Noisy Stock Prices and Corporate Investment

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Firms significantly reduce their investment in response to nonfundamental drops in the stock price of their product-market peers. We argue that this results stems from managers' limited ability to filter out the noise in the stock prices when using them as signals about their investment opportunities. Ensuing losses of capital investment and shareholders' wealth are economically large and even affect firms not facing severe financing constraints or agency problems. Our findings offer a novel perspective on how stock market inefficiencies can affect the real economy, even in the absence of financing or agency frictions. (*JEL* G14, G31)

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Stock prices respond to fundamental shocks (news) and nonfundamental shocks (noise). In this paper, we provide evidence that nonfundamental shocks to stock prices affect corporate investment because managers have limited ability to separate information from noise when using stock prices as signals about their prospects. Thus, as suggested by Morck, Shleifer, and Vishny (1990), stock

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prices are "faulty informants" for corporate managers. Our findings have a novel important implication, namely the noise in stock prices matters for real decisions even when managers focus on maximizing long-term firm value and face no financial constraints. This possibility considerably broadens the set of firms that can be affected by stock market inefficiencies.

To empirically isolate the faulty informant channel, we use a new approach and consider the response of a firm's investment to the noise in its product market peers' stock prices instead of its own stock price. In this way, we can analyze the effect of the noise in stock prices, controlling for the effect of firms' own stock price. Doing so is important because existing theories (described below) predict that managers may alter their investment in response to noise in their *own* stock price (that is, abnormally high or low investors' valuation given the actual investment opportunities of the firm) for other reasons than the faulty informant role of prices (e.g., financial or agency frictions). However, these theories do not predict that the noise in the stock prices of *other* firms should affect a firm's investment, holding its stock price constant. In contrast, the faulty informant channel does—provided that managers use these prices as signals and have limited ability to filter out the noise therein.[1]

The specification and the interpretation of our main test is grounded in a standard investment model in which a manager chooses how much to invest in a growth opportunity. The optimal investment increases in her expectation of the payoff of this opportunity, which depends on her internal information, the firm's own stock price, and the stock prices of its peers (i.e., firms with correlated fundamentals). We show that the noise in stock prices affect the manager's expectation, and therefore her investment decision, if and only if she cannot perfectly filter it out from stock prices. If, instead, she can, investment is sensitive to stock prices (because they convey relevant information), but *not* to the noise in these prices.

These observations have an important implication for testing whether peers' stock prices truly are *faulty* signals and not just fundamental signals. Namely, estimating the sensitivity of a firm's investment to its peers' stock prices (e.g., Foucault and Frésard 2014) is inadequate to test the faulty informant channel because investment can be sensitive to peers' stock prices even if these are *not* faulty signals. Instead, one must estimate the sensitivity of a firm investment to the noise in its peers' stock prices. Indeed, in theory, this sensitivity differs from zero if and only if stock prices provide faulty signals. Our model suggests to estimate the sensitivity of a firm's investment to the noise in stock prices by projecting its investment on an *observable* component

[1] Managers frequently refer to their peers' valuations when assessing their own growth opportunities and thus plausibly use their product-market peers' stock prices as signals (see Section A of the Internet Appendix for field evidence gleaned from managers' reports, such as earnings call, and Graham and Harvey 2001 for survey evidence).

of this noise (observable ex post by the econometrician, but not ex ante by the manager), and its orthogonal component.

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 Maksimovic (2015). We decompose the annual stock price (Tobin's q) of each firm into a nonfundamental component and its orthogonal component.[2] We measure the nonfundamental 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. Like Edmans, Goldstein, and Jiang (2012), we find that these fire sales are associated with large negative price pressures that eventually revert, consistent with the view that these sales represent nonfundamental demand shocks.

As uniquely predicted by the faulty informant channel, we show 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 1.5% (a 4.3% decrease relative to the average level of investment) following a 1-standard-deviation decrease in the nonfundamental component of its peers' stock prices. We quantify the resultant loss in aggregate investment to be about $29 billion per year. According to the faulty informant hypothesis, this loss generates an opportunity cost for shareholders that corresponds to forgone investments when managers become "excessively" pessimistic about their growth opportunities after observing a drop in their peers' valuations. However, in truth, this drop contains no fundamental information. Using various approaches, we estimate shareholders' losses to be in the range of $0.9 to $3.7 billion per year.

Furthermore, cross-sectional variations in the sensitivity of a firm investment to the noise in its peers' stock price are consistent with the faulty informant channel. In particular, a firm's investment is more sensitive to the noise in its peers' stock prices when managers are (1) less likely to filter out this noise from prices (e.g., when the firm's ownership by mutual funds does not overlap with that of its peers) and (2) more likely to rely on peers' stock prices as an additional source of information (e.g., when the firm's fundamental is more correlated with its peers' fundamentals, or when managers have less precise internal information).

The correlation between a firm's investment and the noise in its peers' stock prices might be spurious, stemming from omitted variables in our baseline specification. We address this concern in several ways. First, we estimate

[2] For brevity, we refer to the second component as the "fundamental" component. However, as shown in our model, this second component might noise.

our baseline specification at the division level for multi-division firms. This approach is particularly powerful because it enables us to control (with firm-year fixed effects) for any time-*varying* unobserved firm-specific characteristics that could be correlated with both the noise in a firm's peers' stock price and its overall investment (e.g., the firm's financing constraints, its CEO's incentives, or the noise in its own stock price). Confirming our baseline results conglomerates reduce the capital allocated to one division relative to others when *that division's peers* experience nonfundamental drops in their stock price.

In addition, we account for possible omitted variables by directly assessing three alternative explanations for our main finding. First, we consider a "financing channel", that is, the possibility that the noise in peers' stock prices influences a firm's investment by affecting its financing conditions, rather than its managers' beliefs. However, we find that the noise in peers' stock prices is not significantly related to various proxies for the cost and availability of external financing. Moreover, our baseline results continue to hold when controlling for these proxies in our regressions. Thus, the financing channel cannot explain our results.

We also consider the possibility that nonfundamental shocks to peers' stock prices affect managers' personal incentives to invest (the "pressure channel"), without necessarily changing their beliefs about their growth opportunities. For example, a drop in peers' stock prices might (1) alter the intensity of product-market competition, (2) trigger industry consolidation via acquisitions (Edmans, Goldstein, and Jiang 2012), (3) affect managerial compensation (through relative performance evaluation), or (4) change CEO turnover (e.g., through the threat of takeovers). However, we generally find no effect of nonfundamental shocks to peers' stock prices on proxies for the pressure channel, and when an effect is present (like in the case for industry consolidation), controlling for these proxies does not change our main result.

Finally, we consider the possibility that managers react to changes in their peers' investment rather than to changes in their stock prices (the "investment-mimicking channel"). Indeed, a nonfundamental shock to peers' stock prices could lead a firm's peers to cut their investment. Strategic considerations could then lead the firm's manager to invest less if investments decisions are complements, even if the manager's perceptions of her firm's fundamentals are not influenced by the noise in her peers' stock prices. However, a firm's investment remains sensitive to the noise in its peers' stock price when restricting attention to firms whose peers do *not* change investment in response to nonfundamental shocks to their stock price.

Our findings contribute to the literature on the real effects of nonfundamental shocks to stock prices (see Baker and Wurgler 2012 for a survey) by highlighting a new friction through which these shocks can distort firms' investment. Existing research has proposed two channels through which nonfundamental shocks to a firm's *own* stock price can have real effects. First, investors might have incorrect beliefs regarding a firm's growth opportunities, pushing its market valuation away from fundamentals. This distortion might then lead to inefficient investment decisions (e.g., overinvestment when market valuations are excessively high) if managers maximize their stock price (i.e., follow investors' distorted beliefs) rather than the actual value of the firm given its true prospects (see, for instance, Stein 1996 for theory and Polk and Sapienza 2009 for evidence). Second, when their stock price deviates from fundamentals, managers of financially constrained firms might opportunistically issue new shares and undertake investments that could not be funded otherwise (see, for instance, Baker, Stein, and Wurgler 2003). Importantly, these channels do *not* predict that managers should react to the noise in peers' stock prices (after controlling for their own stock price) since these do not matter for financing (Baker, Stein, and Wurgler 2003) and are not relevant for their shareholders (Stein 1996). In contrast, the faulty informant channel does (see our model). Thus, the noise in stock prices influences real decisions even when managers maximize long-term firm value and face no financing constraints. In this sense, our findings imply that the universe of firms for which stock market inefficiencies matter is much broader than what the literature suggests.

Ozoguz and Rebello (2013), Foucault and Frésard (2014), and Yan (2015) show empirically that firms' investment is sensitive to peers' stock prices and find that cross-sectional variations in this sensitivity is consistent with managers learning information from stock prices (as other papers have found by considering the sensitivity of a firm investment to its own stock price; see Bond, Edmans, and Goldstein 2012 for a survey). However, as we show theoretically, this finding does *not* imply that nonfundamental shocks to peers' stock price have real effects. Indeed, investment should be sensitive to peers' stock prices even if managers can perfectly filter out the noise from these prices. In other words, the "informant" role of stock prices identified by existing research does not imply that these prices are sometimes faulty in this role. Thus, testing whether stock prices are faulty informant requires a different approach. Our contribution is to develop such an approach and to motivate it based on theory.

Following Edmans, Goldstein, and Jiang (2012), other papers have used mutual funds' fire sales as an instrument to analyze the effect of nonfundamental shocks to stock prices on corporate policies. For instance, Hau and Lai (2013) show that firms respond to severe drop in their stock price due to mutual fund fire sales during the 2007–2009 crisis by cutting investment. Lou and Wang (2014) show that this finding holds in normal times as well. Closer to our paper, Williams and Xiao (2017) report that suppliers cut research and development (R&D) spending following a nonfundamental decline in their customers' market value (instrumented by large mutual funds' outflows). However, these observations are consistent with *all* possible channels through which noise in stock prices might affect investment, including the faulty informant channel.[3] Thus, they do not constitute strong evidence in favor or against this channel.[4]

1. A Test of the Faulty Informant Channel

This section presents the framework that guides the specification and interpretation of our empirical tests. In particular, Proposition 1 provides the investment model that we estimate in our tests.

1.1 The investment model

The investment model uses two dates, 1 and 2. Like in Subrahmanyam and Titman (1999), at date 1, firm i has a growth opportunity with a payoff at date 2 equal to

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

where K_i is the investment of firm i in its growth opportunity and $\widetilde{\theta}_i$ is the marginal productivity of this investment (firm i's fundamentals). All random variables in the model are normally distributed with mean zero and variance σ_x^2, where index x refers to the variable. For instance, $\widetilde{\theta}_i$ is normally distributed with mean zero and variance $\sigma_{\theta_i}^2$.

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) at date 1. Her set of signals about θ_i is $\Omega_1=\{s_{m_i},P_i,P_{-i},s_{u_i},s_{u_{-i}}\}$ and, conditional on θ_i, all these signals are independent. We describe each in turn. First, the manager possesses internal (private) information about the fundamentals of her growth

[3] Specifically, the findings of Williams and Xiao (2017) are consistent with the faulty informant channel, but their interpretation is difficult because suppliers and their clients often have a cooperative relationship and can directly communicate with their clients to learn about their current situation, rather than make inferences from their stock prices. In addition, suppliers and customers typically offer financing to each other through trade credit agreements, which raises the possibility that the observed decline in suppliers R&D reflects a tightening of trade credit supplied by customers following nonfundamental drops in their stock price, rather than a change in suppliers' beliefs via the faulty informant channel.

[4] In fact, Hau and Lai (2013) argue that their findings support the financial constraints channel proposed by Baker, Stein, and Wurgler (2003), because the sensitivity of a firm's investment to the noise in its own stock price is stronger for financially constrained firms in their sample.

opportunity. We denote this signal by $s_{m_i} = \widetilde{\theta}_i + \chi_i$ where χ_i is an error term. We assume that the manager has imperfect internal information ($\sigma^2_{\chi_i} > 0$), because, otherwise, she would not rely on other sources of Information, such as stock prices.

Second, the manager can obtain external information from the firm's own stock price, P_i, and its peers' stock prices, P_{-i} (index $-i$ refers to the product-market peers of firm i). Peers are firms whose fundamentals are correlated with $\widetilde{\theta}_i$. We assume that $P_i = \widetilde{\theta}_i + u_i$, where u_i is the noise in firm i's stock price. Similarly, $P_{-i} = \widetilde{\theta}_{-i} + u_{-i}$ where $\widetilde{\theta}_{-i}$ is peers' fundamentals and u_{-i} is the noise (from the viewpoint of firm i's manager) in peers' stock price.[5]

We define $\widetilde{\theta}_{-i} = \rho_i \widetilde{\theta}_i$, where ρ_i is a constant, which is equal to either 1 or -1. The sign of ρ_i determines whether the fundamentals of firm i and its peers are positively ($\rho_i = 1$) or negatively correlated ($\rho_i = -1$). In reality, this sign can be negative or positive. Indeed, in our sample, a firm and its peers are related horizontally, which means that their products are probably substitutes to some extent. Thus, holding total demand for these products constant, an increase in sales for one firm (e.g., because of a lower product price) tends to lower sales for others. However, variations in total demand for their products (common demand shocks) tend to affect their sales in the same way. The first effect is a source of negative correlation in firms' sales while the second effect is a source of positive correlation. In our data (see Section 5), the second effect dominates for most firms since the correlation between peers' sales is positive on average and negative for less than 10% of firms. In any case, our test of the faulty informant channel requires only the correlation between the fundamentals of a firm and its peers to be different from zero (see also Footnote 7).

Last, the manager receives 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 the errors in these signals. The variances of these errors, $\sigma^2_{\eta_i}$ and $\sigma^2_{\eta_{-i}}$, determine the extent to which the manager can filter out the noise in her own stock price and her peers' stock price. For instance, a lower value of $\sigma^2_{\eta_i}$ means that the manager is able to interpret more accurately the source of variations in her own stock price.[6]

The faulty informant hypothesis posits that managers use information from stock prices but cannot perfectly filter out noise in stock prices, that is, that $\sigma^2_{\eta_i} > 0$ and $\sigma^2_{\eta_{-i}} > 0$. Our main purpose is to develop a test of this hypothesis. To this end, we take a "reduced form" approach in the sense that we directly postulate that the signals conveyed by stock prices about a firm's fundamentals

[5] The noise term in P_{-i} might also reflect components of peers' fundamentals that are uncorrelated with firm i's own fundamentals. From the viewpoint of firm i's manager, these components are just noise and we fold them into u_{-i}. Conditional on θ_i, P_{-i} and P_i are independent because u_i and u_{-i} are independent. Thus, information in P_{-i} about θ_i is not contained in P_i.

[6] Our results hold whether or not managers are better at filtering out the noise in their own stock price than in their peers' stock prices. Thus, we do not need assumptions on the relative ranking of $\sigma^2_{\eta_i}$ and $\sigma^2_{\eta_{-i}}$, even though $\sigma^2_{\eta_i} < \sigma^2_{\eta_{-i}}$ seems more plausible.

can be decomposed into (1) a component that is informative about the firm's fundamentals and (2) a component that is not. That is, we directly assume that $P_i = \widetilde{\theta}_i + u_i$ and $P_{-i} = \widetilde{\theta}_{-i} + u_{-i}$ instead of deriving these expressions from investors' equilibrium actions and market clearing conditions. We further motivate this approach and its potential limits in Section II.C.

Lemma 1. The optimal investment of firm i is

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

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. As the manager's private information about the fundamentals of her growth opportunity, $\widetilde{\theta}_i$, is imperfect, she can improve her estimate of these fundamentals by using information from stock prices. For instance, suppose that peers' stock prices are informative ($\sigma_{u_{-i}} < \infty$). Then, in this case, $b_{-i} \neq 0$. Indeed, a change in peers' stock prices affect the manager's beliefs about the fundamentals of her growth opportunity and therefore her investment. The sign of this influence (b_{-i}) is the same as the sign of the correlation between the fundamentals of firm i and the fundamentals of its peers, that is, ρ_i (see the proof of Lemma 1,). Indeed, an increase in peers' stock price is a positive (resp., negative) signal about firm i's fundamentals if peers' fundamentals covary positively (resp., negatively) with firm i's fundamentals. In contrast, the manager's response to her own stock price is always positive ($b_i \geq 0$).

Moreover, $c_{-i} \neq 0$, if the manager possesses information about the noise in peers' stock prices ($\sigma^2_{\eta_i} < \infty$). Thus, the manager's signal about the noise in her firm's stock price, s_{u_i}, affects her investment decision as well. By itself, this signal is uninformative about her fundamentals, $\widetilde{\theta}_i$. However, it helps the manager in filtering out the noise contained in peers' stock price, thereby improving the precision of her estimate of the marginal return on her investment. The sign of coefficient c_{-i} is always opposite to that of b_{-i} (see the proof of Lemma 1) because the investor uses her signal about the noise in peers' stock prices to filter it out from these prices.

2. Testing that Stock Prices Are Faulty Signals

The optimal investment of firm i (given in Equation (4)) can be written as

$$K_i^* = (a_i + b_i + b_{-i}) \times \widetilde{\theta}_i + (b_i + c_i) \times u_i + (b_{-i} + c_{-i}) \times u_{-i} + \xi_i, \quad (5)$$

where $\xi_i = a_i \chi_i + c_i \eta_i + c_{-i} \eta_{-i}$. Thus, investment is influenced by the non-fundamental components of stock prices (u_i and u_{-i}) if $\alpha_i \stackrel{def}{=} b_i + c_i \neq 0$ or $\alpha_{-i} \stackrel{def}{=} b_{-i} + c_{-i} \neq 0$. In the proof of Lemma 1, we show that a firm's investment is sensitive to the noise in its own stock price ($\alpha_i > 0$) and its peers' stock price ($\alpha_{-i} \neq 0$) if manager's private signals about the noise in stock prices are *not* perfect (otherwise $\alpha_i = \alpha_{-i} = 0$). In this case, a nonfundamental shock to stock prices affects firm i's investment because it (mistakenly) leads its manager to revise her beliefs about firm i's growth opportunities. Thus, one can test the "faulty informant hypothesis" by testing the null that $\alpha_i = 0$ and $\alpha_{-i} = 0$ against the alternative that $\alpha_i > 0$ or $\alpha_{-i} \neq 0$. A rejection of the null is consistent with the faulty informant hypothesis.

We cannot directly estimate Equation (5) to obtain estimates of the sensitivities of investment to noise (α_i and α_{-i}) because we do not perfectly observe the nonfundamental and fundamental components of firms' stock prices. However, we can circumvent this problem insofar as we can measure part of the nonfundamental 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 ($\lambda_{-i} \in [0,1]$). 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 $P^*_i = \widetilde{\theta}_i + u^{no}_i = P_i - \mathrm{E}(P_i \left| u^o_i \right.)$. the following implication.

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

$$K^*_i = \gamma_i P^*_i + \alpha_i u^o_i + \gamma_{-i} P^*_{-i} + \alpha_{-i} u^o_{-i} + \epsilon_i, \tag{6}$$

where ϵ_i is orthogonal to P^*_i, u^o_i, P^*_{-i}, and u^o_{-i}. Under this optimal investment policy, $\alpha_i > 0$ and $|\alpha_{-i}| \neq 0$ if managers are not fully informed about the noise in their peers' stock price ($\sigma^2_{\eta_i} > 0$ and $\sigma^2_{\eta_{-i}} > 0$). Moreover, $\gamma_i \geq \alpha_i \geq 0$, $|\gamma_{-i}| \geq |\alpha_{-i}|$, and the sign of γ_{-i} and α_{-i} is the same as the sign of ρ_i, the correlation between the fundamentals of firm i and the fundamentals of its peers (expressions for $\alpha_i, \alpha_{-i}, \gamma_i, \gamma_{-i}$ are given in the proof of the proposition).

Equation (6) is obtained by projecting the optimal investment of firm i (given in Equation (5) 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 Equation (6). Thus, in principle, one can obtain unbiased estimates of the true influence of the noise in stock prices on investment, that is, α_i and α_{-i}, by estimating Equation (6) with ordinary least squares (OLS) regressions. This approach forms the backbone of our empirical tests.

The sign of the sensitivity of a firm investment to its own stock price is always positive ($\alpha_i \geq 0$). In contrast, the sign of the sensitivity of a firm investment to its peers' stock price (α_{-i}) is the same as the sign of the correlation (ρ_i) between the fundamentals of a firm and its peers.[7] Our key prediction is that this sensitivity should be different from zero ($\alpha_{-i} \neq 0$) if managers cannot fully distinguish whether variations in these prices are due to changes in fundamentals or noise ($\sigma^2_{\eta_i} > 0$ and $\sigma^2_{\eta_{-i}} > 0$). Our tests focus on this prediction.

3. Remarks

3.1 Investment-to-noise sensitivity versus investment-to-price Sensitivity

Growing evidence indicates that managers learn information from their own stock prices and their peers' stock prices (see Bond, Edmans, and Goldstein 2012 for a survey; Ozoguz and Rebello 2013; Foucault and Frésard 2014). Inferences in this literature are based on estimations of the sensitivity of investment to stock prices and cross-sectional patterns in this sensitivity.

This approach is useful to test whether managers use stock prices as signals. However, it cannot be used to test whether stock prices are sometimes *faulty* signals. To see why, consider the special case in which the manager can perfectly distinguish fundamental from nonfundamental shocks to stock prices (i.e., $\sigma^2_{\eta_{-i}} = \sigma^2_{\eta_i} = 0$). In this case, the optimal investment of firm i is not influenced by the noise in stock prices (in fact, $K^*_i = \theta_i$; see Case 4 in the proof of Lemma 1), even though managers rely on stock prices as a source of information (their internal signal is not perfect). However, Equation (4) implies that, in this case (see Case 4 in the proof of Lemma 1),

$$\mathrm{E}(K^*_i \mid P_i, P_{-i}) = \left(\frac{\tau_{u_i}}{\tau_{u_i} + \tau_{u_{-i}} + \tau_{\theta_i}}\right) P_i + \left(\frac{\rho_i^{-1}\tau_{u_{-i}}}{\tau_{u_i} + \tau_{u_{-i}} + \tau_{\theta_i}}\right) P_{-i}, \quad if \quad \sigma^2_{\eta_{-i}} = \sigma^2_{\eta_i} = 0, \tag{7}$$

where τ_x denotes the precision (inverse of variance) of variable x. It follows that one *cannot* test the faulty informant hypothesis by regressing a firm's investment on its own stock price and its peers' stock prices. Indeed, as shown by Equation (7), the sensitivity of investment to stock prices in this regression should be different from zero *even if* managers can perfectly filter out the noise in stock prices, that is, even if stock prices are not faulty in the signals they send to managers. In particular, the finding that investment is sensitive to peers' stock prices (e.g., Foucault and Frésard 2014) does not imply that investment is truly influenced by the noise in these prices. To avoid this problem, our approach consists in directly estimating the sensitivity of a firm investment to the noise in stock prices (coefficients α_i and α_0). As explained previously, in the model, this sensitivity should be significantly different from zero if and only if stock prices are faulty informant.

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[7] In our model, the fundamentals of firm i and its peers are perfectly correlated because $|\rho_i| = 1$. This assumption simplifies the derivations of the expressions for the coefficients in Equation (6). However, as shown in the Internet Appendix, Proposition 1 holds even when the correlation between the fundamentals of firm i and its peers is imperfect. Moreover, $\alpha_{-i} \neq 0$ if this correlation is not zero.

3.2 Alternative channels

In our model, the noise in stock prices influences managers' beliefs about their growth opportunities and thereby their investment decision. As explained in the introduction, there might be other channels (financing or agency frictions), absent from our model, through which the noise in a firm's *own* stock price influences its investment. In our estimation of Equation (6), the effects of these alternative channels on a firm's investment will be picked by u_i^o. Thus, if they operate, the OLS estimate of α_i should overestimate the effect of the noise in a firm's own stock price on its investment due to the faulty informant channel. In contrast, the alternative channels considered so far in the literature do not *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. For instance, what matters for a firm's financing is the actual price at which it can issue new shares, not the price of its peers' shares. Thus, coefficient α_{-i} provides a cleaner estimate of the extent to which managers' beliefs are influenced by the noise in stock prices. For these reasons, our test of the faulty informant channel focuses on this coefficient and whether it is significantly different from zero as uniquely predicted by the faulty informant channel.

3.3 Who observes what?

Variables u_i^o and u_{-i}^o in Equation (6) are nonfundamental shocks to stock prices that econometricians can measure ex post (possibly, a long time after they happened). Importantly, however, these shocks are *not* observed by managers when they happen. Indeed, managers' beliefs would not be influenced by the effect of these shocks on stock prices if they could observe them perfectly. Hence, one could not use them to assess whether managers' beliefs are influenced by the noise in stock prices.

For simplicity, we have assumed that managers have a signal about the aggregate nonfundamental shock to their stock price (e.g., $u_{-i} = u_{-i}^{no} + u_{-i}^o$) rather than two separate signals (e.g., one about u_{-i}^{no} and one about u_{-i}^o). For this reason, the sensitivity of their investment to, say, u_{-i}^o is the same as the sensitivity of their investment to u_{-i}^{no} (equal to α_{-i}) and does not depend on the size (λ_{-i}) of u_{-i}^o relative to u_{-i}^{no} (see the proof of Proposition 1; for the same reason, α_i does not depend on λ_i). This assumption can be relaxed by allowing managers to have different (imperfect) signals about, say, u_{-i}^o and u_{-i}^{no}. In this case, the sensitivity of a firm investment to u_{-i}^o is different than its sensitivity to u_{-i}^{no}. Yet, the faulty informant channel still implies that the sensitivity of a firm investment to u_{-i}^o should be different from zero. This is what we test empirically.

3.4 Ex post inefficiencies

In our model, the *ex ante* expected value of the growth opportunity (i.e., $E(G(K_i, \widetilde{\theta}_i))$ is higher when the manager uses all available sources of information than when she only uses her internal signal about $\widetilde{\theta}_i$. Thus, relying on signals from stock prices is ex ante efficient even when stock prices can be faulty signals. However, this can lead to decisions that sometimes are inefficient *ex post*. For instance, consider a drop in peers' stock prices due to a negative nonfundamental shock. On average, this drop leads the manager to underinvest relative to what would be optimal. With the benefit of hindsight, this decision appears inefficient, because it results in an opportunity cost for shareholders (a missed positive net present value opportunity). In Section IV.B, we quantify the cost of this inefficiency for the firms in our sample.

3.5 Reduced form for stock prices

For brevity, we have directly assumed that the signals conveyed by stock prices about a firm's fundamental can be decomposed into an informative and an uninformative component about this fundamental. As stock prices are endogenous, our approach naturally raises the question of whether our central prediction ($\alpha_{-i} \neq 0$ if $\sigma^2_{\eta_i} > 0$ and $\sigma^2_{\eta_{-i}} > 0$) would hold in an equilibrium model in which all firms learn from their own and peers' stock prices.

Recent papers (Foucault and Frésard 2014; Huang and Zeng 2015; Schneemeier 2017) have considered models of this type. In these models (like in models with a single firm, e.g., Subrahmanyam and Titman 1999 or Goldstein, Oznedoren, and Yuang 2013), stock prices depend on investors' expectations regarding managers' investment decisions, which in turn depend on stock prices (because stock prices contain information new to managers). Thus, stock prices both reflect investment decisions *and* influence ("feedback on") these decisions. Given these two-way interactions, solving for equilibrium prices and investment decisions is technically complex, even more so in a multiple firms environment. However, in all these models, the signals conveyed by stock prices about a firm's fundamentals can be written as the sum of a fundamental and a nonfundamental component (as an example, in the Internet Appendix (Section B.1), we provide this decomposition in Schneemeier's (2017) equilibrium model).[8] In this paper, we only focus on implications of the faulty informant channel that derive from this fundamental/nonfundamental decomposition of stock prices and the fact that managers are imperfectly informed about each component. Thus, we consider implications that are robust to many possible specifications of equilibrium models in which managers learn from stock prices.

One limitation of this reduced-form approach is that we cannot test more subtle implications of the faulty informant channel, that is, those that depend on equilibrium considerations and the exact specification of the model (e.g., whether or not managers can observe all prices, the exact structure of correlation in firms' payoffs). For instance, in equilibrium models, the noise-to-signal ratios in stock prices (e.g., $\sigma^2_{u_i}/(\sigma^2_{\theta_i}+\sigma^2_{u_i})$) are endogenous and depend on deep

[8] This is a more general property of models of trading with privately informed investors, including those with feedback from stock prices on managers' beliefs (e.g., Subrahmanyam and Titman 1999 or Goldstein, Oznedoren, and Yuang 2013).

parameters (e.g., the mass of informed investors and the precision of their signals). This feature plays *no* role in deriving our test of the faulty informant hypothesis (see Proposition 1 above) but it could be used to derive additional implications. Another example is offered by Schneemeier (2017). In his model, a manager uses the stock prices of its peers of peers to form its beliefs because these prices help her in filtering the noise in her own stock price (i.e., the price of its peers of peers plays the role of $s_{u_{-i}}$ in our model). Schneemeier (2017) shows that this feature may or may not lead to situations in which a firm investment depends on the noise of unrelated firms depending on whether managers observe all prices or just a subset of prices. Such predictions are interesting but more model-specific. Testing them is therefore beyond the scope of our paper.

4. Data and Methodology

This section explains how we estimate Equation (6) and test whether stock prices have a faulty informant role (i.e., whether $\alpha_{-i} \neq 0$).

4.1 Identifying product-market peers

We identify the product-market peers of each publicly listed firm using the Text-Based Network Industry Classification (TNIC) developed by Hoberg and Phillips (2015). This classification starts in 1996 and relies on textual analysis of the product description sections of firms' 10-K filings (Item 1 or Item 1A). Every year, Hoberg and Phillips (2016) compute a measure of product similarity for every pair of U.S. public firms based on the number of common words in their product description. This measure ranges between 0% and 100%. Intuitively, the more common words two firms use in describing their products, the more similar they are. Hoberg and Phillips (2015) define each firm i's product-market peers 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 three-digit SIC industries.[9]

Our sample comprises all firms present in TNIC from 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 network in that year. As firms' relations in TNIC are not transitive (firm B can be a peer of firm A without all peers of B being peers of A), each firm has a unique specific set of peers that varies over time. We obtain stock price and return information from the Center for Research in Securities Prices (CRSP). Investment and other accounting data are from Compustat.

[9] Hoberg and Phillips' (2016) 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. Each firm has its own distinct set of peers. Peers are therefore firm-year specific.

We exclude firms in financial (SIC codes 6000-6999) and utility industries (SIC codes 4000-4999). We also exclude firm-year observations with negative sales, sales less than \$5 million, or missing information on total assets, capital expenditures, fixed assets (property, plant, and equipment), and (end-of-year) stock prices. Appendix B describes the construction of all variables. We winsorize all ratios at 1% in each tail to reduce the effect of outliers.

4.2 Identifying Nonfundamental shocks to stock prices

We identify nonfundamental variation in stock prices (the empirical analog of u_i^o in our model) using stocks' sales by mutual funds experiencing large outflows ("forced sales). Coval and Stafford (2007) show that these sales represent large negative demand shocks for liquidated stocks that create long-lasting downward price pressure. These sales, which are due to investors' redemptions, are unlikely to reflect fund managers' private information about fundamentals, unless fund managers discretely choose the stocks they sell. To mitigate this concern, 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 nonfundamental variation in stock prices.[10]

Specifically, we calculate the hypothetical net selling of a stock (in dollar) by all nonspecialized mutual funds subject to extreme outflows (i.e., greater than 5% of their assets) assuming that in response to these outflows, mutual funds proportionally liquidate their existing holdings and keep the same composition of their portfolios. We define a variable $MFHS_{i,t}$ equal to this amount of sales for firm i in year t, scaled by the total volume of trading, which we label "Mutual Funds Hypothetical Sales." $MFHS_{i,t}$ only takes negative values, so that smaller values of $MFHS_{i,t}$ indicate larger hypothetical sales, and is equal to 0 absent forced sales. By construction, $MFHS_{i,t}$, the details of which are exposed in Appendix C, varies with large mutual funds outflows only. It does not depend on choices made by fund managers about which stocks to sell to meet these redemptions, and is unlikely to reflect changes in investors' views about the firm's industry because of the exclusion of specialized mutual funds. As such, $MFHS_{i,t}$ is a plausible proxy for nonfundamental shocks to stock prices.

In support of this claim, Figure 1 displays the relationship between mutual fund hypothetical sales and stock prices in our sample using quarterly data.

[10] In our model, the effect of nonfundamental shocks to peers' stock prices on a firm's investment is identical whether these shocks are positive or negative. Therefore, fire-sale purchases, due to extreme inflows into mutual flows, could also lead to overoptimism by firms about their growth opportunities. However, fire-sale purchases raise two major empirical difficulties. First, the actual price impact of fire-sale purchases is much weaker than that of fire sales, because mutual funds allocate most of the inflow into buying new stocks, and, doing so, dilutes the effect of extreme inflows on stocks already owned (see Lou 2012). Second, in the data, fire-sale purchases tend to occur directly after a positive abnormal performance of the underlying stocks, but we find no trend before fire-sale events (see Figure 1). Therefore, although we can provide relatively compelling evidence that our measure of mutual funds hypothetical sales is both economically relevant and uninformative about fundamentals, we cannot do the same for mutual funds hypothetical purchases. This means that large mutual funds inflows are not good instruments for positive nonfundamental shocks, not that they do not influence manager's beliefs.

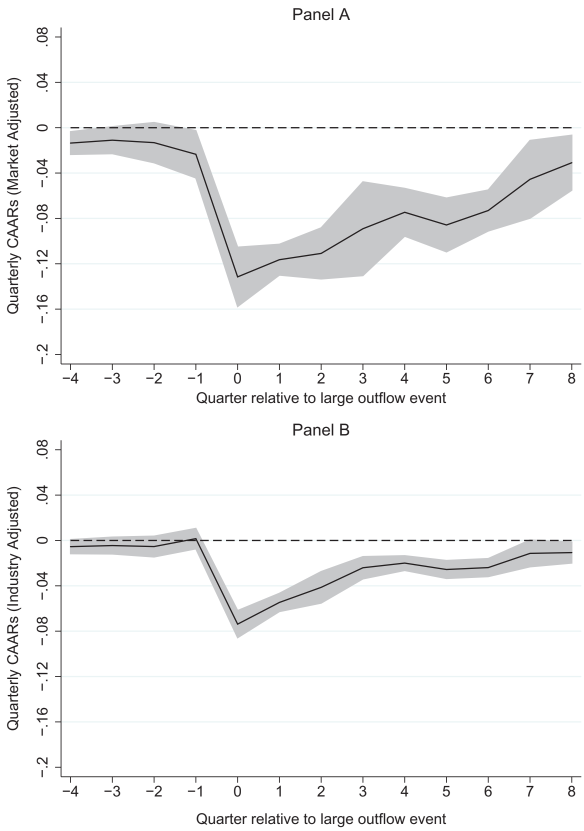

Figure 1
Effect of mutual funds hypothetical sales on stock prices
This figure plots the quarterly cumulative average abnormal returns (CAARs) of stocks subject to mutual fund price pressure around the event, where an event is defined as a firm-quarter observation in which $MFHS$ falls below the tenth percentile of the full sample distribution. 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 (CAARs). In panel A, the benchmark used to estimate the CAARs is the CRSP equally weighted index. In panel B, the benchmark used to estimate the CAARs is the average industry return, defined using TNIC peers. The gray-shaded area delineates the 95% confidence interval.

We define an "event" for stock i in quarter q of year t when $MFHS_{i,q,t}$ is below the tenth percentile of the sample distribution of $MFHS_{i,q,t}$. We then estimate a regression of the quarterly abnormal returns of stocks affected by these events on event-time dummy variables, and plot the cumulated coefficients (i.e., the cumulated average abnormal return, CAAR) around the event. In panel A, we define abnormal returns as stock returns minus the return of the CRSP index. Like Edmans, Goldstein, and Jiang (2012), we find no abnormal decline in stock prices *before* the event quarter, which mitigates the concern that affected funds own stocks with deteriorating fundamentals. Immediately after the event, stock prices drop by about 10%, then revert in the subsequent

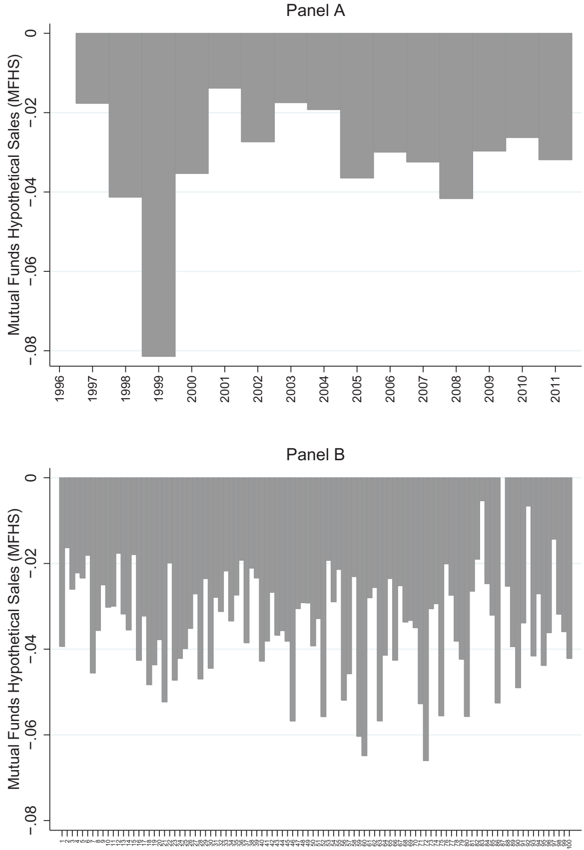

Figure 2
Mutual funds hypothetical sales across time and industries
This figure plots the distribution of large mutual funds downward price pressure ($MFHS$) by year (panel A) and industries (panel B). Industry classification is FIC100 from Hoberg and Phillips (2016).

quarters and recover after about 2 years. This price reversal supports the use of mutual funds hypothetical sales as a measure of nonfundamental price variation. Indeed, if these shocks were fundamental, the resultant decrease in stock prices would be permanent. In panel B, we define abnormal returns as stock returns in excess of the return of an equally weighted portfolio of product-market peers (based on TNIC). The pattern of stock prices is similar to that observed in panel A, suggesting that $MFHS_{i,t}$ captures *localized* (i.e., firm-specific) nonfundamental variation in stock prices.

We perform additional tests that further support using $MFHS$ as a measure of nonfundamental variation. First, we show that $MFHS$ is unlikely to capture economy-wide or industry-specific characteristics. Figure 2 displays the average value of $MFHS$ across firms for each year in our sample and across

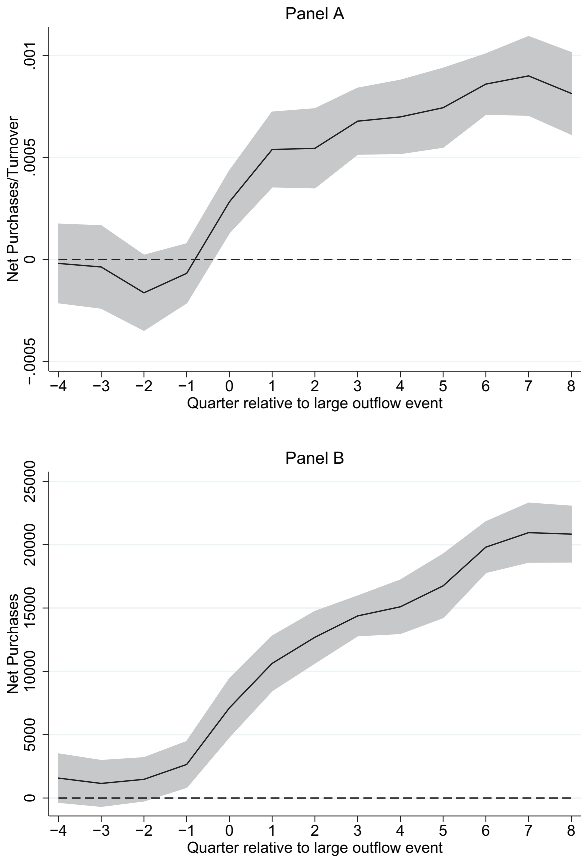

Figure 3
Effect of mutual funds hypothetical sales on insiders' net purchases
This figure plots the quarterly net insiders' purchases for stocks subject to mutual fund price pressure around the event, where an event is defined as a firm-quarter observation in which $MFHS$ falls below the tenth percentile of the full sample distribution. 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 gray-shaded area delineates the 95% confidence interval.

the Hoberg and Phillips (2016) fixed industry classification. We observe no obvious clustering in any particular time period or industry.[11] Second, we find that corporate insiders trade *against* the price pressure generated by mutual fund fire sales (Figure 3). Specifically, the average quarterly net insider purchases (defined either as insiders' purchases minus sales, divided by their stock's turnover, or as the net number of shares purchased) significantly increases in response to downward price pressures triggered by mutual fund sales. This

11 $MFHS$ seems particularly large in 1999, but our main results are unchanged when we exclude this year.

result, which is consistent with that of Ali, Wei, and Zhou (2011) and Khan, Kogan, and Serafeim (2012), who document that, to some extent, managers detect nonfundamental shocks to their *own* stock price, supports our claim that these shocks are unrelated to firms' fundamentals. If they were, insiders would not trade against them.

4.3 Decomposing stock prices

Our decomposition requires a proxy for the signal conveyed by stock prices and for its nonfundamental component. Our proxy for the signal conveyed by the stock prices of the peers of firm i in year t is the equally weighted average Tobin's q of its peers, denoted $\overline{Q}_{-i,t}$. In the following, we refer to $\overline{Q}_{-i,t}$ as "peers' stock price. Our proxy for the noise in peers' stock price is the equally-weighted average value of $MFHS$ across the peers of firm i, denoted $\overline{MFHS}_{-i,t}$.[12] We then decompose $\overline{Q}_{-i,t}$ into a fundamental and nonfundamental component by estimating the following linear regression:

$$\overline{Q}_{-i,t} = \lambda_i + \delta_t + \phi \times \overline{MFHS}_{-i,t} + \upsilon_{-i,t}, \tag{8}$$

where λ_i and δ_t are firm and year fixed effects, respectively. For brevity, we do not tabulate estimates of Equation (8). Consistent with Figure 1, the average stock price of a firm's peers ($\overline{Q}_{-i}$) is positively and significantly correlated with the average realization of $MFHS$ (ϕ is equal to 8.04 with a t-statistic of 4.61).

We define the estimated residuals from regression (8), $\overline{Q}^*_{-i,t} = \widehat{\upsilon}_{-i,t}$, as a proxy for P^*_{-i} in the model.[13] In all our tests, we refer to $\overline{MFHS}_{-i,t}$ as the nonfundamental component of peers' stock price and to $\overline{Q}^*_{-i,t}$ as the "fundamental" component of peers' stock price (even though, like 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 nonfundamental component ($MFHS_{i,t}$) and a fundamental component ($Q^*_{i,t}$).

4.4 Econometric specification

We estimate the coefficients of our investment model (Equation (6)) by OLS using the following specification:

$$I_{i,t} = \lambda_i + \delta_t + \alpha_0 \overline{MFHS}_{-i,t-1} + \gamma_0 \overline{Q}^*_{-i,t-1} + \alpha_1 MFHS_{i,t-1} + \gamma_1 Q^*_{i,t-1} + \Gamma \mathbf{X}_{\mathbf{i},-\mathbf{i},\mathbf{t-1}} + \varepsilon_{i,t}, \tag{9}$$

[12] A large realization of $\overline{MFHS}_{-i,t-1}$ means that the nonfundamental shock to the value of the portfolio of firm i's peers is *less* negative, that is, that u^o_{-i} is smaller in the theory.

[13] The use of linear regressions to decompose stock prices into nonfundamental and fundamental components is standard in the literature (see, for instance, Blanchard, Rhee, and Summers 1993; Galeotti and Schiantarelli 1994; Campello and Graham 2013). Alternatively, we could use (1) $\phi \times \overline{MFHS}_{-i,t}$ as a proxy for u^o_{-i} and (2) $\overline{Q}^*_{-i,t} = \overline{Q}_{-i,t} - \phi \times \overline{MFHS}_{-i,t} = \widehat{\upsilon}_{-i,t} + \lambda_i + \delta_t$ 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.

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 nonfundamental and fundamental components of peers' stock price in year $t-1$ for firm i, while $MFHS_{i,t-1}$ and $Q^*_{i,t-1}$ are the nonfundamental and fundamental components of firm i's stock price in year $t-1$. The vector $\mathbf{X_{i,-i,t-1}}$ includes standard control variables in investment models and variables capturing fundamental information about investment opportunities known to managers at the time they decide on investment. Specifically, we control for the 1-year lagged values of the natural logarithm of assets ("firm size"), cash flows both for firm i and its portfolio of peers, and the average investment of peers. This last control accounts for the possibility that firms' managers also use the investment of their peers as signals about their own investment opportunities. 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). Standard errors are clustered in two ways, by year and by industry using the fixed classification (FIC300) developed by Hoberg and Phillips (2015).[14]

Arguably, price pressures induced by mutual fund hypothetical sales might be correlated *within* industries if funds experiencing extreme outflows have correlated industry allocations.[15] This is not a concern in our setting because we include $MFHS_{i,t}$ and $\overline{MFHS}_{-i,t}$ in the regression. Thus, α_0 captures the effect of the nonfundamental component of firm i's peers' stock price that is not captured by the nonfundamental component of firm i's stock price. Likewise, γ_0 captures the effect of the information contained in $\overline{Q}^*_{-i}$ that is not in Q^*_i. Table 1 presents the summary statistics for the main employed variables. They are in line with previous research.

The coefficient of interest in Equation (9) is α_0, which is the empirical equivalent of α_{-i} in the model (i.e., the average value of α_{-i} across all firms i in our sample). If managers correctly identify $\overline{MFHS}_{-i,t}$ as being a nonfundamental shock to their peers' stock price when they make their investment decision in year t, then this decision should be *unrelated* to $\overline{MFHS}_{-i,t}$ (i.e., the estimated coefficient α_0 should equal 0). In contrast, if they cannot do so, their investment should be sensitive to $\overline{MFHS}_{-i,t}$ (i.e., α_0 should be different from zero).

Our test posits that managers do not observe fire sales of their peer stocks by mutual funds, at least when these sales happen (see the discussion in Section II.C.3). We think that this assumption is plausible. Indeed, data on mutual fund holdings are made available only at the end of every quarter. Thus, market participants (including firms' managers) can, at the earliest, relate stock price movements in a given quarter to mutual funds flows at the end of the quarter only. Moreover, this assumes that managers make the effort of decoding the price

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14 Inferences are similar if we cluster at the firm level, firm and industry-year level, or industry level, using different industry classification: three-digit SIC, five-digit NAICS industries, or FIC300.

15 In our sample the correlation between $MFHS_{i,t}$ and $\overline{MFHS}_{-i,t}$ is 0.36.

Table 1
Summary statistics

Variable	Mean	SD	Min.	Max.	Obs.
$MFHS_i$	−0.033	0.055	−0.538	0.000	45,275
Q_i	1.958	1.473	0.547	10.010	45,275
CF/A_i	0.018	0.216	−1.167	0.361	45,275
$Size_i$	5.622	1.929	1.290	10.644	45,275
$Capex/PPE_i$	0.349	0.388	0.008	2.524	45,275
$\overline{MFHS}_{-i}$	−0.031	0.029	−0.485	0.000	45,275
$\overline{Q}_{-i}$	2.073	0.848	0.547	10.010	45,275
$\overline{CF/A}_{-i}$	0.013	0.109	−1.167	0.361	45,275
$\overline{Size}_{-i}$	5.759	1.060	1.290	10.644	45,275
$\overline{Capex/PPE}_{-i}$	0.380	0.221	0.008	2.524	45,275

This table reports summary statistics for the main employed variables. For each variable, we present its mean, minimum, and maximum; its standard deviation; and the number of nonmissing observations. Table B1 defines all variables. 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 $-i$. Averages are computed by excluding firm i itself. Peers are defined by the TNIC industries developed by Hoberg and Phillips (2016). The sample period is from 1996 to 2011. All variables are winsorized at the 1% level in each tail.

movements of their peers by considering mutual fund outflows as a possible cause of these movements. This is unlikely. Indeed, such outflows are only one out of many possible causes for price movements and considering all these causes is costly for managers (it requires time and attention). Finally, we note that the growth of mutual funds is a recent phenomenon and it is likely that, at least in the early part of our sample, corporate managers had insufficient knowledge for considering mutual funds outflows as a possible cause of nonfundamental variations in stock prices.[16] In any case, if corporate managers are fully able to identify the noisy origin of the drops in their peers' stock price, investment should not respond to such noise; that is, this biases our approach toward finding no effect.

5. The Faulty Informant Role of Stock Prices

5.1 Baseline results

To facilitate interpretation, in estimating Equation (9), we scale all independent variables by their sample standard deviation prior to estimation, such that coefficients represent the estimated change of investment in response to a 1-standard-deviation change in each independent variable. We report the estimates of our baseline specification (9) in the first column of Table 2. Consistent with the faulty informant hypothesis, the coefficient on $\overline{MFHS}_{-i}$ ($\hat{\alpha}_0$) is statistically different from zero. The point estimate for α_0 is 0.015 with a t-statistic of 5.50. This means that a 1-standard-deviation decrease in the nonfundamental component of peers' stock price is associated with a 1.5-percentage-point decrease in firms' investment (4.3% of the average investment level in the sample). The coefficient on the fundamental component of peers' stock price $\overline{Q}^*_{-i}$ ($\hat{\gamma}_0$) is also significantly positive with a point estimate of 0.024.

[16] We thank Sheridan Titman for suggesting this point.

Table 2
Main results: Investment-to-noise sensitivity

Dependent variable:	$Capex/PPE_i$				
Peers' aggregation:	E-W (1)	S-W (2)	Median (3)	5 closest (4)	Agg. (5)
$\overline{MFHS}_{-i}$	0.015***	0.014***	0.009***	0.014***	0.011*
	(5.50)	(5.69)	(4.42)	(5.15)	(2.03)
$\overline{Q}^*_{-i}$	0.024***	0.025***	0.025***	0.019***	0.015***
	(4.96)	(5.17)	(3.83)	(4.96)	(3.66)
$\overline{CF/A}_{-i}$	0.019***	0.011*	0.015***	0.011**	0.005
	(3.39)	(2.08)	(3.29)	(2.11)	(1.38)
$\overline{Size}_{-i}$	0.002	0.001	−0.001	−0.000	0.001
	(0.40)	(0.22)	(−0.21)	(−0.03)	(0.14)
$\overline{Capex/PPE}_{-i}$	0.028***	0.014**	0.027***	0.023***	0.016**
	(3.85)	(2.28)	(3.77)	(4.66)	(2.70)
$MFHS_i$	0.011***	0.011***	0.011***	0.012***	0.012***
	(5.92)	(6.02)	(6.47)	(6.30)	(5.52)
Q^*_i	0.080***	0.080***	0.081***	0.081***	0.085***
	(11.78)	(12.03)	(12.51)	(11.73)	(11.36)
CF/A_i	0.037***	0.036***	0.037***	0.037***	0.038***
	(12.11)	(12.24)	(12.75)	(11.65)	(11.36)
$Size_i$	−0.080***	−0.078**	−0.077**	−0.077***	−0.073**
	(−2.91)	(−2.80)	(−2.80)	(−2.82)	(−2.52)
Obs.	45,275	45,275	45,275	45,275	45,275
Firm FEs	Yes	Yes	Yes	Yes	Yes
Year FEs	Yes	Yes	Yes	Yes	Yes
Adj. R^2	0.371	0.370	0.371	0.370	0.367

This table presents OLS estimations of specification (9). 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 (8) 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 weights are 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, using similarity score as a distance measure. 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. Table B1 defines all variables. Standard errors used to compute t-statistics (in parentheses) are clustered in two ways: by industry (FIC300) and by year. *$p<.01$; **$p<.05$; ***$p<.001$.

The theory predicts that the estimates of α_0 and γ_0 should be positive when the correlation between the fundamentals of firm i and its peers is positive (see Proposition 1). This is, in fact, the case in our data. For instance, the Correlation between sales of a firm and its peers is 0.6, significant at the 1% level.[17] In addition, Proposition 1 predicts that the coefficient on $\overline{Q}^*_{-i}$ should be higher than that on $\overline{MFHS}_{-i}$ ($|\gamma_0| > |\alpha_0|$). This is also the case. Indeed, as all explanatory variables are standardized by their standard deviation, we can directly compare the estimate of the coefficient on $\overline{Q}^*_{-i}$ to that on $\overline{MFHS}_{-i}$. We find that it is about twice bigger, meaning that firm's investment is roughly

[17] We find a negative correlation of sales between a firm and its peers for less than 10% of firms in our sample. We show in the Internet Appendix (Section C.1) that for these firms, the sensitivity of a firm investment to the noise in its peers' stock price is negative (but not always significantly), as predicted by Proposition 1.

two times more sensitive to the fundamental component of its peers' stock price than to the nonfundamental component.

On average, a firm's investment is also significantly and positively related to the nonfundamental component of its own stock price (consistent with empirical findings in Hau and Lai 2013 and Lou and Wang 2014). Specifically, a 1-standard-deviation decrease in $MFHS_i$ is associated with a 1.1-percentage-point drop in investment. In line with previous research, we find 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 11.78.[18]

Columns 2 to 5 in Table 2 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 (2016) (instead of equal weights like 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]

In sum, and in line with the faulty informant hypothesis, Table 2 shows that firms decrease investment in response to negative nonfundamental shocks to the stock price of their peers. As these shocks are nonfundamental, the observed drop in investment may be transient. To test whether this is the case, we estimate the baseline specification (9) with lagged values of $\overline{MFHS}_{-i}$ (namely, $\overline{MFHS}_{-i,t-2}$ and $\overline{MFHS}_{-i,t-3}$). To better assess the dynamics of firm i's investment in response to nonfundamental variations in peers' stock price, we also add the contemporaneous and 1-year-ahead values of $\overline{MFHS}_{-i}$ to this more general specification. Panel A of Figure 4 plots the point estimates (and their confidence interval) for the coefficients on $\overline{MFHS}_{-i}$ at dates $t-3$ to $t+1$.

In line with the baseline results, investment in year t responds positively to noise in peers' stock price measured in year $t-1$. However, it responds *negatively* to the noise in peers' stock price measured in year $t-2$, which

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18 Observe that the sensitivity of a firm investment to the noise in its peers' stock price is higher than that to the noise in its own price ($\alpha_0 > \alpha_1$. In theory, inspection of the expressions for α_i and α_{-i} (given in the proof of Lemma 1 in Appendix A) shows that this happens when (1) the precision of managers' signals about the noise in their own stock price is sufficiently high or (2) the informativeness of their peers' stock price is high enough. It is, in fact, plausible that managers find more novel information (relative to their own private information) about their growth opportunities in their peers' stock price than in their own stock price.

19 Additional tests reported in Sections C.2 and C.3 of the Internet Appendix indicate that our results are similar when we define product market peers as firms in the same SIC or NAICS industry or when we consider actual, rather than hypothetical, mutual fund fire sales. Our results are also robust to the inclusion of leads and lagged investment to control for the lumpy nature of capital expenditures.

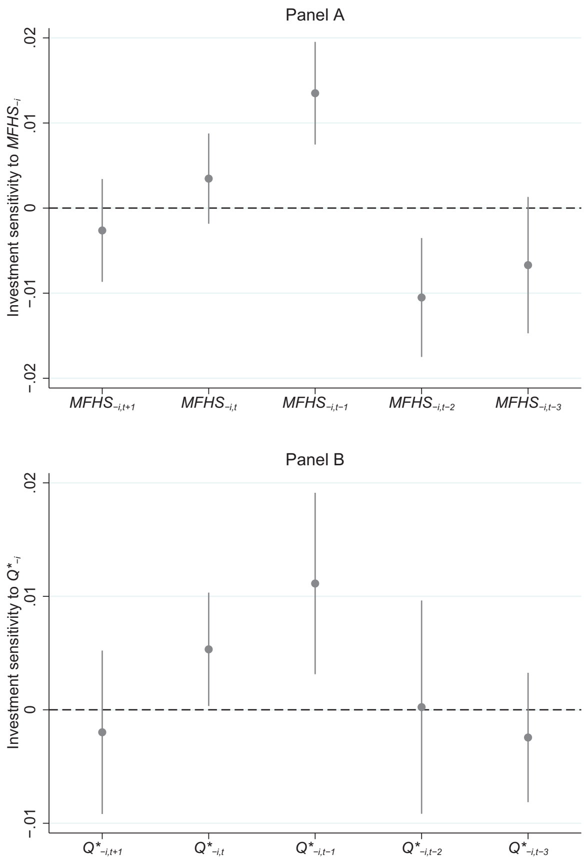

Figure 4
Firm-level sensitivity of investment to noise and fundamentals at various lags
This figure displays the regression coefficients of the baseline specification (9) with leads and lags of each variable. We display the estimates for the leads and lags of $\overline{MFHS}_{-i}$, the investment-to-noise 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 90% confidence interval.

indicates that the real effect of noise on investment is transient. That is, following a negative nonfundamental shock in year $t-2$, investment decreases in year $t-1$, but then increases in year t, so that the impact of noise is subsequently fully corrected on average. 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).

In contrast, panel B of Figure 4 shows that the response of a firm's investment to lagged values of the fundamental component of peers' stock price is permanent: the realization of this component in a given year has a positive and significant effect on investment in the following year but no significant effect on investment in subsequent years. The patterns in Figure 4 are overall consistent with learning. Indeed, on average, signals received by managers about their *previous* investment decisions should in fact confirm (resp., invalidate) those sent by fundamental (resp., nonfundamental) shocks to stock prices *at the time* of their decision.

5.2 Economic magnitude

The main result of the previous section is that nonfundamental variations in peers' stock price have a *direct* effect on corporate investment. This finding is consistent with the idea that managers have limited ability to filter out the noise in stock prices when they use the latter as a signal about their growth opportunities. This result suggests a new channel through which the noise in stock prices has a real effect. In this section, we attempt to quantify the economic impact of this effect.

In our experiment, noise in peers' stock price induce firms to reduce their investment. According to Equation (9), the resultant annual loss in investment as a fraction of PP&E for a firm is $\alpha_0 \times \overline{MFHS}_{-i,t-1}$, that is, in dollar, $\alpha_0 \times \overline{MFHS}_{-i,t-1} \times PP\&E_{i,t-1}$. We can therefore estimate this loss for each firm by using our baseline estimate for α_0 (that is, 0.015; see first column of Table 2) together with the actual values of $\overline{MFHS}_{-i,t-1}$ and $PP\&E_{i,t-1}$. Using this approach, we estimate an aggregate loss of investment (the loss per firm summed over all firms and years in our sample) of \$440 billion or \$29 billion per year, which is about 8% of the average capital expenditures per year in Compustat over the same period.

Under the faulty informant hypothesis, this loss in investment represents an opportunity cost for shareholders. Managers do not invest and postpone valuable projects for shareholders because they mistakenly interpret the drop in their peers' stock price as a bad signal about their fundamentals. Ideally, we could estimate this opportunity cost for a firm by using the net present value (NPV) of all future cash flows per dollar of lost investment for this firm. Unfortunately, this *unit* NPV cannot be readily observed at the firm level. However, we can establish a range of plausible values for this variable by using two benchmarks. First, we consider the unit NPV of completed cash-financed acquisitions of private firms (by public firms) structured as assets sales, which we estimate from the stock price reaction for the acquirer at the time of the deal announcement. We focus on this type of acquisitions because they are very similar to standard investment projects in fixed assets.[20] Using a comprehensive sample of 2,011 such acquisitions from the SDC, we estimate that over our sample period, every dollar invested in these deals yields an average unit NPV of \$0.35, obtained as the product of acquirers' 5-day cumulative abnormal returns

[20] Indeed, in these acquisitions, the new owner only acquires (certain) fixed assets, without the associated liabilities, in contrast to deals structured as shares sales. Moreover, in contrast to acquisitions of public firms, the price of the transaction is not affected by uninformative trading in the market. Therefore, it offers a cleaner estimate of the value created by the transaction.

Table 3
Opportunity costs estimates

		Average unit NPV						
		0.35	*0.45*	*0.55*	*0.65*	*0.75*	*0.85*	*0.96*
	10.0%	14.0	18.0	12.0	26.0	30.0	34.0	38.4
Discount rate	*12.5%*	17.1	22.0	26.9	31.8	36.7	41.6	46.9
	15.0%	20.1	25.8	31.6	37.3	43.0	48.8	55.1

This table reports the results of simulating the total opportunity cost associated with the faulty informant channel over the period 1996–2011. We simulate the value impact for shareholders of postponing $440 billion of capital expenditure for a year assuming that the average NPV of $1 dollar invested ranges between $0.35 and $0.96 and that the appropriate discount rate ranges between 10% and 15%.

and their market capitalization 3 days prior to deal announcement, divided by deal value. Our second benchmark uses the fact that, by definition, a unit NPV is equal to a firm marginal q minus 1. A firm's marginal q is often estimated by its Tobin's q, which is 1.96, on average, in our sample. Thus, another estimate of the average unit NPV for firms in our sample is $0.96.

With an average unit NPV between $0.35 and $0.96, the opportunity cost for shareholders of losing $440 billion of investment ranges between $440 × $0.35 = $154 billion and $440 × $0.96 = $422 billion. If this aggregate investment of $440 billion is only postponed by 1 year (as suggested by Figure 4) then the opportunity cost for shareholders is the time cost of postponing all cash flows associated with this aggregate investment by 1 year. This time cost is equal to the net present value of this $440 billion investment, minus the net present value of the same investment further discounted by 1 year. For example, with a discount rate of 10% and a unit NPV of $0.96, the opportunity cost would be $422 – $422/1.10 = $38 billion.

Table 3 reports various estimates of the opportunity cost of transient cuts in investment due to faulty stock prices for various combinations of unit NPVs (between $0.35 and $0.96) and discount rates (between 10% and 15%, which corresponds to the average rate used by managers for capital budgeting as reported in the survey of Jagannathan et al. 2016). Our baseline estimate of α_0 in Equation (9) implies a total opportunity cost for shareholders ranging between $14 billion (unit NPV of $0.35 and 10% discount rate) and $55.1 billion (unit NPV of $0.96 and 15% discount rate), which is equivalent to $0.9 and $3.7 billion per year. This cost represents between one and four basis points of the overall annual market capitalization over our sample period.

Overall these calculations suggest that the real effects of the faulty informant channel are sizable. Of course, they must be interpreted carefully since they rely on various assumptions, in particular for the unit net present value of investment for the firms in our sample. However, some of these assumptions are conservative in at least three ways. First, we just focus on the effect of noise in peers' stock price due to mutual funds fire sales (the effect that we can estimate). Other nonfundamental shocks to these prices should also result in inefficient investment decisions according to the faulty informant hypothesis. Second, we do not compute the loss in investment and shareholder value for a given firm due to nonfundamental shocks to its *own* stock price. This conservatively assumes that the effects of these shocks are due only to other channels identified in the literature (the financial constraints and agency channels described in the introduction). Last, we assume that cuts in firms' investment due to nonfundamental shocks are transient for *all* firms and that firms postpone investment by only *one* year.

5.3 Heterogeneous exposure to the faulty informant channel

Our baseline specification assumes that the effect of noise in stock prices is the same for all firms. However, the faulty informant hypothesis implies that this effect should vary with firms' characteristics and be stronger for some firms than for others. In particular, using the closed-form solution of α_{-i} (Equation (A11) in Appendix A), we predict that firms' investment should be more sensitive to the noise in peers' stock price when (1) managers are less able to filter out the noise in their peers' stock price (i.e., when their signal about the noise in peers' stock price is noisier; $\sigma^2_{\eta_{-i}}$ is higher), (2) peers' stock prices are more informative, for instance because they are less noisy (i.e., $\sigma^2_{u_{-i}}$ is low) or firm i's fundamentals are more correlated with that of its peers (ρ_i is large in absolute value), and (3) managers have less precise internal information about their fundamentals (i.e., $\sigma^2_{\chi_i}$ is high).[21] Intuitively, in the two last cases, managers rely more on peers' stock price as a source of information either because these signals are more informative or because the manager has less-precise information from other signals. We check whether these cross-sectional implications hold in our sample.

We use two variables as proxies for managers' information about the noise in peers' stock price. First, we conjecture that 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. We define the annual overlap of mutual fund ownership as the pairwise cosine similarity between firms' ownership structure, and compute the average ownership overlap between each firm and its peers in each year. Second, we posit that managers can better identify the noise in their peers' stock price when financial analysts indicate that these stocks are mispriced (e.g., Sulaeman and Wei 2014). We measure analysts' estimate of a firm's mispricing as the average difference between analysts' target price for that firm and its current stock price, and average this difference across firms' peers in each year. We then estimate specifications in which we add interaction terms between each of these proxies and all independent variables of our baseline specification (9), and only report in Table 4 the coefficients on $\overline{MFHS}_{-i,t-1}$ and its interactions. The first two columns reveal that the coefficient on the interaction between $\overline{MFHS}_{-i,t-1}$ and each proxy are negative and statistically

[21] We formally derive the comparative statics results studied in this section in the Internet Appendix (Section B.2).

Table 4
Cross-sectional results

Dependent variable:	$Capex/PPE_i$							
Cross-sectional variation of interest:	Information about Noise $\sigma^2_{\eta_{-i}}$		correlation of fundamentals $\lvert\rho_i\rvert$		Peers' stock price informativeness $\sigma^2_{u_{-i}}$		Information about fundamentals $\sigma^2_{\chi_i}$	
Proxy variable:	$\overline{Common}$ $\overline{Ownership}_{-i}$ (1)	$\overline{Analyst}$ $\overline{Discount}_{-i}$ (2)	$\overline{Sales}$ $\overline{Correlation}_i$ (3)	$\overline{Assets}$ $\overline{Correlation}_i$ (4)	BPS_{-i} (5)	$\overline{AnalystFE}_{-i}$ (6)	$Insider$ CAR_i (7)	$Market$ $share_i$ (8)
$\overline{MFHS}_{-i}$	0.023***	0.021***	0.007	0.008**	0.014***	0.021***	0.015***	0.017***
	(5.09)	(5.12)	(1.67)	(2.12)	(5.81)	(4.53)	(5.40)	(4.82)
$\overline{MFHS}_{-i} \times \sigma^2_{\eta_{-i}}$	−0.006***	−0.006**						
	(−2.79)	(−2.61)						
$\overline{MFHS}_{-i} \times \lvert\rho_i\rvert$			0.007***	0.004*				
			(3.08)	(1.82)				
$\overline{MFHS}_{-i} \times \sigma^2_{u_{-i}}$					0.002*	0.006***		
					(1.78)	(2.84)		
$\overline{MFHS}_{-i} \times \sigma^2_{\chi_i}$							−0.002	−0.004*
							(−0.90)	(−1.94)
Obs.	45,275	33,350	44,137	42,751	45,275	44,408	45,275	45,127
Controls (interacted)	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R^2	.376	.379	.379	.353	.372	.375	.372	.372

This table shows how investment-to-noise sensitivity varies in the cross-section of firms along four dimensions: the quality of managerial information about noise in peers' stock price ($\sigma^2_{\eta_{-i}}$), the degree of correlation between the fundamentals of the firm and the fundamentals of its peers (ρ_i) in absolute value, the informativeness of peers' stock price ($\sigma^2_{u_{-i}}$), and the precision of managerial information about firm fundamentals ($\sigma^2_{\chi_i}$). The table presents OLS estimations of specification (9), where all explanatory variables are interacted with proxies for the cross-sectional variation of interest. The dependent variable is the investment of firm i in year t, defined as capital expenditures divided by lagged property, plant, and equipment (PPE). In Column 1, the proxy for $\sigma^2_{\eta_{-i}}$ is an index of mutual funds ownership overlap between firm i and its peers. In Column 2, the proxy for $\sigma^2_{\eta_{-i}}$ is the average difference between analyst target price and current stock price for every peer of firm i. In Column 3, the proxy for ρ_i is the average pairwise correlation of the (log of) sales. In Column 4, the proxy for ρ_i is the average pairwise correlation of the (log of) assets. In Column 5, the proxy for $\sigma^2_{u_{-i}}$ is the measure of price informativeness proposed by Bai, Philippon, and Savov (2016). In Column 6, the proxy for $\sigma^2_{u_{-i}}$ is the average earnings forecast error by financial analysts covering peers' stock prices. In Column 7, the proxy for $\sigma^2_{\chi_i}$ is the profitability of insiders' trades for firm i. In Column 8, the proxy for $\sigma^2_{\chi_i}$ is the market share of firm i. $\overline{MFHS}_{-i}$ 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. Table B1 defines all variables. All explanatory variables are interacted with the proxy variable, and this proxy variable is included as a control in all specifications. All explanatory variables are divided by their sample standard deviation to facilitate economic interpretation. Standard errors used to compute t-statistics (in parentheses) are clustered in two ways: by industry (FIC300) and by year. $^*p<.01$; $^{**}p<.05$; $^{***}p<.001$.

significant, supporting the prediction that firms' investment is more sensitive to the noise in peers' stock price when managers are less likely to filter out this noise.

The rest of Table 4 also confirms that firms' investment respond significantly more to the noise in peers' stock price when managers are more likely to use these prices as a source of information about their fundamentals; that is, when (1) their fundamentals are more correlated with that of their peers or (2) their peers' stock price is more informative. In Columns 3 and 4, we focus on the correlation of firms' fundamentals with that of their peers, measured in a given year as the average pairwise correlation of sales or assets computed using quarterly data over the last 3 years. In Columns 5 and 6, we consider two proxies for the informativeness of peers' stock price, measured using the ability of current stock prices to forecast future earnings like in Bai, Philippon, and Savov (2016) and the average earnings forecast error of financial analysts. For all measures, the positive coefficients on the interaction term confirm that firms' investment is significantly more sensitive to the noise in peers' stock prices when their fundamentals are more correlated with their peers' fundamentals and when peers' stock prices are more informative.

In the last two columns, we show that the sensitivity of firms' investment to the noise in their peers' stock price is smaller when the precision of managers' internal information about their firm's fundamentals is higher. We first use the profitability of insiders' trades as a proxy for this precision, positing that managers are more likely to generate trading profits if their internal signals are more precise. We measure the profitability of insiders' trades as the average 1-month market-adjusted return of holding the same position as insiders for each insider's transactions. Second, we rely on firms' competitive position within their industry as another proxy for the quality of managerial information, positing that industry leaders possess more precise internal information. As predicted, we observe negative and significant coefficients on the interaction between $\overline{MFHS}_{-i,t-1}$ and these two proxies.

Overall, the results in Table 4 confirm that the intensity of the faulty informant role of prices is heterogeneous and stronger when managers rely more on signals conveyed by peers' stock prices and when it is more difficult for them to identify the noise in these signals.

6. Alternative Channels

Our test of the faulty informant hypothesis assumes that nonfundamental shocks to peers' stock price are not related to other variables that could directly determine a firm's investment. One concern is that this assumption is not valid and that, for this reason, our findings just reflect time-varying omitted variables in our baseline specification (9), correlated with both investment and noise in peers' stock price. We address this concern in this section. We first develop a test that directly controls for the potential effect of omitted variables. Next, we discuss several plausible alternative explanations for our findings regarding the sensitivity of investment to noise in peers' stock price and show that they are not supported by the data.

6.1 Capital allocation within firms

One way to control for *time-varying* firm-level variables potentially correlated with both a firm's investment and the noise in its peers' stock price is to include firm×year fixed effects in our baseline regression. This approach is possible using data on investment at the *division* level in multi-division firms (conglomerates). In this setting, we can test whether noise in peers' stock price across divisions of a given firm affects capital allocation within this firm in a given year, holding possible firm-level omitted variables constant.[22]

We obtain segment level information on annual capital expenditures, total assets, as well as a four-digit SIC code for each segment from Compustat. Because the TNIC classification of Hoberg and Phillips (2016) does not allow identifying product-market peers at the division level, we define peers using three different standard industry classifications (Fama-French 49 industries, two-digit SIC code, and three-digit NAICS code), which allows us to extend our sample back to 1982 (as opposed to 1996 in the baseline test).[23] Within each firm-year (and each industry classification), we then aggregate capital expenditures and total assets by industry. We refer to the resultant firm-industry-year observations as "divisions". The "peers" of a given division comprise either all the firms operating in the same industry of that division or all the single-division firms in that industry, depending on the specification. This sample includes 4,291 distinct conglomerate firms, operating 11,765 divisions (based on Fama-French industries).

Next, we decompose the average value of the (equally weighted) portfolio of peers of division d of firm i in year t ($\overline{Q}_{-i,d,t}$) into a nonfundamental component and a fundamental component, by estimating the following equation:

$$\overline{Q}_{-i,d,t} = \lambda_{i,d} + \delta_{i,t} + \phi \times \overline{MFHS}_{-i,d,t} + \bar{\upsilon}_{-i,d,t}, \quad (10)$$

where $\overline{MFHS}_{-i,d,t}$ is the average mutual fund hypothetical sales across all firms (excluding firm i) belonging to the same FF49 industry as division d of firm i, while $\lambda_{i,d}$ and $\delta_{i,t}$ are firm×division and firm×year fixed effects. Like in firm-level tests, $\overline{MFHS}_{-i,d,t}$ proxies for the nonfundamental component of peers' stock price of division d of firm i and $\bar{\upsilon}_{-i,d,t}$, the estimated residual

[22] For example, the noise in peers' stock price may affect firm-level variables, such as the availability of external financing or CEO's incentives, but these variables do *not* vary across divisions. Indeed, equity or debt is issued by the firm, not by the division. Likewise, the compensation package or career concerns of the CEO do not vary across divisions. Therefore, these variables could explain investment variation at the firm level, but not investment reallocation across divisions for the same firm in the same year, which is what we estimate when including firm×year fixed effects in the specification.

[23] We obtain the same findings when we only use observations after 1996, like for the tests in the rest of the paper. See Section C.4 in the Internet Appendix.

Table 5
Within-conglomerate investment

Dependent variable:	$Capex/Assets_{i,d}$					
Industry:	FF49 (1)	SIC2 (2)	NAICS3 (3)	FF49 (4)	SIC2 (5)	NAICS3 (6)
$\overline{MFHS}_{-i,d}$	0.003*	0.003***	0.003**	0.003*	0.003**	0.004**
	(1.93)	(2.64)	(2.57)	(1.75)	(2.55)	(2.62)
$\overline{Q}^{*}_{-i,d}$	0.008***	0.007***	0.003*	0.007***	0.007***	0.004*
	(5.05)	(3.39)	(1.71)	(5.25)	(3.39)	(1.96)
$\overline{CF/A}_{-i,d}$	0.004***	0.001	0.003	0.003**	0.002	0.003
	(2.70)	(0.97)	(1.57)	(2.58)	(1.31)	(1.49)
$\overline{Size}_{-i,d}$	0.004	0.008*	0.005	0.003	0.007*	0.003
	(1.08)	(2.00)	(1.24)	(1.01)	(1.77)	(0.76)
$\overline{Capex/PPE}_{-i,d}$	0.005***	0.005**	0.004***	0.005***	0.005**	0.003**
	(3.26)	(2.55)	(2.67)	(3.05)	(2.59)	(2.47)
Obs.	62,822	63,263	40,876	62,818	62,242	40,809
Firm-year FEs	Yes	Yes	Yes	Yes	Yes	Yes
Firm-division FEs	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R^2	.369	.365	.396	.369	.367	.396

This table presents OLS estimations of specification (11). The dependent variable is the investment of division d of firm i in year t, defined as capital expenditures divided by lagged total assets. $\overline{MFHS}_{-i,d}$ 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 $\widehat{\upsilon_{-i,d}}$ estimated from Equation (10) 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 49 classification (FF49), in Column 2 we define industry using the two-digit Standard Industry Classification (SIC2), and, in Column 3, we define industry using the three-digit North American Industry Classification System (NAICS3). In Columns 4 to 6, we perform the same tests used in Columns 1 to 3, except that we restrict the definition of peers to single-division firms from the same industry. Table B1 defines all variables. 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. Standard errors used to compute t-statistics (in parentheses) are clustered in two ways: by industry (FF49 in Columns 1 and 4, SIC2 in Columns 2 and 5, and NAICS3 in Columns 3 and 6) and by year. *$p<.01$; **$p<.05$; ***$p<.001$.

of Equation (10), proxies for the fundamental component (denoted $\overline{Q}^{*}_{-i,d,t}$). Following our firm-level specification (9), we finally estimate

$$I_{i,d,t}=\lambda_{i,d}+\delta_{i,t}+\alpha_0\overline{MFHS}_{-i,d,t-1}+\gamma_0\overline{Q}^{*}_{-i,d,t-1}+\Gamma\mathbf{X_{-i,d,t-1}}+\varepsilon_{i,d,t}, \quad (11)$$

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 control for the lagged average size, investment and cash-flow of each division's peers, and include both firm $\times$ division ($\lambda_{i,d}$) and firm$\times$year ($\delta_{i,t}$) fixed effects.[24] The inclusion of firm$\times$year fixed effects ($\delta_{i,t}$) ensures that the estimated differences in investment across divisions only reflects allocation decisions for the same firm in the same year.

Table 5 presents the results. In Columns 1 to 3, we report estimates of Equation (11) for each of the three industry definitions when the peers of a

24 We scale investment by the total assets of the division because property, plant, and equipment are not available at the division level. Also, we no longer control for firm fundamental and nonfundamental price components because of the presence of firm$\times$year fixed effects. Indeed, these fixed effects absorb all (observed and unobserved) firm-level variables; that is, variables that are constant across divisions in a given year, such as the stock price of the firm and all its components including the (observed and unobserved) noise.

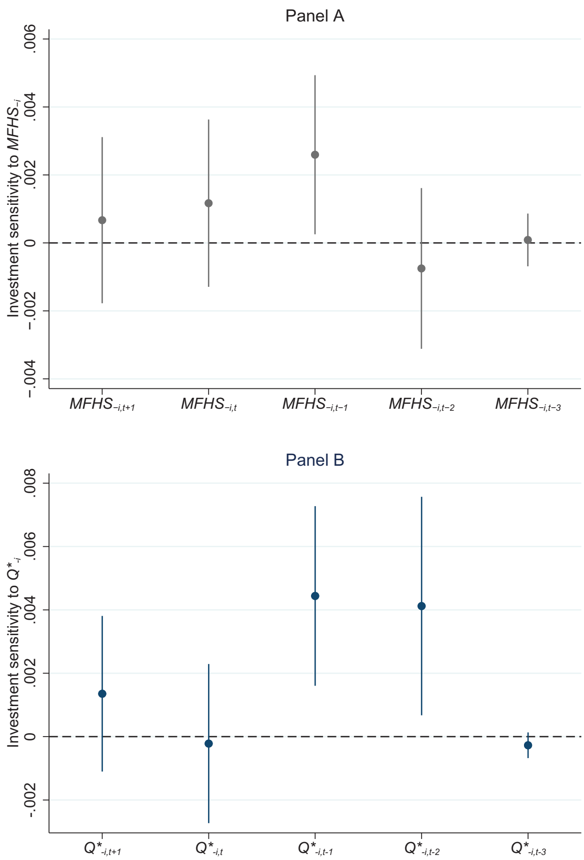

Figure 5
Division-level sensitivity of investment to noise and fundamentals at various lags
This figure displays the regression coefficients of the division-level specification (11) with leads and lags of each variable. We display the estimates for the leads and lags of $\overline{MFHS}_{-i,d}$, the investment-to-noise sensitivity, in panel A, and the estimates for the leads and lags of $\overline{Q}^{*}_{-i,d}$, the investment-to-fundamentals sensitivity, in panel B. Each point estimate is accompanied by its 90% confidence interval.

given division are all firms operating in the same industry (whether single-industry firms or not) while in Columns 4 to 6, we define the peers of a given division as single industry firms operating in firm i's industry. The coefficient on $\overline{MFHS}_{-i,d}$ is positive, statistically significant, and almost identical across all specifications. Thus, as predicted by the faulty informant hypothesis, capital allocation across divisions is sensitive to both the fundamental, *and* the nonfundamental component of the stock price of the peers of each division.

Figure 5 displays the dynamic of these sensitivities (with the same methodology as that used to obtain Figure 4). We observe that fundamental shocks to peers' stock price have a permanent effect on investment. Moreover, non-fundamental shocks to peers' stock price also have a permanent effect on the investment in a particular division, suggesting that division managers do not recover the loss of capital allocated to their division due to a misleading interpretation of the noise in their peers' stock price, even if corrective signals arise in subsequent years. Possible reasons are that division managers lack discretion in making investment decisions or that the capital available in a given year is consumed by the other divisions and is no longer available later on.

In contrast, the effect of the noise in stock prices on the level of investment for all firms in our sample is transient on average (see panel A in Figure 4). However, Figures 4 and 5 are not directly comparable. Indeed, Figure 4 shows the dynamics of the total *level* of investment for a given firm following a nonfundamental shock to its stock price. In contrast, Figure 5 shows the dynamics of the *allocation* of investment across divisions within conglomerates following such a shock. Per se, it says nothing about the effect of the noise in stock prices on the *total level* of investment for conglomerates. In fact, we checked that this effect and the dynamics of investment following nonfundamental shocks to stock prices are not different for conglomerates and single segment firms in our sample.

Overall, this section shows that our main results survive in a setting where these results are, by design, unlikely to stem from omitted variables. We recognize however that this setting is limited to conglomerates (which represent a third of firms in the sample). We thus perform additional analyses to further rule out four possible alternative explanations for our findings.

6.2 Financing channel

Our focus on peers guarantees that the effect of noise on investment cannot reflect a direct financing channel, whereby firms exploit nonfundamental variation in their *own* stock price by timing their share issuances. Nevertheless, the noise in peers' stock price could still affect a firm cost of financing (and thereby its investment) for two reasons. First, capital providers might also rely on peers' stock price to learn information about a firm's fundamentals and set financing conditions accordingly. Second, a decrease in peers' stock price might reduce peers' ability to buy existing assets in the industry (precisely because of the financing channel), which may lower the collateral value of industry-specific assets, and limit firms' borrowing capacity (e.g., Shleifer and Vishny 1992).

To assess whether our results could reflect such a financing channel, we test whether firms' cost of financing and actual financing decisions are sensitive to nonfundamental variation in their peers' stock price. We do so by replacing investment in our baseline specification (9) with various measures of financing costs and policies. We rely on credit default swap (CDS) spreads and spreads on new private debt issues as indicators of the cost of financing. To mitigate the concern that these proxies, which are not available for all firms, may not be representative of the entire population of firms, we also use the measures of financing constraints developed by Hoberg and Maksimovic (2015), which are based on textual analysis of firms' 10-Ks. In particular, we use their scores of the intensity of debt-market and equity-market constraints, where a higher score indicates more binding constraints. These scores are available for all firms since 1997, including firms that are not seeking access to financing, and as such, are free of any selection bias. However, they might reflect subjective opinions of managers. We thus complement this analysis of the cost of financing with an analysis of actual financing decisions, namely, the amount of new security issuances (debt plus equity) and total payout (share repurchases plus dividends) over total assets.

Table 6 reports the results. In the first four columns, the coefficient on $\overline{MFHS}_{-i,t-1}$ is either insignificant or significant (for the spread on new private debt issues) but positive, which means that firms' cost of financing and access to external finance do not deteriorate when peers' stock price is under negative price pressure. Columns 5 and 6 further show that firms' financing decisions do not respond to noise in peers' stock price. Column (7) finally shows that controlling for firms' financing decisions in our baseline specification barely affects the coefficient on $\overline{MFHS}_{-i,t-1}$ (0.014 compared to 0.015). In sum, Table 6 shows that our main results cannot be explained by a potential correlation between firms' financing conditions and the noise in their peers' stock price.

Another prediction of the financing channel is that the sensitivity of investment to the noise in peers' stock price should vary with the intensity of financing constraints. Using various proxies for the presence of such constraints, we show in the Internet Appendix (Section C.5) that this is not the case. For instance, the investment of large and mature firms with a credit rating, which are typically the least constrained ones, is as sensitive to noise in peers' stock price as the other firms. This finding demonstrates that noise in secondary market prices can affect investment even in the absence of financing frictions. This result is fully consistent with the faulty informant channel (which applies to both constrained and unconstrained firms), but not with the financing channel.

6.3 Pressure channel

Another possibility is that our findings reflect a link between the noise in peers' stock price and managers' personal incentives to invest. We call such a link the "pressure channel". It could have three origins. First, the noise in peers' stock price might alter the intensity of product-market competition. For instance, a nonfundamental drop in peers' stock price could trigger industry consolidation through acquisitions (e.g., Edmans, Goldstein, and Jiang 2012 show that a nonfundamental drop in a firm stock price increases its likelihood of being taken over). In this case, after observing a drop in its peers' stock price, a manager might decide to "wait and see," postponing new investments in expectation of significant industry changes. Second, drops in peers' stock price could reduce

Table 6
Alternative explanation: Financing channel

Dependent variable:	$CDS\ spread_i$ (1)	$Debt\ spread_i$ (2)	$Debt\ -Cons._i$ (3)	$Equity\ -Cons._i$ (4)	$Payout_i$ (5)	$Security\ issue_i$ (6)	$Capex\ /PPE_i$ (7)
$\overline{MFHS}_{-i}$	0.077	0.035***	−0.000	0.001	−0.001	0.004	0.014***
	(0.93)	(2.97)	(−0.22)	(1.02)	(−1.32)	(1.59)	(4.85)
$\overline{Q}^*_{-i}$	0.027	−0.022	−0.001	0.000	−0.001**	0.002	0.023***
	(0.38)	(−1.41)	(−1.56)	(0.58)	(−2.29)	(1.17)	(4.97)
$\overline{CF/A}_{-i}$	−0.412***	−0.061**	−0.001	−0.001	0.001	0.006*	0.019***
	(−3.81)	(−2.42)	(−0.59)	(−1.08)	(1.63)	(2.02)	(3.41)
$\overline{Size}_{-i}$	−0.099	−0.009	0.000	0.002	0.000	−0.001	0.002
	(−1.13)	(−0.39)	(0.57)	(1.42)	(0.15)	(−0.32)	(0.47)
$\overline{Capex/PPE}_{-i}$	−0.015	−0.013	0.002*	−0.000	−0.000	−0.005	0.029***
	(−0.10)	(−0.61)	(1.98)	(−0.17)	(−0.51)	(−1.49)	(3.83)
$MFHS_i$	−0.350	0.005	−0.000	0.001	−0.001**	0.002	0.009***
	(−1.26)	(0.35)	(−0.32)	(0.90)	(−2.29)	(1.42)	(5.12)
Q^*_i	−0.115*	−0.130***	−0.001*	0.002***	0.002**	0.016***	0.079***
	(−1.92)	(−11.18)	(−1.76)	(6.17)	(2.57)	(5.90)	(11.33)
CF/A_i	−1.141***	−0.358***	−0.001**	−0.006***	0.005***	−0.032***	0.041***
	(−3.62)	(−6.08)	(−2.41)	(−9.68)	(5.78)	(−8.66)	(13.66)
$Size_i$	−0.887	−0.589***	−0.000	−0.001	0.015***	−0.106***	−0.066**
	(−1.65)	(−10.73)	(−0.09)	(−0.38)	(5.45)	(−7.77)	(−2.45)
$Payout/A_i$							−0.012***
							(−3.69)
$SecurityIssue/A_i$							0.024***
							(3.87)
Obs.	3,763	10,734	33,102	33,102	45,275	43,347	43,347
Firm FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R^2	.650	.640	.484	.591	.359	.463	.370

This table presents OLS estimations of specification (9), where we use firm-level measures of financing costs and access to external capital as dependent or control variables. $\overline{MFHS}_{-i}$ 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 (8) and corresponds to the component of peers' stock price that is unexplained by mutual fund hypothetical sales. Dependent variables include the credit default swap (CDS) spread of firm i in year t (Column 1); the average spread of firm i in year t on new private debt issues (Column 2); and the text-based measure of debt-financing constraints and equity-financing constraints developed by Hoberg and Maksimovic (2015) in Columns 3 and 4, respectively, the payout ratio (repurchases + dividends, scaled by assets) in Column 5, security issue (debt + equity), scaled by assets in Column 6, and Capex, scaled by lagged property, plant, and equipment (PPE) in Column 7. All explanatory variables are divided by their sample standard deviation to facilitate economic interpretation. Table B1 defines all variables. Standard errors used to compute t-statistics (in parentheses) are clustered in two ways: by industry (FIC300) and by year. $*p<.01$; $**p<.05$; $***p<.001$.

managers willingness to invest if their compensation is tied to peers' stock price via relative performance evaluation contracts. Third, a nonfundamental drop in peers' stock price may affect managers' career concerns if it increases the threat of a takeover leading to their replacement. In response, managers might undertake actions, such as postponing profitable investment, to temporarily boost their earnings and thereby their short-term stock price (see Stein 1989, 1996).[25]

25 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).

Table 7
Alternative explanation: Pressure channel

Dependent variable:	HHI_i	$Nb.Peers_i$	$Capex/PPE_i$	$Capex/PPE_i$	$Capex/PPE_i$	$Prob(Target)_i$	CEO
Subsample:				$RPE=1$	$RPE=0$		$turnover_i$
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$\overline{MFHS}_{-i}$	0.002	−0.000	0.015***	0.016***	0.015**	0.004	0.002
	(0.76)	(−0.02)	(5.59)	(3.56)	(2.69)	(1.13)	(0.57)
$\overline{Q}^*_{-i}$	0.000	0.020***	0.023***	0.026***	0.019***	−0.005**	0.005
	(0.32)	(2.81)	(4.95)	(4.74)	(4.27)	(−2.52)	(1.22)
$\overline{CF/A}_{-i}$	0.003	−0.063***	0.019***	0.025***	0.009	0.004*	−0.000
	(0.98)	(−3.96)	(3.40)	(4.14)	(1.23)	(1.76)	(−0.11)
$\overline{Size}_{-i}$	−0.010***	0.015	0.002	−0.005	0.009	0.002	0.007
	(−2.84)	(1.10)	(0.43)	(−0.85)	(1.18)	(0.40)	(1.58)
$\overline{Capex/PPE}_{-i}$	−0.009***	0.037***	0.028***	0.020**	0.037***	−0.005	−0.004
	(−5.46)	(3.43)	(3.86)	(2.17)	(4.75)	(−1.66)	(−0.73)
$MFHS_i$	0.002	−0.014**	0.011***	0.010***	0.011***	−0.007**	−0.003
	(1.08)	(−2.25)	(5.86)	(3.45)	(5.53)	(−2.74)	(−1.08)
Q^*_i	−0.001	0.005	0.080***	0.081***	0.077***	−0.009***	−0.010**
	(−0.87)	(1.21)	(11.76)	(10.93)	(9.36)	(−3.20)	(−2.29)
CF/A_i	−0.005***	0.028***	0.037***	0.031***	0.041***	−0.015***	−0.036***
	(−3.46)	(4.15)	(12.15)	(5.68)	(6.09)	(−3.94)	(−3.72)
$Size_i$	−0.033***	0.179***	−0.080***	−0.073**	−0.089***	0.061***	0.006
	(−6.36)	(7.80)	(−2.91)	(−2.73)	(−3.34)	(4.72)	(0.34)
$Prob(Acquirer)_{-i}$			0.001				
			(0.39)				
$Prob(Target)_{-i}$			−0.005**				
			(−2.42)				
Obs.	45,275	45,275	45,275	23,455	21,820	45,275	18,107
Firm FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R^2	.582	.855	.371	.395	.352	.163	.010

This table presents OLS estimations of specification (9) where we use measures of pressure on CEO's incentives to invest as independent or control variables. $\overline{MFHS}_{-i}$ 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 (8) and corresponds to the component of peers' stock price that is unexplained by mutual fund hypothetical sales. The dependent variable is the Herfindahl-Hirschman index of sales computed over all peers of firm i in year t in Column 1, and the number of peers of firm i in year t in Column 2. In Columns 3 to 5, the dependent variable is the investment of firm i in year t, defined as capital expenditures divided by lagged property, plant, and equipment (PPE). We restrict the sample to industries that use relative performance evaluation ($RPE=1$) in Column 4, and to industries that do not use it ($RPE=0$) in Column 5. In Column 6, the dependent variable is a dummy variable equal to 1 if firm i receives a takeover bid in year t and 0 if not. In Column 7, the dependent variable is a dummy variable equal to 1 if firm i experiences a CEO change in year t and 0 if not. All explanatory variables are divided by their sample standard deviation to facilitate economic interpretation. Table B1 defines all variables. Standard errors used to compute t-statistics (in parentheses) are clustered in two ways: by industry (FIC300) and by year. $*p<.01$; $**p<.05$; $***p<.001$.

Estimates reported in Table 7 do not support the pressure channel. The first two columns indicate that noise in peers' stock price ($\overline{MFHS}_{-i,t}$) does not significantly affect competition intensity, as measured by the (sales based) Herfindahl-Hirschman index or the (log) number of peers.[26] Moreover, Column 3 shows that our baseline estimate of the effect of $\overline{MFHS}_{-i,t}$ does not change if we control for peers' acquisition activity by adding the fraction of peers making

[26] We find the same result when considering changes in competition over longer time periods, such as 2 or 3 years.

acquisitions and the fraction of targeted peers in our baseline specification.[27] Next, using the methodology of Aggarwal and Samwick (1999) to identify the likely use of relative performance evaluation (RPE), we find that the sensitivity of firms' investment to the noise in peers' stock price is similar for firms that tie managerial compensation to their peers' stock price (i.e., RPE=1 in Column 4) and for firms that do not (i.e., RPE=0 in Column 5). Finally, Columns 6 and 7 show that $\overline{MFHS_{-i}}$ does not affect the likelihood of a firm being taken over or the incidence of a CEO turnover, which casts doubt on the possibility that noise in peers' stock price be a serious source of career concerns for firm managers.[28] Overall, results displayed in Table 7 are largely inconsistent with the idea that our results originate from the interplay between noise in peers' stock price and managers' personal incentives.

6.4 Investment-mimicking channel

Once concern is that the sensitivity of a firm's investment to the noise in peers' stock price could be explained by firms' mimicking behaviors (or peer effects) instead of the faulty role of stock prices. Indeed, previous studies report that firms reduce investment in response to nonfundamental drops in their *own* stock price, for reasons unrelated to the faulty informant channel. Thus, a decrease in peers' stock price could lead the peers of firm i to reduce their investment. In turn, this reduction might lead firm i to also cut its investment, either because its manager uses peers' investment as a source of information (e.g., Lieberman and Asaba 2006) or because firms' investment decisions are strategic complements (e.g., Fudenberg and Tirole 1984; Bulow, Geanokoplos, and Klemperer 1985).[29] If these mechanisms operate, they might explain, at least partially, why a firm investment is sensitive to the noise in its peers' stock price and confound the ability of our test to measure the faulty informant channel.

However, in all our specifications so far, we included the lagged investment of a firm's peer as a control variable. This control is likely to capture the direct influence of peers' investment on the investment of a firm since the investment of a given firm is known perfectly by other firms when financial accounts are released, that is, with at least a 1-year delay. Moreover, this control excludes the possibility that the effect of $\overline{MFHS_{-i,t-1}}$ on firm i's investment stems from an effect of this variable on lagged investment of a firm's peer. Nevertheless, in this section, we consider additional analyses (reported in Table 8) to examine

[27] In Section C.5 of the Internet Appendix, we report similar results when we proxy the likelihood for peers to be taken over using their antitakover provisions.

[28] However, the coefficient on the nonfundamental component of a firm's own stock price ($MFHS_i$) is negative and statistically significant, indicating that price pressure at the firm level (not the peer level) increases takeover likelihood, consistent with Edmans, Goldstein, and Jiang (2012).

[29] These models identify conditions under which investment decisions (capacity choices) by firms can be strategic complements, that is, conditions under which an increase in the investment of one firm leads its competitors to also increase their investments.

Table 8
Alternative explanation: Investment-mimicking channel

Dependent variable:	$Capex/PPE_i$		
	(1)	(2)	(3)
$\overline{MFHS}_{-i}$	0.024**	0.016***	0.007***
	(2.20)	(5.49)	(3.28)
$\overline{Q}^*_{-i}$	0.033**	0.028***	0.014***
	(2.63)	(4.90)	(4.15)
$\overline{CF/A}_{-i}$	0.008	0.002	0.015***
	(0.50)	(0.20)	(3.30)
$\overline{Size}_{-i}$	0.005	0.011**	0.002
	(0.35)	(2.11)	(0.43)
$MFHS_i$	0.012**	0.010***	0.010***
	(2.71)	(3.32)	(5.65)
Q^*_i	0.075***	0.080***	0.078***
	(7.50)	(7.37)	(11.88)
CF/A_i	0.032**	0.041***	0.036***
	(2.27)	(5.61)	(11.72)
$Size_i$	−0.098***	−0.097***	−0.080***
	(−4.33)	(−3.66)	(−3.01)
$\overline{Capex/PPE}_{-i}$			0.024***
			(3.85)
$\overline{Contemporaneous Capex/PPE}_{-i}$			0.047***
			(5.80)
Obs.	9,124	21,046	45,244
Firm FEs	Yes	Yes	Yes
Year FEs	Yes	Yes	Yes
Ind-year FE	–	–	–
Adj. R^2	.396	.389	.375

This table presents OLS estimations of specifications similar to specification (9). 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 (8) 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. We restrict the sample to firms whose peers do not change investment in Column 1, and to firms whose peers increase investment in Column 2. All explanatory variables are divided by their sample standard deviation to facilitate economic interpretation. Table B1 defines all variables. Standard errors used to compute t-statistics (in parentheses) are clustered in two ways: by industry (FIC300) and by year. $*p<.01$; $**p<.05$; $***p<.001$.

whether our findings regarding the effect of the noise in peers' stock price could just capture peer effects in investment decisions.

First, we test whether investment is sensitive to the noise in peers' stock price even for sub-samples of firms whose peers do not significantly change their investment (the annual growth of their investment is less than one-tenth of its standard deviation) after nonfundamental shocks to their stock price (Column 1 of Table 8) or even increase it (Column 2 of Table 8). If $\overline{MFHS}_{-i,t-1}$ was significantly related to investment because of strategic complementarities or substitutability in firms' investment (or other types of mimicking behavior), the coefficient on this variable should be zero when estimated with these subsamples. Instead, we find that it is significantly positive and similar to that obtained for the entire sample.

Second, in Column 3 of Table 8, we estimate our baseline specification (9) by adding peers' *contemporaneous* average investment as a control variable.

One caveat is that estimates of this specification are difficult to interpret. Indeed, as previously explained, various theories (including the faulty informant hypothesis) predicts that the average investment of peers should respond to the noise in peers' stock price ($\overline{MFHS}_{-i,t-1}$). If it does, controlling for peers' contemporaneous investment mechanically biases downward the coefficient on $\overline{MFHS}_{-i,t-1}$ on firm i's investment, *even if* peers' contemporaneous investment has no effect on firm i's investment. Using Angrist and Pischke's (2009) terminology, we define peers' contemporaneous investment as a "bad control." Their contemporaneous investment biases the estimate of the effect of interest (here the true effect of the noise in peers' stock price on firm i's investment, regardless of the exact reason for this effect). In any case, with this specification, the coefficient on $\overline{MFHS}_{-i,t-1}$ remains positive and statistically significant at the 1% level. It is smaller than in our main specification (0.007 vs. 0.015), possibly because, peers' contemporaneous investment picks part of the effect of $\overline{MFHS}_{-i,t-1}$ on firm i's investment, even though it does not directly affect this investment.[30]

6.5 Correlated noise in prices

A last concern is that the observed component of the noise in peers' stock price ($\overline{MFHS}_{-i}$) could be correlated with the unobserved component of the noise in firm i's stock price (the empirical analog of u_i^{no} in our model).[31] In this case, α_0—our estimate of α_{-i}—will pick the effect of the noise in firm i's stock price on firm i's investment. One way to control for this is to use firm$\times$year fixed effects as we do in Section 6.6.1 for conglomerates. Using firm $\times$ year fixed effects allows to control for any time-varying characteristic of firm i, including the unobserved noise in its stock price (this is the reason we do not control for the components of this price in specification (11)). Therefore, the tests that we perform in Section 6.6.1 already fully address the above concern. Of course, a limitation is that these tests apply to conglomerates only.

To assess whether 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 estimate our baseline

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30 In unreported tests, we also introduce industry$\times$year fixed effects in the regression using Hoberg and Phillips (2016) fixed industry classification (FIC300) to control for any time-varying unobserved heterogeneity across industries. Doing so is possible because firms have their own distinct set of peers (based on TNIC), even when they belong to the same FIC300 industry. Although we obtain results similar to those reported in Column 3 of Table 8, including these fixed effects comes at the cost of a "bad control" problem. Indeed, the fixed effects used as controls partly absorb, and thus mechanically attenuate, the effect of $\overline{MFHS}_{-i}$ in the regression, which is why we also do not use this specification for our main tests.

31 In our theoretical analysis, we have assumed that the noise components of firm i's stock price and its peers' stock price are independent. Proposition 1 holds more generally as long as 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 (the problem considered in this section), regression (6) yields biased estimates of α_1 and α_0 in Equation (5) (i.e., the true sensitivity of investment to noise). However, in theory, α_0 remains different from zero if and only if the firm's manager has limited ability to filter the noise in stock prices.

Table 9
Alternative explanation: Correlated noise

Dependent variable:	$Capex/PPE$			
	(1)	(2)	(3)	(4)
$\overline{MFHS}_{-i}$	0.015***		0.015***	
	(5.50)		(5.33)	
$\overline{Q}^*_{-i}$	0.024***	0.023***	0.024***	0.023***
	(4.96)	(4.46)	(4.97)	(4.44)
$\overline{CF/A}_{-i}$	0.019***	0.018***	0.019***	0.018***
	(3.39)	(3.29)	(3.39)	(3.28)
$\overline{Size}_{-i}$	0.002	0.001	0.002	0.001
	(0.40)	(0.29)	(0.40)	(0.29)
$\overline{Capex/PPE}_{-i}$	0.028***	0.030***	0.028***	0.030***
	(3.85)	(4.11)	(3.86)	(4.13)
$MFHS_i$	0.011***	0.013***		
	(5.92)	(6.14)		
Q^*_i	0.080***	0.082***		
	(11.78)	(11.52)		
CF/A_i	0.037***	0.036***	0.037***	0.036***
	(12.11)	(12.17)	(12.16)	(12.25)
$Size_i$	−0.080***	−0.079***	−0.080***	−0.079***
	(−2.91)	(−2.88)	(−2.91)	(−2.89)
Q_i			0.122***	0.124***
			(11.79)	(11.48)
Obs.	45,275	45,275	45,275	45,275
Firm FEs	Yes	Yes	Yes	Yes
Year FEs	Yes	Yes	Yes	Yes
Adj. R^2	.371	.371	.371	.371

This table presents the results from estimations of specifications similar to that of Equation (9). 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 (8) 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. Table B1 defines all variables. The standard errors used to compute the t-statistics (in parentheses) are clustered at the firm level. $^*p<.01$; $^{**}p<.05$; $^{***}p<.001$.

specification (9) with and without $\overline{MFHS}_{-i}$. If our results reflect the influence of the unobserved noise component of firms' own stock price, the coefficient on Q^*_i should substantially vary across these two specifications (see Oster 2017).[32] Columns and (2) of Table 9 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. In Columns 3 and 4, we control for firms' own stock price Q_i before its decomposition into Q^*_i and $MFHS_i$. Again, removing $\overline{MFHS}_{-i}$ barely alters the magnitude of the coefficient on Q_i, suggesting that our results are unlikely to be driven by a correlation between observed and unobserved components of noise in stock prices.

32 $\overline{MFHS}_{-i}$ is orthogonal to $\overline{Q}(1)^*_{-i}$, but, by construction, it is not orthogonal to Q^*_i.

7. Conclusion

In this paper, we provide evidence that a firm's investment is sensitive to nonfundamental shocks in stock prices. We argue that this finding is consistent with the faulty informant hypothesis: the notion that managers have limited ability to filter out the noise in stock prices when using them as signals about their growth opportunities. We also show that our findings regarding the sensitivity of firms' investment to the noise in their peers' stock prices cannot be explained by other mechanisms relying on financing and agency frictions or peers' effects in investment decisions.

Overall, our results shed a new light on the links between real and stock market efficiency. First, they imply that stock market efficiency matters even for real decisions of firms facing no financing or agency frictions. Second, they suggest a different type of intervention to mitigate possible harmful real effects of stock market inefficiencies. In the literature, stock market inefficiencies lead to inefficient investment decisions because of agency frictions (Stein 1996). Accordingly, investment distortions due to stock market inefficiencies can be mitigated by improving governance systems (see Jensen 2005). In contrast, our findings suggest that nonfundamental shocks to stock prices can generate investment inefficiencies because they influence managers' beliefs about their growth opportunities. In this case, preventing managers from using stock prices as signals would make things worse on average (see the discussion in Section II.C.4). Instead, to mitigate inefficiencies due to faulty stock prices, one should improve managers' ability to filter out the noise in stock prices or incentivize them to do so. How to do so would be an interesting question for future research.

Another interesting question is whether nonfundamental shocks to a firm's stock price could also affect the investment of fundamentally unrelated firms (its peers of peers).[33] Schneemeier (2017) shows that such contagion can happen if firms' managers have both limited ability to filter out the noise in prices *and* limited attention to stock prices. Testing whether this mechanism is at play in the data would be another interesting venue for future research on the ramifications of the faulty informant channel.

Appendix A. Proofs

In this appendix, we denote by $\psi_i = \sigma^2_{\theta_i}\left(\sigma^2_{\theta_i} + \sigma^2_{\chi_i}\right)^{-1}$, the signal-to-noise ratio for the manager's own private information, s_{mi}, about the fundamentals of the growth opportunity, $\widetilde{\theta}_i$. Similarly, $\kappa_i = \sigma^2_{\theta_i}\left(\sigma^2_{u_i} + \sigma^2_{\theta_i}\right)^{-1}$ and $\kappa_{-i} = \sigma^2_{\theta_i}\left(\sigma^2_{u_{-i}} + \sigma^2_{\theta_i}\right)^{-1}$ denote the signal-to-noise ratios for the signals conveyed by stock prices. These ratios measure, respectively, the informativeness of firm i's own

[33] 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 faulty informant effect highlighted in our paper holds after controlling for the own stock price of the firm, and only stems from imperfect learning from the stock price of other related firms rather than from an effect on credit constraints.

stock price (κ_i) and the informativeness of peers' stock prices (κ_{-i}) about the fundamentals 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 fundamentals). 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 stock price and peers' stock prices, respectively.

Proof of Lemma 1.

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

Remark 1: Let $(X, \widetilde{\theta}_i)$ be a random vector with a multivariate normal distribution. In this case $\mathrm{E}(\widetilde{\theta}_i \mid X) = \mathrm{E}(\widetilde{\theta}_i) + \mathrm{Cov}(\widetilde{\theta}_i, X)^t\, \Omega^{-1}(X - \mathrm{E}(X))$, where Ω^{-1} is the inverse of the variance-covariance matrix of X and $\mathrm{Cov}(\widetilde{\theta}_i, X)^t$ is the transpose of the (column) vector giving the covariance between $\widetilde{\theta}_i$ and each component of X.

As explained in the text, the optimal investment policy is such that $K^*_i = \mathrm{E}(\widetilde{\theta}_i \mid \Omega_1)$. Now we compute $\mathrm{E}(\widetilde{\theta}_i \mid \Omega_1)$. 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 $\mathrm{E}(\widetilde{\theta}_i \mid \Omega_1)$ is a linear function of these variables (with a zero intercept):

$$\mathrm{E}(\widetilde{\theta}_i \mid \Omega_1) = a_i \times s_{m_i} + b_i \times P_i + c_i \times s_{u_i} + b_{-i} \times P_{-i} + c_{-i} \times s_{u_{-i}}. \tag{A1}$$

Using the Law of Iterated Expectations, the assumption that $P_{-i} = \rho_i \theta_i + u_{-i}$, and the fact u_{-i} and $s_{u_{-i}}$ are independent from s_{m_i}, P_i, and s_{u_i}, we deduce from Equation (A1) that

$$\mathrm{E}\left(\widetilde{\theta}_i \,\middle|\, s_{m_i}, P_i, s_{u_i}\right) = a_i s_{m_i} + b_i P_i + c_i s_{u_i} + \rho_i b_{-i} E\left(\widetilde{\theta}_i \,\middle|\, s_{m_i}, P_i, s_{u_i}\right). \tag{A2}$$

Thus,

$$\mathrm{E}\left(\widetilde{\theta}_i \,\middle|\, s_{m_i}, P_i, s_{u_i}\right) = \frac{a_i}{1-\rho_i b_{-i}} s_{m_i} + \frac{b_i}{1-\rho_i b_{-i}} P_i + \frac{c_i}{1-\rho_i b_{-i}} s_{u_i}. \tag{A3}$$

Now, using Remark 1, we also have

$$\mathrm{E}\left(\widetilde{\theta}_i \,\middle|\, s_m, P_i, s_{u_i}\right) = a^*_i s_{m_i} + b^*_i P_i + c^*_i s_{u_i}, \tag{A4}$$

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 Equations (A3) and (A4), we deduce that

$$a_i = a^*_i(1-\rho_i b_{-i}), \tag{A5}$$

$$b_i = b^*_i(1-\rho_i b_{-i}), \tag{A6}$$

$$c_i = c^*_i(1-\rho_i b_{-i}). \tag{A7}$$

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 $\chi^*_i = \left(\frac{a^*_i}{a^*_i+b^*_i+c^*_i}\right)\chi_i + \left(\frac{b^*_i+c^*_i}{a^*_i+b^*_i+c^*_i}\right)u_i + \left(\frac{c^*_i}{a^*_i+b^*_i+c^*_i}\right)\eta_i$. Using these notations, we can rewrite Equation (A1) as

$$\mathrm{E}(\widetilde{\theta}_i \mid \Omega_1) = (a^*_i + b^*_i + c^*_i)(1-b_{-i}) \times s^*_{m_i} + b_{-i} \times P_{-i} + c_{-i} \times s_{u_{-i}}. \tag{A8}$$

Thus, $\mathrm{E}\left(\mathrm{E}(\widetilde{\theta}_i \mid \Omega_1) \,\middle|\, s^*_{m_i}, P_{-i}, s_{u_{-i}}\right) = \mathrm{E}\left(\widetilde{\theta}_i \,\middle|\, s^*_{m_i}, P_{-i}, s_{u_{-i}}\right) = \mathrm{E}(\widetilde{\theta}_i \mid \Omega_1)$, where the first equality follows from from the Law of Iterated Expectations and the second equality from Equation (A8). 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:

$$b_{-i} = \frac{\rho_i^{-1}\sigma_{\theta_i}^2\sigma_{\chi_i^*}^2}{(\sigma_{u_{-i}}^2(1-\phi_{-i})(\sigma_{\theta_i}^2+\sigma_{\chi_i^*}^2)+\sigma_{\theta_i}^2\sigma_{\chi_i^*}^2)} = \frac{\rho_i^{-1}(1-\psi_i^*)\kappa_{-i}}{(1-\phi_{-i})(1-\kappa_{-i})+(1-\psi_i^*)\kappa_{-i}}, \tag{A9}$$

$$c_{-i} = -\frac{\rho_i^{-1}\sigma_{\theta_i}^2\sigma_{\chi^*}^2\phi_{-i}}{\sigma_{u_{-i}}^2(1-\phi_{-i})(\sigma_{\theta_i}^2+\sigma_{\chi_i^*}^2)+\sigma_{\theta_i}^2\sigma_{\chi_i^*}^2\sigma_{u_{-i}}^2} = -\frac{\rho_i^{-1}(1-\psi_i^*)\phi_{-i}\kappa_{-i}}{(1-\phi_{-i})(1-\kappa_{-i})+(1-\psi_i^*)\kappa_{-i}}, \tag{A10}$$

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

Special cases. Four special cases are of interest (cases 3 and 4 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 Equations (A9) and (A10), 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 Equations (A9) and (A10), 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 $b_{-i}\neq 0$ (see Equation (A9)). Moreover, the sign of b_{-i} is the same as the covariance between firm i's fundamentals and its peers' fundamentals, that is, ρ_i. If, in addition, firm i's manager is informed about the noise in her peers' stock price then $\phi_{-i}>0$ and therefore $c_{-i}\neq 0$ (see Equation (A10)). Last, $c_{-i}=-\phi_{-i}b_{-i}$. Thus, b_{-i} and c_{-i} have opposite signs

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, that is, $\sigma_{\eta_{-i}}=0$. In this case, we deduce from Equations (A9) and (A10) that $b_{-i}=1$ and $c_{-i}=-1$. Moreover, $a_i=b_i=c_i=0$. Thus, using Equation (A8), we deduce that $K_i^*=\theta_i$. It follows from Remark 1 that $\mathrm{E}(K_i^* \mid P_{-i}, P_i)=\mathrm{E}(\theta_i \mid P_{-i}, P_i)=$ $\frac{\tau_{u_i}}{\tau_{u_i}+\tau_{u_{-i}}+\tau_{\theta_i}}P_i + \frac{\rho_i^{-1}\tau_{u_{-i}}}{\tau_{u_i}+\tau_{u_{-i}}+\tau_{\theta_i}}P_{-i}$ where τ_{u_i} (resp., $\tau_{u_{-i}}$) is the inverse of the variance of u_i (resp., u_{-i}).

The signs and sizes of α_i and α_{-i}. We have, $\alpha_{-i}=b_{-i}+c_{-i}=(1-\phi_{-i})b_{-i}$ where the first equality is the definition of α_{-i} and the second follows from Equations (A9) and (A10). Using Equation (A9), we deduce that

$$\alpha_{-i} = \frac{\rho_i^{-1}(1-\phi_{-i})(1-\psi_i^*)\kappa_{-i}}{(1-\phi_{-i})(1-\kappa_{-i})+(1-\psi_i^*)\kappa_{-i}}. \tag{A11}$$

Thus, $\alpha_{-i}\neq 0$ is strictly different from zero if and only if (1) the manager's private signal is not perfect ($\psi_i^*<1$), (2) peers' stock prices are informative ($\kappa_{-i}>0$), and (3) the manager cannot perfectly filter out the noise in her peers' stock prices ($\phi_{-i}<1$). Moreover, the sign of α_{-i} is the same as the sign of ρ_i.

Symmetrically, we have $\alpha_i=b_i+c_i=(b_i^*+c_i^*)(1-\rho_i b_{-i})=(1-\phi_i)b_i^*(1-\rho_i b_{-i})$ where the first equality is the definition of α_i, the second follows from Equations (A5) and (A6), and the last from the expressions for b_i^* and c_i^*. As ϕ_i, b_i^*, b_{-i} and ρ_i belong to $[0,1]$, we deduce that $\alpha_i\geq 0$. Moreover, it is strictly positive if and only if (1) the manager's private signal is not perfect ($\psi_i^*<1$ so that $b_{-i}<1$), (2) firm i's stock price is informative ($\kappa_i>0$ so that $b_i^*>0$), and (3) the manager cannot perfectly filter out the noise in her firm's stock price ($\phi_i<1$).

Proof of Proposition 1

Using Equation (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:

$$E(K_i^* \,|\, P_i, u_i^o, P_{-i}, u_{-i}^o) = a_i E(\theta_i \,|\, P_i, u_i^o, P_{-i}, u_{-i}^o) + b_i P_i + c_i E(u_i \,|\, P_i, u_i^o, P_{-i}, u_{-i}^o)$$
$$+ b_{-i} P_{-i} + c_{-i} E(u_{-i} \,|\, P_i, P_{-i}, u_{-i}^o, u_i^o). \quad \text{(A12)}$$

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:

$$E(\theta_i \,|\, P_i, u_i^o, P_{-i}, u_{-i}^o) = E(\theta_i \,|\, P_i^*, P_{-i}^*) = \pi_i P_i^* + \delta_i P_{-i}^*, \quad \text{(A13)}$$

$$E(u_{-i} \,|\, P_i, u_i^o, P_{-i}, u_{-i}^o) = E(u_{-i}^{no} \,|\, P_i^*, P_{-i}^*) + u_{-i}^o = \pi_i' P_i^* + \delta_i' P_{-i}^* + u_{-i}^o, \quad \text{(A14)}$$

$$E(u_i \,|\, P_i, u_i^o, P_{-i}, u_{-i}^o) = E(u_i^{no} \,|\, P_i^*, P_{-i}^*) + u_i^o = \widehat{\pi}_i P_i^* + \widehat{\delta}_i P_{-i}^* + u_i^o. \quad \text{(A15)}$$

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

$$\pi_i = \frac{(1-\lambda_{-i})\sigma_{u_{-i}}^2 \sigma_{\theta_i}^2}{\sigma_{\theta_i}^2((1-\lambda_i)\sigma_{u_i}^2 + (1-\lambda_{-i})\sigma_{u_{-i}}^2) + (1-\lambda_i)(1-\lambda_{-i})\sigma_{u_{-i}}^2 \sigma_{u_i}^2},$$

$$\delta_i = \frac{\rho_i^{-1}(1-\lambda_i)\sigma_{u_i}^2 \sigma_{\theta_i}^2}{\sigma_{\theta_i}^2((1-\lambda_i)\sigma_{u_i}^2 + (1-\lambda_{-i})\sigma_{u_{-i}}^2) + (1-\lambda_i)(1-\lambda_{-i})\sigma_{u_{-i}}^2 \sigma_{u_i}^2},$$

$$\widehat{\delta}_i = -\delta_i$$

$$\widehat{\pi}_i = (1-\pi_i)$$

$$\delta_i' = (1-\rho_i \delta_i),$$

$$\pi_i' = -\rho_i \pi_i.$$

We deduce from Equations (A12), (A13), (A14), and (A15) that

$$E(K_i^* \,|\, P_i, u_i^o, P_{-i}, u_{-i}^o) = \gamma_i P_i^* + \alpha_i u_i^o + \gamma_{-i} P_{-i}^* + \alpha_{-i} u_{-i}^o, \quad \text{(A16)}$$

with

$$\gamma_i = (a_i \pi_i + b_i + c_i \widehat{\pi}_i + c_{-i} \pi_i'),$$

$$\alpha_i = b_i + c_i,$$

$$\gamma_{-i} = (a_i \delta_i + b_{-i} + c_i \widehat{\delta}_i + c_{-i} \delta_i')$$

$$\alpha_{-i} = b_{-i} + c_{-i}.$$

Consequently,

$$\gamma_{-i} - \alpha_{-i} = a_i \delta_i + c_i \widehat{\delta}_i - c_{-i}(1-\delta_i') = \delta_i (a_i - \rho_i c_{-i} - c_i),$$

where the last equality follows from the expressions for $\widehat{\delta}_i$ and δ_i'. The product $\rho_i c_{-i}$ is always positive because ρ_i and c_{-i} have opposite signs. Moreover $c_i < 0$. Thus, the term in parentheses in the last equation is positive and the sign of $\gamma_{-i} - \alpha_{-i}$ is the same as the sign of δ_i. We deduce from the expression for δ_i that δ_i has the same sign as ρ_i. We deduce that $\gamma_{-i} > \alpha_{-i} > 0$ when $\rho_i > 0$ and $\gamma_{-i} < \alpha_{-i} < 0$ when $\rho_i < 0$. Thus, $|\gamma_{-i}| > |\alpha_{-i}|$. A similar reasoning shows that $\gamma_i > \alpha_i$.

Last, let $\epsilon_i = K_i^* - E(K_i^* \,|\, P_i, u_i^o, P_{-i}, u_{-i}^o)$. By construction, ϵ_i is independent from P_i, u_i^o, P_{-i}, and u_{-i}^o. Moreover, we deduce from Equation (A16) and the definition of ϵ_i that

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

Appendix B

Table B.1
Variable definitions

Variable	Definition
$AnalystDiscount_i$	Average price discount identified by financial analysts covering the stock of firm i in a given year. Price discount is defined as target price (from I/B/E/S) over stock price (from CRSP) on recommendation date minus 1.
$AnalystFE_i$	Average forecast error by financial analysts covering the stock of firm i over the last 3 years. Forecast error is defined as the difference (in absolute value) between actual and predicted EPS (from I/B/E/S) scaled by the stock price of the firm (from CRSP) at the time of the forecast issue.
$AssetsCorrelation_i$	Correlation between the total assets of firm i and the total assets of peer firm $-i$ over the last 3 years. This correlation is estimated in the time series by regressing the (log-transformed) total assets of firm i at the end of each quarter (Compustat item atq) on the same variable for peer firm $-i$.
BPS_i	Measure of price informativeness developed by Bai, Philippon, and Savov (2016). BPS_i measures the ability of peers' stock prices to predict peers' future earnings. For each firm-year observation, we regress the 3-year forward-looking earnings (Compustat item ebit), scaled by current assets (Compustat item at) on Q in the cross-section of all peers of firm i, and include peers' current earnings (Compustat item ebit divided Compustat item at) as a control variable. BPS_i is the average regression coefficient on Q for firm i over the last 3 years.
$Capex/Assets_{i,d}$	Division capex scaled by the lagged total assets of the division. Divisions of firm i are defined by industry (e.g., Fama-French 49, SIC2, or NAICS3) based on the industry description provided by Compustat Segment (Compustat Segment item sics). Capex for division d of firm i are obtained by aggregating all segment capital expenditures (Compustat Segment item capxs) at the firm-division-year level. Likewise, total assets for division d of firm i are obtained by aggregating all segment assets (Compustat Segment item ats) at the firm-division-year level.
$Capex/PPE_i$	Capex (Compustat item capx) for firm i scaled by lagged Property, Plant and Equipment (Compustat item ppent).
$CDS\ Spread_i$	Average annual CDS spread of firm i from Markit.
$CEO\ Turnover_i$	Dummy variable equal to 1 if the CEO of firm i in Execucomp changes and 0 otherwise.
CF/A_i	Income before extraordinary items (Compustat item ib) plus depreciation (Compustat item dp) of firm i, scaled by assets (Compustat item at).
$CommonOwnership_{i,-i}$	Overlap in mutual funds ownership between firm i and peer $-i$, computed as the cosine similarity between their mutual fund holdings structure. For each firm i in a given year, we define a $N \times 1$ vector v_i, where the n^{th} entry of v_i is equal to 1 if fund $n \in \{1,...,N\}$ holds shares of firm i and 0 if not. The ownership overlap between firms i and $-i$ is measured by the cosine similarity between v_i and v_{-i}. Data about mutual funds holdings are obtained from Thomson Mutual Funds Holdings.
$Debt\ Spread_i$	Average spread of firm i on new debt issues from Dealscan.
$Debt\text{-}Cons._i$	Text-based measure of debt-financing constraints for firm i from Hoberg and Maksimovic (2015) (higher score indicates greater constraints).
$Equity\text{-}Cons._i$	Text-based measure of equity-financing constraints for firm i from Hoberg and Maksimovic (2015) (higher score indicates greater constraints).
HHI_i	Herfindahl-Hirschman index based on sales (Compustat item sale), and computed over all peers of firm i in a given year.

(continued)

Table B.1 (continued)
Variable definitions

Variable	Definition
$InsiderCAR_i$	Average profitability of insiders' trades over the last 3 years. Trade profitability is equal to the 1-month market-adjusted return in absolute value following the trade by the insider. Insider trades include any open market stock transaction initiated by the top five executives of firm i from Thomson Insider Data.
$MarketShare_i$	Market Share of firm i computed as sales of firm i over total market sales in a given year. Total market sales is defined as the sum of all sales by peers $-i$ of firm i including firm i.
$MFHS_i$	Mutual Funds Hypothetical Sales. Measure of hypothetical sales of the stock of firm i in a given year by mutual funds experiencing large outflows. This measure is taken from Edmans, Goldstein, and Jiang (2012) and is constructed using data from CRSP and Thomson Mutual Fund Holdings. (We provide a detailed description of the construction of this variable in Appendix C.)
$NbPeers_i$	Number of peers of firm i in a given year.
$NetPurchases_i$	Number of shares bought minus number of shares sold by insiders of firm i. Insider trades include any open market stock transaction initiated by the top five executives of firm i from Thomson Insider Data.
$Payout_i$	Dividend (Compustat item divc) plus repurchases (Compustat item prstkc) scaled by total assets (Compustat item at) for firm i.
$Prob(Acquirer)_{-i}$	Fraction of the peers of firm i that make an acquisition over the next 3 years and zero if not. Acquisitions are identified using M&A data from SDC.
$Prob(Target)_i$	Dummy variable equal to 1 if firm i receives a takeover bid in a given year and 0 if not. Takeover bids are identified using M&A data from SDC.
$Prob(Target)_{-i}$	Fraction of the peers of firm i that receive a takeover bid over the next 3 years and zero if not. Takeover bids are identified using M&A data from SDC.
Q_i^*	Error term $\hat{\upsilon}_i$ estimated from specification (8) corresponding to the component of firm i's stock price that is unexplained by mutual fund hypothetical sales.
Q_i	Book value of assets (Compustat item at) - Book value of equity (Compustat item ceq) + Market value of equity (Compustat item cshomutiplied by Compustat item prcc), scaled by book value of assets (Compustat item at) of firm i.
$SalesCorrelation_i$	Correlation between the sales of firm i and the sales of peer firm $-i$ over the last 3 years. This correlation is estimated in the time series by regressing the (log-transformed) quarterly sales of firm i (Compustat item saleq) on the same (log-transformed) variable for peer firm $-i$.
$SecurityIssue_i$	Equity issue (Compustat item sstk) plus Debt issue (Compustat item dltis) scaled by total assets (Compustat item at) for firm i.
$Size_i$	Logarithm of the book value of assets (Compustat item at) of firm i.
RPE_i	Dummy variable equal to 1 if firm i operates in an industry in which relative performance evaluation is more likely to be used. For each industry-year, we estimate whether CEO compensation is sensitive to the stock return of industry peers, after controlling for the stock return and size of firm i. We define an industry as being an industry in which RPE is more likely to be the common practice when CEO compensation from Execucomp is negatively related with peers' stock returns.

Appendix C. Constructing 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 U.S. funds that are not specialized in a given industry using CRSP mutual funds data. For every fund, CRSP reports the monthly return and the Total Net Asset (TNA) by asset class. The average return of fund j in month m of year t is given by

$$Return_{j,m,t} = \frac{\sum_k (TNA_{k,j,m,t} \times Return_{k,j,m,t})}{\sum_k TNA_{k,j,m,t}}, \tag{C1}$$

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

$$Flow_{j,q,t} = \frac{TNA_{j,q,t} - TNA_{j,q-1,t} \times (1 + Return_{j,q,t})}{TNA_{j,q-1,t}}. \tag{C2}$$

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 U.S. 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

$$SHARES_{i,j,q,t} \times PRC_{i,q,t}, \tag{C3}$$

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

$$MFHS^{dollars}_{i,q,t} = \sum_j (Flow_{j,q,t} \times SHARES_{j,i,q-1,t} \times PRC_{i,q-1,t}). \tag{C4}$$

This variable corresponds to the hypothetical net selling of stock i, in dollar, by all mutual funds subject to extreme outflows (outflow is greater than 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

$$MFHS_{i,t} = \sum_{q=1}^{q=4} \frac{\sum_j (Flow_{j,q,t} \times SHARES_{j,i,q-1,t} \times PRC_{i,q-1,t})}{VOL_{i,q,t}}. \tag{C5}$$

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