Product market competition, stock price informativeness, and managerial learning

Nihat Aktas, Eric de Bodt, and Jean-Gabriel Cousin

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Abstract

This paper posits product market competition as a potential driver of stock returns and quantifies its impact on stock price informativeness. R^2 of stock return regressions increase on average by 8.70 percentage points after accounting for the firm's strategic interactions with its nearest product market neighbors. We find that stock prices reflecting product market competition enhance learning, as managers incorporate these signals into their investment decisions. The contribution of the product market competition channel to managerial learning is particularly strong and remains robust to endogeneity concerns for R&D investments. It is also more pronounced in subsamples where focal firms are less financially constrained, are industry leaders, operate in R&D-intensive markets, and interact with rivals in high-quality information or highly competitive environments. Additional analyses of innovation outcomes, including patents and changes in the firm's product offerings, confirm the robustness of the R&D results. These findings reveal how product market-driven improvements in stock price informativeness shape corporate decision-making.

JEL classification: G14, G31.

Keywords: Product market competition, stock price informativeness, managerial learning, corporate investment, innovation outcomes

Nihat Aktas is from WHU Otto Beisheim School of Management (nihat.aktas@whu.edu). Eric de Bodt is from NHH Norwegian School of Economics (eric.debodt@nhh.no). Jean-Gabriel Cousin is from Université de Lille (jgcousin@univ-lille.fr).

1. Introduction

Understanding the informational content of stock prices is crucial not only for asset pricing but also due to its significant implications for corporate finance. Stock prices indeed have real effects and serve as a key source of information for managers.[1] Depending on the sampling choice and data frequency, at most twenty percent of daily stock price changes is explained by the classical market model augmented with a broad industry factor (Roll, 1988). While more sophisticated asset pricing models improve the explanatory power by a few percentage points, they still leave a large portion of daily stock price changes unexplained. This unexplained component, $1 - R^2$, which is also known as price nonsynchronicity, is widely used as a proxy for the quantity of firm-specific information embedded in stock prices (Durnev, Morck, Yeung and Zarowin, 2003). It is also well-established that managers learn from this idiosyncratic component, but the specific nature of the information driving this learning effect remains largely unexplored in existing literature.[2]

This paper examines product market competition as a potential driver of managerial learning from the firm's own stock prices, referred hereafter to as the product market competition (PMC) channel. Firms do not operate in isolation; they actively engage with competitors in the product market, influencing both their own outcomes and those of their rivals. These interactions affect investment decisions and cash flows (Frésard and Valta, 2016), while peer valuations shape investment behavior (Foucault and Frésard, 2014; Eaton, Guo, Liu, and Officer, 2022). Additionally, industries are a key area for news dissemination in stock markets (Hou, 2007), where firm-specific news can affect the value of other firms in the same industry due to their interconnectedness. Consequently, after quantifying the extent to which product market

[1] See Bond, Edmans, and Goldstein (2012) or Goldstein (2023) for a review of the theoretical and empirical literature devoted to the financial markets' real effect.

[2] Prior literature provides ample empirical evidence about managerial learning from stock prices in various settings like investment, merger and acquisition, cash holdings, and firm productivity (see, e.g., Chen, Goldstein, and Jiang, 2007; Luo, 2005; Kau, Linck, and Rubin, 2008; Edmans, Goldstein, and Jiang, 2012; Frésard, 2012; Foucault and Frésard, 2012; Edmans, Jayaraman, and Schneemeier, 2017; Bennett, Stulz, and Wang, 2020; Chen and Doukas, 2024).

competition drive the focal firm's stock price, we assess whether managerial learning is enhanced when stock prices better reflect the informational content of PMC.

We acknowledge that firms may directly learn from the behaviors and actions of their industry rivals (see, e.g., Spence, 1981; Gilbert and Lieberman, 1987; Grenadier, 2002; Leary and Roberts, 2014; Décaire, Gilje, and Taillard, 2020; Bustamente and Frésard, 2021; Krieger, 2021), as well from their stock prices (Foucault and Frésard, 2014; Yan, 2024). Observing a rival's investment or innovation provides valuable insights, and changes in a rival's stock price can signal information about future growth opportunities in the industry. However, an equally crucial factor is the information content of PMC—understanding how rival actions affect the information content of the focal firm's stock price. We posit that a firm's own stock price becomes more informative thanks to product market-driven interactions, improving the firm's learning process.

Our empirical approach proceeds in two stages. The first stage quantifies the contribution of rival firms' strategic actions to the stock price changes of the focal firm. This requires addressing two empirical challenges: (i) identifying rival firms operating within the same product market space; and (ii) constructing a proxy to measure the information content of strategic interactions with these rivals.

The Hoberg and Phillips (2010, 2016) database addresses the first challenge.[3] By analyzing product descriptions from SEC 10-K filings, the authors calculate yearly similarity scores between firm pairs across the entire Compustat universe. These similarity scores measure proximity in the product market space and correlate with the degree of direct rivalry between firms. To identify a firm's closest rivals in any given year, we follow the approach of Hoberg and Phillips (2010) and select the ten nearest neighbors (10NN) in the product market space.

To overcome the second empirical challenge, we start with a simple observation: firm-specific news about industry rivals affects the stock prices of firms in the same product market through

[3] http://hobergphillips.tuck.dartmouth.edu/industryclass.htm.

the competition (or cooperation) channel. For example, on July 6, 2021, the Pentagon canceled Microsoft's $10 billion JEDI cloud contract, resulting in Amazon stock rising by 4.69%. This Microsoft-specific news benefited Amazon, as its Amazon Web Services platform competes with Microsoft Azure for the Pentagon contract. However, not all rival interactions are as obvious. When Apple announced its shift to in-house silicon in June 2020, the stock price of its former supplier, Intel, saw little change, likely because the move was anticipated by analysts. In such cases, identifying stock price impacts requires pinpointing the exact days when rumors or leaks hit the market. While feasible for a small sample of industries, large-scale collection over extended periods of such data is certainly challenging. Nonetheless, if good news for some firms is bad news for others in the same product market (or good news for both in cases of cooperation), firm-specific return correlations should reveal this dynamic. To account for rival firms' strategic interactions in explaining stock price changes, we therefore incorporate the idiosyncratic returns of the 10NN rivals into the baseline stock return regressions of the focal firm.[4]

We assemble our sample by merging the Hoberg and Phillips database with the CRSP universe over the 1989–2021 period. After excluding utility and financial industries, the data requirements result in a sample averaging 2,870 firms per year. We isolate the contribution of rivals' product market interactions to the information content of stock prices by starting with a baseline model. This model regresses the daily excess returns of the focal firm on the excess returns of the market portfolio and a value weighted industry portfolio. The industry portfolio is formed by firms within the same 3-digit SIC code, following standard practices in prior learning literature. The use of the broad industry factor allows us to control for shocks that are common to all industry firms (typically, shocks on product demand due to technological innovation or change in input prices). We then augment the baseline model with the daily idiosyncratic returns of the 10NN rivals. By

[4] See de Bodt, Eckbo, and Roll (2024) for the use of idiosyncratic within-industry return comovements to identify industry rival's strategic reactions to competitive shock in the industry.

comparing the R^2 of the full model with that of the baseline model, we isolate the contribution of the 10NN rivals' strategic interactions to the stock price informativeness of the focal firm.

Relying on a firm-by-firm yearly regressions over the 1989–2021 period, we document that the average R^2 obtained with the baseline model is 16.96%, which is of the same magnitude as the average R^2 reported in Chen, Goldstein, and Jiang (2007). The inclusion of the 10NN rivals idiosyncratic returns increases the average R^2 by 8.70 percentage points, a highly statistically significant increase in R^2. This result confirms that PMC is important in explaining the information content of stock returns.

We use the difference between the $1 - R^2$ of the baseline model and that of the full model controlling for the 10NN rivals' stock returns to measure the contribution of product market competition to the stock price informativeness of the focal firm.[5] This variable aims to quantify the product market competition-induced component of the focal firm's stock price informativeness, which we denote as SPI^{PMC}.

We next test our prediction. Relying on various investment variables, we examine whether learning from the firm's own stock price is amplified when the contribution of product market competition to the firm's stock price informativeness is higher (i.e., the PMC channel of managerial learning). We follow prior literature and adopt a standard linear investment equation which relates the focal firm's investment ratio to its own stock price, thereby estimating investment-to-*Q* sensitivities. We start with the capex-to-assets ratio as dependent variable and confirm the well-established finding from prior literature that capex investment is highly sensitive to Tobin's *Q* (Chen, Goldstein, and Jiang, 2007). The coefficient estimate of Tobin's *Q* is positive and statistically significant at the 1% level in our sample. Next, we augment the specification by including our variable of interest, SPI^{PMC}, along with its interaction term with Tobin's *Q*. The interaction term tests whether the

[5] Before calculating the difference between the two stock price informativeness variables, we apply a logistic transformation to both, as is common in prior literature to address the skewness and boundedness of $1 - R^2$ (Durnev, Morck, and Young, 2004).

sensitivity of the firm's capex to its stock price increases when the contribution of the 10NN rival's returns to the stock price informativeness is higher. This is the case, as the interaction term is associated with a statistically significant positive coefficient. The economic effect is sizeable, with a one standard deviation change in SPI^{PMC} inducing a 6% increase in the sensitivity of the capex ratio to the firm's Tobin's *Q* relative to the baseline effect.

We repeat our analysis by also controlling for the stock price of industry peers using the industry average Tobin's *Q*, as firms may also learn directly from the valuation of their peers (Foucault and Frésard, 2014). The inclusion of the industry peers' Tobin's *Q* does not affect our main finding. The PMC channel of managerial learning that we document extends therefore beyond merely observing rivals' stock prices. This further implies that understanding the informational content of PMC is important to identify sources of managerial learning. Note that the coefficient estimate of the industry peers' Tobin's *Q* loads also with a significantly positive coefficient estimate in the capex ratio regression, indicating that direct learning from rival stock prices is also at play in our sample.[6]

Performing the same analysis with R&D and total investment ratios further emphasizes the importance of learning from the product market-driven component of the firm's stock price informativeness.[7] It is also important to emphasize that the economic magnitude of the documented PMC channel is notably stronger for R&D investments compared to capex. This aligns with the critical role of R&D in driving firm growth (Brown, Fazzari, and Petersen, 2009) and the challenges of financing R&D using external source of funding (Hall, 2002). These characteristics likely explain R&D's increased sensitivity to stock prices, particularly when those prices reflect substantial product market-driven information. Interestingly, direct learning from

[6] Relying on the average Tobin's *Q* of a broad industry [i.e., TNIC industries developed by Hoberg and Phillips (2016)] or that of the 10NN rivals as an additional control does not alter our conclusion.
[7] We define total investment as the sum of capex, R&D and cash acquisition, less asset sales, scaled by lagged total assets.

peer valuations do not appear to play a significantly positive effect for both R&D and total investment.

Numerous robustness checks confirm our result. Specifically, our main finding remains robust when: (i) we use the relative increase in the R^2 between the baseline and full models as an alternative proxy for the product market-driven component of stock price informativeness; (ii) we replace the one-factor model with the Fama-French five-factor model (Fama and French, 2015); (iii) we adjust return regressions using asymmetric betas to account for differential responses to good and bad news affecting rivals (Ang, Chen, and Xing 2006); and (iv) we control for managerial private information using earnings surprises and analyst coverage, following Chen, Goldstein, and Jiang (2007). This additional test ensures that managers rely on stock prices to access information beyond their private knowledge. Finally, a placebo test, which consists in allocating randomly 10 firms as nearest rivals to the focal firm, confirms that our learning result is not due to chance.

To gain a better sense of the magnitude of the PMC-induced learning effects that we capture, we compare the contributions of the *residual* firm-specific information in stock returns (after controlling for co-movements with the returns of the 10NN rivals) to the PMC-driven stock price informativeness to managerial learning. This analysis should be informative about the relative economic importance of PMC-driven stock price informativeness. The results suggest that both components are important sources of information for managerial learning. While the coefficient estimate of Tobin's *Q* in the capex regression is more sensitive to the residual component, for both R&D and total investment, the economic impact of the PMC-driven component is as important as that of the residual component.

We next study cross-sectional determinants that influence the contribution of the PMC channel to managerial learning. To this end, we consider five contexts that may amplify or attenuate managerial learning: financial constraints, informational environment quality, competition intensity, R&D intensity, and industry leadership. Specifically, we find that PMC-induced learning effects are strongest for R&D investments, particularly among firms that are less financially constrained, competing in high-quality informational environments, in leadership positions, and operating in R&D-intensive and competitive product markets. Collectively, these results highlight the importance of PMC-driven market signals for R&D investments, particularly in settings where strategic interactions are essential.

Our finding that firms with higher PMC-driven SPI exhibit greater sensitivity to Tobin's *Q* can be driven by factors that impact both price discovery and investment. For instance, as noted by Bennett, Stulz, and Wang (2020), one possible omitted factor is technological shocks, which could enhance price informativeness and influence investment decisions. To strengthen the causal interpretation of our results, we follow Bennett, Stulz, and Wang's (2020) approach, using a quasi-natural experiment to address potential endogeneity concerns. We specifically examine the addition of the focal firm's 10NN rivals to the S&P 500 index as an exogenous shock to SPI^{PMC}. The inclusion of a rival firm in the index is beyond the focal firm's control. Furthermore, such inclusion is expected to increase the co-movement of the rival firm's stock returns with the index (Vijh, 1994; Barberis, Shleifer, and Wurgler, 2005). As a result, this inclusion can reduce the co-movement between the idiosyncratic stock returns of the rival firm and the focal firm. We begin by testing this conjecture, showing that S&P 500 additions negatively impact SPI^{PMC}. In the investment regressions, we replace SPI^{PMC} by a dummy variable identifying the addition of rival firms tothe S&P 500 index and find that such additions significantly reduce the sensitivity of the focal firm's R&D expenses to its Tobin's *Q*. This result supports the existence of a causal relationship between R&D expenses and SPI^{PMC}. However, the effects on capex and total investment are not statistically significant.

Taken collectively, our various identification strategies indicate that among the investment decisions, R&D investment appears to be the most sensitive to PMC-induced signals in stock prices. To further assess the robustness of our R&D results, we turn to variables capturing innovation outcomes over the next three years, since it may take time for R&D to translate into tangible innovation (Griliches, 1990). We replicate our baseline analysis with three different innovation outcomes: (i) granted patents[8], (ii) future citations of the granted patents, and (iii) changes in product offerings using the self-fluidity variable of Hoberg, Phillips, and Prabhala (2014). These additional results are in-line with the R&D results, showing that PMC-driven stock price informativeness amplifies the sensitivity of the considered innovation outcomes to the firm's Tobin's *Q*.

Our research contributes to literature examining the feedback effect of financial markets, in general, and to literature on managerial learning from stock prices, in particular. As emphasized in Goldstein (2023), the discovery of information is one of the central roles of financial markets. Stock prices aggregate information from various sources, and information embedded in stock prices enhance the efficiency of the decision-making processes in the real economy (see, among others, Dow and Gorton, 1997; Subrahmanyam and Titman, 1999; Peress, 2014).

Numerous articles provide empirical evidence emphasizing that managers learn from their own stock prices in the context of investment decisions. Chen, Goldstein, and Jiang (2007) show that firm-specific information in stock prices affects positively the sensitivity of corporate investments (such as capex and R&D) to stock prices. Frésard and Foucault (2012) document that cross-listing in a relatively more efficient market affects positively the sensitivity of corporate investment to stock prices. Edmans, Jayaraman, and Schneemeier (2017) develop a theoretical model predicting that managers do not only learn from the total information embedded in stock prices, but that the source of that information also matters. Reyling on an international setting and the adoption of insider trading laws, the authors document that the sensitivity of capex to stock prices is amplified when stock prices incorporate information unknown to managers. We also consider the information source and document that the component driven by PMC is important for managerial learning in the context of investment. Our paper shed therefore important light on the

[8] Patent data are from the KPSS patent data library (Kogan, Papanikolaou, Seru, and Stoffman, 2017), available at https://github.com/KPSS2017.

nature of information driving the learning effects and emphasize the role of product market competition.

Our research also relates to studies examining learning from peers' stock prices and valuations.[9] Foucault and Frésard (2014) develop a theoretical model to lay out their empirical predictions and provide evidence that the stock prices of industry peers matter for capex investments. Yan (2024) focuses on private firms, and document that their investments are sensitive to the stock prices of industry peer listed firms. While firms can derive insights from observing their rivals' stock prices, this alone may not provide a complete picture. It's equally important to understand implications of rivals' actions on the focal firm's stock price information content. To capture these PMC effects, we rely on idiosyncratic within-industry return comovement in stock return regressions. Accounting for PMC improves stock price informativeness, which, in turn, enhance managerial learning. Our specifications control for the Tobin's *Q* of industry peers, and therefore, the learning effect that we document extends beyond merely observing rivals' stock prices.

2. Data and empirical approach

This section begins by detailing the identification of product market rivals and describing the sample. Next, we outline the method used to isolate the PMC-driven component of stock price informativeness (SPI). We then present the results of stock return regressions, which we use to estimate SPI variables. Finally, we introduce the regression specification used to test whether PMC channel is an important source of information for managerial learning from stock prices, referred as the PMC channel.

2.1. Rival identification and sample construction

[9] Stock prices of peers are also important in capital budgeting and M&A decisions, where corporate executives and investment bankers derive pricing multiples from listed comparable firms to value investment opportunities (Graham and Harvey, 2001; Eaton et al., 2020; Aktas, Boone, Witkowski, Xu and, Yurtoglu, 2021). In M&A valuation, Eaton et al. (2020) document that the product market space is more important as a factor for the selection of peers than the SIC industry classification.

A key step to isolate the PMC-driven component of SPI is identifying direct competitors, a challenging task as emphasized in Eckbo (1983). Broad industry classifications like SIC codes, which focus more on technology than competition and are known to be sticky, are not suited for our emphasis on product market interactions between rival firms.[10] We therefore use the Text-Based Network Industry Classification (TNIC) dataset introduced in Hoberg and Phillips (2010, 2016).[11] This dataset leverages Item 1 product descriptions from annual SEC 10-K filings to generate yearly similarity scores between U.S. firm pairs based on their product offerings. These scores serve as a widely accepted proxy for product market competition.

To assemble our sample, we start from the TNIC dataset that spans the 1989 to 2021 period at the time of this writing. We keep the ten nearest neighbors (10NN) ranked by similarity scores as in Hoberg and Phillips (2010). Next, we apply the following filters to our sample: we retain only firms present in the Center for Research in Security Prices (CRSP) database, keep ordinary U.S. shares (CRSP share class codes10 and 11), exclude penny stocks, and remove observations with missing data for shares outstanding (CRSP field '*shrout*') or missing closing prices ('*prc*' CRSP field). We also exclude firm-year observations with fewer than 90 daily returns in a given year, as well as firms in financial (SIC codes 6000-6999) and utility industries (SIC codes 4000-4999). These filters reduce our initial sample of 171,536 firm-year observations to 94,695.

Table 1 presents the sample characteristics by year. Column 1 lists the number of unique firms, column 2 reports the aggregate market value of equity at year-end in US$ billions, column 3 provides the average similarity score for all firm pairs, and column 4 shows the average similarity score of firm pairs in the 10NN clusters.

The peak number of unique firms in our sample occurred in 1997 with 4,405 firms. From that point onward, there is a steady year-by-year decline, reaching a low of 2,203 firms by 2020, followed by

[10] See Bhojraj, Lee, and Oler (2003) for a discussion on the limitations associated with SIC code classification to explain stock return comovements or to form group of firms with similar characteristics.
[11] Available at http://hobergphillips.tuck.dartmouth.edu/tnic_poweruser.htm.

a notable reversal in 2021 with 2,679 firms. The sharp decline in the number of U.S. listed firms over the last three decades has been well documented in the literature, raising concerns about a U.S. listing gap (Doidge, Karolyi, and Stulz, 2017). In terms of aggregate equity value, a first peak is reached in 1999, coinciding with the dot.com bubble, the second in 2007 before the financial crisis, and the third in 2021, the final year of our sample period. Notably, despites a drastic reduction in the number of unique firms from 1997 to 2021, the aggregate market value more than quintupled, driven largely by the rise of tech giants such as Google, Amazon, Facebook, Apple and Microsoft (GAFAM). In terms of similarity scores, the average similarity across all firm pairs is 0.015 in our sample, while the one of the 10NN cluster is mechanically considerably higher at 0.173. These statistics are in line with Hoberg and Phillips (2010).

2.2. Regression specification to isolate PMC-driven SPI

We measure stock price informativeness (SPI) using asset pricing regressions, building on Roll's (1988) seminal work. The baseline model regresses the focal firm's excess stock return on the excess returns of the market and industry portfolios:

$$r_{i,t} - r_{F,t} = \alpha_i + \beta_i^M \left(r_{M,t} - r_{F,t}\right) + \beta_i^{IND} \left(r_{IND,t} - r_{F,t}\right) + \varepsilon_{i,t}, \tag{1}$$

where *i* denotes the focal firm, $r_{i,t}$ is the firm's stock return on day *t*, and $r_{F,t}$, $r_{M,t}$, and $r_{IND,t}$ represent the risk-free rate, the CRSP value-weighted market portfolio return, and the value-weighted SIC3 industry portfolio return, respectively. This regression specification decomposes the firm's stock returns into systematic components, driven by co-movements with market and industry returns, and an unexplained component, which captures firm-specific information. In particular, the inclusion of the industry portfolio return controls for common industry-wide shocks, such as technological changes or supply chain disruptions, that impact all firms in the industry. A larger unexplained component reflects weaker co-movement between the firm's return and those of the market and industry, resulting in a lower R^2 and indicating a greater amount of firm-specific information embedded in the stock price (Durnev et al., 2003). Therefore,

$1 - R^2$ serves as a measure of SPI. Following Durnev, Morck, and Young (2004), we apply the logistic transformation to $1 - R^2$ to derive the *total* SPI (*SPI^{TOT}*) for each firm:

$$SPI_i^{TOT} = log\left(\frac{1 - R_i^2}{R_i^2}\right). \tag{2}$$

The logistic transformation tackles the skewness and bounded nature of $1 - R^2$.

We next augment the baseline model in Equation (1) by including the idiosyncratic stock returns of the 10NN rivals in the product market space:

$$r_{i,t} - r_{F,t} = \alpha_i + \beta_i^M(r_{M,t} - r_{F,t}) + \beta_i^{IND}(r_{IND,t} - r_{F,t}) + \sum_{j=1}^{10} \beta_i^j idio\ r_{i,j,t} + \varepsilon_{i,t}, \tag{3}$$

where $idio\ r_{i,j,t}$ is the idiosyncratic return of rival *j* on day *t*, derived from a one-factor model.[12]. The inclusion of the 10NN rivals' stock returns in Equation (3) enables us to isolate the effects of firm-specific competitive interactions while controlling for broader common market and industry shocks on stock return variations, as emphasized by de Bodt, Eckbo, and Roll (2024). We denote R^{*2} the R^2 of this augmented model, and rely on the logistic transformation of $1 - R^{*2}$ to quantify the *residual* SPI (*SPI^{RES}*), which corresponds to SPI after accounting for product market interactions with the 10NN rivals:

$$SPI_i^{RES} = log\left(\frac{1 - R_i^{*2}}{R_i^{*2}}\right). \tag{4}$$

To identify the product market-driven component of stock price informativeness (*SPI^{PMC}*), we take the difference between Equations (2) and (4):

$$SPI_i^{PMC} = SPI_i^{TOT} - SPI_i^{RES}. \tag{5}$$

2.3. Estimation of SPI variables

We estimate the SPI variables by running stock return regressions for each firm-year using daily observations. We obtain stock price and return information from CRSP and factor data from

[12] Note that using raw rival returns instead of idiosyncratic rival returns yields similar results as a consequence of the regression anatomy formula (Angrist and Pischke, 2009).

Kenneth French's data library.[13] Variable definitions are provided in Appendix A. Table 2 presents the results obtained running these firm-year regressions. Panel A provides descriptive statistics for the daily returns and factor variables used in the firm-year stock return regressions. Panel B summarizes the R^2 and adjusted R^2 estimates obtained from the 94,695 firm-year stock return regressions, highlighting the explanatory power of the estimated models.

We begin by summarizing the results of the one-factor (1F) model, which regresses the firm's excess stock returns on the excess returns of the market portfolio. The average R^2 is 13.15% (see Panel B, column 1), meaning that, on average, about 13% of the variation in firm excess returns is explained by market excess returns. In panel B, column 2, we summarize the results obtained estimating Equation (1), which corresponds to the 1F model expanded with the excess returns of the 3-digit SIC industry portfolio (1F+IND model) The average R^2 increases by 3.82 percentage points.

In Panel B, column 3, we further augment the model by including the daily idiosyncratic returns of the 10NN rivals (1F+IND+10NN model), as specified in Equation (3). Results show that the average R^2 increases by 8.70 percentage points, compared to the estimates from the 1F+IND model (Panel B, column 2). This increase in R^2 is statistically significant at the 1% level. The size of the contribution of 10NN rivals' idiosyncratic returns to the average R^2 is remarkable, as it amounts to (roughly) two thirds of the explanatory power of the one factor model and two times the contribution of 3-digit SIC3 index.

Figure 1 shows the yearly average R^2 from these firm-level time series regressions, and the last column of Table 1 reports the change in R^2 between the 1F+IND+10NN and 1F+IND models. The explanatory power of these models varies significantly over time, with the three models exhibiting similar trends, largely shaped by the 1F model. The R^2 of the 1F model ranges from a low of 2.85% in 1993 to a high of 46.36% in 2011. Since 2011, it has gradually reverted to the pre-financial crisis

[13] See https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html.

level, consistent with the findings of Parsley and Poper (2020). We note also that the contributions of both the industry portfolio return and the 10NN rivals' stock returns to R^2 decrease substantially when the R^2 of the 1F model reaches its peak.

We use these regression results to calculate the SPI variables as specified in Equations (2), (4) and (5). Panel A of Table 3 reports the summary statistics for the three SPI variables. The mean value of SPI^{TOT} is 2.385 in our sample, consistent with previous literature (see, e.g., Chen, Goldstein, and Jiang, 2007; Bennett, Stulz, and Wang, 2020). The mean values of SPI^{PMC} and SPI^{RES} are 1.124 and 1.261, respectively. The decomposition of the total stock price informativeness indicates that both the PMC-driven and residual components carry almost equal amount of information, with average shares of 47% and 53%, respectively. This suggests that about half of the total firm-specific information in stock returns is generated through competitive product market interactions.

2.4. Framework for testing the PMC channel of managerial learning

To test whether product market interactions are an important source of information for managerial learning from stock prices, we follow existing literature and adopt a standard linear investment equation which relates the focal firm's investment ratio to its own stock price, thereby estimating investment-to-*Q* sensitivities. Our analysis centers on the following regression specification:

$$INV_{i,t} = \alpha_i + \delta_t + \beta_1 Q_{i,t-1} + X_{i,t-1}\Gamma + \varepsilon_{i,t}, \tag{6}$$

where the dependent variable, $INV_{i,t}$, is the investment ratio of firm *i* at the end of year *t*. We consider three different investment measures for the dependent variable: capital expenditures (*capex*); research and development expenses (*R&D*); and *total investment*, measured as the sum of *capex* plus *R&D* plus cash acquisition minus asset sales, following Richardson (2006). All three investment measures are scaled by lagged total assets.[14] $Q_{i,t-1}$ is the Tobin's *Q* of firm *i* at the end

[14] Scaling the investment variables by lagged fixed assets (*property plant and equipment*) instead of total assets does not alter our findings (unreported).

of year $t - 1$, serving as a proxy for the firm's stock price at year-end. X is the vector of control variables, with Γ representing the coefficient vector for these controls.

Following prior research, our regression model controls for two important firm characteristics known to correlate with investment decisions: *firm size*, represented by the logarithm of total assets; and *cash flow*, measured as income before extraordinary items plus depreciation divided by total assets. The model also includes firm (α_i) and year (δ_t) fixed effects. Year fixed effects absorb aggregate trends in investment, while firm fixed effects limit concerns about omitted variable biases due to time-invariant unobservable factors at the firm level. We report *t-statistics* based on clustered standard errors at the firm level. $\varepsilon_{i,t}$ is the error term.

The regression coefficient β_1 measures the sensitivity of firm investment to its own stock price. A positive β_1 is a necessary condition for the learning hypothesis (i.e., managers learning from their firm's stock prices). However, as emphasized by Foucault and Frésard (2014), this condition is not sufficient, as the firm's Tobin's *Q* may correlate with managers' private information about the firm's investment opportunities. Therefore, it is important to assess whether the coefficient β_1 is sensitive to the degree of stock price informativeness (i.e., amount of firm-specific information in stock prices). Our focus is on firm-specific information related to competitive product market interactions.

To test whether managerial learning is enhanced when stock prices incorporate more firm-specific information generated by PMC, we augment the previous model with our information variable of interest, SPI^{PMC}, the PMC-driven component of stock price informativeness, and its interaction with the firm's Tobin's *Q*. The augmented specification is as follows:

$$INV_{i,t} = \alpha_i + \delta_t + \beta_1 Q_{i,t-1} + \beta_2 SPI_{i,t-1}^{PMC} + \beta_3\left(Q_{i,t-1} \times SPI_{i,t-1}^{PM}\right) + X_{i,t-1}\Gamma + \varepsilon_{i,t}. \tag{7}$$

The regression coefficient β_3 helps us evaluate whether managerial learning improves when stock prices better capture product market-driven competitive interactions. A statistically significant positive coefficient suggests that firm investment becomes more sensitive to stock prices when they incorporate more information from product market-driven competitive interactions.

In additional analyses, we control for direct learning by extending Equation (7) with the average Tobin's *Q* of industry peers. We use either the average for all firms in the TNIC industry or that of the 10NN rivals. In these models, following Foucault and Frésard (2014), we also include the mean values of firm size and cash flow within the corresponding peer group as additional controls.

2.5. Summary statistics

To estimate the investment regressions introduced in Equations (6) and (7), we rely on stock price data from CRSP and investment and accounting data from Compustat. In addition to the filters used to gather the sample for the stock return regressions in Section 2.3, we follow Foucault and Frésard (2014) and implement additional filters for the investment regressions. Specifically, we exclude firms with negative sales or missing data on total assets, capital expenditures, or fixed assets. These filters further reduce our sample from 94,695 firm-year observations to 92,088.[15]

Table 3 presents descriptive statistics for the main variables used in the learning tests, with variable definitions provided in Appendix A. To mitigate the influence of outliers, all financial ratios are winsorized at the top and bottom 1% of the distribution. The average Tobin's *Q* is 2.219 in our sample. The mean values of both capex and R&D ratios are 6.5%. In addition to capex and R&D, when accounting for cash acquisitions, and asset sales, firm investment averages 17% of its lagged total assets. These statistics align with prior literature adopting similar variable definitions (see, e.g., Richardson, 2006; Chen, Goldstein, and Jiang, 2007; Foucault and Frésard, 2014; Edmans, Jayaraman, and Schneemeier, 2017).

We also provide summary statistics for the peer group. Compared to the average focal firm, the average peer firm in both the TNIC industry and 10NN cluster is larger in terms of total assets but

[15] Note that data availability for some variables, along with the use of lagged observations in both the control variables and the denominator of the investment ratios, further reduces the sample size in the multivariate regressions.

has a comparable Tobin's *Q*. In terms of operating cash flow, the mean values are comparable for the focal firm and TNIC peers but lower for 10NN peers. Notably, the median values across the three groups are similar, indicating that the 10NN cluster is more sensitive to the presence of outliers.

3. Empirical evidence

In this section, we begin by presenting the baseline investment results. Next, we turn to robustness checks and report results of additional investigations.

3.1. Baseline investment results

Table 4 presents our baseline investment results. We first estimate the investment-to-*Q* sensitivities in our sample using Equation (6), with three different investment measures as the dependent variables: capex in Panel A, R&D in Panel B, and total investment in Panel C. Column 1 reports the result. For brevity, we do not report the coefficient estimates for the control variables (firm size and cash flow) and fixed effects, though they are included in the model.

Starting with capex, consistent with previous studies (e.g., Chen, Goldstein, and Jiang, 2007; Foucault and Frésard, 2014), firm investment is positively and significantly related to Tobin's *Q*. The coefficient estimate of $Q_{i,t-1}$ in the capex regression is 0.0078 with a t-statistic of 21.76. Specifically, a one standard deviation increase in the average firm's Tobin's *Q* is associated with an increase of 1.57 percentage point in its capex ratio. This economic effect is substantial, as the corresponding change in the capex ratio represents 24.14% of its mean value of 6.5% (see Table 3). In column 1 of Panels B and C, we observe a similar positive effect of Tobin's *Q* on R&D and total investment ratios. The economic magnitude is comparable for total investment, but the effect on R&D is larger than that on capex. A one standard deviation increase in the average firm's Tobin's *Q* is associated with an increase of 2.05 percentage points in its R&D ratio and 4.59 percentage points in its total investment ratio. These economic effects are substantial, representing 31.57% of the mean value of R&D and 26.98% of the mean value of total investment ratio.

Next, we estimate Equation (7), which augments the initial investment model by including our independent variable of interest, SPI^{PMC}, and its interaction term with Tobin's Q. For brevity, the coefficient of SPI^{PMC} term is not reported. The interaction term coefficient reported in column 2 allows us to test the sensitivity of the firm's investment decision to its stock price information increases when product market rivals' returns contribute more to its stock price informativeness. Concerning capex, the estimation results confirm that PMC-driven stock price informativeness enhances managerial learning, with a statistically significant positive coefficient for the interaction term at the 5% level (see Panel A). Economically, the effect is also noteworthy: a one standard deviation increase in SPI^{PMC} leads to a 0.00043 increase in the sensitivity of the capex ratio to Tobin's Q. This represents approximately a 6% increase relative to the baseline sensitivity observed in the capex model. In column 2 of Panels B and C, we repeat the analysis with R&D and total investment as the dependent variables, respectively. The interaction term is positive and statistically significant at the 1% level in both panels.

Comparing the PMC-driven information effects on the three investment variables in terms of economic magnitude, we observe the following ranking: the highest effect is on R&D, followed by total investment and capex, in the order. A one standard deviation increase in SPI^{PMC} leads to a 26.24% (11.72%) increase in the sensitivity of R&D (total investment) to Tobin's Q. This ordering of the economic effect does not come out as a surprise, given the critical role of R&D as an input for innovation and growth (e.g., Brown, Fazzari, and Petersen, 2009). Unlike capex, which serves both to acquire new assets and maintain or replace existing ones, R&D is focused on future growth. Additionally, R&D is typically harder to finance through external sources of funding, and many firms face financing constraints for their investments in innovation (Hall, 2002). This unique characteristic of R&D likely explains its greater sensitivity to information feeding from stock prices, especially when those prices incorporate significant product market-driven competitive information.

Firms also learn directly from the stock prices of their industry rivals (Foucault and Frésard, 2014; Yan, 2024). To control for this additional learning channel, we augment our specification by including the average Tobin's *Q* of industry peers, excluding the focal firm. We use two alternative definitions of industry peers, all firms in the corresponding TNIC industry (column 3), and 10NN closest rival firms respectively (column 4).

In Panel A, where the dependent variable is the capex ratio, the coefficient estimate of the industry peers' Tobin's *Q* is significantly positive in both columns 3 (TNIC peers) and 4 (10NN peers). This confirms the presence of a direct learning channel from rival stock prices to capex investment decisions, consistent with the findings of Foucault and Frésard (2014). However, in Panels B and C, where R&D and total investment ratios are the dependent variables, coefficient estimates of industry peers' Tobin's *Q* are either negative or statistically insignificant. This suggests that direct learning from rival stock prices plays a less prominent role in these contexts. In the three panels, the coefficient of the interaction between the focal firm Tobin's Q and SPI^{PMC} is positive and statistically highly significant, confirming the importance of the PMC information channel.

Overall, our results suggest that the learning effect extends beyond simply tracking rivals' stock prices, highlighting the importance of understanding how PMC-driven interactions impact the focal firm's stock price informativeness and enhance learning form its own stock price signals.

3.2. Additional checks and results

Table 5 presents various tests to assess the robustness of our baseline results, replicating the specification in column 3 of Table 4. Column 1 of Table 5 shows that our main finding remains robust with an alternative proxy for the product market-driven component of stock price informativeness. This proxy corresponds to the relative increase in R^2 when the 10NN rivals' idiosyncratic stock returns are included as independent variables in the stock return regressions.[16] This test confirms that our conclusions hold across two different measures of stock price informativeness.

In column 2, we replace the one-factor model with the Fama-French five-factor model (Fama and French, 2015), capturing additional risk factors. The considered five factors are *market*, *size*, *value*, *profitability*, and *investment*. The increase in the average R^2 after the inclusion of the 10NN rivals' idiosyncratic returns is both statistically significant and of similar magnitude in comparison to our baseline stock return model (i.e., one-factor model augmented with the SIC3 industry portfolio return). The learning effect persists, demonstrating that our findings are not sensitive to the choice of alternative asset pricing models.

In column 3, we incorporate asymmetric betas in the baseline stock return model, following the methodology outlined in Ang, Chen, and Xing (2006). This adjustment accounts for firms' differential responses to good and bad news about their rivals. Specifically, we interact each of the 10NN rivals' idiosyncratic returns with dummy variables that distinguish between positive and negative idiosyncratic returns. This allows us to estimate two distinct beta coefficients for each rival. Our results continue to support the presence of product market-driven learning.

In column 4, we control for managerial private information using earnings surprises as a proxy, ensuring that managers rely on stock prices to access information beyond their private knowledge. Following, Chen, Goldstein, and Wang (2007), earnings surprises (denoted as *ERC*, or *Earnings Response Coefficient*) are measured as the average of absolute 3-day abnormal stock returns (in %) over the prior year's four quarterly earnings announcements. Abnormal returns are market-adjusted using the value-weighted CRSP index. The intuition behind the use of earnings surprises is that managers have access to earnings information before its public release; thus, the surprise in the announcement serves as a proxy for the extent of managerial private information. As column 4 shows, in all three panels, *ERC* has a statistically insignificant negative

[16] More explicitly, we use $log\left(\frac{R_i^{*2}-R_i^2}{R_i^2}\right)$ as an alternative proxy for SPI^{PMC}, see Section 2.2 for the notation.

effect on the sensitivity of investment to Tobin's *Q*. Most importantly, in all three panels, the coefficient estimate of our interaction term of interest, $Q \times SPI^{PMC}$, is almost insensitive to controlling for managerial private information. This result indicates that SPI^{PMC} reflect some information that is not known to managers.

In column 5, we use analyst coverage as additional proxy for managerial private information. Chen, Goldstein, and Wang (2007) argue that a large fraction of the information analysts process is derived from their interactions with managers. If this indeed the case, information produced by analysts may impact stock prices but without necessarily affecting managerial decisions, such as corporate investment. This reasoning predicts a negative relationship between analyst coverage and investment-to-*Q* sensitivity. We measure analyst coverage, denoted as *#Analyst* in column 5 of Table 5, as the logarithm of one plus the number of analysts issuing forecasts or recommendations in the previous year. As predicted, and consistent with the findings in Chen, Goldstein, and Wang (2007), analyst coverage attenuates the sensitivity of investment to Tobin's *Q*, with the effects being statistically significant for both R&D and total investment. With the inclusion of analyst coverage, our interaction term of interest, $Q \times SPI^{PMC}$, remains significantly positive for both R&D and total investment. Only the capex result does not survive to the inclusion of analyst coverage in our specification.

Lastly, column 6 presents results of a placebo test, where we randomly assign 10 firms as nearest rivals to the focal firm and re-estimate the information variable, SPI^{PMC}, using the idiosyncratic returns of these pseudo rivals. The statistically insignificant interaction term coefficient confirms that the learning effect is specifically driven by actual product market competitive interactions, rather than by chance.

As an additional investigation and to get a better sense of the magnitude of the PMC channel, we compare the contribution of *residual* firm-specific information in stock returns (after controlling for co-movements with the returns of the 10NN rivals) to managerial learning with the one of PMC-driven stock price informativeness. This should give some indication about the relative economic importance of this latter one. Table 6 presents the results. The dependent variable in columns 1-2, 3-4, and 5-6 is the capex ratio, R&D ratio, and total investment ratio, respectively. In columns 1, 3 and 5, we employ the investment model with total stock price informativeness (SPI^{TOT}) as the information variable. In columns 2, 4, and 6, we decompose the effect of SPI^{TOT} into the effects of its two components, SPI^{RES} and SPI^{PM} following the method outlined in Section 2.2, while also controlling for the Tobin's *Q* of industry peers.

Consistent with prior literature (e.g., Chen, Goldstein, and Jiang, 2007), the finding in column 1 shows that a higher stock price informativeness enhances the sensitivity of the capex ratio to Tobin's *Q*. The economic impact is substantial, with a one standard deviation increase in SPI^{TOT} is associated with 11.29% increase in the capex-to-Q sensitivity. This effect is even more pronounced for R&D and total investment, with respective increases of 39.87% and 17.04% in columns 3 and 5.

Column 2, that focuses on capex investment, shows that although both the residual and PMC-driven components of stock price informativeness interact positively with Tobin's *Q*, only the residual component shows a statistically significant effect. In contrast, columns 4 and 6, which respectively focus on R&D and total investment, reveal a different picture: both the PMC-driven and residual components serve as significant sources of information for managerial learning. In both cases, the economic impact of the PMC-driven component is as substantial as that of the residual component (see point estimates of coefficients of interaction terms.

These results collectively emphasize the substantial impact of stock price informativeness improvements driven by product market competitive interactions on managerial learning, particularly in areas with potentially high growth opportunities such as R&D investment.

4. Cross-sectional determinants of managerial learning

We consider five contexts that may amplify or diminish managerial learning from stock prices to better understand cross-sectional determinants of stock price-induced managerial learning.

These are financial constraints, information environment quality, competition intensity, R&D intensity, and industry leadership. Table 7 reports the results of the cross-sectional comparisons by replicating the specification in column 3 of Table 4. The dependent variable in columns 1-2, 3-4, and 5-6 is the capex ratio, R&D ratio, and total investment ratio, respectively. For brevity we only report the coefficient estimate of the interaction term of interest, $Q \times SPI^{PMC}$. For each panel-specification, the last row reports z-statistics for a test of the difference in the coefficients of $Q \times SPI^{PMC}$ between the corresponding two sub-samples.

Financial constraints. First, we examine the firm's financial constraint status. Financially constrained firms have incentives to allocate their scarce resources to most profitable opportunities and may therefore be more willing to listen to their investors (Bennett, Stulz, and Wang, 2020). However, these firms may also have limited flexibility in adjusting their investment behaviors based on stock price information (Chen, Goldstein, and Jiang, 2007). To determine which of these potential effects dominates in our sample, Panel A compares firms with low versus high financial constraints, using three measures of financial constraints: the KZ index (Kaplan and Zingales (1997), the WW index (Whited and Wu, 2006), and the SA index (Hadlock and Pierce, 2010). Firms are classified as having low (high) financial constraints if they rank in the bottom (top) tercile of the sample for a given year. Across the three financial constraint measures, the cross-sectional effects of SPI^{PMC} on the R&D investment-to-Q sensitivity is stronger for the low financial constraints subsample (columns 3 and 4). Financial constraints appear not to mitigate the effect of SPI^{PMC} on investment-to-Q sensitivity for capex (columns 1 and 2) and total investment (columns 5 and 6) decisions. These results echo findings in Chen, Goldstein, and Jiang (2007), suggesting that firms are more responsive to stock prices when they are more financially flexible, but this effect seems to be specific to R&D investments.

Information environment quality. Next, we examine how cross-sectional heterogeneity related to the quality of the information environment in the 10NN cluster influences the effect of SPI^{PMC} on the investment-to-Q sensitivity. We hypothesize that learning from stock price will be amplified when the focal firm's stock price reflects information from rival firms' stock prices that are relatively more efficient. The high- and low-quality informational environment subsamples are constructed based on three variables that capture key aspects of the information environment: (i) *cluster size*, the total market value of equity of the 10NN rivals, as large firms tend to be more visible, produce more information, and have more liquid stocks; (ii) *Analyst coverage*, the total number of analysts following the 10NN rivals, because analyst activity promotes information dissemination and price discovery (Brennan, Jegadeesh, and Swaminathan, 1993; Huang, Lehavy, Zang, and Zheng, 2018); and (iii) *Stock liquidity*, the inverse of the average stock illiquidity of the 10NN rivals, as more liquid stocks are expected to better reflect private information, with liquidity known to facilitate arbitrage (Roll, Schwartz, and Subrahmanyam, 2007).[17]

For each of these three variables, we assign tercile-based scores annually, with values of 1, 2, and 3 for observations in the first, second, and third terciles, respectively. These scores are then summed across the three variables to create an information environment index, ranging from 3 to 9. Each year, focal firms are classified into high- or low-quality information environments based on whether the index falls into the top or bottom tercile of the distribution, respectively. The index is structured such that a higher score indicates a higher-quality information environment.

Panel B presents the cross-sectional analysis results, comparing firms within high- and low-quality information environments. Across all three investment measures, the coefficient point estimates of the interaction term, $Q \times SPI^{PMC}$, are positive and relatively larger for the subsample of focal firms interacting with rivals in a high-quality information environment. The difference in coefficient estimates of the interaction term between the high- and low-quality subsamples is statistically significant for both capex and R&D investments. Consistent with our conjecture, firms

[17] Table 3 reports summary statistics for these three variables. The average cluster size in our sample is $39 billion. The total number of analysts covering the 10NN rivals averages 80, translating to about 8 analysts per rival firm, a statistic which is in line with prior literature (Chang, Dasgupta, and Hilary, 2006; Chen, Goldstein, and Jiang, 2007; Yu, 2008). Stock illiquidity is calculated as in Amihud (2002). The average stock illiquidity of the 10NN cluster is 0.841, notably higher than the 0.337 reported by Amihud (2002) for NYSE-only firms. Our sample includes also NASDAQ stocks, and NASDAQ firms are known to display higher stock illiquidity ratios (Brennan, Huh, and Subrahmanyam, 2013).

show more investment responsiveness to their stock prices when those prices correlate with relatively more informative rival stock prices.

Competition intensity. Adam Smith was among the first economists to emphasize that a lack of competition poses a significant threat to effective management (Smith, 1776). In non-competitive industries, managers without proper incentives may be tempted to enjoy the quiet life (Bertrand and Mullainathan, 2003), often evading difficult decisions and costly efforts. Competition is thus regarded as an important external governance mechanism that enforces managerial discipline, helping to reduce inefficiencies and preventing bankruptcies in extreme cases (Alchian, 1950; Stigler, 1958; Grossman and Hart, 1983). We therefore expect managers to be more responsive to market signals related to product market interactions in competitive industries, particularly when making growth-oriented investment decisions such as R&D.

Panel C explores heterogeneity effects arising from variations in the competitive landscape faced by the focal firm. We use two text-based proxies of competition obtained thanks to information collected in the business and product descriptions in firms' 10-K filings item 1: (i) the average similarity score between the focal firm and its 10NN rivals; and (ii) the product market fluidity of the focal firm. A higher *average similarity score* suggests that firms within the same product market offer closely related products, indicating stronger competitive interactions (Hoberg and Phillips 2010, 2016). In contrast, *product market fluidity* assesses the intensity of competitive dynamics, quantifying *ex-ante* competitive threats to the firm (Hoberg, Phillips, and Prabhala, 2014).

The high and low subsamples are constructed based on the terciles of the respective competition proxy distributions. Consistent with economic theory, for both competition proxies the effect of SPI^{PMC} on investment-to-Q sensitivity is significantly larger in highly competitive environments for R&D investments. For capex investment, this difference in coefficient estimates is larger in the low competition environment when using *product market fluidity* as a proxy. One possible interpretation of this latter result is that firms facing ex-ante competitive threats adopt more conservative financial policies, such as precautionary cash savings (Hoberg, Phillips, and Prabhala, 2014). Consequently, these firms may prioritize responsiveness to market signals for growth-oriented investments like R&D, while becoming less sensitive to such signals for CAPEX investments.

R&D-intensity and focal firm's leadership status. The last factors that we examine as potential drivers of cross-sectional heterogeneity of the documented learning effect are the R&D-intensity of the product market in which the firm operate and its leadership status We anticipate in particular that industry leaders are likely to closely monitor rival actions to maintain a competitive edge, given the heightened risk of disruption posed by competitor moves. Panels D and E report the results.

In Panel D, we measure R&D-intensity using the average R&D ratio of the 10NN rivals and group firms into high and low R&D-intensive product market clusters based on terciles of that distribution. As expected, across the three investment measures, the effect of SPI^{PMC} on investment-to-*Q* sensitivity is more pronounced in the high R&D-intensive product market subsample. However, the difference between the high and low R&D-intensive groups is statistically significant only for R&D investments.

In Panel E, we compare industry leaders to industry followers. We identify industry leaders using two distinct proxies. For the first proxy, following de Bodt, Eckbo, and Roll (2024), we define leaders as focal firms with both sales and return on assets exceeding their industry median in a given year. The second proxy identify leaders as focal firms with market shares in their product market (i.e., the focal firm plus the 10NN rivals) that fall within the highest tercile of the distribution for that year. Consistent with our arguments, the product-market driven learning effect is significantly more pronounced for industry leaders, but only for R&D investments.

5. Additional tests

In this section, we perform two additional tests to further explore the robustness of our results. We begin by presenting the endogeneity test employed to strengthen the causal interpretation of our results, followed by a discussion of additional investigations that examine the relationship between PMC-driven signals and innovation outcomes.

Endogeneity test. Our primary finding that firms with higher PMC-driven stock price informativeness show evidence of greater sensitivity to Tobin's *Q* indicates that PMC signals are fundamental drivers of investment decisions. However, this relationship may be contaminated by factors that impact both price discovery and investment. As pointed out by Bennett, Stulz, and Wang (2020), technological shocks represent a potential omitted factor that could enhance price informativeness and simultaneously influence firm decisions. To mitigate this concern, we adopt the authors' approach and employ a quasi-natural experiment to address endogeneity issues in our analysis. Specifically, we examine the inclusion of the focal firm's 10NN rivals in the S&P 500 index as an exogenous shock to stock price informativeness, particularly to its PMC-driven component.

The inclusion of a rival firm in the S&P 500 index is beyond the control of the focal firm and is likely to have a significant impact on the co-movement of the rival firm's stock returns with the broader market index. This effect, as documented in prior literature (Vijh, 1994; Barberis, Shleifer, and Wurgler, 2005), can decrease the co-movement between the idiosyncratic stock returns of the rival firm and the focal firm. We first test this conjecture in Panel A of Table 8, using total stock price informativeness (SPI^{TOT}) as the dependent variable in column 1, and its two components: the product-market induced component (SPI^{PMC}) in column 2 and the residual component (SPI^{RES}) in column 3. The independent variable of interest is *Addition*, which equals one if at least one of the 10NN rivals of the focal firm is added to the S&P 500 index over the previous three years and zero otherwise. The coefficients of *Addition* in all models are negative, but statistically significant at 5% level in columns 1 and 2. These results support the conjecture that the addition of rival firms to the S&P 500 reduces stock price informativeness, with this negative effect primarily driven by the impact on the PMC-induced component.

After confirming that S&P 500 additions of rival firms serve as a negative exogeneous shock to *SPI*^{PMC}, we turn to the investment regression analyses. We are not in position to replicate the Bennett, Stulz, and Wang (2020) difference-in-differences specification because we focus on the coefficient of an interaction variable but parallel the authors' approach by interacting the Tobin's *Q* variable with the *Addition* dummy variable, used in Panel A. Panel B of Table 8 replicates columns 2 and 3 of Table 4, respectively in columns 1, 3, and 5, and columns 2, 4, and 6, with this newly defined interaction term. The dependent variable in columns 1-2, 3-4, and 5-6 is the capex ratio, R&D ratio, and total investment ratio, respectively. The coefficient of the interaction variable of interest, Q_i × *Addition*, is significantly negative in columns 3 and 4, with R&D ratio as dependent variable. The effects on capex and total investment are not statistically significant, indicating that R&D investment is particularly responsive to PMC signals compared to other forms of investment.

Innovation outcomes. To further test the robustness of our R&D results, we extend our analysis to variables capturing the outcomes of innovation in the years following the R&D expenditure. Since R&D investments may take time to translate into tangible innovations (Griliches, 1990), Table 9 replicates our baseline analysis using three distinct innovation outcomes over the next three years as dependent variables. In columns 1-2, the dependent variable is *patent count*, which corresponds to the total number of patents granted to the focal firm over the next three years, scaled by the total number of patents granted to all firms within the same period. In columns 3-4, the dependent variable is *patent citations*, which corresponds to the total number of future citations received by the patents granted to the focal firm over the next three years, scaled by the total number of future citations received by patents across all firms during the same period. In columns 5-6, the dependent variable is *self-fluidity*, a variable introduced in Hoberg, Phillips, and Prabhala (2014) to proxy changes in a firm's product offerings over time. It is calculated as one minus the cosine similarity between the firm's current and previous years' business descriptions.

We use as dependent variable the average of the focal firm's self-fluidity over the next three years and apply a logistic transformation to tackle the boundedness of the variable.

The coefficients of the interaction term of interest, $Q_i \times SPI^{PMC}$, is consistently positive and statistically significant across all specifications, indicating that product market-induced stock price informativeness amplifies the sensitivity of innovation outcomes to the focal firm's Tobin's *Q*. These findings further underscore the importance of PMC signals in driving growth-oriented investment decisions, such as R&D investment.

6. Conclusion

This paper examines product market interactions as potential drivers of stock returns and quantifies their impact on stock price informativeness driving managerial learning. By analyzing stock return regressions, we find that the R^2 increases on average by 8.70 percentage points after accounting for strategic interactions with the firm's nearest product market rivals, an economically and statistical highly significant effect. We further show that stock prices reflecting these dynamics facilitate more effective learning, as managers incorporate these signals into their investment decisions. The contribution of the PMC channel to managerial learning is especially robust and strong for R&D investments and is further amplified when focal firms are financially unconstrained, hold industry leadership positions, and interact with rivals from high-quality information environments. The learning effect is also more pronounced in R&D-intensive and competitive product market clusters. Further analysis on innovations outputs, such as patents and changes in product offerings, supports the importance of managerial learning from product market signals in the context of R&D investments.

Our findings underscore the role of PMC-driven improvements in stock price informativeness in shaping corporate decision-making. Building on past research on feedback effects from financial markets, this study highlights how managerial learning benefits from stock prices that better reflect product market competitive interactions. Our contribution to the literature on managerial learning is twofold: First, we pinpoint product market competitive interactions as a crucial component of the information driving learning. Second, we show that this PMC-driven component plays a substantial role in investment decisions, especially in R&D, where timely strategic adjustments are essential for firm survival and growth.

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Appendix A. Variable definitions

Unless explicitly mentioned otherwise, Compustat is the data source for financial- and accounting-related variables, CRSP for stock market-related variables, K. French Data Library[1] for factor returns, and Hoberg and Phillips Data Library[2] for product market variables. Analyst coverage data are from the Institutional Brokers' Estimate System (IBES). Patent data are from the KPSS patent data library (Kogan, Papanikolaou, Seru, and Stoffman, 2017).[3]

A.1. Returns and factors

$r_{i,t}$: firm i's stock return on day *t*.

$r_{F,t}$: risk-free rate on day *t*.

idio $r_{i,t}$: firm i's daily idiosyncratic return on day *t*, which corresponds to the residual of the one-factor model.

$Mktrf_t$: excess market return, which corresponds to the return of the value-weighted market portfolio on day *t* less the risk-free rate on the same day.

$r_{IND,t}$: return of the value-weighted 3-digit SIC industry portfolio on day *t*.

A.2. Stock price informativeness (SPI) variables

SPI^{TOT}: *total stock price informativeness*, calculated as the logistic transformation of $1 - R^2$, where R^2 is obtained from the baseline model (1F+IND).

SPI^{RES}: *residual stock price informativeness*, calculated after augmenting the baseline model with the stock returns of the 10 nearest neighbors (10NN) rivals. It is defined as the logistic transformation of $1 - R^{*2}$, where R^{*2} represents the R^2 of the full model (1F+IND+10NN).

SPI^{PMC}: component of stock price informativeness driven by *product market* interactions. It is calculated as the difference between SPI^{TOT} *and* SPI^{RES}.

A.3. Firm characteristics

Capex: capital expenditures divided by lagged total assets.

R&D: research and development expenses divided by lagged total assets.

Total investment: the sum of capex plus R&D plus cash acquisition minus asset sales, divided by lagged total assets.

Patent count: total number of patents granted to the focal firm over the next three years, scaled by the total number of patents granted to all firms within the same period.

Patent citations: total number of future citations received by the patents granted to the focal firm over the next three years, scaled by the total number of future citations received by patents across all firms during the same period.

Self-fluidity: a variable developed by Hoberg, Phillips, and Prabhala (2014) to proxy changes in a firm's product offerings over time. It is calculated as one minus the cosine similarity between the firm's current and previous years' business descriptions.

Q_i: Tobin's *Q* of the focal firm *i*, calculated as the sum of total assets plus market value of equity minus book value of equity divided by total assets.

Firm size: log of total assets in US$ million.

Cash flow: income before extraordinary items plus depreciation divided by total assets.

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[1] https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html.
[2] https://hobergphillips.tuck.dartmouth.edu.
[3] https://github.com/KPSS2017.

ERC: average of the absolute 3-day abnormal stock returns (in %) over the prior year's four quarterly earnings announcements, where abnormal returns are market-adjusted based on the value-weighted CRSP index.

#Analyst: number of analysts issuing forecasts or recommendations for the firm in the previous year.

Leader: a dummy variable that identifies firms with both sales and ROA above the median values for their SIC3 industry in a given year.

Market share: the firm's sales as a proportion of total sales within its 10NN cluster.

Product market fluidity: a text-based firm-level measure of competitive threat, introduced in Hoberg, Phillips, and Prabhala (2014), which captures the extent of competitive dynamism based on product descriptions and rival moves reported in firms' 10-K filings.

SA index: The Size-Age (SA) index constructed following Hadlock and Pierce (2010).

KZ index: The Kaplan-Zingales (KZ) index constructed following Kaplan and Zingales (1997).

WW index: The Whited-Wu (WW) index constructed following Whited and Wu (2006).

A.4. Industry and 10NN cluster characteristics

Q_{-i}: the average Tobin's Q of all firms, excluding the focal firm, in the corresponding TNIC industry.

Q_{10NN}: the average Tobin's Q of the focal firm's 10NN rivals.

Mean similarity score: the average similarity score of the focal firm with its 10NN rivals.

Mean R&D: the average R&D ratio of the focal firm's 10NN rivals.

Cluster size: total market value of equity of the focal firm's 10NN rivals in $US billions.

Analyst coverage: total number of analysts following the focal firm's 10NN rivals.

Stock illiquidity: the average Amihud illiquidity ratio of the focal firm's 10NN rivals. The Amihud stock illiquidity ratio is calculated as the yearly average of the firm's daily ratio of absolute return to dollar volume. The ratio is multiplied by 10^6 for proper display, as in Amihud (2002).

Addition: a dummy variable equal to one if at least one of the 10 nearest rivals of the focal firm has been included in the S&P 500 index over the previous three years and zero otherwise.

Figure 1. Average R^2 by year

This figure presents yearly average R^2 from firm-level time-series regressions. The sample covers the 1989–2021 period and includes firms from the Hoberg and Phillips universe that meet the necessary data requirements (see Section 2.1). *1F* refers to the one-factor model, in which the firm's daily excess stock return is regressed on *mktrf*, which corresponds to the excess return of the CRSP value-weighted market portfolio. *1F+IND* builds on this by adding the excess return of the value-weighted 3-digit SIC industry portfolio, as an additional independent variable. Finally, *1F+IND+10NN* extends the model further by incorporating the idiosyncratic returns of the 10 most similar rivals in the product market space, as determined by their similarity scores (see Equation 3).

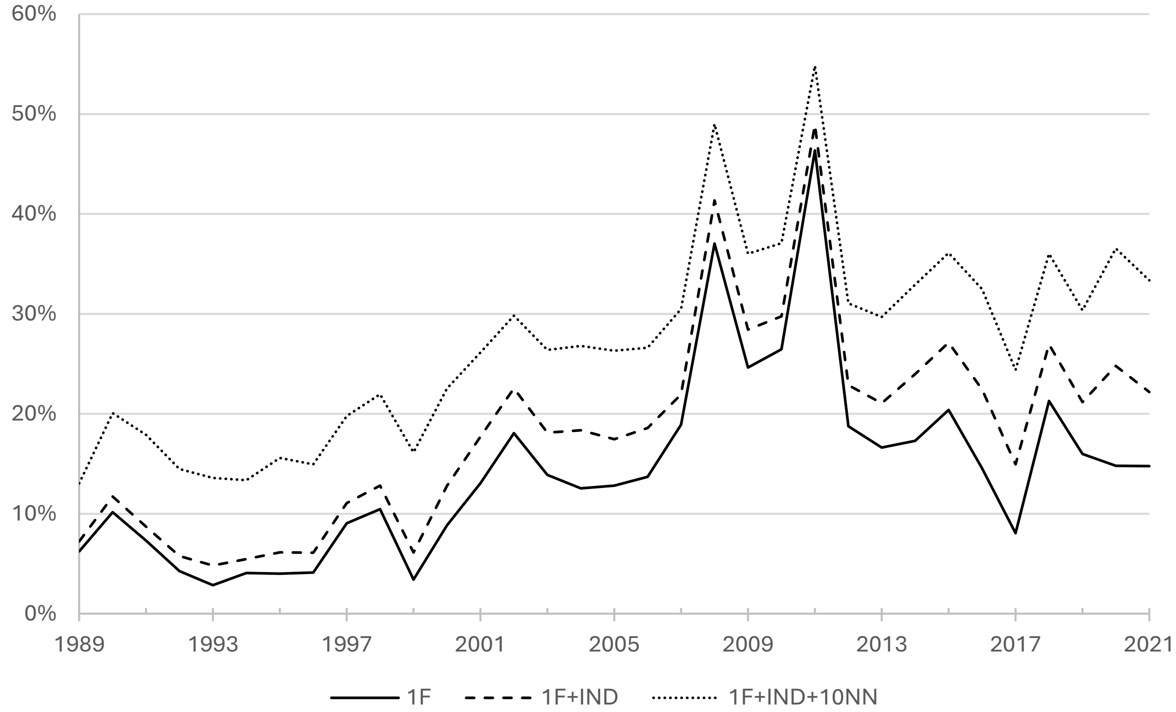

Table 1. Sample characteristics by year

The table provides statistics of firms by year. The sample spans the 1989–2021 period and includes firms from the Hoberg and Phillips universe that meet the necessary data requirements (see Section 2.1). The first two columns present respectively the number of firms in the sample each year and the corresponding aggregated market value of equity at year-end, in US$ billions. Column 3 reports the average similarity score of all firm pairs. Column 4 reports the average similarity score of firm pairs in the 10NN clusters. Column 5 shows the average change in the R^2 after including the idiosyncratic stock returns of the 10NN rivals in the baseline stock return regression model.

Year	Number of firms	Aggregate market value	Similarity score all firms	Similarity score 10NN cluster	ΔR^2
	(1)	(2)	(3)	(4)	(5)
1989	2,729	1,876	0.013	0.158	5.81%
1990	2,589	1,801	0.013	0.157	8.35%
1991	2,651	2,448	0.013	0.165	9.19%
1992	2,977	2,503	0.014	0.167	8.70%
1993	3,345	2,836	0.013	0.166	8.76%
1994	3,685	2,935	0.013	0.169	7.90%
1995	3,905	3,972	0.014	0.169	9.44%
1996	4,332	5,089	0.015	0.175	8.85%
1997	4,405	6,414	0.015	0.175	8.70%
1998	3,998	8,036	0.014	0.171	9.14%
1999	3,837	10,421	0.015	0.168	10.03%
2000	3,410	8,912	0.015	0.169	9.75%
2001	3,128	8,552	0.015	0.171	8.43%
2002	2,859	6,549	0.015	0.168	7.27%
2003	2,844	8,542	0.015	0.167	8.27%
2004	3,016	9,337	0.015	0.167	8.45%
2005	2,931	9,762	0.015	0.167	8.85%
2006	2,903	10,430	0.014	0.168	8.04%
2007	2,791	11,122	0.015	0.170	8.56%
2008	2,288	6,990	0.014	0.167	7.64%
2009	2,188	8,851	0.014	0.164	7.59%
2010	2,411	10,135	0.014	0.164	7.32%
2011	2,333	10,207	0.014	0.167	5.90%
2012	2,269	11,294	0.015	0.170	8.20%
2013	2,303	14,750	0.015	0.174	8.63%
2014	2,340	15,150	0.016	0.181	8.96%
2015	2,347	14,870	0.017	0.184	8.96%
2016	2,228	15,490	0.017	0.185	10.04%
2017	2,272	18,667	0.017	0.187	9.44%
2018	2,266	17,352	0.019	0.194	9.05%
2019	2,233	22,136	0.019	0.200	9.20%
2020	2,203	28,055	0.020	0.194	11.76%
2021	2,679	35,636	0.021	0.196	11.19%
Average	2,870	10,640	0.015	0.173	8.70%

Table 2. Product market competition and stock price informativeness

This table reports descriptive statistics and regression results relating product market competition and the stock price informativeness of the focal firm *i*. Panel A reports summary statistics of the variable used to run the firm-year stock return regressions (see Section 2.3), while Panel B displays summary statistics of the R^2 derived from those regressions. The sample covers the 1989–2021 period and includes firms from the Hoberg and Phillips universe that meet the necessary data requirements (see Section 2.1). Variable definitions are provided in Appendix A. In Panel B, *1F* refers to the one-factor model, in which the firm's daily excess stock return is regressed on *mktrf*, that corresponds to the excess return of the CRSP value-weighted market portfolio. *1F+IND* builds on this by adding the excess return of the value-weighted 3-digit SIC industry portfolio as an additional independent variable. Finally, *1F+IND+10NN* extends the model further by incorporating the idiosyncratic returns of the 10 most similar rivals in the product market space, as determined by their similarity scores (see Section 2.2). *SD* stands for the standard deviation. *SD Mean* corresponds to the standard error of the mean. *Difference in Means* is the difference of means between successive columns, and *t-stat* is the corresponding Student's t statistic.

Panel A. Summary statistics of variables used in the stock return regressions

	Mean	p25	p50	p75	SD
r_i	0.086%	-1.366%	0.000%	1.354%	3.848%
r_F	0.012%	0.003%	0.012%	0.020%	0.009%
idio r_i	0.000%	-1.313%	-0.084%	1.148%	3.673%
mktrf	0.038%	-0.430%	0.070%	0.550%	1.093%
r_{IND}	0.097%	-0.677%	0.088%	0.859%	1.758%

Panel B. R^2 of firm-level stock return regressions

	1F model	1F+IND model	1F+IND+10NN model
	(1)	(2)	(3)
Firm-year observations	94,695	94,695	94,695
R^2			
Mean	13.15%	16.96%	25.66%
SD Mean	0.05%	0.06%	0.06%
Skewness	1.602	1.404	1.131
Kurtosis	5.418	4.399	3.708
Difference in Means		3.82%	8.70%
[t-stat]		[48.60]	[103.48]

Table 3. Summary statistics

This table reports summary statistics of variables used in our analyses. Variable definitions are in Appendix A.

	Mean	p25	P50	p75	SD
A. Stock price informativeness					
SPI^{TOT}	2.385	1.032	2.222	3.588	1.834
SPI^{RES}	1.261	0.588	1.369	1.998	1.018
SPI^{PMC}	1.124	0.359	0.757	1.539	1.076
B. Firm characteristics					
Capex	0.065	0.019	0.039	0.076	0.083
R&D	0.065	0.000	0.006	0.077	0.135
Total investment	0.170	0.047	0.104	0.210	0.213
Patent count (in %)	0.022	0.000	0.000	0.003	0.176
Patent citations (in %)	0.026	0.000	0.000	0.002	0.343
Self-fluidity (in %)	20.364	9.273	15.793	26.270	16.306
Q_i	2.219	1.147	1.575	2.469	2.012
Firm size	5.673	4.165	5.558	7.084	2.061
Cash flow	0.018	0.011	0.074	0.122	0.239
ERC (in %)	6.442	3.398	5.398	8.305	4.315
#Analyst	7.303	1.000	5.000	10.000	8.268
Leader	0.373	0.000	0.000	1.000	0.484
Marke share	0.079	0.012	0.035	0.094	0.118
Product market fluidity (in %)	6.737	4.124	6.083	8.637	3.597
KZ index	-8.754	-6.364	-1.267	0.781	31.231
WW index	-0.209	-0.331	-0.243	-0.155	0.416
SA index	-3.189	-3.703	-3.166	-2.674	0.772
C. TNIC industry					
Q_{-i}	2.274	1.459	1.930	2.791	1.180
Firm size	6.849	5.809	6.978	8.006	1.634
Cash flow	0.015	-0.010	0.058	0.094	0.132
D. 10NN cluster					
Q_{10NN}	2.247	1.471	1.892	2.646	1.220
Firm size	6.822	5.662	6.811	7.955	1.572
Cash flow	-0.004	-0.036	0.052	0.090	0.159
Mean similarity score	0.170	0.122	0.157	0.202	0.072
Mean R&D	0.072	0.001	0.023	0.119	0.099
Analyst coverage	80.366	46.000	72.000	106.000	45.736
Cluster size ($US billions)	39.461	3.927	11.576	34.278	103.428
Mean stock illiquidity (10^6)	0.841	0.034	0.262	1.090	1.370
Addition	0.139	0.000	0.000	0.000	0.346

Table 4. Investment-to-Q sensitivity – the effect of product-market competition induced SPI

The table reports the estimation results of investment-to-Q regressions (see Equations (6) and (7)). The dependent variable in Panels A, B, and C is capex, R&D, and total investment, respectively, with all variables scaled by lagged total assets. Total investment is defined as the sum of capex, R&D, cash acquisitions, minus proceeds from asset sales. Column 1 regresses the corresponding investment ratio on Tobin's *Q*, controlling for firm size and cash flow whose coefficients are not reported for brevity. In column 2, we augment the specification with SPI^{PMC} and its interaction term with *Q*. The coefficient of the single term is also unreported for brevity. In columns 3 and 4, we additionally control for the average Tobin's *Q* of the focal firm's peers. Specifically, Q_{-i} is the average Tobin's *Q* of all other firms in the same TNIC industry, while Q_{10NN} denotes the average Tobin's *Q* of the focal firm's 10NN rivals. In column 3 (column 4), the model also includes the mean values of firm size and cash flow for all firms in the TNIC industry (10NN cluster) as additional controls. Variable definitions are provided in Appendix A. All models include firm and year fixed effects, and standard errors used to compute t-statistics (within brackets) are clustered at the firm level. ***, **, and * indicate significance at 1%, 5%, and 10%, respectively.

Panel A. Dependent variable is capex, scaled by lagged total assets

	(1)	(2)	(3)	(4)
Q_i	0.0078***	0.0073***	0.0068***	0.0070***
	[21.76]	[18.08]	[16.97]	[17.28]
$Q_i \times SPI^{PMC}$		0.0004**	0.0004**	0.0004***
		[2.04]	[1.98]	[2.05]
Q_{-i}			0.0022***	
			[4.29]	
Q_{10NN}				0.0015***
				[3.88]
Controls	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Adjusted R^2	0.587	0.588	0.588	0.588
Observations	77,064	77,064	77,064	76,677

Panel B. Dependent variable is R&D, scaled by lagged total assets

	(1)	(2)	(3)	(4)
Q_i	0.0102***	0.0082***	0.0087***	0.0083***
	[14.72]	[11.49]	[11.79]	[11.52]
$Q_i \times SPI^{PMC}$		0.0020***	0.0020***	0.0020***
		[4.31]	[4.53]	[4.30]
Q_{-i}			-0.0030***	
			[-3.72]	
Q_{10NN}				-0.0005
				[-0.74]
Controls	yes	yes	yes	yes
Firm FE	yes	yes	yes	yes
Year FE	yes	yes	yes	yes
Adjusted R^2	0.789	0.790	0.790	0.790
Observations	77,064	77,064	77,064	76,677

Panel C. Dependent variable is total investment, scaled by lagged total assets

	(1)	(2)	(3)	(4)
Q_i	0.0228***	0.0202***	0.0201***	0.0201***
	[19.57]	[15.73]	[15.29]	[15.61]
$Q_i \times SPI^{PMC}$		0.0022***	0.0023***	0.0023***
		[4.07]	[4.13]	[4.06]
Q_{-i}			0.0001	
			[0.08]	
Q_{10NN}				-0.0003
				[-0.25]
Controls	yes	yes	Yes	yes
Firm FE	yes	yes	Yes	yes
Year FE	yes	yes	Yes	yes
Adjusted R^2	0.403	0.404	0.405	0.404
Observations	74,060	74,060	74,060	73,693

Table 5. Robustness checks

The table replicates column 3 of Table 4 with the following alterations. Column 1 uses the logarithmic transform of the percentage increase in R^2 after augmenting the baseline model with the 10NN rivals' stock returns, as an alternative measure of product-market driven stock price informativeness (SPI^{PMC}). Column 2 uses the Fama-French five-factor model instead of the one-factor model. Column 3 relies on asymmetric betas to account for differential effects of good and bad news about rivals on the focal firm's stock return. Column 4 accounts for managerial private information using earnings surprise (*ERC*) as a proxy, measured as the average of the absolute 3-day abnormal stock returns over the prior year's four quarterly earnings announcements. Column 5 controls for analyst coverage, with *#Analyst* representing the log of one plus the number of analysts following the focal firm in the previous year. Column 6 relies on a placebo test which consists in replacing the 10NN rivals with 10 randomly drawn (pseudo) rivals. Variable definitions are provided in Appendix A. The corresponding single terms (SPI^{PMC} in all columns, *ERC* in column 4, and *#Analyst* in column 5), along with the controls and fixed effects from Table 4, are included in the model but not reported for brevity. Standard errors, used to compute t-statistics [in brackets], are clustered at the firm level. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Panel A. Dependent variable is capex, scaled by lagged total assets

	Log(%ΔR^2)	Five-factor model	Asymmetric betas	Managerial information	Analyst coverage	Placebo test
	(1)	(2)	(3)	(4)	(5)	(6)
Q_i	0.0072***	0.0068***	0.0066***	0.0073***	0.0077***	0.0070***
	[19.74]	[15.71]	[15.45]	[12.82]	[8.79]	[13.12]
Q_i × SPI^{PMC}	0.0003***	0.0008*	0.0004**	0.0004**	0.0003	0.0001
	[2.70]	[1.82]	[2.36]	[2.13]	[1.40]	[0.98]
Q_i × ERC				-0.006		
				[-1.20]		
Q_i × #Analyst					-0.001	
					[-1.62]	
Q_{-i}	0.0022***	0.0022***	0.0022***	0.0023***	0.0021***	0.0023***
	[4.16]	[4.28]	[4.23]	[4.50]	[4.23]	[4.39]
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.589	0.588	0.589	0.591	0.595	0.587
Obs.	77,064	77,064	77,064	76,182	73,882	75,344

Panel B. Dependent variable is R&D, scaled by lagged total assets

	Log(%ΔR^2)	Five-factor model	Asymmetric betas	Managerial information	Analyst coverage	Placebo test
	(1)	(2)	(3)	(4)	(5)	(6)
Q_i	0.0109***	0.0091***	0.0080***	0.0091***	0.0126***	0.0109***
	[14.90]	[10.09]	[10.10]	[8.82]	[8.05]	[11.26]
Q_i × SPI^{PMC}	0.0015***	0.0031**	0.0019***	0.0021***	0.0012**	0.000
	[4.97]	[2.48]	[4.82]	[4.94]	[2.22]	[0.12]
Q_i × ERC				-0.0072		
				[-0.68]		
Q_i × #Analyst					-0.0023***	
					[-4.11]	
Q_{-i}	-0.0031***	-0.0030***	-0.0030***	-0.0026***	-0.0023***	-0.0028***
	[-3.85]	[-3.60]	[-3.78]	[-3.28]	[-2.97]	[-3.38]
Controls	yes	yes	yes	yes	yes	Yes
Firm FE	yes	yes	yes	yes	yes	Yes
Year FE	yes	yes	yes	yes	yes	Yes
Adjusted R^2	0.791	0.790	0.790	0.7930	0.7910	0.789
Obs.	77,064	77,064	77,064	76,182	73,882	75,344

Panel C. Dependent variable is total investment, scaled by lagged total assets

	Log(%ΔR^2)	Five-factor model	Asymmetric betas	Managerial information	Analyst coverage	Placebo test
	(1)	(2)	(3)	(4)	(5)	(6)
Q_i	0.0224***	0.0201***	0.0191***	0.0216***	0.0236***	0.0227***
	[18.80]	[13.55]	[14.18]	[12.12]	[9.84]	[14.22]
$Q_i \times SPI^{PMC}$	0.0017***	0.0041**	0.0022***	0.0024***	0.0016**	0.0000
	[4.27]	[2.30]	[4.57]	[4.25]	[2.13]	[0.01]
Q_i × ERC				-0.0220		
				[-1.39]		
Q_i × Analyst					-0.0027***	
					[-2.96]	
Q_{-i}	-0.0001	0.0001	0.0000	0.0008	0.0001	0.0002
	[-0.06]	[0.06]	[0.02]	[0.54]	[0.08]	[0.17]
Controls	yes	yes	yes	yes	yes	Yes
Firm FE	yes	yes	yes	yes	yes	Yes
Year FE	yes	yes	yes	yes	yes	Yes
Adjusted R^2	0.405	0.405	0.405	0.3950	0.3950	0.404
Obs.	74,060	74,060	74,060	71,003	71,003	72,401

Table 6. Controlling for the residual component of SPI

This table examines whether the product market competition-driven component of stock price informativeness influences investment-to-Q sensitivities, while accounting for the residual firm-specific component. The dependent variable in columns 1-2, 3-4, and 5-6 is the capex ratio, R&D ratio, and total investment ratio, respectively. In column 1, SPI^{TOT} represents *total* stock price informativeness, calculated as in Equation (2). SPI^{RES} quantifies *residual* stock price informativeness after augmenting the baseline model with the stock returns of the 10NN rivals, calculated as in Equation (4). SPI^{PMC} measures the contribution of the 10NN rivals' stock returns to the focal firm's stock price informativeness, calculated as the difference between SPI^{TOT} and SPI^{RES}. Variable definitions are in Appendix A. All models control for the single term of the considered information variable, along with firm size and cash flow, and include firm and year fixed effects (coefficients omitted for brevity). In columns 2, 4, and 6, the model also includes the mean values of firm size and cash flow for all firms in the TNIC industry (10NN cluster) as additional controls. Standard errors, used to compute t-statistics [in brackets], are clustered at the firm level. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

	Capex		R&D		Total investment	
	(1)	(2)	(3)	(4)	(5)	(6)
Q_i	0.0065***	0.0060***	0.0069***	0.0074***	0.0183***	0.0184***
	[14.61]	[13.36]	[8.71]	[9.11]	[13.46]	[13.19]
$Q_i \times SPI^{TOT}$	0.0004***		0.0015***		0.0017***	
	[3.17]		[5.10]		[4.44]	
$Q_i \times SPI^{RES}$		0.0009***		0.0016***		0.0017**
		[3.25]		[3.65]		[2.30]
$Q_i \times SPI^{PMC}$		0.0001		0.0015***		0.0018***
		[0.61]		[3.13]		[3.10]
Q_{-i}		0.0019***		-0.0034***		-0.0009
		[3.64]		[-4.07]		[-0.60]
Controls	yes	yes	yes	yes	yes	yes
Firm FE	yes	yes	yes	yes	yes	yes
Year FE	yes	yes	yes	yes	yes	yes
Adjusted R^2	0.5870	0.5890	0.7900	0.7900	0.4040	0.4040
Observations	77,064	77,064	77,064	77,064	74,060	74,060

Table 7. Cross-sectional determinants of managerial learning

This table replicates column 3 of Table 4 across various subsamples. The dependent variable in columns 1-2, 3-4, and 5-6 is the capex ratio, R&D ratio, and total investment ratio, respectively. For brevity we only report the coefficient estimate of the interaction term of interest, $Q \times SPI^{PMC}$. Panel A compares firms with low versus high financial constraints. We use three measures of financial constraints: the KZ index, the WW index, and the SA index. Firms are classified as having low (high) financial constraints if they rank in the bottom (top) tercile of the sample for a given year. Panel B differentiates between 10NN rival firms operating in high- and low-quality information environments. The subsamples are constructed using a three-variable index capturing key aspects of the 10NN rivals' informational environment: (i) cluster size, (ii) analyst coverage, and (iii) stock liquidity. For each variable, we assign tercile-based scores for observations in the first, second, and third terciles, respectively. These scores are then summed across the three variables to create an information environment index. Each year, focal firms are classified into high- or low-quality information environments based on whether their information environment index falls into the top or bottom tercile of the distribution, respectively. Panel C compares focal firms operating in high- and low-competition environments, relying on two proxies, respectively the average similarity score of the focal firm with its 10NN rivals, and the focal firm's product market fluidity score. High and low subsamples are respectively based on the terciles of the distribution. Panel D differentiates between firms operating in high- and low-R&D-intensive product market spaces, using terciles of the average R&D ratios of firms within the 10NN cluster for each year. Panel E compares industry leaders and followers using two measures. The first classifies focal firms with both sales and ROA above (below) the median values for their SIC3 industry as industry leaders (followers). The second identifies leaders (followers) as firms in the top (bottom) tercile of market share within their 10NN cluster for each year. In each panel-specification, the last row reports z-statistics for a test of the difference in the coefficients of $Q \times SPI^{PMC}$ between the corresponding two sub-samples. Standard errors, used to compute t-statistics [in brackets], are clustered at the firm level. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Panel A. Financial constraints

	Capex		R&D		Total investment	
	Low	High	Low	High	Low	High
	(1)	(2)	(3)	(4)	(5)	(6)
KZ index						
$Q_i \times SPI^{PMC}$	0.0004**	-0.0002	0.0029***	-0.0002	0.0003	0.0007
	[2.21]	[-0.44]	[6.75]	[-0.25]	[0.25]	[0.43]
z-stat	1.23		3.41		-0.20	
WW index						
$Q_i \times SPI^{PMC}$	0.0002	0.0003	0.0040***	0.0005	0.0015	0.0004
	[0.56]	[1.18]	[10.86]	[0.85]	[1.41]	[0.26]
z-stat	-0.23		5.04		0.59	
SA index						
$Q_i \times SPI^{PMC}$	0.0004	0.0001	0.0042***	0.0001	0.0012	0.0002
	[1.06]	[0.60]	[14.24]	[0.17]	[1.44]	[0.16]
z-stat	0.73		6.23		0.67	

Panel B. Information environment quality

	Capex		R&D		Total investment	
	High	Low	High	Low	High	Low
	(1)	(2)	(3)	(4)	(5)	(6)
$Q_i \times SPI^{PMC}$	0.0015**	-0.0001	0.0044***	0.0007	0.0008	-0.0009
	[2.41]	[-0.48]	[2.95]	[0.94]	[0.39]	[-0.56]
z-stat	2.44		2.22		0.65	

Panel C. Product market competition

	Capex		R&D		Total investment	
	High	Low	High	Low	High	Low
	(1)	(2)	(3)	(4)	(5)	(6)
Average similarity score						
$Q_i \times SPI^{PMC}$	0.0002	0.0004	0.0027***	0.0013**	0.0016	0.0004
	[0.71]	[1.17]	[5.07]	[2.06]	[1.35]	[0.33]
z-stat	-0.45		1.70		0.71	
Product market fluidity						
$Q_i \times SPI^{PMC}$	0.0001	0.0012**	0.0022***	0.0004	0.0012	0.0008
	[0.56]	[2.31]	[4.09]	[0.87]	[1.10]	[0.64]
z-stat	-2.00		2.54		0.24	

Panel D. R&D-intensive cluster

	Capex		R&D		Total investment	
	High	Low	High	Low	High	Low
	(1)	(2)	(3)	(4)	(5)	(6)
$Q_i \times SPI^{PMC}$	0.0005***	-0.0003	0.0021***	0.0000	0.0012	-0.0015
	[2.58]	[-0.29]	[3.70]	[-0.57]	[1.20]	[-0.68]
z-stat	0.76		3.70		1.12	

Panel E. Focal firms' leadership status

	Capex		R&D		Total investment	
	Yes	No	Yes	No	Yes	No
	(1)	(2)	(3)	(4)	(5)	(6)
Industry leaders by profitability and sales						
$Q_i \times SPI^{PMC}$	0.0005	0.0003	0.0035***	0.0013**	0.001	-0.0002
	[1.44]	[1.06]	[5.62]	[2.17]	[1.14]	[-0.14]
z-stat	0.45		2.55		0.72	
Industry leaders by market share						
$Q_i \times SPI^{PMC}$	0.0004	0.0005*	0.0038***	0.0013**	0.0005	0.0011
	[1.16]	[1.66]	[8.77]	[2.12]	[0.39]	[0.82]
z-stat	-0.22		3.33		-0.32	

Table 8. Endogeneity test

Panel A shows the effect of S&P 500 additions on stock price informativeness. The dependent variable is SPI^{TOT} in column 1, SPI^{PMC} in column 2, and SPI^{RES} in column 3. *Addition* equals one if at least one of the ten nearest rivals of the focal firm is added to the S&P 500 index over the previous three years and zero otherwise. Panel B shows the effect of S&P 500 additions to the investment-to-Q sensitivity by replicating columns 2 and 3 of Table 4, respectively in columns 1, 3, and 5, and columns 2, 4, and 6. The dependent variable in columns 1-2, 3-4, and 5-6 is the capex ratio, R&D ratio, and total investment ratio, respectively. Variable definitions are in Appendix A. All models include the controls from the baseline models, along with firm and year fixed effects. Standard errors used to compute t-statistics (within brackets) are clustered at the firm level. ***, **, and * indicate significance at 1%, 5%, and 10%, respectively.

Panel A. The effect of S&P 500 additions on stock price informativeness

	SPI^{TOT}	SPI^{PMC}	SPI^{RES}
	(1)	(2)	(3)
Addition	-0.0359**	-0.0220**	-0.0138
	[-2.54]	[-2.38]	[-1.63]
Q_i	-0.1310***	-0.0598***	-0.0711***
	[-26.95]	[-18.91]	[-28.63]
Firm size	-0.3217***	-0.1398***	-0.1820***
	[-23.63]	[-16.77]	[-23.21]
Cash flow	-0.3266***	-0.2031***	-0.1235***
	[-7.38]	[-6.39]	[-5.54]
Firm FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Adjusted R^2	0.638	0.427	0.638
Observations	76,545	76,545	76,545

Panel B. The effect of S&P 500 additions on investment-to-Q sensitivity

	Capex		R&D		Total investment	
	(1)	(2)	(3)	(4)	(5)	(6)
Q_i	0.0078***	0.0073***	0.0107***	0.0112***	0.0230***	0.0229***
	[20.80]	[19.23]	[14.74]	[14.36]	[18.92]	[18.02]
Q_i × Addition	0.0004	0.0004	-0.0040***	-0.0040***	-0.0017	-0.0016
	[0.71]	[0.72]	[-4.83]	[-4.78]	[-1.03]	[-0.99]
Addition	-0.0009	-0.0010	0.0074***	0.0073***	0.0023	0.0018
	[-0.73]	[-0.84]	[4.55]	[4.44]	[0.67]	[0.52]
Q_{-i}		0.0024***		-0.0040***		0.0006
		[4.56]		[-4.78]		[0.38]
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.587	0.588	0.789	0.790	0.403	0.404
Observations	76,545	76,545	76,545	76,545	73,566	73,566

Table 9. The effect of product-market competition induced SPI on innovation outcomes

The table replicates columns 2 and 3 of Table 4 using three different dependent variables capturing innovation outcomes over the next three years: patent count in columns 1-2, patent citation in columns 3-4, and self-fluidity in columns 5-6. Variable definitions are provided in Appendix A. All models include controls from the baseline models, along with firm and year fixed effects. Standard errors used to compute t-statistics (within brackets) are clustered at the firm level. ***, **, and * indicate significance at 1%, 5%, and 10%, respectively.

	Patent count		Patent citation		Self-fluidity	
	(1)	(2)	(3)	(4)	(5)	(6)
Q_i	-0.0015	-0.0019*	-0.0025	-0.0023*	-0.0002	-0.0061**
	[-1.46]	[-1.68]	[-1.47]	[-1.68]	[-0.06]	[-2.09]
$Q_i \times SPI^{PMC}$	0.0007**	0.0007**	0.0011*	0.0011*	0.0031**	0.0025*
	[2.13]	[2.11]	[1.83]	[1.77]	[2.08]	[1.86]
Q_{-i}		0.0019*		-0.0012		0.0341***
		[1.88]		[-0.40]		[6.25]
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.814	0.814	0.473	0.473	0.531	0.532
Observations	77,064	77,064	77,064	77,064	76,658	76,658