Does Firm Investment Respond to Peers' Investment?

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ABSTRACT

Yes, it responds positively. Using a new instrumental variable based on the presence of location-specific information externalities, we estimate that firms increase investment by 10% in response to a one standard-deviation increase in the investment of their product market peers. The influence of peers' investment is stronger in concentrated industries, featuring more heterogeneous firms, and for relatively smaller firms that possess less precise information. These findings are consistent with a model in which firms compete and use peers' investment as a source of information about product market fundamentals. The positive influence of peers' investment could amplify variation in aggregate investment and thus affect productivity and output.

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I Introduction

Corporate investment is positively correlated within industries.[1] This empirical fact might simply indicate that firms selling similar products or services are exposed to the same fundamental shocks, which lead them to passively invest alike. The commonality of firms' investment could also result from "peer effects", whereby firms' investment is *actively* influenced by that of their product market peers. Deciphering the origins of investment commonality is important since, unlike exposure to common shocks, the presence of peer effects could amplify (or attenuate) the effect of firm-specific shocks within and across industries, and therefore affects the dynamics of aggregate investment.

Attributing the interdependence of firms' investments to peer effects is difficult for both theoretical and empirical reasons. First, peer effects can originate from different economic channels, leading some firms to respond positively to peers' investment, and others to respond negatively. In learning models for instance, imperfectly informed firms respond positively to peers' investment because firms use peers' decisions as a source of information about investment opportunities (Bikhchandani, Hirshleifer, and Welch (1992)). In contrast, in investment models featuring strategic interactions, firms' respond negatively to the investment of peers when peers' competitive actions hurt their prospects (Fudenberg and Tirole (1984)). Second, identifying peers effects in the data requires isolating firms' responses to the decisions of their peers from correlated decisions due to common information among related firms (Manski (1993) or Glaeser, Sacerdote, and Scheinkman (2003)).

This paper provides direct evidence that firms' investment respond positively to the investment of their product market peers. To guide our tests, we develop a strategic model of investment in which firms compete in the product market but have imperfect information about fundamentals (e.g., future demand). The model serves three purposes. First, it explains when and why peer effects arise in industry equilibrium. Second, it characterizes the conditions for their empirical identification when firms' information is imperfect. Third,

[1] For instance, based on our working sample of firms in Compustat between 1996 and 2011, the correlation between public firms' investment and that of their product market peers ranges between 0.35 and 0.40 depending on the definition of the industry group. Industry fixed effects explain more than 10% of the total variability in corporate investment.

it delivers novel testable predictions.

Our model builds on Gal-Or (1987) and features two firms A and B that offer differentiated products and face an uncertain demand for their products. Firms invest in production capacity, and future cash flows are determined by the chosen capacity (i.e. their investment) and the resulting equilibrium price that firms can charge for their respective products. Before investing, each firm receives imperfect private information about future demand (i.e., the fundamental) that is positively correlated with the private information of the other firm. Firms decide sequentially on how much to invest. Firm B receives its private information and chooses its investment, strategically taking into account the equilibrium effect of the future investment by firm A. Then, firm A chooses its investment after obtaining its private information and observing the investment of firm B. In industry equilibrium, the investment of firm A is a linear function of its private information and the investment of firm B. The theoretical influence of B's investment – the "equilibrium" peer effect – can be either positive or negative, depending on the relative importance of the effects of learning from peers' investments versus the strategic effect of peers' investments.

We then use the model to show that an econometrician cannot identify the equilibrium peer effect by regressing the investment of firm A on that of firm B, unless she *perfectly* observes firms' private information. Since the private information received by firm A is correlated with the investment of firm B (firms' private information is positively correlated), we prove that an estimation by ordinary least squares introduces an upward bias, and the magnitude of such bias depends on the precision of the econometrician's knowledge about firms' private information. We conclude that the econometrician can correctly estimate the equilibrium peer effect if she uses an instrument for the investment of firm B that (i) contains information relevant for firm A's investment, but (ii) is orthogonal to the private information of firm A. Instrumentation in our setting has to isolate variation in *information* relevant for firm A's investment that is only possessed by firm B, and not variation in firm B's fundamentals that is orthogonal to that of firm A.[2]

In the spirit of Bartik (1991), we combine industry and geography variations to construct

[2]This is because firm A should not respond that the variation in firm B's investment that is irrelevant for its prospects. In this case, we do not expect to observe any peer effects.

an instrument satisfying these conditions. To illustrate, imagine that firms A and B manufacture furniture and are located in Austin and Boston respectively. We use the average investment of firms in Boston that operate in product markets that are *unrelated* to furniture (e.g., optical equipment or footwear) as an instrument for the investment of firm B. In the data, the average investment of unrelated firms located in Boston correlates strongly with firm B's investment, reflecting local knowledge diffusion, technology transfer, or consumption externalities between neighboring firms operating in different industries (Glaeser, Kallal, Scheinkman, and Shleifer (1992)).[3] We argue that the local information leading to investment commonality in Boston (e.g., shared information about business trends) is not observed by firm A in Austin, but it is plausibly related to its future growth opportunities.

We estimate firms' response to the investment of their peers on a large sample of more than 6,000 public firms over the period 1996 to 2011. We define firms' product market peers using the Hoberg and Phillips (2015) industry definitions, and firms' local peers as firms headquartered in the same Metropolitan Statistical Area (MSA). To ensure that our instrument truly removes the influence of common fundamentals, we construct it using only *unrelated non-local* firms in order to purge direct and indirect horizontal and vertical links among firms.

Using the average investment of non-local unrelated peers as an instrument for the average investment of a firm's non-local product market peers, we find that firms respond positively to the investment of their product market peers. The economic magnitude of peers' influence on corporate investment is substantial. The average firm in the sample increases its investment by 10% (compared to its average) in response to a one standard deviation increase in the (instrumented) average investment of its product market peers.

Our identification could arguably be threatened if firms can directly observe the localized information leading to investment commonality in other locations, or if the construction of our instrument fails to completely purge economic links between firms and the unrelated neighbors of their product market peers. To mitigate this concern, we artificially replace

[3]The idea that important knowledge and technology transfers occur between unrelated industries in specific locations starts with Jacobs (1969), who argues that the variety and diversity of geographically proximate industries promote innovation and growth. Consistent with this idea, Ellison, Glaser, and Kerr (2010) show that industries co-agglomeration is related to the sharing of ideas and knowledge.

each true non-local product market peer in our sample (i.e., firm B) by a random firm that is located in the same location as the true peer but operating in unrelated product markets (e.g. a footwear manufacturer also located in Boston). Across 1,000 distinct artificial samples, we find no evidence that firms' investment (e.g., firm A in Austin) responds to the instrumented investment of unrelated non-local firms (such as footwear manufacturer in Boston). The insignificance of peer effects in these placebo samples are obtained despite strong first-stage estimates, and therefore provide direct support for the validity of our instrumental variables approach.

To further understand the nature of peer effects, we use the model to predict how the equilibrium peer effect varies with the model's parameters. We derive four unique predictions and find empirical support for each of them using firm and industry-level proxies. First, the model predicts that the equilibrium peer effect decreases with the relative precision of firm A's private information. In equilibrium, firm A relies more on the investment of firm B as a source of information when its own information is relatively less precise. Second, the equilibrium peer effect also decreases as firms' private information becomes more correlated. In that case, firm A puts less weight on the investment of firm B since a larger portion of the information revealed through this investment is already known to firm A. Third, the model further predicts that the equilibrium peer effect decreases with the relative size of firm A (i.e., its initial capacity). Intuitively, a smaller firm has stronger incentives to learn from its peer (increasing the equilibrium peer effect). Fourth, peers' influence is predicted to be larger in concentrated product markets, in which a fringe of smaller firms has stronger incentives to learn from larger product market peers. These results confirm the importance for firms to use peers' investment as a source of strategic information.

Finally, we invalidate two possible alternative explanations for our findings. First, we show that the influence of peers' investment is unlikely to reflect herding behavior arising because some managers are more favorably evaluated when they follow the decisions of their peers than if they behave independently (Scharfstein and Stein (1990)). Second, we show that our results cannot be explained by a scenario in which firms have *perfect* information about their prospects and actions are strategic complements, as we find significant positive peer influence in markets featuring competition in strategic substitutes (as in our model).

Our main contribution is to empirically establish that the investment of product market peers has a *direct* positive influence on firms' investment decisions, and to provide theory-based evidence for *why* these peer effects arise in equilibrium. Our analysis thus adds to existing research that shows that firms' investment is positively associated with that of geographically-close firms (Dougal, Parsons, and Titman (2015) and firms whose executives share social ties (Shue (2013) and Fracassi (2016)). Other studies indicate that investment is positively correlated within industries because firms over-react to common investment opportunities, either because they neglect the impact of competition on future profits (Hoberg and Phillips (2010) and Greenwood and Hanson (2015)) or because they blend with the crowd (Povel, Sertsios, Kosava, and Kumar (2015)). To the best of our knowledge, our paper is the first to show that firms's investment positively respond to that of their product market peers, and to provide evidence that such peer effects arise because firms use peers' investment to infer information about their prospects.

Our paper belongs to a growing literature examining peer effects in corporate decisions.[4] We differ from most existing research by combining learning and strategic effects in a model of investment to clarify possible economic mechanisms leading to peer effects within industries, and to facilitate their empirical detection. Our theoretical and empirical analyses contribute to the existing literature in showing that identification in settings where firms have imperfect information and can learn from each other relies on exogenous variation in the information they possess about their fundamentals, and not on exogenous variation in their fundamentals. This distinction is important to correctly interpret empirical estimates.

[4]For instance, Lerner and Malmendier (2013) find peer effects in entrepreneurship; Leary and Roberts (2014) find evidence of peer effects in capital structure; Kaustia and Rantala (2015) report peer effects in firms' decision to split their stocks; Bouwman (2011) finds that firms with shares directors have more similar governance; Popadak (2012) finds that industry peers' influence firms' dividend policy; and Matray (2015) reports that innovation by one firm fosters innovation by neighboring firms.

II Equilibrium Peer Effects

A The Model

We adapt the model of Gal-Or (1987) to study a setting in which two firms A and B offer differentiated products and have the ability to increase their production by investing in additional physical capital. The model features two key ingredients. First, similar to standard games of strategic interaction, the investment decision of one firm is strategic and negatively affects the prospects of the other firm as an increased supply of products lowers the equilibrium market prices. Second, both firms are imperfectly informed about future demand for their products, but each firm can potentially learn information about the demand for its own product by observing the investment decision of the other firm.

Firms' cash flows. Both firms optimally decide on investment (i.e., choose their productive capacity) by considering its impact on expected future cash flows in equilibrium. At any point in time, the operating profits (π) of each firm $i = A, B$ are given by:

$$\pi_i [K_i, K_{-i}, \varepsilon] \equiv p_i [K_i, K_{-i}, \varepsilon] \times K_i \tag{1}$$

where K_i is the installed capital of firm i, p_i is the price that firm i charges for its product, and ε is a common demand shock that affects the profits and investment decisions of both firms in the market. For simplicity, we assume that firms' production is equal to their installed capital K, and that firms face no marginal costs of production. The unit price charged by firm i is given by the following linear inverse demand function:

$$p_i [K_i, K_{-i}, \varepsilon] = \alpha - \gamma \times K_i - \theta \times K_{-i} + \varepsilon, \quad \alpha, \gamma, \theta > 0 \tag{2}$$

where the parameter $\gamma > 0$ reflects the negative effect of the supply of firm i's product on its own price. The parameter $\theta > 0$ indicates that firms' products are strategic substitutes: an increase in capacity by the rival firm affects the price of firm i negatively.[5] The inverse demand function in Equation (2) further allows for product differentiation, such that each firm can charge a slightly different price for its own product. To capture this feature, we follow Singh and Vives (1984) and assume that the influence of a firm's production (K_i) on

[5]We analyze the alternative case in which $\theta < 0$ and goods are strategic complements in Section V.

its product price (p_i) is weakly stronger than the influence of its rivals' production (K_{-i}), such that $\gamma \geq \theta$. The price charged by both firms is the same and their products are perfect substitutes in the special case in which $\gamma = \theta$.

We define investment as the ratio of investment to capital $I_i \equiv K_i^+/K_i^- - 1$, which reflects the change in the installed capital of firm i from an initial stage in which firms operate with capital $K_i^- > 0$, to a subsequent stage in which firms operate with capital K_i^+. We take the initial installed capacity K_i^- as given, and use the superscripts $^-$ and $^+$ to denote before and after investment, respectively. When firms modify their capital stock, they are subject to the following cost:

$$\Phi\left[I_i, K_i^-\right] = \kappa \times I_i \times K_i^- + \frac{\phi}{2} \times (I_i)^2 \times K_i^- \tag{3}$$

where $\kappa > 0$ is the price of purchasing capital. Following Abel and Eberly (1994), the second term in Equation (3) captures convex costs of investment such that $\phi > 0$.

Sequence of actions. We assume that firms have imperfect information about the future demand shock ε in Equation (2), as a mean of arguing in reduced form that firms are imperfectly informed about the value of their growth opportunities. When firms decide on investment, the future demand shock ε is unknown, but they receive a private signal s_i that contains imperfect information about ε. As a result, firms' investment decisions may reveal information about the private information they possess. To study the propensity for a firm to condition its own investment on that of its peer, we assume that firms invest sequentially. The sequence of decisions in the model contains three stages as shown in Figure 1. First, firm B receives its private signal s_B, and chooses its investment I_B. Second, firm A receives its private signal s_A, observes I_B, and then chooses its investment I_A. Once firms have committed to their corresponding strategies, investments are undertaken, the demand shock materializes, and cash flows are realized.

[Insert Figure 1 about Here]

Information structure. We assume that firms' private signal s_i does not contain information about the product market's demand as a whole, but rather about a *portion* of the demand. For instance, firms may possess proprietary information concerning the future demand pertaining to their geographical area, or for a given segment of customers (e.g., young or female customers). We denote by ϵ_i the demand shock related to the portion of the market observed by firm i, and we assume that the private signal s_i is a signal about the demand shock ϵ_i. The overall market demand shock ε in Equation (2) is then equal to $\varepsilon \equiv (\epsilon_A + \epsilon_B)/2$. In other words, the demand shock ε that influences equilibrium prices in the product market is given by the average portion-specific shock about which firms receive private signals.[6]

Consistent with standard models of imperfect information (Welch (1992)), firms are imperfectly informed about the demand shock ε, but they know its underlying distribution. We assume that $E[\epsilon_i] = \mu > 0$ such that the shocks to the alternative portions of the market have identical means, as well as $Var[\epsilon_i] = 1 > 0$. In addition, the demand shocks affecting the portions of the market observed by each firm are such that $cov[\epsilon_A, \epsilon_B] \equiv \rho > 0$. The parameter ρ thus captures both the covariance and the correlation between the portion-specific demand shocks ϵ_A and ϵ_B.[7] We require $\rho \neq 0$ to ensure that a fully revealing equilibrium exists and we focus on the case $\rho > 0$ to simplify exposition.

Firms also know the underlying distribution of the signals they receive. We assume that the private signal received by each firm s_i is an unbiased but noisy estimator of the demand shock ϵ_i. As a result, the expected value and the variance of s_i are such that $E[s_i|\,\epsilon_i] = \epsilon_i$ and $Var[s_i|\,\epsilon_i] = \sigma_i^2 < \infty$, respectively. The corresponding signal precision is given by $1/\sigma_i^2 > 0$. Furthermore, the correlation between the portion-specific shocks ϵ_i implies that firms' private signals are correlated. When $0 < \rho < 1$, firms' private signals s_i are partially correlated. When $\rho = 1$, the shocks ϵ_i are perfectly correlated such that each private signal s_i is the sum of the common demand shock ε and additional white noise.

Last, we need not impose a specific prior distribution function of the shocks ϵ_i, nor a specific posterior distribution function of the signals s_i. We assume instead that these

[6]We define ε using a simple average of ϵ_A and ϵ_B for analytical convenience. It can be shown that any weighted average of the shocks ϵ_i (i.e. weighted by the relative product differentiation) yields the same results shown in this paper. This is because the demand function is linear in the demand shock ε.

[7]The parameter ρ captures within-industry co-movement in demand shocks. Note however that since the portions of the market observed by firms A and B may overlap, the parameter ρ may simply capture such overlap.

distribution functions yield linear posterior expectations on the future demand. Moreover, we require that the posterior distributions of the signals s_i for each firm have the same functional form. Several sets of prior and posterior distributions comply with these properties.[8]

Other assumptions. We make additional parametric assumptions that are without loss of generality and help us simplify exposition. We set $\alpha = \kappa$ to reduce the number of parameters in the model. We assume firms discount cash flows at a rate equal to zero and invest positive amounts. We thus impose a lower bound on the expected demand shock such that $\mu > \overline{\mu}$.[9] Intuitively, the expected demand shock should not be too low for investment to stay positive. Last, we require $\sigma_B^2 < 2\rho - 1$; the reason why this constraint is analytically convenient is clarified in the Appendix.

B Investment in Industry Equilibrium

We solve for firms' equilibrium investment decisions, assuming that each firm chooses the level of investment that maximizes its value. The equilibrium concept is Nash-Cournot, and we provide all proofs in the Appendix.

To better understand the derivation of the equilibrium, consider first the investment decision of firm A. Firm A chooses I_A given its private signal s_A and the observed investment of firm B (I_B). As a result, the problem of firm A is given by:

$$\max_{I_A \equiv K_A^+/K_A^- - 1} \mathrm{E}\left[\pi_A^+\left[K_A^+, K_B^+, \varepsilon\right] - \Phi_A\left[I_A, K_A^-\right] \middle| s_A, I_B\right], \tag{4}$$

where we set π_i^- for $i = A, B$ equal to zero without loss of generality. The solution to Equation (4) yields the *reaction function* of firm A, which we define as $I_A^{\mathcal{R}}\left[I_B, s_A\right]$. Firm B chooses its investment before firm A, taking into account both its private signal and the reaction function of its peer:

$$\max_{I_B \equiv K_B^+/K_B^- - 1} \mathrm{E}\left[\pi_B^+\left[K_B^+, K_A^+, \varepsilon\right] - \Phi_B\left[I_B, K_B^-\right] \middle| s_B, I_A^{\mathcal{R}}\right]. \tag{5}$$

[8] For instance, these properties hold when both ϵ_i and $s_i|\,\epsilon_i$ are normally distributed. Since ϵ_i are defined as demand shocks to (strictly positive) prices, an alternative specification that yields linear conditional expectations with non-negative values is a Gamma distribution for ϵ_i and a Poisson distribution for $s_i|\,\epsilon_i$.

[9] The expression for $\overline{\mu}$ is provided in Equation (17) in the Appendix. The inequality $\mu > \overline{\mu}$ is a necessary condition such that the investment to capital ratio I_B is positive in equilibrium. We impose $I_B > 0$ to better interpret the reaction of firm A to firm B's investment decision in equilibrium. Investment in our working sample is also pervasively positive.

Consistent with standard games of strategic interaction, Equation (5) indicates that firm B chooses investment by taking into account the optimal reaction of firm A to its investment I_B. Unlike standard games of strategic interaction, however, the reaction function $I_A^{\mathcal{R}}$ is *itself* a function of the private signal received by firm B, through I_B.

Proposition 1. *[Equilibrium Investment Strategies] The unique pure strategy equilibrium is such that:*

$$I_B\left[s_B\right] = \delta_B + \eta_B \times s_B \tag{6}$$

$$I_A\left[s_A, I_B\right] = \delta_A + \eta_A \times s_A + \beta \times I_B \tag{7}$$

where the parameters $\delta_B > 0$, $\eta_B > 0$, $\eta_A > 0$ are defined in the Appendix, and the parameter β is such that:

$$\beta = \underbrace{\frac{-\theta \times K_B^-}{\left(2 \times \gamma \times K_A^- + \phi\right)}}_{\text{Strategic channel } <0} + \underbrace{\frac{(1+\rho) \times \left(1 - \rho + \sigma_A^2\right) \times K_B^-}{2 \times \Lambda \times \left(2 \times \gamma \times K_A^- + \phi\right) \times \eta_B}}_{\text{Learning channel } >0} \tag{8}$$

where the first term represents the strategic effect of firm B on firm A's decision, the second term represents the effect of learning from firm B on on firm A's decision, and $\Lambda \equiv \left(\sigma_B^2 + 1\right)\left(\sigma_A^2 + 1\right) - \rho^2 > 0$.

Proposition 1 characterizes the unique pure strategy equilibrium of the game. As shown in Equation (6), the equilibrium investment of firm B is a linear function of its private signal s_B. The parameter $\eta_B > 0$ is strictly positive since firm B optimally increases investment if the expected demand is higher.[10] Similarly, the equilibrium investment of firm A is a linear function of its private signal s_A and the investment strategy I_B (Equation (7)). As in the case of firm B, the sign of the parameter η_A is strictly positive. In equilibrium, the investment of firm B is *fully revealing*, such that firm A perfectly infers the signal s_B by observing I_B.[11]

Equation (8) shows how the investment of firm B influences the investment of firm A in equilibrium. The parameter β captures the *peer effect*, defined as the equilibrium partial covariance between I_A and I_B (after accounting for the effects of the fundamental signals).

[10]Put together, the parameters $\delta_B > 0$ and $\eta_B > 0$ ensure that there exists a unique mapping between the signal s_B and the investment to capital ratio I_B.

[11]In the Appendix, we elaborate on the reasons why the parameter choice in our setting ensures that there exists a unique fully revealing equilibrium, and that there are no partially revealing equilibria.

The key feature of the peer effect β is that its sign depends on the opposing effects of the strategic and learning forces. The first term in Equation (8) captures the strategic channel and is strictly negative. If firm B increases production capacity, firm A invests relatively less since their products are strategic substitutes. The second term captures the learning channel when firms operate under imperfect information. This term is non-negative and remains strictly positive as long as firms' signals are imperfectly correlated ($0 < \rho < 1$) or signals remain imperfect ($\sigma_i > 0$).[12] Firm A follows the investment of firm B because it rationally relies on I_B as a source of information about future demand. Equation (8) further indicates that the equilibrium peer effect β is a function of η_B. In particular, the coefficient β is strictly positive as long as firm B reacts moderately to its own private signals (i.e. η_B is fairly low). If instead firm B invests aggressively upon observing a positive signal, the strategic effect dominates such that β is strictly negative.

C The Econometrician's Problem

We now use the model to understand how an econometrician can identify the equilibrium peer effect (i.e., parameter β) in the data. We show that the estimation of β is challenging because, unlike the firms in the model, the econometrician does not perfectly observe firms' private signals about investment opportunities (Erickson and Whited (2000)).

To understand the econometrician's problem, assume for simplicity that she observes the investments I_A and I_B, but none of the private signals s_A and s_B. Using what she observes, she (naively) estimates Equation (7) by ordinary least squares (OLS) such that:

$$I_A = \omega + \alpha_A \times I_B + \xi_A \tag{9}$$

where ω is a constant and the normally distributed error term ξ_A contains the unobserved private signal s_A and white noise u_A (i.e. $\xi_A = \eta_A \times s_A + u_A$). The inference from this regression is problematic since the coefficient α_A^{OLS} is a biased estimator of the equilibrium peer effect β. Using Equation (7), the OLS estimate α_A^{OLS} is given by:

$$\alpha_A^{OLS} = \beta + \eta_A \times \frac{Cov\left[s_A, I_B\right]}{Var\left[I_B\right]} \tag{10}$$

[12] In case that $\rho = 1$ or signals are perfect, there is no learning in equilibrium. Under perfect information, the peer effect relates exclusively to the first term in Equation (8).

where $\eta_A > 0$. Using Equation (6), we obtain that $cov\,[s_A, I_B] = cov[s_A, \delta_B + \eta_B \times s_B] = \rho \times \eta_B > 0$. By replacing $cov\,[s_A, I_B]$ into Equation (10) we conclude that $\alpha_A^{OLS} > \beta$, i.e., the OLS estimate contains an upward bias. In other words, even if peer effects are absent ($\beta = 0$), the coefficient estimate α_A^{OLS} could be positive in the data simply because the fundamental signals that firms use to decide on investment are positively correlated ($\rho > 0$). As it is well-known in studies of peer effects (Manski (1993)), the bias originates in the inability of the econometrician to perfectly observe (and hence control for) all fundamental determinants of agents' decisions (s_A and s_B in our context).

The model however highlights the necessary conditions for the empirical identification of the peer effect β by instrumental variables. To understand the properties of a prospective instrument, recall that each firm's signal is defined as $s_i = \epsilon_i + v_i$ where $cov\,[s_A, s_B] = cov\,[\epsilon_A,\ \epsilon_B] = \rho$ and v_A is orthogonal to v_B. Given the model's information structure, any prospective instrument Z_B must be (i) correlated with firm B's investment such that $cov\,[I_B, Z_B] \neq 0$ (i.e., satisfies the inclusion restriction), (ii) unrelated with firm A's private signal s_A such that $cov\,[s_A, Z_B] = 0$ (i.e., satisfies the exclusion restriction), and (iii) relevant for firm A's investment decision. Put differently, Z_B should capture a portion of the private signal of firm B that does not overlap with the private signal of firm A, but is a fundamental determinant of firm A's investment. If the econometrician observes Z_B (ex-post), she can identify the peer effect β by estimating Equation (9) by instrumental variables (IV), such that:

$$\alpha_A^{IV} = \beta + \eta_A \times \underbrace{\frac{Cov\,[s_A, Z_B]}{Cov\,[I_B, Z_B]}}_{=0 \text{ since } s_A \perp z_B} + \underbrace{\frac{Cov\,[v_A, Z_B]}{Cov\,[I_B, Z_B]}}_{=0 \text{ since } v_A \perp z_B} = \beta$$

It is important to note that in our model the identification of the equilibrium peer effect β requires the use of an instrument that is related to the *private information* of firm B (i.e., the peer) that firm A does not possess, and not to growth opportunities that are unique to firm B and orthogonal to firm A. Similar in spirit to Bursztyn, Ederer, Ferman, and Yuchtman (2014), a valid instrument Z_B must empirically isolate the private information about future industry conditions that firm B uses to determine its investment, but that firm A does not observe. This condition arises in our setting because firms have imperfect information, and therefore have incentives to learn from each other.

Intuitively, a variable that empirically isolates fundamental variation that is specific to firm B but orthogonal to firm A's prospects (e.g., a shock that only affects firm B's investment opportunities in other unrelated product markets) is unsuitable to identify β. Intuitively, firm A's investment should rationally *not* respond to any variation that is unrelated to its own investment opportunities in equilibrium.[13]

D The Instrumental Variable (Z_B)

To isolate the variation of firm B's investment that is orthogonal to the private information used by firm A to determine its investment strategy (s_A), we build on the intuition of Bartik (1991) and develop an instrument that combines industry and geography variation in corporate investment.[14] The logic of our instrument is best explained with a simple example that we illustrate in Figure 2.

[Insert Figure 2 about Here]

Consider that firms A and B in the model manufacture furniture and are headquartered in Austin and Boston, respectively. Both firms compete and sell their differentiated products nationally. As highlighted by the model, their investment can be positively correlated because both firms receive common signals about the future demand for furniture (s_A and s_B) that we observe imperfectly. The crux of our identification strategy is to use the average investment of firms that are also headquartered in Boston, but operate in markets that are economically *unrelated* to the furniture market as an instrument for the investment of firm B.[15]

[13]Consistent with this logic, Leary and Roberts (2014) report that they do not find any evidence of peer effects in investment decisions. They use the average *idiosyncratic* return of industry peers as instrument for product market peers' investment. To the extend that their instrument isolates variation in peers' investment that is orthogonal to a given firm's prospects, our model predicts that firms should not respond to such variation.

[14]The idea of using geography to construct instruments is common in the literature. Starting with Bartik (1991), various studies use averages national employment growth across industries using local industry employment shares as weights to produce a measure of local labor demand that is unrelated to changes in local labor supply, the so-called "Bartik" instrument (see Bartik (1991), and Autor and Duggan (2003)).

[15]Note that the use of average characteristics of peers as an instrument for peers' behavior is common in the literature, see for instance Leary and Roberts (2014), Duflo and Saez (2002), Case and Katz (1991).

Take for instance firms X and Y that are also located in Boston but operate in the optical equipment and footwear business, both of which are arguably unrelated to furniture. Nevertheless, we expect the investment of firms X and Y to be positively correlated with the investment of firm B. Indeed, Dougal, Parsons, and Titman (2015) show that corporate investment has a strong geographical component: the investment of a given firm is strongly related to the investment of firms headquartered nearby that are operating is very different industries. In line with the large literature on agglomeration economies (pioneered by Marshall (1890)), such a local commonality of investment reflects local externalities that arise between unrelated industries from the interactions of people living in the same area (Glaeser, Kallal, Scheinkman, and Shleifer (1992), Glaeser, Kolko, and Saez (2001) or Moretti (2004)). These local interactions lead to knowledge and information diffusion between workers, technology spillovers between neighboring firms, or consumption externalities between neighbors.

We posit that the significant link between the investments of firms B, X, and Y translates the presence of localized information about future demand that is only available to firms in Boston. This could happen for instance because employees at firm B learn information from interacting with employees of firms X and Y, or because investment of firms X and Y provide specific information relevant to firm B's market. Using the terminology of the model, the investment of X and Y contains information that is plausibly *relevant* for the furniture market, and therefore for firm A's investment. However, because this information is localized in Boston, firm A in Austin does not observe it. There is therefore little reason to believe that it is relate to its private information.

We emphasize that our objective is *not* to identify the origin and nature of local information externalities. Instead, we simply use the empirical regularity that such local externalities exist to isolate the variation in the investment of firm B that is unrelated to the private information of firm A (i.e. s_A), but plausibly relevant for its investment decisions (i.e., contain information about future demand).

III Data and Methodology

A Data and Definitions

We focus our analysis on a large sample of U.S. publicly-listed firms. To construct our instrument, we need (i) to identify the product markets in which firms operate to link each firm (firm A in the model) with other firms selling similar products or services (firm B in our model), and (ii) the location of every firm to link each firm to neighboring firms (i.e., firms X and Y).

We use the Text-based Network Industry Classification (TNIC) developed by Hoberg and Phillips (2015) to identify product market peers. This classification is based on textual analysis of the product description sections of firms' 10-K (Item 1 or Item 1A) filed every year with the Securities and Exchange Commission (SEC). The classification covers the 1996 to 2011 period because TNIC industries require the availability of 10-K annual filings in electronically readable format. Specifically, in each year, Hoberg and Phillips (2015) compute a measure of product similarity 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 (2015) then define each firm i's industry to include all firms 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. We define as "product market peer" of firm i all the firms that belong to its TNIC industry in a given year.[16]

Following Dougal, Parsons, and Titman (2015), we define a firm's location as the location

[16] Hoberg and Phillips (2015)'s TNIC industries have three important features. First, unlike industries based on the Standard Industry Classification (SIC) or the North American Industry Classification System (NAICS), they change over time. In particular, when a firm modifies its product range, innovates, or enters a new product market, the set of peer firms changes accordingly. Second, TNIC industries are based on the products that firms supply to the market, rather than 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.

of its headquarters. Arguably a firm's headquarters is often separated from its operations. Nevertheless, to the extent that investment decisions are taken by the firm's executives that are usually working at the headquarters, this helps us by rendering our instrument stronger. We use the zip code listed in Compustat to place each firm's headquarters in a metropolitan statistical area (MSA). We then define as "local peer " of firm i all the firms whose headquarter is located in same MSA as firm i's in a given year.

B Empirical Specification

To identify firms' response to the investment of their product market peers, we estimate the following baseline (linear-in-mean) model of investment:

$$I_{i,t} = \omega + \alpha \bar{I}_{-i,t} + \varphi' X_{i,t} + \phi' \bar{X}_{-i,t} + \delta' \mu_i + \eta' \nu_{msa \times t} + \varepsilon_{i,t} \tag{11}$$

where the subscripts i and t correspond to a firm and a year, respectively. The dependent variable, I, is the ratio of capital expenditure of firm i (firm A in the model) in year $t$scaled by lagged fixed assets (property, plant, and equipment). The subscript $-i$ identifies all non-local product market peers of firm i (firm B in the model). Non-local peers are defined as product market peers headquartered in a different MSA than firm i. The variable of interest $\bar{I}_{-i,t}$ measures the (equally-weighted) average investment of all non-local product market peers of firm i in year t. Similar to Leary and Roberts (2014), we use a contemporaneous measure of peers' investment because it limits the amount of time for firms to respond to one another, making it more difficult to detect peer effects.

The vectors X include control variables known to be fundamental drivers of firms' investment. Following previous research, $X_{i,t}$ includes Tobin's Q, defined as a firm's market capitalization plus the book value of assets minus the book value of equity divided by book assets, the natural logarithm of assets ("firm size"), and the ratio of cash flows over assets. We also include the same characteristics averaged across product market peers ($\bar{X}_{-i,t}$). These controls capture the portion of firms private signals (s_A and s_B) that the econometrician can observe. In addition, we account for time-invariant firm heterogeneity by including firm fixed effects (μ_i), and time-specific local effects by including year×MSA fixed effects ($\nu_{msa \times t}$). The fixed effects structure absorbs any variation in a firm's investment that is either firm-specific or location specific (e.g., a positive productivity shock in a given location in a given year inducing all firms in this location to increase investment).[17] Because the set of product market peers is specific to each firm, we allow the error term ($\varepsilon_{i,t}$) to be correlated within firms.

Using the logic developed in Figure 2, our instrument for $\bar{I}_{-i,t}$ is defined as the average investment of all firms unrelated to firm i' product market that are neighbors of the non-local product market peers of firm i (firms X and Y in the example in Figure 2). Ellison, Glaeser, and Kerr (2010) show that industries tend to co-agglomerate in a given location to benefit from natural advantages, economic linkages (e.g., customer-supplier relationships), and informational spillovers. Because we want to isolate local externalities that stem from *information* that is shared only among local firms, we eliminate firms operating in related product markets. To do so, we start by consider all firms headquartered in the same MSA as all the non-local TNIC peers of firm i. From this initial set we apply the following filters:

1. We eliminate all firms that are in the same Fama-French 12 industry classification as firm i. This step removes direct broad horizontal links.

2. We eliminate all firms that are vertically related to firm i based on the input-output tables obtained from the Bureau of Economic Analysis (BEA) and the customer segment files from Compustat. This step removes direct vertical links.

3. We eliminate all firms that are neighbors of the non-local product market peers of firm i that are themselves TNIC peers with any firm located in firm i's MSA. This step removes indirect links occurring through agglomeration economies in firm i's MSA.

We then compute the (equally-weighted) average investment across the remaining set of firms and label it as $\bar{I}^*_{-i,t}$. It is this empirical counterpart to Z_B in the model and we use it to instrument $\bar{I}_{-i,t}$ in specification (11).

Estimated by two-stages least squares, the coefficient α in specification (11) measures how a firm's investment responds to the average investment of its (non-local) peers. Therefore,

[17] We do not include the average investment of "local" since the variation in their investment is absorbed by $\nu_{msa \times t}$.

α^{IV} is the empirical counterpart of α_A^{IV} in the model, and we use it to identify the presence and sign of the equilibrium peer effects β. Recall that an estimation of specification (11) by ordinary least squares (α^{OLS}) does not properly isolate the influence of peers' investment due to our inability to perfectly observe firms' private information about their investment opportunities.

An important dimension of our identification strategy rests on two key properties of the TNIC network developed by Hoberg and Phillips (2015). First, TNIC features non-transitive industry relationships, such that each firm has its own set of peers, and the number of peers varies across firms. Second, industry relationships change over time as firms' product descriptions evolve. Both sources of variation limit the scope for weak instrument bias and increase our ability to detect peer effects (see Angrist (2014)). As a result, our identification strategy resembles that using exogenous characteristics of "peers of peers" and agent-specific variation in peer group composition to identify peers effects in social networks (Bramoulle, Djebbari, and Fortin (2009)).

Our sample includes all firms with available TNIC industries. We obtain investment and other accounting and stock market data 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 further remove firm-year observations if they have missing information on any of the variable we use in the baseline specification (11). To reduce the effect of outliers all ratios are winsorized at 1% in each tail. The construction of all the variables is presented in the Appendix.

[Insert Table 1 about Here]

Table 1 presents descriptive statistics. The sample includes 44,013 firm-year observations (6,592 distinct firms). The average number of product market peers (TNIC) is 56, and the average number of non-local product market peers is 48, suggesting that product markets are mostly non-local. The average number of local peers (MSA) is 89, and the average number of local unrelated peers is 41, indicating that on average MSAs feature diverse economic activities. Summary statistics for the main variables used in the analysis resemble those reported in related studies. In particular, the average (median) investment rate (capital expenditure divided by lagged PPE, I_i) is 36% (23%). The average (median) Tobin's is 1.97 (1.48). We also report statistics for the characteristics of non-local product market peers (average across all non-local peers for each firm-year). They are very close to the their own firm counterpart, although aggregation lowers their standard deviation.

IV The Positive Influence of Peers' Investment

A Baseline Results

Table 2 presents estimates for various specifications of our baseline investment specification (11). To facilitate interpretation of magnitudes, all coefficients are scaled by their corresponding variable's standard deviation. The first column reports the OLS estimates. Confirming a strong co-movement of firms' investment within product markets, we find a positive and significant relation between a firm's investment and that of its (non-local) product market peers ($\alpha^{OLS} > 0$). The magnitude of investment co-movement is substantial: a one standard deviation increase in the average investment of peers is associated with a 4.6 percentage point increase in a firm's investment (with t-statistic of 10.41). Peers' investment is the second strongest determinant of a firm's investment, representing roughly 35% of the effect of Tobin's Q.

[Insert Table 2 about Here]

Columns (2) and (3) display the instrumental variable estimates. Column (2) reports the first-stage results. Consistent with the presence of positive local agglomeration externalities (Dougal, Parsons, and Titman (2015)), the first-stage results indicate a strong local component in corporate investment. The average investment of a firm's product market peers ($\bar{I}_{-i,t}$) is positively related to the average investment of their neighboring unrelated peers ($\bar{I}^*_{-i,t}$). The statistical significance of the first-stage estimate (with a t-statistic of 12.48) indicates that the instrument easily passes weak instrument tests (Stock and Yogo (2005)).

The second-stage results, reported in column (3), reveal that the estimated coefficient on the instrumented average peers' investment is positive and significant (with a t-statistic of 2.45). The estimates indicate that, on average, firms' investment is positively influenced by the average investment of their (non-local) product market peers. Interpreted in light of our model, our estimates indicate that part of the product market commonality of investment is due to fact that firms respond to the investment of their peers. Moreover, the positive influence of peers' investment suggests that the learning channel is the dominant force for the average firm in our sample.

The estimated peer effect is economically large. The point estimate implies that the investment of the average firm in our sample increases by 3.7 percentage points in response to a one standard deviation increase in the instrumented average investment of its product market peers. This increase represents about 10% of the sample average ratio of capital expenditures to lagged fixed capital. Comparing the economic magnitude implied by the OLS and IV estimates confirm the model's prediction that the OLS estimate is biased upward ($\alpha^{OLS} > \alpha^{IV}$), due to the positive correlation between peers' investment and the portion of firms' private signal about its future prospects that the econometrician does not observe.

[Insert Figure 3 about Here]

To provide a different perspective on the magnitude of the influence of peers' investment, we estimate the baseline specification (11) separately for each industry, using the fixed industry classification (FIC) developed by Hoberg and Phillips (2015). Panel A of Figure 3 reports the t-statistics corresponding to the coefficients on the instrumented peers' investment ($t_{\alpha^{IV}}$) estimated across (76 distinct) industries. We find positive peer effects in 61 industries. They are significant at the 5% (10%) level in 16 (20) industries, comprising 2,717 (3,171) distinct firms, or 41% (48%) of firms in the sample. Alternatively, we estimate the baseline specification (11) on 1,000 bootstrapped samples including 3,000 randomly selected firms and display the t-statistics ($t_{\alpha^{IV}}$) in Panel B of Figure 3. Peer effects in investment are positive in 95% of the bootstrapped samples. They are significant at the 5% (10%) level in 25% (40%) of the samples. The average estimated coefficient on the (standardized) instrumented peers' investment is 0.039, very close to the baseline estimate (0.037).

B Checking the Validity of our Instrument

Our identification strategy rests on the assumption that the average investment of the unrelated neighbors of a firm's non-local product market peers ($\bar{I}^{*}_{-i,t}$) contains information that is relevant for this firm' investment, but orthogonal to the information that is already possesses (i.e. the firm cannot observe it). Our inference could therefore be threatened if a firm can directly observe the localized information leading to investment commonality in other locations, or if the construction of our instrument fails to completely purge economic links between a firm and the unrelated neighbors of its product market peers.

Using the example in Figure 2, these cases could happen for instance if the investment of firm Z in Boston (i.e., the unrelated neighbor of firm B we use to construct our instrument) is correlated with the investment of other firms located in Boston (e.g. firm X) that we exclude when constructing the instrument because they are directly linked to B. Hence, the same localized information argument that we use to justify the validity of our instrument could make the investment of firm A linked to that of firm Z through the investment of the firms in Boston we exclude.

To assess this possibility, we perform the following placebo test. For each firm-year in the sample (e.g., firm A in the model), we replace each of its non-local product market peer (e.g., firm B) by one randomly selected firm that is located in the same MSA as the original peer but that operates in an unrelated product market (e.g., firm X). If our baseline estimate of peer effects is spurious and arises because a firm can observe the localized information in the regions where their product market peers are located, or because of a residual link between our instrument and firms' investment opportunities, we should find that firms' investment respond significantly to the instrumented average investment of these random non-local unrelated firms ($\alpha^{IV} \neq 0$). If, however, our baseline results occur because our instrument influences a firm's investment *only through* its effect on the investment of non-local product market peers, we should *not* observe any significant peer effects when we consider these random peers ($\alpha^{IV} = 0$).

[Insert Table 3 about Here]

Table 3 presents the results of 1,000 placebo estimations of the investment specification (11) where we replace true non-local product market peers by randomly-selected unrelated neighbors. We report the results of the first-stage and second-stage estimations. Panel A indicates that the first-stage results are strong across these 1,000 estimations. Mirroring our baseline first-stage estimates, the average coefficient on the average investment of firms' neighboring unrelated peers is 0.155, and the average average t-statistic is 20. This result is largely expected and confirms the prevalence and pervasiveness of localized investment co-movement. Panel B, however, reveals that firms do not respond to the instrumented investment of randomly-selected unrelated neighbors of their product market peers. The average second-stage coefficient (α^{IV}) across the 1,000 placebo estimations is -0.001 and the average t-statistic is -0.032, well below significance levels. These results mitigates concerns about a possible residual economic link between the instrument and firms' investment, or the ability of firms to observe localized information in distant locations.

[Insert Table 4 about Here]

As an alternative validity test, we examine the residual correlations between our instrument and firm i's own characteristics. We examine the correlations with both contemporaneous and one-period lead to determine whether our instrument contains information about current and future firm i's characteristics. The correlation between the instrument and firm i's characteristics is not problematic because we control for these characteristics in specification (11). Nevertheless, as argued by Leary and Roberts (2014) economically large relations between the instrument and observable determinants of firm i's investment would raise concerns about the validity of the instrument. Table 4 reveals one statistically significant coefficient between firm i's characteristics and the average investment of the unrelated neighboring firms of its non-local product market peers in the one-period lead specification, and none in the contemporaneous specification. The economic magnitudes of the estimated coefficients are tiny.[18] Table 4 thus indicates that our instrument contains no significant

[18]For the only significant estimate, cash flow over assets, a one standard deviation increase in a firm' cash flow is associated with a 0.85 basis point decrease in the lagged instrument. The other coefficients reveal (non-significant) sensitivities of less than 0.5 basis points. In particular, the instrument is unrelated with firm i's Tobin's Q, which is a traditional measure of investment opportunities.

information related to current or near-future observable determinants of investment.

C Robustness Tests

In Table 5, we assess the robustness of the peers' influence to various changes in the baseline specification (11). We only report the second-stage (standardized) coefficient estimates on the investment of product market peers (α^{IV}) for brevity. In columns (1) and (2), we augment the baseline specification by including industry×year fixed effects. The transitive nature of the TNIC network enables us to further absorb common industry shocks using fixed effects generated using the fixed industry classifications of Hoberg and Phillips (2015). Defining industries using the FIC100 and FIC300 classifications (breaking the universe of firms into 100 and 300 industries, respectively), we continue to observe strong effects of peers' investment. If anything, the results in columns (1) and (2) suggest that our baseline estimate is conservative. In column (3), we further control for common observable fundamentals by including additional control variables measuring firms' and peers' characteristics (sales growth, tangibility, leverage, and the ratio of cash over assets). Our results are virtually unchanged.

[Insert Table 5 about Here]

In column (4), we define non-local peers (and re-compute all variables) as product market peers headquartered at least 300 miles away. In columns (5) and (6), we define peers' characteristics by computing weighted averages (by sales in column (5) and assets in column (6)) instead equally-weighted averages. In column (7), we define peers using 3-digit standard industry classification (SIC) codes instead of TNIC. In columns (8) and (9), we change the definition of investment, and consider the annual growth of capital stock in column (8), and the annual growth of assets in column (9). Our results remain virtually unaffected across these alternative specifications. In addition, the magnitude of the peer effect remains remarkably stable, with point estimates ranging between 0.021 and 0.060.

V Why do Firms Follow their Peers?

To get more insights on the nature of peer influence (i.e., learning or strategic) we use the model to predict how the equilibrium peer effect β varies with the key parameters and use observable firms' and markets' characteristics to test these predictions. We also verify that our results cannot be explained by plausible alternative mechanisms that are not featured in the model.

A Variation of Peer Effects Across Markets

We derive four testable predictions. The formulation of these predictions depends on whether a parameter only influences the learning channel (Corollaries 1-2), or both channels simultaneously (Corollaries 3-4). When a parameter solely affects the extent to which firm A learns from firm B, we can derive *unconditional* predictions that do not depend on the sign of the peer effect β. In contrast, when a parameter influences the learning and the strategic channels, predictions are *conditional* on the sign of β, because the sign of β is determined by the combination of *all* the parameters influencing the interaction between firms.

Corollary 1. *[Relative signal precision] All else equal, the peer effect β is strictly decreasing in the precision of the signal of firm A relative to that of firm B, such that $\partial\beta/\partial\Delta_\sigma < 0$ where $\Delta_\sigma \equiv \sigma_B^2/\sigma_A^2$.*

Corollary 1 indicates that the positive effect of learning on the equilibrium peer effect β is weaker when the investment of firm B conveys less information to firm A about future demand. This happens unconditionally when the private signal that firm A receives becomes relatively more precise than the private signal of firm B (i.e., when $\sigma_A < \sigma_B$). As the private signal of firm A becomes more precise, the incentive of firm A to rely on firm B's investment as a source of information is reduced, and the strategic channel becomes more prevalent (hence β decreases).

Corollary 2. *[Overlap in private signals] All else equal, the peer effect β is strictly decreasing in the correlation between firms' private signals ρ such that $\partial\beta/\partial\rho < 0$.*

Corollary 2 complements the prediction of Corollary 1. It highlights that the information about future demand that firm A can infer from the investment of firm B is less relevant when their private signals contain more common information (i.e., when the parameter $\rho > 0$ is higher). Therefore, as the signals ϵ_A and ϵ_B convey more similar information, the learning component of the peer effect decreases, and the negative strategic component becomes more important. At the limit, if private signals are perfectly correlated ($\rho = 1$), firm A rationally ignores the investment of firm B as a relevant source of information.

Corollary 3. *[Relative installed capacity] All else equal, the peer effect β varies with the relative differences in installed capacity $\Delta_K \equiv K_A^-/K_B^-$ such that: (i) if $\beta < 0$, then $\partial\beta/\partial\Delta_K > 0$; and (ii) if $\partial\beta/\partial\Delta_K < 0$, then $\beta > 0$.*

Corollary 3 shows that the sensitivity of the peer effect β with respect to differences in installed capacity Δ_K is non-monotonic, because an increase in Δ_K affects both the strategic and learning channels in equilibrium. The first part of Corollary 3 states that, when β increases with Δ_K, it is because the strategic channel is sufficiently strong such that the peer effect β is negative in equilibrium. Holding K_B^- constant, an increase in K_A^- makes firm A a stronger rival such that firm B invests less aggressively in equilibrium. Conversely, the second part of Corollary 3 predicts that relatively smaller firms benefit the most from inferring information from their peers' investment. When the parameter β is strictly decreasing in Δ_K, it must be the case that the learning channel is sufficiently strong such that the peer effect β is positive in equilibrium.

Corollary 4. *[Peer concentration] The peer effect β varies with the peer concentration h such that, given $\Delta_K < 1$: (i) if $\beta < 0$, then $\partial\beta/\partial h < 0$, and (ii) if $\partial\beta/\partial h > 0$, then $\beta > 0$.*

Defining h as a Herfindahl-Hirshman Index over firms' installed capacity K_i^-, Corollary 4 predicts that the sensitivity of β to concentration h depends jointly on the within-industry variance in capacity ($\Delta_K > 0$) and the relative size of firm A compared to B (i.e., $\Delta_K > 1$ or $\Delta_K < 1$). We focus on the case in which $\Delta_K < 1$ due to its empirical relevance. This case is consistent with a positively skewed industry distribution of firm size, i.e. an industry with few large firms and a fringe of small firms.[19] Under this configuration, the predictions of the model are consistent with those in Corollary 3. Intuitively, firms' incentives to learn from peers' investment is stronger in more concentrated industries, such that smaller firms learn the most from the relatively larger players in the product market.

To empirically test the above Corollaries, we use firm and industry variables as proxies for the model parameters (Δ_σ, ρ, Δ_K,and h). We modify the baseline specification (11) by adding interaction terms between each independent variable with two indicator variables identifying the lower (D_{low}) and upper (D_{high}) half of each interaction variable distribution. We measure all proxies with one year lag, and assign firm-year observations into each group every year. Specifically, we augment the baseline specification (11) as follows:

$$I_{i,t} = \omega + \alpha_{low}[\bar{I}_{-i,t} \times D_{low}] + \alpha_{high}[\bar{I}_{-i,t} \times D_{high}] + ... + \varepsilon_{i,t}. \tag{12}$$

We estimate specification (12) by two-stage least squares, using the interactions between the average investment of non-local peers' neighboring unrelated peers ($\bar{I}^*_{-i,t}$) and the indicator variables as instrument for the interacted variables $\bar{I}_{-i,t} \times D_{low}$ and $\bar{I}_{-i,t} \times D_{high}$. Comparing the estimated coefficients α_{low} and α_{high} enables us to assess whether the sensitivity of firms' investment to peers' investment varies across groups of firms as predicted by the model. To facilitate the interpretation of differences across groups, we divide each interaction term by its sample standard deviation, and report p-values corresponding to equality tests across group-specific coefficients (i.e., $\alpha_0 = \alpha_1$).[20] We report the results in Table 6.

[Insert Table 6 about Here]

[19] The empirical evidence in the literature shows that the distribution of firm size is positively skewed, with few large firms and a fringe of small firms. See, for instance, Sutton (1998) for a discussion on this topic. In our working sample, the distribution of firm's book value of assets (i.e., firm size) has a positive skewness of 28, while the logarithm of the book value of assets has a positive skewness of 0.23. Taking firm B as the industry leader, the case of $\Delta_K < 1$ holds when firm B is on average larger than the industry fringe.

[20] Besides understanding the economic forces underlying the positive effect of peers' investment, testing the corollaries reinforces our identification strategy. We formally show in the Appendix that in the absence of any peer effect (i.e., when $\beta = 0$ in our model), we should not observe any heterogeneity in the coefficients α_i (i.e., $\alpha_{low} = \alpha_{high} = 0$).

A.1 Relative Signals' Precision (Δ_σ)

We first study how the influence of peers varies with the relative precision of the fundamental signals received by firms. We use two variables as proxies for the precision of a firm's signal. First, we use the volatility of stock returns. We focus on firm-specific volatility, computed from the residuals obtained from an regression of a firm's daily returns on the market returns and peers' value-weighted returns. Second, we use firms' age, conjecturing that older firms have more experience with their underlying business and hence receive more precise signals. To construct proxies for relative precision (Δ_σ), we compute for each variable and each year the difference between a firm (i) and the average of its non-local product market peers ($-i$), and label these variables $\Delta Vol_{i,-i}$ and $\Delta Age_{i,-i}$ respectively.

Consistent with the model's prediction, columns (1) and (2) of Table 6 indicates that the tendency of firms to respond positively to the investment of their product market peers depends on the relative precision of their own signal. We observe that firms that have more volatile stock returns and that are younger than their peers are significantly more sensitive to peers' investment. Consistent with the learning motive being the dominant force in the data, firms with the greatest incentives to use peers' investment as a source of information display the strongest sensitivity to peers' investment.

A.2 Correlation of private signals (ρ)

To assess whether the equilibrium peer effect decreases when firms' private signals contain more common information about future demand (Corollary 2), we the similarity of firms' products and the overlap in firms' analyst coverage. We conjecture that the correlation in firms' private signals is higher when their products are more similar. Similarly, because of economies of scope, we assume that financial analysts tend to follow firms that offer more similar products (Kaustia and Rantala (2015)). We measure product similarity between firms using the Hoberg and Phillips (2015) pairwise similarity scores that range between 0% (perfectly dissimilar) and 100% (identical), and are available for each pair of firms that are above a minimum similarity threshold (21.23%). For each firm-year observation, we sum the similarity score between the firm and all its non-local product market peers, and label this variable $Similarity_{i,-i}$.[21] We construct an index of analyst coverage overlap for each pair of firms and each year by computing the cosine similarity between firms' coverage structure.[22] We then compute the average analyst overlap between a firm and its non-local product market peers ($CoCoverage_{i,-i}$).

Consistent with Corollary 2, column of Table 6 reveals that the positive influence of peers' investment is stronger for firms that are *less* similar than their product market peers. Column (4) indicates that the peer effect is also larger for firms that share fewer analysts with their peers, although coefficients are not statistically different. Interestingly, these results corroborate the validity of our identification strategy because if the coefficient on the instrumented peers' investment (α^{IV}) captured correlated fundamentals (i.e., common investment opportunities), we should expect α^{IV} to be larger when firms are more similar with their peers. We find the opposite.

A.3 Relative Capacity (Δ_K)

Corollary 3 indicates that if the learning channel dominates, the equilibrium peer effect increases with the relative difference in capital between firms A and B (Δ_K). To verify whether this claim holds in the data, we directly approximate Δ_K using differences in "size" between a firm and its non-local product market peers. Specifically, we compute the difference between the logarithm of installed capital (property, plant, and equipment) and total assets of a firm and the average of its non-local product market peers ($\Delta \log(PPE)_{i,-i}$ and $\Delta \log(A)_{i,-i}$).

Columns (5) and (6) of Table 6 show that the peer effect is only present for firms that are smaller than their peers. For both proxies, the estimated coefficients on $\bar{I}_{-i,t} \times D_{high}$ are not significant. In contrast, the estimated coefficients on $\bar{I}_{-i,t} \times D_{low}$ point to substantial peer influence. The magnitude of the peer effects is statistically different across groups. Our estimates indicate that firms with lower than peers capacity ($\Delta_K < 0$) increase investment by roughly 10 percentage points in response to a one standard deviation increase in the

[21] Using the average similarity instead of the total similarity yield similar results.

[22] If there are N analysts active in year t, we define for each firm i a $N \times 1$ vector ω_i. The nth entry of ω_i is equal to one if analyst n$\in \{1, ..., N\}$ covers firm i and is equal to zero otherwise. The analyst overlap between firms i and j is then measured by the cosine similarity between ω_i and ω_j, that is $\frac{\omega_i \omega_j}{\|\omega_i\| \|\omega_j\|}$

instrumented average investment of their non-local peers. These results are consistent with the model's prediction, and more generally in line with other studies indicating that the influence of peers is stronger for smaller firms (Leary and Roberts (2014)).

A.4 Concentration (h)

To examine how the peer effect changes with industry concentration, we use two variables as proxies for h. First, strictly mapping the model, we compute the concentration of installed capacity for each firm-year observation (HHI_i) using the sum of squared capacity shares define as a firm PPE divided by the sum of that firm's and its non-local peers' PPE. Second, we use the number of non-local peers ($\#Peers_i$) to measure the strength of competitive pressure.

We observe in column (7) of Table 6 that the investment of peers only influences firms' investment in more concentrated industries. The coefficient on $\bar{I}_{-i,t} \times D_{high}$ is significant (with a t-statistic of 2.87). On the opposite, firms operating in less concentrated industries do not significantly respond to the investment of their peers. This pattern is consistent with the model (Corollary 4), which predicts that fringe firms in more concentrated industries have higher incentives to use the investment of their peers as a source of information. This pattern is also confirmed by the results displayed in column (8), in which we find that peer influence concentrates in markets populated by fewer firms.

B Blending with the Crowd

In our model, we assume that managers make investment decisions to maximize the value of their firm, and thus we ignore the potential role of agency conflicts on the equilibrium peer effects. It is nevertheless possible that the positive influence of peers that we observe in the data reflects the presence of agency conflicts as suggested in Scharfstein and Stein (1990). In their model, managers' "utility" (e.g., their reputation in the labor market or their compensation) depends on the relative performance of their firms compared to peers. In this context, Scharfstein and Stein (1990) show that some managers (i.e., "dumb" managers in their model) have incentives to mimic the investment decisions of their peers because they are more favorably evaluated if they follow the decisions of their peers than if they behave independently (i.e., a bad investment decision is not as bad for a given manager when others make the same mistake).[23]

[Insert Table 7 about Here]

To assess whether our results are driven by distorted managerial incentives, we examine whether the influence of peers' investment depends on the use of relative performance metrics in managers' contracts. We argue that if the observed peer effect is due to distorted incentives, we should find that the influence of peers is stronger when managers' compensation depends more on their performance relative that of their peers. We use the methodology of Aggarwal and Samwick (1999) to estimate the likely use of relative performance evaluation (RPE) in compensation contracts. Specifically, for each industry-year, we estimate whether CEO compensation is sensitive to the stock returns of industry peers (2-digit SIC industries), after controlling for firms' own stock return and size. We then classify firms as using RPE if the compensation of their CEO is negatively related to peers' stock returns (conditional on their own stock returns), and estimate specification (12) using indicator variables for the likely use of RPE ($D_{RPE=1}$ and $D_{RPE=0}$). The first column of Table 7 reveals no statistically significant difference in the response of firms to the investment of their peers across groups. The coefficient estimate on $\bar{I}_{-i,t} \times D_{RPE=1}$ is in fact lower than that on $\bar{I}_{-i,t} \times D_{RPE=0}$, indicating that peer effects appear stronger when firms do not use RPE in their CEO contracts. We obtain the same results if we define RPE using 3-digit SIC industries instead of 2-digit SIC industries (column (2)). We conclude that herding incentives are unlikely to explain our findings.

C Strategic Complementarity

Last, our model assumes that firms' products are strategic substitutes. In reality, firms' products may show strategic complementarity, such that the investment of firm B has a positive effect on the price that firm A can charge for its products. As we show in the Appendix, introducing strategic complementarity in the model implies that the equilibrium

[23]Note that, unlike our model, the model of Scharfstein and Stein (1990) abstracts from strategic interaction among firms and the possibility for a firm to extract information from the decisions of others.

peer effect β could be positive even if firms have perfect information about their prospects and do not rely on peers' investment as a source of information.

To assess whether our results could solely be explained by firms competing in strategic complements in our sample, we rely on the methodology by Bulow, Geanakoplos, and Klemperer (1985) to distinguish between markets where firms' competitive actions are strategic substitutes or strategic complements. Accordingly, the quantity of interest is the cross-partial derivative of a firm's value with respect to peers' competitive actions. A positive value for the cross-partial derivative indicates competition in strategic complements, whereas a negative value indicates competition in strategic substitutes. To approximate this cross-partial derivative in the data, we use the Competitive Strategy Measure (CSM) developed by Sundaram, John, and John (1996). For a given firm, CSM is defined as the correlation between the ratio of the change of its profits to the change of its sales, and the change in the combined sales of its rivals. As in Chod and Lyandres (2011), we use quarterly data and compute this correlation for each firm-year using rolling windows over the past five years. Next, we aggregate the CSM for each firm taking the average across all TNIC peers. A positive value for CSM indicates that actions are strategic complements, while a negative value indicates that actions are strategic substitutes.

We classify firms using indicator variables for whether their market features strategic substitution (D_{SUBS}) or strategic complementarity (D_{COMP}). Column (3) of Table 7 indicates that the influence of peer investment is positive and significant for both both types of strategic interactions. As expected, the coefficient on $\bar{I}_{-i,t} \times D_{COMP}$ is larger than that on $\bar{I}_{-i,t} \times D_{SUBS}$, but the difference is statistically insignificant. The empirical evidence in Column (3) of Table 6 is therefore inconsistent with a scenario in which firms have perfect information about product market fundamentals.[24]

[24]Note also that the cross-sectional variation predicted by corollaries (1) and (2) (and observed in Table 6) only arises when firms do not have perfect information about their future growth opportunities.

VI Conclusion

This paper shows empirically that firms' investment actively responds to the investment of their product market peers. We estimate that a firm increases its investment by 10% in response to a one standard deviation increase in the average investment of its product market peers. We also observe that the influence of peers is stronger in concentrated industries, industries with more heterogeneous firms, and for relatively smaller firms with more imprecise signals. Our analysis shows that the strong interdependence of investments within industries is partly due to peer influence. Moreover, the empirical evidence is broadly consistent with our model of strategic investment, in which firms rely on the investment by peers to infer information about product market fundamentals.

The empirical findings in our paper suggest that the presence of peer effects could matter for aggregate investment and the efficient allocation of capital in the economy. The aggregate influence of peer effects in the economy is however non-trivial, as we show that firms' response to peers' investment is heterogeneous (e.g., is stronger for small firms). Moreover, whether or not responding to peers' investment leads to more or less efficient investment decisions remains unclear. Understanding how one can go from the micro evidence we offer in this paper to the macro impact of peer effects in investment and their real consequences (e.g., for GDP and productivity) represents an interesting challenge that we intend to tackle in future research.

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Appendix A. Definition of the Variables

Variable	Definition	Source
$Capex/PPE$	Capex (capx) scaled by lagged Property, Plant and Equipment (ppent)	Compustat
MB	Book value of assets (at) - Book value of equity (ceq) + Market value of equity, scaled by book value of assets	Compustat
$ln(A)$	Logarithm of the book value of assets (at)	Compustat
CF/A	Income before extraordinary items (ib) plus depreciation (dp), scaled by assets	Compustat
ΔPPE	Annual growth rate of Property, Plant and Equipment (ppent)	Compustat
ΔA	Annual growth rate of book value of assets (at)	Compustat
$\Delta Vol_{i,-i}$	Difference between a firm's idiosyncratic volatility and the average idiosyncratic volatility of its non-local product market peers. Idiosyncratic volatility is computed from the residuals obtained from an annual regression of a firm's daily returns on the market returns and peers' value-weighted returns	CRSP - Hoberg/Phillips
$\Delta Age_{i,-i}$	Difference between a firm's age and the average age of its non-local product market peers.	Compustat - Hoberg/Phillips
$Similarity_{i,-i}$	Average text-based similarity score between a firm and its non-local product market peers.	Hoberg/Phillips
$CoCoverage_{i,-i}$	Average overlap in analyst coverage between a firm and its non-local product market peers. If there are N analysts active in year t, we define for each firm i a $N \times 1$ vector ω_i. The nth entry of ω_i is equal to one if analyst n$\in \{1, ..., N\}$ covers firm i and is equal to zero otherwise. The analyst overlap between firms i and j is then measured by the cosine similarity between ω_i and ω_j, that is $\frac{\omega_i \omega_j}{\|\omega_i\|\|\omega_j\|}$. We then compute the average analyst overlap between a firm and its non-local product market peers	IBES - Hoberg/Phillips
$\Delta ln(PPE)_{i,-i}$	Difference between a firm's logarithm of PPE (ppent) and the average logarithm of PPE of its non-local product market peers	Compustat - Hoberg/Phillips

$\Delta ln(A)_{i,-i}$	Difference between a firm's logarithm of assets (at) and the average logarithm of assets of its non-local product market peers	Compustat - Hoberg/Phillips
$HHI(k)_i$	Concentration of firms' property, plant, and equipment (ppent), computed as the sum of squared PPE among a firm and its non-local product market peers	Compustat - Hoberg/Phillips
$\#Peers_i$	Number of non-local product market peers	Hoberg/Phillips
$\#RPE$	Dummy variable equals to one if an industry is likely to use relative performance evaluation. For each industry-year, we estimate whether CEO compensation is sensitive to the stock returns of industry peers, after controlling for firms' own stock return and size. Industries are classified as using RPE if compensation is negatively related to peers' stock returns	Execucomp - CRSP
CSM	Competitive Strategy Measure (CSM) developed by Sundaram, John, and John (1996). For a given firm, CSM is defined as the correlation between the ratio of the change of Income before extraordinary items (ib) plus depreciation (dp) to the change of its sales (sale), and the change in the combined sales of its non-local product market peers. We use quarterly data and compute this correlation for each firm-year using rolling windows over the past five years. We aggregate the CSM for each firm taking the average across all its non-local product market peers	Compustat - Hoberg/Phillips

Appendix B. Proof of Proposition 1

Conditional Expectations

In the main text, we specify the assumption that ϵ_i is a random variable such that $E[\epsilon_i] = \mu > 0$, $Var\left[\epsilon_i\right] = 1 > 0$ and $cov\left[\epsilon_A, \epsilon_B\right] \equiv \rho$. Conditional on observing the demand shocks ϵ_A and ϵ_B, we assume that the private signals s_B and s_A are such that $E\left[s_i|\, \epsilon_i\right] = \epsilon_i$ and variance $Var\left[s_i|\, \epsilon_i\right] = \sigma_i^2$ such that $0 < \sigma_i^2 < \infty$. Last, we require that the distributions of these random variables yield linear functions for the conditional expectations $E\left[\varepsilon|\, s_A, s_B\right]$, $E\left[\varepsilon|\, s_B\right]$ and $E\left[s_A|\, s_B\right]$.

Given these assumptions, we derive expressions for $E\left[\varepsilon|\, s_A, s_B\right]$, $E\left[\varepsilon|\, s_B\right]$ and $E\left[s_A|\, s_B\right]$ which we use to derive the equilibrium investment strategies below. It is straightforward to prove that $Var[\varepsilon] = (1+\rho)/2$; $E[s_i^2] = 1 + \mu + \sigma_i^2; E[s_A s_B] = \mu^2 + \rho$; and $E\left[s_i|\, \varepsilon\right] = \varepsilon$. Using the Law of Total Variance, we obtain: $Var[s_i] = 1 + \sigma_i^2$; $Var[E\left[s_i\right]|\ \varepsilon] = Var[\varepsilon]$; and $E[Var\left[s_i\right]|\, \varepsilon] = (1-\rho)/2 + \sigma_i^2$. Given the results in Ericson (1969) which also apply to our model, we obtain:

$$E\left[\varepsilon|\, s_i\right] = s_i\,(\rho+1)/2\left(\sigma_i^2+1\right)^{-1} + \mu\left(1-(\rho+1)/2\left(\sigma_i^2+1\right)^{-1}\right). \tag{13}$$

Last, we use the assumed linearity of the conditional expectations $E\left[\ \epsilon|\, s_A, s_B\right]$ and $E\left[s_A|\, s_B\right]$ to obtain

$$\begin{aligned} E\left[\varepsilon|\, s_B, s_A\right] &= \mu\left((1-\rho)\left(\sigma_B^2+\sigma_A^2\right) + 2\sigma_A^2\sigma_B^2\right)/2\Lambda \qquad (14)\\ &\quad + (\rho+1)\left(s_B\left(1+\sigma_A^2-\rho\right) + s_A\left(1+\sigma_B^2-\rho\right)\right)/2\Lambda, \\ E\left[s_A|\, s_B\right] &= \mu + (s_B-\mu)\,\rho\left(\sigma_B^2+1\right)^{-1}, \qquad (15) \end{aligned}$$

where $\Lambda \equiv \left(\sigma_B^2+1\right)\left(\sigma_A^2+1\right) - \rho^2 > 0$ given $0 < \rho \leqslant 1$ and $0 < \sigma_i^2 < \infty$.

Derivation of the Industry Equilibrium

The derivation of the equilibrium strategies follows Gal-Or (1987). The manager of each firm $i = A, B$ solves for the optimal investment policy that is value maximizing. Since the installed capacity before investment K_i^- is predetermined, this is analogous to stating that managers choose optimally the installed capacity K_i^+. For convenience, we derive the first order conditions for both firms with respect to K_i^+. We re-express the investment cost function in Equation (3) and impose $\kappa = \alpha$ such that

$$\Phi_i = \alpha\left(K_i^+ - K_i^-\right) + \phi/2\left(K_i^+/K_i^- - 1\right)^2 K_i^-.$$

Consider the problem of firm A. Firm A chooses the optimal K_A^+ once she has observed K_B^+. The value of firm A after observing K_B^+ is given by

$$V_A^- \equiv (\alpha - \gamma K_A^- - \theta K_B^-)K_A^- + E\left[\left((\alpha - \gamma K_A^+ - \theta K_B^+)K_A^+ - \Phi_A\right)\middle|\, K_B^+, s_A\right].$$

The corresponding first order condition equals $\partial V_A^-/\partial K_A^+ = 0$. We assume and later verify that the strategy of firm B is a continuous, monotone and invertible function $K_B^+ = f(s_B)$. Given this property, firm A can infer signal s_B by inspection of K_B^+. Using the first order condition of the optimization problem of firm A, and the fact that $K_B^+ = f(s_B)$, the reaction function of firm A determining K_A^+ is given by

$$\begin{aligned} K_A^+\left[s_A, K_B^+\right] &= \left(-\alpha + K_A^-\left(\alpha+\phi\right) - \theta K_A^- K_B^+\right)/\left(2\gamma K_A^- + \phi\right)^{-1} \\ &\quad + K_A^- E\left[\varepsilon|\, s_B \in f^{-1}(s_B), s_A\right]/\left(2\gamma K_A^- + \phi\right)^{-1}. \end{aligned} \tag{16}$$

Consider now the problem of firm B. Firm B determines the optimal amount K_B^+ before firm A decides on her own strategy. The value of firm B at the time of making the investment decision is given by

$$V_B^- \equiv (\alpha - \gamma K_B^- - \theta K_A^-)K_B^- + E\left[\left((\alpha - \gamma K_B^+ - \theta K_A^+)K_B^+ - \Phi_B\right)\middle|\, s_B\right],$$

and the first order condition of firm B is such that $\partial V_B^- / \partial K_B^+ = 0$.

Consistent with standard games of strategic interaction, firm B determines its optimal K_B^+ taking into a count that a higher installed capacity deters investment by firm A. Unlike standard games of strategic interaction, however, the reaction function of firm A is itself a function of the private signal of firm B. As a result, the solution to the equilibrium strategies entails a fixed point.

To solve for the equilibrium outcome, we guess and later verify the functional form of the optimal capacity choices by both firms. We guess that both investment strategies are linear such that

$$\begin{aligned} K_B^+ &= b_0 + b_1 s_B, \\ K_A^+ &= a_0 + a_1 s_A + a_2 K_B^+, \end{aligned}$$

where $b_1 \neq 0$ such that $f(s_B)$ is well defined.

We solve for the coefficients b_0, b_1, a_0, a_1 and a_2 in multiple steps. Using Equations (16) and (14), we first obtain the coefficients of the reaction function of firm A, namely: a_0, a_1 and a_2.

To obtain the coefficients b_0 and b_1 related to the strategy of firm B, we replace the term $\partial K_A^+ / \partial K_B^+$ in the first order condition $\partial V_B^- / \partial K_B^+ = 0$. We replace the terms $E\left[s_A | s_B\right]$ and $E\left[\varepsilon | s_B\right]$ in Equation (16) using the corresponding expressions in Equations (13) and (15). Consequently, we obtain the coefficients b_0 and b_1 from a system of two equations with two unknowns. The first equation of the system is such that $\partial V_B^- / \partial K_B^+ = 0$ if $s_B = 0$. The second equation of the system is such that $\partial V_B^- / \partial K_B^+ = 0$ if $s_B \neq 0$.

While the proof characterizes reaction functions of firms A and B in terms of their optimal capacity choice, Proposition 1 specifies the equilibrium in terms of firms' investment strategies. The correspondence between the parameters δ_i, η_i and β referred in Proposition 1 and the parameters b_0, b_1, a_0, a_1 and a_2 is such that

$$\begin{aligned} &\delta_B = \tfrac{b_0}{K_B^-} - 1; \qquad \eta_B = \tfrac{b_1}{K_B^-}; \\ &\delta_A = \tfrac{a_0 + a_2 K_B^-}{K_A^-} - 1; \quad \eta_A = \tfrac{a_1}{K_A^-}; \quad \text{and } \beta = a_2 \tfrac{K_B^-}{K_A^-}. \end{aligned}$$

where the expressions for the parameters $\delta_B > 0$, $\eta_B > 0$, and $\eta_A > 0$ are provided in the subsection below. The expression for the peer effect parameter β is provided in Equation (8).

Parameter space and alternative equilibria

Proposition 1 states that $\delta_B > 0$, $\eta_B > 0$ and $\eta_A > 0$. To prove this, consider first the parameter δ_B. The parameter δ_B is given by

$$\delta_B \equiv -1 + \left(2\Lambda \Psi_1 \Psi_2 K_B^-\right)^{-1} \left(\Psi_3 \Psi_4\right),$$

where the constants $\Psi_1 > 0$, $\Psi_2 > 0, \Psi_3 > 0$ and $\Psi_4 \lesseqgtr 0$ are defined as:

$$\begin{aligned} \Psi_1 &\equiv \left(K_A^- \left(2\gamma - \theta\right) + \phi\right), \\ \Psi_2 &\equiv \left(\phi \left(2\gamma K_B^- + \phi\right) + 2K_A^- \left(\left(2\gamma^2 - \theta^2\right) K_B^- + \gamma\phi\right)\right) \left(1 + \sigma_B^2\right), \\ \Psi_3 &\equiv \Lambda\phi + K_A^- \left(\left(2\gamma - \theta\right)\Lambda - \left(1 - \rho + \sigma_A^2\right)\left(1 + \sigma_B^2\right)\theta\right), \\ \Psi_4 &\equiv \mu K_B^- \Psi_1 \left(1 - \rho + 2\sigma_B^2\right) + \left(1 + \sigma_B^2\right)\left(-2\alpha\left(2\gamma K_A^- + \phi\right) + 2K_B^- \left(\left(\phi + \alpha\right)\Psi_1 + \alpha\theta\right)\right). \end{aligned}$$

The condition $\delta_B > 0$ holds under the inequality $\mu > \overline{\mu}$ imposed in Section II. The threshold $\overline{\mu}$ is such that

$$\mu > \overline{\mu} \equiv \frac{2(\Psi_1 \Psi_2 \Lambda + \Psi_3 \left(1 + \sigma_B^2\right) \Psi_5)}{K_B^- \Psi_3 \left(1 - \rho + 2\sigma_B^2\right) \Psi_1}, \tag{17}$$

where Ψ_5 is defined as

$$\Psi_5 \equiv \alpha\left(\Psi_1 + K_A^- \theta\right) - K_B^- \left(\alpha\theta + \Psi_1\left(\alpha + \phi\right)\right).$$

Consider $\eta_B > 0$. Intuitively, η_B is strictly positive since it reflects the sensitivity of the investment strategy of firm B to an expected increase in the demand. The solution of the model implies that the parameter η_B is given by

$$\eta_B \equiv \frac{(1 + \rho)\Psi_3}{2\Lambda\Psi_2} > 0,$$

where the numerator is strictly positive and the denominator is strictly positive given $\Psi_2 > 0$ and $\Psi_3 > 0$.

Consider $\eta_A > 0$. The solution of the model implies that the parameter η_A is given by

$$\eta_A \equiv \frac{1-\rho^2+(1+\rho)\,\sigma_B^2}{2\Lambda\left(\left(2K_A^-\gamma+\phi\right)\right)} > 0,$$

where $\eta_A > 0$ given $\Lambda > 0$ and $0 < \rho \leqslant 1$.

Concerning the equilibrium described in Proposition 1, consider first the argument of the existence of a fully revealing equilibrium in our setting. The reaction function of firm B is continuous, monotone and invertible. The inequality $\mu > \overline{\mu}$ discussed in the previous subsection ensures both $\eta_B > 0$ and $\delta_B > 0$. The specified ranges for the exogenous parameters in our basic setup ensure that $\eta_A > 0$ in strict sense. The function $I_B\left[s_B\right]$ is defined from the domain of real numbers to the co-domain of real numbers. Given these properties, there exists a unique mapping between $I_B\left[s_B\right]$ and s_B.

Given the assumption of linear conditional expectations in our setting, the reaction functions of firms A and B are linear. Hence there exists at most one fixed point such that both reaction functions intersect. This yields the equilibrium outcome of the model.

Finally, note that partially revealing equilibria arise when the reaction function $I_B\left[s_B\right]$ is either not continuous, not monotone or not invertible in a given parameter space. The parameter constraints in our setting prevents this situation, and ensures instead that $I_B\left[s_B\right]$ is continuous, monotone and invertible.

Appendix C. Proof of Corollaries 1 to 4

Proof of Corollary 1 [Differences in signal precision]

To prove Corollary 1, we define the ratio of the precision of the signal of firm A relative to the precision of the signal of firm B such that $\Delta_\sigma \equiv \sigma_B^2/\sigma_A^2 > 0$. We replace σ_B^2 by $\Delta_\sigma\sigma_A^2$ in Equation (8) and derive β with respect to Δ_σ.

Corollary 1 states than an increase in Δ_σ leads to a reduction in the coefficient β, such that $\partial\beta/\partial\Delta_\sigma < 0$. We derive the peer effect β in Equation (8) with respect to Δ_σ such that

$$\frac{\partial\beta}{\partial\Delta_\sigma} = -\frac{\Psi_1\Psi_2\rho^2\left(1-\rho+\sigma_A^2\right)\sigma_A^2}{\left(2\gamma K_A^-+\phi\right)\left(\Psi_3\right)^2} < 0 \tag{18}$$

where the negative sign of Equation (18) holds since $\Psi_1 > 0$ and $\Psi_2 > 0$.

Proof of Corollary 2 [Correlation between private signals]

Corollary 2 characterizes the effect of an increase in ρ on the parameter β. By inspection of Equation (8), it is straightforward to notice that an increase in ρ impacts the second term in Equation (8). The second term in Equation (8) is strictly positive and relates to learning peer effects. To prove the prediction of Corollary 2, we derive Equation (8) to obtain the derivative of β with respect to ρ:

$$\frac{\partial\beta}{\partial\rho} = -\frac{\Psi_1\Psi_2\Psi_6}{\left(2\gamma K_A^-+\phi\right)\left(1+\sigma_B^2\right)\left(\Psi_3\right)^2} < 0 \tag{19}$$

where $\Psi_1 > 0$, $\Psi_2 > 0$ and $\Psi_3 > 0$ have been previously defined. The constant Ψ_6 is defined as:

$$\Psi_6 \equiv \rho^2 - 2\rho\left(1+\sigma_A^2\right) + \left(1+\sigma_A^2\right)\left(1+\sigma_B^2\right).$$

The constant Ψ_6 is strictly positive as long as $\sigma_B^2 > 2\rho - 1$. The positive sign of constant Ψ_6 ensures the negative sign of Equation (19).

Proof of Corollary 3 [Differences in installed capacity]

We define initial differences in installed capacity are given by the ratio $\Delta_K \equiv K_A^-/K_B^- > 0$. We derive β with respect to Δ_K by replacing $K_A^- = \Delta_K K_B^-$ in Equation (8). As a first step, we derive η_B with respect to Δ_K to obtain

$$\frac{\partial \eta_B}{\partial \Delta_K} = -\frac{\theta \left(K_B^-\right)^2 \phi \left(1+\rho\right) \Psi_7}{2\Lambda \left(\Psi_2\right)^2 \left(1+\sigma_B^2\right)^{-1}} \tag{20}$$

where the negative sign of $\partial \eta_B / \partial \Delta_K$ is given by $\theta > 0$ and the positive sign of the constant Ψ_7, defined as

$$\Psi_7 \equiv \begin{array}{c} \phi \left(\Lambda + \left(1-\rho+\sigma_A^2\right)\left(1+\sigma_B^2\right)\right) + 2K_B^- \Lambda \left(\gamma - \theta\right) \\ +2K_B^- \gamma \left(\Lambda + \left(1-\rho+\sigma_A^2\right)\left(1+\sigma_B^2\right)\right) \end{array} > 0.$$

As a second step, we derive Equation (8) with respect to Δ_K to obtain

$$\frac{\partial \beta}{\partial \Delta_K} = -\frac{K_B^-}{\left(2\gamma K_A^- + \phi\right)} \left[2\gamma\beta + \frac{\left(1+\rho\right)\left(1-\rho+\sigma_A^2\right)}{2\Lambda \left(\eta_B\right)^2} \frac{\partial \eta_B}{\partial \Delta_K}\right], \tag{21}$$

where the sign of Equation (21) depends on the sign of β. Given $\partial \eta_B / \partial \Delta_K < 0$, it follows that if $\beta < 0$ then it also holds that $\partial \beta / \partial \Delta_K > 0$. Conversely, if it holds that $\partial \beta / \partial \Delta_K < 0$, then the learning effect predominates such that $\beta > 0$. This proves Corollary 3.

Proof of Corollary 4 [Peer concentration]

The core of the proof of Corollary 4 stems from noting that the peer concentration measure K_A^-/K_B^-, namely

$$h \equiv \frac{1}{2} \frac{\left(K_A^{-2} + K_B^{-2}\right)}{\left(K_A^- + K_B^-\right)^2} = \frac{1}{2} \frac{\left(1+\Delta_K^2\right)}{\left(1+\Delta_K\right)^2}$$

where the sign of $\partial h / \partial \Delta_K$ depends on whether Δ_K is greater or equal than one such that

$$\frac{\partial h}{\partial \Delta_K} \equiv \frac{\Delta_K - 1}{\left(1+\Delta_K\right)^3}$$

Applying the chain rule, the derivative of Equation (8) with respect to h is thus given by

$$\frac{\partial \beta}{\partial h} \equiv \frac{\partial \beta}{\partial \Delta_K} \frac{\partial \Delta_K}{\partial h} \tag{22}$$

where the overall sign of Equation (22) depends on whether Δ_K is larger or lower than 1.

Given $\Delta_K > 1$, we obtain the same comparative statics as in Corollary 3, since $\partial \Delta_K / \partial h > 0$. Given $\Delta_K < 1$, we obtain the reverse comparative statics relative to Corollary 3. The more intuitive case consistent with the empirical evidence is $\Delta_K < 1$. Given $\Delta_K < 1$, it follows that if $\beta < 0$ then it also holds that $\partial \beta / \partial h < 0$. Conversely, if it holds that $\partial \beta / \partial h > 0$, then it must be the case that the learning effect predominates such that $\beta > 0$.

Appendix D. Null Hypothesis: Model with No Peer Effects

Consider an alternative game in which firms do not invest strategically. When each firm decides on her investment, she does it *myopically*: each firm takes prices *as given* when deciding how much to invest. The demand shock ε is uncertain and each firm receives a private signal about the demand shock. To eliminate the learning from peers effect in a simple way, we assume $\rho = 1$ and also $s_i \equiv s$ such that firms have the same information about future demand. Firms determine their investment strategy based on the expectation of the demand shock ε conditional on the private signal s.

Given these assumptions, the sequence of moves in the game is not relevant and the reaction functions of both firms are the same. Firms choose the investment strategy that maximizes their value, and the value of firm i is given by $V_i^- \equiv p_i^- K_i^- + E\left[\left(p_i^+ K_i^+ - \Phi_i\right)\middle| s\right]$. The corresponding first order condition equals $\partial V_i^- / \partial I_i = 0$. Solving for the equilibrium investment strategies, we obtain:

$$I_i = \widetilde{\delta}_i + \widetilde{\eta}_i \times s, \tag{23}$$

for $i = A, B$ such that:

$$\begin{aligned}
\widetilde{\delta}_i &= \frac{2\mu\left(\left(\gamma-\theta\right)K_{-i}^- + \phi\right)\sigma_i^2 - 2\left(1+\sigma_i^2\right)K_{-i}^-\theta\left(\alpha+\phi\right) + K_i^-\left(-\alpha\theta + \left(\gamma^2-\theta^2\right)K_{-i}^- + \gamma\phi\right)}{2\left(1+\sigma_i^2\right)\left(\phi\left(\gamma K_{-i}^- + \phi\right) + K_i^-\left(\left(\gamma^2-\theta^2\right)K_{-i}^- + \gamma\phi\right)\right)}, \\
\widetilde{\eta}_i &= \frac{\left(\left(\gamma-\theta\right)K_{-i}^- + \phi\right)}{\left(1+\sigma_i^2\right)\left(\phi\left(\gamma K_{-i}^- + \phi\right) + K_i^-\left(\left(\gamma^2-\theta^2\right)K_{-i}^- + \gamma\phi\right)\right)} > 0.
\end{aligned}$$

By construction, there are no strategic or learning peer effects in this model. Also, the equilibrium outcome in Equation (23) yields no cross-sectional predictions on peer effects as the ones discussed in the body of the paper.

We now verify that the econometrician would infer $\beta = 0$ using the instrument variable Z_B defined in Section 2.3. Assuming that the econometrician does not observe s, she regresses I_A and I_B using ordinary least squares (OLS) as shown in Equation (9). The resulting coefficient $\widehat{\alpha_1}^{OLS}$ capturing the covariance between I_A and I_B is given by:

$$\widehat{\alpha_1}^{OLS} = \eta_A \times \frac{Cov\left[s, I_B\right]}{Var\left[I_B\right]} = \eta_A \times \eta_B > 0, \tag{24}$$

where $\eta_i > 0$. Comparing Equation (10) with Equation (24), we conclude that $\beta = 0$. Paraphrasing, the OLS estimate is only capturing the positive correlation in firms' investments due to the fact that both firms are receiving the same fundamental signal. The econometrician can verify that $\beta = 0$ by estimating Equation (9) using Z_B as the instrumental variable. In this case, the coefficient estimate yields $\widehat{\alpha_1}^{IV} = 0$.

Appendix E. Model with Strategic Complementarity

To derive the alternative case in which firms' products are strategic complements, we follow Vives (1985) and modify the sign of parameter θ in the inverse demand function such that $\theta < 0$. When $\gamma = -\theta$, firms' products are perfect complements. Product differentiation implies $\gamma > |\theta|$.

The resulting peer effect β when firms' products are strategic complements is given by the same equation shown in Proposition (1). However, given $\theta < 0$, the sign of the first term in Equation (8) is strictly positive. The second term remains positive as long as $0 < \rho < 1$ and $\sigma_i > 0$. If $\rho = 1$ or signals are perfect such that $\sigma_i = 0$, firms have perfect information and the hence second term in Equation (8) is equal to zero. Hence, given $\theta < 0$, we obtain $\beta > 0$ regardless of whether the strategic channel or the learning channel predominate.

The cross-sectional predictions for Corollaries (1-2) are the same as in the body of the paper. Note that these corollaries relate exclusively to the learning channel, and hence their predictions do not depend on the overall sign of the peer effect β.

In the case of Corollaries (3-4), the original predictions are conditional on the sign of the peer effect β and hence we revisit them. Consider first the sensitivity of β with respect to intra-industry differences in installed capacity Δ_K. Using Equation (20) and the fact that $\theta < 0$, it is straightforward to see that η_B is now strictly increasing in Δ_K. Given $\partial\eta_B/\partial\Delta_K > 0$ and $\beta > 0$, it follows that $\partial\beta/\partial\Delta_K < 0$ unconditionally. This can be inferred from Equation (21). Consider now the sensitivity of the peer effect β with respect to intra-industry differences in concentration h. We conclude that if $\Delta_K < 1$, it holds that $\partial\beta/\partial\Delta_K > 0$ unconditionally. In sum, the comparative statics in Corollaries (3-4) for the case in which $\theta > 0$ and $\beta > 0$ still apply for the alternative case in which products are strategic complements such that $\theta < 0$. Yet the predictions of the model given $\theta < 0$ are unconditional, since it is always the case that $\beta > 0$.

Figure 1. Sequence of Actions

Firm A observes $\{s_A, I_B\}$
and commits to I_A

↓

↓ Firm B observes s_B and commits to I_B

↓ Investments and cash flows are realized

Figure 2: Identification Strategy: An illustrative Example

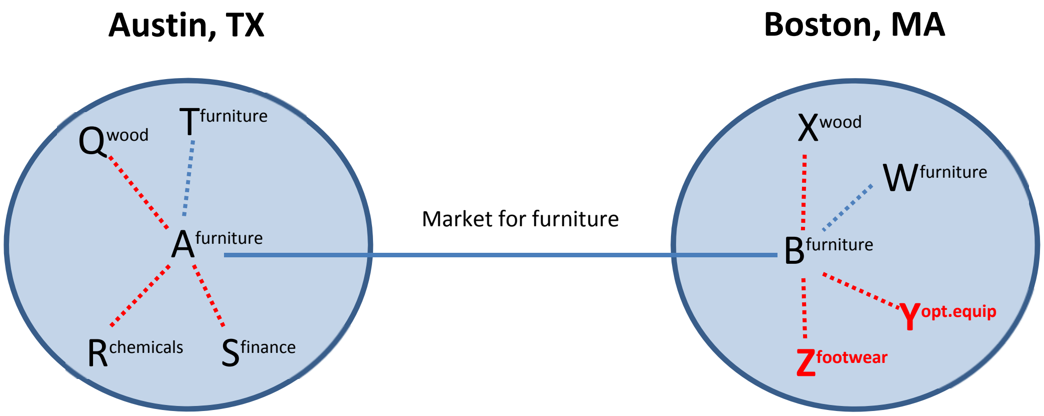

Figure 3: Peer Effects in Corporate Investment: Prevalence

This figure displays the *t*-statistics corresponding to the second-stage IV coefficient estimates on the instrumented average peers' investment from specification (11) in the text. Panel A reports t-statistics obtained separately for each Fixed Industry Classification (FIC100) developed by Hoberg and Phillips (2015). Panel B reports t-statistics obtained separately across 1,000 bootstrapped samples composed of 3,000 distinct firms.

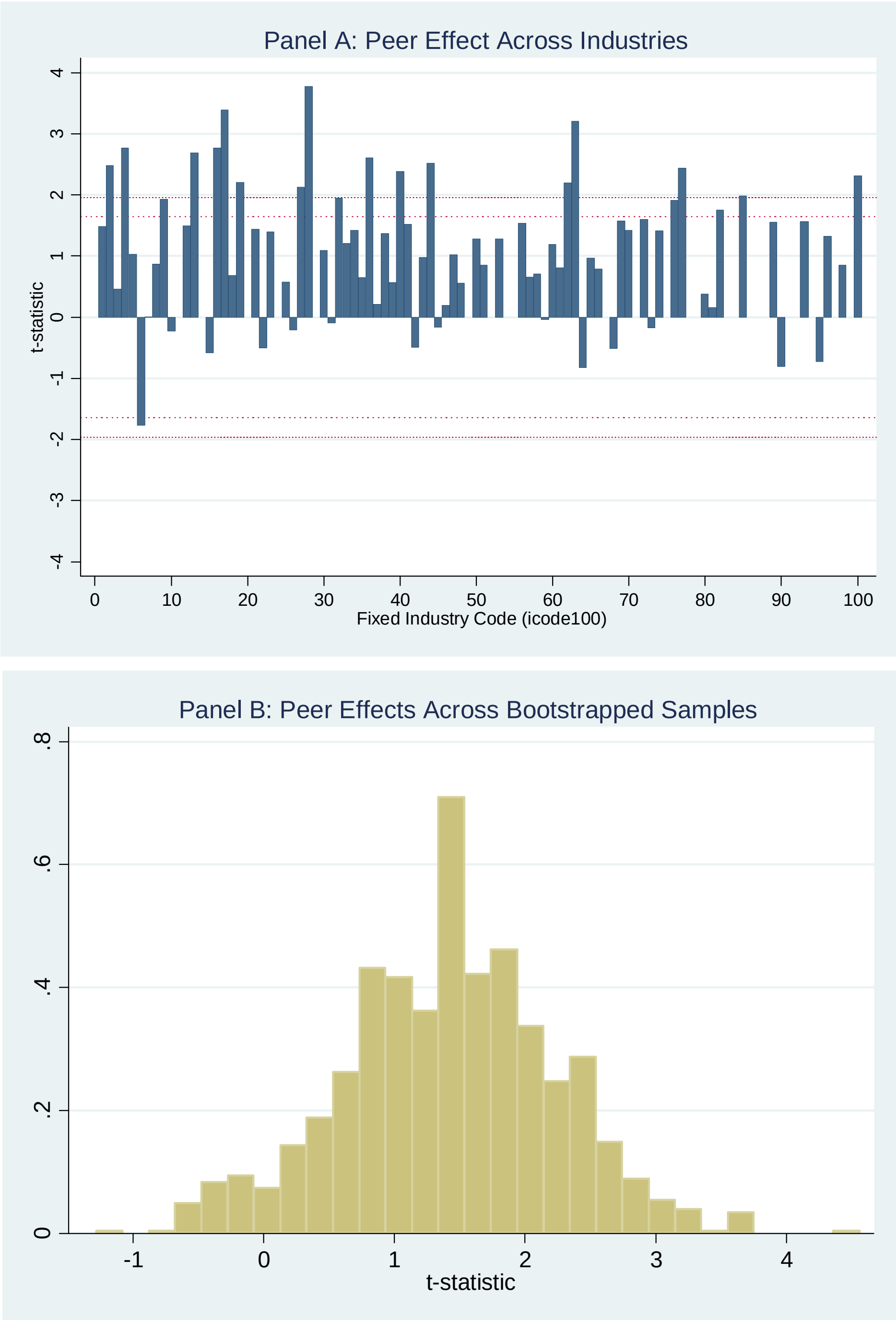

Table 1: Descriptive Statistics

This table reports the summary statistics for the main variables used in the analysis. For each variable, we present its mean, median, 25th and 75th percentile, and its standard deviation, as well as the number of non-missing observations for the variable. All variables are defined in the Appendix. In the upper panel, we present the statistics for firm-level observation (firm i). In the middle panel, we present statistics for non-local peers' average (i.e., the equally-weighted average of peers for each firm-year observation), where non-local peers are defined as TNIC peers that are outside of a firm's MSA. In the lower panel, we present statistics about product market and local peers for each firm-year observation. The sample period is from 1996 ton 2011.

	Mean	25th	median	75th	St. dev	#Obs.
			Own firm (i)			
I_i (=Capex/PPE)	0.36	0.12	0.23	0.42	0.42	44,013
MB_i	1.97	1.10	1.48	2.23	1.50	44,013
$Ln(A)_i$	5.60	4.19	5.51	6.90	1.91	44,013
Cash flow (CF/A_i)	0.02	0.00	0.07	0.12	0.22	44,013
			Average of non-local TNIC peers (-i)			
$\overline{I}_{-i}$	0.38	0.22	0.33	0.48	0.23	44,013
$\overline{MB}_{-i}$	2.08	1.48	1.83	2.48	0.87	44,013
$\overline{ln(A)}_{-i}$	5.73	4.98	5.65	6.42	1.07	44,013
$\overline{CF/A_i}$	0.01	-0.04	0.05	0.09	0.11	44,013
$\overline{I}_{-i}^{*}$ (=the instrument)	0.36	0.28	0.36	0.42	0.10	44,013
			TNIC and Local Peers			
# TNIC peers	56.12	11.00	30.00	82.00	63.78	44,013
# Non-local TNIC peers	48.62	8.00	25.00	69.00	58.01	44,013
# Local peers	89.86	26.00	80.00	147.00	69.95	44,013
# Unrelated local peers	41.27	29.50	38.73	50.57	17.59	44,013

Table 2: The Influence of Peers' Investment: Main Results

This table presents panel OLS and Instrumental Variables (IV) estimations of the baseline investment specification (specification (11) in the text). The dependent variable is investment of firm *i*, defined as capital expenditures divided by lagged property, plant, and equipment (I_i). The independent variables include average peers' characteristics (market-to-book ratio, size, and cash flows) and investment, as well as firms' own characteristics. For each firm-year observation, peers' averages are constructed as equally-weighted averages of all non-local TNIC peers. The subscript –*i* refers to the average value of the variable across firm *i*'s peers. Column (1) reports the OLS estimates. Column (2) reports the first-stage estimates, and column (3) reports the second-stage estimates. The endogenous variable is the average investment of non-local TNIC peers. The instrument is the average investment of the local MSA peers of non-local TNIC peers ($\overline{I_{-i}}^*$). All specifications include Firm and MSA×Year fixed effects. All variables are defined in the Appendix. To facilitate economic interpretation, all dependent variables are standardized to have a unit standard deviation. Standard errors are clustered by firm. We report *t*-statistics in parenthesis. Symbols *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

Dependent Variable:	Capex/PPE (I_i)		
Specification:	OLS	IV	
	(1)	(2)	(3)
Peers' Characteristics			
$\overline{I_{-i}}$	0.046***		0.037**
	(10.41)		(2.45)
$\overline{MB_{-i}}$	0.033***	0.419***	0.02
	(6.79)	(32.39)	(1.46)
$\overline{ln(A)_{-i}}$	0.002	-0.017*	0.003
	(0.67)	(-1.83)	(0.82)
$\overline{CF/A_i}$	0.008**	0.044***	0.007*
	(2.02)	(4.37)	(1.73)
Firm Characteristics			
MB_i	0.130***	0.068***	0.128***
	(24.46)	(12.25)	(23.27)
$Ln(A)_i$	-0.084***	0.01	-0.084***
	(-6.44)	(0.65)	(-6.69)
CF/A_i	0.034***	0.019***	0.033***
	(9.02)	(3.46)	(5.47)
Instrument			
$\overline{I_{-i}}^*$		0.113***	
		(12.48)	
Firm Fixed Effects	Yes	Yes	Yes
MSA×Year Fixed Effects	Yes	Yes	Yes
#Obs.	44,013	44,013	44,013
Adj. R^2	0.46	0.68	0.34

Table 3: Checking the Validity of the Instrument: Placebo Peers

This presents the results of 1,000 estimations a modified investment specification (specification (11) in the text) in which we change replace non-local product market peers by one randomly selected firm that is located in the same MSA as the original peer but operates in an unrelated product market, as described in section 4.B. Panel A reports descriptive statistics obtained across 1,000 first-stage estimates and their respective *t*-statistics, and panel B reports the corresponding second-stage estimates and their respective *t*-statistics.

	mean	sd	p10	p25	p50	p75	p90	N
Panel A: First-stage estimates								
Coefficient on $\overline{I}_{-i}^{*}$	0.155	0.003	0.151	0.154	0.155	0.157	0.159	1,000
t-statistic	20.001	0.495	19.417	19.680	19.954	20.397	20.668	1,000
Panel B: Second-stage estimates								
Coefficient on $\overline{I}_{-i}$	-0.001	0.017	-0.021	-0.011	-0.001	0.010	0.022	1,000
t-statistic	-0.032	0.997	-1.219	-0.670	-0.076	0.591	1.280	1,000

Table 4: Instrument Properties: Correlation with Fundamentals

This table presents results from panel OLS estimations, in which the dependent variable is the average investment of the local peers of non-local product market peers (I^{+}_{-i}) measured in year *t*. The independent variables include firm's characteristics (displayed), average peers' characteristics and investment (not-displayed). For each firm-year observation, peers' averages are constructed as equally-weighted averages of all non-local TNIC peers. Both specifications include Firm and MSA×Year fixed effects. Column (3) and (4) further include FIC×Year fixed effects, where FIC is the Fixed Industry Classification (100) developed by Hoberg and Phillips (2015). In columns (1) and (3), the independent variable is also measured in year *t*, while in columns (2) and (4) they are measured with a one-year lead (i.e. in year *t+1*). All variables are defined in the Appendix. To facilitate economic interpretation, all dependent variables are standardized to have a unit standard deviation. Standard errors are clustered by firm. We report *t*-statistics in parenthesis. Symbols *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

Dependent Variable:	Local Capex/PPE ($\overline{I_{-i}}^{*}$)			
Specification:	Contemp.	one-year lead	Contemp.	one-year lead
	(1)	(2)	(1)	(2)
MB_i	0.000	-0.001	0.000	-0.000
	(0.77)	(-1.19)	(1.47)	(-1.39)
$Ln(A)_i$	0.001	0.001	0.000	0.001
	(0.72)	(1.02)	(0.49)	(1.11)
Cash flow (CF/A_i)	-0.000	-0.001**	-0.000	-0.000
	(-0.87)	(-2.02)	(-0.78)	(-1.48)
Peers' Characteristics	Yes	Yes	Yes	Yes
Peers' Investment ($\overline{I_{-i}}$)	Yes	Yes	Yes	Yes
Firm Fixed Effects	Yes	Yes	Yes	Yes
MSA×Year Fixed Effects	Yes	Yes	Yes	Yes
FIC×Year Fixed Effects	No	No	Yes	Yes
#Obs.	44,013	44,013	44,013	44,013
Adj. R^2	0.77	0.74	0.81	0.79

Table 5: The Influence of Peers' Investment: Robustness

This table presents panel Instrumental Variables (IV) estimations of various modifications of the baseline investment specification (specification (11) in the text). The dependent variable is investment of firm *i*, defined as capital expenditures divided by lagged property, plant, and equipment (I_i). The independent variables include average peers' characteristics (market-to-book ratio, size, and cash flows) and investment, as well as firms' own characteristics. For each firm-year observation, peers' averages are constructed as equally-weighted averages of all non-local TNIC peers. The subscript –*i* refers to the average value of the variable across firm *i*'s peers. The endogenous variable is the average investment of non-local TNIC peers. The instrument is the average investment of the local MSA peers of non-local TNIC peers (I^{+}_{-i}). All specifications include Firm and MSA×Year fixed effects. For brevity we only report the estimated coefficient on peers' average investment (I_{-i}). Column (1) and (2) further include FIC×Year fixed effects, where FIC is the Fixed Industry Classification (100 or 300) developed by Hoberg and Phillips (2015). Column (3) includes additional peers- and firm-level controls (sales growth, PPE/assets, leverage, and cash/assets). Column (4) only use non-local peers that are located more than 300 miles away. Columns (5) and (6) compute peers' weighted averages instead of equally-weighted averages, with weights based on sales and assets. Column (6) defines product market peers using the 3-digit Standard Industry Classification (SIC) definition. Columns (8) and (9) replace the dependent variables with the growth in PPE and the growth in assets. All variables are defined in the Appendix. To facilitate economic interpretation, all dependent variables are standardized to have a unit standard deviation. We report the t-statistic of the instrument from the first-stage estimation at the bottom of each column. Standard errors are clustered by firm. We report *t*-statistics in parenthesis. Symbols *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

Dependent Variable:	Capex/PPE (I_i)							ΔPPE (I_i)	ΔA(I_i)
Specification:	FIC100	FIC300	Controls	>300m	w(sales)	w(A)	SIC		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
$\overline{I}_{-i}$	0.038***	0.044***	0.029**	0.021**	0.039***	0.037***	0.023***	0.060*	0.052***
	(2.60)	(3.01)	(1.97)	(2.21)	(3.58)	(3.33)	(2.65)	(1.67)	(4.06)
Peers Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
MSA×Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Ind×Year Fixed Effects	Yes	Yes	No	No	No	No	No	No	No
#Obs.	44,013	44,013	42,829	43,399	44,013	44,013	44,013	44,013	44,013
First-Stage *t*-statistic	10.68***	11.25***	12.31***	11.68***	11.51***	13.93***	14.23***	6.95***	11.97***

Table 6: Peer Effects in Corporate Investment: Learning vs. Strategic Channel

This table presents panel Instrumental Variables (IV) estimations of the interaction investment specification (specification (12) in the text). The dependent variable is investment of firm *i*, defined as capital expenditures divided by lagged property, plant, and equipment (I_i). We consider eight different variables as proxies for the model key parameters (Δ_σ, ρ, Δ_K, and h). We interact the average investment of non-local TNIC peers ($\overline{I_{-i}}$) and each other independent variable with two indicator variables identifying the lower (D_{low}) and upper (D_{high}) half of each proxy variable distribution. We measure all proxies with one year lag, and assign firm-year observations into each group every year. The independent variables include average peers' characteristics (market-to-book ratio, size, and cash flows) and investment, as well as firms' own characteristics. For each firm-year observation, peers' averages are constructed as equally-weighted averages of all non-local TNIC peers. The subscript –*i* refers to the average value of the variable across firm *i*'s peers. The endogenous variables are the interactions between the average investment of non-local TNIC peers and the two indicator variables. We instrument each interaction term with the interaction between the instrument (i.e., the average investment of the local MSA peers of non-local TNIC peers ($\overline{I_{-i}^*}$)) and each indicator variable. All specifications include Firm and MSA×Year fixed effects. For brevity we only report the estimated coefficients on the interaction terms between peers' average investment (I_{-i}) and the indicator variables (D_{low} and D_{high}). All variables are defined in the Appendix. To facilitate economic interpretation, all dependent variables are standardized to have a unit standard deviation. We report the F-statistic corresponding to a test of equality between $\overline{I_{-i}} \times D_{low}$ and $\overline{I_{-i}} \times D_{high}$, as well as the F-statistic corresponding to the first-stages Craag-Donald Wald test. Standard errors are clustered by firm. We report *t*-statistics in parenthesis. Symbols *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

Dependent Variable:	Capex/PPE (I_i)							
Model's Parameter:	Δ_σ		ρ		Δ_K		h	
Proxy (to construct D):	$\Delta Vol_{i,-i}$	$\Delta Age_{i,-i}$	$Similarity_{i,-i}$	$Co\text{-}Coverage_{i,-i}$	$\Delta ln(PPE)_{i,-i}$	$\Delta ln(A)_{i,-i}$	$HHI(k)_i$	$\#Peers_i$
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\overline{I_{-i}} \times D_{low}$	0.031	0.087***	0.095***	0.074***	0.104***	0.110***	0.024	0.065**
	(1.21)	(2.82)	(2.54)	(2.91)	(3.78)	(4.06)	(0.56)	(2.22)
$\overline{I_{-i}} \times D_{high}$	0.076***	0.056	0.012	0.056***	0.035	0.017	0.077***	0.021
	(2.82)	(0.55)	(0.23)	(4.54)	(1.18)	(0.55)	(2.87)	(0.40)
Test coefficient F-Stat	6.32**	3.89**	5.26**	0.71	13.59***	21.45***	5.27**	3.45*
First-Stage F-Stat	245.03***	200.44***	163.51***	188.51***	212.78***	208.64***	184.93***	157.34***
Peers Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
MSA×Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
#Obs.	44,013	44,013	44,013	44,013	44,013	44,013	44,013	44,013

Table 7: Blending with the Crowd and Strategic Complementarity

This table presents panel Instrumental Variables (IV) estimations of the interaction investment specification (specification (12) in the text). The dependent variable is investment of firm *i*, defined as capital expenditures divided by lagged property, plant, and equipment (I_i). We interact the average investment of non-local TNIC peers ($\overline{I_{-i}}$) and each other independent variable with indicator variables identifying whether firms use relative performance evaluation in their CEO compensation contract (columns (1) and (2) and whether firms compete in strategic substitutes or complements (column (3)).The variable $D_{RPE=0}$ is equal to one if firms do not use RPE while $D_{RPE=1}$ is equal to one if firms use RPE. We assign firm-year observations into the two groups based on a proxy for RPE obtained by regressing (for each industry-year) CEO compensations on their firm's lagged annual stock return and the lagged average stock return of their industry peers. We define that firms do not use RPE is the estimate on the peer returns is larger than zero. In column (1) we define peers using 2-digit SIC industries, and in column (2) we define peers using 3-digit SIC industries. The variable D_{SUBS} is equal to one if firms have a negative value for the Competitive Strategy Measure (CSM), and D_{COMP} is equal to one if firms have a positive value for CSM. The independent variables include average peers' characteristics (market-to-book ratio, size, and cash flows) and investment, as well as firms' own characteristics. For each firm-year observation, peers' averages are constructed as equally-weighted averages of all non-local TNIC peers. The subscript *–i* refers to the average value of the variable across firm *i*'s peers. The endogenous variables are the interactions between the average investment of non-local TNIC peers and the two indicator variables. We instrument each interaction term with the interaction between the instrument (i.e., the average investment of the local MSA peers of non-local TNIC peers ($\overline{I_{-i}}^*$)) and each indicator variable. All specifications include Firm and MSA×Year fixed effects. For brevity we only report the estimated coefficients on the interaction terms between peers' average investment (I_{-i}) and the indicator variables. All variables are defined in the Appendix. To facilitate economic interpretation, all dependent variables are standardized to have a unit standard deviation. We report the F-statistic corresponding to a test of equality between coefficients, as well as the F-statistic corresponding to the first-stages Craag-Donald Wald test. Standard errors are clustered by firm. We report *t*-statistics in parenthesis. Symbols *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

Dependent Variable:	Capex/PPE		
Proxy (to construct D):	RPE (SIC2)	RPE (SIC3)	CSM (TNIC)
	(1)	(2)	(3)
$\overline{I_{-i}} \times D_{RPE=0}$	0.066***	0.0075***	
	(2.68)	(2.92)	
$\overline{I_{-i}} \times D_{RPE=1}$	0.031	0.046*	
	(1.27)	(1.79)	
$\overline{I_{-i}} \times D_{SUBS}$			0.050**
			(2.14)
$\overline{I_{-i}} \times D_{COMP}$			0.071***
			(2.79)
Test coefficient F-Stat	1.85	1.91	1.14
First-Stage F-Stat	199.51***	212.50***	210.38***
Peers Controls	Yes	Yes	Yes
Firm Controls	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes
MSAxYear FE	Yes	Yes	Yes
# Obs	44,013	44,013	44,013