Do Private Firms (Mis)Learn from the Stock Market? *

Dong Yan †

Stockholm School of Economics & CEPR

December 3, 2022

Abstract

This paper examines whether and to what extent private firms learn from the stock market. Using a large panel data set for the United Kingdom, I find that private firms' investment responds positively to the valuation of public firms in the same industry. The sensitivity increases with price informativeness. To further pin down the information channel, I construct a price noise measure based on public firms' *unrelated* minor segments and show that it positively affects the investment of private firms in the major-segment industry. The results are consistent with models featuring learning from noisy signals and are not driven by alternative channels in the absence of learning. My findings suggest that the stock market can have real effects on private firms through an information-spillover channel, even when these firms do not list their shares on the stock exchanges.

JEL classification: G30, G31, G14

Keywords: Corporate Investment, Learning, Information Diffusion, Private Firms

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*I am deeply indebted to my advisor, Sudipto Dasgupta. For valuable comments, I thank Bo Becker, Utpal Bhattacharya, Philip Bond, Ling Cen, Gonul Colak, Nicholas Crain, Laurent Frésard, Mariassunta Giannetti, Itay Goldstein, Denis Gromb, Ran Guo, Clair Hong, Harrison Hong, Sheng Huang, Erica Li, Alexander Ljungqvist, Fangyuan Ma, Abhiroop Mukherjee, Kasper Nielsen, Joël Peress, Giuseppe Pratobevera, Konrad Raff, Laura Starks, Per Strömberg, Pengfei Wang, K.C. John Wei, Alminas Žaldokas, Hong Zhang, an anonymous referee, as well as participants at the Finance Down Under 2019, NICE 2019, SAIF Summer Institute of Finance 2019, EFA 2017, CICF 2016, WFA 2015 Early Career Women in Finance Mini-Conference, SAEe, FMA Europe, FMA Asia, AsianFA, NFN Young Scholars Workshop, BI, City University of Hong Kong, Erasmus School of Economics, HKUST, Manchester Business School, Norwegian School of Economics, Tsinghua PBC, Queen's University, UNSW, University of Southern Denmark, and Stockholm School of Economics. I gratefully acknowledge financial support from the Jan Wallander and Tom Hedelius Foundation. All errors are mine.

†Stockholm School of Economics and CEPR, Stockholm, Sweden. Dong.Yan@hhs.se.

1 Introduction

How financial markets affect real economic activity has been a central question for financial economists. Over the last decade, increasing attention has been paid to the stock market's role in producing information and its possible feedback effects on corporate decisions. As information does not flow freely among investors and firms, diverse pieces of information produced by different market participants can be aggregated into stock prices through trading (Grossman and Stiglitz, 1980 and Kyle, 1985). As a result, stock prices could reflect information that may not be known to corporate managers. If managers learn from this information and use it when making real decisions, the stock market can have a real effect via the transmission of information, even without any capital flowing to firms.[1]

The learning mechanism predicts a positive relationship between a firm's investment and the price signal. However, identifying learning through the investment-to-price sensitivity is challenging because corporate managers' information sets are not perfectly observable to econometricians, and a positive investment-to-price sensitivity could be confounded by other channels. For example, the stock price may passively reflect what the manager has already known. Unobserved investment opportunities may also simultaneously affect the firm's stock price and investment. Furthermore, public firms, which are predominantly used in the literature, have long been known to suffer from agency problems (Jensen and Meckling 1976). They may adjust their investments in response to fundamental and non-fundamental movements in stock prices due to managers' catering incentives (Polk and Sapienza 2009).

In this paper, I adopt a novel empirical strategy, which combines the unique features of privately held firms and a price noise measure based on public firms' conglomerate structure,

[1]Incremental information may reflect, among other things, aggregate demand for a product, potential investment opportunities, prospects of the industry, and the state of the economy. See Bond et al. (2012) for an excellent survey of the real effects of financial markets that stem from the informational role of market prices.

to more plausibly establish the learning channel. My empirical setting builds on the fact that private firms do not have shares listed on the stock exchanges and hence do not have their own stock prices. This feature mitigates the concern for the passive reflection problem since it is less likely that firm-specific information known by a private firm manager is only passively reflected in public peers' stock prices. Moreover, as mostly owned by their managers, private firms' investments are less distorted by short-termism (Asker et al., 2014) and other agency concerns. Thus, alternative channels that have confounded public firms' learning behavior have a much narrower scope when inferring learning from private firms.

Building on these advantages, I first draw predictions on private firms' investment sensitivity to price. To the extent firms are exposed to common shocks, peer firms' stock prices could inform about industry-wide investment opportunities (Foucault and Frésard, 2014). Hence, private firms should learn from their public peers' stock prices, and when they do so, their investment is expected to be positively associated with the industry valuation. Using a large panel data set for the United Kingdom, I test this baseline prediction and find strong evidence that the investment of private firms reacts positively to the industry valuation, proxied by the average beginning-of-period market-to-book ratio of assets of all public firms in the industry.

Still, there is room for endogeneity: If some industry-wide information reflected in stock prices were already known by private firms, an association between private firms' investment and industry stock valuation could still be generated even without learning. I rely on noise in stock prices to sharpen the identification. As suggested by Morck et al. (1990), the prices are noisy signals (or "faulty informants"). If corporate managers learn from stock prices and cannot completely filter out the noise in the price signal, their investment will be sensitive to the noise component *ex post*. On the contrary, if they do not learn from prices, the noise should not play a role since it is unrelated to the firm's investment opportunities. Therefore, the investment-to-noise sensitivity provides a unique prediction for the learning mechanism.

I develop a noise measure for private firms using their public peers' conglomerate structure. The idea is based on the fact that, while private firms are mostly pure players, many public firms have multiple business segments, sometimes in industries unrelated to the major line of business (and hence unrelated to private firms in the major industry). When learning from industry valuation, private firms react to the price signal, which incorporates a noisy component reflecting their public peers' *unrelated* minor-segment industries. Consequently, their investment will be sensitive to noise. For each private firm, I construct the noise as the average valuation of industries in which its public industry leaders have *unrelated* minor segments.[2] To satisfy the exclusion restriction, I exclude minor industries that potentially share economic links with private firms, such as industries proximate to the major industry, industries in which private firms also have minor segments, and industries likely to have supply-chain relationships. In the end, the price noise constructed using the remaining minor-segment industries is, to a large extent, unrelated to the investment opportunities of private firms.

The identification strategy requires that the decision-maker cannot completely filter out the noise. Otherwise, investments will not follow the noise even if learning takes place. This condition is likely to hold here for two reasons. First, as public pure players are more scarce, private firms often have to consider multi-segment firms as their peers. Second, since pure players are usually much smaller in size, their valuation is contaminated by that of larger firms, often conglomerates, in the industry (Hou, 2007 and Cen et al., 2013). Thus, even when private firms only select peers from pure players, the noise is likely to be embedded in the price signal.

Consistent with learning, I find that the investment of private firms reacts positively and significantly to the noise in the price signal, and the economic magnitude is considerable: A

[2]For example, public firms in the construction industry have unrelated minor segments in printing and chocolate production. The price noise for each private firm in the construction industry is constructed as the average valuation of the printing industry and the chocolate production industry.

one standard deviation increase in the valuation of industry leaders' *unrelated* minor-segment industries is associated with a 0.8% increase in capital expenditure of private firms, which is about 4% of the average investment-to-capital ratio in my sample. This effect is estimated after controlling for the component of industry valuation that relates to the major industry, lagged characteristics of the firm and industry known to affect investment, contemporaneous investment of public and private peers, characteristics of minor-segment industries, unobserved time-varying shocks common to all firms (by using year fixed effects), and unobserved heterogeneity at the firm level (by using firm fixed effects). Again, as catering and market timing are less likely to drive private firms' investment, especially those that never attempted IPOs and remain private throughout their lives, the inferences drawn from the investment-to-noise sensitivity can largely be attributed to managerial learning.

I also perform several additional tests to validate the learning framework. First, I find that private firms with financial institutions as their investors react to a lesser extent to the price noise, consistent with the notion that they are better able to filter out the noise. Second, using various proxies, I show that the sensitivity of private firms' investment to industry valuation and price noise is stronger when the stock prices are more informative and when firms in the same industry are more likely to face common shocks. Third, I perform a dynamic analysis and find that private firms operate a correction in the subsequent year to their mistake. But due to their limited capacity to understand stock prices and the more persistent nature of the noise, the correction is only partial.

Finally, I show that the results are not driven by alternative channels such as competition, internal resource allocation, and market timing. I first examine segment-level investments of public leaders and find that their major-segment investment is not affected by the minor industry valuation.[3] Therefore, private firms' reactions are not due to strategic responses to

[3]This is not surprising since industry leaders are not financially constrained and have less need to finance

public firms' internal resource allocation. Furthermore, I adopt a similar strategy as in Baker et al. (2003) to address the concern that the external financier's sentiment may affect the cost of capital of private firms. I find that the reaction of financially unconstrained firms is as strong as that of constrained firms, which suggests that market timing cannot explain the findings.

My paper contributes to a few strands of literature. The idea that stock prices aggregate information and improve the efficiency of the real economy dates back to Hayek (1945), and has been enriched by theoretical works including Dow and Gorton (1997), Subrahmanyam and Titman (1999), Goldstein and Guembel (2008), Peress (2014), among others. Based on reduced-form sensitivities of *public* firms, several studies show empirically that stock prices are associated with decision-making for capital investment (Chen et al., 2007 and Foucault and Frésard, 2014), mergers and acquisitions (Luo, 2005), and cash savings (Frésard, 2012). My paper is the first to utilize the identification advantages of *private* firms to more plausibly establish the learning channel.[4] My results suggest that stock prices provide informative signals to private firms and, through the learning channel, can have real effects on their investment even when private firms do not list their shares.

Also, I extend the existing identification based on the "faulty informant" hypothesis (Morck et al. 1990) by implementing the noise test on private firms and using a new measure exploring public firms' conglomerate structure. My paper complements recent studies using price pressure caused by mutual fund outflows to instrument non-fundamental shocks for public firms (cf. Dessaint et al. 2018). Moreover, by showing a source of noise that does not result from public firms' mis-valuation can have real impacts on private firms' investment, my paper provides

their major-segment investment by cash flows from minor segments. Furthermore, they are better informed of the valuation in the minor-segment industries and are in a better position to filter out the noise.

[4]Relatedly, Foucault and Frésard (2014) show that the investment sensitivity to peer price drops after going public. Their test is based on *Compustat* firms for a period shortly before IPO. Also, using data from Sageworks for the US, Badertscher et al. (2019) show that private firms' investment is associated with the residual income value of public firms, which could be explained by market timing, learning, and unobserved growth opportunities.

a new case in which price efficiency and (*ex post*) real efficiency may diverge. Lastly, I document that whether the noise has any real effects through learning depends on agents' ability to filter it out. This notion reconciles the findings that mispricing does not affect investments (Morck et al. 1990 and Bakke and Whited 2010) with the literature that finds the opposite.

The paper is organized as follows. Sections 2 describes the data. Section 3 develops the hypotheses and the empirical strategy under a "learning" framework. Section 4 discusses the empirical findings. Section 5 show additional evidence. Section 6 concludes the paper.

2 Data

2.1 Panel data for public and private firms

My sample starts with all private and public firms in the United Kingdom for the period 1993 to 2010. The primary data source is the Financial Analysis Made Easy (FAME) database provided by Bureau Van Dijk (BvD), which contains accounting variables in the balance sheet, the profit & loss account, and the statement of cash flow for all private and public companies. I also rely on the Worldscope database to cross-check the financial data of public firms and to obtain their stock prices. All pound values are converted to 2005 constant million pounds using the UK consumer price index from the World Development Indicators (WDI).

The primary advantage of FAME is that the 1967 Companies Act in the UK requires that all limited liability companies, private and public, file their financial statements annually with the UK Companies House. The 1981 Companies Act further requires that all companies submit full financial statements, except for the "small" and "medium"-sized firms which meet two of the three criteria: (i) sales less than £1.4 million, (ii) book assets less than £1.4 million; (iii) number of employees less than 50. Thus, compared to other databases, FAME has a much broader coverage of private firms and their financial items.[5] Moreover, private and public firms in the UK face equivalent tax laws and accounting standards. All their statements must be audited if the annual sales exceed £0.35 million before June 2000 and £1 million after.

FAME does not remove historical information if a firm stops reporting financial data. But it only keeps information for up to 10 years in the web version, and hence may bias towards firms that survived or incorporated in recent years. To avoid this "survivorship" bias, I obtained the archived disks from BvD from their earliest possible release (release 90, 1996) to the more recent ones (release 270, 2011). Each disk contains a snapshot of the web version in December of each year. Therefore, by appending the archived disks, I collect financial data backward in time and expand the time series to 18 years.[6] Also, static ("header") information such as listing status and ownership structures in the web version only reports the most recent value. The archived disks allow me to obtain this type of information at an annual frequency.

Following Brav (2009) and Michaely and Roberts (2012), I classify firms as public if they are quoted on the London Stock Exchange, OFEX or AIM, and as private if their company type in FAME is "Private," or "Public Unquoted." I only keep firms that do not change their status from private to public (or public to private) over the sample period. This is to address the concern that the transition firms may not represent the general population of private firms, and the stock prices may affect these IPO firms for reasons other than learning.

I collect firms' ownership information (at an annual frequency) from the archived disks of FAME, which contains the number and identity of shareholders at the end of each filing date. I classify shareholders as institutional shareholders if their type in FAME is "Bank," "Financial company," "Insurance company," "Mutual & Pension fund," "Trust," or "Private equity firms."

[5]For example, Amadeus and Orbis also contain private firms, but they only cover much larger private firms and do not provide any information about capital expenditure.

[6]My sample period starts from 1993 since the 1996 disk kept financial data for the past three years.

2.2 Segment information

I obtain segment industry codes and financials of public firms from Worldscope and aggregate product segments within each firm at the two-digit SIC level each year. My results are robust if I use three-digit SIC segments. But using two-digit SIC helps ensure that minor-segment industries are unrelated to the major industry. Private firms in the UK are required to report the SIC codes for all the industries they operate, providing another advantage to the setting. I retrieve their secondary SIC codes from FAME to identify their minor-segment industries.

I use the 2012 US Input-Output Tables from the Bureau of Economic Analysis to identify potential supply-chain relationships between two industries. For a given industry, I define its supplier or customer industries as those industries that account for over 25% of the total flows of the goods and services that comprise the product process of that industry.

2.3 Sample selections

My sample selections follow Michaely and Roberts (2012). First, I keep consolidated financial statements and restrict the sample to limited liability companies to which the Companies Act applies. Second, I exclude small firms as defined by the Companies House to prevent a large number of missing data, observations that do not satisfy the auditing requirements, and firm-year observation that has missing values on the book value of assets, sales, or shareholders' equity. Third, I require that each firm should have five consecutive years of data. Following standard practice, I exclude financial, insurance, and real estate firms (SIC code 6000–6900), utilities (SIC code 4900–4999), and public sector firms (SIC code above 8999). My final sample consists of 14,033 private firms and 1,761 public firms.

Variable constructions are presented in the Appendix. Ratios are winsorized separately for public and private firms at the 1% level at both tails of the distribution to alleviate the impact of outliers. Table 1 presents summary statistics for the sample.

[TABLE 1 ABOUT HERE]

Consistent with previous studies, private firms are much smaller in size than public firms. They depend more on debt and have fewer institutional shareholders. While private firms do not have lower capital expenditures than public firms, their investments in fixed assets are significantly lower. This is likely due to less intensive mergers and acquisitions by private firms. Finally, the distribution of public firms' q is consistent with those using the US sample.

3 Hypothesis Development and Empirical Strategies

In this section, I develop hypotheses for empirically examining the stock market's impact on private firms' investment through learning. In doing so, I also outline the endogeneity issues and my identification strategy to tackle the problem.

3.1 The informational role of stock prices

The rationale for managers to learn from stock prices stems from the role of the stock market in producing and aggregating information. The financial market is a place where investors with different beliefs and information meet to trade (Hayek 1945). Through their trading activities, diverse pieces of information can be aggregated into stock prices (Grossman and Stiglitz, 1980 and Kyle, 1985). As a result, stock prices could reflect information incremental to managers. In turn, managers should use this information to guide their real decisions because doing so allows them to form more precise predictions about the future state of the economy.[7]

[7] This intuition lies behind the theoretical works that examine the benefits and limitations when decision makers learn from the stock prices, including Dow and Gorton (1997), Subrahmanyam and Titman (1999), Foucault and Gehrig (2008), Goldstein and Guembel (2008), Foucault and Frésard (2014), and Peress (2014).

Note that for the stock market to have a real effect through the learning channel, it does not require that investors have superior knowledge to managers, but only that they possess new information that could complement managers' information set. For example, investors may come across valuable information about the demand for a product in their day-to-day activities. When they trade, such "serendipitous information" could be aggregated in stock prices (Subrahmanyam and Titman 1999). Moreover, stock prices may reveal investors' information and assessment of other aspects of uncertainty facing a firm, such as its potential investment opportunities, the prospects of the industry, the state of the economy, the position of competitors, and the likely synergies in an acquisition (cf. Morck et al. 1990, Luo 2005, Bond et al. 2012), and hence provide useful signals for corporate managers when they make real decisions.

As stock prices are observable to all, managers can also learn from peer firms' stock prices (see Foucault and Frésard 2014 and Dessaint et al. 2018). This is particularly relevant to private firms, which do not have their own stock prices but are exposed to common shocks as their public peers. Intuitively, when the industry has a sufficiently large number of public firms, as firm-specific shocks are canceled out, the industry valuation can inform about industry-wide (demand and cost) shocks. This signal still contains some noise.[8] But as long as private firm managers do not possess perfect information about the common component, relying on the industry valuation signal improves their *ex ante* investment efficiency.

3.2 The response of private firms to the industry valuation

To guide the empirical specification, I compare the investment responses of private firms when they learn from the industry valuation with a counterfactual scenario when they do not.[9]

[8]The noise, possibly due to investor sentiment or inattention, could be correlated among stocks (as the same friction could affect a group of stocks or the entire market) and hence could not be eliminated by aggregation.

[9]A more formal theoretical framework, which shares the same spirit with the ones in Foucault and Frésard (2014) and Dessaint et al. (2018) for public firms, can be found in the Internet Appendix.

Under the "No Learning" scenario, the manager of a private firm will update her prior belief based on the private signal she receives. Thus, her posterior belief about future productivity (and the firm's optimal investment) will reflect her prior knowledge and private signal but not the industry valuation. Under the "Learning" scenario, however, her posterior expectation will reflect the industry valuation signal, as long as the firm faces uncertainty about the common environment and that her private information is not perfect. It follows that, in this case, the private firm's investment will respond positively to the industry valuation.

Hypothesis 1: After controlling for private signals, the investment of private firms responds positively to the industry valuation if and only if its manager learns from the stock market.

I test Hypothesis 1 with the following linear investment regression.[10]

$$I_{i,t} = \alpha + \beta \times Industry\_q_{i,t-1} + \lambda \times X_{i,t-1} + \theta \times Industry\_X_{i,t-1} + \kappa_i + \delta_t + \epsilon_{i,t} \quad (1)$$

where the subscripts i and t index firms and years, respectively; $I_{i,t}$ is capital expenditure scaled by beginning-of-period capital; $Industry\_q_{i,t-1}$ is industry valuation, measured by the average market-to-book ratio of assets at the beginning of period t of all public firms in the three-digit SIC industry to which private firm i belongs. $X_{i,t-1}$ and $Industry\_X_{i,t-1}$ are a set of firm and industry characteristics documented in the literature to affect investment. In addition, I control for the unobserved time-varying shocks common to all firms (by using year fixed effects) and the unobserved heterogeneity at the firm level (by using firm fixed effects).

Hypothesis 1 predicts $\beta > 0$ under the "Learning" mechanism, assuming we can perfectly control for managers' information set. However, neither her prior belief nor private signal is observable to us as econometricians. As the private signal may also contain information about

[10] As in a q theory-setting, a firm's optimal investment is a linear and increasing function of marginal q and hence is increasing in the manager's expectation of future productivity.

common shocks, omitting it will result in a positive coefficient on the industry valuation even in the absence of learning. In section 3.3, I discuss a sharper test strategy using the price noise.

3.3 The response of private firms to the price noise

3.3.1 The "faulty informant" hypothesis

As suggested by Morck et al. (1990), stock prices are "faulty informants" for managers, and the noise in the price signal could influence corporate investment through the learning channel. This prediction also extends to the setting I analyze. Since it is unlikely that a private firm manager can completely filter out the noise when learning from their industry valuation, the noise in the industry valuation will affect private firms' investment.

Hypothesis 1b: The investment of private firms responds positively to the noise in the industry price signal, if and only if private firm managers learn from the stock market.

Hypothesis 1b is a unique prediction from the learning mechanism. This is because the noise component is (by construction) *orthogonal* to the firm's investment opportunities. Under the "No Learning" scenario, it does not affect the manager's posterior belief and the firm's investment. Thus, the investment-to-noise sensitivity can identify the learning channel even when the manager's private signal cannot be perfectly controlled for.

3.3.2 The noise measure: industry leaders' minor-segment industry valuation

An ideal noise measure to test learning must satisfy two conditions. First, the decision-maker cannot completely filter it out from the signal. Otherwise, she will only react to the relevant component, and we should not observe any relationship between investment and the noise even when learning takes place. Second, the noise should be unrelated to the fundamental investment opportunities of private firms (the exclusion restriction). If violated, a spurious relationship between investment and noise could still be observed in the absence of learning.

In light of these conditions, I develop a measure of noise for private firms in the context of learning based on the valuation of public peers' *unrelated* minor-segment industries. The rationale for this measure is the following. While private firms are mostly pure players, many public firms have fairly complicated business segments, which often involve industries unrelated to their major line of business. To the extent that the stock valuation of conglomerate firms reflects the information in both their major and minor segments, private firms' price signals contain a noise component reflecting minor segments of public firms.

There are two reasons why the noise reflecting minor-segment industries could have a feedback effect on private firms' real decision-making. First, as public firms are more scarce, even when it is in the interest of private firms to find pure players that are more comparable to them, it is not always feasible. As a result, they often have to consider firms with multiple business segments as their peers in trading off the quality of the match and estimate consistency. Second, due to market imperfections, new information is usually incorporated into the stock prices of large firms before it spreads to other firms within the industry, and less sophisticated investors often price smaller firms based on the valuation of industry leaders (Hou 2007 and Cen et al. 2013). As pure public players are usually much smaller in size, their valuation is contaminated by that of larger firms, often conglomerates, which ensures the identifying condition is met even when private firms only select peers from pure players.

To construct the noise measure, I define "industry leaders" as firms whose major-segment sales rank in the top five among all firms in that industry, where the "major-segment industry" of a firm is defined as the two-digit SIC industry in which the firm generates more than 50% of its total sales. In turn, "Industry pure players" are defined as firms that are not industry leaders and generate all their sales from the major-segment industry. When industry leaders have product segments in industries other than the "major-segment industry", these industries are defined as "minor-segment industries", and the leaders in minor-segment industries are called "minor-segment industry leaders".[11] For each private firm, I first obtain a list of minor-segment industries of its public industry leaders. To satisfy the exclusion restriction, I exclude minor-segment industries that potentially share economic links with the major-segment industry, such as industries within the same one-digit SIC industry as the major-segment industry, industries in whose leaders have a minor segment in the major industry, industries likely to have supplier or customer relationships with the major industry, and industries in which private firms also have minor segments. So, the remaining minor-segment industries (referred to as "unrelated minor-segment industries") are, to a large extent, unrelated to private firms in the major-segment industry. I then construct my main noise measure, "unrelated minor-segment industry valuation" ($Minor\_Industry\_q$), as the average industry valuation across all *unrelated* minor-segment industries.[12] As a robustness test, I construct an alternative noise measure, denoted by $Minor\_PurePlay\_q$, which includes only pure-play firms to compute the industry valuation of each *unrelated* minor-segment industry.

As a sanity check for the exclusion restriction, I find that cash flows generated by industry leaders' major segment are not correlated with cash flows by their unrelated minor segments, suggesting that the unrelated minor-segment industries do not co-move with the major industry in fundamentals.[13] I also show in a later section that industry leaders' major-segment investment is not affected by the valuation of their unrelated minor-segment industry, which

[11] I require that there be at least five industry leaders and at least five pure players in each two-digit SIC industry. My results are not sensitive to the number of industry leaders and pure players.

[12] For example, public industry leaders in the construction industry have minor segments in printing and publishing, furniture, chocolate production, and real estate. Furniture and real estate have economic links with construction. So, the noise for construction is the average industry valuation of printing and chocolate production.

[13] The unconditional correlation between cash flows in the major and unrelated minor segments is –0.014.

again confirms that my noise measure does not likely capture underlying fundamentals related to the major industry.

3.3.3 The proxy for the fundamental component

Having established the orthogonality of my noise measure to the investment opportunities, I now move on to decompose the industry valuation into a noise component reflecting information about industry leaders' unrelated minor-segment industries and a fundamental component informative about the major-segment industry. I do so by regressing the overall industry valuation on my noise measure using the following specification.[14]

$$Industry\_q_{j,t} = \alpha + \zeta \times Minor\_q_{j,t} + \chi_j + \delta_t + \nu_{j,t} \tag{2}$$

where the subscripts j and t denote industries and years, respectively; $Industry\_q_{j,t}$ is the average valuation of industry j in year t; $Minor\_q_{j,t}$ is the noise measure for firms in industry j in year t, as discussed in Section 3.3. I estimate Equation (2) with industry and year fixed effects. I then obtain a proxy for the major-segment industry valuation ($Major\_\bar{q}_{j,t}$) by subtracting the predicted value of noise from the industry valuation (i.e., $Industry\_q_{j,t} - \hat{\zeta} \times Minor\_q_{j,t}$, or equivalently, $\hat{\alpha} + \chi_j + \delta_t + \hat{\nu}_{j,t}$) and assign it to each private firm in that industry-year.[15]

Table 2 presents summary statistics for the industry-level variables. The distribution of the industry valuation is largely consistent with those of previous studies using the US sample.

[TABLE 2 ABOUT HERE]

[14] The purpose of the decomposition is mainly to obtain an estimate of the investment sensitivity to the fundamental component for a later test. All my results hold if I use the 2SLS approach.

[15] By including the fixed effects in $Major\_\bar{q}_{j,t}$, I attribute more variation of the industry valuation to its fundamental component. Point estimates for Equation (3) are identical if I use the residual term $\hat{\nu}_{j,t}$ alone to proxy for the fundamental component. Relatedly, as ζ is a scaling factor, using $\hat{\zeta} \times Minor\_q_{j,t}$ for Equation (3) will only scale the point estimate of β but do not change the economic magnitude.

3.3.4 Testing the "faulty informant" hypothesis

I test whether the investment of private firms responds to noise in the industry price signal (Hypothesis 1b) by estimating the following regression.

$$I_{i,t} = \alpha + \beta \times Minor\_q_{i,t-1} + \gamma \times Major\_\bar{q}_{i,t-1} + \lambda \times X_{i,t-1} + \theta \times Industry\_X_{i,t-1} + \kappa_i + \delta_t + \epsilon_{i,t} \quad (3)$$

where the subscripts i and t index firms and years, respectively; $I_{i,t}$ is the capital expenditure scaled by beginning-of-period capital. $Minor\_q_{i,t-1}$, as discussed in Section 3.3.2, is the noise for firm i in the beginning of year t, measured by its industry leaders' ***unrelated*** minor-segment industry valuation. $Major\_\bar{q}_{i,t-1}$ is the proxy for the fundamental component in firm i's industry valuation, as estimated in Section 3.3.3. $X_{i,t-1}$ and $Industry\_X_{i,t-1}$ represent an extended set of firm and industry controls, including, among other things, lagged cash flows and size. Hypothesis 1b predicts $\beta > 0$ when they learn from the stock market.

3.4 The role of key parameters

The learning mechanism also generates predictions regarding several key parameters, such as the role of the manager's ability to filter out the noise, price informativeness, and the relative importance of common shocks. Testing firms' heterogeneous responses with respect to these parameters offers validation for the learning mechanism.

I first examine the heterogeneity across firms in managers' ability to filter out noise from the overall industry valuation. If some managers are better informed or less attention constrained than others, their reaction to the noise component will be more muted. Therefore,

Hypothesis 2: The sensitivity of private firms' investment to the noise in the price signal is less pronounced when it is easier for the manager to filter out the noise.

Next, the precision of the price signal affects how much weight the manager puts on the average stock price when updating her belief: The more precise is the industry price signal, the more pronounced is the investment-to-price sensitivity. This is consistent with Chen et al. (2007) and Foucault and Frésard (2014) for the case of public firms.

Hypothesis 3: The sensitivity of private firms' investment to the industry valuation is stronger when the price informativeness is higher.

Finally, the rationale behind learning from the industry valuation is that the average stock price provides useful information about common shocks (cf. Foucault and Frésard 2014 and Dessaint et al. 2018). When uncertainty is more likely to come from industry-wide shocks, this additional piece of information is more valuable and accounts for a higher weight when managers decide on the optimal investment. Therefore,

Hypothesis 4: The sensitivity of private firms' investment to industry valuation is stronger when the common shock is more important relative to the firm-specific shock.

While Hypothesis 3 and 4 directly apply to the overall industry valuation, as noise is a component of the overall industry valuation, when it is challenging for managers to filter it out, both hypotheses apply to the noise. Therefore, in Section 5, I perform the cross-sectional tests on the investment sensitivity to both the industry valuation and noise.

3.5 Empirical inferences on the response of public firms

When public firms learn from the stock prices of their own and their peers, their investment also responds to the industry valuation and the noise component (see Foucault and Frésard 2014, Dessaint et al. (2018) and the Internet Appendix of this paper). However, additional insights on their empirical inferences are worth discussing.

First, the optimal response of *public* firms' investment to the industry valuation can be *negative* under the learning framework. When the price noise terms are highly correlated or when the common shock accounts for a small proportion of the uncertainty, managers could subtract the industry valuation from their own price to obtain the firm-specific shock. When the industry average valuation is higher, they will infer a lower firm-specific shock and adjust investment downward.[16] For private firms, the sign is not sensitive to model specifications.

Second, since public firms' noise terms are correlated, when their own and industry valuations are included in the same regression, the estimates are likely biased. This bias can further be magnified by agency problems. As public firm managers may cater to investors' opinions and protect their own livelihood (Polk and Sapienza, 2009), they have additional incentives than learning to respond to the price and noise (of their own and peers). In contrast, testing the investment-to-noise sensitivity of private firms is subject less to such concerns.

Finally, since public firms are less dependent on the industry valuation when their own price is informative, the learning framework predicts a larger weight on the industry valuation by private firms than "twin" public firms. However, testing this prediction requires that (i) private and public firms have the same underlying fundamentals, (ii) managers' private signals are equally precise, and (iii) public firms do not have any agency cost. Given these conditions do not hold in the data, the observed difference is likely an outcome of all these forces.

3.6 Remarks

The conceptual framework in my paper also broadly relates to firms' decision to go public. In a preceding paper, Subrahmanyam and Titman (1999) examine the incentive to learn from

[16]The intuition is in line with recent papers by Brown and Wu (2014) studying cross-fund learning within mutual fund families and Ozdenoren and Yuan (2017) studying risk-taking behaviors when agents have incentives to match the industry average effort.

prices and private firms' decisions to go public. Their model does not feature a common shock across firms. Hence, unless going public, firms cannot learn about the incremental "serendipitous" information in stock prices. In my framework, private firms can interpolate the common component through learning, and the extent to which they can exploit the positive externality depends on price informativeness. If peer firms' stock prices become too noisy about common shocks (a potential result of massive delistings), private firms cannot free-ride as much from prices. In that case, private firms will have a higher incentive to go public, converging to the setting in Subrahmanyam and Titman (1999).

Furthermore, while my paper focuses on firms that remain private throughout their lives to achieve sharper identification, my empirical predictions are likely to hold for firms that attempt IPOs and other players in the private domain, such as venture capital firms and private equity funds. For example, Liu and Tian (2021) examine whether VCs learn from the stock market. However, VCs may have their own information production.[17] Also, VCs' information is more likely to correlate with that of the stock market, and their exit decision depends more on market sentiment. My setting is less likely to incur these empirical challenges.

4 Empirical Results

4.1 Baseline: Private firms' investment and industry valuation

I test Hypothesis 1 with the classic linear investment regression, as in Equation (1). In the baseline specification, I control for firm characteristics such as lagged cash flow scaled by beginning-of-period assets and the logarithm of its lagged total assets, and the average characteristics of all public firms and private peers in the industry. In an extended specification,

[17]Consistent with this notion, I show in Section 4.4 that private firms with financial institutions as their investors react less to the price noise.

more firm and industry characteristics (such as sales growth and leverage), as well as lagged industry valuation and peer firms' average contemporaneous investments, are controlled for. The results are reported in Table 3.

[TABLE 3 ABOUT HERE]

Consistent with Hypothesis 1, the sensitivity of private firms' investment to the industry valuation is significantly positive (columns 1 and 2 of Table 3). The economic magnitude is considerable: A one standard deviation increase in the industry valuation is associated with a 1.5% increase in the investment of private firms ($\beta \times SD(Industry\_q) = 0.023 \times 0.635 = 1.5\%$), which is about 7% of the average investment-to-capital ratio in my sample.

My results are robust to how industry valuation is measured. In columns 3 and 4 of Table 3, I measure $Industry\_q$ by the median market-to-book ratio of assets at the beginning of period t of all public firms in the same three-digit SIC industry. The results are consistent with the baseline results.[18] Moreover, Raff and Verwijmeren (2013) and Bustamante and Frésard (2020) find that the investment of public firms responds to peer firms' investment. Since the control variables in columns 2 and 4 include the investment of all public firms and private peers in the same industry, the findings I show here suggest that the effect of stock prices on private firms' investment goes beyond their influence through peer firms' investment.

4.2 Identification: Private firms' response to the noise

I dig deeper into identification by examining whether the investment of private firms reacts to the noise in the price signal (Hypothesis 1b). As demonstrated in Section 3.3, the noise, by construction, is orthogonal to the investment opportunities of private firms. Therefore, regardless

[18] Also, all results hold if the industry valuation is constructed with pure-play public firms or with bellweather public firms which are the industry leaders. The results are also robust to how investment is measured.

of whether the unobserved investment opportunities are omitted, a positive investment-to-noise sensitivity can only be obtained under the "Learning" scenario. To implement, I estimate Equation (3) using my noise measure based on the industry leaders' *unrelated* minor-segment industry valuation. The results are reported in Table 4.

[TABLE 4 ABOUT HERE]

As shown in column 1 of Table 4, the evidence supports the learning mechanism. Specifically, I find that the investment of private firms in the industry leaders' major-segment industry reacts positively and significantly to the price noise originating from the valuation of industry leaders' unrelated minor-segment industries: A one standard deviation increase in unrelated minor-segment industry valuation is associated with a 0.82% increase in capital expenditure (scaled by the beginning-of-year capital) of private firms in the major segments ($\beta \times SD(Minor\_Industry\_q) = 0.022 \times 0.373 = 0.82\%$), about 4% of the average investment-to-capital ratio. The results are obtained after controlling for the unobserved time-varying shocks common to all firms (by using year fixed effects), the unobserved heterogeneity at the firm level (by using firm fixed effects), and an extended set of firm and industry controls that may affect investment. In addition, I control for the component of the industry valuation that relates to the major-segment industry, $Major\_\bar{q}_{i,t-1}$. As expected, this fundamental component is positively associated with the investment of private firms. Its economic magnitude is larger than that of the response to noise and comparable to that of the overall industry valuation.[19]

To further alleviate the possibility that minor-segment industries affect the investment of private firms in the major-segment industry through channels other than stock prices, I also control for the characteristics of the minor-segment industries and major-segment industries separately, where major-industry characteristics are obtained by operating the same decom-

[19] A one standard deviation increase in the fundamental component is associated with a 1.5% increase in capital expenditure of private firms ($\gamma \times SD(Major\_\bar{q}) = 0.023 \times 0.657 = 1.5\%$).

position as for the valuation variable.[20] As shown in column 2 of Table 4, the investment-to-noise sensitivity is not affected.

4.3 Robustness tests

I conduct a number of robustness checks in this section. First, I use an alternative measure for the price noise. My main noise measure includes all public firms in the unrelated minor-segment industries to construct the industry valuation, as long as they do not have any minor segment related to the major-segment industry (in case they do, the entire minor-segment industry is removed from the measure). This follows the notion that industry average valuation provides a consistent estimate of the common shock for the industry and the work by Hou (2007) and Cen et al. (2013) that the stock prices of industry leaders incorporate fundamental information relatively quickly as they are closely watched by analysts and other sophisticated market participants. As a robustness test, I construct an alternative noise measure, namely "unrelated minor-segment industry pure-play valuation" ($Minor\_PurePlay\_q$), using only pure-play public firms in each unrelated minor-segment industry to construct industry valuation. As in columns 3 and 4 of Table 4, I find consistent results with this alternative noise measure: A one standard deviation increase in this alternative noise measure is associated with a 0.92% increase in capital expenditure of private firms in the major segments ($\beta \times SD(Minor\_PurePlay\_q) = 0.020 \times 0.458 = 0.92\%$), which is comparable to the economic magnitude estimated with the main noise measure.

Second, I perform additional screenings to ensure that the results I obtained are, to a large extent, from unrelated minor-segment industries. One may argue that some minor-segment

[20] Specifically, for each control variable (such as lagged cash flow, size, sales growth, and leverage), I regress their average value across firms in the major-segment industry on the average value across the minor-segment industries. I then take the sum of residual and fixed effects as the proxy for the major industry characteristic.

industries could still relate to the major industry. This concern is likely far-fetched because minor-segment industries proximate to or potentially share vertical relationships with the major industry have already been excluded. Also, if the remaining minor-segment industries were to capture fundamental information of the major industry, we would observe it to be associated with the cash flows or investments in the major segments. Nonetheless, I remove economic ties that may not be observable by excluding minor-segment industries in which private firms also have operations. I retrieve the secondary SIC codes of private firms from FAME, exclude all common industries shared by private firms and public industry leaders, and repeat the tests in Section 4.2. The results are presented in Table 5.

[TABLE 5 ABOUT HERE]

I find consistent results using both noise measures, $Minor\_Industry\_q$ (columns 1 and 2 of Table 5) and $Minor\_PurePlay\_q$ (column 3 and 4 of Table 5). The findings again support the prediction that private firms learn from the stock prices and cannot filter out the noise from the industry valuation.

4.4 Firm heterogeneity in the ability to filter noise

In this section, I examine the heterogeneity across firms in their ability to filter out the noise (Hypothesis 2). While private firms, on average, cannot perfectly distinguish the noise component from the overall valuation signal, the fact that their reaction to the noise is to a lesser extent than that to the overall industry valuation implies that (some) private firms are capable of doing so.[21] I hypothesize that institutional investors, such as private equity firms, insurance companies, and banks, are better informed and less attention constrained than individuals.

[21] Also, I show in Section 5.3.1 that industry leaders do not adjust their major-segment investment in response to the minor-segment industry valuation, consistent with the notion that they are better informed.

They often have their in-house information production and are better able to scrutinize the information in the stock market. In turn, private firms held by financial institutions should respond less to the noise relative to firms without institutional holdings.

I define a dummy variable, $Inst.\ Shareholder$, which equals 1 if the private firm has one or more institutional shareholders at any point in time and 0 otherwise. I estimate Equation (3) with this variable and its interaction with the noise, controlling for the proxy for major-segment industry valuation, its interaction with the institutional shareholder dummy, as well as the full set of firm and industry controls. The results are reported in Table 6.

[TABLE 6 ABOUT HERE]

Private firms with one or more institutional investors account for 20% of the full sample. As shown in Table 6, they react significantly less to the noise.[22] The median private firm, however, does not have any institutional shareholders (see Panel A of Table 1). They are more difficult to precisely estimate the noise component *ex ante* and therefore, present a more pronounced investment-to-noise sensitivity.

My findings suggest that when agents learn from the stock prices, whether a positive association between investment and noise could be observed depends on the agents' ability to filter the noise out. This notion can reconcile the findings that mispricing does not affect investments (Morck et al. 1990 and Bakke and Whited 2010) with the literature that finds mispricing to have real effects. Essentially, the same prediction and test strategy can be applied to mispricing measures used in various contexts.[23] Whether they have any real effect through learning depends on the agent's ability to filter them out.

[22]The results are robust if I define the shareholder types based on the ultimate owner or in a given year.

[23]These measures may include subsequent stock returns (Baker et al., 2003 and Polk and Sapienza, 2009), valuation residuals (Rhodes-Kropf et al., 2005), price pressure caused by mutual fund fire sales (Coval and Stafford, 2007; Edmans et al., 2012; Dessaint et al., 2018), and sentiment indices.

4.5 Persistence of the real effect

I further examine whether firms realize *ex post* that they conditioned on noise and whether they learn from their mistakes. In a related context, Dessaint et al. (2018) show that public firms operate a correction in subsequent periods after transient, nonfundamental shocks to stock prices. Following this line of investigation, I perform a dynamic analysis to study the persistence of the effect of noise on private firms' investment.

I look at firms without institutional shareholders, as these firms incur the mistake in the first place. I estimate Equation (3) with lagged values of $Minor\_q_{t-1}$ (namely, $Minor\_q_{t-2}$, $Minor\_q_{t-3}$, and $Minor\_q_{t-4}$), as well as the contemporaneous value ($Minor\_q$). To better assess the dynamics of private firms' investment, I also include lagged and contemporaneous values of $Major\_\bar{q}_{t-1}$ and standardize all the coefficients by multiplying the corresponding standard deviation. Point estimates and 95% confidence intervals are displayed in Figure 1.

[Figure 1 ABOUT HERE]

Consistent with the findings so far, private firms' investment in year t responds positively and significantly to the noise measured by the valuation of unrelated minor-segment industries in year $t-1$. Similar to the pattern documented in Dessaint et al. (2018), firms respond *negatively* to the noise in year $t-2$, which implies that some firms realize that their responses were partly due to movements unrelated to their investment opportunities (maybe after observing realizations of cash flows to the major segment) and attempt to correct the mistake. However, compared to public firms' corrections to non-fundamental shocks in Dessaint et al. (2018), the corrections made by private firms are both smaller in magnitude and weaker in statistical significance (only half of the impact of noise is corrected and is insignificant at 10%).

There are two possible explanations for why the real effect of noise on private firms is more persistent. First, unlike their public peers whose managers care about stock prices for their shareholders' interest or their own compensation, private firm managers' day-to-day operations do not involve stock prices (that is, except for the need to learn from prices). Therefore, they naturally lack the attention and expertise to fully understand the information contained in stock prices, especially if they do not have any institutional shareholders. Second, the noise I adopt depends less on the mis-valuation of public firms and hence is not normally accompanied by a notable price reverse (which is often the case for mispricing). This feature makes it more challenging for managers to completely correct the investment in subsequent periods.

Taken together, the evidence I show suggests that private firms rely on stock prices as an important source of information for real decisions. Upon observing the price movements of public firms in the same industry, private firms adjust their investment in the same direction. Doing so is *ex ante* more efficient than ignoring it because stock prices can inform about common shocks. Since the price signals are noisy, the first-best scenario for private firms would be to filter out the noise and only react to the fundamental component. However, I show that the vast majority of private firms are not able to do so. For them, an inevitable consequence when managers (rationally) learn from noisy price signals is that they make investment decisions in response to noise, which compromises real efficiency from an *ex post* perspective. I present further evidence suggesting that these mistakes can be reduced if decision-makers possess more sophisticated knowledge about the stock market and are partially corrected in the subsequent year after observing realizations of fundamentals.

5 Additional Evidence

To further validate that the evidence is consistent with learning, this section examines the cross-sectional predictions with respect to price informativeness (Hypothesis 3) and the industry competition structure (Hypothesis 4). Alternative mechanisms are also addressed.

5.1 Cross-sectional tests on price informativeness

I use three measures for the industry price informativeness. The first is the industry price non-synchronicity. Under the learning framework, stock prices are more informative if they synchronize less with the market. As is standard in the literature (cf. Durnev et al., 2004; Chen et al., 2007), I first construct price non-synchronicity for individual prices as $1 - R^2_{i,t}$ in each year, where $R^2_{i,t}$ is obtained by regressing public firm i's weekly stock returns on the market portfolio returns and the industry portfolio returns. Following Foucault and Frésard (2014), I then construct the industry non-synchronicity by taking the average of the price non-synchronicity of all public firms in a three-digit SIC industry in a given year. I define a dummy $H\_Nonsynchronisity$, which equals 1 if the industry non-synchronicity is above the 70th percentile in that year, and equals 0 if it is below the 30th percentile.[24]

The second measure is based on the number of *public* firms in the industry. Under the learning framework, each individual stock price can be considered as a noisy signal about the common and idiosyncratic shocks. With a higher number of public firms in the industry, the industry valuation will be more informative about common shocks because idiosyncratic shocks will be more likely to be canceled out, and also, the noise of the industry valuation will be less volatile.[25]. Also, as in Chemmanur et al. (2010), the more firms that are already listed in an industry, the easier it is for outsiders, such as unsophisticated investors, sophisticated investors, financial analysts and market makers, to evaluate firms in that industry. Therefore, I use a dummy $H\_\#Public$, which equals 1 if the logarithm of 1 plus the number of public firms in the industry is above the 70th percentile and equals 0 if it is below the 30th percentile.

Finally, I use $H\_\%Public$, a dummy based on the fraction of public firms in a three-digit SIC industry, as the third measure for price informativeness. Badertscher et al. (2013) argue that

[24] This is for easier interpretations. The results are robust if I use the continuous variable.

[25] The derivation of this prediction (i.e., $\frac{\partial \sigma^2_{\bar{\omega}}}{\partial N} < 0$) is shown in Formula IA.10 of the Internet Appendix.

a high fraction of public firms indicates a more transparent information environment of the industry. While they use the measure to show that financial statements of public firms reduce information uncertainty for all firms in the industry, the cross-sectional prediction also applies here when examining the effect of stock prices beyond what public information provides.

[TABLE 7 ABOUT HERE]

As shown in columns 1, 3, and 5 of Table 7, the interaction terms of industry valuation and informativeness measures are positive and significant across all specifications. The results are consistent with Hypothesis 2, that in industries where the stock prices are more informative about future fundamentals, private firms' investment responds more to the industry. Moreover, I show that when firms are not likely to filter out the noise, these industries also present a higher investment-to-noise sensitivity (see columns 2, 4, and 6 of Table 7).

5.2 Cross-sectional tests on common shocks

To test whether the sensitivity of private firms' investment to the industry valuation is stronger when common (demand or cost) shocks are more important to firms relative to firm-specific shocks, I use three measures for how likely firms in the same industry are to face common shocks: (i) $H\_\#Firms$, which is a dummy equal to 1 if the logarithm of 1 plus the number of all firms of the industry is above the 70th percentile and equal to 0 if it is below the 30th percentile; (ii) L_HHI, which is a dummy equal to 1 if the Herfindahl-Hirschman Index in a three-digit SIC industry is below the 30th percentile and equal to 0 if it is above the 70th percentile; and (iii) L_Top4_Shares, which is a dummy equal to 1 if the market share of the top four firms in a three-digit SIC industry is below the 30th percentile and equal to 0 if it is above the 70th percentile. I adopt these commonly used competition measures in the empirical industrial organization literature because, in competitive industries, cost reductions and demand surges are more likely to be common across all firms in the same industry (see Giroud and Mueller, 2011; among others).

[TABLE 8 ABOUT HERE]

As shown in columns 1, 3, and 5 of Table 8, the interaction terms of industry valuation and competitiveness measures are positive and significant across all specifications. The results support the prediction that private firms' investment responds more to the industry valuation when they are more likely to face common shocks. Furthermore, consistent with Hypothesis 3, when firms are not likely to filter out the noise, these industries also present a higher investment-to-noise sensitivity (see columns 2, 4, and 6 of Table 8).

5.3 Alternative hypothesis

5.3.1 Market competition and internal allocation within industry leaders

Alternative to the learning mechanism, it may be argued that market competition between public firms and private firms may generate the investment-valuation relationship. However, this explanation is not supported by the data for several reasons. First, since the results I obtained are after controlling for the investment of public firms and private firms, the effect of the stock price on private firms' investment goes beyond its influence through peer firms' investment. Second, the optimal response of private firms to competition pressure depends on the competition structure. Under Cournot competition, the sensitivity of private firms' investment to industry valuation is expected to be negative, which contradicts the findings up to now. Third, the competition argument predicts that the effect is stronger for concentrated industries in which strategic behaviors are more predominant, which is the opposite of the findings in Section 5.2. Finally, market competition cannot explain why private firms' investment reacts to the valuation of industry leaders' unrelated minor-segment industries. Therefore, it is unlikely for competition to explain the results in this paper.

It may still be argued that industry leaders may allocate resources towards or out of the major segment when the unrelated minor-segment industries are experiencing high valuation shocks.[26] If this is the case, private firms in the major-segment industry may adjust their investment in expectation of any investment (or disinvestment) by the industry leaders in the major-segment industry. However, it is unclear whether this alternative mechanism predicts a positive or negative relationship between private firms' investment and their industry leaders' minor-segment valuation as the prediction depends on the competition structure.[27] Nonetheless, I address this concern by directly testing whether there is indeed any internal allocation among the segments of industry leaders.

I obtain segment-level financial information for public firms from Worldscope and examine whether the investment in industry leaders' major segment is affected by the valuation of their unrelated minor-segment industries. As shown in Table 9, I observe no such relationship.

[TABLE 9 ABOUT HERE]

These findings suggest that the internal allocation view cannot explain the responses of private firms in the major industry to noise because industry leaders do not allocate resources across their major and minor segments. This is not surprising. Theory predicts internal allocation to be more likely if the firm is financially constrained (see Giroud and Mueller, 2015 for a summary of theory and evidence). Industry leaders are at the top of the pyramid to obtain financing and thus rely less on the internal capital market to finance their major-segment investment. Moreover, the results confirm that the set of unrelated minor-segment industries

[26] The direction of the allocation depends on the financial deficit of the minor segments and the competition environments in which the conglomerate derives its optimal policy.

[27] To fit the evidence, one has to assume industry leaders' major segment receives an inflow (outflow) following an increase in the unrelated minor-segment valuation and Bertrand (Cournot) competition.

that I end up with do not co-move with the major-segment industry in fundamentals. The findings also suggest that public firms, especially public industry leaders, are better informed of the valuation of their minor-segment industries and are better able to filter out the noise.

5.3.2 Sentiment and cost of capital

Another possible channel for the minor-segment valuation to affect private firms' investment is through the sentiment of financiers (most likely banks) and the effective cost of capital. When minor-segment industry valuation goes up, banks paying attention to the industry valuation may also have a more positive sentiment towards lending to private firms in the major industry. In such a case, cheaper external financing allows private firms to invest even when these firms do not learn any new investment opportunities from the stock market.[28]

To address this concern, I rely on the predictions of Stein (1996) in the context of equity market sentiment. The model in Stein (1996) implies that the investment made by financially constrained firms will be more sensitive to market sentiment, as they need external financing to fund the marginal project that would be less likely to proceed under unfavorable market conditions. This is indeed how Baker et al. (2003) examine whether market sentiment affects the effective cost of equity of public firms. Following these earlier works, I test whether the responses of private firms to the noise are predominantly from financially constrained firms. I use size, dividend payout, and the Whited-Wu Index as classification schemes for financial constraints of private firms, and consider small firms, firms that do not pay dividends, and firms that have high indices as financially constrained firms.[29]

[28]Note that the cost of capital may be affected by the industry valuation through a demand channel, that is, if the firm perceives an investment opportunity as the industry valuation increases and successfully obtain financing from the bank. I do not consider this to be an alternative to the learning channel.

[29]I obtain similar results when using the Hadlock-Pierce Index to classify financially constrained firms. The results are suppressed due to space limitations.

[TABLE 10 ABOUT HERE]

As presented in Table 10, financially constrained firms do not react more to the noise than the rest of the firms, which suggests that the results are not fully driven by sentiment-induced cost of capital in the absence of learning.

6 Conclusion

Whether the stock market affects real efficiency through its role of producing and aggregating information has long been one of the interests of finance studies. In this paper, I hypothesize and test the idea that private firms learn from the stock prices of public firms about common shocks. Using data for the United Kingdom, I find that private firms' investment responds positively to the valuation of public firms in the same industry, as well as "noise" in the price signal measured by the valuation of public industry leaders' unrelated minor-segment industries

By exploring the unique feature of private firms and the noise that does not capture private firms' investment opportunities, my results plausibly establish that private firms learn from prices about new information relevant to their real decisions. Moreover, since private firms are less subject to agency-related incentives, their investment responses are more likely to result from value-maximizing actions that increase real efficiency. To this end, my paper provides concrete evidence that the efficiency of the stock price goes beyond the traditional sense to accurately forecast the future value of firms (known as Forecasting Price Efficiency, or FPE) and, more importantly, lies in its extent to reveal information that is useful for the efficiency of real decisions (known as Revelatory Price Efficiency, or RPE, as defined in Bond et al. 2012).

Also, the findings I document shed light on the potential economic importance of the real effects of stock prices. Private firms account for a substantial fraction of the economy globally.

They represent more than 90% of all incorporated entities and around 60% of aggregate sales in the United States (Asker et al. 2014) and the United Kingdom (by my estimates). By showing that they rely on stock prices to steer their real decisions even without listing their shares, my paper suggests that price efficiency matters to the real efficiency of a larger part of the economy that has not received much attention.

Furthermore, as stated in Hayek (1945), “the price system is just one of those formations which man has learned to use (though he is still very far from having learned to make the best use of it) after he had stumbled upon it without understanding it.” This description resembles the learning behavior of private firms. I show that while private firms benefit from new information from stock prices, when their managers cannot perfectly distinguish the noise from relevant information, their investment may respond to the noise in the price signal, resulting in real inefficiency in an *ex post* sense. I further show that these mistakes are partially corrected in the subsequent year after observing realizations of fundamentals and can be avoided if decision-makers possess more sophisticated knowledge about the stock market.

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Appendix A Variable Definitions

In this appendix, I discuss the definitions of the main variables. All definitions coincide with line items in corporate balance sheets, profit and loss (P&L) accounts, and the cash flow statement in the FAME database or other studies utilizing the FAME database.

A.1 Firm-level variables

$\mathbf{Total\ Assets}$ is the balance sheet item Total Assets in 2005 constant million pounds;

$\mathbf{K}$ (capital) is the balance sheet item Fixed Asset reported in 2005 constant million pounds, which is the sum of the tangible asset and the intangible asset;

$\mathbf{Capx/K}$ is the cash flow statement item Capital Expenditures scaled by the beginning-of-period capital;

$\mathbf{Major\_Capx/K}$ is Capital Expenditures from the firm's major segment scaled by its capital at the beginning of period, where major (minor) segments are the two-digit SIC industry in which the firm generates more (less) than 50% of its total sales;

$\mathbf{\Delta K}$ is the annual change of capital scaled by the beginning-of-period capital;

$\mathbf{Ln(Asset)}$ is the logarithm of Total Assets;

$\mathbf{Cash\ Flow}$ is the sum of the profit & loss account items Profit (Loss) for the Period and Depreciation scaled by the beginning-of-period Total Assets;

$\mathbf{\Delta Sales}$ is the annual change of sales scaled by the beginning-of-period Total Assets, where sales correspond to the profit & loss account item Turnover;

$\mathbf{\Delta Cash}$ is the annual change of cash holdings scaled by the beginning-of-period Total Assets, where cash holdings are the sum of Bank & Deposits and Investment;

$\mathbf{Tangibility}$ is the sum of Land & Buildings, Fixtures & Fittings, and Plant & Vehicles, scaled by the beginning-of-period Total Assets;

$\mathbf{Leverage}$ is Book Debt plus Trade Creditors, scaled by the beginning Total Assets;

$\#\ \mathbf{Inst.\ Shareholders}$ is the number of institutional shareholders. A shareholder is classified as an institutional shareholder if their type in FAME is “Bank,” “Financial company,” “Insurance company,” “Mutual & Pension fund,” “Trust,” or “Private equity firms;”

$\mathbf{Market\text{-}to\text{-}book}$ for public firms is defined as $($Total Assets $-$ Book Equity $+$ stock price at the end of the fiscal year $\times$ number of shares outstanding$)/$Total Assets;

$\mathbf{Own}\ q$ for public firms is the firm's own beginning-of-period *Market-to-book*;

$\mathbf{FC\_Size}$ is a dummy that equals 1 if the firm's total asset ranks below the bottom 30th percentile among all private firms in the three-digit SIC industry in a given year and 0 otherwise;

FC_Dividend is a dummy that equals 1 if the firm does not pay any dividend in the year and 0 if the firm's dividend payout is positive;

FC_WW is a dummy that equals 1 if the Whited-Wu Index is above the top 30th percentile among all private firms in the three-digit SIC industry in a given year and 0 otherwise;

FC_HP is a dummy that equals 1 if the Hadlock-Pierce Index is above the top 30th percentile among all private firms in the three-digit SIC industry in a given year and 0 otherwise;

A.2 Industry-level variables

Industry q is the equal-weighted average of the beginning-of-period *Market-to-book* of public firms in a three-digit SIC industry;

Industry Median q is the median of the beginning-of-period *Market-to-book* of public firms in a three-digit SIC industry;

Minor Industry q is the average beginning-of-period *Market-to-book* of all firms in the *unrelated* minor-segment industries;

Minor PurePlay q is the average beginning-of-period *Market-to-book* of all pure play firms in the *unrelated* minor-segment industries;

Major Industry q is the proxy for the major-segment industry valuation obtained from decomposing the industry valuation in Section 3.3.3;

Nonsynchronisity is the $1 - R^2$ from running weekly firm return on the market return and three-digit SIC industry return and then average across firms in the same industry-year;

$\#$ **Public** is the logarithm of 1 plus the number of public firms in a industry;

$\%$ **Public** is the fraction of number of public firms to all firms in a three-digit SIC industry;

$\#$ **Firms** is the logarithm of 1 plus the number of all firms in a three-digit SIC industry;

HHI is the Herfindahl-Hirschman Index of a three-digit SIC industry calculated as the sum of squared market shares;

Top4 Share is the market share of the top four firms in a three-digit SIC industry;

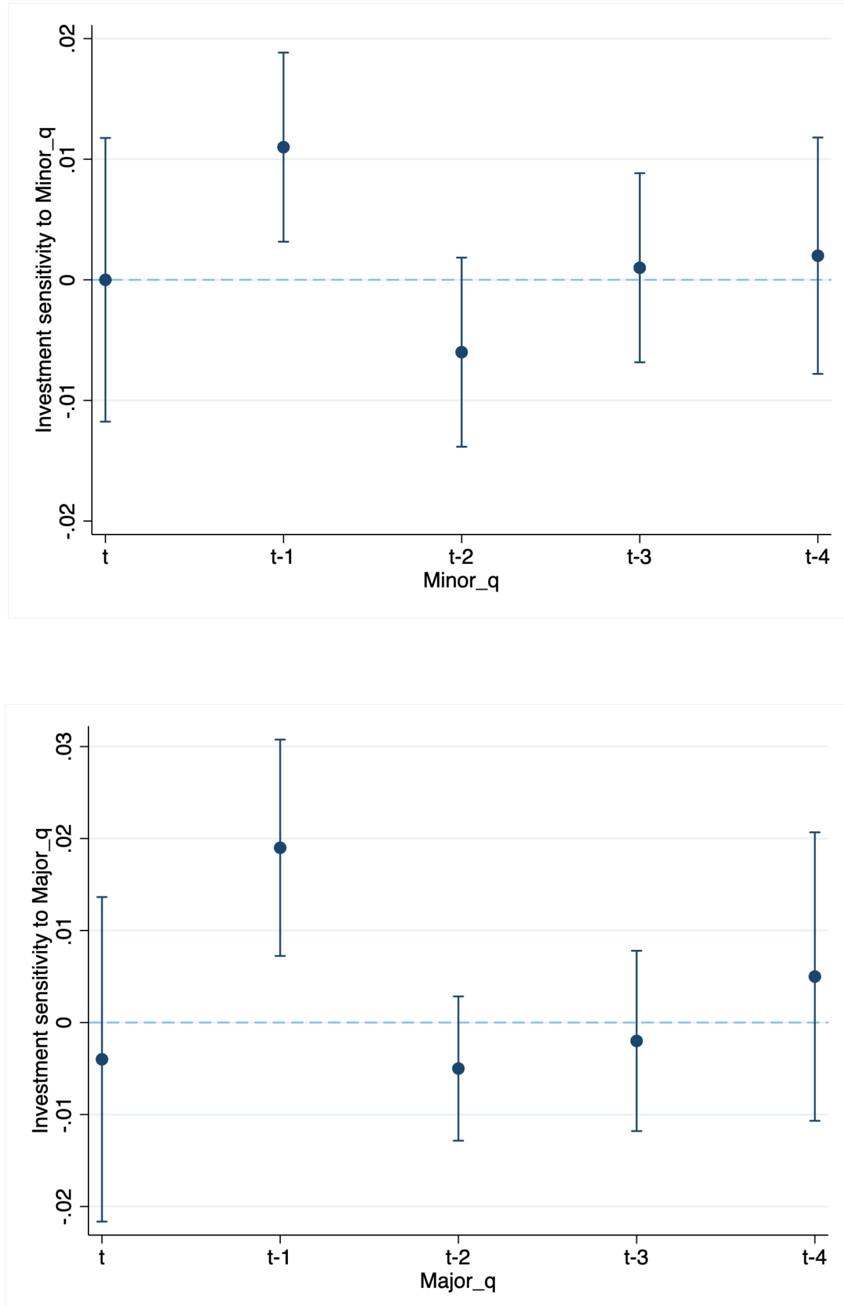

Figure 1. Sensitivity of private firms' investment to the noise and the fundamental components This figure presents the *standardized* regression coefficients from estimating Equation (3) with leads and lags. The upper panel displays the estimates for the noise, $Minor\_q_{t-1}$ and its lead and lags. The lower panel does so for the fundamental component $Major\_\bar{q}_{t-1}$ and its lead and lags. 95% confidence interval for each estimate is presented.

Table 1. Summary statistics: firms

This table reports the descriptive statistics of the main firm-level variables from 1993 to 2010. Statistics for private firms are presented in Panel A and public firms in Panel B. All variables are defined in Appendix A. The accounting variables are from the FAME database. The stock prices used to calculate public firms' q are from Worldscope. The sample is restricted to consolidated financial statements of limited liability companies to which the Companies Act applies. I exclude the small firms as defined by the Companies House and firm-year observations that do not satisfy the auditing requirements. I also exclude financial firms (US SIC code 6000-6900), utilities (US SIC code 4900-4999), public sector firms (US SIC code above 8999), and any observation that has a missing book value of asset, sales, or shareholders' equity. I further require that each firm should have 5 consecutive years of data. All pound values are converted to 2005 constant million pounds using the UK consumer price index from the WDI. Ratios are winsorized separately for public and private firms at the 1% level at both tails.

Panel A. Private Firms

	Observations	Mean	Median	SD
$Capx/K$	69,962	0.216	0.095	0.453
ΔK	109,154	0.119	–0.018	0.676
Ln(Asset)	110,292	2.720	2.506	1.487
Cash Flow	110,114	0.055	0.051	0.134
ΔSales	110,294	0.114	0.045	0.570
ΔCash	99,573	0.013	0.000	0.110
Tangibility	108,722	0.276	0.215	0.237
Leverage	106,295	0.392	0.371	0.266
Equity Issue	109,454	0.046	–0.003	0.513
Debt Issue	109,512	0.058	0.000	1.500
# Inst. Shareholders	108,860	0.658	0.000	1.609

Panel B. Public Firms

	Observations	Mean	Median	SD
$Capx/K$	12,177	0.174	0.100	0.242
ΔK	12,177	0.267	0.025	0.978
Ln(Asset)	12,178	4.563	4.313	2.053
Cash Flow	12,177	0.074	0.081	0.149
ΔSales	12,178	0.132	0.059	0.425
ΔCash	12,146	0.019	0.001	0.139
Tangibility	12,178	0.277	0.228	0.232
Leverage	12,158	0.322	0.305	0.198
Equity Issue	12,177	0.280	–0.001	1.558
Debt Issue	12,177	0.084	0.000	0.587
# Inst. Shareholders	11,987	1.809	32.000	26.375
Own q	11,480	1.809	1.425	1.245

Table 2. Summary statistics: industries

This table reports the descriptive statistics of the industry-level variables used in the analysis. The sample period is from 1993 to 2010. All variables are defined in Appendix A. Detailed steps for constructing the noise measures, *Minor Industry q* and *Minor PurePlay q* are discussed in Section 3.3.2. The fundamental component, *Major Industry* $\bar{q}$, is estimated in Section 3.3.3. The main industry code is the three-digit SIC. The accounting variables for public and private firms are from the FAME database. The stock prices used to calculate the industry market-to-book valuations are from the Worldscope database. The product segment industry codes and product segment financials of public firms are from Worldscope, and the secondary industry codes of private firms are from FAME. I follow the same sample screening process as described in Table 1. All pound values are converted to 2005 constant million pounds using the UK consumer price index from the WDI. Reported statistics include the number of industry-year observations, mean, median, and standard deviation (SD).

	Observations	Mean	Median	SD
Industry q	2,126	1.639	1.501	0.635
Industry Median q	2,126	1.483	1.368	0.561
Minor Industry q	1,355	1.748	1.704	0.373
Major Industry $\bar{q}$	1,355	0.000	–0.150	0.657
Minor PurePlay q	1,351	1.696	1.615	0.458
# Public	2,126	1.801	1.609	0.642
% Public	2,126	0.202	0.154	0.176
Nonsynchronicity	2,126	0.648	0.670	0.162
# Firms	2,126	3.585	3.526	0.983
HHI	2,126	0.224	0.156	0.198
Top4 Share	2,126	0.691	0.719	0.217

Table 3. Industry valuation and private firms' investment

This table presents the results from estimating Equation (1) for private firms as shown below:

$$I_{i,t} = \alpha + \beta \times Industry\_q_{i,t-1} + \lambda \times X_{i,t-1} + \theta \times Industry\_X_{i,t-1} + \kappa_i + \delta_t + \epsilon_{i,t}$$

The dependent variable investment, $I_{i,t}$, is measured by $Capx/K$, which is capital expenditures scaled by the beginning-of-period capital. The main independent variable, $Industry\_q_{i,t-1}$, in columns 1 and 2 is the equal-weighted average of the beginning-of-period (equivalently, end of year $t-1$) market-to-book ratio of public firms in the three-digit SIC industry to which the private firm belongs, and in columns 3 and 4 is the median value. All columns control for private firms' own lagged $CashFlow$ and $Ln(Asset)$, and the average lagged $CashFlow$ and $Ln(Asset)$ of all private and public peers. Columns 2 and 4 further control for an extended set of lagged firm and industry characteristics (such as sales growth and leverage), lagged industry valuation, as well as peer firms' average contemporaneous investments. All variable constructions are described in Appendix A. All regression models are estimated with firm-fixed effects and year-fixed effects. Since the main right-hand-side variable is at the three-digit SIC industry level, t-statistics in parentheses are adjusted using the Huber-White estimator allowing within industry clusters. Coefficients significant at the 10%, 5%, and 1% levels are marked with *, **, and ***, respectively.

Dependent variable:	$Capx/K$	$Capx/K$	$Capx/K$	$Capx/K$
	(1)	(2)	(3)	(4)
Industry q	0.023***	0.024***		
	(3.11)	(3.03)		
Industry Median q			0.027***	0.027***
			(4.06)	(3.62)
Cash Flow	0.625***	0.518***	0.625***	0.518***
	(18.03)	(15.14)	(18.02)	(15.15)
Ln(Asset)	–0.159***	–0.159***	–0.159***	–0.159***
	(–13.87)	(–12.34)	(–13.87)	(–12.33)
Year FE & Firm FE	Yes	Yes	Yes	Yes
Industry Characteristics	Yes	Yes	Yes	Yes
Extended Characteristics	No	Yes	No	Yes
$Adj.R^2$	0.216	0.224	0.216	0.224
Obs.	64,392	52,904	64,392	62,904

Table 4. Minor-segment industry valuation and private firms' investment

This table presents the results from estimating Equation (3) for private firms as shown below:

$$I_{i,t} = \alpha + \beta \times Minor\_q_{i,t-1} + \gamma \times Major\_\bar{q}_{i,t-1} + \lambda \times X_{i,t-1} + \theta \times Industry\_X_{i,t-1} + \kappa_i + \delta_t + \epsilon_{i,t}$$

The dependent variable is $Capx/K$. The primary independent variable $Minor\_q_{i,t-1}$ in columns 1 and 2 is *Minor Industry q*, which is the average beginning-of-period (equivalently, end of year $t-1$) market-to-book of all public firms in the *unrelated* minor-segment industries, and in columns 3 and 4 is *Minor PurePlay q*, which only includes pure-play public firms in each unrelated minor-segment industry. To ensure private firms do not share economic links with the minor-segment industries, I exclude minor-segment industries within the same one-digit SIC industry as the major industry, industries that potentially have supplier or customer relationships with the major industry, and industries whose leaders have a minor segment in the major industry. I also exclude a private firm if it shares one or more minor-segment industries with its industry leaders. For all regressions, I control for a proxy for the major-segment industry valuation obtained from decomposing the industry valuation in Section 3.3.3 (*Major Industry* $\bar{q}$), as well as the full set of firm and industry controls used in Table 3. In columns 2 and 4, I control for minor-segment industry characteristics by operating a decomposition for the industry characteristics. All variable constructions are described in Appendix A. All regression models are estimated with firm-fixed effects and year-fixed effects. t-statistics in parentheses are adjusted allowing within industry clusters. Coefficients significant at the 10%, 5%, and 1% levels are marked with *, **, and ***, respectively.

Dependent variable:	$Capx/K$	$Capx/K$	$Capx/K$	$Capx/K$
	(1)	(2)	(3)	(4)
Minor Industry q	0.022***	0.023***		
	(3.01)	(2.87)		
Minor PurePlay q			0.020***	0.021***
			(3.80)	(3.55)
Major Industry $\bar{q}$	0.023***	0.023***	0.023**	0.022**
	(2.73)	(2.70)	(2.61)	(2.60)
Cash Flow	0.515***	0.513***	0.517***	0.515***
	(12.00)	(11.85)	(11.99)	(11.85)
Ln(Asset)	–0.152***	–0.154***	–0.153***	–0.155***
	(–9.81)	(–9.67)	(–9.69)	(–9.54)
Year FE & Firm FE	Yes	Yes	Yes	Yes
Industry Characteristics	Yes	Yes	Yes	Yes
Extended Characteristics	Yes	Yes	Yes	Yes
Minor Industry Controls	No	Yes	No	Yes
$Adj.R^2$	0.216	0.213	0.216	0.213
Obs.	37,012	36,628	36,915	36,531

Table 5. Robustness tests: minor-segment industry valuation

This table presents the robustness tests from estimating Equation (3) for private firms as shown below:

$$I_{i,t} = \alpha + \beta \times Minor\_q_{i,t-1} + \gamma \times Major\_\bar{q}_{i,t-1} + \lambda \times X_{i,t-1} + \theta \times Industry\_X_{i,t-1} + \kappa_i + \delta_t + \epsilon_{i,t}$$

All the regression specifications follow that in Table 4. To further remove potential economic links, on top of the screenings done in Table 4, I also exclude minor-segment industries shared by industry leaders and private firms in the industry leaders' major-segment industries. All regressions control for the component of the industry valuation that relates to the major-segment industry, $Major\_\bar{q}$, as well as the full set of firm and industry controls used in Table 3. In columns 2 and 4, I control for minor-segment industry characteristics by operating a similar decomposition for the industry characteristics. Minor segments of private firms are classified by the secondary SIC industries reported in FAME. All variable constructions are described in Appendix A. All regression models are estimated with firm-fixed effects and year-fixed effects. t-statistics in parentheses are adjusted allowing within industry clusters. Coefficients significant at the 10%, 5%, and 1% levels are marked with *, **, and ***, respectively.

Dependent variable:	$Capx/K$	$Capx/K$	$Capx/K$	$Capx/K$
	(1)	(2)	(3)	(4)
Minor Industry q	0.013**	0.011**		
	(2.31)	(2.03)		
Minor PurePlay q			0.013**	0.015***
			(2.62)	(2.90)
Major Industry $\bar{q}$	0.023***	0.022***	0.022***	0.022***
	(2.77)	(2.73)	(2.64)	(2.62)
Cash Flow	0.518***	0.514***	0.520***	0.516***
	(11.89)	(11.78)	(11.90)	(11.79)
Ln(Asset)	–0.164***	–0.166***	–0.164***	–0.167***
	(–13.61)	(–13.35)	(–13.42)	(–13.15)
Year FE & Firm FE	Yes	Yes	Yes	Yes
Industry Characteristics	Yes	Yes	Yes	Yes
Extended Characteristics	Yes	Yes	Yes	Yes
Minor-Industry Controls	No	Yes	No	Yes
$Adj.R^2$	0.222	0.219	0.222	0.219
Obs.	34,873	34,489	34,776	34,392

Table 6. Firm heterogeneity in the ability to filter out the noise

This table presents the results from estimating Equation (3) for private firms, adding an interaction term of the noise with a dummy variable that indicates whether the private firm has one or more institutional shareholders at any point in time. Minor-segment screenings follow that in Table 4. All regressions control for the component of the industry valuation that relates to the major-segment industry, $Major\_\bar{q}$, its interaction with the institutional shareholder dummy, as well as the full set of firm and industry controls. In columns 2 and 4, I control for minor-segment industry characteristics by operating a similar decomposition for the industry characteristics. All variable constructions are described in Appendix A. All regression models are estimated with firm-fixed effects and year-fixed effects. t-statistics in parentheses are adjusted allowing within industry clusters. Coefficients significant at the 10%, 5%, and 1% levels are marked with *, **, and ***, respectively.

Dependent variable:	$Capx/K$	$Capx/K$	$Capx/K$	$Capx/K$
	(1)	(2)	(3)	(4)
Minor Industry q	0.030***	0.031***		
	(3.76)	(3.62)		
... × Inst. Shareholder	–0.022***	–0.021**		
	(–2.64)	(–2.50)		
Minor PurePlay q			0.024***	0.026***
			(3.84)	(4.22)
... × Inst. Shareholder			–0.013*	–0.014**
			(–1.86)	(–1.99)
Major Industry $\bar{q}$	0.029***	0.029***	0.027***	0.027***
	(3.11)	(3.09)	(2.70)	(2.75)
... × Inst. Shareholder	–0.015	–0.016	–0.011	–0.011
	(–1.38)	(–1.49)	(–1.02)	(–1.06)
Cash Flow	0.515***	0.513***	0.517***	0.515***
	(11.99)	(11.84)	(11.99)	(11.84)
Ln(Asset)	–0.152***	–0.154***	–0.153***	–0.155***
	(–9.79)	(–9.65)	(–9.67)	(–9.52)
Year FE & Firm FE	Yes	Yes	Yes	Yes
Industry Characteristics	Yes	Yes	No	Yes
Extended Characteristics	Yes	Yes	Yes	Yes
Minor-Industry Controls	No	Yes	No	Yes
$Adj.R^2$	0.216	0.213	0.216	0.213
Obs.	37,012	36,628	36,915	36,531

Table 7. Private firms' investment and the informativeness of industry valuation

This table presents the heterogeneous responses with respect to informativeness of the industry valuation. Measures for informativeness include: (i) H_Nonsynchronisity, a dummy equals 1 (0) if the Non-synchronisity of a three-digit SIC industry is above (below) the 70th (30th) percentile; (ii) $H\_\#Public$, a dummy equals 1 (0) if the logarithm of 1 plus the number of public firms of the industry is above (below) the 70th (30th) percentile; and (iii) $\%Public$, a dummy equals 1 (0) if the fraction of public firms in a three-digit SIC industry is above (below) the 70th (30th) percentile. In Panel A, I estimate Equation (1) with informativeness at the beginning-of-period and its interaction with the industry valuation. In Panel B, I estimate Equation (3) with informativeness and it interactions with the noise and the fundamental components. I control for the full set of firm and industry controls. In Panel B, I further require the firm not to have an institutional shareholder when the informativeness dummies are set to 1, and I also control for minor-segment industry characteristics. Variable constructions are described in Appendix A. All regression models are estimated with firm-fixed effects and year-fixed effects. t-statistics in parentheses are adjusted allowing within industry clusters. Coefficients significant at the 10%, 5%, and 1% levels are marked with *, **, and ***, respectively.

Panel A: The response of private firms' investment to the industry valuation

Informativeness Measure:	$H\_Nonsynchronisity$		H_# Public		% Public	
Dependent variable:	$Capx/K$	$Capx/K$	$Capx/K$	$Capx/K$	$Capx/K$	$Capx/K$
	(1)	(2)	(3)	(4)	(5)	(6)
Industry q	0.012		0.012		0.005	
	(0.93)		(1.14)		(0.48)	
... × Informativeness	0.033**		0.052***		0.041**	
	(2.26)		(3.52)		(2.25)	
Industry Median q		0.008		0.017**		0.007
		(0.93)		(2.21)		(0.65)
... × Informativeness		0.038***		0.064***		0.042**
		(3.26)		(7.36)		(2.26)
Year FE & Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm & Industry Characteristics	Yes	Yes	Yes	Yes	Yes	Yes
Extended Characteristics	Yes	Yes	Yes	Yes	Yes	Yes
$Adj.R^2$	0.259	0.259	0.265	0.265	0.280	0.280
Obs.	29,977	29,977	30,015	30,015	17,504	17,504

Panel B: The response of private firms' investment to the noise

Informativeness Measure:	$H\_Nonsynchronisity$		H_# Public		% Public	
Dependent variable:	$Capx/K$	$Capx/K$	$Capx/K$	$Capx/K$	$Capx/K$	$Capx/K$
	(1)	(2)	(3)	(4)	(5)	(6)
Minor Industry q	–0.005		0.001		0.009	
	(–0.46)		(0.12)		(0.66)	
... × Informativeness	0.030***		0.022***		0.055**	
	(2.75)		(2.42)		(2.33)	
Minor PurePlay q		0.005		0.007		0.012
		(0.67)		(0.96)		(1.50)
... × Informativeness		0.013*		0.021**		0.036**
		(1.76)		(2.10)		(2.11)
Year FE & Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm & Industry Characteristics	Yes	Yes	Yes	Yes	Yes	Yes
Extended Characteristics	Yes	Yes	Yes	Yes	Yes	Yes
Minor-Industry Controls	Yes	Yes	Yes	Yes	Yes	Yes
$Adj.R^2$	0.234	0.234	0.231	0.231	0.231	0.229
Obs.	18,738	18,729	18,255	18,255	11,988	11,988

Table 8. Private firms' investment and industry common shocks

This table presents the heterogeneous responses with respect to industry competitiveness. Measures for competitiveness include: (i) $H\_\#Firms$, a dummy equals 1 (0) if the logarithm of 1 plus the number of all firms of the industry is above (below) the 70th (30th) percentile; (ii) L_HHI, a dummy equals 1 if HHI in a three-digit SIC industry is below (above) the 30th (70th) percentile; and (iii) L_Top4_Shares, a dummy equals 1 (0) if the market share of the top four firms in a three-digit SIC industry is below (above) the 30th (70th) percentile. In Panel A, I estimate Equation (1) with the competitiveness measure at the beginning-of-period and its interaction with the industry valuation. In Panel B, I estimate Equation (3) with competitiveness and it interactions with the noise and fundamental components. I control for the full set of firm and industry controls. In Panel B, I further require the firm not to have an institutional shareholder when the informativeness dummies are set to 1, and I control for minor-segment industry characteristics. Variable constructions are described in Appendix A. All regression models are estimated with firm-fixed effects and year-fixed effects. t-statistics in parentheses are adjusted allowing within industry clusters. Coefficients significant at the 10%, 5%, and 1% levels are marked with *, **, and ***, respectively.

Panel A: The response of private firms' investment to the industry valuation

Competitiveness Measure:	$H\_\#Firms$		L_HHI		L_Top4_Shares	
Dependent variable:	$Capx/K$	$Capx/K$	$Capx/K$	$Capx/K$	$Capx/K$	$Capx/K$
	(1)	(2)	(3)	(4)	(5)	(6)
Industry q	–0.008		0.012		0.012	
	(–0.68)		(1.12)		(1.11)	
... × Competitiveness	0.046***		0.041**		0.034**	
	(2.83)		(2.24)		(2.07)	
Industry Median q		–0.007		0.017*		0.015
		(–0.60)		(1.74)		(1.49)
... × Competitiveness		0.064***		0.042**		0.036**
		(4.66)		(2.31)		(2.23)
Year FE & Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm & Industry Characteristics	Yes	Yes	Yes	Yes	Yes	Yes
Extended Characteristics	Yes	Yes	Yes	Yes	Yes	Yes
$Adj.R^2$	0.261	0.261	0.266	0.228	0.256	0.256
Obs.	31,253	31,253	34,493	34,493	33,542	33,542

Panel B: The response of private firms' investment to the noise

Competitiveness Measure:	$H\_\#Firms$		L_HHI		L_Top4_Shares	
Dependent variable:	$Capx/K$	$Capx/K$	$Capx/K$	$Capx/K$	$Capx/K$	$Capx/K$
	(1)	(2)	(3)	(4)	(5)	(6)
Minor Industry q	0.012		0.006		0.007	
	(1.18)		(0.53)		(0.59)	
... × Competitiveness	0.021**		0.022**		0.019**	
	(2.33)		(2.13)		(2.07)	
Minor PurePlay q		0.008		0.007		0.009
		(0.86)		(0.53)		(1.37)
... × Competitiveness		0.020**		0.020**		0.021*
		(2.04)		(2.53)		(1.91)
Year FE & Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm & Industry Characteristics	Yes	Yes	Yes	Yes	Yes	Yes
Extended Characteristics	Yes	Yes	Yes	Yes	Yes	Yes
Minor-Industry Controls	Yes	Yes	Yes	Yes	Yes	Yes
$Adj.R^2$	0.224	0.224	0.217	0.217	0.217	0.217
Obs.	22,415	22,405	23,252	23,242	23,014	23,004

Table 9. Alternative hypothesis: internal allocation within industry leaders

This table presents the results to examine whether the major-segment investment of industry leaders reacts to the valuation of industry leaders' *unrelated* minor-segment industries. The sample consists of public firms that are the industry leaders of a two-digit SIC industry. Major (minor) segments are the two-digit SIC industry in which the firm generates more (less) than 50% of its total sales. Industry leaders are firms whose major-segment industry sales rank in the top five among all firms in that industry. Segment-level data are from Worldscope. The dependent variable is $Major\_Capx/K$, which is capital expenditures scaled by the lagged capital for the major segment. The primary independent variable $Minor\_Industry\_q_{i,t-1}$ in columns 1 and 2 is the average beginning-of-period market-to-book of all minor-segment industries for the two-digit SIC industry; in columns 3 and 4 it is the $Minor\_PurePlay\_q_{i,t-1}$, which is the average beginning-of-period market-to-book of all minor-segment industry pure-play firms for a two-digit SIC industry. All regressions control for the fundamental component of the industry valuation that relates to the major-segment industry, $Major\_\bar{q}$, as well as the full set of firm and industry controls. In columns 2 and 4, I control for minor-segment industry characteristics by operating a similar decomposition for the industry characteristics. Variable constructions are described in Appendix A. All regression models are estimated with firm-fixed effects and year-fixed effects. t-statistics in parentheses are adjusted allowing within industry clusters. Coefficients significant at the 10%, 5%, and 1% levels are marked with *, **, and ***, respectively.

Dependent variable:	$Major\_Capx/K$			
	(1)	(2)	(3)	(4)
Minor Industry q	0.005	0.005		
	(0.76)	(0.54)		
Minor PurePlay q			0.006	0.005
			(1.19)	(0.94)
Major Industry $\bar{q}$	0.024*	0.022*	0.025*	0.023**
	(1.79)	(1.84)	(1.88)	(1.99)
Cash Flow	0.064*	0.065*	0.074*	0.074*
	(1.71)	(1.80)	(1.78)	(1.80)
Ln(Asset)	–0.018**	–0.022**	–0.018**	–0.023**
	(–2.10)	(–2.42)	(–2.14)	(-2.52)
Year FE & Firm FE	Yes	Yes	Yes	Yes
Industry Characteristics	Yes	Yes	Yes	Yes
Extended Characteristics	Yes	Yes	Yes	Yes
Minor-Industry Controls	No	Yes	No	Yes
$Adj.R^2$	0.404	0.410	0.407	0.418
Obs.	1,012	1,003	1,008	999

Table 10. Alternative hypothesis: sentiment and cost of capital

This table presents the results on whether the investment of financially constrained (private) firms is more sensitive to the noise in the industry valuation. The dependent variable is $Capx/K$, which is capital expenditures scaled by the beginning-of-period capital. The noise measure in columns (1), (3), and (5) is $Minor\_Industry\_q_{i,t-1}$, and in columns (2), (4), and (6) is $Minor\_PurePlay\_q_{i,t-1}$. For each specification, I interact the noise with a financial constraint dummy, where financial constraint is classified by size, dividend payout, and the Whited-Wu Index, respectively. All specifications control for the FC dummy, the component of the industry valuation that relates to the major-segment industry, $Major\_\bar{q}$, its interaction with the FC dummy, as well as the full set of firm and industry controls. I control for minor-segment industry characteristics by operating a similar decomposition for the industry characteristics. All variable constructions are described in Appendix A. All regression models are estimated with firm-fixed effects and year-fixed effects. t-statistics in parentheses are adjusted allowing within industry clusters. Coefficients significant at the 10%, 5%, and 1% levels are marked with *, **, and ***, respectively.

FC Scheme:	Size		Dividend		WW Index	
Dependent variable:	$Capx/K$	$Capx/K$	$Capx/K$	$Capx/K$	$Capx/K$	$Capx/K$
	(1)	(2)	(3)	(4)	(5)	(6)
Minor Industry q	0.021**		0.022**		0.017**	
	(2.48)		(2.03)		(2.13)	
... × FC	–0.003		–0.002		0.011	
	(–0.31)		(–0.19)		(0.73)	
Minor PurePlay q		0.023***		0.018**		0.019***
		(3.87)		(2.40)		(3.05)
... × FC		–0.007		0.006		0.007
		(–0.73)		(0.68)		(0.61)
Year FE & Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm & Industry Characteristics	Yes	Yes	Yes	Yes	Yes	Yes
Extended Characteristics	Yes	Yes	Yes	Yes	Yes	Yes
Minor-Industry Controls	Yes	Yes	Yes	Yes	Yes	Yes
$Adj.R^2$	0.213	0.213	0.213	0.214	0.213	0.213
Obs.	36,560	36,463	36,628	36,531	36,560	36,463

Internet Appendix to
"Do Private Firms (Mis)Learn from the Stock Market?"

Dong Yan [*]

Stockholm School of Economics & CEPR

December 3, 2022

[*]Stockholm School of Economics and CEPR, Stockholm, Sweden. Dong.Yan@hhs.se.

A Framework for the Hypothesis

This appendix illustrates the mechanism for the stock market to affect the investment of private firms through a learning channel.

A.1 Production Technology

Consider a market (say, an industry) with N public firms and M private firms.[1] They sell products for which demand (or productivity) is uncertain, and generate cash flow at date 1. At date 0, each firm i is endowed with constant capital k_0, and needs to decide whether to adjust its capacity or not. Through investing the amount of I_i, the firm can adjust the level of capital to k_i, i.e.,

$$k_i = k_0 + I_i \, . \tag{IA.1}$$

As is standard in a q theory-setting, I assume a quadratic investment adjustment cost.[2] Then, the project value V_i is given by the reduced-form function

$$V_i = \mathrm{E}\left[v_i \pi\left(k_i\right) - I_i - \left(a_1 I_i + \frac{a_2}{2} I_i^2 \right) \mid \Omega_i \right] \, , \tag{IA.2}$$

where E is the expectations operator, Ω_i is the information set of firm i's manager at date 0, $\pi\left(k_i\right)$ is the continuous production function, $\pi\left(0\right) = 0$, $\pi_k\left(k_i\right) > 0$, $\pi_{kk}\left(k_i\right) < 0$, and $\lim_{k \to 0} \pi_k\left(k_i\right) = \infty$.

The demand (or productivity) shock v_i is a linear combination of two shocks:

$$v_i = \Phi + \eta_i \, , \tag{IA.3}$$

where Φ is common to all firms in the market and is normally distributed with mean $\mu_\Phi > 0$ and variance σ_Φ^2, while η_i is specific to firm i and is an i.i.d. normal variable with mean 0 and variance σ_η^2. Moreover, η_i is independent of Φ.

The first-order condition for maximizing the firm value in Equation (IA.2) subject to (IA.1) is

$$\mathrm{E}\left(v_i \mid \Omega_i\right) \pi_k\left(k_i^*\right) = 1 + a_1 + a_2\left(k_i^* - k_0\right) \, . \tag{IA.4}$$

Thus, the optimal investment can be expressed as a linear function of marginal q, which consists of the manager's expectation of the future productivity and the marginal contribution

[1] The analysis applies to a continuum of firms in the market. The finite number N will only be useful when studying the effect of the informativeness of the market signal, as discussed later.

[2] What is distinct from the standard q theory is whether the information set Ω_i automatically incorporates all available information.

of new capital goods to future profit:

$$I_i^* = (k_i^* - k_0) = \frac{1}{a_2}\mathrm{E}\left(v_i \mid \Omega_i\right)\pi_k - \frac{a_1+1}{a_2}\,. \tag{IA.5}$$

Since the optimal investment I_i^* is increasing in $\mathrm{E}\left(v_i \mid \Omega_i\right)$, from now on, I will focus on how managers put weight on the signals in forming their expectations of the demand shock v.

A.2 Information Structure

At date 0, firm i's manager receives a signal m_i about i's future demand (or productivity):

$$m_i = \Phi + \eta_i + \varepsilon_i\,, \tag{IA.6}$$

where the signal noise term ε_i is normally distributed with mean 0 and variance σ_ε^2. It is assumed to be independent of Φ and η_i, and is independent of ε_j for any $j \in (1,\ldots,N+M)$ and $j \neq i$.

Moreover, for public firm i where $i \in (1,\ldots,N)$, with some noise ω_i, information on future demand (or productivity) is also reflected in the stock price p_i[3]

$$p_i = \Phi + \eta_i + \omega_i\,, \tag{IA.7}$$

where ω_i is normally distributed with mean 0 and variance σ_ω^2. ω_i is independent of Φ, η_i and ε_i, but could be correlated with ω_j with some correlation $0 \leq \rho \leq 1$ for any $j \in (1,\ldots,N)$ and $j \neq i$. In other words, the stock price contains some "false" signal possibly due to investor sentiment, investor inattention, or any other frictions that affect a group of stocks or the entire market.

Therefore, the average of stock prices $\bar{p}$ reveals the common shock with some noise:

$$\bar{p} = \Phi + \bar{\omega}\,, \tag{IA.8}$$

where $\bar{\omega}$ is the price noise term for $\bar{p}$. Since ω_i follows an N-dimensional joint-normal distribution, $\bar{\omega}$ follows a normal distribution with a mean of 0 and a variance of $\sigma_{\bar{\omega}}^2$.[4] When N goes

[3] Note that I do not attempt to model the price generating process in detail and explicitly show how the shocks are linked to the stock price, but rather rely on the predictions from existing models. One could think of a framework as in Kyle (1985). That is, among the investors of a public firm, a fraction of investors receive a signal about the future demand for the firm's product and will accordingly trade shares of the firm's stock. Their information is aggregated in the equilibrium stock price, which is set by the dealers according to the expectations of the firm's value conditioning on the order flow.

[4] If ω_i is i.i.d. instead, then $\bar{\omega}$ vanishes so that $\bar{p}$ is a perfect signal of the common shock Φ.

to infinity, $\sigma_{\bar{\omega}}^2$ converges to $\rho\sigma_{\omega}^2$, whereas with finite N, $\sigma_{\bar{\omega}}^2$ is given by

$$\sigma_{\bar{\omega}}^2 = \frac{1}{N}\sigma_{\omega}^2 + \frac{N-1}{N}\rho\sigma_{\omega}^2, \tag{IA.9}$$

which equals σ_{ω}^2 if $\rho = 1$ or $N = 1$, and have the following properties otherwise:

$$\frac{\partial\sigma_{\bar{\omega}}^2}{\partial N} = -\frac{(1-\rho)\,\sigma_{\omega}^2}{N} < 0; \tag{IA.10}$$

$$\text{and} \qquad \frac{\partial\sigma_{\bar{\omega}}^2}{\partial \rho} = \frac{N-1}{N}\sigma_{\omega}^2 > 0, \tag{IA.11}$$

which suggests that when there is more than one public firm in the market and there exists some but not perfect correlation across the price noise terms, the average stock price is more informative (less volatile) if (i) the number of public firms in the market is higher; or (ii) the price noise terms are less correlated. These results motivate the use of the number of public firms in the industry and price-nonsynchronicity as proxies for informativeness of the industry average price.

A.3 Stock Prices and Private Firms' Investment

In this subsection, I derive the investment decision of the private firm under two scenarios: "No Learning" and "Learning".

No Learning. If private firm i's manager $(i = 1, \ldots, M)$ does not learn from the stock market, her expectation of future shocks will only be conditional on the private signal (i.e., $\Omega_i = m_i$) and can be expressed as a weighted average of the unconditional belief of the shock (which is a constant known to all agents by assumption) and the managerial private signal:

$$\mathrm{E}\left(v_i \mid m_i\right) = \left(1 - \lambda_{Pri}^{No}\right)\mu_{\Phi} + \lambda_{Pri}^{No} m_i \tag{IA.12}$$

where

$$\lambda_{Pri}^{No} = \frac{\sigma_{\Phi}^2 + \sigma_{\eta}^2}{\sigma_{\Phi}^2 + \sigma_{\eta}^2 + \sigma_{\varepsilon}^2} \tag{IA.13}$$

It follows suit that when the private signal is more precise, manager puts a higher weight on her private signal (i.e. $\frac{\partial\lambda_{Pri}^{No}}{\partial\sigma_{\varepsilon}^2} < 0$).

Suppose that the manager's information set, m_i, could be controlled for, then regressing the investment on both signals will give us a coefficient of λ_{Pri}^{No} on m_i, and a coefficient of zero on $\bar{p}$ (i.e, $\beta_{Pri}^{No} = 0$) as the stock price was not used by the manager.

Learning from the Stock Market. If private firm i's manager learns from the stock market, her information set will contain both signals (i.e., $\Omega_i = [\bar{p}, m_i]$), and the conditional expectations of the shocks will be a weighted average of three components: the unconditional belief of the shock, the signal from the average stock price, and the private signal to the manager, i.e.

$$\mathrm{E}\left(v_i \mid \bar{p}, m_i\right) = \left(1 - \beta_{Pri}^{Learn} - \lambda_{Pri}^{Learn}\right)\mu_\Phi + \beta_{Pri}^{Learn}\bar{p} + \lambda_{Pri}^{Learn} m_i \tag{IA.14}$$

where

$$\beta_{Pri}^{Learn} = \frac{\sigma_\Phi^2 \sigma_\varepsilon^2}{\sigma_\Phi^2\left(\sigma_\eta^2 + \sigma_\varepsilon^2\right) + \sigma_{\bar{\omega}}^2\left(\sigma_\Phi^2 + \sigma_\eta^2 + \sigma_\varepsilon^2\right)} \tag{IA.15}$$

$$\text{and} \qquad \lambda_{Pri}^{Learn} = \frac{\sigma_\Phi^2 \sigma_\eta^2 + \sigma_{\bar{\omega}}^2\left(\sigma_\Phi^2 + \sigma_\eta^2\right)}{\sigma_\Phi^2\left(\sigma_\eta^2 + \sigma_\varepsilon^2\right) + \sigma_{\bar{\omega}}^2\left(\sigma_\Phi^2 + \sigma_\eta^2 + \sigma_\varepsilon^2\right)} \tag{IA.16}$$

Here, investment responds positively to the average valuation ($\beta_{Pri}^{Learn} > 0$) as long as (i) there exists uncertainty in the common shock (i.e. $\sigma_\Phi^2 > 0$), and (ii) the manager's private signal is not perfect (i.e. $\sigma_\varepsilon^2 > 0$). Both conditions are satisfied for the model to be non-trivial. Therefore,

***Hypothesis* 1:** After controlling for private signals, the investment of private firms responds positively to the industry valuation if and only if its manager learns from the stock market.

When Hypothesis 1 is taken to the data, however, we cannot perfectly control for the manager's information set (m_i) as it is not observable to us as econometricians. To solve this problem, rearranging the terms in Equation (IA.14) yields

$$\mathrm{E}\left(v_i \mid \bar{p}, m_i\right) = \left(1 - \beta_{Pri}^{Learn} - \lambda_{Pri}^{Learn}\right)\mu_\Phi + \beta_{Pri}^{Learn}\bar{\omega} + \lambda_{Pri}^{Learn}\left(\eta_i + \varepsilon_i\right) + \left(\beta_{Pri}^{Learn} + \lambda_{Pri}^{Learn}\right)\Phi \tag{IA.17}$$

where β_{Pri}^{Learn} and λ_{Pri}^{Learn} are derived in Equations (IA.15) and (IA.16). Thus, a testable version of Hypothesis 1 can be developed, which explores $\bar{\omega}$, the component in the price signal that is orthogonal to the manager's (relevant) information set.

***Hypothesis* 1b:** The investment of private firms responds positively to the noise in the price signal, if and only if private firm managers learn from the stock market.

While I do not model how the manager separates the noise $\bar{\omega}$ from the fundamentals, it follows from Hypothesis 1b that if some managers are better informed or less attention constrained than others, their reaction to the noise component will be more muted than β_{Pri}^{Learn}. Therefore,

Hypothesis 2: The sensitivity of private firms' investment to the noise in the price signal is less pronounced when it is easier for the manager to filter out the noise.

A.4 Comparative Statics under the "Learning" Scenario

The "Learning" scenario predicts a positive relationship between the precision of the price signal and the sensitivity of firms' investment to the average stock price. This can be seen from the following partial derivative:

$$\frac{\partial \beta_{Pri}^{Learn}}{\partial \sigma_{\bar{\omega}}^{2}} = -\frac{\sigma_{\Phi}^{2}\sigma_{\varepsilon}^{2}\left(\sigma_{\Phi}^{2}+\sigma_{\eta}^{2}+\sigma_{\varepsilon}^{2}\right)}{\left[\sigma_{\Phi}^{2}\left(\sigma_{\eta}^{2}+\sigma_{\varepsilon}^{2}\right)+\sigma_{\bar{\omega}}^{2}\left(\sigma_{\Phi}^{2}+\sigma_{\eta}^{2}+\sigma_{\varepsilon}^{2}\right)\right]^{2}} < 0 \tag{IA.18}$$

As shown in Equations (IA.10) and (IA.11), the industry average stock price is more informative ($\sigma_{\bar{\omega}}^2$ is smaller) when the number of public firms (N) is higher, or when the correlation of the stock price across firms (ρ) is lower. Using N as a proxy and ρ as an inverse proxy for the informativeness of the average industry stock price, the model predicts that

***Hypothesis* 3:** The sensitivity of private firms' investment to the industry valuation is stronger when the industry has a larger number of public firms or when there is less co-movement of stock prices within the industry.

Finally, when firms are more likely to face common shocks, the information from the average valuation is more valuable. To see this, define f as the fraction of the variance of common shocks to the variance of total shocks (i.e., $f = \frac{\sigma_{\Phi}^2}{\sigma_{\Phi}^2+\sigma_{\eta}^2}$ and $0 < f < 1$). Taking the partial derivative of β_{Pri}^{Learn} with respect to f yields

$$\frac{\partial \beta_{Pri}^{Learn}}{\partial f} = \frac{\sigma_{\eta}^{2}\sigma_{\varepsilon}^{2}\sigma_{\bar{\omega}}^{2}\left(\sigma_{\eta}^{2}+\sigma_{\varepsilon}^{2}\right)}{(1-f)\left[\sigma_{\Phi}^{2}\left(\sigma_{\eta}^{2}+\sigma_{\varepsilon}^{2}\right)+\sigma_{\bar{\omega}}^{2}\left(\sigma_{\Phi}^{2}+\sigma_{\eta}^{2}+\sigma_{\varepsilon}^{2}\right)\right]^{2}} > 0 \tag{IA.19}$$

As the f increases, uncertainty is more likely to come from the common demand shock rather than the firm-specific shock, and firms put more weight on the average stock price when deciding on the optimal investment. Therefore,

***Hypothesis* 4:** The sensitivity of private firms' investment to industry valuation is stronger when the industry common shock is more important relative to the firm-specific shock.

A.5 The Response of Public Firms without Agency Costs

In this subsection, I derive the optimal investment responses of public firms without any agency cost.[5] Therefore, the public firms discussed here differ from private firms only in one

[5] Using a full-fledged model, Foucault and Frésard (2014) examine how public firms' managers learn from their own stock prices and peer firms' stock prices. They predict a positive investment-to-peer price sensitivity, which increases with the informativeness of the signals and drops after going public. Dessaint, Foucault, Frésard and Matray (2018) extend the analysis to examine price noise. Much of the prediction continues to hold in my framework, and I discuss some additional insights at the end of this subsection.

dimension: the presence of the firm's own stock price. I later discuss the impact of introducing agency costs on the predictions.

A.5.1 Stock Prices and Private Firms' Investment

No Learning. When managers do not learn from prices, public firms will follow the same decision rule as private firms under the "No Learning" scenario as in Equation (IA.12).

Learning from Own Stock Price. If the public firm i ($i = 1, \ldots, N$) makes use of i's own stock price, but ignores the average stock price (i.e., $\Omega_i = [p_i, m_i]$), the conditional expectation of the future state can be derived as a linear function of μ_Φ, p_i, and m_i.

$$\mathrm{E}\left(v_i \mid p_i, m_i\right) = \left(1 - \gamma_{Pub}^{Narrow} - \lambda_{Pub}^{Narrow}\right)\mu_\Phi + \gamma_{Pub}^{Narrow} p_i + \lambda_{Pub}^{Narrow} m_i \tag{IA.20}$$

where

$$\gamma_{Pub}^{Narrow} = \frac{\sigma_\varepsilon^2\left(\sigma_\Phi^2 + \sigma_\eta^2\right)}{\sigma_\varepsilon^2\left(\sigma_\Phi^2 + \sigma_\eta^2\right) + \sigma_\omega^2\left(\sigma_\Phi^2 + \sigma_\eta^2 + \sigma_\varepsilon^2\right)} \tag{IA.21}$$

$$\text{and} \qquad \lambda_{Pub}^{Narrow} = \frac{\sigma_\omega^2\left(\sigma_\Phi^2 + \sigma_\eta^2\right)}{\sigma_\varepsilon^2\left(\sigma_\Phi^2 + \sigma_\eta^2\right) + \sigma_\omega^2\left(\sigma_\Phi^2 + \sigma_\eta^2 + \sigma_\varepsilon^2\right)} \tag{IA.22}$$

Learning from Own and Average Stock Price. When firm i learns from both i's own stock price and the industry average stock price (i.e., $\Omega_i = [\bar{p}, p_i, m_i]$), the conditional expectation of the future state can be derived as

$$\mathrm{E}\left(v_i \mid \bar{p}, p_i, m_i\right) = \left(1 - \beta_{Pub}^{Learn} - \gamma_{Pub}^{Learn} - \lambda_{m_i}^{Learn}\right)\mu_\Phi + \beta_{Pub}^{Learn}\bar{p} + \gamma_{Pub}^{Learn} p_i + \lambda_{Pub}^{Learn} m_i \tag{IA.23}$$

As N goes to infinity, we have $\sigma_{\bar{\omega}}^2 = \rho\sigma_\omega^2$. Then, the weights on each signal become

$$\beta_{Pub}^{Learn} = \frac{\sigma_\varepsilon^2\sigma_\omega^2}{\Lambda}\left[\left(1-\rho\right)\sigma_\Phi^2 - \rho\sigma_\eta^2\right] \tag{IA.24}$$

$$\gamma_{Pub}^{Learn} = \frac{\sigma_\eta^2\sigma_\varepsilon^2}{\Lambda}\left(\sigma_\Phi^2 + \rho\sigma_\omega^2\right) \tag{IA.25}$$

$$\lambda_{Pub}^{Learn} = \frac{\sigma_\omega^2}{\Lambda}\left[\sigma_\Phi^2\sigma_\eta^2 + \rho\left(1-\rho\right)\sigma_\omega^2\left(\sigma_\Phi^2 + \sigma_\eta^2\right)\right] \tag{IA.26}$$

$$\text{and} \qquad \Lambda = \sigma_\Phi^2\sigma_\eta^2\sigma_\varepsilon^2 + \sigma_\eta^2\sigma_\omega^2\left(\sigma_\Phi^2 + \rho\sigma_\varepsilon^2\right) + \left(1-\rho\right)\sigma_\omega^2\left[\sigma_\Phi^2\sigma_\varepsilon^2 + \rho\sigma_\omega^2\left(\sigma_\Phi^2 + \sigma_\eta^2 + \sigma_\varepsilon^2\right)\right] \tag{IA.27}$$

The analysis of public firms reveals two challenges for estimating Equation (IA.23) to infer learning, even without considering any agency costs. First, since the noise terms among public firms are correlated, when p_i and $\bar{p}$ are included in the same regression, the estimate for β_{Pub}^{Learn} is likely to be biased. This bias is further magnified by agency problems, as public firms will have additional incentives to respond to the stock valuation and the price noise than what has been suggested by the learning mechanism.

Second, the response of public firms is sensitive to the value of the parameters. Since $\Lambda > 0$ for all possible values of ρ, the sign of β_{Pub}^{Learn} depends on the value of ρ and $f = \frac{\sigma_\Phi^2}{\sigma_\Phi^2+\sigma_\eta^2}$.[6]

(1) when $\rho = 0$, $\beta_{Pub}^{Learn} > 0$;

(2) when $0 < \rho < 1$ and $f > \rho$, $\beta_{Pub}^{Learn} > 0$;

(3) when $0 < \rho < 1$ and $f <= \rho$, $\beta_{Pub}^{Learn} <= 0$;

(4) when $\rho = 1$, $\beta_{Pub}^{Learn} < 0$.

The above results suggest that the investment of public firms responds *negatively* to the industry stock price when the price noise terms among public firms are highly correlated or when the common shock accounts for a small proportion of the uncertainty. In such cases, the manager of a public firm could subtract the industry valuation from its own price to obtain the firm-specific shock. Conditioning on the firm's own stock price, the higher is the industry average, the lower is the estimated firm-specific shock and hence the firm's investment. This is in line with recent papers by Brown and Wu (2014) studying the cross-fund learning within mutual fund families and Ozdenoren and Yuan (2017) studying the risk-taking behavior when agents have incentives to match the industry average effort. For private firms, the sign is not sensitive to the model specifications, which creates less challenge when drawing some inferences from the empirical results.

A.5.2 Comparison of Public and Private Firms

Given any value of ρ, if the only difference between the public and the private firm is the presence of the own stock price, the difference in their investment-to-industry stock price sensitivity is given by

$$\beta_{Pri}^{Learn} - \beta_{Pub}^{Learn} = \frac{\left(\sigma_\Phi^2 + \rho\sigma_\omega^2\right)\left[\sigma_\Phi^2\sigma_\varepsilon^2 + \rho\sigma_\omega\left(\sigma_\Phi^2 + \sigma_\eta^2 + \sigma_\varepsilon^2\right)\right]}{\Lambda\left[\sigma_\Phi^2\left(\sigma_\eta^2 + \sigma_\varepsilon^2\right) + \rho\sigma_\omega^2\left(\sigma_\Phi^2 + \sigma_\eta^2 + \sigma_\varepsilon^2\right)\right]} \tag{IA.28}$$

where β_{Pri}^{Learn} is the private firm's weight on the industry average stock price under the "Learning" scenario, β_{Pub}^{Learn} is the public firm's weight on the industry average stock price when the manager learns from its own stock price and the industry average price, and Λ is given in Equation (IA.27).

It can be show that $\beta_{Pri}^{Learn} - \beta_{Pub}^{Learn} > 0$ if (i) there is uncertainty about the common shock (i.e. $\sigma_\Phi^2 > 0$), and (ii) managers do not receive a perfect signal about future shocks (i.e. $\sigma_\varepsilon^2 > 0$). Therefore, private firms respond more to the average stock price than do identical public firms.

[6] The weights on the other two signals do not suffer from the same problem. For all possible values of ρ, $\gamma_{Pub}^{Learn} > 0$ and $\lambda_{Pub}^{Learn} > 0$.

However, this prediction is under the nearly impossible conditions that (i) private and public firms have the same underlying fundamentals; (ii) the private signal received by private firms is as precise as that received by public firms; and (iii) public firms do not have any agency cost so that their managers have the same objective functions as they would have in an identical private firm and the managers do not have additional weights on the price noise. Given that these conditions do not hold in the data, the observed difference is likely an outcome of all these forces.

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