the econometrician. Again we assume that u_{-i}^o and u_{-i}^{no} are independent and normally distributed with means zero and variances $\lambda_{-i}\sigma^2_{u_{-i}}$ and $(1 - \lambda_{-i})\sigma^2_{u_{-i}}$, respectively.

Proposition 1. *: The optimal investment policy of firm i is such that:*

$$E(K_i^* \,|P_i, P_{-i}, u_{-i}^o) = \beta_i P_i + \gamma_{-i} P_{-i}^* + \rho_{-i} u_{-i}^o, \tag{21}$$

where $P_{-i}^* = \theta + u_{-i}^{no}$, $\rho_{-i} = b_{-i} + c_{-i} \geq 0$, $\beta_i \geq 0$, and $\gamma_{-i} \geq \rho_{-i}$ (expressions for β_i and γ_{-i} are given in the proof of the proposition).

As in the baseline case, one can obtain an unbiased estimate of ρ_{-i} by regressing firm i's investment on its own stock price, the residual of a regression of the peer of firm i stock price on u_{-i}^o, and the component of the noise in the peer stock price that can be measured by the econometrician. On that ground, our main empirical test is to estimate the following regression:

$$K_i^* = \beta P_i + \gamma P_{-i}^* + \rho u_{-i}^o + \epsilon_i, \tag{22}$$

and test whether $\rho > 0$. Observing $\rho = 0$ indicates that either managers do not learn information from their peer stock price or that they are perfectly able to distinguish non-fundamental variations in the peer's stock price from fundamental variations. Moreover, the model delivers additional predictions of the faulty informant hypothesis about the cross-sectional determinants of ρ.

Corollary 1. *If managers rely on stock prices for their decision ($\psi < 1$) and cannot perfectly distinguish fundamental from non fundamental variations in stock prices ($\phi_i < 1$ and $\phi_{-i} < 1$) then a firm investment should be less sensitive to the noise in its peer stock price (ρ_{-i} goes down) when:*

1. *Its peer stock price is less informative ($\frac{\partial \rho_{-i}}{\partial \kappa_{-i}} > 0$).*
2. *Its manager's private information about the noise in its peer stock price is more informative ($\frac{\partial \rho_{-i}}{\partial \phi_{-i}} < 0$).*
3. *Its manager's private information about its fundamentals or its own stock price are more informative (i.e., $\frac{\partial \rho_{-i}}{\partial \psi} < 0$ and $\frac{\partial \rho_{-i}}{\partial \kappa_i} < 0$).*

When firm i's peer stock price is more informative (κ_{-i} increases), the investment of firm i is more sensitive (b_{-i} goes up) to its peer stock price since the latter affects his belief about firm i's fundamental more. One inescapable consequence is that the manager also reacts more to the non fundamental component of variations in his peer stock price. His optimal investment policy accounts for this ($c_{-i} < 0$) but if $\phi_{-i} < 1$ (the manager is not perfectly informed about u) then $\rho_{-i} = b_{-i} + c_{-i}$ increases with κ_{-i}. This yields the first prediction in Corollary 1. When the manager's private information about the noise in his peer stock price is better, the manager can better filter out the noise from this price and is therefore less sensitive to non fundamental variation in his peer stock price. Last, when the manager's private information is more precise or when his own stock price is more informative, he relies less on his peer stock price as a source of information (b_{-i} declines). As a result the investment of firm i is less sensitive to non fundamental variations in its peer stock price.

In all, absent other channels through which the noise in the peer's stock price affects firm i investment, observing $\rho > 0$ unambiguously indicates that the manager relies on stock prices, but cannot perfectly distinguish between the fundamental and non-fundamental component. Hence, our empirical strategy proceeds in three steps. First, we estimate equation (22) on a large sample of publicly-listed firms and establish that $\rho > 0$. Second, we provide further support for the faulty informant hypothesis by showing that the cross-sectional determinants of ρ derived in Corollary 1 are at play in the data. Third, we show that our findings are hard to reconcile with plausible alternative explanations.

III Implementing the Test

In this section, we explain how we proceed to estimate ρ in eq.(22), the sensitivity of firms' investment to the noise in their peers' stock prices. In Section A, we describe how we identify the peers of each firm in our sample. Then, in Section B, we explain how decompose the price of each firm's peers into a non fundamental component (the empirical analog of u^o_{-i}) and a component orthogonal to this component (the empirical analog of P^*_{-i}). Finally, in Section C, we present the baseline specification of the investment equation that we use in our tests.

A Identifying Peers and Sample Construction

For our tests, we must identify a set of peers for each firm in our sample. To this end, we use the Text-based Network Industry Classification (TNIC) developed by Hoberg and Phillips (2015). This classification is based on textual analysis of the product description sections of firms' 10-K (Item 1 or Item 1A) filed every year with the Securities and Exchange Commission (SEC). The classification covers the period 1996 to 2011 because TNIC industries require the availability of 10-K annual filings in electronically readable format. For each year in this period, Hoberg and Phillips (2015) compute a measure of product similarity for every pair of public firms in the U.S. by parsing the product descriptions from their 10-Ks. This measure is based on the relative number of words that two firms share in their product description. It ranges between 0% and 100%. Intuitively, the more common words two firms use in describing their products, the more similar are these firms. Hoberg and Phillips (2015) then define each firm i's industry to include all firms j with pairwise similarities relative to i above a pre-specified minimum similarity threshold – chosen to generate industries with the same fraction of industry pairs as 3-digit SIC industries.[17]

Thus, our sample comprises all firms present in TNIC industries over the period 1996 to 2011. For each firm in the sample, we define its set of "peers" in a given year as all firms that belong to its TNIC industry in this year. For all firms, we obtain stock price and return information from the Center for Research in Securities Prices (CRSP). Investment and other accounting data are from Compustat. We exclude firms in financial industries (SIC code 6000-6999) and utility industries (SIC code 4000-4999). We also exclude firm-year observations with negative sales or missing information on total assets, capital expenditure, fixed assets (property, plant and equipment), and (end of year) stock prices.

The construction of all the variables is described in the appendix. To reduce the effect of outliers, all ratios are winsorized at 1% in each tail. As usual in the literature, we measure a firm's stock price by its Tobin-Q (its market value divided by book value). We denote by Q_{it}, the Tobin-Q of firm i in year t and by $\overline{Q}_{-it}$, the equally weighted average of its peers' Tobin-Q in year t.

B The Non-Fundamental Component of Peers' Stock Prices

To obtain a measure of the non-fundamental component of peers' stock prices, we use the price pressure measure ($MFFlow$) developed by Edmans, Goldstein and Jiang (2012). Specifically, for each stock i in our sample, we measure the *hypothetical* sales

[17] Hoberg and Phillips (2015)'s TNIC industries have three important features. First, unlike industries based on the Standard Industry Classification (SIC) or the North American Industry Classification System (NAICS), they change over time. In particular, when a firm modifies its product range, innovates, or enters a new product market, the set of peer firms changes accordingly. Second, TNIC industries are based on the products that firms supply to the market, rather than their production processes as, for instance, is the case for NAICS. Thus, firms within the same TNIC industry are more likely to be exposed to common demand shocks and therefore share common fundamentals. Third, unlike SIC and NAICS industries, TNIC industries do not require relations between firms to be transitive. Indeed, as industry members are defined relative to each firm, each firm has its own distinct set of peers. This provides a richer definition of similarity and product market relatedness.

of this stock in year t (denoted by $MFF_{i,t}$) due to large outflows (i.e., larger than 5% of their assets) experienced by U.S. mutual funds holding this stock, excluding funds specializing in specific industries.[18] These sales are hypothetical, in the sense that they are computed assuming that mutual funds hit by large outflows in a given quarter respond to these shocks by liquidating their holdings, so as to keep the distribution of their holdings constant. The appendix provides technical details for the construction of $MFF_{i,t}$. Importantly, by construction, $MFF_{i,t}$ only takes negative values. Thus, the smaller is $MFF_{i,t}$, the larger are hypothetical sales of stock i in year t due to outflows in year t of mutual funds holding this stock.

Hypothetical sales of a stock due to large redemptions of mutual funds holding the stock provides a good instrument for non-fundamental price changes in this stock. Indeed, sales by mutual funds experiencing large outflows are known to create downward price pressures on stocks (Coval and Stafford, 2007). If mutual funds' managers have the discretion to choose which stocks to sell to meet investors' redemptions, they might liquidate in priority stocks for which they have negative information on fundamentals. This is why we use hypothetical rather than actual sales, rather of mutual funds hit by large outflows as an instrument for non-fundamental price pressures in a stock. Indeed, by construction, these sales reflect a change in mutual funds' positions that is mechanically driven by outflows and not managers' views of fundamentals. Moreover, outflows from funds are unlikely to be driven by changes in investors' views about stocks held by these funds due to the exclusion of industry-specialized mutual funds in the construction of $MFF_{i,t}$.[19]

Figure 1 shows the relationship between large mutual funds outflows for stocks in our sample and stock prices. We define an "event" as a large hypothetical sale of stock i due to large mutual funds redemptions in quarter q of year t, i.e., a realization of $MFF_{i,t,q}$ is below the 10^{th} percentile of the distribution of MFF in the full sample. We then estimate the cumulative abnormal returns (CAAR), over the CRSP equal-

[18] Results are similar if we also include industry-specialized funds.

[19] Investors might have negative information about a stock held by some mutual funds. However, in this case, it is not clear why they should speculate on these views by withdrawing money from mutual funds owning this stock rather than directly selling it in the market.

weighted index, around the event for each affected firm, and report the average behavior of this variable.[20] As in Coval and Stafford (2007) and Edmans, Goldstein, and Jiang (2012), we observe no significant decline in stock prices prior to a large hypothetical sale of stocks in our sample. Yet, following this event, stock prices drop by about 10% and then recover after about two years. This price reversal is consistent with the hypothesis that the price pressures associated with large mutual funds outflows are non-fundamental shocks to prices.

The fact that we observe no decline in prices for stocks that experience large hypothetical sales *before* the event date is particularly reassuring. It suggests that funds experiencing large outflows are not funds that invested in stocks with weak fundamental and that therefore had a poor performance before the event date. This comforts our interpretation that price pressures due to large mutual funds outflows are not due to changes in fundamentals.

[Insert Figure 2 and Figure 3 About Here]

Additional evidence supports this interpretation. In Figure 2 and Figure 3, we plot the average value of MFF across stocks in our sample for each year in our sample (Figure 2) and across the Hoberg and Phillips (2015) industry classification (FICicode100; Figure 3). These figures show that extreme mutual funds outflows do not cluster in any particular time period or industry. Finally, Figure 4 displays the average evolution of prices of the closest peer of each firm i that experiences a large hypothetical sale in our sample around the time of this event. As the figure shows, these prices do not show any specific patterns around the event date, suggesting that the drop in prices for firm i is non-fundamental since the fundamentals of firm i and its closest peer are likely to be highly correlated.

[Insert Figure 4 About Here]

[20] $MFF_{i,t,q}$ is persistent at the firm-level with a coefficient of autocorrelation of 0.50 in our sample. We account for this high degree of persistence by estimating linear regressions of quarterly abnormal returns on event-time dummy variables for affected firms, and display the cumulated coefficients in Figure 1.

We decompose peers' Tobin-Q into a fundamental and non-fundamental component as follows. We denote by $\overline{MFF}_{-i,t}$ the equally weighted average value of MFF across all peers of firm i. Then, in each year, we decompose the variation in $\overline{Q}_{-i,t}$, the value of the equally weighted average portfolio of all peers of firm i in year t into two components by estimating the following regression:

$$\overline{Q}_{-i,t} = \alpha_i + \delta_t + \phi\overline{MFF}_{-i,t} + \upsilon_{-i,t} \tag{23}$$

where α and δ are firm and year fixed effects.

For brevity, we do not tabulate estimates of eq.(23). Consistent with Figure 1, ϕ is negative and significant (-2.59 with a t-stat of 21). The average value of the portfolio of firm i's peers, $\overline{Q}_{-i,t}$, is negatively correlated with the average realization of MFF for the stocks in this portfolio. As explained above, this source of variation for $\overline{Q}_{-i,t}$ is likely to be due non-fundamental reasons. Thus, we use (i) $\overline{MFF}_{-i,t}$ as a proxy for u^o_{-i}, the non-fundamental variation in the stock price of firm $-i$ that can be observed (ex post) by the econometrician and (ii) $\overline{Q}^*_{-i,t} = \hat{\upsilon_{-i,t}}$, the estimated residual of regression (23) as a proxy for $P^*_{-i} = P_{-i} - \mathrm{E}(P_{-i} \left| u^o_{-i} \right.)$ in the model.[21] We refer to $\overline{MFF}_{-i,t}$ as the non-fundamental component of $\overline{Q}_{-i,t}$ and to $\overline{Q}^*_{-i,t}$ as the fundamental component (even though, as in the theory, $\overline{Q}^*_{-i,t}$ might include some noise).[22]

C Econometric Specification

Our main goal is to estimate the investment-to-noise sensitivity, ρ, in eq. (22). To this end, we estimate a standard linear investment equation with our proxies for the non-fundamental and fundamental components of peers' stock prices for each firm in our sample. Specifically, we estimate the following baseline specification:

$$I_{i,t} = \lambda_i + \delta_t + \alpha_0 Q^*_{-i,t-1} + \alpha_1 MFF_{-i,t-1} + \alpha_2 Q^*_{i,t-1} + \alpha_3 MFF_{i,t-1} + \mathbf{\Gamma X_{i,-i,t}} + \varepsilon_{i,t} \tag{24}$$

[21] Alternatively, we can use $\phi \times \overline{MFF}_{-i,t}$ as a proxy for u^o_{-i}. Results with this approach as qualitatively similar since ϕ is a scaling factor common to all portfolio of peers.

[22] Blundell et al. (1992), Blanchard et al. (1993), Galeotti and Schiantarelli (1994), or Campello and Graham (2013) also use linear regressions to decompose stock prices into non-fundamental and fundamental components.

where $I_{i,t}$, is the ratio of capital expenditure scaled by lagged fixed assets (property, plant, and equipment) in year t for firm i and $\overline{MFF}_{-i,t-1}$ and $\overline{Q}^*_{-i,t-1}$ are, respectively, the non-fundamental and fundamental components of the value of the portfolio of firm i's peers in year $t-1$. We also control for firm i's own stock price in year $t-1$ that we decompose in a non-fundamental ($MFF_{i,t-1}$) and a fundamental component ($Q^*_{i,t-1}$) using the same methodology as that followed to obtain $\overline{MFF}_{-i,t-1}$ and $\overline{Q}^*_{-i,t-1}$ (see eq. (23)). The vector **X** include control variables known to be correlated with investment decisions, namely the natural logarithm of assets ("firm's size") and cash-flows, both for firm i and its portfolio of peers in year $t-1$. In addition, we account for time-invariant firm heterogeneity by including firm fixed effects (λ_i), and time-specific effects by including year fixed effects (δ_t). We allow the error term ($\varepsilon_{i,t}$) to be correlated within firms. Finally, in all our tests, we scale the independent variables by their sample standard deviation. Hence, the coefficient for a given independent variable gives the estimated change in investment for a firm in our sample for a one standard deviation change in this variable.

Coefficients α_0 and α_1 in eq. (24) are the empirical counterparts of γ and ρ in the model.[23] The model implies that if managers imperfectly learns information from stock prices then $\alpha_1 > 0$ and $\gamma > \alpha_1$.

Outflows-induced price pressures could be correlated *within* industries if funds experiencing extreme outflows have correlated industry allocations. In this case, α_1 could potentially reflect the effect of the non-fundamental component of firm i's stock price on its investment decisions (u_i), rather than only the effect of the non-fundamental component of the value of firm i's peer portfolios. By including MFF_i in specification (24), we control for this possibility so that α_1 measures the effect MFF_{-i} that is unrelated to MFF_i.

[23] A large realization of $MFF_{i,t-1}$ means that the non-fundamental shock to the value of the portfolio of firm i's peers is *less* negative, i.e., that u^o_{-i} is larger in the theory.

IV Empirical Findings

A The Faulty Informant Channel ($\rho > 0$)

We report estimates of eq. (24) in Column 1 of Table III. As predicted by the faulty informant hypothesis, the coefficient on $MFF_{-i,t-1}$ is positive and statistically significant (0.018 with a t-statistic of 7.51). It implies that a one standard deviation decrease in the non-fundamental component of peers' stock price is associated with a 1.8 percentage point decrease of investment, which represents a 5% drop relative to the average level of investment (0.36% of PPE).

Moreover, as predicted by our model, the coefficient on the fundamental component of peers' stock price is also significantly positive and larger than the coefficient on $MFF_{-i,t-1}$ (0.029 with a t-statistics of 12.71). The coefficient on the other variables have the expected signs. In particular, consistent with Hau and Lai (2013), a firm's investment is lower when its own stock price is subject to (negative) non-fundamental price pressure ($MFF_{i,t-1}$ is positive and significant), and is highly sensitive to the fundamental component of its own price ($Q^{*}_{i,t-1}$).

[Insert Table III About Here]

In the rest of Table III (Column 2 to 7), we check the robustness of our estimates in Column 1 to various changes in our baseline specification. In columns (2) to (4), we consider various ways of aggregating $MFF_{-i,t}$ and $Q_{-i,t}$ across peers to obtain $\overline{MFF}_{-i,t}$, $\overline{Q}_{-i,t}$, and $\overline{Q}^{\star}_{-i,t}$. In Column (2), $\overline{MFF}_{-i,t}$ and $\overline{Q}_{-i,t}$ are a weighted average of $MFF_{-i,t}$ and $Q_{-i,t}$ across peers of firm i, where the weights are the similarity score computed in Hoberg and Phillips (2015) while in Column (3) $\overline{MFF}_{-i,t}$ and $\overline{Q}_{-i,t}$ are the median values of $MFF_{-i,t}$ and $Q_{-i,t}$. Column (4) uses "aggregated" values, where all accounting variables are first summed across peers, and ratios are then calculated using these aggregated variables.

In Columns (5) and (6), we add State $\times$ Year fixed effects (Column (5)) and State $\times$ Year fixed effects and Industry $\times$ Year fixed effects (Column (6)) to our baseline specification, to further control for time-varying unobserved heterogeneity.[24] Finally, in Column (7), we include additional further controls for firms' fundamentals.[25] Our conclusion remains robust across all these additional specifications.

Overall, Table III provides strong support the the faulty informant hypothesis. Firm's investment is significantly related to the non-fundamental component of its peers' stock prices. As predicted by our model, it arises when managers rely on the stock prices of their peers as a source of information, but cannot perfectly distinguish the fundamental from the non-fundamental component of these prices. Besides confirming our model's central prediction, our findings have another novel implication. They suggest that the deviation of a firm's stock price from its fundamental value can have real externalities on related firms. The presence of such externalities can potentially trigger amplification effects via a feed-back loop between stock price valuation and investments, and exacerbate the impact of misvaluation on the real economy.[26] Our theoretical setting suggests that this type of externality is particularly relevant when managers rationally condition their decisions on the stock price of related firms, but can imperfectly filter out the noise in these stock prices.

B Cross-Sectional Implications

As predicted by the faulty informant hypothesis, a firm investment is positively related to the noise in the value of its peers' portfolio. In this section, to provide further support for the faulty informant hypothesis, we test whether the investment-to-noise sensitivity of firms in our sample varies with firms characteristics as predicted by our

[24] State $\times$ Year fixed effects absorb state (of location) business cycles and account for all local state policies that may influence firms' investments (such as investment tax credit, labor regulation, etc.). Industry $\times$ Year fixed effects absorb any industry specific business cycles, technological shocks and account for the fact that some industries may have a greater sensitivity of investment to peers' stock price. We report the result with FIC-icode300 industry classification but we obtain similar results with SIC-3 or SIC-4 classification

[25] Following Campello and Graham (2013), we include two lags for sales growth, fixed assets, cash and leverage ratios of firm i and the equally weighted average values of these variables for the portfolio of its peers.

[26] e.g. Dow, Goldstein and Guembel (2015) in the case of negative shocks. It should be noted that our mechanism is different from situations where feedback loops happen because firms borrow against the stock market value of their collateralized assets to finance investment (e.g. Miao and Wang, 2012)

model (Corollary 1). We test the cross-sectional predictions by interacting proxies for managerial information or peers' stock price informativeness (both described in Section B.1) with $MFF_{-i,t}$ with these proxies in our baseline specification (24).[27]

B.1 Managerial Information (ψ and ϕ)

The faulty informant hypothesis predicts that managers should be *less* responsive to the non-fundamental component of their peers' stock prices when they are better privately informed, either about their firm's fundamentals (their signal s_{mi} is more precise), or about the noise in peers' stock prices (their signal s_{ui}). To test these predictions, we use four different proxies for the amount of managerial information, that we generically label as $ManagerInfo$). The faulty informant hypothesis predicts that the coefficient on $MFF_{-i} \times ManagerInfo$ should be negative (see Corollary 1).

Following Foucault and Fresard (2014), we first use the profitability of insiders' trades as proxy for managerial information. We posit that managers are more likely to make profitable trades if they are more informed. We measure the profitability of insiders' trades ($InsiderAR$) as the average one month market adjusted returns of holding the same position as insiders for each insider's transaction. We obtain insiders' trades from the Thomson Financial Insider Trading database, and as in other studies (e.g. Peress, 2010), we restrict our attention to open market stock transactions initiated by the top five executives (CEO, CFO, COO, President, and Chairman of the Board).

Second, we conjecture that managers are more likely to detect noise in stock prices if their firm has experienced itself episodes of severe downward price pressure due to mutual fund firesales in the past. To capture this idea empirically, we create a dummy variable ($PreviousFiresale$) that is equal to one if a firm has been in the lowest decile of MFF (i.e. extreme mutual funds outflows) in the past three years, and zero otherwise.

Our third proxy relies on the overlap in mutual funds ownership between a firm and its peers. Arguably, managers should be more able to identify non-fundamental shocks

[27] Importantly, we also interact all the other RHS variables to guarantee the consistency of the estimator.

to the value of their portfolio of peers due to large sales by mutual funds facing large redemptions when they share more common mutual funds holdings with their peers, as mutual funds are likely to convey information across the different firms they hold. For each pair of firms and each year, we construct an index of mutual fund ownership overlap by computing the cosine similarity between firms' ownership structure.[28] We then compute the average ownership overlap between a firm and its peers in a given year, and label this variable $CommonOwnership$.

Our fourth proxy uses the target price estimates provided by financial analysts. Sulaeman and Wei (2014) document that some analysts detect mutual fund flow-driven mispricing. We thus conjecture that managers should be better able at identifying noise in their peers' stock prices when analysts' estimates point towards mispricings. For each firm-year we compute the average difference between analyst target stock price and current stock price. We then define $AnalystDiscount$ for a given firm-year as the average discount calculated across its peers.

[Insert Table IV About Here]

Table IV presents the results. To preserve space, we only report the estimated coefficients on MFF_{-i} and $MFF_{-i} \times ManagerInfo$. We find the coefficients on $MFF_{-i} \times ManagerInfo$ are negative across all specifications, while the coefficients on MFF_{-i} remain positive. Firms' investment is less sensitive to the noise in their peers' stock prices when managers appear more informed about fundamentals or about the non-fundamental components of peers' prices. The coefficients are significant in two specifications out of four, while the other two are borderline significant (p-val = 0.12). Thus, as predicted by Corollary 1, the investment-to-noise sensitivity of managers is lower when they are better informed about fundamentals, or the noise in their peers' stock prices.

[28] If there are N funds active in year t, we define for each firm i a $N \times 1$ vector v_i. The n^{th} entry of v_i is equal to one if fund $n \in \{1, ..., N\}$ holds shares of firm i and is equal to zero otherwise. The ownership overlap between firms i and j is then measured by the cosine similarity between v_i and v_j, that is $\frac{v_i \cdot v_j}{\|v_i\| \|v_j\|}$.

B.2 Peers' Stock Price Informativeness (κ)

The faulty informant hypothesis uniquely predicts that investment should be *more* sensitive to the non-fundamental component of peers' price when these prices are more informative about fundamentals (see Corollary 1). This happens because imperfectly informed managers optimally put more weights on the stock prices of their peers, when they expect these prices to be more informative about fundamentals.

Our first measure of price informativeness is taken from Bai, Philipon, and Savov (2014) and relies on the ability of current stock prices to forecast future earnings. To compute this measure, we estimate for each year and each firm a cross-sectional regression of all its peers' three-year ahead earnings on their current prices (Tobin Qs') and current earnings (before interests and taxes) over assets. We call $BPS_{-i,t}$ the coefficient on peers' stock prices in these predictive regressions and use it as a measure of the informativeness of a firm's peer stock prices. The stock prices of a firm's peers are more informative if they better forecasts future earnings, i.e., if the coefficient on current prices is larger. We label these estimated coefficients BPS.

Second, as in Durnev, Morck, and Yeung (2004), or Chen, Goldstein, and Jiang (2007), we measure the informativeness of a firm stock price by its firm-specific return variation (or price non-synchronicity), defined as $\ln((1 - R^2_{i,t})/R^2_{i,t})$, where $R^2_{i,t}$ is the R^2 from the regression in year t of firm i's weekly returns on market returns and its peers' value-weighted portfolio returns. The idea, due to Roll (1988), is that trading on firm-specific information makes stock returns less correlated and thereby increases the fraction of total volatility due to idiosyncratic returns. Thus, stock price informativeness is higher when firm-specific return variation is higher. Accordingly, as another proxy for a firms' peer stock price informativeness, we use the variable $Nonsync_{i,t}$, defined as the average firm-specific return variation of the peers of firm i in year t.

Third, we use the average earnings forecast error of financial analysts to measure the informativeness of peers' stock price. Analysts facilitate the dissemination of information among investors. They often directly communicate with company's management and are used to vehicle information more broadly (e.g. Womack, 1996; Barber et al., 2001; Jegadeesh et al., 2004; Loh and Stulz, 2011). Hence, we conjecture that peers' stock prices should be more informative when financial analysts following these stocks convey more precise signals about fundamentals to market participants, i.e., when their average earnings forecast error is smaller.

Our fourth proxy relies on the intensity of previous fund-driven price pressure in peers' stock prices. In our model, peers' stock prices are less informative about the fundamental (θ) when the non-fundamental component is large. To capture this idea empirically, we average the dummy variable $PreviousFiresale$ (that is equal to one if a firm has been in the lowest decile of MFF in the past three years, and zero otherwise) across the peers of each firm-years.

[Insert Table V About Here]

Estimates reported in Table V reveals that on average, investment responds more to the noise in peers' stock prices when prices are more informative. For instance, columns (1) and (2) indicate that the interacted coefficients on $MFF_{-i} \times BPS$ and $MFF_{-i} \times Nonsync$ are positive, and significant at a 10% confidence level. We obtain similar results in columns (3) and (4), where we see that investment is less responsive to the noise in peers' prices when analysts forecast errors are large, and when peers stock prices have experienced fund-driven price pressure in the past. Taken together, the findings in Table V are again supportive of the model's cross-sectional predictions. The faulty information channel is more important when managers rely more on the stock market because the prices are more informative about fundamentals.

C Assessing Alternative Explanations

Our results so far are consistent with the implications of the faulty informant hypothesis: (i) a firm's investment is sensitive to the noise in its peers' stock prices and (ii) this sensitivity varies with firms' characteristics as predicted by the faulty informant hypothesis. In this section, we study alternative explanations for these findings.

C.1 Financing Channel

The investment of financially constrained firms might be sensitive to non-fundamental variations in their stock prices, because these variations affect their cost of capital (e.g. Baker et al.(2003) and references therein). This mechanism, however, cannot explain why firms are also sensitive to the noise in their peer stock prices after controlling for the noise in a firm's own stock price, as we find in our sample.

Nevertheless, the noise in peers' stock price could still indirectly affect a firm cost of debt (and thereby its investment) for two reasons. First, debtholders might also rely on peers' stock price to learn information about a firm's fundamentals and set their financing conditions accordingly. Second, a decrease in peers' stock price might lower their ability to buy new assets if they are financially constrained (precisely due to the financing channel). One indirect effect is that the collateral value of firm i assets, and therefore its borrowing capacity, might then become lower since firm i's peers might be the natural buyers of its assets (Shleifer and Vishny, 1992).

These mechanisms imply that a firm's cost of debt could be sensitive to the noise in its peers' stock prices. We test directly if it the case by using measures of the cost of debt and access to external capital as the dependent variable in our baseline specification (24) with firm-level measures of financing costs and access to external capital. We rely on credit default swap (CDS) spreads and spreads on new private debt issues as indicators of the costs of debt. We obtain average annual CDS spreads from Markit, and the average spreads on new debt issues from Dealscan. Alternatively, we use text-based measures of financing constrained developed by Hoberg and Maksimovic (2015) using textual analysis of the Management's Discussion and Analysis (MD&A) section of firms' 10Ks.[29] In particular, we use their score of debt-market constraints, where a higher score indicate more binding constraints debt markets, respectively. For completeness, we also use their score of equity-market constraints. Due to data constraints, the tests are performed for a subset of firms in our sample (the text-based measures of financial constraints are available only starting in 1997, not 1996 while

[29]We thank Jerry Hoberg and Max Maksimovic for sharing their data with us.

CDS spreads and spreads on new private debt issues are not available for all firms).

[Insert Table VI About Here]

Table VI report our estimates of the sensitivity of borrowing costs for a firm to the noise in its peers' stock price (Columns (1) to (4)). This sensitivity is always positive and it is significant only for the spread on new private debt issues. Thus, downward non-fundamental pressures on its peers' stock prices do not increase, and if anything *reduce*, borrowing costs for a firm. This is inconsistent with the idea that the effect of these pressures on the firm's investment are due to change in financing conditions for the firm.

C.2 Pressure Channel

A non-fundamental drop in a firm's stock price increases the likelihood of a take-over of this firm, as shown by Edmans, Goldstein and Jiang (2012). In response to this threat, managers might undertake actions that will temporarily boost the short term value of their stock, due to career concerns as in Stein (1988, 1989). Survey evidence indicate that such actions include postponing positive NPV projects so as to increase current earnings.[30]

Managers' career concerns might therefore explain our findings if a non-fundamental drop in its peers' stock price increases the likelihood of replacement of its CEO for a firm, e.g., through a take-over. We check whether this effect is present in our data by replacing the dependent variable in our baseline specification with a binary variable equals to one if (i) a firm receives a takeover bid in a given year or (ii) a firm experiences a CEO change in a given year. Data on takeover bids are taken from the SDC database, while data on CEO turnover are obtained from Execucomp.

The results are reported in Columns (5) and (6) of table VI. Column (6) shows that a firm's CEO turnover is unrelated to the noise in its peers' stock prices. Similarly,

[30]For instance, almost 80% of managers admit that they are willing to decrease investment in order to meet analysts' earnings estimates (see Graham, Harvey, and Rajgopal (2005)).

Column (5) reveals that this noise has no effect on the likelihood that a firm becomes a takeover target, as the coefficient on MFF_{-i} is not statistically significant. In contrast, as found by Edmans, Goldstein and Jiang (2012), the coefficient on MFF_i is positive and statistically significant (the likelihood of a takeover for a firm is higher when its stock price experiences a non-fundamental price drop).

In sum, we find no evidence that the sensitivity of a firm's investment to the noise in its peers' stock price might stem from managerial career concerns.

C.3 Peer Effects

Previous researches find that firms lower their investment in response to drop in their own stock price due to large sales by mutual funds (e.g., Hau and Lai (2013)). This suggests that $\overline{MFF}_{-i,t}$ is positively correlated with the investment of firm i's peers. Hence, our findings that $\overline{MFF}_{-i,t}$ is positively related to firm i's investment might reflect complementarities in firms' investment decisions rather than managerial learning from stock prices.[31]

To address this possibility, we re-estimate our baseline specification (24) with a measure of peers' investment in each year as an additional control.

[Insert Table VII About Here]

Table VII presents the results (every column mirrors the specifications reported in our main Table III). The coefficients on peers' investment are in general positive and significant (except when we include Industry×Year fixed effects in columns (5) and (6)), confirming that on average corporate investment co-moves positively between firms within the same TNIC industry. Yet, accounting for these co-movements does not alter our main finding: The coefficients on MFF_{-i} remain positive and statistically significant in every specification. The magnitude of the coefficients on MFF_{-i} and Q^*_{-i}

[31]Models such as Fudenberg and Tirole (1984) or Bulow, Geanakoplos, and Klemperer () identify conditions under which investment decisions (capacity choices) by firms can be strategic complements, i.e., conditions under which an increase in the investment of one firm leads its competitors to also increase their investments.

is about half that obtained when we do not control for co-movements in investment (as in Table III). Yet, we continue to observe that the effect of peers' non-fundamental price component is about half the size of the effect of peers' fundamental price. We conclude that our results cannot be explained solely by mimetic behaviors of firms.

C.4 Alternative Test: Capital Allocation Within Firms

To further mitigate the concern that other explanations than the active informant channel may affect our results, we study capital allocation decisions *within* firms. Specifically, we investigate how managers of diversified conglomerates reallocate investment across divisions, when the peers of one division experience significant downward price pressure and the peers of the other divisions do not. The logic of this test is that reallocation decisions within firms are difficult to reconcile with the financing or the pressure channels because financing constrains and CEO incentives affect presumably all divisions equally. Hence, by concentrating on variation of investment within firms, we can assess the impact of the non-fundamental component of division peers' stock prices, holding firms' financing costs and CEO incentives constant.

To implement this test, we use data from Compustat segment files. From these files, we retrieve segment level information on annual capital expenditures, total assets, as well as a four-digit SIC code for each segment, which we match with the relevant 48 Fama-French industry (FF48) as in Krueger, Landier and Thesmar (2015). Within each firm, we then aggregate capital expenditures and total assets by FF48 industry. We label as "divisions" the resulting firm-industry-year observations and we define as "peers" of a given firm-division all the firms that operate in the same FF48 industry in a given year.[32]. That is, in contrast to tests in the previous sections, we use FF48 industries rather than the TNIC industries because the latter do not allow to identify product market peers at the division level.

To measure the non-fundamental component of peers' stock prices for a given firm division, we proceed as in section III.B. We decompose the average value, $\overline{Q}_{-i,d,t}$ of the

[32]We find similar results if we restrict to all stand-alone firms that operate in the same FF48 to define peers.

portfolio of peers for a given firm-division i, d in a given year t into a non-fundamental component and a fundamental component, by estimating the following regression:

$$\overline{Q}_{-i,d,t} = \alpha_{i,d} + \delta_{i,t} + \phi \overline{MFF}_{-i,d,t} + \upsilon_{-i,d,t} \tag{25}$$

where the subscripts i, d and t refer to firms, divisions, and years respectively, and $-i$ represents an equally-weighted portfolio of industry peers. Hence, $\overline{Q}_{-i,d,t}$ and $\overline{MFF}_{-i,d,t}$ are the average Q and mutual funds outflows across all firms belonging to the same FF48 industry as division d of firm i (excluding firm i), and $\alpha_{i,d}$ and $\delta_{t,d}$ are Firm×Division and Firm×Year fixed effects. As in our baseline tests, we use $\overline{MFF}_{-i,d,t}$ as our estimate of the component of the noise in peers' stock price and the estimated residual $\overline{\upsilon}_{-i,d,t}$ of eq. (25) as our estimate of the fundamental component of peers' stock price, denoted $\overline{Q}^{*}_{-i,d,t-1}$.

Using firm-division-year observations, we estimate the following specification:[33]

$$I_{i,d,t} = \lambda_{i,d} + \delta_{i,t} + \alpha_0 \overline{Q}^{*}_{-i,d,t-1} + \alpha_1 \overline{MFF}_{-i,d,t-1} + \mathbf{\Gamma X_{-i,d,t}} + \varepsilon_{i,d,t}.$$

where the dependent variable, $I_{i,d,t}$ is the ratio of capital expenditures of a division d of firm i in year t scaled by previous year total fixed assets of that division (we cannot use property, plant and equipment as in the baseline tests because these variables are not available at the division level). We control for the average size and the average cash-flow of each division's peers and include Firm×Division fixed effects ($\lambda_{i,d}$), as well as Firm×Year fixed effects ($\delta_{i,t}$) to control for unobserved time-varying fluctuations at the firm level.[34]. This strategy ensures that the estimated differences in investment across divisions only reflect *within*-firm reallocation decisions.

The inclusion of Firm×Year fixed effects is a critical component of the test as they allow us to measure the effect of noise in peers' stock prices on the investment of a division, holding constant financing constraints and CEO characteristics (assuming that they affect similarly all divisions of a given firm). Indeed, these Firm×Year fixed

[33]We have 3,409 distinct conglomerate firms, operating a total of 8,342 divisions over the 1996-2011 period.

[34]This is why we no longer include firm level controls and in particular firm fundamental and non-fundamental price components. They are all absorbed by the Firm×Year fixed effects.

effects absorb common factors related to the financing channel or the pressure channel. Therefore, differences in capital allocation across firms' divisions can be plausibly attributed to differences in the signals conveyed by the stock prices of the peers of each division about their growth opportunities.

[Insert Table VIII About Here]

Table VIII presents the results and confirm our previous findings. The capital invested in one division relative to the capital invested in the other divisions is sensitive to the non-fundamental component of the corresponding peers' stock prices. Whether we control for peers' investment (column 2) or not (column 1), the coefficient on $MFF_{-i,d,t-1}$ is positive and statistically significant. When the peers of one division are temporarily undervalued relative to the peers of the other divisions of the group, managers reallocate capital to the other divisions, consistent with the active informant hypothesis.

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Proofs

Proof of Lemma 1.

As in the baseline case, the optimal investment policy is such that $K_i^* =\mathrm{E}(\theta\,|\Omega_2)$. Now we compute this conditional expectation. Using the fact that $s_m, P_i, P_{-i}, s_{u_{-i}}$ have a normal distribution, we deduce that $\mathrm{E}(\theta\,|\Omega_2)$ is linear in s_m, P_i, P_{-i} and $s_{u_{-i}}$:

$$K_i^*(\Omega_2) = E(\theta\,|\Omega_2) = a_i \times s_m + b_i \times P_i + b_{-i} \times P_{-i} + c_{-i} \times s_{u_{-i}}. \tag{26}$$

Using the Law of Iterated Expectations and the fact that u_{-i} is independent from s_m and P_i, this implies:

$$E(\theta\,|s_m, P_i) = a_i s_m + b_i P_i + b_{-i} E(P_{-i}\,|s_m, P_i) = a s_m + b_i P_i + b_{-i} E(\theta\,|s_m, P_i)\,.$$

Thus:

$$E(\theta\,|s_m, P_i) = \frac{a_i}{1 - b_{-i}} s_m + \frac{b_i}{1 - b_{-i}} P_i.$$

Now, standard calculations also imply:

$$E(\theta\,|s_m, P_i) = a_i^* s_m + b_i^* P_i \tag{27}$$

where $a^* = \frac{\psi(1-\kappa_i)}{(1-\kappa_i)+(1-\psi)\kappa_i}$ and $b^* = \frac{(1-\psi)\kappa_i}{(1-\kappa_i)+(1-\psi)\kappa_i}$. Thus:

$$\begin{aligned} a_i &= a_i^*(1 - b_{-i}), \\ b_i &= b_i^*(1 - b_{-i}). \end{aligned}$$

Let $s_m^* = \frac{(a \times s_m + b_i \times P_i)}{(a+b)(1-b_{-i})} = \theta + \chi^*$ with $\chi^* = \left(\frac{a_i^*}{a_i^*+b_i^*}\right)\theta + \left(\frac{b_i^*}{a_i^*+b_i^*}\right)u_i$. Using these notations, we can rewrite eq.(26) as:

$$E(\theta\,|\Omega_2) = (a_i^* + b_i^*)(1 - b_{-i}) \times s_m^* + b_{-i} \times P_{-i} + c_{-i} \times s_{u_{-i}}. \tag{28}$$

Thus, using the Law of Iterated expectations: $\mathrm{E}(E(\theta\,|\Omega_2)\left|s_m^*, P_{-i}, s_{u_{-i}}\right.)) = E(\theta\,|\Omega_2) = E(\theta\left|s_m^*, P_{-i}, s_{u_{-i}}\right.) = \widehat{a}_i s_m^* + b_{-i} \times P_{-i} + c_{-i} \times s_{u_{-i}}$, where the last equality follows from the normality of all variables. Thus, we are back to a problem that is identical to that considered in the baseline case, except that the role of s_m is now played by s_m^*. Thus for the same reason as in the baseline case:

$$
\begin{aligned}
b_{-i} &= \frac{\sigma_\theta^2 \sigma_{\chi^*}^2}{(\sigma_{u_{-i}}^2 (1-\phi_{-i})(\sigma_\theta^2+\sigma_{\chi^*}^2)+\sigma_\theta^2\sigma_{\chi^*}^2)} = \frac{(1-\psi^*)\kappa_{-i}}{(1-\phi_{-i})(1-\kappa_{-i})+(1-\psi^*)\kappa_{-i}}, \quad (29)\\
c_{-i} &= -\frac{\sigma_\theta^2 \sigma_{\chi^*}^2 \phi_{-i}}{\sigma_{u_{-i}}(1-\phi_i)(\sigma_\theta^2+\sigma_{\chi^*}^2)+\sigma_\theta^2\sigma_{\chi^*}^2\sigma_{u_{-i}}^2} = -\frac{(1-\psi^*)\phi_{-i}\kappa_{-i}}{(1-\phi_i)(1-\kappa_{-i})+(1-\psi^*)\kappa_{-i}} \quad (30)
\end{aligned}
$$

Proof of Proposition 1

Using eq.(26) and the independence of χ and η_{-i} with P_i, P_{-i}, and u_{-i}^o, we deduce that:

$$E(K_i^* \left| P_i, P_{-i}, u_{-i}^o \right.) = a_i E(\theta \left| P_i, P_{-i}, u_{-i}^o \right.) + b_i P_i + b_{-i} P_{-i} + c_{-i} E(u_{-i} \left| P_i, P_{-i}, u_{-i}^o \right.) . \quad (31)$$

Now observe that $E(u_{-i} \left| P_i, P_{-i}, u_{-i}^o \right.) = E(u_{-i}^{no} \left| P_i, P_{-i} - u_{-i}^o \right.) + u_{-i}^o$ and $E(\theta \left| P_i, P_{-i}, u_{-i}^o \right.) = E(\theta \left| P_i, P_{-i} - u_{-i}^o \right.)$. Let $P_{-i}^* = P_{-i} - u_{-i}^o$. Using the normality of all variables, we deduce:

$$
\begin{aligned}
E(\theta \left| P_i, P_{-i}, u_{-i}^o \right.) &= \pi_i P_i + \delta_i P_{-i}^* + u_{-i}^o,\\
E(u_{-i} \left| P_i, P_{-i}, u_{-i}^o \right.) &= \pi_i' P_i + \delta_i' P_{-i}^*.
\end{aligned}
$$

Thus, we deduce from eq.(31) that:

$$E(K_i^* \left| P_i, P_{-i}, u_{-i}^o \right.) = \beta_i P_i + \gamma_{-i} P_{-i}^* + \rho_{-i} u_{-i}^o,$$

with

$$
\begin{aligned}
\beta_i &= (a_i \pi_i' + b_i + c_{-i}\pi_i),\\
\gamma_{-i} &= (a_i \delta_i' + b_{-i} + c_{-i}\delta_i)\\
\rho_{-i} &= b_{-i} + c_{-i}.
\end{aligned}
$$

Moreover, standard computations yield:

$$
\begin{aligned}
\pi_i &= \frac{(1-\lambda)\sigma^2_{u_{-i}}\sigma^2_\theta}{\sigma^2_\theta(\sigma^2_{u_i}+(1-\lambda)\sigma^2_{u_{-i}})+(1-\lambda)\sigma^2_{u_{-i}}\sigma^2_{u_i}},\\
\delta_i &= \frac{\sigma^2_\theta\sigma^2_{u_i}}{\sigma^2_\theta(\sigma^2_{u_i}+(1-\lambda)\sigma^2_{u_{-i}})+(1-\lambda)\sigma^2_{u_{-i}}\sigma^2_{u_i}},\\
\pi'_i &= -\pi_i\\
\delta'_i &= \frac{(1-\lambda)\sigma^2_{u_{-i}}(\sigma^2_\theta+\sigma^2_{u_i})}{\sigma^2_\theta(\sigma^2_{u_i}+(1-\lambda)\sigma^2_{u_{-i}})+(1-\lambda)\sigma^2_{u_{-i}}\sigma^2_{u_i}}.
\end{aligned}
$$

Observe that $\delta_i < 1$ and $a_i > 0$ and $\delta'_i > 0$. Thus,

$$\gamma_{-i} - \rho_{-i} = a_i\delta'_i - c_{-i}(1-\delta_i) > 0,$$

since $c_{-i} < 0$.

Proof of Corollary 1

Using eq.(18) and (18), we deduce:

$$\rho_{-i} = b_{-i} + c_{-i} = \frac{(1-\psi^*)(1-\phi_{-i})\kappa_{-i}}{(1-\phi_i)(1-\kappa_{-i})+(1-\psi^*)\kappa_{-i}}.$$

The claims in Corollary **1** follow from differentiating ρ_{-i} with respect to ϕ_{-i}, κ_{-i}, κ_i and ψ.

Appendix B. Construction Mutual Fund Price Pressure

This appendix explains how, for each stock i, we construct $MFF_{i,t}$, a measure of hypothetical sales in stock i in year t due to large outflows in mutual funds owning the stock. Our approach follows the three-step approach proposed by Edmans, Goldstein and Jiang (2012).

First, in each year t, we estimate quarterly mutual fund flows for all US 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 Asset (TNA) by asset class. The average return of fund j in month m of year t is given by

$$Return_{j,m,t} = \frac{\sum_k (TNA_{k,j,m,t} \times Return_{k,j,m,t})}{\sum_k TNA_{k,j,m,t}},$$

where k indexes asset class. We compound monthly fund returns to estimate average quarterly returns and aggregate TNAs across asset classes in March, June, September and December to obtain the TNA of fund j at the end of every quarter in each year.

An estimate of the net inflow experienced by fund j in quarter q of year t is then given by

$$Flow_{j,q,t} = \frac{TNA_{j,q,t} - TNA_{j,q-1,t} \times (1 + Return_{j,q,t})}{TNA_{j,q-1}}.$$

where $TNA_{j,q,t}$ is the total net asset value of fund j at the end of quarter q in year t and $Return_{j,q,t}$ is the return of fund j in quarter q of year t. $Flow_{j,q,t}$ is therefore the net inflow experienced by fund j in quarter q of year t as a percentage of its net asset value at the beginning of the quarter.

Second, we calculate the dollar value of fund's j holdings of stock i at the end of every quarter using data from CDA Spectrum/Thomson. CDA Spectrum/Thomson provides the number of stocks held by all US funds at the end of every quarter. The total value of the participation held by fund's j in firm i at the end of quarter q in year t is

$$SHARES_{i,k,q,t} \times PRC_{i,q,t},$$

where $SHARES_{j,i,,q,t}$ is the number of stocks i held by fund j at the end of quarter q in year t, and $PRC_{i,q,t}$ is the price of stock i at the end of quarter q in year t.

Finally, for all mutual funds for which $Flow_{j,t} \leq -0.05$, we compute

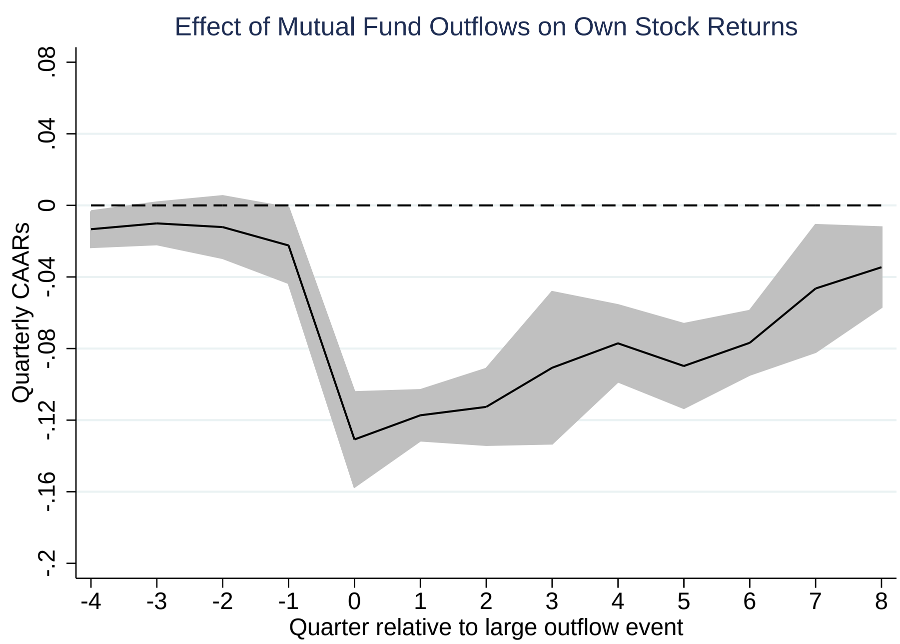
$$MFFlow^{\$}_{i,q,t} = \sum_{j} (Flow_{j,q,t} \times SHARES_{j,i,q} \times PRC_{i,q,t}).$$

This variable corresponds to the hypothetical net selling of stock i, in dollar, by all mutual funds subject to extreme outflows (outflow is greater or equal to 5%. We then normalize $MFFlow^{\}}_{i,q,t}$ by the dollar volume of trading in stock i in quarter q of year t and finally define $MFF_{i,t}$ as:

$$MFFlow_{i,t} = \frac{\sum_{q=1}^{q=4} \sum_j (Flow_{j,q,t} \times SHARES_{j,i,q,t} \times PRC_{i,q,t})}{VOL_{i,q,t}}$$

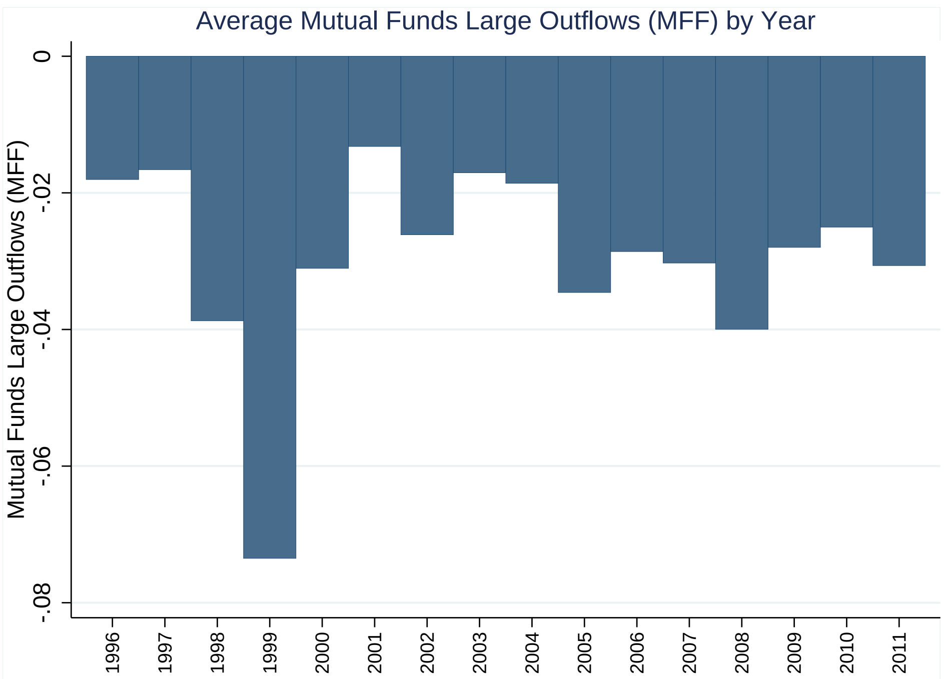
Table I: . Variable Definition

Figure 1: : Effect of Extreme Mutual Fund Outflow on Firm CAAR



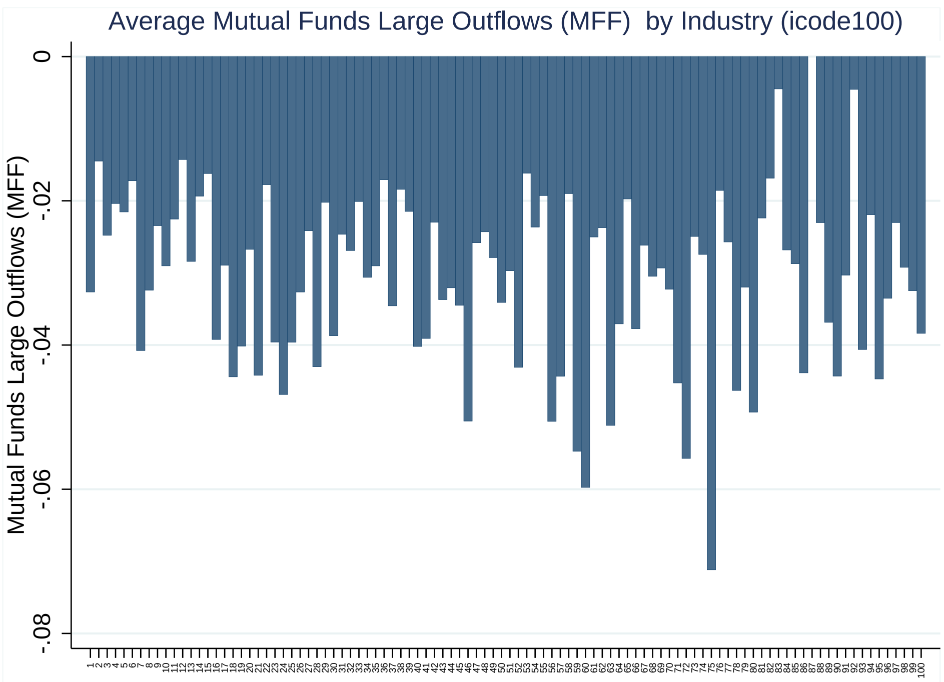
This figure plots the quarterly cumulative average abnormal returns (CAAR) of stocks subject to mutual fund price pressure around the event, where an event is defined as a firm-quarter observation in which MFFlow falls below the 10th percentile value of the full sample. The benchmark used to estimate the CAAR is the CRSP equally-weighted index.

Figure 2: : Extreme Mutual Fund Outflow across Time



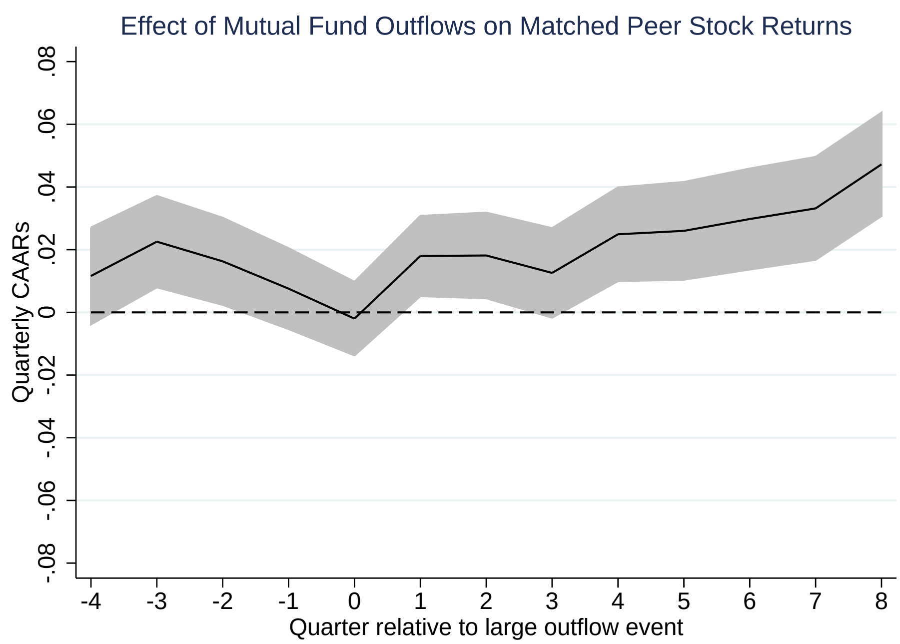
This figure plots the distribution of extreme mutual fund outflows by year

Figure 3: : Extreme Mutual Fund Outflow across Industries



This figure plots the distribution of extreme mutual fund outflows by industry. Industry classification is FIC-icode100 (Hoberg and Phillips, 2015))

Figure 4: : Effect of Mutual Fund Outflow on Matched Peer CAAR



This figure plots the quarterly cumulative average abnormal returns (CAAR) of a firm's stock when its peers are under mutual fund price pressure. The event is defined as a firm-quarter observation in which MFFlow for one peer falls below the 10th percentile value of the full sample. The benchmark used to estimate the CAAR is the CRSP equally-weighted index.

Table II: Summary Statistics

This table reports the summary statistics of the main variables used in the analysis. For each variable, we present its mean, minimum and maximum, and its standard deviation as well as the number of non-missing observations for this variable. All variables are defined in the Appendix. Statistics for firm are indexed by i and statistics for peers average (i.e., the average of peers for each firm-year observation) are indexed by $(-i)$. Average are computed by excluding firm i itself. Peers are defined using the TNIC industries developed by Hoberg and Phillips (2015). The sample period is from 1996 to 2011.

Variable	Mean	Std. Dev	Min.	Max.	N
Capex(i)	0.362	0.407	0.008	2.524	52928
MFF(i)	-0.03	0.053	-0.542	0	56730
Q*(i)	0.001	1.06	-6.48	8.045	54275
Q(i)	2.049	1.61	0.547	10.01	56730
CF/A(i)	0.01	0.227	-1.167	0.361	56639
Size(i)	5.466	1.928	1.29	10.644	56730
MFF(-i)	-0.03	0.028	-0.487	0	54275
Q*(-i)	0.001	0.481	-3.772	7.728	54275
Q(-i)	2.126	0.907	0.547	10.01	54275
CF/A(-i)	0.012	0.111	-1.167	0.361	54272
Size(-i)	5.664	1.082	1.29	10.644	54275

Table III: Main Results: The Faulty Informant Channel

This table presents the results from estimations of Eq. (24). The dependent variable is the investment of firm i in year t, defined as capital expenditures divided by lagged property, plant, and equipment (PPE). $MFF_{-i,t-1}$ is the average mutual funds extreme outflows of all firms belonging to the same TNIC industry as firm i in year $t-1$, excluding firm i. $Q^*_{-i,t-1}$ is the error term $\hat{\upsilon_{-i,t-1}}$ estimated from Eq. (23) and corresponds to the component of peers stock price unexplained by mutual funds price pressure. Other explanatory variables are defined in Appendix. The subscript -i for a variable refers to the average value of the variable across firm i's peers, except in column 2, 3, and 4 where it refers to the median (column 2), the weighted average where the weight is the product description similarity score (column 3), and the sum (column 4) of this variable. All explanatory variables are divided by their sample standard deviation to facilitate economic interpretation. The standard errors used to compute the t-statistics (in brackets) are clustered at the firm level. All specifications include firm and year fixed effects. Symbols ***,** and * indicate statistical significance at the 1%, 5% and 10% levels, respectively.

Dep Variable:	Capex/PPE						
Peers Average:	EW	VW	Median	Agg.	EW	EW	EW
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
MFF(-i)	0.018***	0.015***	0.010***	0.014***	0.009***	0.009***	0.009***
	(7.51)	(7.12)	(4.95)	(4.51)	(3.34)	(3.18)	(4.02)
Q*(-i)	0.029***	0.028***	0.029***	0.019***	0.017***	0.017***	0.018***
	(12.71)	(12.17)	(12.09)	(8.19)	(6.60)	(6.21)	(8.08)
CF/A(-i)	0.012***	0.007**	0.010***	0.004*	-0.002	-0.002	0.011***
	(3.40)	(2.17)	(2.91)	(1.67)	(-0.50)	(-0.49)	(3.06)
Size(-i)	0.002	0.001	-0.001	-0.001	-0.001	-0.001	-0.002
	(0.66)	(0.44)	(-0.17)	(-0.15)	(-0.26)	(-0.41)	(-0.45)
MFF(i)	0.011***	0.011***	0.012***	0.013***	0.009***	0.009***	0.005***
	(6.55)	(6.70)	(7.23)	(7.60)	(5.31)	(4.83)	(3.03)
Q*(i)	0.081***	0.081***	0.082***	0.086***	0.076***	0.076***	0.053***
	(27.52)	(27.42)	(27.89)	(29.02)	(24.92)	(24.48)	(16.72)
CF/A(i)	0.035***	0.036***	0.035***	0.037***	0.032***	0.033***	0.028***
	(10.30)	(10.41)	(10.27)	(10.79)	(9.13)	(9.32)	(7.97)
Size(i)	-0.074***	-0.073***	-0.070***	-0.068***	-0.075***	-0.072***	-0.087***
	(-6.79)	(-6.71)	(-6.48)	(-6.22)	(-6.50)	(-6.22)	(-7.63)
Obs.	45388	45390	45388	45390	45388	44648	35463
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Ind-Year FE	-	-	-	-	Yes		-
State-Ind-Year FE	-	-	-	-	-	Yes	-
Adj. R^2	0.485	0.484	0.485	0.482	0.498	0.496	0.502

Table IV: Cross-Sectional Tests: Managerial Information Variables

This table presents estimates of Eq. (24) where all explanatory variables are interacted with a proxy for managerial information about the firm's fundamentals or the ability of the manager to detect the noise in peers' stock prices (ϕ). The dependent variable is the investment of firm i in year t, defined as capital expenditures divided by lagged property, plant, and equipment (PPE). $MFF_{-i,t-1}$ is the average mutual funds extreme outflows of all firms belonging to the same TNIC industry as firm i in year $t-1$, excluding firm i. In Column 1, ϕ is the profitability of insiders' trades. In Column 2, ϕ is a dummy variable equal to 1 if the firm has experienced itself episodes of severe downward price pressure due to mutual funds outflows. In column 3, ϕ is an index of mutual funds ownership overlap between firm i and its peers obtained by computing the cosine similarity between firms' ownership structure. In column 4, ϕ is the average difference between analyst target stock price and current stock price for every peer of firm i. All other explanatory variables are also interacted with ϕ. We do not report estimated coefficients on these variables for brevity. These variables are defined in Appendix. All explanatory variables are divided by their sample standard deviation to facilitate economic interpretation. The standard errors used to compute the t-statistics (in brackets) are clustered at the firm level. All specifications include firm and year fixed effects. Symbols ***,** and * indicate statistical significance at the 1%, 5% and 10% levels, respectively.

Dep. Variable	Capex/PPE			
Int. Variable ϕ:	Ins.CARs	Lowdec	Common MF	Anal Discount
	(1)	(2)	(3)	(4)
MFF(-i)	0.018***	0.019***	0.026***	0.024***
	(7.54)	(6.95)	(6.53)	(8.20)
MFF(-i) $\times$ ϕ	-0.052	-0.008	-0.054***	-0.006**
	(-1.56)	(-1.54)	(-3.97)	(-2.17)
Observations	45388	45388	45388	33398
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes
Adj. R^2	0.394	0.393	0.397	0.406

Table V: Cross-Sectional Tests: Peers' Price Informativeness Variables

his table presents estimates of Eq. (24) where all explanatory variables are interacted with a proxy for price informativeness (ϕ). The dependent variable is the investment of firm i in year t, defined as capital expenditures divided by lagged property, plant, and equipment (PPE). $MFF_{-i,t-1}$ is the average mutual funds extreme outflows of all firms belonging to the same TNIC industry as firm i in year $t-1$, excluding firm i. In Column 1, ϕ is the measure of price informativeness proposed by Bai, Philipon, and Savov (2014) which relies on the ability of current stock prices to forecast future earnings. In Column 2, ϕ is the intensity of previous fund-driven price pressure in peers' stock prices. In Column 3, ϕ is the firm-specific return variation (or price non-synchronicity), defined as $\ln((1-R^2_{i,t-1})/R^2_{i,t-1})$, where $R^2_{i,t-1}$ is the R^2 from the regression in year $t-1$ of firm i's weekly returns on market returns and the peers' value-weighted portfolio returns. In Column 4, ϕ is the average earnings forecast error of financial analysts. All other explanatory variables are also interacted with ϕ. We do not report estimated coefficients on these variables for brevity. These variables are defined in Appendix. All explanatory variables are divided by their sample standard deviation to facilitate economic interpretation. The standard errors used to compute the t-statistics (in brackets) are clustered at the firm level. All specifications include firm and year fixed effects. Symbols ***,** and * indicate statistical significance at the 1%, 5% and 10% levels, respectively.

Dep. Variable	Capex/PPE			
Int. Variable ϕ:	BPS	Lowdec	1-R2	Ana.Disp
	(1)	(2)	(3)	(4)
MFF(-i)	0.016***	0.009*	0.024***	0.031***
	(6.16)	(1.70)	(7.17)	(7.44)
MFF(-i) $\times$ ϕ	0.017*	0.005*	-0.453***	-0.023***
	(1.83)	(1.82)	(-3.06)	(-2.48)
Observations	45388	45089	44360	45178
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes
Adj. R^2	0.394	0.394	0.397	0.395

Table VI: Alternative Explanations: Financing and Pressure Channels

This table presents estimates of Eq. (24) where we replace the dependent variable with firm-level measures of financing costs and access to external capital (column 1 to 4), or measures of stock price pressure for the CEO (column 5 to 6). In Column 1, the dependent variable is the Credit Default swap (CDS) spread of firm i in year t. In Column 2, the dependent variable is the CDS spread of firm i in year t on new private debt issues. In Column 3, the dependent variable is the text-based measure of equity-financing constraints developed by Hoberg and Maksimovic (2015). In Column 4, the dependent variable is the text-based measure of debt-financing constraints developed by Hoberg and Maksimovic (2015). In Column 5, the dependent variable is a dummy equal to one if firm i receives a takeover bid in year t and zero if not. In Column 6, the dependent variable is a dummy equal to one if firm i experiences a CEO change in year t. $MFF_{-i,t-1}$ is the average mutual funds extreme outflows of all firms belonging to the same TNIC industry as firm i in year $t-1$, excluding firm i. All other variables are defined in Appendix. All explanatory variables are divided by their sample standard deviation to facilitate economic interpretation. The standard errors used to compute the t-statistics (in brackets) are clustered at the firm level. All specifications include firm and year fixed effects. Symbols ***,** and * indicate statistical significance at the 1%, 5% and 10% levels, respectively..

Dep Variable:	CDS Spread (1)	Debt Spread (2)	Eq.-Cons. (3)	Debt-Cons. (4)	P(Target) (5)	CEO Turn. (6)
MFF(-i)	0.075	0.032**	0.001	-0.000	0.004	0.002
	(1.08)	(2.24)	(1.22)	(-0.27)	(1.43)	(0.38)
Q*(-i)	0.027	-0.025**	0.000	-0.001**	-0.006***	0.005
	(0.55)	(-2.07)	(0.66)	(-2.45)	(-3.54)	(1.50)
CF/A(-i)	-0.409***	-0.062***	-0.001	-0.001*	0.006*	0.000
	(-3.36)	(-2.77)	(-1.32)	(-1.94)	(1.88)	(0.07)
Size(-i)	-0.098	-0.007	0.001	0.000	0.002	0.007
	(-1.62)	(-0.36)	(1.31)	(0.52)	(0.54)	(1.31)
MFF(i)	-0.360**	0.009	0.001	-0.000	-0.007***	-0.003
	(-2.19)	(0.74)	(1.09)	(-0.37)	(-3.43)	(-0.76)
Q*(i)	-0.116*	-0.132***	0.002***	-0.001***	-0.010***	-0.010***
	(-1.75)	(-9.14)	(5.29)	(-4.57)	(-5.95)	(-3.36)
CF/A(i)	-1.140***	-0.358***	-0.006***	-0.001***	-0.015***	-0.036***
	(-4.65)	(-10.79)	(-9.38)	(-3.24)	(-5.58)	(-5.17)
Size(i)	-0.893**	-0.595***	-0.001	0.000	0.060***	0.006
	(-2.24)	(-12.51)	(-0.47)	(0.02)	(7.92)	(0.53)
Obs.	3765	10759	33198	33198	45388	18121
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R^2	0.659	0.643	0.592	0.486	0.184	0.010

Table VII: Main Results: Controlling for Peers' Investment

This table presents the results from estimations of Eq. (24) controlling for peers' investment. The dependent variable is the investment of firm i in year t, defined as capital expenditures divided by lagged property, plant, and equipment (PPE). $MFF_{-i,t-1}$ is the average mutual funds extreme outflows of all firms belonging to the same TNIC industry as firm i in year $t-1$, excluding firm i. $Q^{*}_{-i,t-1}$ is the error term $\hat{\upsilon_{-i,t-1}}$ estimated from Eq. (23) and corresponds to the component of peers stock price unexplained by mutual funds price pressure. Other explanatory variables are defined in Appendix. The subscript i for a variable refers to the average value of the variable across firm i's peers, except in column 2, 3, and 4 where it refers to the median (column 2), the weighted average where the weight is the product description similarity score (column 3), the sum (column 4) of this variable. All explanatory variables are divided by their sample standard deviation to facilitate economic interpretation. The sample period is from 1985 to 2013. The standard errors used to compute the t-statistics (in brackets) are clustered at the firm level. All specifications include firm and year fixed effects. Symbols ***,** and * indicate statistical significance at the 1%, 5% and 10% levels, respectively.

Dep Variable:	Capex/PPE						
Peers Average:	EW	VW	Median	Agg.	EW	EW	EW
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
MFF(-i)	0.009***	0.011***	0.004**	0.014***	0.009***	0.009***	0.005**
	(3.85)	(5.20)	(2.19)	(4.53)	(3.21)	(3.01)	(2.07)
Q*(-i)	0.018***	0.022***	0.019***	0.019***	0.017***	0.016***	0.012***
	(7.94)	(9.20)	(7.80)	(8.17)	(6.32)	(5.95)	(5.52)
CF/A(-i)	0.009***	0.005	0.007**	0.004*	-0.002	-0.002	0.008**
	(2.55)	(1.47)	(2.06)	(1.66)	(-0.54)	(-0.53)	(2.44)
Size(-i)	0.002	0.002	-0.000	-0.000	-0.001	-0.001	-0.001
	(0.76)	(0.75)	(-0.13)	(-0.13)	(-0.20)	(-0.38)	(-0.43)
Capex(-i)	0.051***	0.034***	0.049***	-0.000	0.003	0.005	0.031***
	(11.42)	(9.17)	(10.87)	(-0.43)	(0.68)	(0.94)	(7.68)
MFF(i)	0.010***	0.011***	0.011***	0.013***	0.009***	0.009***	0.005***
	(6.01)	(6.36)	(6.56)	(7.61)	(5.29)	(4.81)	(2.83)
Q*(i)	0.079***	0.080***	0.080***	0.086***	0.076***	0.075***	0.052***
	(26.84)	(27.08)	(27.07)	(28.99)	(24.83)	(24.40)	(16.47)
CF/A(i)	0.034***	0.035***	0.034***	0.037***	0.032***	0.033***	0.028***
	(10.10)	(10.25)	(10.08)	(10.77)	(9.10)	(9.30)	(7.85)
Size(i)	-0.074***	-0.075***	-0.071***	-0.068***	-0.075***	-0.072***	-0.087***
	(-6.86)	(-6.87)	(-6.60)	(-6.24)	(-6.52)	(-6.23)	(-7.65)
Obs.	45355	45390	45355	45357	45355	44618	35451
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Ind-Year FE	-	-	-	-	Yes		-
State-Ind-Year FE	-	-	-	-	-	Yes	-
Adj. R^2	0.489	0.487	0.489	0.482	0.498	0.496	0.503

Table VIII: Robustness: Within-Conglomerate Reallocation

This table presents the results from estimations of Eq. (26). The dependent variable is the investment of division d of firm i in year t, defined as capital expenditures divided by lagged total assets (Asset). $MFF_{-i,d,t-1}$ is the average mutual funds extreme outflows of all firms operating in the same FF48 industry as division d of firm i in year $t-1$, excluding firm i. $Q^*_{-i,d,t-1}$ is the error term $\upsilon_{-i,\hat{d},t-1}$ estimated from Eq. (25) and corresponds to the component of division peers stock price unexplained by mutual funds price pressure. Other explanatory variables are defined in Appendix. The subscript -i for a variable refers to the average value of the variable across peers of division d of firm i. All explanatory variables are divided by their sample standard deviation to facilitate economic interpretation. The sample period is from 1985 to 2013. The standard errors used to compute the t-statistics (in brackets) are clustered at the firm level. All specifications include firm-division and firm-year fixed effects. Symbols ***,** and * indicate statistical significance at the 1%, 5% and 10% levels, respectively

Dep Variable:	Capex/Asset	
	(1)	(2)
MFF(-i)	0.0044**	0.0033*
	(2.43)	(1.83)
Q*(-i)	0.0055***	0.0043***
	(3.40)	(2.57)
CF/A(-i)	0.0026	0.0007
	(1.29)	(0.33)
Size(-i)	-0.0047	-0.0032
	(-0.93)	(-0.62)
Capex/Asset(-i)		0.0092***
		(2.73)
Obs.	34538	34538
Firm-Year FE	Yes	Yes
Firm-Division FE	Yes	Yes
Adj. R^2	0.366	0.366