Learning from Peers' Stock Prices and Corporate Investment[*]

Thierry Foucault[†]
(HEC Paris)

Laurent Frésard
(University of Maryland)

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Abstract

Peers' valuation matters for firms' investment: a one standard deviation increase in peers' valuation is associated with a 5.9% increase in corporate investment. This association is stronger when a firm's stock price informativeness is lower or when its managers appear less informed. Also, the sensitivity of a firm's investment to its stock price is lower when its peers' stock prices informativeness is higher or when demands for its products and its peers' products are more correlated. Furthermore the sensitivity of firms' investment to their peers' valuation drops significantly after going public. These findings are uniquely predicted by a model in which managers learn information from their peers' valuation.

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1. Introduction

Firms' managers, financial analysts, bankers, or investment professionals often rely on price "multiples" of peer firms (e.g., price-to-book or price-to-earnings ratios) to value new investments. For instance, survey evidence indicates that corporate executives use peers' valuation for capital budgeting decisions (see Graham and Harvey (2001)). Hence, one expects firms' investment to be influenced by the market valuation (stock price) of their peers. Whether and why this influence exists has not received much attention, however. In this article, we examine these questions.

Specifically, we test the hypothesis that the market valuation of a firm's peers influences its investment because this valuation informs managers about the firm's growth opportunities, complementing thereby other information available to managers, such as the firm's own stock price.[1] For instance, managers might learn additional information about growth opportunities in a particular activity from stock prices of firms focused on this activity.

If managers use their peers' valuation to make investment decisions then firms' investment and their peers' valuation should covary. Evidence thereof is however insufficient to conclude that managers learn information from peers' stock prices since stock prices and investment can covary due to unobserved factors. To address this problem, we rely on theory.

We consider a simple model in which peers' valuation complements managers' knowledge about their investment opportunities.[2] In this model, a firm sells a product for which demand is uncertain and correlated with the demand for another firm's product (its peer).[3] The firm's manager must decide whether to expand production capacity or not. This growth opportunity has a positive net present value only if future demand for the firm's product is strong enough.

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[1] Subrahmanyam and Titman (1999) argue that stock prices are particularly useful to managers because they aggregate investors' dispersed signals about future product demand. This is the case for peers' stock prices since product demands for related firms are affected by common shocks (e.g., Menzly and Ozbas (2010) show that firms' Return on Assets (ROAs) are positively correlated with related firms' ROAs).

[2] Existing models in which firms learn from stock prices have focused on the case in which firms learn from their own stock prices, not the case in which they also learn from their peers (see, for instance, Bresnahan, Milgrom; and Paul, 1992; Dow and Gorton, 1997; Subrahmanyam and Titman, 1999; Goldstein and Guembel, 2008; Foucault and Gehrig, 2008; Dow, Goldstein, and Guembel, 2011; and Edmans, Goldstein, and Jiang, 2013). See Bond, Edmans, and Goldstein, (2012) for an excellent survey of this literature.

[3] Peers are not necessarily competing firms. Firms can be exposed to common demand shocks because they are vertically related (suppliers/customers firms) or because their products are complements. For instance, if the demand for computer hardware is strong, the demand for softwares is likely to be strong as well.

As investors trade on private information about future demand, the firm's stock price and its peer's stock price provide signals to the manager, in addition to his own private information, about the net present value of the growth opportunity. We compare three different scenarios: (i) the manager ignores stock market information ("no managerial learning"); (ii) the manager only relies on his own stock price ("narrow managerial learning"); and (iii) the manager uses the information contained in each stock price ("learning from peers").

When the manager ignores stock prices, the firm's investment and stock prices covary because the manager's private signal and investors' signals are correlated. This "correlated information" channel also operates when the manager *learns* information from stock prices. However, in this case, it is supplemented by the fact that stock prices *influence* the manager's decision. Thus, in each scenario, we split the covariance between the investment of a firm and (a) its own stock price or (b) its peer stock price into two parts: one due to the correlated information channel and another one due to the learning channel. We exploit the fact that some firms' characteristics affect differently these two parts to develop null hypotheses specific to the learning from peers scenario.

Consider first the informativeness of a firm's *own* stock price. If the firm's manager ignores the information in stock prices, this informativeness does *not* affect the covariation between the firm's investment and its *peer* stock price. If instead the firm's manager learns information from stock prices then an increase in the firm's own stock price informativeness reduces the sensitivity of its investment to its peer stock price (prediction 1). Indeed, as the signal conveyed by its own stock price becomes more informative, the manager's beliefs are less influenced by its peer stock price and therefore his investment decision is less sensitive to this price.

Symmetrically, an increase in the informativeness of its *peer* stock price reduces the sensitivity of a firm's investment to its *own* stock price if the manager learns information from its peer stock price (prediction 2), but not otherwise. The same prediction holds for an increase in the correlation of the fundamentals of a firm and its peer (prediction 3) because, other things equal, this increase strengthens the informativeness of the peer stock price about the firm's future cash-flows.

An increase in the quality of the manager's private information implies that (i) his investment decision becomes more correlated with investors' private information, and (ii) his belief about future demand is less influenced by stock prices. The first effect strengthens the correlated information channel while the second dampens the learning channel. In the absence of learning, only the first effect operates. Thus, the sensitivity of investment to stock prices increases when the quality of managerial information improves. In contrast, with learning, an improvement in managerial information always reduces the sensitivity of a firm's investment to its *peer* stock price (prediction 4) because, for this price, effect (ii) dominates. This reduction however indirectly reinforces the correlation between a firm's investment and its own stock prices (effect (i)), especially when its peer stock price informativeness is large. For this reason, with learning from peers, the effect of the quality of managerial information on the sensitivity of a firm's investment to its own stock price switches from being negative (effect (ii) dominates) to being positive (effect (i) dominates) when the informativeness of the firm's peer stock price is high enough (prediction 5).

In sum, the model generates five predictions that only hold if managers learn information from their peer stock price. The learning from peers hypothesis has other implications but these hold even if managers do *not* learn from prices. For instance, the sensitivity of a firm's investment to its peer stock price increases with the informativeness of this price *whether or not* managers learn from stock prices because a more informative peer stock price strengthens both channels of covariation between investment and stock prices.

Thus, the model is critical to weed out predictions that are specific to the learning from peers hypothesis from those that are not. The former predictions naturally form the backbone of our empirical strategy. We test them on a large sample of U.S. firms. The peers of a given firm are defined as firms in its industry according to the Text-based Network Industry Classification (TNIC) developed by Hoberg and Phillips (2011). This classification is based on firms' products description in their annual 10Ks (from 1996 to 2008). Hence, a firm and its peers according to this classification are likely to be exposed to correlated demand shocks, as assumed in our model.

We find that firms' investment is positively and significantly related to their peers' valuation,

proxied by their Tobin's Q, after controlling for their own valuation and other characteristics.[4] The economic magnitude of this correlation is substantial: A one standard deviation increase in peers' valuation is associated with a 5.9% increase in corporate investment, about 15% of the average level of investment in our sample. Furthermore, the sensitivity of firms' investment to their peers' valuation is about half the sensitivity to their own valuation. Notably, the sensitivity of a firm's investment to a peer's valuation disappears once the firm and its peer stop operating in the same product space. In addition, the investment of a firm becomes sensitive to its peer's valuation *before* this peer actually enters into its TNIC industry. As there is often a delay between the development of a product and the product launch, this "advanced sensitivity" effect might reflect managers' decision to develop new products after learning about their profitability from incumbent firms' stock prices.

Importantly, we find empirical support for the five implications specific to the "learning from peers" hypothesis. First, a firm's investment is *less* sensitive to its peers' valuation when its own stock price is more informative.[5] The economic magnitude of this effect is large: for the average firm, a one standard deviation increase in stock price informativeness reduces the sensitivity of its investment to a one standard deviation shock to its peer valuation by 1.6%. Symmetrically, a firm's investment is *less* sensitive to its own Tobin's Q when its peers' valuations are more informative. In addition, and again as uniquely predicted by the learning from peers hypothesis, the sensitivity of a firm's investment to its own Tobin's Q *increases* when its demand shocks are less likely to be correlated with those of its peers.

We also study the role of managerial information using the trading activity of firms' insiders and the profitability of their trades as proxies for the quality of managers' information. As predicted, the investment of a firm is more sensitive to its peers' valuation when its managers appear less informed. In addition, the effect of the quality of managerial information on the sensitivity of a firm's investment switches from being negative to positive when its peers' stock price informativeness is large enough.

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[4]Findings are qualitatively similar if we measure firms' valuation with price-earnings ratio rather than Tobin's Q.

[5]We use a firms' specific return variation as proxy for the level of informed trading in a stock (as, for instance, in Durnev, Morck, and Yeung 2004; Chen, Goldstein and Jiang, 2007; and Bakke and Whited, 2010).

Finally, we focus on firms that go public during our sample period. Before being public, these firms cannot learn information from their stock price. Hence, their IPO represents a positive shock to their stock price informativeness. Thus, it dampens the learning channel for the covariation between a firm's investment and its peers' stock prices and strengthens the correlated learning channel (if managers at least learn from their own stock price). Our model then predicts that the sensitivity of a firm's investment to its peer's valuation should *decrease* after an IPO if managers use information from peer stock prices. Otherwise, this sensitivity should either remain unchanged (if managers do not learn from stock prices), or increase if managers only learn from their own stock price. Empirically, we find that the investment of private firms is highly sensitive to their public peers' valuation prior to their IPO. However, this sensitivity drops significantly once these firms become public, as uniquely predicted by the learning from peers hypothesis.

The learning hypothesis implies that stock prices have a *causal* effect on corporate investment. We do not seek to identify this effect. In fact, according to our model, the sensitivity of invest-ment to stock prices should stem both from the learning and the correlated information channels. Instead, our strategy is to test whether cross-sectional predictions – unique to the learning hy-pothesis – about the sensitivity of investment to stock prices hold in the data. This approach is similar in spirit to Chen, Goldstein, and Jiang (2007) but our focus on peer stock prices is new. This focus is useful because, as our model shows, the "learning from peers" scenario generates more predictions, and therefore more ways to reject the learning hypothesis, than the "narrow managerial learning" scenario. Ozoguz and Rebello (2013) confirm, for a different set of firms, the positive relationship between investment and peers' valuation found in our paper. They also find that this relationship is stronger when peer's valuation is more informative (as predicted in all scenarios by our model) and that it varies according to firms' operating environment.

Overall, our findings indicate that peers' valuations matter in shaping the investment behavior of firms. Thus, they complement the growing empirical literature on the real effects of financial markets.[6] They also add to the literature on the role of peers in firms' decision making (e.g.,

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[6]See for instance Durnev, Morck, and Yeung (2004), Luo (2005), Chen, Goldstein, and Jiang (2007), Fang, Noe, and Tice (2009), Bakke and Whited (2010), Ferreira, Ferreira, and Raposo (2011), Edmans, Goldstein, and Jiang (2012), or Foucault and Frésard (2012). See Bond, Edmans, and Goldstein for a survey.

Gilbert and Lieberman, 1987; Leary and Roberts, 2012; and Hoberg and Phillips 2011). Fracassi (2012) and Dougal, Parsons, and Titman (2012) provide evidence of "peer effects" in investment decisions, that is, an influence of peers' investment on a firm's investment. Our paper does not attempt to identify such peer effects. It suggests, however, that investment decisions of related firms might be linked because they learn from each other stock prices.

The next section derives testable implications unique to the learning from peers hypothesis. In Section 3 we describe the data and discuss the methodology that we use to test these predictions. In Section 4 we present the empirical findings and we conclude in Section 5. Proofs of theoretical results are in the appendix.

2.   Hypotheses Development

2.1.   Model

We consider two firms A and B. Products demands and cash-flows are realized at date 3. At date 2, before knowing the demand for its product, firm A can expand its production capacity or not. At date 1, investors trade shares of firms A and B at prices p_{A1} and p_{B1}. Figure 1 recaps the timing of the model.

[Insert Figure 1 about here]

Firms' cash flows. At date 3, demand d_j for the product of firm j can be High (H) or Low (L) with equal probabilities. Firms' demands share a common factor, that is,

$$\Pr(d_A = H \,|d_B = H\,) = \Pr(d_B = H\,|d_A = H\,) = \rho, \tag{1}$$

where $\rho \neq \frac{1}{2}$.

The cash flow of firm B at date 3, θ_B, is θ_B^H if demand for its product is high and θ_B^L ($< \theta_B^H$) otherwise. The cash flow of firm A is equal to the cash-flow of its assets in place plus the cash-flow of its growth opportunity if the firm invests (expands its production capacity). Specifically, when

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demand for firm A's product is $j \in \{H, L\}$, its cash-flow at date 3 is $\theta_A^j + I \times \Sigma_j$, where $I = 1$ if firm A invests at date 2 ($I = 0$ otherwise) and Σ_j is the incremental revenues for firm A if it invests. As in Goldstein and Guembel (2008), the investment outlay for capacity expansion is indivisible and equal to K. Thus, the net present value, NPV, of firm A's investment is:

$$
NPV = \begin{cases}
\Sigma_H - K & \text{if } d_A = H, \\
\\
\Sigma_L - K & \text{if } d_A = L.
\end{cases}
\tag{2}
$$

We assume that $\Sigma_H > K > \Sigma_L$, that is, expanding production capacity is a positive NPV project if and only if the demand for firm A's product is high. To simplify, and without affecting the results, we set $\Sigma_L = 0$.

The manager of firm A. At date 2, the manager of firm A observes stock prices realized at date 1. Moreover, he observes a signal $s_m \in \{H, L, \varnothing\}$ about the payoff of his growth opportunity. Specifically, when $d_A = j$, $s_m = j$ with probability γ or $s_m = \varnothing$ with probability $(1 - \gamma)$, where $\varnothing$ is the null signal corresponding to no signal. Thus, γ measures the likelihood that the manager has full information about the payoff of his growth opportunity. We refer to s_m as "direct managerial information" and to γ as the quality of this information.

At date 2, for a given investment decision, I, the expected value of firm A is:

$$
V_A(I) = \mathrm{E}(\theta_A \,|\, s_m, p_{A1}, p_{B1}) + I \times \mathrm{E}(NPV \,|\, s_m, p_{A1}, p_{B1}),
\tag{3}
$$

where the first term on the R.H.S is the expected cash-flow of assets in place and the second term is the expected NPV of the growth opportunity, conditional on the information available to the manager at date 2. The firm faces no financing constraints and the manager chooses the investment policy that maximizes $V_A(I)$. We denote by $I^*(s_m, p_{A1}, p_{B1})$ the optimal investment policy. We assume that, unconditionally, the expected NPV of the growth opportunity is negative. That is:

$$
\text{A.1}: \mathrm{E}(NPV) = K\left(\frac{R_H}{2} - 1\right) \leq 0,
\tag{4}
$$

where $R_H = \frac{\Sigma_H}{K}$. Hence if the manager had no information, he would not invest at date 2. Moreover we assume that the correlation in demands for both firms is such that if the manager of firm A learns that demand for firm B is high then he invests. That is:

$$\text{A.2: } \mathrm{E}(NPV \,|d_B = H\,) = K(\rho R_H - 1) > 0, \tag{5}$$

or, $\rho > \frac{1}{R_H} > \frac{1}{2}$ (the second inequality follows from A.1). We relax assumptions A.1 and A.2 in Section 2.3.4.

The Stock Market. There are three types of investors in the stock market: (i) a continuum of risk-neutral speculators, (ii) liquidity traders with an aggregate demand z_j, uniformly distributed over $[-1, 1]$, for firm j, and (iii) risk neutral dealers.

Each speculator receives a signal $\widehat{s}_{ij} \in \{H, L, \varnothing\}$. Subrahmanyam and Titman (1999) argue that individuals are well placed (e.g., through their consumption experience) to obtain information not readily available to managers about demand for a firm's products. They view this information as being obtained serendipitously, "that is, by luck and without cost" and treat the number of investors with serendipitous information as exogenous.[7] Following their approach, we assume that a fraction π_j of speculators receives a perfect signal (i.e., $\widehat{s}_{ij} = d_j$) about the future demand for the product of firm $j \in \{A, B\}$. Remaining speculators observe no signal about the future demand of firm j: $\widehat{s}_{ij} = \varnothing$ for these speculators.

After receiving her signal on stock j, a speculator can choose to trade one share of this stock or not.[8] A speculator with a perfect signal on stock j is also imperfectly informed about the

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[7]The results go through even when the fraction of speculators is endogenous and determined so that speculators' expected profit is equal to the cost of information acquisition. Results are unchanged because the fraction of speculators acquiring information is not zero in equilibrium (if the cost of information acquisition is not too large) and therefore prices convey information to managers even when the fraction of informed investors is endogenous.

[8]As there is a continuum of speculators, they act competitively and therefore, in choosing their order, they ignore their impact on prices. For this reason, we restrict a speculator's trade size to one share. An alternative specification is to assume that, in each stock, there is one liquidity trader and one monopolistic speculator (informed with probability π_j), as in Goldstein and Guembel (2008). If the liquidity trader buys one share, sells one share or does nothing with equal probabilities, the speculator optimally chooses to buy (sell) one share when he receives good (bad) news in order to avoid detection by dealers. This specification delivers qualitatively the same results as the specification chosen here. The presentation of the equilibrium is more complex however. Indeed, with our specification, equilibrium prices are either non informative or fully revealing (see Propositions 1 and 2 below). In contrast, with a monopolistic speculator, prices can also be partially revealing, making the analysis more involved without adding new insights for our purposes.

payoff of the other stock since $\rho \neq \frac{1}{2}$. Thus, an informed speculator might want to trade both assets. To simplify the analysis, we assume that a speculator only trades a stock for which she receives perfect information.[9] We denote by $x_{ij}(\widehat{s}_{ij}) \in \{-1, 0, +1\}$ the demand of speculator i for stock j given her signal for this stock.

Let f_j be the order flow – the sum of speculators and liquidity traders' net demand – for stock j:

$$f_j = z_j + x_j, \tag{6}$$

where $x_j = \int_0^1 x_{ij}(\widehat{s}_{ij}) di$ is speculators' aggregate demand of stock j. As in Kyle (1985), order flow in each stock is absorbed by dealers at a price such that they just break even given the information contained in the order flow. That is,

$$p_{A1}(f_A) = \mathrm{E}(V_A(I^*) \mid f_A), \quad \text{and} \quad p_{B1}(f_B) = \mathrm{E}(\theta_B \mid f_B). \tag{7}$$

Hence, using the Law of Iterated Expectations, the stock prices of firms A and B at date 0 are $p_{A0}(I^*) = \mathrm{E}(V_A(I^*))$ and $p_{B0}(f_B) = \mathrm{E}(\theta_B)$. The change in price of stock j from date 0 to date 1 is denoted by $\Delta p_j = p_{j1} - p_{j0}$.

The stock price of firm A depends on the manager's optimal investment policy, $I^*(s_m, p_{A1}, p_{B1})$, which itself depends on the stock price of firm A. Thus, in equilibrium, the investment of firm A and its stock price are jointly determined. Formally, a stock market equilibrium for firm A is a set $\{x_A^*(\cdot), p_{A1}^*(\cdot), I^*(\cdot)\}$ such that (i) the trading strategy $x_A^*(\cdot)$ maximizes the expected profit for each speculator, (ii) the investment policy $I^*(\cdot)$ maximizes the expected value of firm A, $V_A(I)$, at date 2, given dealers' pricing rule $p_{A1}^*(\cdot)$, and (iii) the pricing rule $p_{A1}^*(\cdot)$ solves (7) given that agents behave according to $x_A^*(\cdot)$, and $I^*(\cdot)$. The definition of a stock market equilibrium for firm B is similar, except that $I^*(\cdot)$ plays no role.

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[9]This behavior is optimal for speculators if there is a fixed cost of trading per asset (the formal proof is available upon request). Indeed, when $\rho < 1$, speculators with perfect information on only stock A would trade sometimes in the wrong direction if they trade stock B because their signal about the payoff of stock B is not perfect. Thus, their expected profit is smaller than the expected profit of speculators with perfect information on stock B. This is sufficient to crowd out speculators who only have perfect information on stock A from the market for stock B (and vice versa) when there is a fixed cost of trading per stock.

2.2. Investment decisions and stock prices

In this section, we solve for stock prices and the optimal investment policy of firm A in equilibrium. This step is key for deriving our empirical implications (see Section 2.3).

Proposition 1 : *The stock market equilibrium for firm B is as follows:*

1. *A speculator buys stock B when she knows that demand for firm B's product is high $(x^*_{iB}(H) = +1)$, sells it when she knows that demand for firm B's product is low $(x^*_{iB}(L) = -1)$, and does not trade otherwise $(x^*_{iB}(\varnothing) = 0)$.*

2. *The stock price of firm B at date 1, $p^*_{B1}(f_B)$, is an increasing step function of investors' net demand for this stock, f_B. Specifically, $p^*_{B1}(f_B)$, is equal to θ^H_B when $f_B > 1 - \pi_B$; $E(\theta_B)$ when $-1 + \pi_B \leq f_B \leq 1 - \pi_B$; and θ^L_B when $f_B < -1 + \pi_B$.*

If investors' net demand is relatively strong $(f_B \geq 1 - \pi_B)$, dealers infer that speculators have received a good signal about the demand for firm B's product and the price of stock B is therefore θ^H_B. If instead, investors' net demand for stock B is relatively low $(f_B \leq -1 + \pi_B)$, dealers infer that speculators have received a bad signal and the price of stock B is θ^L_B. Intermediate realizations for investors' net demand $(-1 + \pi_B \leq f_B \leq 1 - \pi_B)$ are not informative. Hence, for these realizations, the price of stock B is just equal to the unconditional expected cash-flow of this firm.

Remember that $\Delta p_B = p_B - E(\theta_B)$ is the change in the price of stock B from dates 0 to 1. Proposition 1 implies:

$$\frac{\Pr(\Delta p_B \geq 0 \,|\, d_A = H)}{\Pr(\Delta p_B \leq 0 \,|\, d_A = H)} = \frac{\rho + (1 - \rho)(1 - \pi_B)}{\rho(1 - \pi_B) + (1 - \rho)} = \frac{1 - (1 - \rho)\pi_B}{1 - \rho\pi_B} \quad . \tag{8}$$

As $\rho > \frac{1}{2}$, this likelihood ratio is strictly greater than 1 and increases in π_B or ρ. That is, as π_B or ρ increase, the price of stock B is more likely to increase (decrease) from date 0 to date 1 when the demand for the product of firm A is high (low). Hence, the change in the price of stock B from dates 0 to 1 is informative about the demand for firm A's product and its informativeness increases with π_B or ρ.

As explained previously, speculators' trading strategy in stock A, the price of this stock, and the investment policy of firm A are jointly determined in equilibrium. Hence, in the next proposition, we describe both the equilibrium in the market for stock A at date 1 and the optimal investment policy of this firm at date 2. Let denote $p_A^H = \theta_A^H + (\Sigma_H - K)$; $p_A^M = \mathrm{E}(\theta_A) + \frac{1}{2}(\gamma + (1 - \gamma)\pi_B)(\Sigma_H - K)$; and $p_A^L = \theta_A^L$. Note that $p_A^H > p_A^M > p_A^L$.

Proposition 2 : *There is a stock market equilibrium for firm A in which:*

1. *A speculator buys stock A when she knows that demand for firm A's product is high ($x_{iA}^*(H) = +1$), sells it when she knows that demand for firm A's product is low ($x_{iA}^*(L) = -1$), and does not trade otherwise ($x_{iA}^*(\varnothing) = 0$)*

2. *The stock price of firm A at date 1, $p_{A1}^*(f_A)$, is an increasing step function of investors' net demand for this stock, f_A. Specifically, $p_{A1}^*(f_A)$ is equal to p_A^H when $f_A > 1 - \pi_A$; p_A^M when $-1 + \pi_A \leq f_A \leq 1 - \pi_A$; and p_A^L when $f_A < -1 + \pi_A$.*

3. *When the manager of firm A receives managerial information at date 2, he optimally invests if his signal indicates a high demand at date 3 ($I^* = 1$ if $s_m = H$). If the manager of firm A does not receive managerial information ($s_m = \varnothing$), he optimally invests if (i) the stock price of firm A is p_A^H or (ii) the stock price of firm B is θ_B^H and the stock price of firm A is p_A^M. In all other cases, the manager optimally chooses not to invest at date 2.*

As for stock B, investors' net demand for stock A, f_A, affects its stock price because this demand is informative about the future demand for firm A's product. Moreover, as for stock B, the informativeness of the stock price of firm A about future demand for this firm increases with the proportion of informed speculators in stock A, π_A.[10]

Equation (7) and the second part of Proposition 2 imply that:

$$p_{A0}(I^*) = \mathrm{E}(\mathrm{E}(V_A(I^*) \mid f_A)) = \mathrm{E}(p_{A1}(f_A)) = \mathrm{E}(\theta_A) + \frac{1}{2}(\gamma + (1 - \gamma)(\pi_A + \pi_B))(\Sigma_H - K), \quad (9)$$

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[10] In our model, speculators' private information is firm specific but it contains a market-wide component if $\rho \neq \frac{1}{2}$. The market wide component is a source of correlation in informed investors' trades across stocks. Indeed, Propositions 1 and 2 imply that $cov(x_A^*, x_B^*) = (2\rho - 1)\pi_A \pi_B$, which is different from zero if $\rho \neq \frac{1}{2}$. This is consistent with empirical findings in Albuquerque, De Francisco, and Marques (2008).

where the first term on the R.H.S ($E(\theta_A)$) is the unconditional expected value of firm A's assets in place and the second term is the unconditional expected value of its growth opportunity. If $-1 + \pi_A \leq f_A \leq 1 - \pi_A$, the stock price of firm A is not informative, which reduces the likelihood that the firm will invest. For this reason, we have $p_A^L \leq p_A^M \leq p_{A0}(I^*) \leq p_A^H$.

We deduce from these inequalities and the last part of Proposition 2 that when the manager does not receive direct managerial information ($s_m = \varnothing$), he invests if and only if (a) the change in price of stock A (from date 0 to date 1), Δp_A, is positive *or* (b) the change in price of stock B is positive *and* the change in price of stock A is moderately negative ($\Delta p_A = p_A^M - p_{A0}(I^*)$). Actually, an increase in the stock price of firm B is a good signal about future demand for the product sold by firm A, that compensates the mildly bad signal sent by a moderate drop in price for stock A. Thus, the investment policy of firm A is determined both by its own stock price and the price of stock B, as Figure 2 shows.

[Insert Figure 2 about here]

The stock market equilibrium for firm A is not unique because, as usual in signaling games, the manager's posterior belief about the payoff of the investment opportunity can be arbitrarily chosen for prices out-of-the equilibrium path for stock A. Indeed prices out-of-the equilibrium path have a zero probability of occurrence and therefore the manager's belief conditional on these prices cannot be computed by Bayes rule. For these prices we have assumed that the manager's belief was set at its prior belief, which explains why for prices different from p_A^L, p_A^M, and p_A^H, the manager does not invest. The equilibrium considered in Proposition 2 would be the unique equilibrium if we assumed that, in addition to stock prices, the manager could also directly observe the order flow in stock A. It is therefore natural to focus the attention on this equilibrium.

2.3. Empirical implications

We now use the characterization of equilibrium stock prices for firms A and B and the optimal investment policy of firm A to derive predictions that we test in the next section. If managers

use information from stock prices, investment and stock prices should covary because stock prices are determinants of investment, as we have just shown. However, investment and stock prices are correlated even without managerial learning because stock prices are correlated with managers' private information about their growth opportunities (s_m in our model). Thus, evidence of covariation between a firm's investment and its peers' stock price would only weakly support the learning from peers hypothesis.

To design stronger tests, we compare the effects of π_j, γ, and ρ on the covariance between investment and stock prices, $cov(I, p_j)$, in three different scenarios: (i) managers ignore stock market information; (ii) managers learn solely from their own stock price; and (iii) managers learn from their stock price and that of their peers.[11] In this way, we isolate effects that should only arise if managers learn information from their peers' stock prices. To simplify notations, in this section, we denote $\left(\theta_j^H - \theta_j^L \right)/2$ by σ_j and $\left(\sigma_A + \frac{\Sigma_H - K}{2} \right)$ by σ_A^H.

2.3.1. No managerial learning

First consider the case in which managers *ignore* the information contained in stock prices, either because they are always informed ($\gamma = 1$), or because they fail to realize that stock prices contain information. We focus on the latter case because it encompasses the first as a special case when $\gamma = 1$.

When the manager of firm A does not learn information from stock prices, his optimal investment policy just depends on his private information. Thus, he optimally invests if $s_m = H$ and does not invest if $s_m = L$ or $s_m = \varnothing$. The price of stock B is as given in Proposition 1 since it does not depend on the investment policy of firm A. In contrast, the equilibrium price of stock A differs from that in Proposition 2 since it depends on firm A's investment policy. We account for this in proving the next corollary.

Corollary 1 *(benchmark 1: no managerial learning) In the absence of managerial learning, the*

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[11] To simplify notations, we focus on the covariance between the investment decision (I) and stock prices. Results are identical for the covariance between the size of the investment, $K \times I$, and stock prices since $cov(KI, p_j) = K \times cov(I, p_j)$.

covariance between the price of stock B and the investment of firm A is:

$$cov_{No}(I, p_{B1}) = \frac{\gamma \pi_B (2\rho - 1) \sigma_B}{2}. \tag{10}$$

Hence, when $\rho \geq \frac{1}{2}$, this covariance is positive and it increases with (i) the quality of managerial information (γ), (ii) the fraction of informed speculators in stock B (π_B), and (iii) the correlation in demands for the products of firms A and B (ρ). Moreover the covariance between the price of stock A and the investment of firm A is also positive and equal to:

$$cov_{No}(I, p_{A1}) = \frac{\gamma \pi_A (\sigma_A + \frac{\gamma}{2}(\Sigma_H - K))}{2}. \tag{11}$$

Hence, this covariance increases with (i) the quality of managerial information (γ) and (ii) the fraction of informed speculators in stock A (π_A).

Even in the absence of managerial learning, the investment of firm A is correlated with its peer's stock price and its own stock price when $\pi_j > 0$. Actually, the signals received by the manager and the speculators are correlated and this link is sufficient to create a correlation between investment (which depends on the manager's signal) and stock prices (which reflect speculators' signals). We refer to this source of covariation between investment and stock prices as the "correlated information" channel. When investment and stock prices are related only through this channel, they covary more strongly when γ increases because this increase strengthens the correlation between the signals of the manager and the speculators.

2.3.2. Narrow managerial learning

We now consider the intermediate case in which the manager of firm A only pays attention to his own stock price ("narrow managerial learning"), either because the price of stock B is uninformative ($\pi_B = 0$) or because the manager of firm A does not realize that this price is informative. We focus on the latter case because it encompasses the former.

As in the previous case, the equilibrium in the market for stock B is given by Proposition 1.

The stock market equilibrium for firm A is identical to the case in which $\pi_B = 0$ in Proposition 2 since the manager behaves as if the price of stock B contains no information. Thus, the manager of firm A optimally invests if he knows that future demand is high ($s_m = H$) or if his stock price is high ($p_A = p_A^H$). Otherwise he does not invest. We obtain the following implication.

Corollary 2 (benchmark 2: narrow managerial learning). *When the manager of firm A only uses the information contained in the price of his stock, the covariance between the price of stock B and the investment of firm A is:*

$$cov_{Narrow}(I, p_{B1}) = cov_{No}(I, p_{B1}) + \frac{1}{2}(1 - \gamma)\pi_A\pi_B(2\rho - 1)\sigma_B. \tag{12}$$

Hence, it is positive if $\rho \geq \frac{1}{2}$. It increases with the fraction of informed speculators in firm A (π_A) and the effects of the other parameters (ρ, π_B and γ) on $cov(I, p_{B1})$ are as when the manager of firm A does not learn information from prices (Corollary 1). Moreover the covariance between the price of stock A and the investment of firm A is also positive and given by:

$$cov_{Narrow}(I, p_{A1}) = \underbrace{cov_{No}(I, p_{A1})}_{Correlated\ information} + \underbrace{\frac{1}{2}(2 - (1 - \gamma)\pi_A)\pi_A(1 - \gamma)\sigma_A^H}_{Learning\ from\ stock\ A\ only}. \tag{13}$$

Hence, it decreases with the quality of managerial information (γ) and the effect of π_A on $cov_{Narrow}(I, p_{A1})$ is as when the manager of firm A does not learn information from prices (Corollary 1).

With narrow managerial learning, the manager obtains an informative signal about future demand (either directly or from the stock market) with probability $\gamma + (1 - \gamma)\pi_A$, rather than just γ as in the case with no managerial learning. For this reason, when γ or π_A increase, his investment decision becomes more strongly correlated with the the future demand for firm B and therefore its peer stock price (first part of Corollary 2). Thus, with narrow managerial learning, the investment of a firm covaries more with the stock price of its peers when the quality of managerial information (γ) or the level of informed trading in the firm's stock (π_A) increase. Opposite predictions will hold when the manager also learns information from his peer's stock

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price (Corollary 3 below).

In addition, with narrow managerial learning, the investment of firm A covaries more strongly with its own stock price than in the case with no managerial learning ($cov_{Narrow}(I, p_{A1}) > cov_{No}(I, p_{A1})$). Actually, with narrow managerial learning, the stock price of firm A influences its manager's investment decision. This effect constitutes an additional source of covariation between investment and the firm's stock price captured by the second component in the expression for $cov_{Narrow}(I, p_{A1})$. This component, specific to the learning channel, decreases with γ because the manager puts less weight on the signal conveyed by his stock price when his private information is of higher quality. As a result, the net effect of an increase in the quality of managerial information on the covariance between the investment of firm A and its stock price is *negative* while the opposite prediction holds in the absence of managerial learning (Corollary 1).

2.3.3. Learning from peers' stock prices

Now, we turn to the more general case in which both the stock price of firm A and the stock price of firm B influence the investment decision of the manager of firm A, as described in Proposition 2.

Corollary 3 *In equilibrium, the covariance between the investment of firm A and the stock price of firm B is:*

$$cov_{Peer\ learning}(I, p_{B1}) = \underbrace{cov_{Narrow}(I, p_{B1})}_{Correlated\ information} + \underbrace{\frac{1}{2}(1 - \gamma)(1 - \pi_A)\pi_B\sigma_B}_{Learning\ from\ peers}. \tag{14}$$

Thus, it is positive since $cov_{Narrow}(I, p_{B1}) > 0$ when $\rho > \frac{1}{2}$. It increases in the fraction of informed speculators in stock B (π_B) while it decreases in (i) the likelihood that the manager of firm A receives direct managerial information, γ, and (ii) the fraction of informed speculators in stock A (π_A). Moreover the covariance between the price of stock A and the investment of firm

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A is:

$$cov_{Peer\ learning}(I, p_{A1}) = cov_{Narrow}(I, p_{A1}) - \underbrace{\frac{1}{2}(1 + (1-\gamma)(1-\pi_A))\pi_B\pi_A(1-\gamma)\sigma_A^H}_{Learning\ from\ peers}. \quad (15)$$

For all parameter values, the covariance between the investment of firm A and the stock price of firm A is positive. This covariance increases in (i) the fraction of informed speculators in stock A (π_A), and (ii) it decreases in the fraction of informed speculators in stock B (π_B). Moreover, it decreases in the likelihood that the manager of firm A receives managerial information, γ if $\pi_B < \widehat{\pi}_B$ and increases in this likelihood if $\pi_B > \widehat{\pi}_B$ where $\widehat{\pi}_B = \frac{2(1-\gamma)(1-\pi_A)}{1+2(1-\gamma)(1-\pi_A)}$.

As $(1-\gamma)(1-\pi_A)\pi_B \geq 0$, equation (14) implies that the investment of firm A and the stock price of firm B covary more strongly (relative to previous cases) when the manager of firm A learns from its peer's stock price. The reason is that, in this case, the stock price of firm B is a determinant of the manager's investment decision. This influence is reflected in the last term of equation (14).

When the manager learns from his peer stock price *and* his own stock price, the covariance between the price of stock B and the investment of firm A decreases with the fraction of informed speculators in firm A, π_A, and the quality of direct managerial information, γ. Thus, we obtain opposite predictions for the effects of γ or π_A on $cov(I, p_{B1})$ when the manager learns from its peer's stock price and when he does not. The reason is as follows. When he learns from all stock prices, the manager has three sources of information: (i) direct managerial information, (ii) his stock price, (iii) the stock price of its peer. As γ or π_A increase, the two first signals become more informative relative to the third. Hence, the manager relies relatively less on its peer stock price and as a result its investment covaries less with this price. This substitution effect is absent when the manager ignores the information contained in stock prices (no managerial learning) or when he only uses the information contained in his own stock price (narrow managerial learning).

As shown by equation (15), the covariation between the investment of firm A and its own stock price is equal to its level with narrow learning *minus* an additional component specific to

the learning from peers channel. As this second component is always positive, the learning from peers channel always dampens the covariation between the investment of firm A and its own stock price. Indeed, the stock price of firm B become another determinant of the investment of firm A when the manager learns from this price. As a result, the investment of firm A becomes less linked to its own stock price.

This dampening effect has two implications that only arise when the manager of firm A learns information from its peer's stock price. First, the covariance between the investment of firm A and its stock price declines when the level of informed trading *in stock B* (π_B) increases. Indeed, such an increase strengthens the dampening effect because an increase in the informativeness of the price of stock B leads the manager of firm A to rely more on this signal.

Second, the effect of the quality of direct managerial information, γ, on the covariance between the investment of firm A and its stock price switches from being negative to being positive when the level of informed trading in firm B becomes high enough (larger than $\widehat{\pi}_B$). When γ increases, the manager of firm A relies relatively less on (i) his own stock price and (ii) the stock price of its peer for his investment decision. As explained in Section 2.3.2, the first effect (the manager relies less on his own stock price) lowers the covariance between his investment and his own stock price. However, the second effect strengthens this covariance because it reduces the role of peer learning and therefore the dampening effect.[12] When $\pi_B < \widehat{\pi}_B$, the dampening effect is small and therefore the first effect dominates ($\frac{\partial cov_{Peer\ learning}(I,p_{A1})}{\partial \gamma} < 0$). In contrast, when $\pi_B > \widehat{\pi}_B$, the dampening effect is strong and the second effect dominates ($\frac{\partial cov_{Peer\ learning}(I,p_{A1})}{\partial \gamma} > 0$).

Chen, Goldstein, and Jiang (2007) find that the sensitivity of a firm' investment to its stock price is negatively related with a proxy for managerial information (see their Table 3). However, this relationship is not statistically significant in their sample. Corollary 3 suggests a possible explanation. The effect of managerial information on the investment-to-price sensitivity of a firm can be negative or positive depending on the level of informed trading in its peers' stocks. Hence, the unconditional effect (i.e., the average effect across peers with different π_B's) may well be zero. According to Corollary 3, a stronger test is to allow the effect of managerial information on

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[12] Formally, the first component in (15) increases in γ while the second decreases with γ and is zero when $\gamma = 1$.

the investment-to-price sensitivity to differ according to π_B. We carry out such a test in Section 4.3.2.

Last, an increase in the level of informed trading in stock A also reduces the dampening effect because it leads the manager of firm A to rely less on the price of stock B as a source of information. Thus, this increase results in a larger covariation between its investment and its stock price. This implication however is not specific to the learning from peers scenario (see Corollaries 1 and 2).

2.3.4. The role of correlation in firm demands and manager's belief about the project NPV

So far we have assumed that $\rho \geq 1/R^H$ (Assumption A.2). We now analyze the case in which $\rho < 1/R^H$. First, suppose that $\frac{1}{2} \leq \rho < 1/R^H$. In this case, demands for firms A and B remain positively correlated. However, the informativeness of the price of stock B about the demand for firm A's product is too small to influence the manager's investment decision.[13] Hence, this decision only depends on his own signal and his own stock price, as in the narrow managerial learning scenario. The only difference is that when $\frac{1}{2} \leq \rho < 1/R^H$, manager's inattention to its peer stock price is rational. Hence, when $\frac{1}{2} \leq \rho < 1/R^H$, the predictions of the model for π_A, π_B, and γ are given by Corollary 2.

Now, suppose that $\rho < 1 - 1/R^H < \frac{1}{2}$. This case is symmetric to the case $\rho > 1/R^H$: the demands for the products of both firms are negatively correlated. Thus, intuitively, a low (resp., high) realization of the stock price for firm B signals a strong (resp. low) demand for firm A. Accordingly, the covariance between the investment of firm A and the stock price of firm B is negative. However, *in absolute value*, this covariance is identical to that obtained when $\rho > 1/R^H$, for all cases considered so far. Furthermore, the expressions for the covariance between the investment of firm A and its stock price are also unchanged. Thus, the predictions derived in the previous sections still hold, except that for $cov(I, p_{B1})$, they apply to the absolute value of this variable. For brevity, we omit the proof of this result (available upon request).

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[13]Indeed, $\mathrm{E}(\Sigma_A \,|r_B > 0\,) = \mathrm{E}(\Sigma_A \,|d_B = H\,) = K(\rho R_H - 1) < 0$. Thus, even when the price of stock B reveals that the demand for product B is strong, the manager of firm A chooses not to invest. Thus, his decision cannot be influenced by the price of stock B.

When $1 - 1/R^H < \rho \leq \frac{1}{2}$, the price of stock B is not informative enough to influence the investment decision of firm A, as when $\frac{1}{2} \leq \rho < 1/R^H$. Thus, the predictions of the model regarding the effects of parameters π_A, π_B, and γ are given in Corollary 2, except that they again hold for $|cov(I, p_{B1})|$ rather than $cov(I, p_{B1})$.

Let $c(\rho) = |\rho - \frac{1}{2}|$. The higher is $c(\rho)$, the more correlated (positively or negatively) are the demands for the products of firms A and B. The previous discussion yields the following corollary about the effect of $c(\rho)$ on $cov(I, p_{A1})$ and $|cov(I, p_{B1})|$.

Corollary 4 *The covariance between the investment of firm A and its own stock price weakly declines in $c(\rho)$ if and only if the manager of firm A uses its peer stock price as a source of information. Otherwise this covariance does not depend on $c(\rho)$. In contrast, the absolute value of the covariance between the investment of firm A and the stock price of firm B increases in $c(\rho)$ whether or not the manager of firm A uses the stock price of firm B as a source of information.*

The first part of the corollary is again an implication of the dampening effect discussed in the previous section. When the manager of firm A uses information contained in its peer stock price (i.e., $c(\rho)$ large enough), his investment is relatively less driven by his own stock price than when he rationally ignores peer stock price (i.e., $c(\rho)$ low enough). Hence, the covariance between a firm's investment and its stock price becomes *smaller* when the correlation in firms' fundamentals becomes higher in absolute value, as claimed in the first part of Corollary 4. As this prediction is specific to the scenario in which managers learn from peer stock prices, it offers another way to test the learning from peers hypothesis. In contrast, in all cases, the covariance between the investment of firm A and the stock price of firm B increases in $c(\rho)$ because a larger $c(\rho)$ strengthens both the correlated information and the learning from peers parts of this covariance.

We have also assumed that the unconditional expected NPV of the firm's growth opportunity is negative (Assumption A.1). As Assumption A.2, this assumption is not necessary for our predictions. Indeed, the case in which the expected NPV of the growth opportunity is positive is symmetric to the case analyzed so far. That is, in the absence of information, the manager would invest but a low price for the stock price of firm A or firm B induces the manager not to

invest (or to disinvest) because low stock prices signal that demand for firm A's product is low. Thus, investment and peer stock prices co-vary positively even when the unconditional expected NPV of the project is positive.

2.4. Summary and Discussion

Table 1 summarizes the predictions of the model for the effects of π_j, γ, and ρ on the covariation between a firm's investment and stock prices. We highlight with an "$*$" the predictions that are unique to the case in which the manager learns from its peer stock price. These predictions provide null hypotheses specific to the scenario in which managers learn from their peers' market valuation and are therefore the focus of our empirical analysis.

[Insert Table 1 about here]

Two issues arise when we take the model to the data. First, empirically, we estimate the extent to which investment and stock prices covary by regressing investment on stock prices and controls for well-known determinants of investment (e.g., firm size or cash-flows). As a regression coefficient is a ratio of a covariance to a variance, one might wonder whether the predictions of the model are robust for such ratios (as the variance of stock prices also depends on π_j, γ, and ρ.) To address this issue, we use "standardized" stock prices $p_j^s = \frac{p_j}{sd(p_j)}$, where $sd(p_j)$ is the standard deviation of p_j, rather than raw stock prices in our tests. Indeed, $cov(I, p_j^s)/var(p_j^s) = cov(I, p_j^s)$ since $var(p_j^s) = 1$. In Appendix B, we show that all the predictions of Table 1 hold for $cov(I, p_B^s)$ (instead of $cov(I, p_B)$). These also hold for $cov(I, p_A^s)$ in the "no learning" case. When the manager of firm A learns information from stock prices, it is difficult to differentiate the expression for $cov(I, p_A^s)$ with respect to the parameters. However, we have checked numerically (and proved analytically for $c(\rho)$) that the effects of all parameters on $cov(I, p_A^s)$ are as predicted in Table 1 (see Figure 3 in Appendix B for an example).

Second, the model assumes that when the manager makes his investment decision (at date 2), the price of stock A does not yet reflect the information contained in its peer stock price. Suppose instead that dealers in stock A adjust their quotes after observing the price of stock B, at some

date τ between dates 1 and 2. In this case, we have $p_{A\tau} = \mathrm{E}(V_A(I^*) \mid p_{A1}, p_{B1})$. Thus, the price of stock A at date τ is a sufficient statistic for the information contained in $\{p_{A1}, p_{B1}\}$ about the fundamental of firm A. Hence, the manager of firm A makes exactly the same investment decisions whether he conditions his investment policy on $p_{A\tau}$ only or on $\{p_{A1}, p_{B1}\}$.

This case, however, is quite special for at least two reasons. First, in reality information contained in prices diffuses only gradually across stocks (e.g., Hou, 2007; Hong, Torous, and Valkanov, 2007; Cohen and Frazzini, 2008; Menzly and Ozbas, 2010). Hence, managers can improve their forecasts of fundamentals by using the information contained in their peers' stock price, not yet impounded in their own stock price, as in the model.

Second, and maybe more important, a firm stock price reflects the value of its entire product portfolio, not the incremental value of each growth opportunity within this portfolio. Thus, stock prices of "pure players" or at least firms with cash-flows more correlated with those of a specific growth opportunity provide more accurate signals about this opportunity than the stock price of the firm, even if the latter swiftly reflects the information available in other stock prices.[14] A simple example illustrating this point in the context of our model is available upon request.

3. Data and Methodology

3.1. Sample construction and definition of peer firms

Our empirical analysis is based on a sample of U.S. public firms. For our tests, we must pair each firm with other firms selling similar products (the empirical counterpart of firm B in our model). To this end, we use the new Text-based Network Industry Classification (TNIC) developed by Hoberg and Phillips (2011).[15] This classification is based on textual analysis of the product description sections of firms' 10-K (Item 1 or Item 1A) filed every year with the Securities and Exchange Commission (SEC). The classification covers the 1996 to 2008 period because TNIC industries require the availability of 10-K annual filings in electronically readable format.

Specifically, in each year, Hoberg and Phillips (2011) compute a measure of product similarity

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[14]See Bresnahan, Milgrom, and Paul (1992) for a similar point.

[15]The data can be found at: http://www.rhsmith.umd.edu/industrydata/industryclass.htm

for every pair of firms by parsing the product descriptions from their 10-Ks. This measure is based on the relative number of words that two firms share in their product description. It ranges between 0% and 100%. Intuitively, the more common words two firms use in describing their products, the more similar are these firms. Hoberg and Phillips (2011) then define each firm i's industry to include all firms j with pairwise similarities relative to i above a pre-specified minimum similarity threshold – chosen to generate industries with the same fraction of industry pairs as 3-digit SIC industries (equals to 21.32%). We define as "peers" of firm i all the firms that belong to its TNIC industry in a given year.

Hoberg and Phillips (2011)'s TNIC industries have three important features. First, unlike industries based on the Standard Industry Classification (SIC) or the North American Industry Classification System (NAICS), they change over time. In particular, when a firm modifies its product range, innovates, or enters a new product market, the set of peer firms changes accordingly. Second, TNIC industries are based on the products that firms supply to the market, rather than its 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 shock, as in our model. Third, unlike SIC and NAICS industries, TNIC industries do not require relations between firms to be transitive. Indeed, as industry members are defined relative to each firm, each firm has its own distinct set of peers. This provides a richer definition of similarity and product market relatedness.

For firms with available TNIC industries, we obtain stock price and return information from the Center for Research in Securities Prices (CRSP). Investment and other accounting data are from Compustat. We exclude firms in financial industries (SIC code 6000-6999) and utility industries (SIC code 4000-4999). We also exclude firm-year observations with negative sales or missing information on total assets, capital expenditure, fixed assets (property, plant and equipment), and (end of year) stock prices. We detail the construction of all the variables in Table 2. To reduce the effect of outliers all ratios are winsorized at 1% in each tail.

[Insert Table 2 about here]

Table 3 presents descriptive statistics. The sample includes 46,077 firm-year observations (7,521 distinct firms). The average number of peers per firm (#*peers*) is sixty-five and the median is twenty-eight. Summary statistics for the main variables used in the analysis resembles those reported in related studies. The average (median) rate of investment (capital expenditures divided by lagged PPE, I_i) is 39.2% (24.2%). Following other studies on the sensitivity of investment to stock price, we use Tobin's Q as a proxy for a firm's stock price. It is defined as a firm's stock price times the number of shares outstanding plus the book value of assets minus the book value of equity, scaled by book assets. There is a large heterogeneity in Tobin's Q in our sample: It ranges from 0.55 to 13.79 with a mean of 2.18 and a median of 1.54. We also report summary statistics for peers' characteristics (average across all peers for each firm-year). They are very close from their own firm counterpart, although aggregation lowers their standard deviation.

[Insert Table 3 about here]

3.2. Empirical methodology

To estimate the covariation between a firm's investment and (i) the stock prices of its peers and/or (ii) its own stock price, we include peers' characteristics in a standard linear investment equation. Specifically, we consider the following baseline specification:

$$I_{i,t} = \alpha_i + \delta_t + \eta Q_{-i,t-1} + \beta Q_{i,t-1} + \boldsymbol{\varphi} \mathbf{X}_{-i,t-1} + \boldsymbol{\Phi} \mathbf{X}_{i,t-1} + \varepsilon_{i,t}, \tag{16}$$

where the subscripts i and t represent respectively firm i (firm A in the model) and the year, while the subscript $-i$ represents an equally-weighted portfolio of peer firms based on the TNIC industries (firm B in the model). The dependent variable, $I_{i,t}$, is the ratio of capital expenditure in that year scaled by lagged fixed assets (property, plant, and equipment). The explanatory variable $Q_{i,t-1}$ is the Tobin's Q of firm i in year $t-1$ as defined above and $Q_{-i,t-1}$, is the Tobin's Q of firm i's peers, computed as the average Q of all firms belonging to the same TNIC industry as firm i in year $t-1$, excluding firm i.[16]

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[16]Following common practice (e.g., Chen, Goldstein, and Jiang (2007)), we impose a lag of one year between the measurement of investment and the measurement of Tobin's Qs. We have checked that the findings holds when

The vectors **X** include control variables known to correlate with investment decisions. Following previous research, $\mathbf{X}_i$ includes the natural logarithm of assets ("firm's size") and cash-flows for firm i in year $t-1$ to control for the well-documented association between these variables and corporate investment. We also include the same characteristics ($\mathbf{X}_{-i}$) for the portfolio of peers to further control for product market characteristics. In addition, we account for time-invariant firm heterogeneity by including firm fixed effects (α_i) and time-specific effects by including year fixed effects (δ_t). The coefficients β and η therefore measure how, over time, the average firm's investment is related to its own stock price and its peers' stock price. We allow the error term ($\varepsilon_{i,t}$) to be correlated within firms and we correct the standard errors as in Petersen (2009).

We scale all independent variables by their standard deviation. Hence, coefficients η and β are the empirical counterparts of $cov(I, p_{B1}^s)$ and $cov(I, p_{A1}^s)$ (see the discussion in Section 2.4). Another advantage of this scaling is that the magnitude of the estimated coefficients is directly informative about the economic significance of the effects. By construction η measures the change in firm i's investment for a one standard deviation increase in its peers' average Tobin's Q. Similarly β measures the change in firm i's investment for a one standard deviation increase in its own Tobin's Q.

We use estimates of these coefficients to test the main implications of the model. We proceed in two steps. First, in Sections 4.1 and 4.2, we establish that estimates for η and β are both statistically significant in our sample. This is indeed a necessary condition for the "learning from peers" channel to play a role (see Corollary 3). This condition is not sufficient, however. Indeed, as highlighted by the model, Q_i and Q_{-i} play a dual role in equation (16): they are both (i) proxies for unobserved managers' private information about their investment opportunities and (ii) determinants of investment if managers learn information from stock prices. Thus, a significant association between investment and Tobin's Qs might exist even if managers do not learn from stock prices, simply because Tobin's Qs act as a proxy for unobserved managers' signals (the correlated information channel).

Hence, in a second step (Section 4.3), we test the predictions of the model about η and β that

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investment and Qs are measured contemporaneously (results are available upon request).

are specific to the "learning from peers" scenario. That is, we test whether proxies for the model's parameters (price informativeness, managerial information, and the correlation in demand shocks between firms) affect η and β as Table 1 predicts when managers learn from their peers, with a special focus on the five predictions specific to this scenario.

4.   Empirical Findings

4.1.   Corporate investment and stock market prices

Table 4 presents estimates for various specifications of the investment equation (16). The first column reports the estimates for our baseline specification. As found in many other studies (e.g., Chen, Goldstein, and Jiang (2007)), there is a positive and significant relation between a firm's own Q and its investment in our sample. Specifically, a one standard deviation increase in a firm's own Q is associated with a 13.7% increase in its investment (t-statistic of 23.68).

More important for our purpose, the sensitivity of a firm's investment to its *peers'* Q is also positive and highly significant with a t-statistic of 11.11.[17] The economic magnitude of this relationship is substantial. Indeed, the estimate for η implies that a one standard deviation increase in peers' Q is associated with a 5.9% increase in investment on average. This increase represent about 15% of the sample average ratio of capital expenditures to fixed capital. Moreover, it means that the sensitivity of a firm's investment to its peers' Q is about *half* that of its own Q.[18]

[Insert Table 4 about here]

In the remaining columns of Table 4, we check the robustness of these findings to changes in our baseline specification. In column 2, we use the median values of peers' Tobin's Q and firms' characteristics (size and cash flow) rather than their average values. In Columns 3 and 4, peers are defined as firms within the same 3-digit SIC or 4-digit NAICS industries instead of firms

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[17]The fact that η is positive suggests that, for the average peer, the case in which $\rho > \frac{1}{2}$ in the model is the relevant one empirically.

[18]The correlation between Q_i and Q_{-i} is 0.40 in the sample. Thus the coefficient on Q_{-i} captures an information distinct from the information in Q_i.

within the same TNIC industry. In each of these specifications, the investment of a firm is still significantly and positively related to its peers' Tobin's Q.

[Insert Figure 4 about here]

We also check that the investment of a firm is *not* sensitive to the Tobin's Q of *unrelated* firms. To this end, we artificially generate 1,000 sets of "pseudo" peers, that is, firms randomly selected outside of TNIC industries.[19] We then estimate equation (16) for each of these artificial sets of peers. Figure 4 shows the resulting empirical distributions of the 1,000 estimates of η and β. Clearly, a firm's investment is not sensitive to the Tobin's Q of pseudo peers (the average of η is 0.001). This finding is expected since the correlation between the fundamentals of these pseudo peers and a firm should be close to zero on average. This corresponds to the case $\rho \approx \frac{1}{2}$ in the model, in which case, $cov(I, p_{B1}) \approx 0$.[20]

We have performed additional robustness tests that are omitted for brevity but available upon request. In these tests, we show that our inference is robust to various forms of fixed effects (e.g., the inclusion of industry and industry-year fixed effects), different forms of clustering, and different definitions of corporate investment. Also, our conclusions remain identical if we use price-to-earning ratio (PE) or (idiosyncratic) stock returns instead of Tobin's Q as proxies for firms' valuations. We also estimated additional specifications with a larger set of control variables such as leverage, cash holdings, asset tangibility, sale growth, future returns (three years ahead) of firms and their peers, and peers' investment (lagged capital expenditures).[21] The main results remain unaffected.[22]

Overall the results in Table 4 and Figure 4 highlight that the investment of a firm is positively

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[19] The number of peers varies across sets so as to match the empirical distribution of this number in our sample (average of 65 with a standard deviation of 83; see Table 3).

[20] When ρ is close to $\frac{1}{2}$, $cov(I, p_{B1})$ is given either by equations (10) or (12). In either case, this covariance goes to zero when ρ goes to $\frac{1}{2}$.

[21] By controlling for peers' investment, we account for the possibility that part of the association between a firm's investment and its peers' Tobin's Qs comes from the effect of the latter on peers' investment.

[22] As pointed by Erickson and Whited (2000, 2012), Q_i imperfectly measures the information in stock prices relevant to managers, which biases the estimate of β downward and may lead to spurious correlation of investment with other variables (e.g., cash-flows or, in our case, peers' Q). Hence, we have also used the Erickson and Whited's estimator to account for this error-in-measurement problem. As expected, we find that estimates of β are significantly larger when we use this estimator. However, we still find a positive and significant coefficient for η, with a very similar magnitude to that reported in Table 4. This additional robustness check is also available upon request.

and significantly correlated with its Tobin's Q and the average Tobin's Q of its peers. The first empirical finding is well known. The second is new to our paper.

4.2. Dynamic peers classification

The set of peers for each firm is changing over time in TNIC industries because firms' product descriptions change over time. Hence, we can study how the investment of a firm is related to the Tobin's Q of past, present, and future peers. Consider a firm B that becomes a peer of firm A at date t. This entry in the set of A's peers is like a positive shock on ρ in the model. Hence, we should observe an increase in the sensitivity of firm A's investment to the stock price of firm B. Symmetrically, the investment of firm A should become *less* sensitive to the stock price of a firm that exits its set of peers. These effects should hold whether or not managers learn information from stock prices (see Corollary 4) as long as the price of a peer (new or old) contains information correlated with the cash flows of firm A's growth opportunities.

The investment of a firm might even become sensitive to the stock price of another firm years before the latter becomes a peer. Indeed, suppose that in year t, firm A contemplates entering firm B's product market. If the investment required to enter this new product market takes time, there will be a lag between the year in which firm A invests (year t) and the year, say $t+1$, in which firm A actually enters firm B's product market. In this case, firm B will be in firm A's TNIC industry only in year $t+1$, even though investments required to enter the new market began in year t.[23] If the decision of firm A's manager was influenced by the stock price of firm B, the investment of firm A will therefore appear to be sensitive to its peer stock price *before* the latter effectively becomes a peer according to the TNIC classification.

To test these implications, we construct for each firm-year four distinct sets of peers: (i) new peers, (ii) still peers, (iii) past peers, and (iv) future peers. For firm i and year t, we define *new* peers as firms that are in the same TNIC industry as firm i in year t but that were not in year $t-1$. Following the same logic, *past* peers are firms that were in the TNIC industry of firm i in year $t-1$ but that are not anymore in year t while *still* peers are firms that were in the TNIC

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[23] Indeed, firms are legally required to accurately describe the products they actually sell in their 10-Ks and these descriptions must be representative of the fiscal year of the 10-Ks (see Hoberg and Phillips (2011)).

industry of firm i in year $t-1$ and continue to be in year t. Finally, $future$ peers are firms that are not in the TNIC industry of firm i in year t but will be therein in year $t+1$ (or $t+2$, depending on specification). Then, we compute the average Tobin's Q for each set of peers and use these instead of the average Tobin's Q of current peers in equation (16).

[Insert Table 5 about here]

Table 5 presents the results. In column 1 we observe a positive and significant relation between firms' investment and the Tobin's Q of their new peers. The estimated coefficient is 0.032 with a t-statistic of 7.63.[24] In contrast Column 2 shows that the investment of firms stops being sensitive to the market valuation of firms that exit their set of peers. Finally, coefficient estimates for $still$ peers largely mirror those obtained in the baseline specification (see Table 4) with a large coefficient on the Tobin's Q of $still$ peers (0.039 with a t-statistic of 7.00).

In columns 4 and 5 of Table 5, we report the sensitivity of a firm's investment to the average Tobin's Q of one-year or two-years ahead $future$ peers. This sensitivity is equal to 0.025 for one-year ahead Tobin's Q and 0.018 for two years ahead Tobin's Q. Moreover, it is statistically significant at the 1%-level in each case. These empirical findings fit well with a scenario in which firms' managers extract information about the profitability of breaking into a new product space from the valuation of firms already active in this space.

4.3. Testing the learning from peers' hypothesis

We now test the implications that are $unique$ to the learning from peers hypothesis (see Table 1). Specifically, we study how the covariation between investment and own's and peers' stock prices varies with measures of (i) informed trading (π_A and π_B), (ii) managerial information other than stock prices (γ), and (iii) the correlation in demand shocks between a firm and its peers ($c(\rho)$).

To this end, we add interaction terms between each of our control variable and proxies for parameters π_j, γ, and $c(\rho)$ in our baseline regression (16).[25] Specifically, we augment the baseline

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[24] The sample size is smaller than that used in previous tests because we exclude from the analysis firms that keep the same peers over the entire sample period.

[25] In a previous version of the paper, we used a sample split approach instead of the current interaction approach to test the predictions of Table 1. Results are qualitatively identical with both approaches.

specification as follows:

$$I_{i,t} = \alpha_i + \delta_t + \eta_0 Q_{-i,t-1} + \eta_1[Q_{-i,t-1} \times \phi_{i,t-1}] + \beta_0 Q_{i,t-1} + \beta_1[Q_{i,t-1} \times \phi_{i,t-1}] + ... \qquad (17)$$

where ϕ_i represents a proxy for one of the model's parameters. For consistency, all proxies are measured contemporaneously with Qs and are also divided by their respective standard deviation. Furthermore, all control variables are interacted with these proxies, even though our focus is only on η_1 and β_1.[26] Equation (17) enables us to decompose the sensitivities of investment to Tobin's Qs (η and β) into an unconditional component and a component that depends linearly on the interacted variable of interest (ϕ_i). For instance, the sensitivity of a firm's investment to its peers' Tobin's Q is given by $\mathrm{E}(\frac{\partial I_i}{\partial Q_{-i}}) = \eta_0 + \eta_1 \times \phi_{i,t-1}$ and the marginal effect of ϕ_i (say π_A) on this sensitivity is therefore $\mathrm{E}(\frac{\partial^2 I_i}{\partial Q_{-i}\partial \phi}) = \eta_1$. Similarly, the marginal effect of ϕ_i on the investment of firm i to its own stock price is given by β_1. Hence, in this section, we test whether the signs of the interaction terms η_1 and β_1 are as predicted when managers learn from their peer stock prices.

4.3.1. Informed trading (π_j)

We first study how the sensitivities of investment to stock prices vary with the level of informed trading in the stock of a firm (π_A) and the stocks of its peers (π_B). As explained in Section 2.2, an increase in π_j is associated with an increase in stock price informativeness. Accordingly, we use a measure of price informativeness as proxy for the level of informed trading in a stock.

As in many other papers (e.g., Durnev, Morck, and Yeung (2004), or Chen, Goldstein, and Jiang (2007)), we measure the informativeness of a firm stock price by its firm-specific return variation (or price non-synchronicity), defined as $\Psi_{i,t} = \ln((1 - R_{i,t}^2)/R_{i,t}^2)$, where $R_{i,t}^2$ is the R^2 from the regression in year t of firm i's weekly returns on market returns and the peers' value-weighted portfolio returns.[27] The idea, due to Roll (1988), is that trading on firm-specific information

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[26]We obtain very similar results if we only interact Q_i and Q_{-i} with ϕ_i.

[27]In unreported results (available upon request), we show the robustness of the findings in this section, using two other proxies for the level of informed trading in a stock: one based on Llorente, Michaely, Saar, and Wang (2002) and another one based on the PIN measure developed by Easley, Kiefer, and O'Hara (1996).

makes stock returns less correlated and thereby increases the fraction of total volatility due to idiosyncratic returns. Stock price informativeness is higher when Ψ is high. In each year, we regress Ψ_{-i} on Ψ_i and we define the regression residuals as Ψ_{-i}^+. Similarly, in each year, we regress Ψ_i on Ψ_{-i} and we define the regression residuals as Ψ_i^+. We use Ψ_{-i}^+ as a proxy for π_B and Ψ_i^+ as a proxy for π_A.

By construction, the mean values of these proxies are zero. Furthermore, Ψ_{-i}^+ is independent from Ψ_i and Ψ_i^+ is independent from Ψ_{-i}. Thus, analyzing the marginal effects of, say, Ψ_{-i}^+ on the sensitivities of investment to stock prices is similar to analyzing the effects of π_B on the covariations between investment and stock prices, holding π_A fixed.[28] Panel A of Table 6 presents estimates for (17) when $\phi_{i,t} = \Psi_{-i}^+$ (Column 1) and $\phi_{i,t} = \Psi_i^+$ (Column 2). For brevity, we only show the estimated coefficients on Q_{-i} and Q_i (η_0 and β_0) as well as their interactions with $\phi_{i,t-1}$ (η_1 and β_1).

[Insert Table 6 about here]

The learning from peers hypothesis uniquely predicts that the sensitivity of a firm's investment to its stock price should be *lower* when the level of informed trading in its peers is high. This is the case empirically, as shown by Column 1 in Table 6: the coefficient on the interaction between Q_i and Ψ_{-i}^+ is significantly negative ($\beta_1 = -0.012$ with a t-statistic of 2.63). The magnitude of this coefficient is also substantial. To see this, suppose that the level of informed trading in peers' stocks (Ψ_{-i}^+) is set at its mean value (zero). In this case, a one standard deviation increase in a firm's Tobin's Q is associated with a 13.9% increase in investment ($\beta_0 = 0.139$). Now suppose that we increase by a one standard deviation the level of informed trading in peers' stocks. Then, the effect of a one standard deviation increase in peers' valuation is smaller since it increases investment by only 12.7% ($\beta_0 + \beta_1 = 0.127$).

Column 1 of Table 6 also shows that η_1 is positive (equal to 0.005) and marginally significant (t-statistic of 1.83). Thus, an increase in the level of informed trading in peers' stocks marginally strengthens the sensitivity of a firm's investment to its peers' valuation. This effect is consistent

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[28] This would not be the case if we used directly Ψ_i and Ψ_{-i} as proxies for π_A and π_B because the sample correlation between Ψ_i and Ψ_{-i} is 0.421.

with the learning from peers channel but it may also be present even if firms' managers do not learn from their peers' stock prices (see Corollaries 1 and 2). All else equal (i.e., keeping Ψ_i fixed), these results show that firms rely less on their own stock price and more on the stock prices of their peers when peers' stock prices are more informative.

In Column 2 of Table 6, we study how the level of informed trading in a firm's own stock (π_A) affects the sensitivity of its investment to its own Q and its peers' Q. We observe that the sensitivity of a firm's investment to its peers' Tobin's Q *decreases* with the level of informed trading in its own stock, as uniquely predicted in the scenario in which firms learn from their peers' stock price. Indeed, the coefficient on the interaction between Q_{-i} and Ψ_i^+ is significantly negative ($\eta_1 = -0.016$ with a t-statistic of 5.55). Furthermore, the economic size of the effect is large. A one standard deviation increase in peers' Tobin 's Q is associated with a 5.5% increase in a firm's investment when the level of informed trading in its own stock is at its mean value ($\Psi_i^+=0$) vs. a 3.9% increase when the level of informed trading in its own stock is one standard deviation above its mean.

As in Chen, Goldstein, and Jiang (2007) and Bakke and Whited (2010), we also find that a firm's investment is more sensitive to its own Tobin's Q when its market displays a higher level of informed trading ($\beta_1 = 0.005$). This effect, which is predicted whether or not managers learn from their peers' stock prices, is significant only at the 10% level, however.

4.3.2. Managerial information (γ)

According to the learning from peers hypothesis, an increase in the quality of managerial information (γ) should decrease the sensitivity of a firm's investment to its peers' valuation. Moreover, the effect of a higher γ on the sensitivity of a firm's investment to its own stock price should depend on the level of informed trading in its peers' stocks. If this level is high, the effect should be positive while if this level is low, the effect should be negative. None of these predictions are obtained if the learning from peers hypothesis does not hold (see Table 1).

We test these two predictions using the trading activity of firms' insiders and the profitability of their trades as proxies for the quality of their private information (Chen, Goldstein, and Jiang

(2007) use similar proxies). Indeed, managers should be more likely to trade their own stock and make profit on these trades if they possess more private information (γ higher). We measure the trading activity ($Insider_{i,t}$) of firm i's insiders in year t as the number of shares traded by its insiders during that year divided by the total number of shares traded for stock i in year t. The profitability of insiders' trades in firm i in year t ($InsiderAR_{i,t}$) is measured by the average one month market-adjusted returns of holding the same position as insiders for each insider's transaction.[29]

To build these proxies for managerial information, we obtain corporate insiders' trades from the Thomson Financial Insider Trading database.[30] As in other studies (e.g., Beneish and Vargus (2002), or Peress (2010)), we restrict our attention to open market stock transactions initiated by the top five executives (CEO, CFO, COO, President, and Chairman of the Board). Finally, we use CRSP to compute the total number of shares traded (turnover) in each stock and market-adjusted returns on insiders' positions.

Panel B of Table 6 presents estimates for (17) when $\phi_{i,t} = Insider_{i,t}$ (Column 3) and $\phi_{i,t} = InsiderAR_{i,t}$ (Column 4). In each case, we find that the coefficients on the interaction between peers' Tobin's Q and the proxies for γ are significantly negative at the 5%-level and equal to -0.009. The investment of a firm is thus more sensitive to its peers' valuation when managers are *less* informed. This finding is predicted when managers learn information from their peers' stock prices but not otherwise (see Table 1).

As in Chen, Goldstein, and Jiang (2007), we also observe no significant relationship between the sensitivity of a firm's investment to its own Tobin's Q and our proxies for managerial information: β_1 is insignificant with both proxies. As explained previously, the learning from peers hypothesis predicts that the sign of the relation between the quality of managerial information (γ) and the sensitivity of a firm's investment to its own stock price (β) can be positive or nega-

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[29]The average value of $InsiderAR$ is 1.56% in our sample and is significantly different from zero at the 1%-level. This finding supports the notion that insiders have private information and is in line with findings on the profitability of insiders' trades in the literature (for recent evidence, see Seyhun (1998), or Ravina and Sapienza (2010)).

[30]This database contains all insider trades reported the the SEC. Corporate insiders include those who have "access to non-public, material, insider information" and required to file SEC forms 3, 4, and 5 when they trade in their firms stock.

tive, depending on the level of informed trading in its peers' stocks. These conflicting predictions regarding the sign of the effect of γ on β may explain why, on average, we find no effect of our proxies for γ on β.

We therefore perform a stronger test by allowing the sign of the effect of γ on β to depend on the level of informed trading in peers' stocks. For this additional test, we modify equation (17) to allow for a triple interaction between a firm's own stock price, the quality of managerial information, and the level of informed trading in its peers. In this specification, the average marginal effect of γ on β (η_1) is allowed to depend linearly on the level of informed trading trading in peers' stock (Ψ^+_{-i}), i.e., $\eta_1 = E(\frac{\partial^2 I_i}{\partial Q_i \times \partial \gamma}) = E(\frac{\partial \beta}{\partial \gamma}) = \omega_0 + \omega_1 \times \Psi^+_{-i}$. According to the learning hypothesis, we expect $\omega_1 > 0$ and $\omega_0 < 0$. Furthermore, we expect the effect of managerial information on the sensitivity of a firm investment to its Tobin's Q to be positive if and only if the level of informed trading in peers' stock (Ψ^+_{-i}) is high enough $(\eta_1 = \omega_0 + \omega_1 \times \Psi^+_{-i} > 0$ for Ψ^+_{-i} large enough).

We report the estimates with this richer specification for (17) in Column 5 of Table 6, using $Insider_i$ as a proxy for γ. As uniquely predicted by the learning from peers hypothesis, the coefficient on the triple interaction term $(Q_i \times Insider_i \times \Psi^+_{-i})$ is significantly positive $(\omega_1 = 0.012$ with a t-statistic of 4.20). Furthermore, the unconditional average marginal effect of managerial information on the sensitivity of a firm's investment to its own stock price (ω_0) is negative. However, this coefficient is not significant $(\omega_0 = -0.001$ with a t-statistic of 0.64).

[Insert Figure 5 about here]

In Figure 5, we plot the estimated marginal effect of γ on β as a function of Ψ^+_{-i} based on the point estimates obtained for ω_0 and ω_1 in Column 5 of Table 6. That is, Figure 5 shows the line with equation: $\omega_0 + \omega_1 \times \Psi^+_{-i} = -0.001 + 0.012 \times \Psi^+_{-i}$. As predicted, the marginal effect of managerial information on the sensitivity of a firm's investment to its stock price switches from a negative value when the informativeness of peers' stock prices is low (e.g., smaller than -1.01, which is the 90th percentile for Ψ^+_{-i}) to a positive value when the informativeness of peers' stock prices is sufficiently high (e.g., greater than 0.98, which is the 90th percentile for Ψ^+_{-i}).

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That is, the sensitivity of a firm' investment to its own stock price increases with the quality of managerial information only when its peers' valuations are sufficiently informative. Column 6 of Table 6 show that identical conclusions are obtained when we use $InsiderAR_i$ as a proxy for managerial information.

4.3.3. Correlated demand for products $(c(\rho))$

If firms learn information from their peers' valuation, the sensitivity of a firm's investment to its own stock price should decrease when the correlation in product demands between the firm and its peers increases in absolute value (Corollary 4). We now test this prediction.

We use three different proxies for the correlation between the demands for firms' products. First, we use the correlation of sales $(c(\rho)_{sales})$ between a firm and its peers. We compute this correlation for each firm-year using quarterly sales over the previous three years. Second, we use the correlation between a firm's stock returns and that of its peers $(c(\rho)_{returns})$ computed using monthly observations over the previous three years. Finally, we use a direct measure of product similarity based on firms' product description. As explained in Section 3.1, the TNIC industries developed by Hoberg and Phillips (2011) are constructed based on similarity scores (ranging from 0% to 100%) for each pair of firms that are above a minimum similarity threshold (21.32%). We use these scores to compute the average similarity score (denoted *similarity*) of a firm with its peers in a given year.[31]

Panel C of Table 6 reports estimates for (17) when $\phi_{i,t} = c(\rho)_{sales_{i,t}}$ (Column 7), $\phi_{i,t} = c(\rho)_{returns_{i,t}}$ (Column 8), and $\phi_{i,t} = similarity_{i,t}$ (Column 9). In each case, we find that the coefficient (β_1) on the interaction between Q_{-i} and the proxy for $c(\rho)$ is positive and statistically significant. Thus, a firm's investment is more sensitive to its peers' Tobin's Q when the demand for its product is more correlated with that of its peers. This finding is consistent with the learning from peers hypothesis but it is also expected if there is no learning from peers (see Table 1).

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[31]We are especially grateful to Jerry Hoberg and Gordon Phillips for sharing the data required for this test with us.

Furthermore, and as uniquely predicted by the learning hypothesis, Panel C of table 6 shows that a firm's investment is *less* sensitive to its own Tobin's Q when the demand for its product is more correlated with that of its peers. This effect is statistically significant at the 5%-level when we proxy this correlation with $c(\rho)_{sales_{i,t}}$ or $similarity_{i,t}$ and significant only at the 10%-level with $c(\rho)_{returns_{i,t}}$.

4.4. Going public and learning from peers' stock prices

In this section, we provide an additional piece of evidence in favor of the learning from peers hypothesis by looking at the investment behavior of a subset of firms before and after they go public. By definition private firms cannot learn from their own stock price. Hence, they are likely to rely on their peers' stock price as a source of information. More importantly for our purpose, when these firms go public, they can start learning information from their own stock price. Thus, going public is similar to an increase in π_A in our model: a switch from a situation where a firm stock price is completely uninformative to a situation in which it is informative. If the investment of a firm is influenced by its peers' valuation because managers extract information from these prices, we should therefore observe a *drop* in the sensitivity of a firm's investment to its peers' valuation after a firm IPO. In contrast, we should observe (i) no change in this sensitivity after an IPO if managers do not learn information from stock prices or (ii) an increase in this sensitivity if they learn information only from their own stock price (see the predictions regarding π_A in Table 1).

To test these predictions, we compare the investment of firms before and after their IPO using a sample of 3,166 U.S. IPOs (provided to us by Jay Ritter) for the 1996 to 2008 period. In this sample, we identify 1,342 firms for which we can obtain data on investment and peers' stock prices before and after these firms go public (we consider a maximum of five years post-IPO).[32] We examine whether the investment of these firms is sensitive to the Tobin's Q of their public peers before they go public and how this sensitivity changes after firms become public. To this

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[32]The investment data are from Compustat. As observed in Teoh, Welch and Wong (1998), Compustat typically contains information for firms prior to their public offering. We follow their approach and concentrate on firms for which we can obtain data for at least one year before the IPO.

end, we regress the investment of IPO firms (I_i) on the Q their peers (Q_{-i}), a dummy variable $Post_i$ that equals one for the years that follow the IPO, the interaction between Q_{-i} and $Post_i$, and the usual control variables (including firms' own post-IPO stock price). As in previous tests, all the independent variables are divided by their standard deviations.

[Insert Table 7 about here]

Table 7 presents the results of this 'event-time' analysis. Consistent with the idea that the stock market matters for private firms, we find that their investment is sensitive to their public peers' Tobin's Q. The coefficient on Q_{-i} is positive (0.036) and significant (t-statistic of 4.56). More importantly, the coefficient on $Q_{-i} \times Post_i$ is significantly negative (-0.022 with a t-statistic of 2.95). Thus, firms' investment becomes *less* sensitive to their peers' valuation once they are publicly listed. The same result obtains when we add sales growth to further control for firms' investment opportunities before they are publicly listed. As explained previously, this evolution of the sensitivity of investment to peers' valuation is consistent with the scenario in which managers learn information from their peers' stock prices, but not with other scenarios in our model.

5. Conclusion

In this article, we show that a firm's investment is positively related to its peers' valuation. Our hypothesis is that this relationship arises in part because peers' valuation conveys information to managers about their growth opportunities. We formalize this idea in a simple model and we derive five predictions about the relationship between investment and stock prices that hold only when firms extract information from their peers' valuation. For instance, the sensitivity of a firm's investment to its peers' valuation should decrease with the quality of managers' private information if the latter learn from their peers' valuation but should increase with this quality if they do not. Our tests do not reject the five predictions specific to the learning from peers hypothesis.

If firms learn information about future demand from their peers' valuation then product market choices by firms exert an externality on other firms. For instance, if a firm increases the

differentiation between its products and those of its peers, the ability of peers to learn from its stock price is weaker. Analyzing the effects of these learning externalities on product market choices and firms' valuation is an interesting venue for future research. In particular, they could be one channel through which the stock market affects product market choices and the degree of competition within an industry.[33]

From a different perspective, learning externalities could also affect the behavior of privately held firms. The precision and nature of the information they can gather from the stock prices of publicly-listed peers could impact their willingness to go public, the type of securities issued, their listing location, and the type of investors they want to attract. More generally, it would be interesting to better understand the characteristics (firm, product, or stock markets) that determine the extent to which firms can learn from each other stock prices. We plan to investigate these questions in future research.

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[33]Some papers suggest that the degree of competition within an industry affects stock market returns and price efficiency (see Peress (2010) and Tookes (2008)). If firms learn from their peers' valuation, there might also be an effect of the stock market on firms' product choices and therefore the dynamics of competition in an industry.

Appendix A

Proof of Proposition 1. We show that the strategies described in Proposition 1 form an equilibrium. Let $\Pi(x_{iB}, \widehat{s}_B)$ be the expected profit of a speculator who trades $x_{iB} \in \{-1, 0, +1\}$ shares of firm B when his signal is $\widehat{s}_{iB}$ and let

$$\sigma_B = \theta_B^H - \mathrm{E}(\theta_B) = \mathrm{E}(\theta_B) - \theta_B^L = \frac{\theta_B^H - \theta_B^L}{2}.$$

First, consider an informed speculator who observes $\widehat{s}_{iB} = H$. If he buys the asset, his expected profit is:

$$\Pi(+1, H) = \mathrm{E}(\theta_B - p_{B1}(f_B) \,|\widehat{s}_B = H, x_{iB} = 1)$$

$$= \Pr(-1 + \pi_B < f_B < 1 - \pi_B \,|\widehat{s}_B = H, x_{iB} = 1) \times \sigma_B + \Pr(f_B < -1 + \pi_B \,|\widehat{s}_B = H, x_{iB} = 1) \times 2\sigma_B.$$

When $\widehat{s}_{iB} = H$, the informed speculator expects other informed speculators to buy the asset and uninformed speculators to stay put. Hence, using equation (6), he expects $f_B = z_B + \pi_B$. We deduce that

$$\Pr(-1 + \pi_B < f_B < 1 - \pi_B \,|\widehat{s}_B = H, x_{iB} = 1) = \Pr(-1 < z_B < 1 - 2\pi_B) = 1 - \pi_B.$$

and

$$\Pr(f_B < -1 + \pi_B \,|\widehat{s}_B = H, x_{iB} = 1) = \Pr(z_B < -1) = 0.$$

Thus,

$$\Pi(+1, H) = (1 - \pi_B)\sigma_B > 0.$$

If instead, the speculator sells, his expected profit is:

$$\Pi(-1, H) = \mathrm{E}(\theta_B - p_{B1}(f_B) \,|\widehat{s}_B = H, x_{iB} = -1) = -(1 - \pi_B)\sigma_B < 0,$$

where we have used the fact that each speculator's demand has no impact on aggregate specu-

lators' demand since each speculator is infinitesimal. Thus, the speculator optimally buys the asset when he knows that demand for firm B is strong at date 3. A symmetric reasoning shows that the speculator optimally sells the asset when he knows that this demand is low at date 3.

Now consider dealers' prices at date $t = 1$. Remember that $p_{B1}(f_B) = \mathrm{E}(\theta_B \,|\, f_B)$. Speculators' aggregate demand is $x_B = -\pi_B$ when they observe a low realization for their signal $(\widehat{s}_B = L)$ and $x_B = \pi_B$ when they observe a high realization for their signal $(\widehat{s}_B = H)$. Thus, $f_B > 1 - \pi_B$ is impossible when $\widehat{s}_B = L$ since (i) $f_B = z_B + x_B$ by definition and (ii) $z_B \le 1$. In contrast, when $z_B > 1 - 2\pi_B$ and $\widehat{s}_B = H$ then $f_B > 1 - \pi_B$. Thus, if $f_B > 1 - \pi_B$ then dealers infer that $d_B = H$. We deduce that:

$$p_{B1}(f_B) = \mathrm{E}(\theta_B \,|\, f_B) = \mathrm{E}(\theta_B \,|\, \widehat{s}_B = H) = \theta_B^H \text{ for } f_B > 1 - \pi_B.$$

A symmetric reasoning implies:

$$p_{B1}(f_B) = \mathrm{E}(\theta_B \,|\, f_B) = \mathrm{E}(\theta_B \,|\, \widehat{s}_B = L) = \theta_B^L \text{ for } f_B < -1 + \pi_B.$$

Finally, for $-1 + \pi_B \le f_B \le 1 - \pi_B$, we have:

$$p_{B1}(f_B) = \mathrm{E}(\theta_B \,|\, -1 + \pi_B < f_B < 1 - \pi_B) = \mathrm{E}(\theta_B) + (2\Pr(d_B = H \,|\, -1 + \pi_B < f_B < 1 - \pi_B) - 1)\sigma_B.$$

Now:
$$\Pr(d_B = H \,|\, -1 + \pi_B < f_B < 1 - \pi_B) = \left(\frac{1 - \pi_B}{1 - \pi_B + 1 - \pi_B} \right) = \frac{1}{2}.$$

Hence,
$$p_{B1}(f_B) = \mathrm{E}(\theta_B) \text{ for } -1 + \pi_B \le f_B \le 1 - \pi_B.$$

Proof of Proposition 2.

Speculators' optimal trading strategy. It can be shown that speculators' order placement strategy in stock A is optimal following the same steps as in the proof of Proposition 1. Hence,

we skip this step for brevity.

The manager's optimal investment policy. Now consider the investment policy for the manager of firm A given the equilibrium price function $p_{A1}^*(\cdot)$. If the manager receives managerial information, he just follows his signal since this signal is perfect. Hence, in this case, he invests if $s_m = H$ and he does not invest if $s_m = L$. If he receives no managerial information $(s_m = \varnothing)$, the manager relies on stock prices. If he observes that $p_{A1} = p_A^H$, the manager deduces that $f_A > 1 - \pi_A$ and infers that $d_A = H$ (the reasoning is the same as that followed for firm B when $f_B > (1 - \pi_B)$; see the proof of Proposition 1). Thus the manager optimally invests. If instead the manager observes that $p_{A1} = p_A^L$ then the manager deduces that $f_A < -1 + \pi_A$ and he infers that $d_A = L$. In this case, the manager optimally abstains from investing at date 2.

Finally if he observes $p_{A1} = p_A^M$ then the manager deduces that $-1 + \pi_A \leq f_A \leq 1 - \pi_A$. In this case, investors' demand in stock A is uninformative $(\Pr(d_A = H \,|-1 + \pi_A \leq f_A \leq 1 - \pi_A) = \frac{1}{2})$. Hence, the manager of firm A relies on the price of stock B as a source of information. If $p_{B1} = \theta_B^H$, he deduces that $f_B > 1 - \pi_B$ and that the demand for product B will be high. Thus

$$\mathrm{E}(NPV \,|p_B = \theta_B^H, \, p_A = p_A^M) = \mathrm{E}(NPV \,|d_B = H) > 0, \tag{18}$$

where the last inequality follows from Assumption A.2. If $p_{B1} = \theta_B^L$ or $p_{B1} = \mathrm{E}(\theta_B)$, the manager deduces that $f_B \leq 1 - \pi_B$, in which case either investors' demand in stock B is uninformative or it signals that the demand for product B will be low. Hence, when (a) $p_{A1} = p_A^M$ and $p_{B1} = \theta_B^L$ or (b) $p_{B1} = \mathrm{E}(\theta_B)$, the manager of firm A assigns a probability less than or equal to $\frac{1}{2}$ to $d_A = H$. Using Assumption A.1, we deduce that the manager of firm A does not invest in this case.

These observations imply that:

$$I^*(s_m, p_{A1}^*, p_{B1}^*) = \begin{cases} 1 \text{ if } s_m = H \\ 1 \text{ if } \{s_m, p_{A1}^*\} = \{\varnothing, p_A^H\} \\ 1 \text{ if } \{s_m, p_{A1}^*, p_{B1}^*\} = \{\varnothing, p_A^M, \theta_B^H\} \\ 0 \text{ otherwise} \end{cases}, \tag{19}$$

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as claimed in the last part of Proposition 2.

Equilibrium prices. Now consider the stock price of firm A. We must check that the following equilibrium condition is satisfied:

$$p_{A1}(f_A) = \mathrm{E}(V_A(I^*)|f_A), \tag{20}$$

where $I^*(s_m, p_A, p_B)$ is given by (19). We check that the pricing policy given in the second part of Proposition 2 satisfies Condition (20).

Suppose first that $f_A \geq (1 - \pi_A)$. In this case, investors' net demand in stock A reveals that demand for product A is strong, i.e., $d_A = H$ (the reasoning is the same as that followed for firm B when $f_B > (1 - \pi_B)$; see the proof of Proposition 1). Moreover, the stock price of firm A is p_A^H according to the conjectured equilibrium. Hence, $I^* = 1$ and we deduce that:

$$\mathrm{E}(V_A(I^*)|f_A) = \theta_A^H + (\Sigma_H - K) \text{ for } f_A \geq (1 - \pi_A),$$

which is equal to p_A^H. Hence, for $f_A > (1 - \pi_A)$, Condition (20) is satisfied.

Now suppose that $f_A \leq -1 + \pi_A$. In this case, investors' net demand in stock A reveals that demand for product A is low, i.e., $d_A = L$. Moreover, the stock price of firm A is p_A^L according to the conjectured equilibrium. Hence, $I^* = 0$ and we deduce that:

$$\mathrm{E}(V_A(I^*)|f_A) = \theta_A^L \text{ for } f_A \leq -1 + \pi_A,$$

which is equal to p_A^L. Hence, for $f_A \leq -1 + \pi_A$, Condition (20) is satisfied.

Last, consider the case in which $-1 + \pi_A \leq f_A \leq 1 - \pi_A$. In this case the investors' demand for stock A is uninformative about the demand for product A, that is $\Pr(d_A = H | -1 + \pi_A < f_A < 1 - \pi_A) = \frac{1}{2}$ (the reasoning is as for firm B). Moreover, the stock price of firm A is p_A^M according to the conjectured equilibrium. Hence, the manager of firm A will invest ($I^* = 1$) if and only if (i) he receives a signal that demand for product A is strong or (ii) he observes a high price for stock B.

We deduce that:

$$\mathrm{E}(I^*(\Sigma_H - K) \,|-1 + \pi_A \leq f_A \leq 1 - \pi_A)$$

$$= \Pr(s_m = H \,|-1 + \pi_A \leq f_A \leq 1 - \pi_A) + \Pr(s_m = \varnothing \cap p_{B1} = \theta_B^H \,|-1 + \pi_A \leq f_A \leq 1 - \pi_A)\,(\Sigma_H - K).$$

Now,

$$\Pr(s_m = H \,|-1 + \pi_A < f_A < 1 - \pi_A) = \frac{\gamma}{2},$$

and

$$\Pr(s_m = \varnothing \cap p_{B1} = \theta_B^H \,|-1 + \pi_A \leq f_A \leq 1 - \pi_A)$$

$$= (1 - \gamma)\Pr(f_B > 1 - \pi_B \,|d_B = H)\Pr(d_B = H \,|-1 + \pi_A < f_A < 1 - \pi_A)$$

$$= \frac{(1 - \gamma)}{2}\pi_B$$

We deduce from the expression for $V_A(I^*)$ (equation (3)) that,

$$\mathrm{E}(V_A(I^*) \,|-1 + \pi_A \leq f_A \leq 1 - \pi_A) = \mathrm{E}(\theta_A) + \frac{1}{2}\,(\gamma + (1 - \gamma)\pi_B)\,(\Sigma_H - K),$$

which is equal to p_A^M. Hence, for $-1 + \pi_A \leq f_A \leq 1 - \pi_A$, Condition (20) is satisfied.

Proof of Corollary 1. When the manager of firm A does not learn information from prices, his investment policy, $I^{\mathrm{No}}(\cdot)$, is:

$$I^{\mathrm{No}}(s_m) = \begin{cases} 1 \ \text{if } s_m = H \\ 0 \ \text{if } s_m \neq H \end{cases}. \tag{21}$$

Given this investment policy, the equilibrium price of stock A solves

$$p_{A1}^{\mathrm{No}}(f_A) = \mathrm{E}(\theta_A \,|f_A) + \mathrm{E}(I^{\mathrm{No}} \times (\Sigma_H - K) \,|f_A), \tag{22}$$

when the manager of firm A does not use information from stock prices. We can compute

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$E(\theta_A | f_A)$ as we do for firm B in Proposition 1. Moreover, using equation (21), we deduce:

$$E(I^{\text{No}}(\Sigma_H - K) | f_A) = \Pr(s_m = H | f_A))(\Sigma_H - K).$$

As

$$\Pr(s_m = H | f_A)) = \begin{cases} \gamma & \text{if } f_A > 1 - \pi_A, \\ \gamma/2 & \text{if } -1 + \pi_A \leq f_A \leq 1 - \pi_A, \\ 0 & \text{if } f_A < -1 + \pi_A, \end{cases}$$

we deduce that:

$$p_{A1}^{\text{No}}(f_A) = \begin{cases} \theta_A^H + \gamma(\Sigma_H - K) & \text{when } f_A \geq 1 - \pi_A, \\ \\ \bar{p}_A^M & \text{when } -1 + \pi_A < f_A < 1 - \pi_A, \\ \\ \theta_A^L & \text{when } f_A \leq -1 + \pi_A. \end{cases} \tag{23}$$

where $\bar{p}_A^M = E(\theta_A) + \gamma(\Sigma_H - K)/2$. The cash flow for firm B is the same whether or not the manager of firm A relies on stock prices as a source of information. Hence, the stock price of firm B is given by Proposition 1 even when the manager of firm A does not learn information from prices. That is, $p_B^{No}(\cdot) = p_{B1}^*(\cdot)$.

By definition, the covariance between the price of stock j and the investment of firm A when there is no learning is:

$$cov(I^{\text{No}}, p_{j1}^{\text{No}}) = E(I^{\text{No}} p_{j1}^{\text{No}}) - E(I^{\text{No}})E(p_{j1}^{\text{No}}). \tag{24}$$

Using equations (21), (23), and the identity $p_B^{No}(\cdot) = p_{B1}^*(\cdot)$, we deduce that

$$
\begin{aligned}
E(I^{No} p_{A1}^{No}) &= \frac{\gamma}{2}(\pi_A p_A^H + (1 - \pi_A)\bar{p}_A^M), \\
E(I^{No} p_{B1}^{No}) &= \frac{\gamma}{2}(E(\theta_B) + (2\rho - 1)\pi_B \sigma_B), \\
E(I^{No}) &= \frac{\gamma}{2}, \\
E(p_{A1}^{No}) &= \bar{p}_A^M, \\
E(p_{B1}^{No}) &= E(\theta_B).
\end{aligned}
$$

After substituting these expectations in (24) and replacing p_A^H and $\bar{p}_A^M$ by their expressions, we obtain the expressions for $cov_{No}(I, p_{A1})$ and $cov_{No}(I, p_{B1})$ in Corollary 21 (equations (10) and (11)).

Proof of Corollary 2. In this case, the stock market equilibrium for firm A is given by:

$$
I^{\text{Narrow}}(s_m, p_{A1}) = \begin{cases} 1 & \text{if } s_m = H \text{ or } \{s_m, p_{A1}\} = \{\varnothing, p_A^H\}, \\ 0 & \text{otherwise}; \end{cases} \tag{25}
$$

and

$$
p_{A1}^{\text{Narrow}}(f_A) = \begin{cases} p_A^H & \text{when } f_A \geq 1 - \pi_A, \\ \bar{p}_A^M & \text{when } -1 + \pi_A < f_A < 1 - \pi_A, \\ p_A^L & \text{when } f_A \leq -1 + \pi_A, \end{cases} \tag{26}
$$

where $\bar{p}_A^M = E(\theta_A) + \gamma(\Sigma_H - K)/2$. The proof follows the same steps as the proof of Proposition 2, except that $\bar{p}_A^M$ plays the role of p_A^M.

The stock price of firm B is given by Proposition 1 since the cash flow for this firm does not depend on whether the manager of firm A relies on stock prices or not as a source of information. Thus, $p_{B1}^{\text{Narrow}} = p_{B1}(\cdot)$. By definition, the covariance between the price of stock j and the

investment of firm A is:

$$cov(I^{\text{Narrow}}, p_{j1}^{\text{Narrow}}) = \text{E}(I^{\text{Narrow}} p_{j1}^{\text{Narrow}}) - \text{E}(I^{\text{Narrow}})\text{E}(p_{j1}^{\text{Narrow}}). \tag{27}$$

Using equations (25), (26), and Proposition 1, we deduce that:

$$
\begin{aligned}
\text{E}(I^{\text{Narrow}} p_{A1}^{\text{Narrow}}) &= \frac{\gamma}{2}(\pi_A p_A^H + (1 - \pi_A)\overline{p}_A^M) + (1 - \gamma)\frac{\pi_A}{2} p_A^H, \\
\text{E}(I^{\text{Narrow}} p_{B1}^{\text{Narrow}}) &= \left(\frac{\gamma}{2} + (1 - \gamma)\frac{\pi_A}{2}\right)(\text{E}(\theta_B) + (2\rho - 1)\pi_B \sigma_B), \\
\text{E}(I^{\text{Narrow}}) &= \frac{\gamma}{2} + (1 - \gamma)\frac{\pi_A}{2}, \\
\text{E}(p_{A1}^{\text{Narrow}}) &= \pi_A\left(\text{E}(\theta_A) + \frac{\Sigma_H - K}{2}\right) + (1 - \pi_A)\overline{p}_A^M, \\
\text{E}(p_{B1}^{\text{Narrow}}) &= \text{E}(\theta_B).
\end{aligned}
$$

Equations (12) and (13) in Corollary 2 are obtained by substituting the previous expressions and the expressions for p_A^H and $\overline{p}_A^M$ in equation (27).

Proof of Corollary 3. The covariance between the price of stock B and the investment of firm A in equilibrium is:

$$cov(I^*, p_{B1}^*) = \text{E}(I^* p_{B1}^*) - \text{E}(I^*)\text{E}(p_{B1}^*),$$

where I^* is given by equation (19) and p_{B1}^* in Proposition 1. We deduce that:

$$\text{E}(I^* p_{B1}^*) = \frac{\gamma}{2}(\text{E}(\theta_B) + \pi_B(2\rho - 1)) + \frac{(1 - \gamma)}{2}(\text{E}(\theta_B)\pi_A + \sigma_B \pi_B(1 - 2\pi_A + \pi_A \rho)).$$

Moreover, $\text{E}(p_{B1}) = \text{E}(\theta_B)$ and

$$\text{E}(I^*) = \frac{\gamma}{2} + \frac{(1 - \gamma)}{2}(\pi_A + \pi_B(1 - \pi_A)). \tag{28}$$

Thus, after some algebra, we obtain

$$cov(I^*, p_{B1}^*) = ((\gamma + (1 - \gamma)\pi_A)\pi_B(2\rho - 1) + (1 - \gamma)(1 - \pi_A)\pi_B)\frac{\sigma_B}{2}, \tag{29}$$

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which yields equation (14) since $cov_{\text{Narrow}}(I, p_{B1}) = (\gamma + (1-\gamma)\pi_A)\pi_B(2\rho - 1)\sigma_B/2$. We deduce from (29) that:

$$\frac{\partial cov(I^*, p_{B1}^*)}{\partial \pi_B} = ((2\rho - 1)(\gamma + (1-\gamma)\pi_A) + (1-\gamma)(1-\pi_A))\sigma_B/2 > 0,$$

$$\frac{\partial cov(I^*, p_{B1}^*)}{\partial \pi_A} = -(1-\gamma)\pi_B(1-\rho) < 0, \text{ if } \gamma < 1,$$

$$\frac{\partial cov(I^*, p_{B1}^*)}{\partial \gamma} = -(1-\pi_A)\pi_B(1-\rho)\sigma_B < 0.$$

This proves the first part of Corollary 3.

The covariance between the price of stock A and the investment of firm A is given by:

$$cov(I^*, p_{A1}^*) = \mathrm{E}(I^* p_{A1}) - \mathrm{E}(I^*)\mathrm{E}(p_{A1}). \tag{30}$$

Calculations yield:

$$\mathrm{E}(I^* p_{A1}^*) = \frac{\gamma}{2}\left(\pi_A p_A^H + (1-\pi_A)p_A^M\right) + \left(\frac{1-\gamma}{2}\right)\left(\pi_A p_A^H + (1-\pi_A)\pi_B p_A^M\right). \tag{31}$$

Equation (28) gives the expression for $\mathrm{E}(I^*)$ and equation (9) gives $\mathrm{E}(p_{A1})$ since $p_{A0} = \mathrm{E}(p_A)$. Using these observations and substituting p_A^H and p_A^M by their expressions in (31), we can express (30) as follows:

$$cov(I^*, p_{A1}^*) = \frac{1}{2}\left(\begin{array}{c} \gamma\pi_A(\sigma_A + \frac{\gamma}{2}(\Sigma_H - K)) \\ + \\ \pi_A(1-\gamma)(\sigma_A + (\frac{\Sigma_H - K}{2})(2 - \pi_B - (1-\gamma)(\pi_A(1-\pi_B) + \pi_B))) \end{array}\right). \tag{32}$$

Clearly, $cov(I^*, p_{A1}^*)$ is positive and this equation can be rewritten as (15) after straightforward manipulations.

Differentiating equation (32), it is straightforward that $\frac{\partial cov(I^*, p_{A1}^*)}{\partial \pi_B} < 0$, and

$$\frac{\partial cov(I^*, p_{A1}^*)}{\partial \pi_A} = \frac{1}{2}\sigma_A + (\Sigma_H - K)\left((1-\gamma)(1 + \pi_A + \pi_B) + 1 - \gamma^2\pi_A + (1-\gamma)^2\pi_B\pi_B\right) > 0,$$

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and

$$\frac{\partial cov(I^*, p^*_{A1})}{\partial \gamma} = -\pi_A \left(\frac{\Sigma_H - K}{2} \right) ((1-\gamma)(1-\pi_A)(1-\pi_B) - \frac{\pi_B}{2}).$$

Clearly, $\frac{\partial^2 cov(I^*, p_{A1})}{\partial \pi_B \partial \gamma} > 0$; Thus, $\frac{\partial cov(I^*, p^*_{A1})}{\partial \gamma}$ increases in π_B. Moreover, for $\pi_B = 1$, $\frac{\partial cov(I^*, p_{A1})}{\partial \gamma}$ is positive while for $\pi_B = 0$, it is negative. Thus, there exists a value $\widehat{\pi}_B$ such that $\frac{\partial cov(I^*, p_{A1})}{\partial \gamma} = 0$. This implies that $\frac{\partial cov(I^*, p_{A1})}{\partial \gamma} > 0$ if $\pi_B > \widehat{\pi}_B$, $\frac{\partial cov(I^*, p_{A1})}{\partial \gamma} < 0$ if $\pi_B < \widehat{\pi}_B$, as claimed in the last part of the corollary. Calculations yield $\widehat{\pi}_B = \frac{2(1-\gamma)(1-\pi_A)}{1+2(1-\gamma)(1-\pi_A)}$.

Proof of Corollary 4.

Suppose first that the manager uses information from stock prices. In this case, as explained in the text, when $1 - \frac{1}{R_H} \leq \rho < \frac{1}{R_H}$, the equilibrium is identical to the case in which the manager ignores the information contained in the price of stock B. Thus, when $c(\rho) \leq \frac{1}{R_H} - \frac{1}{2}$, $cov(I^*, p_{A1})$ is given by equation (13) in Corollary 2. In contrast, when $\rho < 1 - \frac{1}{R_H}$ or $\rho > \frac{1}{R_H}$, investment is influenced by the stock price of B. Thus, when $c(\rho) > \frac{1}{R_H} - \frac{1}{2}$, $cov(I^*, p_{A1})$ is given by equation (15) in Corollary 3. Calculations show that the expression for $cov(I^*, p_{A1})$ in (15) is smaller than in (13). We deduce that when the manager of firm A uses information from stock prices, $cov(I^*, p_{A1})$ weakly decreases with $c(\rho)$. This proves the first part of Corollary 4.

When the manager of firm A ignores the information contained in the stock price of firm B, $cov(I^*, p_{A1})$ is given by equations (13) or (11). In either case, it does not depend on ρ. Thus, the covariance between the investment of firm A and its stock price does not depend on $c(\rho)$ if the manager does not learn information from its peer stock price.

Last, equations (10), (12), and (14) imply that $|cov(I, p^*_{B1})|$ increases in ρ whether or not the manager learns from its peer stock price, as claimed in the last part of the corollary.

Appendix B

In this appendix we show that the predictions of Table 1 also holds for $cov(I, p^s_{j1})$ where $p^s_{j1} = \frac{p_{j1}}{sd(p_{j1})}$ and $sd(p_{j1})$ is the standard deviation of the stock price of firm j at date 1.

Consider $cov(I, p^s_{B1})$ first. The stock price of firm B is given in Proposition 1 whether the

manager of firm A learns from stock prices or not. We deduce from Proposition 1 that:

$$sd(p_{B1}) = \sqrt{\pi_B}\sigma_B.$$

Using this result, we deduce from equations (12), (15), and (14) that:

$$
\begin{aligned}
cov_{No}(I, p_{B1}^s) &= \frac{cov_{No}(I, p_{B1})}{sd(p_{B1})} = \frac{\gamma\sqrt{\pi_B}(2\rho - 1)}{2}, \\
cov_{Narrow}(I, p_{B1}^s) &= \frac{cov_{Narrow}(I, p_{B1})}{sd(p_{B1})} = cov_{No}(I, p_B^s) + \frac{1}{2}(1 - \gamma)\pi_A\sqrt{\pi_B}(2\rho - 1), \\
cov_{Peer\ learning}(I, p_{B1}^s) &= \frac{cov_{Peer\ learning}(I, p_{B1})}{sd(p_{B1})} = cov_{Narrow}(I, p_B^s) + \frac{1}{2}(1 - \gamma)(1 - \pi_A)\sqrt{\pi_B}.
\end{aligned}
$$

Hence, the predictions of Table 1 regarding the effects the parameters on $cov_k(I, p_{B1})$ also hold for $cov_k(I, p_{B1}^s)$, for $k \in \{\text{No, Narrow, Peer learning}\}$.

Now consider firm A. The probability distribution of its stock price, p_{A1}, depends on whether the manager learns information from stock prices or not. When the manager of firm A does not learn from stock prices, we deduce from equation (23) that:

$$sd_{No}(p_{A1}) = \sqrt{\pi_A}(\sigma_A + \frac{\gamma}{2}(\Sigma_H - K)).$$

Thus, using equation (13), we obtain:

$$cov_{No}(I, p_{A1}^s) = \frac{cov_{No}(I, p_{A1})}{sd_{No}(p_{A1})} = \frac{\gamma\sqrt{\pi_A}}{2}.$$

Hence, the predictions of Table 1 for $cov_{No}(I, p_{A1}^s)$ also hold for $cov_{No}(I, p_{A1}^s)$.

Now consider the situation in which the manager of firm A learns from its stock price but not the stock price of firm B ("narrow learning"). In this case, we deduce from (26) that:

$$sd_{Narrow}(p_{A1}) = \frac{\pi_A}{2}\left[\left(\sigma_{AH}^{Narrow}\right)^2 + \left(\sigma_{AL}^{Narrow}\right)^2 + \frac{(1 - \pi_A)\pi_A(1 - \gamma)^2}{2}(\Sigma_H - K)\right]^{1/2},$$

with $\sigma_{AH}^{Narrow} = \sigma_A + \frac{(\Sigma_H - K)}{2}(2 - \gamma - (1 - \gamma)\pi_A)$ and $\sigma_{AL}^{Narrow} = \sigma_A + \frac{(\Sigma_H - K)}{2}(\pi_A + (1 - \pi_A)\gamma)$.

We have:

$$cov_{Narrow}(I, p_{A1}^s) = \frac{cov_{Narrow}(I, p_{A1})}{sd_{Narrow}(p_{A1})}.$$

Observe that $sd_{Narrow}(p_{A1})$ does not depend on π_B and ρ. Thus, the effects of these parameters on $cov_{\text{Narrow}}(I, p_{A1}^s)$ are identical to their effects on $cov_{\text{Narrow}}(I, p_{A1})$. The effects of π_A and γ on $cov_{\text{Narrow}}(I, p_{A1}^s)$ are more difficult to study analytically because the effect of these parameters on $sd_{\text{Narrow}}(p_{A1})$ is non monotonic. However, we have checked numerically that the effects of these parameters on $cov_{\text{Narrow}}(I, p_{A1}^s)$ are as shown in Table 1 for $cov_{\text{Narrow}}(I, p_{A1})$.

[Insert Figure 3 about here]

Figure 3 (Panels A and B) provides an example. This figure shows the effects of the parameters on $cov_{\text{Peer Learning}}(I, p_{A1}^s)$. When $\pi_B = 0$ (dashed lines in Panels A and B of Figure 3), $cov_{Peer\ learning}(I, p_{A1}^s) = cov_{Narrow}(I, p_{A1}^s)$ because the manager of firm A cannot learn information from the stock price of firm B in this case. We deduce from Figure 3 that $cov_{Narrow}(I, p_{A1}^s)$ decreases with γ and increases with π_A, as predicted for $cov_{Narrow}(I, p_{A1})$ (see Table 1).

Finally consider the case in which the manager of firm A also learns information from its peer stock price. In this case, we deduce from Proposition 2 that:

$$sd_{Peer\ learning}(p_{A1}) = \frac{\sqrt{\pi_A}}{2} \left[\left(\sigma_{AH}^{Peer\ learning} \right)^2 + \left(\sigma_{AL}^{Peer\ learning} \right)^2 + \frac{(1 - \pi_A)\pi_A(1 - \gamma)^2}{2}(\Sigma_H - K) \right]^{1/2},$$

with $\sigma_{AH}^{Peer\ learning} = \sigma_A + \frac{(\Sigma_H - K)}{2}(1 - \phi)$ and $\sigma_{AL}^{Peer\ learning} = \sigma_A + \frac{(\Sigma_H - K)}{2}\phi$, where $\phi \equiv \frac{\gamma + (1 - \gamma)(\pi_A + \pi_B)}{2}$.

We have:

$$cov_{Peer\ learning}(I, p_{A1}^s) = \frac{cov_{Peer\ learning}(I, p_{A1})}{sd_{Peer\ learning}(p_{A1})}.$$

The standard deviation of p_{A1} does not depend on ρ, whether the manager uses the stock price of B as a source of information or not (because ρ is too close to $\frac{1}{2}$). Hence, the effect of $c(\rho)$ on $cov_{Peer\ learning}(I, p_{A1}^s)$ is identical to its effect on $cov_{Peer\ learning}(I, p_{A1})$ and therefore as shown in Table 1.

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It is difficult to study analytically the effects of π_B, π_A, and γ on $cov_{\text{Peer learning}}(I, p_{A1}^s)$ because the effect of these parameters on $sd_{\text{Peer learning}}(p_{A1})$ is non monotonic. However, we have checked numerically that these effects are as shown in Table 1 for $cov_{\text{Peer learning}}(I, p_{A1})$.

Figure 3 illustrates this claim. Panels B and C show that $cov_{Peer\ learning}(I, p_{A1}^s)$ increases with π_A and decreases with π_B as Table 1 predicts for $cov_{Peer\ learning}(I, p_{A1})$. Moreover, Panel A shows that the effect of γ on $cov_{Peer\ learning}(I, p_{A1}^s)$ is not monotonic. It tends to be negative for π_B small (dashed and dotted lines in Panel A) and positive for π_B large (plain line in Panel A).

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	Date 1	Date 2	Date 3

1. Investors trade shares of firms A and B

1. The manager of firm A observes stock prices, p_{A1} and p_{B1} and his private signal s_{mA}

Demands and firms' cash-flows are realized

2. Stock prices, p_{A1} and p_{B1}, are realized

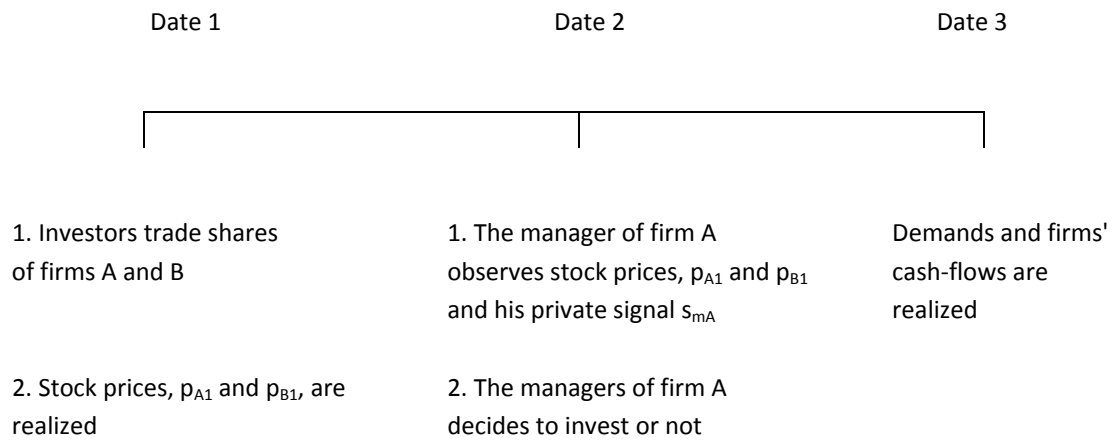2. The managers of firm A decides to invest or not
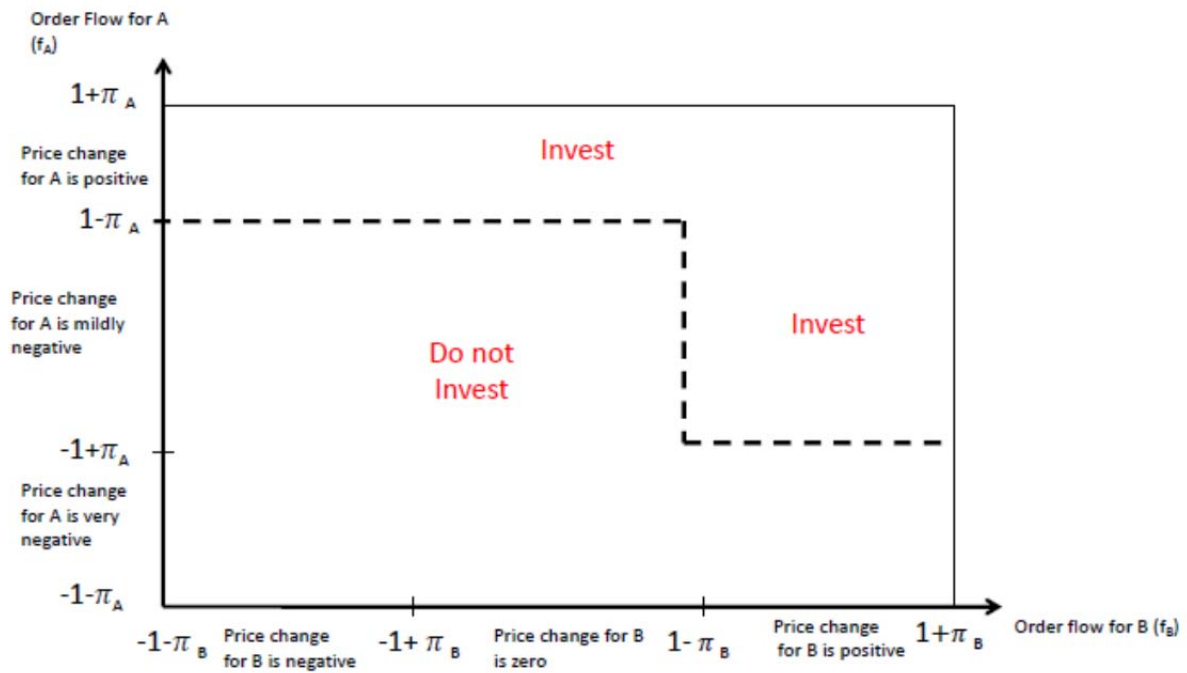
Fig. 1. Timing of the model.

Fig. 2. Equilibrium Investment Policy for firm A. This Figure shows for each realization of the order flow in stock A (Y-axis) and stock B (X-axis), the sign of the changes in prices realized between dates 0 and 1 in each stock and the corresponding investment decision for firm A .
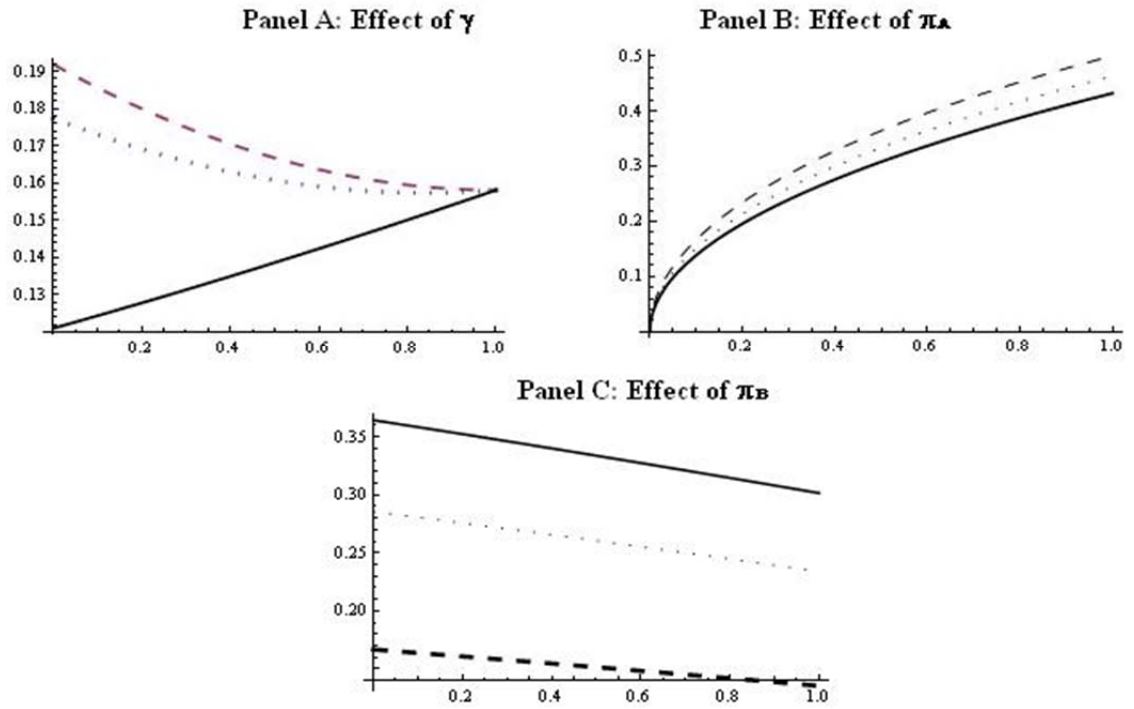
Fig. 3. The covariance of the investment of firm A and its standardized stock price. This figure shows the effects of a change in the parameters on $cov_{Peer\ learning}(I, p^s_{A1})$ when K=60, Σ_H=80, σ_A=25 and $\rho \geq 3/4$. In Panel A, we set π_A =0.1 and we show the effect of a change in γ for various values of π_B; namely, π_B=0 (dashed line), π_B =0.2 (dotted line) and π_B =0.9 (plain line). In Panel B, we set γ =0.5 and we show the effect of a change in π_A for π_B =0 (dashed line), π_B = 0.5 (dotted line) and π_B = 0.9 (plain line). In Panel C, we again set γ =0.5 and we show the effect of a change in π_B for various values of π_A; namely, π_A = 0.1 (dashed line), π_A = 0.3 (dotted line) and π_A = 0.5 (plain line).
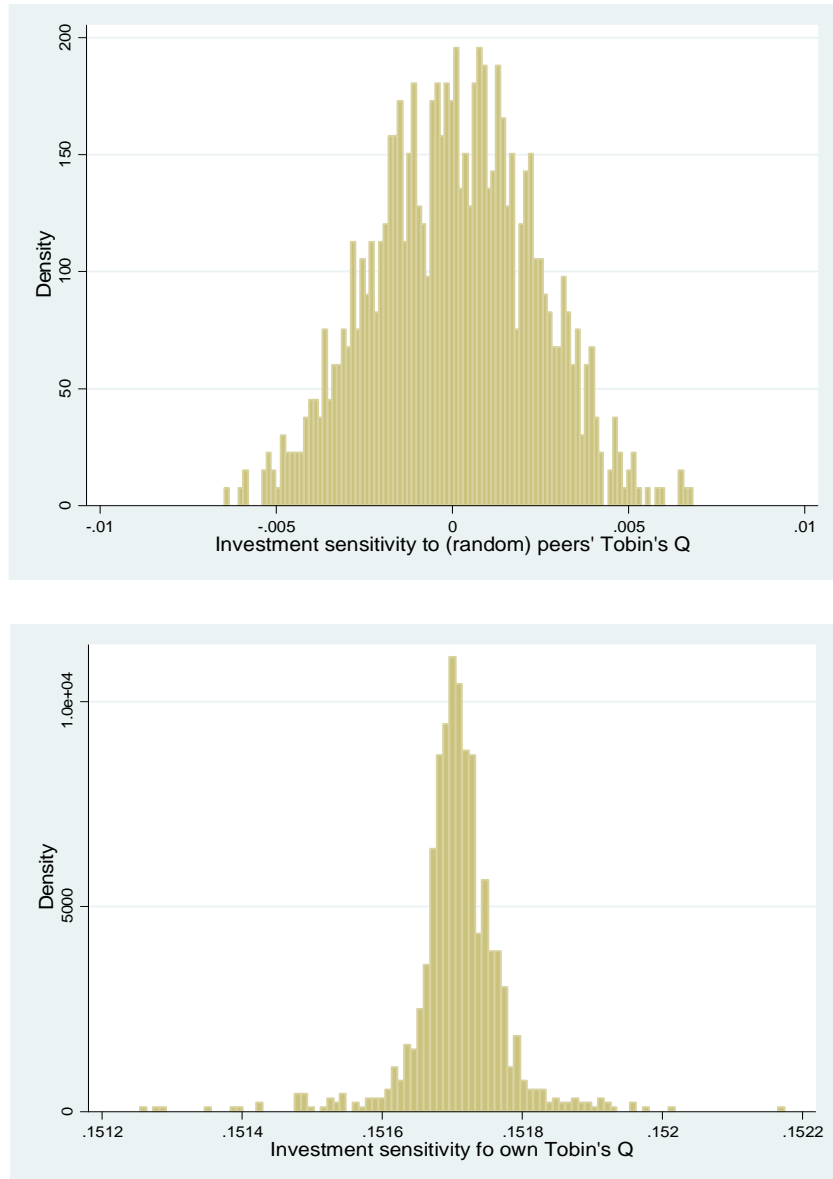
Fig. 4. Investment-to-price sensitivities: Pseudo peers. This figure shows the empirical distribution of η (Upper Panel) and β (Bottom Panel) across 1,000 estimations of equation (16) in which we replace actual peers for a firm (i.e., firms belonging to the same TNIC industry as the firm) by pseudo peers. Pseudo peers for a firm are randomly selected from firms outside of the TNIC industry of the firm, as explained in the paper. We generate 1,000 samples of pseudo peers and we estimate equation (16) for each sample, measuring the variables pertaining to peers in this equation (e.g., Tobin's Q of peers)) using pseudo peers' characteristics. Other variables (e.g., investment of firm i) are measured as in the baseline regression (16).

Fig. 5. The effect of managerial information on the sensitivity of a firm's investment to its own stock price for various levels of peers' stock price informativeness. This figure presents the estimated marginal effect of managerial information (γ) on the sensitivity of a firm's investment to its own Tobin's Q (β) as a function of the informativeness of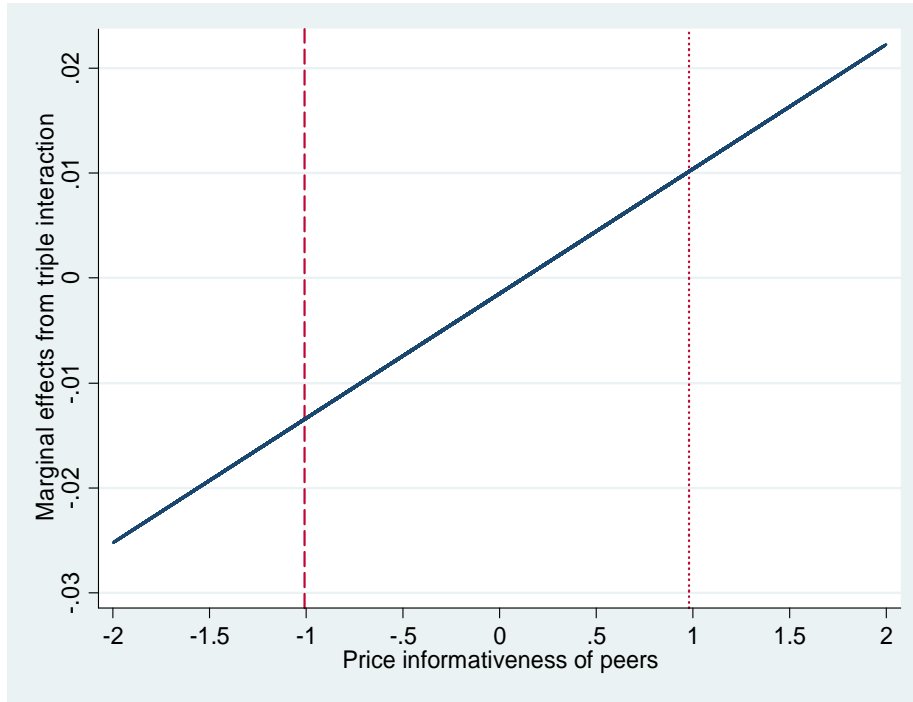 its peers' stock prices (π_B). The marginal effect is obtained from a triple interaction regression model in which firm i's investment is regressed on its own Tobin's Q, the interaction between its Tobin's Q and a proxy for managerial information (Insider$_i$), and the triple interaction between Q_i, Insider$_i$, and Ψ_{-i}^+ (a proxy for the informativeness of peers' stock prices for firm i). Other independent variables in the regression model are as in the interaction model (17). Insider$_i$ is the number of shares traded by insiders of a firm i in a given year divided by the total number of shares traded in the stock of this firm in the same year. Ψ_{-i}^+ is peers' average (de-correlated) firm-specific return variation. See section 4.3.2 for more details. The dashed vertical line cuts the x-axis at the 10th percentile of the empirical distribution of Ψ_{-i}^+ (equal to -1.01) while the dotted vertical line cuts the x-axis at the 90th percentile of this distribution (equal to 0.98).

Table 1
Investment-to-price sensitivities: Model's Predictions

This table summarizes the predictions of the model derived in Section 2.3. The model generates predictions for the covariation ("sensitivity") between a firm's investment and its own stock price and the covariation between a firm's investment and the price of its peers as a function of four parameters: the fraction of informed trading in a firm's stock π_{own} (π_A in the model), the fraction of informed trading in the peer's stock π_{peer} (π_B in the model), the private information of managers (γ), and the correlation between the demands for firms' products ($c(\rho)= |\rho\text{-}1/2|$). We present the predictions for three scenarios: (i) managers ignore stock market information: (ii) managers only rely on the information contained in their own stock price, and (iii) managers rely on their stock price and the stock price of their peers. We highlight with an "*" the predictions that are unique to the scenario in which managers learn from the stock prices of their peers (iii).

Sensitivity of Investment to:	Own stock price ($\mathrm{Cov}(I,p_A)$)				Peer stock price ($\mathrm{Cov}(I,p_B)$)			
Effect of	π_{own}	π_{peer}	γ	$|\rho\text{-}1/2|$	π_{own}	π_{peer}	γ	$|\rho\text{-}1/2|$
(i) No managerial learning	+	0	+	0	0	+	+	+
(ii) Narrow managerial learning	+	0	-	0	+	+	+	+
(iii) Learning from peers	+	-*	-/+* (function of π_{peer})	-*	-*	+	-*	+

Table 2
Definition of the Variables

Variable	Definition	Source
Capex	Capital expenditures (capx)	Compustat
PPE	Property, Plant and Equipement (ppent)	Compustat
Q	[Book value of assets (at) – book value of equity (ceq) + market value of equity (csho*prcc_f)] / book value of assets (at)	Compustat
TA	Book value of total assets (at)	Compustat
Size	Logarithm of the book value of assets (at)	Compustat
CF (cash flow)	Income before extraordinary items (ib) plus depreciation (dp) divided by total assets	Compustat
Sale	Total sales (sale)	Compustat
Ψ	Firm specific return variation computed as $\psi_{i,t} = \ln[(1-R^2_{i,t})/R^2_{i,t}]$, where $R^2_{i,t}$ represents the R^2 from a regression of firm i weekly returns on the returns on the (value-weighted) market portfolio and a (value-weighted) portfolio of peers, where peers are defined using the TNIC industries.	CRSP
Insider	Number of shares traded by insiders in a given year divided by the total total number of shares traded. We only consider open market stock transactions initiated by the top five executives (CEO,CFO, COO, President, and Chairman of the board)	Thomson Financial Insider Trading Database and CRSP
InsiderAR	The annual average (absolute value) of the one-month market-adjusted returns following insider trades. We only consider open market stock transactions initiated by the top five executives (CEO,CFO, COO, President, and Chairman of the board)	Thomson Financial Insider Trading Database and CRSP
ρ_{sales}	Correlation between firm i's sales and the average sales of its peers (using quarterly observation over the past three years)	Compustat
$P_{returns}$	Correlation between firm i's monthly returns and the average returns of its peers (using monthly observations over the pst three years).	CRSP
Similarity	Average similarity score across the peers of firm i. Similarity scores (ranging from 0% to 100%) are from the detailed text-based analysis of Hoberg and Phillips (2011)	Hoberg -Phillips data library

Table 3
Descriptive statistics

This table reports the summary statistics of the main variables used in the analysis. For each variable, we present its mean, median, 25th and 75th percentiles, and its standard deviation as well as the number of non-missing observations for this variable. All variables are defined in the Appendix. In the upper panel, we present the statistics for firm-level observations. In the lower panel, we present statistics for peers' average (i.e., the average of peers for each firm-year observation). Peers are defined using the TNIC industries developed by Hoberg and Phillips (2011). The sample period is from 1996 to 2008.

	Mean	25th	Median	75th	St. Dev.	Obs.
			Own firm			
Capital expenditures (I_i)	0.392	0.130	0.242	0.457	0.469	46,077
Q_i	2.182	1.116	1.546	2.425	1.919	46,077
Cash Flow (CF_i)	-0.029	-0.032	0.067	0.118	0.312	46,077
Total assets (mio.)	1,419.7	44.1	169.3	732.2	4,584.1	46,077
			Average of peers			
# Peers	64.89	9	28	89	83.01	46,077
Capital expenditures (I_{-i})	0.403	0.234	0.362	0.518	0.231	45,984
Q_{-i}	2.291	1.503	1.935	2.812	1.103	46,077
Cash flow (CF_{-i})	-0.031	-0.085	0.032	0.084	0.169	46,077
Total assets (mio)	1,473.4	374.6	845.6	1,736.7	2,090.8	46,077

Table 4
Investment-to-price sensitivities: Baseline Results

This table presents the results from estimations of equation (16). The dependent variable is investment, defined as capital expenditures divided by lagged property, plant and equipment (PPE). Q_i is the market-to-book ratio of firm i, defined as the market value of equity plus the book value of debt minus the book value of assets, scaled by book assets. Q_{-i} is the average market-to-book of the peers of firm i, where peers as defined using the TNIC industries developed by Hoberg and Phillips (2011). Other explanatory variables are defined in Table 2. The subscript −i for a variable refers to the average value of the variable across firm i's peers, except in Column 2 where it refers to the median value of this variable. All explanatory variables are divided by their sample standard deviation to facilitate economic interpretation. Column (1) presents estimates for the baseline specification. In column (2) we use the median peers' characteristics instead of the average. In column (3) the peers of firm i are all the firms that belong to firm i's 3-digit SIC industry. In column (4) the peers of firm i are all the firms that belong to firm i's 4-digit NAICS industry. The sample period is from 1996 to 2008. The standard errors used to compute the t-statistics (in squared brackets) are adjusted for heteroskedasticity and within-firm clustering. All specifications include firm and year fixed effects. Symbols ** and * indicate statistical significance at the 1% and 5% levels, respectively.

	Baseline	Median	SIC-3	NAICS-4
	(1)	(2)	(3)	(4)
Q_{-i}	0.059**	0.054**	0.040**	0.047**
	[11.11]	[9.79]	[7.08]	[7.64]
CF_{-i}	0.024**	0.022**	0.027**	0.024**
	[4.36]	[4.00]	[4.69]	[3.82]
$Size_{-i}$	-0.004	-0.006	-0.012	-0.006
	[0.96]	[1.25]	[1.42]	[0.72]
Q_i	0.137**	0.139**	0.143**	0.141**
	[23.68]	[24.07]	[24.46]	[23.98]
CF_i	0.100**	0.100**	0.100**	0.100**
	[18.72]	[18.73]	[18.48]	[18.27]
$Size_i$	-0.125**	-0.121**	-0.118**	-0.120**
	[8.56]	[8.30]	[8.03]	[8.13]
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Obs.	43,919	43,919	43,925	43,925
Adj. R^2	0.359	0.358	0.356	0.356

Table 5
Investment-to-price sensitivities: Dynamic peers' classification

     This table presents the results from estimations of equation (16) for different definitions of firm i's peers that account for the dynamics of the set of peers for a given firm. The dependent variable is investment, defined as capital expenditures divided by PPE. Q_i is the Tobin's Q of firm i. Q_{-i} is the average Tobin's Q of the peers of firm i, where peers as defined using the TNIC industries developed by Hoberg and Phillips (2011). The other explanatory variables are defined in Table 2. All independent variables are divided by their sample standard deviation to facilitate economic interpretation. The subscript –i for a variable refers to the average value of the variable across firm i's peers. In column (1), peers are firms in the same TNIC industry as firm i in year t that were not in its set of peers in year t-1 (new peers). In column (2), peers are firms in the same TNIC industry as firm i in year t-1 but not in year t (past peers). In column (3), peers are firms in the same TNIC industry as firm i in years t and t-1 (old peers). In columns (4) and (5) peers are firms that are not in the same TNIC industry as firm i in year t but will be in year t+1 and t+2, respectively (future peers). The sample period is from 1996 to 2008. The standard errors used to compute the t-statistics (in squared brackets) are adjusted for heteroskedasticity and within-firm clustering. All specifications include firm and year fixed effects. Symbols [**] and [*] indicate statistical significance at the 1% and 5% levels, respectively.

	New	Past	Still	Future (+1)	Future (+2)
	(1)	(2)	(3)	(4)	(5)
Q_{-i}	0.032**	0.006	0.039**	0.025**	0.018**
	[7.63]	[1.79]	[7.00]	[5.92]	[3.88]
CF_{-i}	0.027**	0.023**	0.025**	0.024**	0.026**
	[4.45]	[3.82]	[4.23]	[3.44]	[3.44]
$Size_{-i}$	-0.008	-0.008	-0.006	-0.008	-0.012
	[1.50]	[1.53]	[1.26]	[1.32]	[1.88]
Q_i	0.140**	0.123**	0.115**	0.142**	0.147**
	[22.97]	[19.34]	[18.31]	[22.11]	[21.20]
CF_i	0.094**	0.087**	0.086**	0.098**	0.098**
	[17.30]	[15.63]	[15.52]	[16.74]	[15.20]
$Size_i$	-0.100**	-0.088**	-0.092**	-0.085**	-0.074**
	[5.84]	[5.10]	[5.55]	[4.43]	[3.48]
Firm FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Obs.	37,598	34,041	35,580	33,720	28,467
Adj. R^2	0.351	0.31	0.318	0.355	0.368

Table 6
Investment-to-price sensitivities: Learning from Peers' Stock Prices

This table presents estimates of the interaction model (17). The dependent variable is investment, defined as capital expenditures divided by lagged property, plant and equipment (PPE). Explanatory variables include: (i) Q_i is the Tobin's Q of firm i, defined as the market value of equity plus the book value of debt minus the book value of assets, scaled by book assets, (ii) Q_{-i} is the average Tobin's Q of the peers of firm i, where peers as defined using the TNIC industries developed by Hoberg and Phillips (2011), and (iii) ϕ represents various proxies for the model parameters. We add other explanatory variables (see equation (17)) but we do not report estimated coefficients on these variables for brevity. In Panel A, ϕ is either Ψ_{-i}^{+}, a proxy for the informativeness of firm i's peer stock price or Ψ_i^{+}, the informativeness of firm i's own stock price. In Panel B, ϕ is a proxy for managerial information, either Insider or InsiderAR. In Panel C, ϕ is a proxy (ρ_{sales}, $\rho_{returns}$, and Similarity) for the correlation in demand between a firm and its peers. The sample period is from 1996 to 2008. All independent variables are divided by their sample standard deviation to facilitate economic interpretation. The standard errors used to compute the t-statistics (in squared brackets) are adjusted for heteroskedasticity and within-firm clustering. All specifications include firm and year fixed effects. Symbols ** and * indicate statistical significance at the 1% and 5% levels, respectively.

$\phi=?$	Panel A		Panel B				Panel C		
	Ψ_{-i}^{+}	Ψ_i^{+}	Insider	InsiderAR	Insider	InsiderAR	ρ_{sales}	$\rho_{returns}$	Similarity
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Q_{-i}	0.053**	0.055**	0.053**	0.065**	0.053**	0.054**	0.038**	0.042**	0.043**
	[9.75]	[11.08]	[6.93]	[7.69]	[6.27]	[8.23]	[6.11]	[3.47]	[2.83]
$Q_{-i} \times \phi$	0.005	-0.016**	-0.009**	-0.009*	-0.010**	-0.009**	0.007**	0.009**	0.012**
	[1.83]	[5.55]	[3.95]	[2.26]	[4.03]	[3.63]	[2.92]	[3.61]	[3.66]
Q_i	0.139**	0.134**	0.138**	0.130**	0.142**	0.137**	0.116**	0.138**	0.149**
	[27.21]	[24.76]	[18.47]	[13.82]	[18.04]	[16.28]	[19.42]	[14.38]	[8.12]
$Q_i \times \phi$	-0.012**	0.005	0.000	-0.007	-0.001	-0.003	-0.008**	-0.004	-0.010**
	[2.63]	[1.88]	[0.10]	[1.12]	[0.64]	[0.98]	[3.54]	[1.88]	[3.73]
$Q_{-i} \times \phi \times \Psi_{-i}^{+}$					0.012**	0.008**			
					[4.20]	[2.87]			
Obs.	42,692	42,692	25,932	24,136	25,541	23,986	38,355	43,050	43,919
Adj. R^2	0.357	0.357	0.408	0.423	0.406	0.399	0.332	0.353	0.36

Table 7
Going public firms

In this table, we use a subsample of 1,342 firms that go public at some point during our sample period (1996-2008). We compare sensitivity of investment to peers' stock prices for these firms before and after they go public by regressing their investment on their peers' Tobin's Q, a dummy variable equal to one after a firm goes public, and the interaction between this dummy variable and peers' Tobin's Q. Investment is defined as capital expenditures divided by PPE. Peers' Tobin's Q (Q_{-i}) is the average market-to-book ratio of firm i's peers, where peers are defined using the TNIC industries developed by Hoberg and Phillips (2011). Post is a dummy variable equal to one after firm i IPO, and zero otherwise. The other control variables (including the post IPO firm's own Tobin's Q, measured by market-to-book) are defined in Table 1. In Column 2, we also control for firms' sales growth before and after their IPO. As in other tests, all independent variables are divided by their sample standard deviation. The standard errors used to compute the t-statistics (in squared brackets) are adjusted for heteroskedasticity and within-firm clustering. All specifications include firm and year fixed effects. Symbols ** and * indicate statistical significance at the 1% and 5% levels, respectively.

	IPO Firms	
	(1)	(2)
Q_{-i}	0.036**	0.027**
	[4.56]	[3.45]
Post	0.014	0.012
	[0.79]	[0.67]
Q_{-i} x Post	-0.022**	-0.015*
	[2.95]	[2.00]
Sales Growth$_i$		0.028**
		[5.28]
Control variables	Yes	Yes
Firm FE	Yes	Yes
Year FE	Yes	Yes
Obs.	5,878	5,728
Adj. R^2	0.53	0.55