Ripple Effects of Noise on Corporate Investment

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ABSTRACT

We show that firms significantly reduce their investment in response to non-fundamental drops in the stock price of their product-market peers. This spillover is consistent with the hypothesis that managers have limited ability to filter out the noise in stock prices when using these as a source of information. As predicted by this hypothesis, the influence of the noise in peers' stock prices on a firm's investment is stronger when peers' prices are more informative, and weaker when managers are better informed. Our findings suggest a new channel through which local non-fundamental shocks to stock prices have real effects.

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I Introduction

Transient shocks to the demand for a stock, due to noise trading or investors' liquidity needs, generate fluctuations in its price above and beyond those due to changes in its fundamentals (see Duffie (2010) for examples). Understanding whether and *how* non-fundamental variations in stock prices influence the corporate sector is important to assess the real effects of financial markets and their potential inefficiencies in allocating resources in the economy.

In this paper, we provide evidence of a novel channel through which non-fundamental shocks (henceforth noise) to stock prices have real effects. We show that these shocks influence corporate investment because managers have limited ability to filter out noise from stock prices when they use these as a source of information. In other words, stock prices can provide faulty signals to managers, as originally suggested by Morck, Shleifer and Vishny (1990).

To empirically isolate the role of this faulty informant channel, we study whether a firm's investment is influenced by the noise in its product market *peers'* stock prices. Firms' reports (see Section II) and survey evidence (e.g., Graham and Harvey (2001)) indicate that corporate executives frequently rely on their peers' valuations (e.g., their price-to-book or price-to-earnings ratios) for capital budgeting decisions. Thus, noise in peers' stock prices can plausibly influence these decisions if managers cannot perfectly distinguish fundamental from non-fundamental shocks to their peers' valuations. Of course, for the same reason, a firm's investment might also respond to the noise in its *own* stock price. However, this response could also stem from the fact that non-fundamental shocks to a firm's stock price affect its cost of capital (e.g., Fisher and Merton (1984) or Baker, Stein, and Wurgler (2003)) or exert pressure on their managers (e.g., Jensen (2005) or Stein (1989)). These mechanisms do not predict that a firm's investment should also respond to the noise in its peers' stock prices while the faulty informant channel does. Thus, by measuring the sensitivity of a firm's investment to the noise in its peers' stock prices, we narrow down the set of alternative explanations for this sensitivity.

The specification of our tests follows from a standard investment model. In this model, a manager must choose how much to invest in a growth opportunity. Her optimal investment increases in her expectation of the payoff of this opportunity. This expectation is determined by the manager's internal information about this payoff, the firm's own stock price, and its peers' stock prices. We show that the noise in stock prices affect the manager's expectation, and therefore investment, if and only if the manager cannot perfectly filter it out from stock prices. If instead the manager can, investment is sensitive to stock prices (because they convey information to the manager) but not to the noise in these prices.

These observations have an important implication for testing whether peers' stock prices are faulty signals. Namely, for this purpose, estimating the sensitivity of a firm's investment to its peers' stock prices is useless since investment can be sensitive to peers' stock prices even if these are *not* faulty signals. Instead, as suggested by the model, we directly estimate the sensitivity of a firm investment to the noise in its peers' stock prices by projecting its investment on an *observable* component of this noise (observable ex-post for the econometrician, not the manager), and its orthogonal component. If stock prices are faulty signals then the estimate of the sensitivity of investment to the observable component of the noise in peers' stock prices must theoretically differ from zero.

We implement this approach using a panel of U.S. firms over the period 1996-2011. For each firm-year, we identify product market peers using the Text-based Network Industry Classification (TNIC) developed by Hoberg and Phillips (2015). We decompose the annual stock price (Tobin's Q) of each firm into a non-fundamental component and its orthogonal component.[1] We measure the non-fundamental component of a firm's stock price as the predicted value of a regression of this price on *hypothetical* sales of the firm's stock by mutual funds experiencing large investors' redemptions. These sales are hypothetical in the sense that they are derived assuming that, in response to redemptions, mutual funds rebalance their portfolios to keep the distribution of their holdings constant. As in Edmans, Goldstein, and Jiang (2012), we find that these forced sales are associated with large negative price pressures that last for long but eventually disappear. This pattern is consistent with the view that they represent demand shifts that are not driven by information about fundamentals.

[1] We refer to the second component as the "fundamental" component for brevity. However, this second component might itself contain noise. Our tests only require the fundamental and non-fundamental components to be orthogonal.

As uniquely predicted by the faulty informant channel, we find that a firm's investment is sensitive to the noise component of its peers' stock prices, after controlling for its own stock price. The average firm in our sample cuts its investment in fixed capital by 2.5% (a 7% decrease relative to the average level of investment) following a 5% non-fundamental drop in its peers' stock prices. Moreover, we find that changes in investment triggered by non-fundamental shocks to peers' stock prices subsequently revert, suggesting that managers correct these changes, presumably once they realize that they were not driven by fundamentals. In contrast, changes in investment triggered by variations in the fundamental component of peers' stock prices are not corrected.[2]

The correlation between a firm's investment and the noise in its peers' stock prices might be spurious, just reflecting the fact this noise is correlated with unobserved variables that affect a firm investment (e.g., its cost of capital or managerial incentives). We address this concern in various ways. First, using data on multi-division firms, we show that investment in a division is sensitive to the noise in the stock prices of *that division's peers*. 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 price. This test of the faulty informant channel is particularly powerful because it enables us to introduce firm-year fixed effects in our specification and to control for any time-*varying* heterogeneity across firms, such as a possible correlation between our measure of the noise in peers' stock price and unobserved noise in a firm's stock price or the effect of time-varying financing constraints and managerial incentives.

Second, we find no evidence that firms' financing costs change when their *peers* experience downward price pressures due to large funds sales triggered by investors' redemptions. Also, the noise in its peers' stock price affects neither the likelihood that a firm becomes a takeover target, nor its CEO turnover. Moreover, the sensitivity of investment to the noise in peers' stock prices is identical whether firms use relative performance evaluation (i.e., firms whose managers' compensation depends on the stock returns of their industry peers)

[2] Firms also cut their investment in reaction to a fundamental drop in their peers' stock prices. A firm's investment is two times more sensitive to the fundamental component of its peers' stock price than to the non-fundamental component, consistent with the notion that managers have some ability to filter out the noise in the firm peers's stock prices, but that this ability is imperfect.

or not. Collectively, these findings suggest that the sensitivity of a firm's investment to the noise in its peers' stock price does not stem from changes in the firm's cost of financing or managers' career concerns. Last, our results also persist when we include the investment of peers as a control in our regressions or industry-year fixed effects. Therefore, the sensitivity of a firm's investment to the noise in its peers' stock price does not reflect interdependences (complementarity or substitutability) among competing firms' investment decisions (e.g., Hoberg and Phillips (2010)).

Finally, we test specific cross-sectional implications of the faulty informant channel, namely that a firm's investment should be *more* sensitive to the noise in its peers' stock prices when these prices are more informative (as proxied, for instance, by the ability of prices to forecast future earnings) or when a manager's internal information about the pay-off of her growth opportunities is less accurate or when she is less able to filter out noise from stock prices. We find supporting evidence for these predictions as well.

Two papers (Hau and Lai (2013) and Foucault and Frésard (2014)) are closely related to ours. Hau and Lai (2013) shows that financially constrained firms experiencing severe underpricings, due to fire sales by distressed equity funds, during the 2007-2009 crisis cut investment because their cost of raising capital increases. In contrast, we show that noise in stock prices affects investment even for firms that do *not* need to access primary markets, because stock prices act as faulty signals for managers. Moreover, our effect operates in normal times while Hau and Lai (2013) focus on a period in which the stock market as a whole is severely depressed.

Foucault and Frésard (2014) show that firms' investment is sensitive to their peers' stock prices. This finding is in line with anecdotal and survey evidence indicating that managers use their peers' valuations as a signal for their own growth opportunities. However, it does not per se imply that a firm's investment is influenced by the noise in their peers' stock prices. As we show theoretically, this influence should be observed only if managers cannot perfectly filter out noise in their peers' stock prices. Whether this is the case or not is an open question. On the one hand, the literature on market timing suggests that managers can detect and take advantage of deviations of their own stock prices from their fundamental.

On the other hand, our findings suggest that managers have limited ability to do so for the noise in their peers' stock prices. To our knowledge, our paper is the first to show empirically that this limitation has real effects.

More broadly, our analysis adds to existing research on two main fronts. First, our findings contribute to the literature on the real effects of non-fundamental shocks to stock prices (see Baker and Wurgler (2012) for a survey). This literature suggests that a firm's investment is sensitive to non-fundamental shocks to its own stock price because managers opportunistically take advantage of inflated prices to issue new shares at a cheap cost when they are financially constrained (e.g., Baker, Stein, and Wurgler (2003)) or because they cater to investors' expectations (e.g., Polk and Sapienza (2009)). Our contribution to this literature is to provide evidence for another channel, the faulty informant channel, through which non-fundamental shocks to stock prices can affect investment. This channel uniquely predicts that a firm's investment should respond to the noise in its peers' stock prices and, to our knowledge, we are the first to provide evidence supporting this prediction. This (unintended) ripple effect of noise in stock prices suggests that local non-fundamental shocks to stock prices could have systemic effects.[3]

Second, our findings contribute to the literature studying whether managers use stock prices as signals for their decisions (see Bond, Edmans, and Goldstein (2012) for a survey). Indeed, evidence that stock prices act as faulty informant is *prima facie* evidence that managers use these prices as a source of information. Existing studies in this area have largely focused on whether cross-sectional variations in the sensitivity of investment to stock prices are consistent with the idea that managers learn information from stock prices (see, for instance, Chen, Goldstein, and Jiang (2007)). In contrast, our main tests do not rely on cross-sectional contrasts. Rather, we directly test whether a firm investment is sensitive to

[3]Williams and Xiao (2014) report that suppliers reduce spending on relationship-specific assets (R&D and patents) when large customers experience drops in prices triggered by mutual fund sales. They conclude that better informational environment can mitigate supply chain frictions. Relatedly, Yan (2015) shows that private firms' investment correlates positively with the stock prices of publicly-listed firms in the same industry. Campello and Graham (2013) show that mispricings' spillovers from high-tech stocks to non-high-tech stocks in the 1990s triggered an increase in investment for financially constrained firms in non-high-tech sectors. In contrast, the ripple effect highlighted in our paper stem from imperfect learning from managers, not from stock price spillovers across related firms.

an exogenous shock to the noise in its peers' stock price. This new approach offers a sharp test of the notion that managers learn information, albeit imperfectly, from stock prices since there are no obvious alternative explanations for why, as we find in the data, this sensitivity should be different from zero.

The rest of the paper is organized as follows. In the next section, we present the model of investment that we test in this paper and discuss its implications. In Section III, we explain how we construct our sample and the main variables used in our tests. We present our empirical findings in Section IV, and conclude in Section V.

II A Test of the Faulty Informant Channel

A The Investment Model

This section presents the investment model that guides the specification and interpretation of our empirical tests. The model has two dates, 1 and 2. As in Subrahmanyam and Titman (1999), at date 1, firm i has a growth opportunity whose payoff at date 2 is:

$$G(K_i, \widetilde{\theta}_i) = \widetilde{\theta}_i K_i - \frac{K_i^2}{2}, \tag{1}$$

where K_i is the investment of firm i in its growth opportunity. The marginal productivity of this investment, $\widetilde{\theta}_i$, is normally distributed with mean zero and variance $\sigma^2_{\theta_i}$.

At date 1, the manager of firm i chooses the investment that maximizes the expected payoff of the growth opportunity conditional on her information, Ω_1, about $\widetilde{\theta}_i$. The optimal investment K_i^* solves:

$$Max_{K_i}\ \mathrm{E}(G(K_i, \widetilde{\theta}_i)\,|\Omega_1) = \mathrm{E}(\widetilde{\theta}_i\,|\Omega_1)\,K_i - \frac{K_i^2}{2}, \tag{2}$$

so that,

$$K_i^*(\Omega_1) = \mathrm{E}(\widetilde{\theta}_i\,|\Omega_1)\,. \tag{3}$$

Thus, the optimal investment is equal to the manager's expectation of the marginal return on her investment. To form this expectation, the manager of firm i has access to several sources of information (signals). First, she possesses internal (private) information about the fundamental of her growth opportunity. We denote this signal by $s_{m_i} = \widetilde{\theta}_i + \chi_i$ where the error χ_i is normally distributed with zero mean and variance $\sigma^2_{\chi_i}$.

Second, the manager can obtain external information from its own stock price and its peers' stock prices, i.e., firms whose fundamentals are correlated with $\widetilde{\theta}_i$. Indeed, there is growing evidence that managers rely on their own stock price or the stock price of their peers as a source of information (see Bond, Edmans, and Goldstein (2012) for a survey). In Appendix D, we provide further anecdotal evidence, gleaned from managers' reports (e.g., in earnings calls or shareholders annual meetings), suggesting that managers pay close attention to their peers' stock prices (see, for instance, the shareholders annual meeting address of Belo Corporation's CEO) and view them as signals about their own growth opportunities (e.g., see the earnings conference call of Combinatrix). We denote the signal conveyed by firm i's stock price about $\widetilde{\theta}_i$ by $P_i = \widetilde{\theta}_i + u_i$ and the signal conveyed by peers' stock prices by $P_{-i} = \widetilde{\theta}_i + u_{-i}$ (index $-i$ refers to the product market peers of firm i).[4] We assume that the non-fundamental (or noise) components of stock prices, u_i and u_{-i}, are normally and independently distributed with zero means and variances $\sigma^2_{u_i} > 0$ and $\sigma^2_{u_{-i}} > 0$, respectively.

Finally, we assume that the manager has a signal $s_{u_i} = u_i + \eta_i$ about u_i and a signal $s_{u_{-i}} = u_{-i} + \eta_{-i}$ about u_{-i}, where η_i and η_{-i} are normally and independently distributed with zero means and variances $\sigma^2_{\eta_i}$ and $\sigma^2_{\eta_{-i}}$, respectively.[5] Hence, the model nests the cases in which the manager has perfect information about the noise in her firm's own stock price or the noise in her peers' stock prices ($\sigma^2_{\eta_i} = 0$ or $\sigma^2_{\eta_{-i}} = 0$), or no information on noise ($\sigma^2_{\eta_i} = \infty$ and $\sigma^2_{\eta_{-i}} = \infty$). In sum, the manager's information set at date 1 is $\Omega_1 = \{s_{m_i}, P_i, P_{-i}, s_{u_i}, s_{u_{-i}}\}$. Errors in the manager's signals are independent from each other and from $\widetilde{\theta}_i$.

For brevity, we do not explicitly model price formation in the stock market.[6] Rather, we

[4]The fundamentals of firm i and its peers do not need to be perfectly correlated. For instance, suppose that firm i has only one peer with fundamental $\widetilde{\theta}_{-i} = \widetilde{\theta}_i + \widetilde{F}_{-i}$ where $\widetilde{F}_{-i}$ and $\widetilde{\theta}_i$ are independent. Clearly, the correlation between $\widetilde{\theta}_{-i}$ and $\widetilde{\theta}_i$ is less than one. The stock price of firm i's peer provides a signal $P_{-i} = \widetilde{\theta}_{-i} + \widehat{u}_{-i}$ about $\widetilde{\theta}_{-i}$. Denoting $u_{-i} = \widehat{u}_{-i} + \widetilde{F}_{-i}$, one can also write this signal: $P_{-i} = \widetilde{\theta}_i + u_{-i}$ as assumed in our model. This example also shows that u_{-i} might also reflect the component of peers' fundamental that is uncorrelated with firm i's fundamental.

[5]Ali, Wei, and Zhou (2011) find that insiders trade against downward price pressure due to mutual funds' fire sales, which suggest that some managers can identify, at least to some extent, non-fundamental shocks to stock prices.

[6] When managers learn from stock prices, prices reflect and influence investment decisions. This feedback of prices on investment can lead to non linearities in the mapping between prices and fundamentals in

directly assume that the signal conveyed by the stock price of firm i has two components: (i) a component that is informative about the fundamental, and (ii) a component that is uninformative about this fundamental. This decomposition is standard. In models of informed trading (e.g., Grossman and Stiglitz (1985) or Kyle (1985)), the first component stems from informed investors' signals about $\widetilde{\theta}_i$, and the second component (the noise in prices) is due to uninformative trades from noise traders (non-fundamental demand shocks), and errors in informed investors' signals.[7] The signal conveyed by *each* peers' stock price can be decomposed in the same way. The signal P_{-i} must then be interpreted as the sufficient statistic for these signals and we call it "peers' stock price".[8]

Lemma 1. *The optimal investment of firm i is:*

$$K_i^*(\Omega_1) = E(\widetilde{\theta}_i \,|\Omega_1) = a_i \times s_{m_i} + b_i \times P_i + c_i \times s_{u_i} + b_{-i} \times P_{-i} + c_{-i} \times s_{u_{-i}}, \tag{4}$$

where $a_i, b_i, c_i, b_{-i}, c_{-i}$ are constants defined in the proof of the lemma that are determined by the precisions of the various signals available to the manager.

Lemma 1 describes how the manager's signals at date 1 affect her investment decision.[9] To build intuition, it is useful to consider some special cases. First, if the manager's private

equilibrium. To preserve linearity when managers learn from multiple prices, one can proceed as in Foucault and Gehrig (2008), who extend Subrahmanyam and Titman (1999) to the case in which a stock trades in two markets (a cross-listing). In their model, growth opportunities are traded separately from assets in place (as in Subrahmanyam and Titman (1999)) and firms' managers can learn from two stock prices (their stock price in the domestic market and their stock price in the foreign market). This is formally similar to the case in which a firm's manager learns from its own stock price and its peers' stock prices.

[7] For instance, Theorem 1 in Grossman and Stiglitz (1980) shows that observing the equilibrium stock price for an asset yields a signal $w = \widetilde{\theta} + u$ about its payoff, where $\widetilde{\theta}$ is informed investors' signal and $u = -\frac{\alpha^2\sigma_\epsilon^2}{\lambda}(\widetilde{x} - E(\widetilde{x}))$, where $\widetilde{x}$ is the random supply of the asset, λ is the fraction of informed investors, σ_ϵ^2 is the variance of the asset payoff conditional on informed investors' signal (the residual risk for informed investors), and α is investors' risk aversion. Signal w is what we denote P in our model (to emphasize that this signal comes from stock prices). In Grossman and Stiglitz (1980), the asset supply $\widetilde{x}$ is independent from $\widetilde{\theta}$. Thus, u is independent from $\widetilde{\theta}$ and is normally distributed, as we assume here.

[8] Suppose that firm i has N peers. The signal conveyed by the stock price of its n^{th} peer is $P_n^i = \theta_i + u_n$ where u_n normally distributed with mean zero and is independent from θ_i. Let $\tau_n = \sigma_{u_n}^{-1}$ be the precision of u_n and let $\omega_n = \tau_n / \sum_{k=1}^{k=N} \tau_n$. Suppose that the u_n are i.i.d across all peers. In this case the weighted average price of all peers: $P_{-i} = \sum_{n=1}^{n=N} \omega_n P_n^i$ is a sufficient statistic for the joint observation of all peers' stock prices (See Vives (2008), p.378). Hence $P_{-i} = \theta_i + u_{-i}$ as assumed in the model (setting $u_{-i} = \theta_i + \left(\sum_{n=1}^{n=N} \tau_n u_n\right) / \sum_{n=1}^{n=N} \tau_n)$.

[9] Schneemeier (2016) obtains a similar equation in an equilibrium model in which firms learn from the stock prices of their peers (see his Proposition 1). The information structure in his model is such that the manager of each firm (say i) learns about its fundamental from the price of his peer firm ($i+1$ in his model) and can filter out the noise in this price by using all other firms' stock prices (which therefore play the role of $s_{u_{-i}}$ in our model).

information about $\widetilde{\theta}_i$ is perfect (i.e., $\sigma^2_{\chi i} = 0$), she has no information to learn from stock prices. In this case, firm i's investment is not influenced by stock prices or the manager's information about the noise in these prices, that is, $b_i = c_i = b_{-i} = c_{-i} = 0$ (see the proof of Lemma 1).

In contrast, if the manager's private information about $\widetilde{\theta}_i$ is imperfect (i.e., $\sigma^2_{\chi i} > 0$), the manager can improve her estimate of the fundamental value of the growth opportunity by using information from stock prices. For instance, suppose that peers' stock price is uninformative about $\widetilde{\theta}_i$ ($\sigma_{u_{-i}} = \infty$), but firm i's stock price is informative ($\sigma_{u_{-i}} < \infty$). In this case, $b_{-i} = c_{-i} = 0$ because peers' stock prices is uninformative, but $b_i > 0$. That is, an increase in firm i's stock price induces the manager to invest more in the growth opportunity. The reason is that this price increase leads the manager to revise upward her forecast of the marginal return on her investment. Moreover, in this case, $c_i < 0$ if the manager possesses information about the noise in her own stock price. Thus, the manager's signal about the noise in her firm's stock price, s_{u_i}, affects her investment decision as well. In itself, this signal is uninformative about the fundamental $\widetilde{\theta}_i$. However, it helps the manager in filtering out the noise contained in her firm's stock price, thereby improving the precision of her estimate of the marginal return on her investment. Coefficient c_i is negative because when the manager observes $s_{u_i} > 0$ ($s_{u_i} < 0$), she expects her firm's stock price to exceed (be smaller than) the fundamental. Hence, the manager corrects downward (upward) the positive (negative) effect of the stock price on her estimate of $\widetilde{\theta}_i$.

When peers' stock price is also informative, the manager's forecast of the marginal return on her investment is also influenced by the information conveyed by this price ($b_{-i} > 0$), if her other signals are not perfect. Moreover, the manager uses her information about the noise in peers' stock price, $s_{u_{-i}}$, to filter out this noise in forming her forecast. Thus, $c_{-i} < 0$ and $b_{-i} > 0$ when the manager has information about the noise in peers' stock price.[10]

[10] When stock prices are informative about $\widetilde{\theta}_i$, the manager's forecast of the fundamental of the growth opportunity is determined both by P_i and P_{-i}. This means that there is information about θ_i in P_{-i}, not contained in P_i. One possible reason is that information might flow slowly across markets. Another reason is that firms are portfolios of projects. Their stock price will therefore convey information about the payoff of their portfolio of projects 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.

An interesting case arises when the manager can perfectly distinguish fundamental from non-fundamental shocks to its peers' stock price (i.e., $\sigma_{\eta_{-i}} = 0$). In this case, the optimal investment of firm i is not influenced by the noise in its peers' stock prices (in fact, $K_i^* = \theta_i$; see Case 4 in the proof of Lemma 1) because the manager of firm i can perfectly filter out the noise in its peers' stock price. However, Eq.(4) implies that in this case (see Case 4 in the proof of Lemma 1):

$$E(K_i^* \mid P_i, P_{-i}) = \left(\frac{\tau_{u_i}}{\tau_{u_i} + \tau_{u_{-i}} + \tau_{\theta_i}}\right) P_i + \left(\frac{\tau_{u_{-i}}}{\tau_{u_i} + \tau_{u_{-i}} + \tau_{\theta_i}}\right) P_{-i}, \tag{5}$$

where τ_x denotes the precision (inverse of variance) of variable x. Thus, in a regression of the firm's investment on stock prices, the coefficient on peers' stock price will be strictly positive and increasing with the informativeness of this price (i.e., the inverse of $\sigma_{u_{-i}}$), as found empirically in Foucault and Frésard (2014), even if managers can perfectly filter out the noise from its peers' stock prices (or symmetrically its own stock price).

It follows that one *cannot* test the faulty informant channel by simply regressing a firm's investment on its peers' stock prices and its own stock price. Indeed, the coefficients on stock prices in this regression should be different from zero whether or not stock prices are faulty signals. In particular, the finding that investment is sensitive to peers' stock prices (e.g., Foucault and Frsard (2014)) does not per se imply that investment is influenced by the noise in these prices. Thus, we use a different approach that we present in the next section.

B Testing that prices are faulty signals

The optimal investment of firm i (given in eq.(4)) can be written:

$$K_i^* = (a_i + b_i + b_{-i}) \times \widetilde{\theta}_i + (b_i + c_i) \times u_i + (b_{-i} + c_{-i}) \times u_{-i} + \xi_i, \tag{6}$$

where $\xi_i = a_i\chi_i + b_i\eta_i + a_{-i}\chi_{-i} + b_{-i}\eta_{-i}$. Thus, investment is influenced by the non-fundamental components of stock prices (u_i and u_{-i}) if $\alpha_i \overset{def}{=} b_i + c_i \neq 0$ or $\alpha_{-i} \overset{def}{=} b_{-i} + c_{-i} \neq$

For instance, suppose that firm i has assets in place whose payoff is $\theta_{iA} + \theta_{iB}$ (projects 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* $-i$ reveals θ_{iB} while observing the stock price of firm A only does not, even though prices reflect all available information. In Section IV.B.1, we provide evidence consistent with this scenario by looking at conglomerate firms.

0. In the proof of Lemma 1, we show that:

$$\alpha_i \geq 0, \, \alpha_{-i} \geq 0, \tag{7}$$

and that a firm's investment is sensitive to the noise in its own stock price ($\alpha_i > 0$) and its peers' stock price ($\alpha_{-i} > 0$) if its manager's private signals about the fundamental and the noise in stock prices are *not* perfect (otherwise $\alpha_i = \alpha_{-i} = 0$).

For instance, a negative non-fundamental shock to its peers' price ($u_{-i} < 0$), leads firm i's manager to invest less. With the benefit of hindsight, i.e., once the cause of the price drop is known, this decision appears inefficient. However, when the manager makes her investment decision, this cause is yet unclear and ignoring the signals conveyed by stock prices would be suboptimal. Indeed, the ex-ante expected value of the growth opportunity (i.e., $\mathrm{E}(G(K_i, \widetilde{\theta}_i))$ is higher when the manager conditions her investment decision at date 1 on all available sources of information than when she only uses her internal signal about $\widetilde{\theta}_i$. Thus, it is ex-ante efficient for managers to condition their decisions on stock prices, even if this can appear inefficient ex-post.

Morck, Shleifer, and Vishny (1990) refer to the possibility that managers respond to noise in stock prices – because they rely on stock price information – as the "faulty informant hypothesis." The previous discussion implies that one can test this hypothesis by testing the null that $\alpha_i = 0$ and $\alpha_{-i} = 0$ against the alternative that $\alpha_i > 0$ or $\alpha_{-i} > 0$. A rejection of the null is consistent with the faulty informant hypothesis.

We cannot directly estimate eq.(6) to obtain estimates of the sensitivities of investment to noise (α_i and α_{-i}) because we do not perfectly observe the non-fundamental and fundamental components of firms' stock prices. However, we can circumvent this problem insofar as we can measure part of the non-fundamental component of stock prices.

To see why, let $u_{-i} = u^o_{-i} + u^{no}_{-i}$, where u^o_{-i} is the component of the noise in peers' stock price that can be measured by the econometrician. We assume that u^o_{-i} and u^{no}_{-i} 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 (with $\lambda_{-i} \in [0, 1]$). We decompose the noise in firm i's stock price in the same way ($u_i = u^o_i + u^{no}_i$). Also let $P^*_{-i} = \widetilde{\theta}_i + u^{no}_{-i} = P_{-i} - \mathrm{E}(P_{-i} \left| u^o_{-i} \right.)$ where the second equality follows from the definition of P_{-i}. Thus, P^*_{-i} is the residual of a regression of P_{-i}

on u^o_{-i}. Similarly, we define $P^*_i = \widetilde{\theta}_i + u^{no}_i = P_i - \mathrm{E}(P_i \,|u^o_i)$. We prove the following result in the appendix.

Proposition 1. *The optimal investment policy of firm i, K^*_i, is such that:*

$$K^*_i = \gamma_i P^*_i + \alpha_i u^o_i + \gamma_{-i} P^*_{-i} + \alpha_{-i} u^o_{-i} + \epsilon_i, \tag{8}$$

where ϵ_i is orthogonal to P^*_i, u^o_i, P^*_{-i}, and u^o_{-i}. Moreover, $\gamma_i \geq \alpha_i$, and $\gamma_{-i} \geq \alpha_{-i}$ (expressions for γ_i and γ_{-i} are given in the proof of the proposition).

Equation (8) offers yet another expression for the optimal investment of firm i. Intuitively, it is obtained by projecting the optimal investment of firm i (given in eq.(4)) on a set of explanatory variables (P^*_i, u^o_i, P^*_{-i}, and u^o_{-i}) that can be measured empirically. The term ϵ_i is the residual variation in investment that cannot be explained by these variables. In the model, it is orthogonal to the explanatory variables in eq.(8). Thus, one can obtain unbiased estimates of the true influence of the noise in stock prices on investment, i.e., α_i and α_{-i}, by estimating eq.(8) with ordinary least squares regressions. This approach forms the backbone of our empirical tests.

In reality, there might be other channels, absent from our model, through which the noise in a firm's stock price influences its investment.[11] The literature has proposed two such channels: (i) the "financing" channel, and (ii) the "pressure" channel. According to the financing channel, managers can detect deviations of their own stock price from fundamentals and opportunistically issue new shares when their stock is overvalued and repurchase shares when it is undervalued. In case of overvaluation, a manager can then use the proceeds from stock issuance to make positive NPV investments she could not fund due to financial constraints. In this case, the investment of a firm will be positively influenced by the noise in its own stock price, even if managers do not extract any information from stock prices. Baker, Stein, and Wurgler (2003), Dong, Hirshleifer, and Teo (2012), Hau and Lai (2013), or Campello and Graham (2013) provide evidence supporting this channel.

The pressure channel posits that the investment of a firm is influenced by non-fundamental shocks to its stock price due to managers' career concerns. In particular, a non-fundamental

[11] In the empirical analysis, these other channels will be captured by ϵ_i. If this term is correlated with u^o_i or u^o_{-i} then OLS estimates of α_i and α_{-i} will be biased.

drop in a firm's stock price increases the likelihood of takeover and replacement of managers (e.g., Edmans, Goldstein, and Jiang (2012)). In response, the manager might choose to cut investment to boost short-term profits and enhance its stock price (e.g, Stein (1988), Stein (1989), or Bhojraj, Hribar, Picconi, and McInnis (2009)).

In reality, these mechanisms could co-exist with the faulty informant channel. Thus, assessing empirically its contribution to the sensitivity of a firm's investment to the noise in its *own* stock price is challenging. However, the financing and pressure channels do *not* predict that the investment of a firm should be sensitive to the noise in its peers' stock price, *after* controlling for the firm's own stock price. Indeed, what matters for a firm's financing is the price at which it can issue or repurchase its shares, not the price of its peers' shares. Similarly, peers' stock price should not affect a firm's likelihood of being taken over. Thus, in our tests, we mainly focus on whether $\alpha_{-i} \neq 0$ since, to our knowledge, the faulty informant theory is the only one that makes this prediction.

Last, we have assumed so far that the noise components of firm i's stock price and its peers' stock price are independent. Lemma 1 still holds when this assumption is relaxed (the expressions for the coefficients are more involved as they account for the correlation in noise). Proposition 1 also holds if the observable components of noise are uncorrelated with the unobservable components (which allows for correlation in the noise in stock prices since, for instance, unobservable components can be correlated together). If not, regression (8) yields biased estimates of α_i and α_{-i}. In particular, suppose that the unobservable component of the noise in firm i's stock price is correlated with the observable component in its peers' stock price (i.e., $Cov(u_i^{no}, u_{-i}^{o}) \neq 0$). Then, in this case, the coefficient on u_{-i}^{o} in eq.(8) will capture in part the effect of the unobservable component of the noise on firm i's stock price, even after controlling for P_i^*. In our tests, we address this possibility in Section IV.B.5. Importantly, even in this case, one can show that the OLS estimate of the coefficient on u_{-i}^{o} in eq.(8) should be zero if the faulty informant hypothesis does not hold (i.e., if managers can perfectly filter out the noise in stock prices).[12] Thus, even when the observable components of the noise in stock prices are correlated with unobservable

[12] A proof of these claims are available upon request.

components, rejecting the null that the investment of a firm does not co-vary with the noise its peers' stock price is evidence in favor of the faulty informant channel.

III Sample and Variable Construction

A Identifying Peers and Sample Construction

For our tests, we must first identify for each publicly-traded firm a set of peers sharing the same product market. For this purpose, 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) 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.[13]

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

[13] 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.

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 Appendix B. To reduce the effect of outliers, all ratios are winsorized at 1% in each tail.

B Non-Fundamental Shocks to Stock Prices

To implement our tests, we also need observable non-fundamental shocks to stock prices (the empirical analog of u_i^o in our model) for each year-firm in our sample. Intuitively, sales of mutual funds hit by large outflows ("forced sales") constitute large negative demand shocks for stocks liquidated by these funds. These shocks create downward price pressures on these stocks (e.g., Coval and Stafford (2007)). As they are due to investors' redemptions, these negative demand shocks are unlikely to reflect fund managers' private information about fundamentals. Yet, if mutual funds' managers have discretion in choosing the stocks they sell to meet investors' redemptions, they could primarily liquidate stocks for which they have negative information. In this case, mutual funds' forced sales might be correlated with fundamentals. To avoid this problem, we follow Edmans, Goldstein, and Jiang (2012) and use *hypothetical*, rather than actual, sales of mutual funds hit by large outflows as an instrument for negative non-fundamental shocks to stock prices.

Specifically, for each firm i in our sample, we measure the hypothetical sales of its stock in quarter q of year t (denoted by $MFHS_{i,q,t}$) 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 particular industries (this exclusion does not affect our results). 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 rebalancing their portfolio to maintain the distribution of their holdings constant (see Appendix C for technical details regarding the construction of $MFHS_{i,q,t}$). We then use $MFHS_{i,t} = \sum_{q=1}^{q=4} MFHS_{i,q,t}$ as a measure of a (negative) demand shock to stock i in year t and call this variable "Mutual Funds Hypothetical Sales". By definition, $MFHS_{i,t}$ only takes negative values. Thus, the smaller is $MFHS_{i,t}$, the *larger* are hypothetical sales of stock i in year t.

By construction, $MFHS_{i,t}$ is driven by large outflows from mutual funds holding stock i and is not affected by fund managers' discretion in choosing which stocks to sell to meet these redemptions. 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 specialized mutual funds in the construction of $MFHS_{i,t}$. Hence, $MFHS_{i,t}$ is a plausible measure of non-fundamental negative shocks to stock prices.

[Insert Figure 1 About Here]

In support of this claim, Figure 1 displays the relationship between large mutual fund hypothetical sales and stock prices in our sample. We define an "event" for stock i as a large hypothetical sale of stock i due to mutual fund outflows in quarter q of year t, i.e., a realization of $MFHS_{i,q,t}$ below the 10^{th} percentile of the full sample distribution of $MFHS_{i,q,t}$. For each stock affected by this event, we estimate linear regressions of quarterly abnormal returns on event-time dummy variables, and plot the cumulated coefficients (CAAR) around the event.

In Panel A of Figure 1, we estimate the cumulative abnormal returns over the CRSP index. As in Coval and Stafford (2007) and Edmans, Goldstein, and Jiang (2012), we observe no abnormal decline in stock prices *before* the event quarter, which indicates that funds experiencing large outflows did not own stocks with deteriorating fundamentals. Immediately after the event, stock prices drop by about 10%, then revert in the subsequent quarters and recover after about two years. This price reversal, also observed in prior research, is consistent with the hypothesis that large hypothetical sales due to large mutual fund outflows represent non-fundamental shocks to prices. Indeed, if these shocks were fundamental, the decrease in prices caused by these shocks should be permanent.

In Panel B of Figure 1, we estimate cumulative abnormal returns over an equally-weighted portfolio of product market peers (using TNIC) instead of the CRSP index. The pattern for abnormal changes in prices around the event is similar to that observed in Panel A. This observation shows that $MFHS_{i,t}$ captures *localized* non-fundamental shocks to prices and not industry-wide shocks.

[Insert Figures 2 and 3 About Here]

We perform additional tests that further support the use of $MFHS$. First, we show that mutual fund hypothetical sales are unlikely to capture economy-wide or industry-specific patterns. Figure 2 displays the average value of $MFHS$ across firms for each year in our sample and across the Hoberg and Phillips (2015) fixed industry classification. We observe no obvious clustering in any particular time period or industry. Hypothetical sales seem particularly large in 1999, but we have checked that our main results are unchanged if we exclude this year.

Next, in Figure 3, we show that corporate insiders trade *against* the price pressure generated by large mutual fund sales. Specifically, the average quarterly net insider purchases (defined either as insiders' purchases minus sales, divided by their stock's turnover or the net number of shares purchased) increases significantly in response to downward price pressures triggered by mutual fund sales. This result is consistent with Ali, Wei, and Zhou (2011) and Khan, Kogan, and Serafeim (2012), who document that managers are able to some extent to detect non-fundamental shocks to their own stock price (due to forced sales by mutual funds), and support our claim that these shocks are not driven by changes in firms' fundamentals. If they were, we would not expect insiders to lean against these shocks.

C Decomposing Stock Prices

We now explain how we use $MFHS$ to decompose the signals conveyed by stock prices into a fundamental and non-fundamental component. As a proxy for the signal conveyed by the stock prices of firm i's peers in year t, we use the equally-weighted average Tobin's Q of its peers, denoted by $\overline{Q}_{-i,t}$ (in our empirical tests, we check that our findings are robust to other ways of averaging peers' stock prices). For brevity, we refer to $\overline{Q}_{-i,t}$ as "peers' stock price."

We then estimate the following linear regression:

$$\overline{Q}_{-i,t} = \lambda_i + \delta_t + \phi \times \overline{MFHS}_{-i,t} + \upsilon_{-i,t} \tag{9}$$

where λ_i and δ_t are firm and year fixed effects, respectively. For brevity, we do not tabulate estimates of equation (9). Consistent with Figure 1, the average stock price of firm i's peers, $\overline{Q}_{-i}$, is positively and significantly correlated with the average realization of $MFHS$ (ϕ is equal to 2.59 with a t-statistic of 21).

As explained in the previous section, the variation of peers' stock price due to $\overline{MFHS}$ is non-fundamental. Thus, we use (i) $\overline{MFHS}_{-i,t}$ as a proxy for u^o_{-i}, the component of the noise in firm i's peers' stock price that can be observed *ex-post* by the econometrician,[14] and (ii) $\overline{Q}^*_{-i,t} = \widehat{\upsilon}_{-i,t}$, the estimated residual from regression (9), as a proxy for P^*_{-i} in the model (see eq.(8)).[15] We refer to $\overline{MFHS}_{-i,t}$ as the non-fundamental component of peers' stock price and to $\overline{Q}^*_{-i,t}$ as the "fundamental" component of peers' stock price (even though, as in the theory, $\overline{Q}^*_{-i,t}$ is not necessarily completely purged from noise). Proceeding in the same way, we decompose the stock price of each firm i in each year t (proxied by $Q_{i,t}$, its Tobin's Q in year t) into a non-fundamental component ($MFHS_{i,t}$) and a fundamental component ($Q^*_{i,t}$).

D Econometric Specification

To estimate the coefficients of our investment model (eq.(8)), in particular the investment-to-noise sensitivity α_{-i}, we estimate the following equation:

$$I_{i,t} = \lambda_i + \delta_t + \alpha_{-i}\overline{MFHS}_{-i,t-1} + \gamma_{-i}\overline{Q}^*_{-i,t-1} + \alpha_i MFHS_{i,t-1} + \gamma_i Q^*_{i,t-1} + \mathbf{\Gamma X_{i,-i,t-1}} + \varepsilon_{i,t} \quad (10)$$

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. $\overline{MFHS}_{-i,t-1}$ and $\overline{Q}^*_{-i,t-1}$ are the non-fundamental and fundamental components of peers' stock price in year $t-1$ for firm i (our proxies for u^o_{-i} and P_{-i}) while $MFHS^*_{i,t-1}$ and $Q^*_{i,t-1}$ are the non-fundamental and fundamental components of firm i's stock price in year $t-1$. The vector $\mathbf{X_{i,-i,t-1}}$ controls for variables

[14] A large realization of $\overline{MFHS}_{-i,t-1}$ 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.

[15] The use of linear regressions to decompose stock prices into non-fundamental and fundamental components is standard in the literature, see for instance Blanchard, Rhee and Summers (1993), Galeotti and Schiantarelli (1994), or Campello and Graham (2013). Alternatively, we could use (i) $\phi \times \overline{MFHS}_{-i,t}$ as a proxy for u^o_{-i} and (ii) $\overline{Q}^*_{-i,t} = \overline{Q}_{-i,t} - \phi \times \overline{MFHS}_{-i,t} = \widehat{\upsilon}_{-i,t} + \lambda_i + \delta_t$ as a proxy for P^*_{-i}. Results with this approach are identical because ϕ is a scaling factor common to all firms and all variables in our tests are scaled by the sample standard deviation, and all our tests also include firm and year fixed effects.

known to be correlated with investment decisions, namely the natural logarithm of assets ("firm size") and cash flows, both for firm i and its portfolio of peers in year $t-1$. In addition, we control for time-invariant firm heterogeneity by including firm fixed effects (λ_i), and aggregate fluctuations by including year fixed effects (δ_t). We allow the error term ($\varepsilon_{i,t}$) to be correlated within firms.[16] 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 one standard deviation change in this variable.

As explained in Section II.B, we examine the faulty informant hypothesis by testing the null that $\alpha_{-i} = 0$ against the alternative that $\alpha_{-i} > 0$. We (i.e., the econometricians) observe ex-post that some variations in peers' stock prices are unrelated to firms' fundamentals. If managers ignore stock prices, or had this foresight at the time they made their decisions (i.e. could ex-ante filter out noise in stock prices), the investment of their firm should be *unrelated* to the measurable noise component in the stock prices of their peers.

Arguably, price pressures induced by mutual fund hypothetical sales might be correlated *within* industries if funds experiencing extreme outflows have correlated industry allocations.[17] This is not a concern in our setting because we include $MFHS_{i,t}$ and $\overline{MFHS}_{-i,t}$ in the regression. Thus, α_{-i} captures the effect of the (observable) non-fundamental component of firm i's peers' stock price that is not captured by the non-fundamental component of firm i's stock price. Likewise, γ_{-i} captures the effect of the information contained in $\overline{Q}^*_{-i}$ that is not in Q^*_i. Table I presents the summary statistics for the main variables used in the analysis. They are in line with previous research.

[Insert Table I About Here]

[16]We do so because with TNIC industries, each firm has its own set of peers. Nevertheless, our results are similar if we cluster standard errors at the industry level using the Hoberg and Phillips (2015) fixed industry classification, 3-digit SIC or 5-digit NAICS industries.

[17]In our sample the correlation between $MFHS_{i,t}$ and $\overline{MFHS}_{-i,t}$ is 0.35.

IV Empirical Findings

A Baseline Results

We report the estimates of our baseline specification (10) in the first column of Table II. As predicted by the faulty informant hypothesis, the coefficient on $\overline{MFHS}_{-i}$ (the estimate of α_{-i}) is positive and statistically significant (0.018 with a t-statistic of 7.51). A one standard deviation decrease in the non-fundamental component of its peers' stock price for a firm is associated with a 1.8 percentage point decrease in its investment, which represents 5% of the average investment level in the sample.[18] The coefficient on the fundamental component of peers' stock price ($\overline{Q}^{*}_{-i}$) is also significantly positive (0.029 with a t-statistics of 12.71) and, as predicted (see Proposition 1), this coefficient is larger than that on $\overline{MFHS}_{-i}$. A firm's investment is two times more sensitive to the fundamental component of its peers' stock price than to the non-fundamental component, suggesting that managers have some ability to filter out the noise in their peers' stock price but not a perfect ability to do so.

[Insert Table II About Here]

Consistent with Hau and Lai (2013), a firm's investment is also significantly and positively related to the non-fundamental component of its own stock price. Specifically, a one standard deviation decrease in $MFHS_i$ is associated with a 1.1 percentage point drop in investment. A firm's investment is also highly sensitive to the fundamental component of its own stock price. The coefficient on Q^*_i is equal to 0.08 with a t-statistic of 27. Again, as predicted by Proposition 1, it is (10 times) higher than the coefficient on $MFHS_i$.

Interestingly, the investment of a firm is more sensitive to the noise in its peers' stock price ($\overline{MFHS}_{-i}$) than to the noise in its own noise price ($MFHS_i$), i.e. $\alpha_{-i} > \alpha_i$. According to theory, and in line with intuition, this can happen when managers are better informed about the noise in their own stock price than in their peers' stock prices. This interpretation is also

[18]Equivalently, a 5% non-fundamental drop in peers' stock price ($\overline{Q}_{-i}$) is associate with a 2.5 percentage point decrease in investment, or a 7% drop relative to average. This is obtained using the estimates of Equation (9), in which a one standard deviation drop in $\overline{MFHS}_{-i}$ translates into a 3.6% drop in $\overline{Q}_{-i}$. Indeed, $\overline{Q}_{-i} = 2.59 \times \sigma(\overline{MFHS}_{-i}) = 2.59 \times 0.029 = 0.075$, which corresponds to a 3.6% change compared to the average value of $\overline{Q}_{-i}$ (2.074)). Hence, a 5% non-fundamental drop in peers' stock price corresponds to 1.38 standard deviation of $\overline{MFHS}_{-i}$.

consistent with the fact that the ratio of the sensitivity of investment to the fundamental component of stock prices over its sensitivity to the noise component is much higher when computing this ratio with firms' own stock price than with peers' stock prices ($\gamma_i/\alpha_i > \gamma_{-i}/\alpha_{-i}$)).

Columns (2) to (5) in Table II show that our findings are robust to the methodology used to construct the explanatory variables pertaining to firm i's peers (e.g., $\overline{Q}_{-i}$ and $\overline{MFHS}_{-i}$). In column (2), we obtain these variables as weighted-averages of peer-level variables where the weights are based on the similarity score computed in Hoberg and Phillips (2015) (instead of equal weights as in column (1)). In column (3), we take the median values of these variables across peers and in column (4) the equally-weighted averages of these variables across the five closest peers of firm i. Finally, in column (5), all accounting variables pertaining to firm i's peers are simply summed across peers and explanatory variables are built using these sums. Estimates of investment-to-noise sensitivities are similar across these specifications, indicating that our results are not affected by the way we aggregate variables across peers.[19]

As predicted by the faulty informant channel, negative non-fundamental shocks to a firm's peers' stock price trigger a cut in its investment. If these shocks are non-fundamental, this drop in investment should be transient. Indeed, after realizing that she reacted to noise, a manager should restore investment to its original level. To test whether this is the case, we incorporate additional lagged values of $\overline{MFHS}_{-i}$ (namely, $\overline{MFHS}_{-i,t-2}$ and $\overline{MFHS}_{-i,t-3}$) and all other explanatory variables in our baseline specification (10). To better assess the dynamics of firm i's investment in response to non-fundamental shocks, we also add the contemporaneous and one-year ahead values of all variables in our baseline specification (10). Figure 4 reports the main results from this estimation.

[Insert Figure 4 About Here]

Panel A plots the coefficients on the non-fundamental component of peers' stock price realized at dates ($t-3$ to $t+1$) while Panel B plots the coefficients on the fundamental

[19] Unreported tests indicate that our results are similar if we define product market peers as firms in the same 3-digit SIC industry or 5-digit NAICS industry. Our results are also robust to the inclusion of lagged investment to control for the persistent nature of capital expenditures.

component of peers' stock price for the same leads and lags. Consistent with our previous results, investment in year t responds positively to noise in peers' stock price measured in year $t-1$. However, as conjectured, the effect of noise is transient because in year t, investment responds *negatively* to noise measured in year $t-2$. That is, following a negative non-fundamental shock in year $t-2$, investment decreases in year $t-1$, but then increases in year t, so that the impact of noise on the stock of capital is subsequently corrected. Remarkably, the economic magnitude of the sensitivity to noise at time $t-2$ ($\simeq -0.007$) almost perfectly offsets the magnitude of the response to noise at time $t-1$ ($\simeq +0.006$). Three years after the shock, a firm's investment is no longer sensitive to the noise in peers' stock price (the coefficient for $t-3$ is insignificant).

The response of investment to lagged values of the fundamental component of peers' stock price (Panel B) is very different. In year t, investment responds positively to the fundamental component of peers' stock price in year $t-1$. However, it does not depend on this component in previous years. In other words, the effect of a fundamental shock to peers' stock price is permanent. Following a negative fundamental shock in year $t-2$, a firm reduces its investment in year $t-1$ and does not correct this decision subsequently.

Overall, results in Table II and Figure 4 are consistent with the implications of the faulty informant hypothesis. The ex post difference in magnitude as well as reversion between the two components (noise vs fundamental) show that managers learn from prices but have limited ability to distinguish fundamental from non-fundamental shocks in stock prices, at least in their peers' stock prices. In our tests, these shocks stem from forced sales by mutual funds holding peers' stocks. Even though these sales are observable relatively quickly (with a one quarter delay), it is plausible that managers are not well informed about their origin (i.e., large investor redemptions).

Importantly, our findings imply that non-fundamental shocks to firms' stock prices have real externalities for related firms. These externalities are likely to matter for the economy because affected firms account for a significant fraction of aggregate investment in our sample. Indeed, firms whose peers' stocks experience large hypothetical sales by mutual funds in a given year (i.e., firms with $\overline{MFHS}_{-i,t}$ in the lowest decile of the sample distribution of this variable in year t) account for 9% of the aggregate investment (in our Compustat sample).[20]

B Other Economic Channels?

Our test of the faulty informant hypothesis assumes that non-fundamental shocks to peers' stock price are not related to other variables that could directly determine a firm investment. One concern is that this assumption is not valid and that, for this reason, our findings just reflect the fact that the noise in peers' stock price is correlated with omitted variables in our baseline regression (10). We address this concern in this section. We first develop a test that allows us to mitigate the potential effect of omitted variables. Next, we discuss plausible alternative explanations to our results and test their implications in the data.

B.1 Capital Allocation Within Firms

We first examine whether non-fundamental shocks to peers stock prices also affect the investment of conglomerate firms at the division level. Indeed, with this approach, we can use Firm×Year fixed effects in our baseline regression, which allows us to directly control for any *time-varying* variable affecting firms overall investment that could be correlated with non-fundamental shocks to their peers stock price.[21]

For this test, we use 3,409 distinct conglomerate firms, operating a total of 8,342 divisions over the 1996-2011 period. From Compustat segment 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

[20] These firms are similar to firms in the rest of the sample in terms of their size. Specifically, firms in the lowest decile of $\overline{MFHS}_{-i,t}$ have an average (median) size (logarithm of assets) of 5.57 (5.52) compared to an average (median) size of 5.45 (5.30) for other firms.

[21] For example, the noise in its peers stock prices may affect the access to external financing of a firm or alter its CEO's incentives. By running our tests at the division level for conglomerates, we can control for these effects (with Firm×Year fixed effects) since they should affect the investment of *all* divisions of the same firm. Holding these common effects constant, our tests measure how the noise in the peers' stock prices of a division affects the investment of this division relative to the investment of other divisions (with different product market peers) within the same firm.

same FF48 industry in a given year. In contrast to our baseline tests, we use FF48 industries rather than TNIC industries because these do not allow identifying 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.C. We decompose the average value of the (equally-weighted) portfolio of peers for a given division d of firm i in year t ($\overline{Q}_{-i,d,t}$) into a non-fundamental component and a fundamental component, by estimating the following equation:

$$\overline{Q}_{-i,d,t} = \lambda_{i,d} + \delta_{i,t} + \phi \times \overline{MFHS}_{-i,d,t} + \upsilon_{-i,d,t-1}, \tag{11}$$

where $\overline{MFHS}_{-i,d,t}$ is the average mutual fund hypothetical sales across all firms (excluding firm i) belonging to the same FF48 industry as division d of firm i, while $\lambda_{i,d}$ and $\delta_{i,t}$ are firm×division and firm×year fixed effects. As in our baseline test, we use $\overline{MFHS}_{-i,d,t}$ as our proxy for the non-fundamental component of peers' stock price for division d of firm i and $\bar{\upsilon}_{-i,d,t}$, the estimated residual of eq. (11), as our proxy for the fundamental component of peers' stock price for division d of firm i (denoted $\overline{Q}^{*}_{-i,d,t}$) .

We then estimate our baseline investment equation (10) using firm-division-year observations, i.e., we estimate:

$$I_{i,d,t} = \lambda_{i,d} + \delta_{i,t} + \alpha_{-i}\overline{MFHS}_{-i,d,t-1} + \gamma_{-i}\overline{Q}^{*}_{-i,d,t-1} + \mathbf{\Gamma X_{-i,d,t}} + \varepsilon_{i,d,t} \tag{12}$$

where the dependent variable, $I_{i,d,t}$ is the ratio of capital expenditures of division d of firm i in year t scaled by previous year total 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 ($\lambda_{i,d}$). Importantly, the inclusion of firm×year fixed effects ($\delta_{i,t}$) controls for unobserved time-varying fluctuations at the firm level. Our specification thus ensures that the estimated differences in investment across divisions only reflects allocation decisions for the same firm in the same year. Therefore, differences in capital allocation across firms' divisions can plausibly be attributed to differences in the signals conveyed by the stock price of the peers of each division about their growth opportunities.[22]

[22] We no longer include firm level controls (in particular firm fundamental and non-fundamental price

[Insert Table III About Here]

Table III presents the results and confirms 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. Across all specifications (i.e., different industry definitions), the coefficients on $\overline{MFHS}_{-i,d}$ are positive and statistically significant. Consistent with stock prices acting as faulty informant, when the peers of one division experience temporarily downward price pressure relative to the peers of other divisions, managers reallocate capital to other divisions.

B.2 Financing Channel

Second, we examine whether the noise in peers' stock price is related to a firm's cost of financing. Our focus on peers guarantees that the effect of noise on investment we measure is not reflecting a direct financing channel, whereby firms exploit non-fundamental variation in their stock prices by issuing or repurchasing shares. Nevertheless, the noise in peers' stock price could still indirectly affect a firm cost of financing (and thereby its investment) for two reasons. First, creditors might also rely on peers' stock price to learn information about a firm's fundamental and set 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 a firm's assets, and therefore its borrowing capacity, could decrease because its peers are natural buyers of its assets (as in Shleifer and Vishny (1992)).

[Insert Table IV About Here]

If at play, these mechanisms imply that a firm's cost of financing should be inversely related to the non-fundamental component of its peers' stock price. We test whether this is the case by using firm-level measures of the cost of debt and access to external capital

components) because they are all absorbed by the firm×year fixed effects. Indeed, the firm-year fixed effects control for all variables (observed and unobserved) that are constant across divisions in a given year. That is the case of the stock price, which is constant across divisions for the same firm at the same time, as well as all its components including the noise that is not observable.

as the dependent variable in our baseline specification (10). We rely on credit default swap (CDS) spreads and spreads on new private debt issues as indicators of the cost of financing. We obtain annual average CDS spreads from Markit, and the annual average spreads on new debt issues from Dealscan. Alternatively, we use the measures of financing constraints developed by Hoberg and Maksimovic (2015) using textual analysis of firms' Management's Discussion and Analysis (MD&A) section of firms' 10Ks.[23] In particular, we use their score of debt-market constraints, where a higher score indicates more binding constraints in the debt markets. For completeness, we also use Hoberg and Maksimovic (2015)'s score of equity-market constraints. Due to data limitations, 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, while CDS spreads and spreads on new private debt issues are not available for all firms). The results in Table IV reveal that the sensitivity of a firm's cost of financing and access to external finance to the non-fundamental component of its peers' stock price is either insignificant or significant (for the spread on new private debt issues) but positive. This is inconsistent with the implications of the financing channel.

B.3 Pressure Channel

Third, we assess whether our results could reflect the pressure channel. Existing research indicates that a non-fundamental drop in a firm's own stock price increases the likelihood of a takeover see Edmans, Goldstein and Jiang (2012)). In response to this threat, managers might undertake actions to temporarily boost the short-term value of their stock, due to career concerns as in Stein (1988, 1989). Survey evidence indicates that such actions include postponing positive NPV projects so as to increase current earnings.[24] Managers' career concerns might therefore explain our findings if a non-fundamental drop in the peers' stock price of a given firm increases the likelihood of replacement of its manager (e.g., through a takeover). Relatedly, such a drop could also reduce a firm's manager willingness to exert effort and invest if her compensation is tied to the stock price performance of peer firms (i.e.,

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

[24]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)).

if her contract is based on relative performance).

We check whether the first channel (managerial career's concerns) is present in our data by replacing the dependent variable in our baseline specification with binary variables equal 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. To assess whether our results are driven by the use of relative performance metrics in managers' contracts, we estimate our baseline specification across two subsamples that are partitioned (using the methodology of Aggarwal and Samwick (1999)) based on the likely use of relative performance evaluation (RPE).[25]

[Insert Table V About Here]

The results in Table V dispel the concern that the sensitivity of a firm's investment to the noise in its peers' stock stems from managerial career concerns or the design of compensation contracts. Column (1) shows that the likelihood that a firm becomes a takeover target is unrelated to the non-fundamental component of its peers' stock price ($\overline{MFHS}_{-i}$). In contrast, consistent with Edmans, Goldstein and Jiang (2012), the coefficient on the non-fundamental component of its own stock price, $MFHS_i$, is negative and statistically significant. Similarly, column (2) reveals that a firm's CEO turnover is not affected by the non-fundamental component of its peers' stock price. Columns (3) and (4) further indicate that investment-to-noise sensitivities are positive and significant both for firms using RPE (column (3)) and firms not using RPE (column (4)).

B.4 Complementarity in Investment Decisions

Previous studies report that firms reduce investment in response to non-fundamental drops in their own stock price. This finding suggests that $\overline{MFHS}_{-i}$ could be correlated with the investment of firm i's peers. In this case, the positive relationship between firm i's investment and $\overline{MFHS}_{-i}$ might reflect the fact that managers learn from their peers' investment

[25] For each industry-year, we estimate whether CEO compensation is sensitive to the stock returns of industry peers, after controlling for firms' own stock return and size. We then classify firms as using RPE if CEO compensation is negatively related to peers' stock returns.

decisions or complementarities in firms' investment decisions, rather than imperfect learning from their peers' stock prices.[26]

[Insert Table VI About Here]

To examine this possibility, we augment our baseline specification (10) with the average investment of firm i's peers ($\overline{Capex/PPE}_{-i}$) as an additional control. Table VI presents the results where the first five columns mirror the specifications reported in our main Table II. The coefficients on peers' investment ($\overline{Capex/PPE}_{-i}$) are in general positive and significant, confirming that corporate investment co-moves positively between firms within the same industry. Yet, accounting for these co-movements does not alter our main finding. The coefficients on $\overline{MFHS}_{-i}$ remain positive and statistically significant in every specification. In column (6), we re-estimate our baseline specification with industry×year fixed effects (instead of year fixed effects). These fixed effects absorb time-varying unobserved heterogeneity across industries, such as industry-specific business cycles or technological shocks, and account for the fact that some industries could have a greater sensitivity of investment to peers' investment due to different competition intensity. We continue to observe a positive and significant coefficient on $\overline{MFHS}_{-i}$.

Across all specifications, the magnitude of the coefficients on $\overline{MFHS}_{-i}$ and $\overline{Q}^*_{-i}$ is about half that obtained when we do not control for co-movements in investment or exclude industry×year fixed effects (as in Table II). However, the relative magnitudes of the coefficients on non-fundamental shocks compared to fundamental shocks remain the same as in the baseline specification. For instance, the coefficient on the fundamental component of peers' stock price is always about twice the coefficient on the non-fundamental component of peers' stock price ($\frac{\gamma_{-i}}{\alpha_{-i}} \approx 2$). We conclude that our results cannot be explained solely by complementarities in firms' investment decisions.

[26] Models such as Fudenberg and Tirole (1984) or Bulow, Geanakoplos, and Klemperer (1985) 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.

B.5 Correlated Noise in Prices

Another possibility is that, as discussed in Section II.B, the observed component of the noise in peers' stock price ($\overline{MFHS}_{-i}$) is correlated with the unobserved component of the noise in firm i's stock price. In this case, our estimate of α_{-i} will pick the effect of the noise in firm i's stock price on firm i's investment. If this effect is driven by, say, firm i's financial constraints then our test of the faulty informant hypothesis is problematic.

We first observe that our tests for conglomerates in Section IV.B.1 address this issue. Indeed, in these tests, we control for firm×year fixed effects and therefore for any time-varying characteristics of firm i affecting its investment, including the noise (observed and unobserved) in its stock price in year t (i.e., $u_{it} = u_{it}^{o} + u_{it}^{no}$). That is, the tests for conglomerates give us the unique opportunity to control for the effect of the unobserved component of the noise in firm i's stock price in a given year.

[Insert Table VII About Here]

A limitation is that we can perform this test only for conglomerates. However, if the coefficient on $\overline{MFHS}_{-i}$ in our tests for the entire sample of firms captures the influence of the unobserved noise component of firms' own stock price on their investment decisions, we expect the coefficient on Q_i^* to vary substantially when we estimate our baseline specification (10) with and without $\overline{MFHS}_{-i}$ (e.g., Oster (2014)).[27] Columns (1) and (2) of Table VII indicate that this is not the case. Excluding $\overline{MFHS}_{-i}$ moves the magnitude of the point estimate on Q_i^* from 0.081 to 0.083 only (and the R^2 from 0.485 to 0.484). In columns (3) and (4) we do not decompose firms' own stock price into Q_i^* and $MFHS_i$, but directly control for stock price (Q_i) in our baseline specification (10). Again, removing $\overline{MFHS}_{-i}$ barely alters the magnitude of the coefficient on Q_i. It is therefore unlikely that our results are driven by a correlation between observed and unobserved components of noise in stock prices.

[27]Note that while $\overline{MFHS}_{-i}$ is orthogonal to $\overline{Q}^*_{-i}$ by construction, it is not orthogonal to Q_i^*.

C Additional Implications of the Faulty Informant Hypothesis

We provide further empirical support for the faulty informant hypothesis by testing specific cross-sectional predictions of this hypothesis. Specifically, using the closed form solution of α_{-i} (see eq.(19) in the proof of Lemma 1), we identify characteristics of a firm that should weaken the sensitivity of its investment to the noise in its peers' stock price.

Proposition 2. *If managers rely on stock prices for their investment decision and cannot perfectly distinguish fundamental from non-fundamental shocks to stock prices then a firm's investment should be less sensitive to the noise in its peers' stock price (α_{-i} goes down) when:*

1. *Its manager's private signals about the noise in its peers' stock price or about its fundamentals are more informative.*
2. *Its peers' stock price is less informative.*

When the manager is better informed about the noise in peers' stock prices, she filters out better the noise from these prices and firm i's investment is therefore less sensitive to the noise in peers' stock prices (first prediction in Proposition 2). This is also the case when the manager's private information is more precise because she relies less on peer firms as a source of information. When peers' stock price is less informative ($\sigma_{u_{-i}}$ increases), it influences less the manager's expectation of the marginal return on her investment. As a result, the investment of firm i becomes less sensitive to the noise in its peers' stock price (second prediction in Proposition 2). We test these predictions below by interacting $\overline{MFHS}_{-i,t-1}$ in the baseline specification (10) with proxies for managerial information or peers' stock price informativeness.[28]

C.1 Managerial Private Information

To test the first prediction in Proposition 2, we use four different proxies for the precision of managerial information, that we generically label as $ManagerSignal_i$, and we examine whether investment is negatively related to $\overline{MFHS}_{-i} \times ManagerSignal_i$. First, we posit that managers are more likely to make profitable trades if their internal signals are more precise.

[28]We also interact all other explanatory variables in Equation (10) to guarantee the consistency of the estimation.

Thus, we use the profitability of insiders' trades as proxy for the precision of these signals. We measure this profitability by the average one month market adjusted returns of holding the same position as insiders for each insider's transaction ($InsiderCAR_i$). 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 own firm has experienced episodes of severe downward price pressure due to large mutual fund outflows. Thus, for each firm i, we create an indicator variable ($PreviousFireSale_i$) that is equal to one in year t if its stock has been in the lowest decile of $MFHS$ in the three years preceding year t.

Arguably, managers should more easily identify non-fundamental shocks to their peers' stock price, due to mutual funds' forced sales, when their ownership by mutual funds overlaps more with that of their peers. Hence, 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.[29] We then compute the average ownership overlap ($CommonOwnership_i$) between firm i and its peers in year t, and expect managers to be better informed about the noise in their peers' stock price if ownership overlap is higher.

Sulaeman and Wei (2014) show that some analysts can detect non-fundamental shocks to prices due to mutual funds' fire sales. Hence, we conjecture that managers can better identify the noise in their peers' stock price when financial analysts indicate that these stocks are mispriced. Accordingly, for each firm-year, we compute the average difference between analysts' target price and the current stock price and we use this difference as a measure of analysts' estimate of the non-fundamental component of a firm's price. For each firm i, we then use the average analysts' estimate of this component across its peers ($\overline{AnalystDiscount}_{-i}$) in year t as a measure of analysts' estimate of its peers' mispricing.

[Insert Table VIII About Here]

[29]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 $\frac{v_i \cdot v_j}{\|v_i\| \|v_j\|}$.

Table VIII presents the results. To preserve space, we only report the estimated coefficients on $\overline{MFHS}_{-i}$ and $\overline{MFHS}_{-i} \times ManagerSignal_i$. The coefficients on $\overline{MFHS}_{-i} \times ManagerSignal_i$ are negative across all specifications, while the coefficients on $\overline{MFHS}_{-i}$ remain positive. The coefficients are significant in two specifications out of four, while the other two are borderline significant (with t-statistics above 1.54). In line with the faulty informant channel, firms' investment is less sensitive to the noise in their peers' stock price when managers appear to possess more information about the fundamentals of their firm or the non-fundamental component of their peers' stock price.

C.2 Peers' Stock Price Informativeness

To test the second prediction in Proposition 2, we rely on various proxies for price informativeness. Our first proxy is taken from Bai, Philippon, 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 peers' three-year ahead earnings on their current Tobin's Q and the ratio of current earnings (before interests and taxes) over assets. We call $\overline{BPS}_{-i}$ the t-statistic of the coefficient on peers' Tobin's Q in these predictive regressions for firm i in year t and use this variable as a measure of the informativeness of its peers' stock price.

Second, as in Durnev, Morck, and Yeung (2004), or Chen, Goldstein, and Jiang (2007), we measure the informativeness of a firm's stock price by its 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. We define the variable $\overline{NonSync}_{-i}$ as the average firm-specific return variation of firm i's peers in year t.

Third, we use the size of past hypothetical sales of peers' stocks due to mutual funds' forced sales. As explained previously, these forced sales push the prices of affected stocks away from their fundamental and should therefore make them less informative. Accordingly, for each firm i, we define an indicator variable, $\overline{PreviousFireSale}_{-i}$, equals to one if the realization of $\overline{MFHS}_{-i}$ has been in the lowest decile of this variable (across all firms) in the three years preceding year t.

Our fourth proxy relies on the average earnings forecast error of financial analysts over the three years preceding year t to measure the informativeness of firm i's peers' stock price in year t ($\overline{AnalystFE}_{-i}$). Analysts facilitate the dissemination of information among investors. They often directly communicate with company's management and disseminate information more broadly (e.g. Womack (1996), Barber, Lehavy, McNichols, and Trueman (2001), or Loh and Stulz (2011)). Hence, we conjecture that peers' stock price 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.

[Insert Table IX About Here]

Estimates reported in Table IX show that, as predicted, investment responds significantly more to the noise in peers' stock price when it is more informative. Columns (1) and (2) indicate that the interacted coefficients on $\overline{MFHS}_{-i} \times \overline{BPS}_{-i}$ and $\overline{MFHS}_{-i} \times \overline{NonSync}_{-i}$ are positive, and significant at a 10% confidence level. Similarly, columns (3) and (4) show that investment is significantly (at the 1% level) less responsive to the noise in peers' stock price when analysts forecast errors are large, and when peers' stock prices have experienced fund-driven price pressure in the past.

V Conclusion

In this paper, we show empirically that a firm's investment is sensitive to non-fundamental shocks to its peers' stock price. This finding is consistent with the faulty informant hypothesis, i.e., the hypothesis that managers use stock prices as a source of external information but have limited ability to filter out noise from prices. This finding is hard to explain with other mechanisms.

Overall, our paper suggests a new mechanism through which localized non-fundamental shocks to stock prices for a group of firms might have real effects for other firms and diffuse to the rest of the economy. A preliminary analysis indicates that, similar to our investment results, firms also reduce employment when the stock prices of their peers decrease for non-fundamental reasons. The investment and employment effects might themselves feedback on the stock price of these firms. In this way, a localized non-fundamental shock to stock prices might ultimately have a large effect on aggregate investment and employment.[30] Such an amplification mechanism could explain how micro non-fundamental shocks to asset prices might eventually have real effects at the macroeconomic level. Studying this mechanism is an interesting venue for future research.

[30]For instance, suppose that there are N firms: firm n is a peer of firm $n+1$ etc. A non-fundamental drop in the stock price of firm 1 leads firm 2 to cut its investment. As a result, the stock price of firm 2 drops, which leads firm 3 to cut its investment as well, etc. Ultimately the drop in aggregate investment due to a non-fundamental shock specific to firm 1 can be large.

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APPENDIX A: Proofs

In this appendix, we denote by $\psi_i = \sigma^2_{\widetilde{\theta}_i}\left(\sigma^2_{\widetilde{\theta}_i} + \sigma^2_{\chi_i}\right)^{-1}$, the signal-to-noise ratio for the manager's own private information, s_{mi}, about the fundamental of the growth opportunity, $\widetilde{\theta}_i$. Similarly, $\kappa_i = \sigma^2_{\widetilde{\theta}_i}\left(\sigma^2_{u_i} + \sigma^2_{\widetilde{\theta}_i}\right)^{-1}$ and $\kappa_{-i} = \sigma^2_{\widetilde{\theta}_i}\left(\sigma^2_{u_{-i}} + \sigma^2_{\widetilde{\theta}_i}\right)^{-1}$ denote the signal-to-noise ratios for the signals conveyed by stock prices. These ratios measure, respectively, the informativeness of firm i's own stock price (κ_i) and the informativeness of peers' stock prices (κ_{-i}) about the fundamental of the growth opportunity. As $\sigma^2_{u_i} > 0$ and $\sigma^2_{u_{-i}} > 0$, we have $\kappa_i < 1$ and $\kappa_{-i} < 1$ (i.e., stock prices never perfectly reveal firm i's fundamental). Finally, $\phi_i = \sigma^2_{u_i}\left(\sigma^2_{\eta_i} + \sigma^2_{u_i}\right)^{-1}$ and $\phi_{-i} = \sigma^2_{u_{-i}}\left(\sigma^2_{\eta_{-i}} + \sigma^2_{u_{-i}}\right)^{-1}$ denote the signal-to-noise ratios for the manager's signals about the noise in her own and peers' stock prices.

Proof of Lemma 1.

The following remark is useful for the proof of Lemma 1.

Remark 1: If a vector X and $\widetilde{\theta}_i$ have a multivariate normal distribution then $E(\widetilde{\theta}_i\,|X) = E(\widetilde{\theta}_i) + Cov(\widetilde{\theta}_i, X)^t\Omega^{-1}(X - E(X))$ where Ω^{-1} is the inverse of the variance-covariance matrix of X and $Cov(\widetilde{\theta}_i, X)^t$ is the transpose of the (column) vector giving the covariance between $\widetilde{\theta}_i$ and each component of vector X.

As explained in the text, the optimal investment policy is such that $K_i^* = \mathrm{E}(\widetilde{\theta}_i\,|\Omega_1)$. Now we compute $\mathrm{E}(\widetilde{\theta}_i\,|\Omega_1)$. Using the fact that $s_{m_i}, P_i, s_{u_i}, P_{-i}$, and $s_{u_{-i}}$ are normally distributed with zero means, we deduce that $\mathrm{E}(\widetilde{\theta}_i\,|\Omega_1)$ is a linear function of these variables (with a zero intercept):

$$\mathrm{E}(\widetilde{\theta}_i\,|\Omega_1) = a_i \times s_{m_i} + b_i \times P_i + c_i \times s_{u_i} + b_{-i} \times P_{-i} + c_{-i} \times s_{u_{-i}}. \tag{13}$$

Using the Law of Iterated Expectations and the fact that u_{-i} and $s_{u_{-i}}$ are independent from s_{m_i}, P_i, and s_{u_i}, we deduce from Equation (13) that:

$$\mathrm{E}(\widetilde{\theta}_i\,|s_{m_i}, P_i, s_{u_i}) = a_i s_{m_i} + b_i P_i + c_i s_{u_i} + b_{-i} E(\widetilde{\theta}_i\,|s_{m_i}, P_i, s_{u_i})\,.$$

Thus:

$$\mathrm{E}(\widetilde{\theta}_i\,|s_{m_i}, P_i, s_{u_i}) = \frac{a_i}{1-b_{-i}} s_{m_i} + \frac{b_i}{1-b_{-i}} P_i + \frac{c_i}{1-b_{-i}} s_{u_i}. \tag{14}$$

Now, using Remark 1, we also have:

$$\mathrm{E}(\widetilde{\theta}_i \left| s_m, P_i, s_{u_i} \right.) = a_i^* s_{m_i} + b_i^* P_i + c_i^* s_{u_i}, \tag{15}$$

where $a_i^* = \frac{\psi_i(1-\phi_i)(1-\kappa_i)}{(1-\phi_i)(1-\kappa_i)+(1-\psi_i)\kappa_i}$, $b_i^* = \frac{(1-\psi_i)\kappa_i}{(1-\phi_i)(1-\kappa_i)+(1-\psi_i)\kappa_i}$, $c_i^* = -\frac{(1-\psi_i)\phi_i\kappa_i}{(1-\phi_i)(1-\kappa_i)+(1-\psi_i)\kappa_i}$. Thus, comparing eq.(14) and eq.(15), we deduce that:

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

Let $s_{m_i}^* = \frac{(a_i^* \times s_{m_i} + b_i^* \times P_i + c_i^* s_{u_i})}{(a_i^*+b_i^*+c_i^*)} = \theta_i + \chi_i^*$ with $\chi_i^* = \left(\frac{a_i^*}{a_i^*+b_i^*+c_i^*}\right)\chi_i + \left(\frac{b_i^*}{a_i^*+b_i^*+c_i^*}\right)u_i + \left(\frac{c_i^*}{a_i^*+b_i^*+c_i^*}\right)\eta_i$. Using these notations, we can rewrite eq.(13) as:

$$\mathrm{E}(\theta_i \left| \Omega_1 \right.) = (a_i^* + b_i^* + c_i^*)(1-b_{-i}) \times s_{m_i}^* + b_{-i} \times P_{-i} + c_{-i} \times s_{u_{-i}}. \tag{16}$$

Thus: $\mathrm{E}(\mathrm{E}(\widetilde{\theta}_i \left| \Omega_1 \right.) \left| s_{m_i}^*, P_{-i}, s_{u_{-i}} \right) = \mathrm{E}(\widetilde{\theta}_i \left| s_{m_i}^*, P_{-i}, s_{u_{-i}} \right) = \mathrm{E}(\widetilde{\theta}_i \left| \Omega_1 \right.)$, where the first equality follows from from the Law of Iterated Expectations and the second equality from eq.(16). We deduce the expressions for b_{-i} and c_{-i} by applying again Remark 1 to compute $\mathrm{E}(\theta_i \left| s_m^*, P_{-i}, s_{u_{-i}} \right)$. After some algebra, we obtain:

$$b_{-i} = \frac{\sigma_{\theta_i}^2 \sigma_{\chi_i^*}^2}{(\sigma_{u_{-i}}^2(1-\phi_{-i})(\sigma_{\theta_i}^2 + \sigma_{\chi_i^*}^2) + \sigma_\theta^2 \sigma_{\chi_i^*}^2)} = \frac{(1-\psi_i^*)\kappa_{-i}}{(1-\phi_{-i})(1-\kappa_{-i}) + (1-\psi_i^*)\kappa_{-i}}, \tag{17}$$

$$c_{-i} = -\frac{\sigma_\theta^2 \sigma_{\chi^*}^2 \phi_{-i}}{\sigma_{u_{-i}}^2(1-\phi_{-i})(\sigma_{\theta_i}^2 + \sigma_{\chi_i^*}^2) + \sigma_{\theta_i}^2 \sigma_{\chi_i^*}^2 \sigma_{u_{-i}}^2} = -\frac{(1-\psi_i^*)\phi_{-i}\kappa_{-i}}{(1-\phi_{-i})(1-\kappa_{-i}) + (1-\psi_i^*)\kappa_{-i}}, \tag{18}$$

where $\sigma_{\chi_i^*}^2 = \left(\frac{a_i^*}{a_i^*+b_i^*+c_i^*}\right)^2 \sigma_{\chi_i}^2 + \left(\frac{b_i^*}{a_i^*+b_i^*+c_i^*}\right)^2 \sigma_{u_i}^2 + \left(\frac{c_i^*}{a_i^*+b_i^*+c_i^*}\right)^2 \sigma_{\eta_i}^2$, and $\psi_i^* = \frac{\sigma_{\theta_i}^2}{\sigma_{\theta_i}^2 + \sigma_{\chi_i^*}^2}$.

Special cases. Three special cases are discussed in the text.

Case 1: The manager's private information about θ_i is perfect. In this case, $\sigma_{\chi_i} = 0$ and therefore $\psi_i = 1$. It follows that $b_i^* = c_i^* = 0$ and therefore $b_i = c_i = 0$. Moreover, $\sigma_{\chi_i^*} = 0$ and therefore, using eq.(17) and eq.(18), we have $b_{-i} = c_{-i} = 0$.

Case 2: The manager's private information about θ_i is imperfect and peers' stock prices are uninformative. In this case $\sigma_{\chi_i} > 0$ and $\kappa_{-i} = 0$. Thus, using eq.(17) and (18), we have

$b_{-i} = c_{-i} = 0$. Moreover, if the firm's own stock price is informative then $b_i > 0$ because $\psi_i < 1$ and $\kappa_i > 0$. If in addition, the manager of firm i is informed about the noise in her own stock price then $\phi_i > 0$ and therefore $c_i < 0$.

Case 3: The manager's private information about θ_i is imperfect and peers' stock prices are informative. This case is a more general version of Case 2. As the manager is imperfectly informed we have $\psi_i < 1$ and $\psi_i^* < 1$. As peers' stock prices are informative, we also have $\kappa_{-i} > 0$ and therefore $b_{-i} > 0$ (see eq.(17)). If in addition, firm i's manager is informed about the noise in her peers' stock price then $\phi_{-i} > 0$ and therefore $c_{-i} < 0$ (see eq.(18)).

Case 4: The manager's private information about θ_i is imperfect but the manager has a perfect signal on the noise in its peers' stock price, i.e., $\sigma_{\eta_{-i}} = 0$. In this case, we deduce from eq.(17) and eq.(18) that $b_{-i} = 1$ and $c_{-i} = -1$. Moreover, $a_i = b_i = c_i = 0$. Thus, using eq.(16), we deduce that $K_i^* = \theta_i$. It follows from Remark 1 that $E(K_i^* \mid P_{-i}, P_i) = E(\theta_i^* \mid P_{-i}, P_i) = \frac{\tau_{u_i}}{\tau_{u_i}+\tau_{u_{-i}}+\tau_{\theta_i}} P_i + \frac{\tau_{u_i}}{\tau_{u_i}+\tau_{u_{-i}}+\tau_{\theta_i}} P_{-i}$.

The signs and sizes of α_i and α_{-i}. By definition, $\alpha_{-i} = b_{-i} + c_{-i}$. Using eq.(17) and eq.(18), we deduce that:

$$\alpha_{-i} = \frac{(1-\psi_i^*)(1-\phi_{-i})\kappa_{-i}}{(1-\phi_{-i})(1-\kappa_{-i}) + (1-\psi_i^*)\kappa_{-i}}. \tag{19}$$

Thus, $\alpha_{-i} \geq 0$ and is strictly positive if and only if (i) the manager's private signal is not perfect ($\psi_i^* < 1$), (ii) peers' stock prices are informative ($\kappa_{-i} > 0$) and (iii) the manager cannot perfectly filter out the noise in his peers' stock prices ($\phi_{-i} < 1$). A similar argument shows that α_{-i} is always positive and is strictly positive if and only if (i) the manager's private signal is not perfect ($\psi_i^* < 1$), (ii) firm i's stock price is informative ($\kappa_i > 0$) and (iii) the manager cannot perfectly filter out the noise in his firm's stock price ($\phi_i < 1$).

Proof of Proposition 1.

Using eq.(4) and the independence of χ_i, η_i and η_{-i} with P_i, u_i^o, P_{-i}, and u_{-i}^o, we deduce that:

$$
\begin{aligned}
\mathrm{E}(K_i^* \left| P_i, u_i^o, P_{-i}, u_{-i}^o \right.) &= a_i \mathrm{E}(\theta_i \left| P_i, u_i^o, P_{-i}, u_{-i}^o \right.) + b_i P_i + c_i \mathrm{E}(u_i \left| P_i, u_i^o, P_{-i}, u_{-i}^o \right.) \\
&\quad + b_{-i} P_{-i} + c_{-i} \mathrm{E}(u_{-i} \left| P_i, P_{-i}, u_{-i}^o, u_i^o \right.) . \qquad (20)
\end{aligned}
$$

Let $P_{-i}^* = P_{-i} - u_{-i}^o = \theta_i + u_{-i}^{no}$ and $P_i^* = P_i - u_i^o = \theta_i + u_i^{no}$. Using the normality of all variables and the independence of θ_i, u_{-i}^{no}, and u_i^{no}, we obtain:

$$
\begin{aligned}
\mathrm{E}(\theta_i \left| P_i, u_i^o, P_{-i}, u_{-i}^o \right.) &= \mathrm{E}(\theta_i \left| P_i^*, P_{-i}^* \right.) = \pi_i P_i^* + \delta_i P_{-i}^*, \qquad (21) \\
\mathrm{E}(u_{-i} \left| P_i, u_i^o, P_{-i}, u_{-i}^o \right.) &= \mathrm{E}(u_{-i}^{no} \left| P_i^*, P_{-i}^* \right.) + u_{-i}^o = \pi_i' P_i^* + \delta_i' P_{-i}^* + u_{-i}^o, \qquad (22) \\
\mathrm{E}(u_i \left| P_i, u_i^o, P_{-i}, u_{-i}^o \right.) &= \mathrm{E}(u_i^{no} \left| P_i^*, P_{-i}^* \right.) + u_i^o = \widehat{\pi}_i P_i^* + \widehat{\delta}_i P_{-i}^* + u_i^o. \qquad (23)
\end{aligned}
$$

Using Remark 1 in the proof of Lemma 1, we obtain after some algebra:

$$
\begin{aligned}
\pi_i &= \frac{(1-\lambda_{-i})\sigma_{u_{-i}}^2 \sigma_{\theta_i}^2}{\sigma_{\theta_i}^2((1-\lambda_i)\sigma_{u_i}^2 + (1-\lambda_{-i})\sigma_{u_{-i}}^2) + (1-\lambda_i)(1-\lambda_{-i})\sigma_{u_{-i}}^2 \sigma_{u_i}^2}, \\
\delta_i &= \frac{(1-\lambda_i)\sigma_{u_i}^2 \sigma_{\theta_i}^2}{\sigma_{\theta_i}^2((1-\lambda_i)\sigma_{u_i}^2 + (1-\lambda_{-i})\sigma_{u_{-i}}^2) + (1-\lambda_i)(1-\lambda_{-i})\sigma_{u_{-i}}^2 \sigma_{u_i}^2}, \\
\widehat{\delta}_i &= -\delta_i \\
\widehat{\pi}_i &= (1-\pi_i) \\
\delta_i' &= (1-\delta_i), \\
\pi_i' &= -\pi_i.
\end{aligned}
$$

We deduce from equations (20), (21), (22), and (23) that:

$$
\mathrm{E}(K_i^* \left| P_i, u_i^o, P_{-i}, u_{-i}^o \right.) = \gamma_i P_i^* + \alpha_i u_i^o + \gamma_{-i} P_{-i}^* + \alpha_{-i} u_{-i}^o, \qquad (24)
$$

with

$$
\begin{aligned}
\gamma_i &= (a_i \pi_i + b_i + c_i \widehat{\pi}_i + c_{-i} \pi_i'), \\
\rho_i &= b_i + c_i, \\
\gamma_{-i} &= (a_i \delta_i + b_{-i} + c_i \widehat{\delta}_i + c_{-i} \delta_i') \\
\rho_{-i} &= b_{-i} + c_{-i}.
\end{aligned}
$$

Consequently:

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

because $c_{-i} < 0$. Similarly, we obtain that $\gamma_i > \alpha_i$.

Last, let $\epsilon_i = K_i^* -$ $\mathrm{E}(K_i^* \,\big|P_i, u_i^o, P_{-i}, u_{-i}^o\big)$. By construction, ϵ_i is independent from P_i, u_i^o, P_{-i}, and u_{-i}^o. Moreover, we deduce from eq.(24) and the definition of ϵ_i that:

$$K_i^* = \gamma_i P_i^* + \alpha_i u_i^o + \gamma_{-i} P_{-i}^* + \alpha_{-i} u_{-i}^o + \epsilon_i.$$

Proof of Proposition 2.

The proposition follows from differentiating the expression for α_{-i} (see eq.(19)) with respect to ϕ_{-i} (a measure of the manager's information about the noise in peers' stock price), ψ_i (a measure of the manager's information about the fundamental of her growth opportunity), κ_{-i} (a measure of the informativeness of peers' stock price).

APPENDIX B: Definition of the Variables

Variable	Definition	Source
$Capex/PPE$	Capex (capx) scaled by lagged Property, Plant and Equipment (ppent)	Compustat
Q	Book value of assets (at) - Book value of equity (ceq) + Market value of equity, scaled by book value of assets	Compustat
$MFHS$	Measure of mutual fund hypothetical sales in stock i in year t due to large outflows in mutual funds owning the stock (Edmans, Goldstein and Jiang, 2012). See Appendix C for more details	CRSP - Thomson Mutual Fund Holdings
$Size$	Logarithm of the book value of assets (at)	Compustat
CF/A	Income before extraordinary items (ib) plus depreciation (dp), scaled by assets	Compustat
$InsiderCAR$	Profitability of insiders' trades computed as the annual average (absolute value) of the one-month market-adjusted returns following insider trades. We only consider open market stock transactions initiated by the top five executives	Thomson Insider Data - CRSP
$PreviousFireSale$	Dummy variable equals to 1 if the firm has been in the lowest decile of $MFHS$ in the past three years	CRSP - Thomson Mutual Fund Holdings
$CommonOwnership$	Overlap in mutual funds ownership between a firm and its peers, computed as the cosine similarity between firms' mutual fund holdings structure. 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 . We then compute the average ownership overlap between a firm and its peers in a given year	Thomson Mutual Fund Holdings
$AnalystDiscount$	The average difference between analysts target stock price for a given firm and its current stock price	CRSP - IBES

BPS	t-statistic on the coefficients (on Q) obtained by annual regressions a given firm's peers three-year ahead earnings (earnings before interest and taxes over assets) on their current Tobin's Q and current earnings	Compustat
NonSync	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	Compustat - CRSP
AnalystFE	Average analyst earnings forecast error	CRSP - IBES
CDS Spread	Average annual CDS spreads	Markit
Debt Spread	Average spreads on new debt issues	Dealscan
Debt-Cons.	Text-based measure of financing constraint in the debt market (higher score indicates more constrained)	Hoberg and Maksimovic (2015)
Equity-Cons.	Text-based measure of financing constraint in the equity market (higher score indicates more constrained)	Hoberg and Maksimovic (2015)
Prob(Target)	Dummy variable equals to one if firm i receives a takeover bid in year t and zero otherwise	SDC
CEO Turnover	Dummy variable equals to one if firm i experiences a CEO change in year t, and zero otherwise	Execucomp
RPE	Dummy variable equals to one if an industry is likely to use relative performance evaluation. For each industry-year, we estimate whether CEO compensation is sensitive to the stock returns of industry peers, after controlling for firms' own stock return and size. Industries are classified as using RPE if compensation is negatively related to peers' stock returns	Execucomp - CRSP
Capex/A (conglomerate)	Division capex (capx) scaled by lagged division assets (at). A division is defined at the Fama French 48-industry level	Compustat Segment

APPENDIX C: Construction of Mutual Fund Hypothetical Sales ($MFHS$).

This appendix explains how, for each stock i, we construct $MFHS_{i,t}$, 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 $Flow_{j,q,t} \leq -0.05$, we compute

$$MFHS^{dollars}_{i,q,t} = \sum_j (Flow_{j,q,t} \times SHARES_{j,i,q} \times PRC_{i,q,t}).$$

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 $MFHS^{dollars}_{i,q,t}$ by the dollar volume of trading in stock i in quarter q of year $t$and finally define $MFHS_{i,t}$as:

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

APPENDIX D: Selected Manager Quotes on Peers' Stock Prices

T. Martin, CEO, Vedior

"Our development program will continue. Already in the third quarter we've expanded into a new market, Poland and hopefully the differentiation between our market valuation and our peers will disappear." Source: Q2 2003 Earnings Conference Call (July 31, 2003)

J.C. Smith, CEO, Webster Financial Corporation

"We're encouraged by the gradual reduction in our PE discount relative to the peer group median since we undertook our currents strategic plan in 2001 and are beginning to see improvement in the implied discount rate also. We remain committed to closing these valuation gaps through our strong performance and attainment of our clearly stated strategic goals." Source: Q3 2003 Earnings Conference Call (October 15, 2003)

S. Chamberlain, CEO, Integral Systems

"Everybody else in our industry, with the sole exception of ViaSat, has a P/E ratio half of ours. And ViaSat has the same as we do. So if you look at our ranking with our peers, our stock price is exactly where it should be. It is actually at the top of the pack. And that is really all I had to say." Source: Q3 2005 Earnings Conference Call (August 16, 2005)

A. Kumar, CEO, Combimatrix

"Let me make some contextual remarks regarding the emerging molecular diagnostics market (...). Each of our competitors seeks to enter the molecular diagnostics business as that will be a growth driver and provides strong recurring revenue streams. And one might argue that, considering the multiple of revenues and earnings at which they trade, most of our competitors' stock prices already anticipate big successes of their molecular diagnostic strategies. As many of you know, CombiMatrix began selling microarray products to researchers roughly 2.5 years ago. It was necessary for us to enter this market to validate our technology and products, but our eventual goal was to sell to physicians, patients and clinical laboratories for diagnostic applications (...). We have now achieved that goal and are in the process of expanding our scale" Source: Q2 2007 Acacia Earnings Conference Call (July 26, 2007)

J. Rubright, CEO, Rock-Tenn

"We looked at our assets and we said, "Why are we trading at a discount?" We've got good assets. We've got good peo-ple. And actually, our results wouldn't have justified that discount. We're still fighting that battle today. We are still fighting that battle today in terms of valuation. If you compare our valuation across our sector, you're going, "What's going on?" And I don't know what's going on." Source: Analyst & Investor Meeting (September 18, 2008)

R. Decherd, CEO, A.H. Belo Corporation

"A.H. Belo's stock price and the stock price of its peer media companies experienced dramatic declines in 2008. Much of this decline was due to the conditions that continue today, including investor unease about the economy and the financial markets as a whole, secular concerns about the newspaper industry, and the cyclical impact of advertis-ing-based companies – on

advertising-based companies during recessions." Source: Shareholders Annual Meeting (May 14, 2009)

C. Koliopoulos, CEO, Zigo

"So in our benchmarking of our peer group, last quarter we saw valuations – average valuation of that peer group at over 2 times revenue. And Zygo has been trading at below that level. So I believe that Zygo in comparison with that – those benchmark companies is undervalued.(...) If Zygo shows as we go forward improved operating models, I think Zygo will – should – and it's just a guess on my part – should come up to the levels of our – at least our peer group. And as we improve our operating models, we should improve our valuations." Source: Q1 2011 Earnings Conference Call (November 4, 2010)

D. Wall, CEO, PattersonUTI Energy

"And I think today the one point that I think we're all a little bit concerned about, but you can probably say this about a number of companies in the market, but certainly in our case we're trading at a substantial discount to both historical valuations and to our peers. And I'm not sure that the valuations are really warranted. But we've got to tell our story and run our business." Source: UBS Global Energy Conference (May 23, 2012)

M. Burger, CEO, Cascade Microtech

"Analyst: Even with increased CapEx, you're going to have what I see as tremendous cash flow this year. Might that number go up, or would you rather spend it some other way?"

"Michael Burger: We would love to spend it in R&D. We actually are getting a return today. And we've got a lot of customer pull for stuff. So we actually think we can get probably at – it depends on the multiples and where the stock price is. We watch the multiple very closely compared to our competitor set. So assuming that we are receiving a fair multiple, we'd like to spend it in R&D. The minute we think our multiples are cheap or undervalued, we'll purchase it. But it really depends. R&D would be our first preference." Source: Q1 2014 Earnings Conference Call (April 29, 2014)

G. Henkels, CFO, Swift Transportation

"So this is a chart of our stock price from when we were public in December of 2010, through the end of 2012. So obviously, we did not perform very well in this period. We had – decreased 18% in our stock price where our peers were only down about 7%." Source: Investor Day (May 2, 2014)

D. Allingham, CEO, Lifecore Biomedical

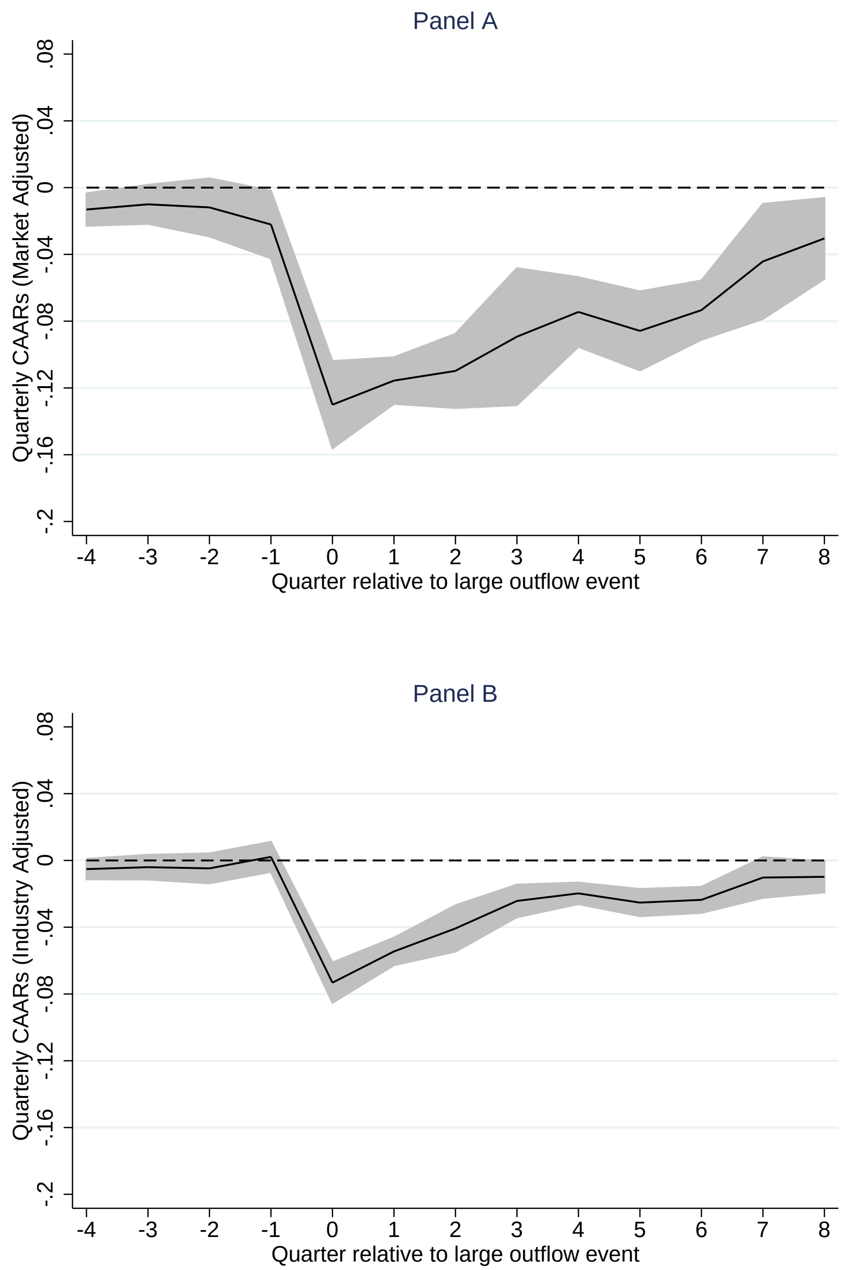
"So, I have inserted a chart that just reflects what the stock price looks like and how it has performed over the last several years. The blue line is Lifecore Biomedical; the green line is the performance of our peer index that includes a number of companies – Align, Anika, Biolase, Dentsply, Integra, Isolagen, LifeCell, Mentor, Nobel Biocare, Regen Technologies, Sirona, Straumann, Sybron, and Young Innovations – pretty elite company to be part of, but again you will see that certainly the blue line, the stock has outperformed that peer group and considerably above the yellow line which is the index for the S&P 500." Source: Annual

Shareholder Meeting (November 16, 2016)

J. Fowden, CEO, Cott Corporation

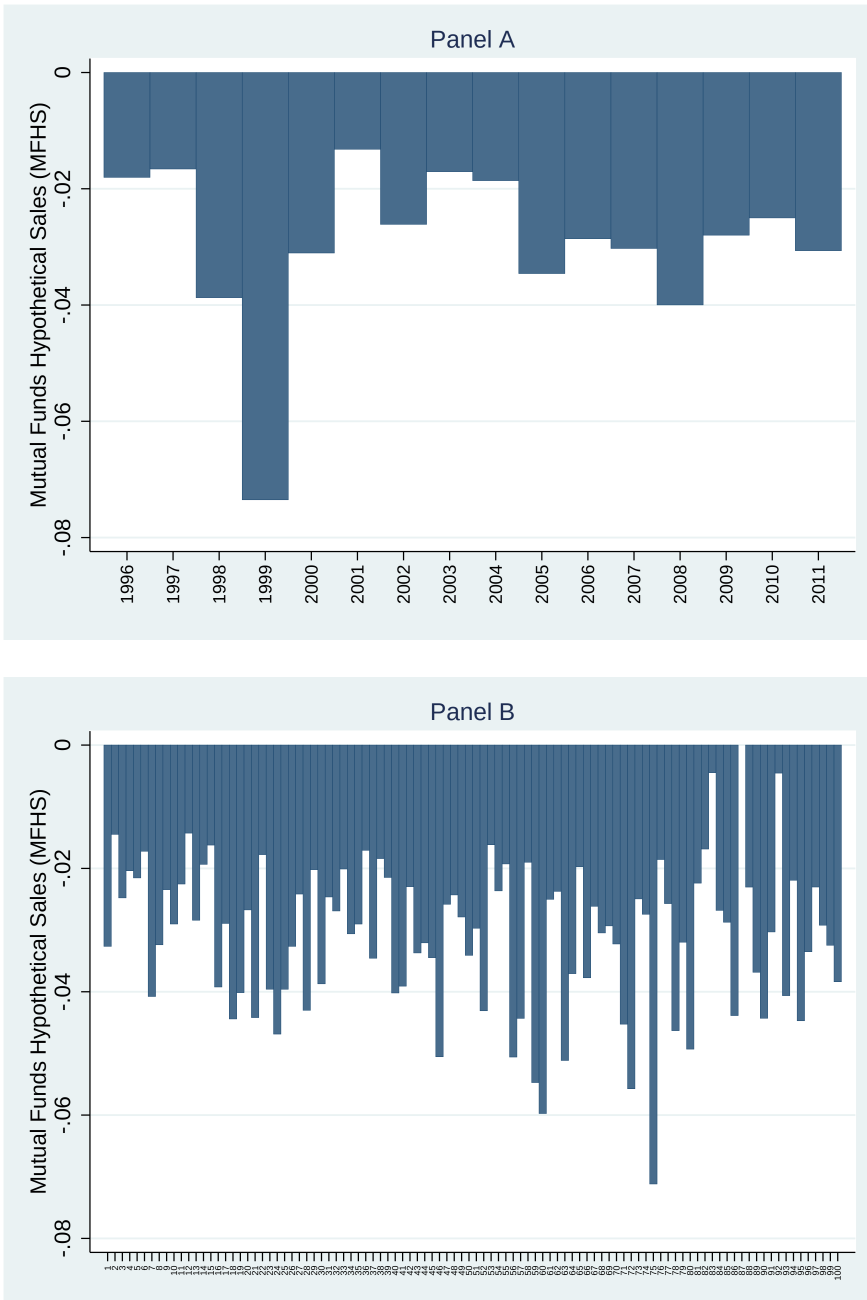
"I believe the valuation of our business should improve over time to be more in line with the valuation of our peers." Source: Q1 2015 Earnings Conference Call (May 7, 2015)

Figure 1: **Effect of Mutual Funds Hypothetical Sales on Stock Prices**



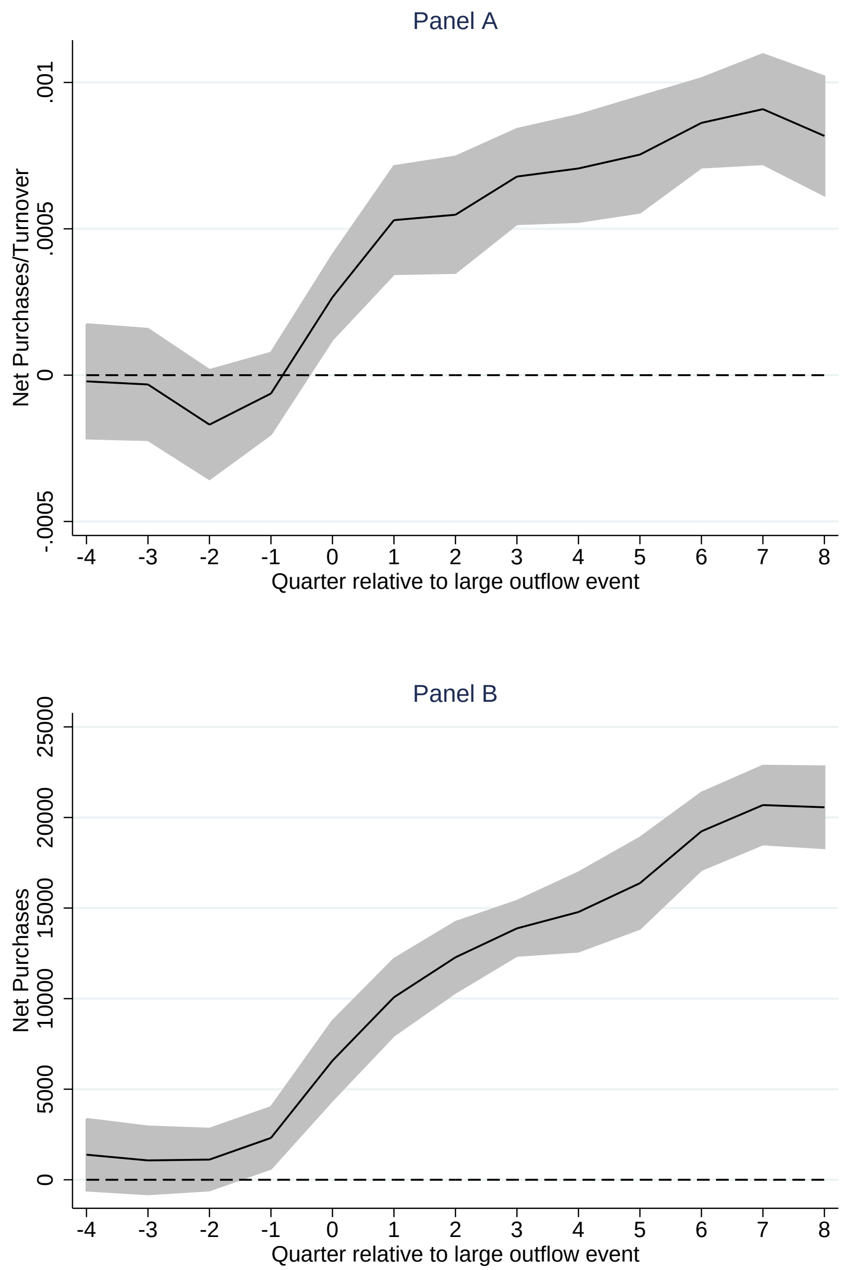
This figure plots the quarterly cumulative average abnormal returns (CAAR) of stocks subject to mutual fund price pressure around the event, where an event is defined as a firm-quarter observation in which $MFHS$ falls below the 10th percentile value of the full sample. We estimate linear regressions of quarterly abnormal returns on event-time dummy variables for affected firms (with firm and calendar time fixed effects), and display the cumulated coefficients (CAAR). In Panel A, the benchmark used to estimate the CAAR is the CRSP equally-weighted index. In Panel B, the benchmark used to estimate the CAAR is the average industry return, defined using TNIC peers. The grey area delineates the 95% confidence interval.

Figure 2: **Mutual Funds Hypothetical Sales across Time and Industries**



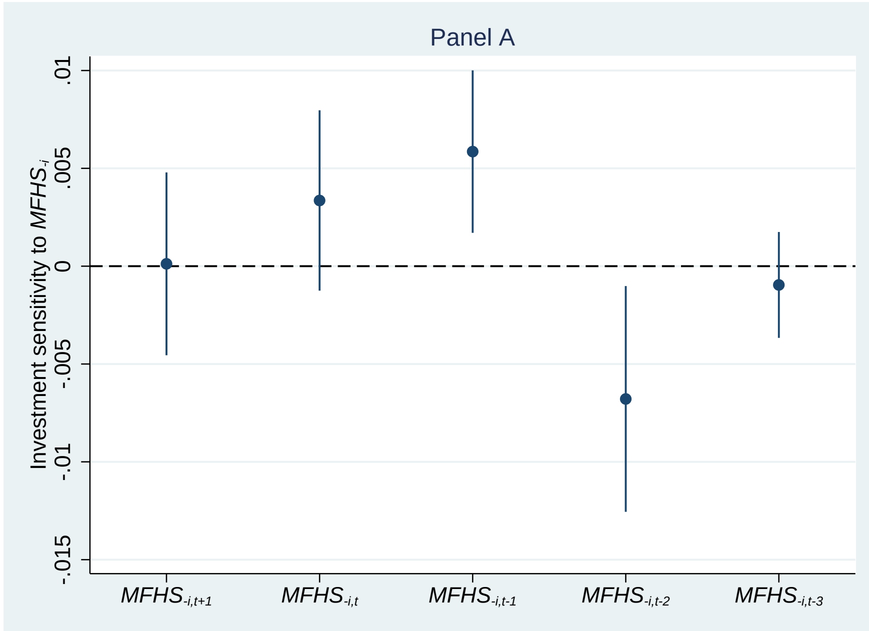
This figure plots the distribution of large mutual funds downward price pressure ($MFHS$) by year (Panel A) and industries (Panel B). Industry classification is FIC-icode100 from Hoberg and Phillips (2015).

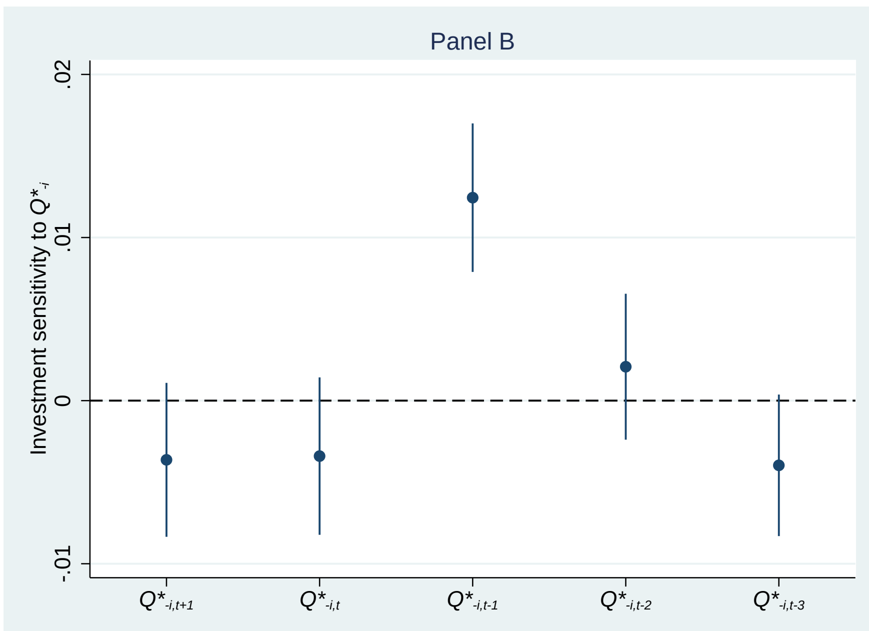
Figure 3: **Effect of Mutual Funds Hypothetical Sales on Insiders' Net Purchases**



This figure plots the quarterly net insiders' purchases, for stocks subject to mutual fund price pressure around the event, where an event is defined as a firm-quarter observation in which $MFHS$ falls below the 10th percentile value of the full sample. We estimate linear regressions of quarterly net purchases on event-time dummy variables for affected firms (with firm and calendar time fixed effects), and display the cumulated coefficients. In Panel A, net purchases are defined as the number of shares bought minus the number of shares sold, divided by share turnover. In Panel B, net purchases are defined as the number of shares bought minus the number of shares sold. The grey area delineates the 95% confidence interval.

Figure 4: **Sensitivity of Investment to Noise and Fundamentals at Various Lags**





This figure displays the regression coefficients of the baseline specification (10) with leads and lags of each variables. We display the estimates for the leads and lags of $\overline{MFHS}_{-i}$, the investment-to-noise sensitivity, in Panel A, and the estimates for the leads and lags of $\overline{Q}^{*}_{-i}$, the investment-to-fundamentals sensitivity, in Panel B. Each point estimate is accompanied by its 95% confidence interval.

Table I: 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 Appendix B. Statistics for a 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. All variables are winsorized at the 1% level.

Variable	Mean	Std. Dev	Min.	Max.	Obs.
$MFHS_i$	-0.033	0.055	-0.542	0	45,388
Q_i	1.957	1.473	0.547	10.01	45,388
CF/A_i	0.018	0.217	-1.167	0.361	45,388
$Size_i$	5.62	1.928	1.29	10.644	45,388
$Capex/PPE_i$	0.35	0.39	0.008	2.524	45,388
$\overline{MFHS}_{-i}$	-0.031	0.029	-0.487	0	45,388
$\overline{Q}_{-i}$	2.074	0.849	0.547	10.01	45,388
$\overline{CF/A}_{-i}$	0.013	0.11	-1.167	0.361	45,388
$\overline{Size}_{-i}$	5.758	1.061	1.29	10.644	45,388
$\overline{Capex/PPE}_{-i}$	0.364	0.205	0.008	2.524	45,388

Table II: Main Results: Investment-to-Noise Sensitivities

This table presents the results from estimations of specification (10). The dependent variable is the investment of firm i in year t, defined as capital expenditures divided by lagged property, plant, and equipment (PPE). $\overline{MFHS}_{-i}$ is the average hypothetical stock sales due to mutual funds large outflows ("price pressure") of all firms belonging to the same TNIC industry as firm i in year $t-1$, excluding firm i. $\overline{Q}^*_{-i}$ is the error term $\hat{\upsilon_{-i}}$ estimated from specification (9) and corresponds to the component of peers' stock price that is unexplained by mutual fund hypothetical sales. The subscript $-i$ for a variable refers to a portfolio that aggregates the peers of firm i. In column (1) we use equally-weighted averages. In column (2) we use weighted averages, where the weights are the product description similarity scores (from Hoberg and Phillips (2015)). In column (3) we use medians. In column (4) we use equally-weighted averages computed across the five "closest" peers, where distance is given by the similarity score. In column (5) we aggregate all variables across firm i's peers before computing ratios. All explanatory variables are divided by their sample standard deviation to facilitate economic interpretation. All variables are defined in Appendix B. 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.

Dependent Variable:	$Capex/PPE$				
Peers' Aggregation:	E-W	S-W	Median	5 Closest	Agg.
	(1)	(2)	(3)	(4)	(5)
$\overline{MFHS}_{-i}$	0.018***	0.015***	0.010***	0.015***	0.014***
	(7.51)	(7.12)	(4.95)	(7.56)	(4.51)
$\overline{Q}^*_{-i}$	0.029***	0.028***	0.029***	0.024***	0.019***
	(12.71)	(12.17)	(12.09)	(10.54)	(8.19)
$\overline{CF/A}_{-i}$	0.012***	0.007**	0.010***	0.006**	0.004*
	(3.40)	(2.17)	(2.91)	(2.16)	(1.67)
$\overline{Size}_{-i}$	0.002	0.001	-0.001	0.000	-0.001
	(0.66)	(0.45)	(-0.17)	(0.07)	(-0.14)
$MFHS_i$	0.011***	0.011***	0.012***	0.012***	0.013***
	(6.55)	(6.70)	(7.23)	(7.13)	(7.60)
Q^*_i	0.081***	0.081***	0.082***	0.082***	0.086***
	(27.52)	(27.42)	(27.89)	(28.16)	(29.02)
CF/A_i	0.035***	0.036***	0.035***	0.035***	0.037***
	(10.30)	(10.40)	(10.27)	(10.34)	(10.78)
$Size_i$	-0.074***	-0.073***	-0.070***	-0.070***	-0.068***
	(-6.79)	(-6.72)	(-6.48)	(-6.46)	(-6.23)
Obs.	45,388	45,388	45,388	45,388	45,388
Firm FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Adj. R^2	0.485	0.484	0.485	0.483	0.482

Table III: Within-Conglomerate Investment

This table presents the results from estimations of specification (12). 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). $\overline{MFHS}_{-i,d}$ is the average hypothetical stock sales due to mutual funds large outflows ("price pressure") of all firms operating in the same industry as division d of firm i in year $t-1$, excluding firm i. $\overline{Q}^{*}_{-i,d}$ is the error term $\hat{\upsilon_{-i,d}}$ estimated from equation (11) and corresponds to the component of division peers' stock price unexplained by mutual funds hypothetical sales. In column (1) we define industry using the Fama-French 48 classification (FF48), column (2) we define industry using the 2-digit Standard Industry classification (SIC2), and in column (3) we define industry using the 3-digit North American Industry Classification System (NAICS3). All the variables are defined in Appendix B. The subscript $-i$ for a variable refers to the (equally-weighted) 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 standard errors used to compute the t-statistics (in brackets) are clustered at the firm level. Symbols ***,** and * indicate statistical significance at the 1%, 5% and 10% levels, respectively.

Dependent Variable:	$Capex/A$		
Industry:	FF48	SIC2	NAICS3
	(1)	(2)	(3)
$\overline{MFHS}_{-i,d}$	0.003**	0.004***	0.003**
	(2.05)	(3.45)	(2.20)
$\overline{Q}^{*}_{-i,d}$	0.008***	0.007***	0.004**
	(4.37)	(4.02)	(2.22)
$\overline{CF/A}_{-i,d}$	0.006***	0.004***	0.004*
	(4.61)	(3.07)	(1.92)
Obs.	63,330	63,758	42,282
Firm-Year FE	Yes	Yes	Yes
Firm-Division FE	Yes	Yes	Yes
Adj. R^2	0.368	0.364	0.388

Table IV: Alternative Explanation: Financing Channel

This table presents estimates of specifications similar to that of equation (10) but where we replace the dependent variable with firm-level measures of financing costs and access to external capital. $\overline{MFHS}_{-i}$ is the average hypothetical stock sales due to mutual funds large outflows ("price pressure") of all firms belonging to the same TNIC industry as firm i in year $t-1$, excluding firm i. $\overline{Q}^{*}_{-i}$ is the error term $\hat{\upsilon_{-i}}$ estimated from specification (9) and corresponds to the component of peers' stock price that is unexplained by mutual fund hypothetical sales. 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 average spread of firm i in year t on new private debt issues. In Column (3), the dependent variable is the text-based measure of debt-financing constraints developed by Hoberg and Maksimovic (2015). In Column (4),the dependent variable is the text-based measure of equity-financing constraints developed by Hoberg and Maksimovic (2015). All explanatory variables are divided by their sample standard deviation to facilitate economic interpretation. All the variables are defined in Appendix B. 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.

Dependent Variable:	$CDS\ Spread$	$Debt\ Spread$	$Debt-Cons.$	$Equity-Cons.$
	(1)	(2)	(3)	(4)
$\overline{MFHS}_{-i}$	0.075	0.032**	-0.000	0.001
	(1.08)	(2.24)	(-0.27)	(1.22)
$\overline{Q}^{*}_{-i}$	0.027	-0.025**	-0.001**	0.000
	(0.55)	(-2.07)	(-2.45)	(0.66)
$\overline{CF/A}_{-i}$	-0.409***	-0.062***	-0.001*	-0.001
	(-3.36)	(-2.77)	(-1.94)	(-1.32)
$\overline{Size}_{-i}$	-0.098	-0.007	0.000	0.001
	(-1.62)	(-0.36)	(0.52)	(1.31)
$MFHS_i$	-0.360**	0.009	-0.000	0.001
	(-2.19)	(0.74)	(-0.37)	(1.09)
Q^{*}_{i}	-0.116*	-0.132***	-0.001***	0.002***
	(-1.75)	(-9.14)	(-4.57)	(5.29)
CF/A_i	-1.140***	-0.358***	-0.001***	-0.006***
	(-4.65)	(-10.79)	(-3.24)	(-9.38)
$Size_i$	-0.893**	-0.595***	0.000	-0.001
	(-2.24)	(-12.51)	(0.02)	(-0.47)
Obs.	3,765	10,759	33,198	33,198
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Adj. R^2	0.708	0.759	0.580	0.667

Table V: Alternative Explanation: Pressure Channel

This table presents estimates of specifications similar to that of equation (10) but where we replace the dependent variable with measures of pressure and incentives on CEOs. $\overline{MFHS}_{-i}$ is the average hypothetical stock sales due to mutual funds large outflows ("price pressure") of all firms belonging to the same TNIC industry as firm i in year $t-1$, excluding firm i. $\overline{Q}^{*}_{-i}$ is the error term $\hat{\upsilon_{-i}}$ estimated from specification (9) and corresponds to the component of peers' stock price that is unexplained by mutual fund hypothetical sales. In Column (1), the dependent variable is a dummy variable equals to one if firm i receives a takeover bid in year t and zero if not. In Column (2), the dependent variable is a dummy variable equals to one if firm i experiences a CEO change in year t. In column (3) the dependent variable is the investment of firm i in year t, defined as capital expenditures divided by lagged property, plant, and equipment (PPE), but the sample is restricted to industries that using relative performance evaluation ($RPE = 1$). In column (4) the dependent variable is the investment of firm i in year t, defined as capital expenditures divided by lagged property, plant, and equipment (PPE), but the sample is restricted to industries that not using relative performance evaluation ($RPE = 0$). All explanatory variables are divided by their sample standard deviation to facilitate economic interpretation. All the variables are defined in Appendix B. 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.

Dependent Variable:	$Prob(Target)$	$CEO\ Turnover$	$Capex/PPE$	$Capex/PPE$
Sub-sample:			$RPE = 1$	$RPE = 0$
	(1)	(2)	(3)	(4)
$\overline{MFHS}_{-i}$	0.004	0.002	0.019***	0.017***
	(1.43)	(0.38)	(6.08)	(4.83)
$\overline{Q}^{*}_{-i}$	-0.006***	0.005	0.032***	0.026***
	(-3.54)	(1.50)	(9.64)	(8.40)
$\overline{CF/A}_{-i}$	0.006*	0.000	0.019***	0.004
	(1.88)	(0.07)	(3.82)	(0.87)
$\overline{Size}_{-i}$	0.002	0.007	-0.005	0.009*
	(0.54)	(1.31)	(-1.13)	(1.91)
$MFHS_i$	-0.007***	-0.003	0.010***	0.010***
	(-3.43)	(-0.76)	(4.12)	(4.52)
Q^{*}_{i}	-0.010***	-0.010***	0.083***	0.077***
	(-5.95)	(-3.36)	(19.15)	(18.24)
CF/A_i	-0.015***	-0.036***	0.030***	0.043***
	(-5.58)	(-5.17)	(5.69)	(8.56)
$Size_i$	0.060***	0.006	-0.068***	-0.084***
	(7.92)	(0.53)	(-4.56)	(-5.36)
Obs.	45,388	18,121	23,518	21,870
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Adj. R^2	0.307	0.127	0.568	0.553

Table VI: Alternative Explanation: Investment Complementarity

This table presents the results from estimations of specification (10). The dependent variable is the investment of firm i in year t, defined as capital expenditures divided by lagged property, plant, and equipment (PPE). $\overline{MFHS}_{-i}$ is the average hypothetical stock sales due to mutual funds large outflows ("price pressure") of all firms belonging to the same TNIC industry as firm i in year $t-1$, excluding firm i. $\overline{Q}^*_{-i}$ is the error term $\hat{\upsilon_{-i}}$ estimated from specification (9) and corresponds to the component of peers' stock price that is unexplained by mutual fund hypothetical sales. The subscript $-i$ for a variable refers to a portfolio that aggregates the peers of firm i. In columns (1) and (6) we use equally-weighted averages. In column (2) we use weighted averages, where the weights are the product description similarity scores (from Hoberg and Phillips (2015)). In column (3) we use medians. In column (4) we use equally-weighted averages computed across the five "closest" peers, where distance is given by the similarity scores. In column (5) we aggregate all variables across firm i's peers before computing ratios. In columns (1) to (5) we include firm and year fixed effects. In column (6) we include firm and industry × year fixed effects. All explanatory variables are divided by their sample standard deviation to facilitate economic interpretation. All the variables are defined in Appendix B. The standard errors used to compute the t-statistics (in brackets) are clustered at the firm level. Symbols ***,** and * indicate statistical significance at the 1%, 5% and 10% levels, respectively.

Dependent Variable:	*Capex/PPE*					
Peers' Aggregation:	E-W	S-W	Median	5 Closest	Agg.	E-W
	(1)	(2)	(3)	(4)	(5)	(6)
$\overline{MFHS}_{-i}$	0.009***	0.011***	0.004**	0.011***	0.014***	0.009***
	(3.85)	(5.20)	(2.19)	(3.85)	(4.53)	(3.34)
$\overline{Q}^*_{-i}$	0.018***	0.022***	0.019***	0.017***	0.019***	0.017***
	(7.94)	(9.20)	(7.80)	(7.39)	(8.17)	(6.60)
$\overline{CF/A}_{-i}$	0.009***	0.005	0.007**	0.003	0.004*	-0.002
	(2.55)	(1.47)	(2.06)	(1.05)	(1.66)	(-0.50)
$\overline{Size}_{-i}$	0.002	0.002	-0.000	0.001	-0.000	-0.001
	(0.76)	(0.75)	(-0.13)	(0.42)	(-0.13)	(-0.26)
$\overline{Capex/PPE}_{-i}$	0.051***	0.034***	0.049***	0.043***	-0.000	
	(11.42)	(9.17)	(10.87)	(11.85)	(-0.43)	
$MFHS_i$	0.010***	0.011***	0.011***	0.011***	0.013***	0.009***
	(6.01)	(6.36)	(6.56)	(6.43)	(7.61)	(5.31)
Q^*_i	0.079***	0.080***	0.080***	0.078***	0.086***	0.076***
	(26.84)	(27.08)	(27.07)	(27.23)	(28.99)	(24.92)
CF/A_i	0.034***	0.035***	0.034***	0.035***	0.037***	0.032***
	(10.10)	(10.25)	(10.08)	(10.33)	(10.77)	(9.13)
$Size_i$	-0.074***	-0.075***	-0.071***	-0.071***	-0.068***	-0.075***
	(-6.86)	(-6.87)	(-6.60)	(-6.60)	(-6.24)	(-6.50)
Obs.	45,355	45,390	45,355	45,355	45,357	45,388
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	No
Ind-Year FE	No	No	No	No	No	Yes
Adj. R^2	0.489	0.487	0.489	0.497	0.487	0.498

Table VII: Alternative Explanation: Correlated Noise

This table presents the results from estimations of specifications similar to that of equation (10). The dependent variable is the investment of firm i in year t, defined as capital expenditures divided by lagged property, plant, and equipment (PPE). $\overline{MFHS}_{-i}$ is the average hypothetical stock sales due to mutual funds large outflows ("price pressure") of all firms belonging to the same TNIC industry as firm i in year $t-1$, excluding firm i. $\overline{Q}^{*}_{-i}$ is the error term $\hat{\upsilon_{-i}}$ estimated from specification (9) and corresponds to the component of peers' stock price that is unexplained by mutual fund hypothetical sales. The subscript $-i$ for a variable refers to an equally-weighted portfolio that aggregates the peers of firm i. All explanatory variables are divided by their sample standard deviation to facilitate economic interpretation. All the variables are defined in Appendix B. The standard errors used to compute the t-statistics (in brackets) are clustered at the firm level. Symbols ***,** and * indicate statistical significance at the 1%, 5% and 10% levels, respectively.

Dependent Variable:	*Capex/PPE*			
	(1)	(2)	(3)	(4)
$\overline{MFHS}_{-i}$	0.017***		0.018***	
	(7.51)		(7.55)	
$\overline{Q}^{*}_{-i}$	0.029***	0.028***	0.029***	0.028***
	(12.71)	(12.53)	(12.74)	(12.59)
$\overline{CF/A}_{-i}$	0.012***	0.010**	0.012**	0.010***
	(3.40)	(2.98)	(3.40)	(2.95)
$\overline{Size}_{-i}$	0.002	0.001	0.002	0.001
	(0.66)	(0.42)	(0.66)	(0.41)
$MFHS_i$	0.011***	0.014***		
	(6.55)	(8.13)		
Q^{*}_i	0.081***	0.083***		
	(27.52)	(28.07)		
CF/A_i	0.035***	0.035***	0.035***	0.035***
	(10.30)	(10.17)	(10.30)	(10.18)
$Size_i$	-0.074***	-0.072***	-0.074***	-0.072***
	(-6.79)	(-6.63)	(-6.79)	(-6.63)
Q_i			0.123***	0.126***
			(27.55)	(28.17)
Obs.	45,388	45,388	45,388	45,388
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Adj. R^2	0.485	0.484	0.485	0.484

Table VIII: Cross-Sectional Tests: Managerial Information

This table presents estimates of specifications similar to that of equation (10) but where all explanatory variables are interacted with proxies for managerial information about the firm's fundamentals or 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). $\overline{MFHS}_{-i}$ is the average hypothetical stock sales due to mutual funds large outflows ("price pressure") of all firms belonging to the same TNIC industry as firm i in year $t-1$, excluding firm i. $\overline{Q}^*_{-i}$ is the error term $\hat{\upsilon_{-i}}$ estimated from specification (9) and corresponds to the component of peers' stock price that is unexplained by mutual fund hypothetical sales. 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 fund 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, and ϕ is included as a control. All explanatory variables are divided by their sample standard deviation to facilitate economic interpretation. All variables are defined in Appendix B. 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.

Dependent Variable:	$Capex/PPE$			
Interaction Variable ϕ:	$InsiderCAR_i$	$PreviousFireSale_i$	$CommonOwnership_i$	$AnalystDiscount_i$
	(1)	(2)	(3)	(4)
$\overline{MFHS}_{-i}$	0.018***	0.019***	0.026***	0.024***
	(7.54)	(6.95)	(6.53)	(8.20)
$\overline{MFHS}_{-i} \times \phi$	-0.052	-0.008	-0.054***	-0.006**
	(-1.56)	(-1.54)	(-3.97)	(-2.17)
Obs.	45,388	45,388	45,388	33,398
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 IX: Cross-Sectional Tests: Peers' Stock Price Informativeness

This table presents estimates of specifications similar to that of equation (10) but where all explanatory variables are interacted with proxies for price informativeness of peers (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). $\overline{MFHS}_{-i}$ is the average hypothetical stock sales due to mutual funds large outflows ("price pressure") of all firms belonging to the same TNIC industry as firm i in year $t-1$, excluding firm i. $\overline{Q}^*_{-i}$ is the error term $\hat{\upsilon_{-i}}$ estimated from specification (9) and corresponds to the component of peers' stock price that is unexplained by mutual fund hypothetical sales. 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 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 (3), ϕ is the intensity of previous fund-driven price pressure in peers' stock prices. In Column (4), ϕ is the average earnings forecast error of financial analysts. All other explanatory variables are also interacted with ϕ, and ϕ is included as a control. All explanatory variables are divided by their sample standard deviation to facilitate economic interpretation. All variables are defined in Appendix B. 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.

Dependent Variable:	Capex/PPE			
Interaction Variable ϕ:	$\overline{BPS}_{-i}$	$\overline{NonSync}_{-i}$	$\overline{PreviousFireSale}_{-i}$	$\overline{AnalystFE}_{-i}$
	(1)	(2)	(3)	(4)
$\overline{MFHS}_{-i}$	0.016***	0.009*	0.024***	0.031***
	(6.16)	(1.70)	(7.17)	(7.44)
$\overline{MFHS}_{-i} \times \phi$	0.017*	0.005*	-0.453***	-0.023***
	(1.83)	(1.82)	(-3.06)	(-2.48)
Obs.	45,388	45,089	44,360	45,178
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