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

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First draft: September 2014
This draft: March 2016

Abstract

This paper develops and tests the hypothesis that the stock market affects private firms through an information-spillover channel. 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 is stronger in industries in which the stock prices are more informative or firms are more likely to face common shocks. To address the concern that unobserved factors in the managers' information set affect both private firms' investment and industry valuation and generate a spurious relationship even in the absence of learning, I further show that the investment of private firms in the industry leaders' major-segment industry reacts strongly to the valuation of industry leaders' unrelated minor-segment industries. Such evidence suggests that private firm managers learn from the stock prices, but cannot completely filter out the irrelevant information.

JEL classification: G30, G31, G14

Keywords: corporate investment, learning, industry information diffusion, private firms

*For valuable comments, I thank Utpal Bhattacharya, Ling Cen, Darwin Choi, Sudipto Dasgupta, Pengjie Gao, Mariassunta Giannetti, Vidhan Goyal, Denis Gromb, Ran Guo, Harrison Hong, Erica X.N. Li, Laura Liu, Fangyuan Ma, Lei Mao, Abhiroop Mukherjee, Kasper Nielsen, Rik Sen, Morten Sorensen, Laura Starks (discussant), Per Strömberg, Baolian Wang, Pengfei Wang, K.C. John Wei, Alminas Žaldokas, Hong Zhang, as well as conference and seminar participants at BI Norwegian Business School, City University of Hong Kong, Erasmus School of Economics, Hong Kong University of Science & Technology, Manchester Business School, Norwegian School of Economics, PBCSF Tsinghua University, Queen's University Belfast, Stockholm School of Economics, University of New South Wales, University of Southern Denmark, SAEe (Palma de Mallorca), FMA Europe (Venice), FMA Asia (Seoul), AsianFA (Changsha), and 10th Early Career Women in Finance Mini-Conference (WFA, Seattle). An earlier version of the paper was circulated under the title "Do Private Firms Learn from the Stock Market?". All remaining errors are mine.

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1 Introduction

Over the last decade, an extensive literature has paid attention to whether corporate managers learn from the stock market when making decisions. The rationale behind such managerial learning is that, because information does not flow freely among investors and firms, diverse pieces of information that are not known to the managers can be aggregated into the stock prices through the trading activities of investors (Grossman and Stiglitz (1980), Kyle (1985)). In addition, new information about stock market-listed (or "public") firms is produced and disseminated by information intermediaries that scrutinize them constantly, such as financial analysts and business media. In turn, the stock market can have real-side consequences on corporate policies if managers explore information in the public domain in the hope of making better decisions.[1]

Testing whether and how the learning mechanism works is challenging, because we as econometricians cannot perfectly observe the information set used by the manager to make investment decisions, nor can we observe the manager's belief on investment opportunities prior to paying attention to the stock market. As a result, it is not conclusive at all that the documented positive relationship between a firm's market valuation and capital investment suggests learning, as alternative explanations that the stock price passively reflects what the manager has already known and that unobserved investment opportunities drive both investment and stock price is not ruled out. Furthermore, public firms, which are predominantly used in the learning literature, have long been viewed as prone to agency problems (Jensen and Meckling (1976)). Their managers may have incentive to cater to investors' opinion to protect the their own livelihood (Polk and Sapienza (2009)), and adjust investment in response to stock prices, which adds another layer of difficulty in uncover managerial learning.

In this paper, I adopt a novel empirical strategy that can disentangle different sources of information and causally study to what extent corporate managers learn from the stock prices. I

[1] See Bond, Edmans and Goldstein (2012) for a comprehensive survey on the real effects of the stock markets from the informational role of market prices.

shift the objective of analysts to private firms, whose shares are not publicly held and traded, and test whether the investment of private firms are sensitive to the stock valuation of public firms in the same industry. In addition, using the industry leaders' minor-segment industry valuation as a measure for the "noise" contained in a price signal for private firms in the industry leaders' major-segment industry, I test whether the investment of private firms are sensitive to the price noise, which would not affect investment in the absence of learning. As a natural implication of my identification strategy, I document evidence of "mislearning" that the investment of private firms reacts to noise in the price signal *ex post* when managers cannot perfectly filter out the "noise" from the stock price signal.

To the extent that market prices aggregate individual pieces of information, it is highly plausible that they contain information not yet in the individual private firm manager's information set. Therefore, managers of private firms have incentive to learn from the stock valuation of the public firms in the same industry as it provides them with additional information about the common demand and productivity. As private firms do not have their own stock prices, it is unlikely that the firm-specific information known by a private firm manager is reflected into the stock price of a public firm in the same industry. Moreover, private firms are mostly owner-managed (Michaely and Roberts (2012)), and their investment decisions are less likely to be affected by shareholder short-termism (Asker, Farre-Mensa and Ljungqvist (2015)) and other agency concerns which may confound the empirical finding for the learning behavior of public firms.

By utilizing a large panel of private and public firms in the United Kingdom, I find that the investment of private firms reacts positively to the industry valuation, proxied by the average Tobin's Q of all public firms in the same industry. The economic magnitude is considerable: A one standard deviation increase in the industry valuation is associated with a 1.4% increase in the capital expenditure (scaled by the beginning-of-year capital) of private firms, which is about 7% of the average investment-to-capital ratio in my sample. This effect is obtained after controlling for firm characteristics known to affect investment decisions, characteristics of both public and private peers in the same industry, the unobserved time-varying shocks common to all firms (by using the year fixed effects), and the unobserved heterogeneity at the firm-level (by using the firm fixed effects).[2]

However, even with private firms, there is still room for endogeneity problems: If some industry investment opportunities have already been known by the private firm manager (but unobserved by econometricians) and are reflected into the stock prices of the public firms at the same time, a spurious relationship between private firms' investment and the industry valuation could still be generated in the absence of learning. To address the concern, the ideal strategy is to test whether the investment of a private firm reacts to the noise in the price signal that would not affect the investment decision if the manager did not learn from the stock price. The logic is as follows. The stock prices of public firms in the same industry contains both information related to private firms and information unrelated ("noise") to private firms. If the manager of a private firm does not learn from the stock price, but observes this "noise" directly from other channels such as golf clubs, she would not adjust the investment decision in response to the false signal. If, instead, she learns from the stock prices of the public firms and cannot completely separate the relevant information from the "noise", then *ex post* the investment of her firm will be sensitive to the stock prices as well as the "noise" in the price signal.[3] Herein lies the second layer of my design.

Using the valuation of industry leaders' unrelated minor-segment industries as the "noise" in the price signal for a private firm in the industry leaders' major-segment industry, I find that the investment of private firms in the industry leaders' major-segment industry reacts positively and significantly to the "noise". I show from a placebo test that co-movements between random

[2]The results are robust and of similar economic magnitude to the baseline if investment is measured by the annual increase of capital scaled by beginning-of-year capital, which also accounts for fixed assets acquired externally through mergers and acquisitions.

[3]This test strategy has been adopted in Morck, Shleifer and Vishny (1990) in search for the impact of investor sentiment on corporate investment. Even though various choices of the "noise" in the price signal have been used to study the effect of non-fundamental component of stock prices on capital investment and M&A, they have been overlooked for a decade in test the learning behavior. A recent paper by Dessaint et al. (2015) also uses a similar test to examine the ripple effects of noise on public firms' investment.

industries cannot explain the results. Such "mislearning" would not be observed if the private firms were not learning from the stock market.

My paper is the first to explore the valuation of industry leaders' unrelated minor-segment industries to be the "noise" in the price signal.[4] It satisfies the two conditions crucial for testing the "learning" hypothesis. Firstly, the "noise" should be unrelated to the fundamental investment opportunities.[5] Most industry leaders have fairly complicated business segments. Sometimes, the minor segments are in industries unrelated to industry of their major segment, thereby unrelated to the private firms in their major segments industries. If the private firms do not learn from the industry valuation, then their investment will not respond to the valuation of industries in which the public leaders have *unrelated* minor segments, as such valuation is irrelevant to the investment opportunity of private firms in the public leaders' major segment industry. To make sure that the results I obtain are, to the largest extent, from minor-segment industries that are unrelated to the industries of private firms, I exclude those minor-segment industries that the private firms may also have business in or are likely to have supplier or customer relationships with.

The second condition the "noise" strategy relies on requires that the decision maker cannot completely filter out the unrelated information.[6] The stock valuation of conglomerate firms reflects information in both their major and minor segments. Based on findings from existing studies, it is indeed difficulty to be filtered out the unrelated minor-segment industry valuation from the (major-segment) industry valuation. Investors and equity analysts have bounded rationality and may price small firms based on returns of large firms. Therefore, industry leaders, which are usually large in size, may lead the pure players (which are usually small firms) in stock returns.[7]

[4]Other measures for non-fundamental shocks on stock valuation considered in the learning and mis-valuation literature include subsequent stock returns, valuation residuals, mutual fund fire-sale pressure, and sentiment index.

[5]Otherwise, spurious relationship between investment and stock price could still be observed in the absence of learning because of comovements in investment opportunities.

[6]Otherwise, even if there is learning, the investment will not be sensitive to the "noise".

[7]Hou (2007) finds that within the same industry, leaders lead followers in stock returns. Cen et al. (2013) further document a strong contemporaneous and a lead-lag relation in stock returns between firms from industry leaders' unrelated minor-segment industries and pure players in the industry leaders' major-segment industry

Therefore, even if the private firms learn from the stock prices of pure players in their industry, the price may still contains "noise" about the industry leaders' minor segments.

Moreover, I find evidence consistent with the predictions from the "Learning" framework through a host of cross-sectional tests. I show that in industries in which the stock prices are more informative about future fundamentals, private firms' investment responds more to the industry average valuation.[8] The economic magnitude of the investment-price sensitivity in those industries increases substantially. A one standard deviation increase in industry valuation is associated with a 3.4% increase in private firms' capital expenditure (scaled by the beginning-of-year capital), about 16% of the average investment-to-capital ratio. In addition, the sensitivity of private firms' investment to industry average Tobin's Q increases when firms in the same industry are more likely to face common shocks.[9]

My results contribute to a few strands of literature. The idea that stock prices aggregate information from various participants and improve the efficiency of real economy dates back to Hayek (1945). Follow-up studies have offered important theoretical insights (Grossman and Stiglitz (1980), Kyle (1985), Subrahmanyam and Titman (1999)), and have provided some evidence that managers use the information learned from their stock prices when they decide on investment (Durnev, Morck and Yeung (2004), Chen, Goldstein and Jiang (2007), and Bakke and Whited (2010)), mergers and acquisitions (Luo (2005)), and cash savings (Frésard (2012)) and learn from peers' valuation when making investment decisions (Foucault and Frésard (2014)). My paper is the first to look at private firms, and the first to examine the real consequences of the lead-lag effects in stock returns (Lo and MacKinglay (1990), Hou (2007), and Cen et al. (2013), among others).

[8] I use (i) number of public firms in the same three-digit standard industrial classification (SIC) industry, (ii) fraction of public firms in the same three-digit SIC industry, and (iii) price non-synchronicity as measures for the informativeness of industry average valuation.

[9] I use (i) number of all firms in the same three-digit standard industrial classification (SIC) industry, (ii) HHI of the three-digit SIC industry, and (iii) the market share of the top 4 firms in the three-digit SIC industry as measures for the the importance of common shocks.

My paper complements the literature by showing that the information content of market prices spreads to a larger part of the economy that has not received much attention. Private firms account for a substantial fraction of the United Kingdom's economy. For the period from 2000 to 2010, I estimate that private firms represent 91% of all incorporated entities in the U.K. and 60% of all corporate assets. On average, 61% of the sales, 53% of the pre-tax profits, and 68% of the aggregate capital expenditure were from private firms.[10] Therefore, extending the attention to private firms helps to more properly evaluate the real effects of the stock market.

This paper also connects to the empirical literature that compares various policies of public and private firms. Using the same data set as in my paper, Brav (2009) finds that private firms rely mostly on debt financing, and Michaely and Roberts (2012) find that private firms smooth dividends less than public firms. Using Sageworks in the United States, Asker, Farre-Mensa and Ljungqvist (2015) find that private firms invest substantially more and are more responsive to changes in investment opportunities compared with matched public firms, and Badertscher, Shroff and White (2013) find that the disclosures of financial statements of public firms affect the investment of private firms. Phillips and Sertsios (2014) show that the private firms' product introductions respond less to the change of investment opportunities. While this paper does not intend to make a comparison of the two types of firms, I find strong evidence that private firm managers exploit information from the stock market.

The paper is organized as follows. Section 2 develops the hypothesis under a learning model. Sections 3 describes the empirical strategies and sample selection. Section 4 presents the empirical findings. Section 5 concludes.

[10] The statistics I use are in large part comparable to the ones reported in Brav (2009) for U.K. private firms for an earlier period (1993 to 2003). Furthermore, a comparison between the public and private firms in the United States can be found in Asker, Farre-Mensa and Ljungqvist (2015). They show that private firms represent 99.94% of all U.S. firms, 59% of sales and 49% of aggregate pre-tax profits in 2010.

2 Hypothesis Development

This section develops hypothesis that the stock market affects the investment of private firms and public firms through a learning channel, and build the framework for the empirical tests.

2.1 Setup

2.1.1 Production Technology

I consider a market with N public firms and M private firms[11]. At date 0, Firm i has constant capital k_0 before making any investment. It sells product for which demand (or productivity) is uncertain, and generate cash flow at date 1. At date 0, manager need to decide whether to adjust production capacity or not. Through investing the amount of I_i, firm can adjust the level of capital to k_i, i.e.,

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

Following the q theory literature, I further assume quadratic investment adjustment cost so that the optimal investment can be expressed as a linear function of marginal q. The project value (net present value) V_i is given by the reduced-form linear function for simplicity

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

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:

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

[11]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.

where Φ is common to all the 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, the firm-specific shock η_i is independent of the common shock Φ.

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

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

Therefore, the optimal investment can be expressed as a linear function of marginal q, which consists manager's expectation of the future productivity and the marginal contribution of new capital goods to future profit:

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

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, which is essentially equivalent to how they put weight on the signals in choosing I_i^*.

2.1.2 Information Structure

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

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

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 given by

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

where ω_i is normally distributed with mean 0 and variance σ_ω^2. For public firm i, ω_i is independent of the shocks Φ, η_i and the noise term of manager's signal ε_i. But unlike managers' signal noise term, the price noise term ω_i 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.

Note that I do not attempt to model the price generating process in precise and show explicitly how the shocks are linked to the stock price, but rather rely on the predictions from existing models. One could think of this link as in Kyle (1985). That is if, among the investors of the public firm i, a fraction of investors receive a perfect signal about future demand of firm i's product (i.e. they observe the true value of v_i at date 0.). The informed speculators will buy or sell shares of this stock based on the this information against the liquidity traders and the dealers. The dealers set the break-even price p_i according to the expectations of firm i's value conditioning on the order flow (i.e. the sum of the net demand from speculators and liquidity traders) for stock i. Such mechanism provides a channel through which investors' information is incorporated into the equilibrium stock price, thereby gives the rationale for managers to learn from the market. It is followed by related papers that study the feedback effects of the firm's own stock price as well as peer firms' stock price on corporate decisions as in Subrahmanyam and Titman (1999) [12],

[12]Subrahmanyam and Titman (1999) do not have a common shock across firms. Therefore, firms' investment will be influenced by the stock price if they go public, and by private financier's information set if remain private. In addition, one type of the shocks (the "serendipitous information" in their paper) can only be observed by the public investors but not the private financier. Hence, unless going public, firms cannot get this piece of information, nor can they interpolate it by looking at peer firms' stock prices as there is no fundamental correlations across stocks. This sets the key difference in the the way private firms use information in stock prices between Subrahmanyam and Titman (1999) and my framework as shown in later sections.

Foucault and Frésard (2014), among others.

Given the individual price structure in (7), the average of stock prices $\bar{p}$ reveals common demand (or productivity) shock with some noise:

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

where $\bar{\omega}$ is the average of price noise terms. In a special case that ω_i is i.i.d., $\bar{\omega}$ vanishes so that the average stock price $\bar{p}$ is a perfect signal of the common shock Φ. In more general cases when ω_i follows a N-dimensional joint-normal distribution, $\bar{\omega}$ follows a normal distribution with mean of 0 and variance of $\sigma^2_{\bar{\omega}}$. When N goes to infinity, $\sigma^2_{\bar{\omega}}$ converge to $\rho\sigma^2_{\omega}$, whereas with finite N, $\sigma^2_{\bar{\omega}}$ is given by

$$\sigma^2_{\bar{\omega}} = \frac{1}{N}\sigma^2_{\omega} + \frac{N-1}{N}\rho\sigma^2_{\omega}, \tag{9}$$

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

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

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

As $\sigma^2_{\bar{\omega}}$ inversely measures the precision of the industry average price signal (i.e. precision $\tau_{\bar{\omega}} = \frac{1}{\sigma^2_{\bar{\omega}}}$), the comparative statics show that when there are more than one public firms in the market and there exists some but not perfect correlation across the price noise terms, the industry average stock price is more informative (less volatile) if (i) the industry has a higher number of public firms; or (ii) the price noise terms are less correlated across stocks. This motivates the use of number of public firms in the industry and price-nonsynchronicity as proxies for informativeness of the industry average price.

2.2 Stock Prices and Private Firms' Investment

In this section, I derive the investment decision of the private firm and develop empirical implications under two scenarios: one is when the private firm manager uses the private signal m_i only, and the other one is when she relies on both the private signal m_i and the information embedded in the average industry stock price $\bar{p}$. According to Equation (5), the optimal investment I_i^* that maximize firm value V_i is linear and increasing in managers' expectations of the shocks. Thus, the problem here can be translated into a comparison of managers' expectation of future conditions between the circumstances of "No Learning" and "Learning".

2.2.1 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 be conditional only 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:

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

where

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

And the manager puts a higher weight on her private signal (λ_{Pri}^{No}) if this signal is more precise (i.e. $\frac{\partial \lambda_{Pri}^{No}}{\partial \sigma_\varepsilon^2} < 0$). The weight to put on this signal is 1 if the manager has perfect signal on future shocks (i.e. $\lambda_{Pri}^{No} = 1$ if $\sigma_\varepsilon^2 = 0$).

Suppose the manager's information set could be controlled for, then running the regression of investment on this signal will give us a coefficient on λ_{Pri}^{No}. The coefficient on the average stock price $\bar{p}$ will be zero (i.e, $\beta_{Pri}^{No} = 0$) as it was not used by the manager.

2.2.2 Learning from the Stock Market

If instead, private firm i's manager actively utilizes the information contained in the average stock price, she will decide the optimal investment based on the expectations of shocks conditional on the average price $\bar{p}$ as well as the private signal m_i (i.e., $\Omega_i = [\bar{p}, m_i]$) derived as

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

where

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

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

When the manager learns from the industry valuation as shown in Equation (14), the conditional expectations of the shocks (equivalently, the optimal investment) is a weighted average of three components: the unconditional belief of the demand shock, the signal from average stock price, and the private signal to the manager. Recall that investment will not respond to the average stock price in "No Learning" scenario. Here, in the case of "Learning", investment response positively to average stock valuation ($\beta_{Pri}^{Learn} > 0$) as long as (i) there exist uncertainty on the future common demand shock (i.e. $\sigma_\Phi^2 > 0$), and (ii) manager's private signal is not perfect about the demand shock (i.e. $\sigma_\varepsilon^2 > 0$). Both conditions are satisfied for the model to be non-trivial. Therefore,

***Hypothesis* 1:** After controlling for manager's information set, investment of private firms responds positively to the valuation of public firms in the same industry if and only if private firm managers learn from the stock market.

However, Hypothesis 1 relies on the assumption that we can perfectly control for the manager's information set, which does not hold when it is taken to the data. To solve the problem, the empirical strategy needs to explore the component in the price signal orthogonal to the manager's (relevant) information set. Then, Equation (14) could be expressed as

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

where β_{Pri}^{Learn} and λ_{Pri}^{Learn} are derived in Equation (15) and (16). A testable version of Hypothesis 1 can be developed.

***Hypothesis* 1b:** Investment of private firms responds positively to the price "noise" of public firms in the same industry if and only if private firm managers learn from the stock market.

Furthermore, under the"No Learning" scenario, the variance of the noise term in average stock price ($\sigma_{\bar{\omega}}^2$) plays no role in the optimal investment decision, whereas under the "Learning" scenario, the magnitude of the weight on the average stock price, β_{Pri}^{Learn}, is decreasing in $\sigma_{\bar{\omega}}^2$: the more precise (the less noisy) the signal from the average stock price, the more sensitively private firms' investment responds to the average stock price. This can be seen from the following partial derivative:

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

As shown in Equation (10) and (11), industry average stock price is more informative (the noise term in the average stock price is smaller) when the number of public firms (N) is higher, or when the correlation of 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* 2:** 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, the rationale behind the benefit of learning from the average stock price is that as firm-specific shock vanishes when taking the average of the individual stock prices, the average price provides managers with useful piece of information about the common demand shock. Therefore, when firms are more likely to face the common demand shock, this additional piece of information is more valuable. To see this, define f as the fraction of the variance of common shock to the variance of total shocks such (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

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

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

***Hypothesis* 3:** The sensitivity of private firms' investment to industry valuation is stronger when the industry common demand shock is more important relative to the firm-specific shock.

2.3 Comparison between Public and Private Firms

In this section, I derive the optimal investment responses of public firms to the industry valuation when they do learn from their own stock prices as well as the industry prices and have no other incentives to react on the stock prices. I do not aim to find consistent evidence when comparing the investment behavior of private firms to that of public firms in the actual data since, as discussed earlier, there are other reasons for public firms to respond to the stock valuation than what have been suggested by the learning hypothesis.

Under the null hypothesis that managers does not learn from the stock market, public firms will follow the same decision rule as private firms in Equation (12) and set the optimal investment level based on the expected shock conditioning soly on m_i. Appendix A derives public firms' investment policies under two scenarios: (i) the public firm's manager uses information conveyed in the firm's own stock price p_i; and (ii) the public firm's manager utilizes all the information possible including the information embedded in the industry average stock price, information in the firm's own stock price, and the manager's private signal. The results I am interested in is the case where the public firm manager utilize all the information possible (case (ii)). Not surprisingly, the optimal investment is a function of the weighted average of the three signals.

However, as shown in Equation (33) of Appendix A, the weight on the industry average stock price (β_{Pub}^{Learn}) may not always be positive for public firms. With more volatile firm-specific shock as oppose to common shock ($0 < \rho < 1$ and $f = \frac{\sigma_\Phi^2}{\sigma_\Phi^2 + \sigma_\eta^2} < \rho$) or with almost perfectly correlated price noise terms ($\rho = 1$), the investment of public firms responds *negatively* to the industry stock price. The rationale for the result is as follows: when the industry average stock price has the same noise as the individual stock price, public firms' manager could subtract the average stock price from its own stock price to obtain the firm-specific shock (η_i). Conditioning on the firm's own stock price, the higher the industry average, the lower the estimate of η_i. In such case, the optimal investment responds *negatively* to the average price. 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 (2014) studying the risk-taking behavior under common and firm-specific uncertainty when agents have incentives to match the industry average effort. For the response of private firms' investment, the sign is not sensitive to the model specifications, thereby putting less challenge when drawing inference from empirical results.

Furthermore, given any value of ρ, if we assume the distribution of managers' signal does not differ across private and public firms, the difference in their investment-to-industry stock price sensitivity is given by

$$\beta_{Pri}^{Learn} - \beta_{Pub}^{Learn} = \frac{\left(\sigma_\Phi^2 + \rho\sigma_\omega^2\right)\left[\sigma_\Phi^2\sigma_\varepsilon^2 + \rho\sigma_\omega\left(\sigma_\Phi^2 + \sigma_\eta^2 + \sigma_\varepsilon^2\right)\right]}{\Lambda\left[\sigma_\Phi^2\left(\sigma_\eta^2 + \sigma_\varepsilon^2\right) + \rho\sigma_\omega^2\left(\sigma_\Phi^2 + \sigma_\eta^2 + \sigma_\varepsilon^2\right)\right]} \tag{20}$$

where β_{Pri}^{Learn} is private firm's weight on industry average stock price under the "Learning" scenario,

β_{Pub}^{Learn} is public firms' weight on industry average stock price when the manager learn from its own stock price and the industry average price, and Λ is in Equation (36) of Appendix A. It can be show that $\beta_{Pri}^{Learn} - \beta_{Pub}^{Learn} > 0$ if (i) there is uncertainty to the common demand or productivity (i.e. $\sigma_{\Phi}^2 > 0$), and (ii) managers do not receive perfect signal about future shocks (i.e. $\sigma_{\varepsilon}^2 > 0$), meaning private firms always have higher sensitivity to the industry average stock price than that of public firms. Therefore,

***Hypothesis* 4:** When both private firms and public firms learn from the stock market and public firms do not have agency concerns, private firms respond more to the average stock price than do public firms.

3 Data

3.1 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, profit & loss account, and statement of cash flow for all private and public companies (approximately 2.9 million) in the United Kingdom. For public firms, the financial data are cross-checked with the Worldscope database provided by Thomson Reuters. Moreover, I obtain from Worldscope the stock prices to calculate the industry market-to-book valuations, the product segment industry codes and product segment financials. All pound values are converted to 2005 constant million pounds using the U.K. consumer price index from the World Development Indicators (WDI).

The primary advantage of using the FAME database is that the 1967 Companies Act in the U.K. requires all limited liability companies, private and public, file their financial statements annually with the U.K. Companies House.[13] Moreover, the 1981 Companies Act requires all companies submit full 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 employee less than 50[14] Thus, the mandatory disclosure policy avoids the selection issues associated with some other databases for private firms.

The second advantage is that private and public firms in the U.K. face equivalent accounting standards. All the statements of public and private firms must be audited if annual sales exceed £0.35 million before June 2000 and £1 million after. Moreover, the U.K. tax laws do not discriminate between public and private firms.[15]

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 or one particular disk. Due to the short period, the sample will be dominated by firms incorporated in more recent years and surviving firms. To avoid this "survivorship" bias, I obtain the archived disks from BvD to expand the time-series from 10 years in previous studies to 18 years and collect the financial data backward in time [16].

Static ("header") information such as listing status, and ownership structures in each disk only reports the last year's value. To obtain this type of information at annual frequency, I append the archived disks from the earliest (release 90, December 1996) to the most recent ones (release 270, December 2011).

Following Brav (2009) and Michaely and Roberts (2012) that utilized the same database, 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

[13]Companies House is an executive agency of the U.K Deparment of Trade and Industry.

[14]Medium firms are allowed to file abbreviated financial statement, while small firms are allowed to submit only an abridged balance sheet without a profit & loss account.

[15]See Brav (2009) and Michaely and Roberts (2012) for more detailed discussions about the FAME database.

[16]My sample period starts from 1993 since the 1996 disk is the earliest archived disk in BvD and it kept financial data for the past three years.

that do not change status from private to public (or public to private) over the sample period to address the concern that the transition firms may not represent the general population of private and public firms.[17]

3.2 Sample Selections

My sample selections follow Brav (2009) and Michaely and Roberts (2012). First, I exclude the following types: assurance company, guarantee, limited liability partnership, not companies act, public investment trusts, and other. I do so to restrict the sample to limited liability companies to which the Companies Act applies. Second, I keep only the consolidated financial statements to mitigate the impact of inter-company dividends on the results, which shrinks the sample substantially. I also exclude the small firms as defined by the Companies House to prevent large number of missing data, and exclude firm-year observations that do not satisfy the auditing requirements.

Following standard practice, I exclude financial, insurance, and real estate firms (US SIC code 6000-6900), utilities (US SIC code 4900-4999), and public sector firms (US SIC code above 8999). I exclude any firm-year observation that has missing book value of asset, sales, or shareholders' equity. I further require each firm have 5 consecutive years of data. My final sample consists of 14,033 private firms and 1,761 public firms.

The variable constructions are presented in Appendix B. Firm characteristics such as sales (scaled by lagged capital), cash flows (scaled by lagged capital) are winsorized separately for public and private firms at 1% level at both tails of the distribution to alleviate the impact of outliers.

Table 1 presents summary statistics for the sample. I report firm-level and industry-level characteristics for private firms as well as public firms. Consistent with previous studies, private firms are much smaller in size than public firms. They depend more on debt (have higher leverage ratio, and involve less in the equity market) than public firms. A notable comparison is that

[17] My results remain the same if I include those firms.

while the private firms do not have lower capital expenditures than do public firms, they have significantly lower investment in fixed assets. This is possibly due to fixed assets acquired through mergers and acquisitions which are associated much more intensively with public firms than private firms. The distributions of individual public firm's Q and the industry average Q are in large consistent with that of previous studies using the U.S sample [18].

4 Empirical Strategies and Results

4.1 Industry Valuation and Private Firms' Investment

The hypothesis in this paper can be tested with the traditional linear investment regression as shown in Equation (5). Substituting $\mathrm{E}(v_i \mid \Omega_i)$ with Equation (12) under the null hypothesis of "No Learning" and with Equation (14) under the hypothesis of "Learning", the following baseline regression is obtained:

$$I_{i,t} = \alpha + \beta \times Industry\_Q_{i,t} + \lambda \times X_{i,t-1} + \theta \times Industry\_X_{i,t-1} + \kappa_i + \delta_t + \epsilon_{i,t} \tag{21}$$

where the subscript i and t index firms and years, respectively; $I_{i,t}$ is the measure of investment, which in the baseline regressions is the capital expenditure (scaled by beginning-of-period capital); $Industry\_Q_{i,t}$ is the average Tobin's Q at the beginning of period t of all public firms in the industry that firm i belongs to; $X_{i,t-1}$ is a set of control variables documented in the literature to affect investment decisions. In the reported results, it contains $CashFlow_{i,t-1}$ which is firm i's lagged cash flow (scaled by beginning-of-period total assets), and $Ln(Asset)_{i,t-1}$ which is the logarithm of lagged total assets. I also check whether the results are robust to controlling for the characteristics at the industry level. The vector $Industry\_X_{i,t-1}$ includes the average size of all public firms and private peers and the average cash flow of all public firms and private peers. As predicted by

[18] In Foucault and Frésard (2014), while a higher mean of individual public firm's Q and the industry average Q for the U.S. public firms is reported, the median values are close to my statistics based on the U.K. firms.

Hypothesis 1, $\beta = 0$ if the private firm manager completely ignores the information in the public domain when making investment decisions ("No Learning"), and $\beta > 0$ if and only if the manager learns from the stock market ("Learning").

The primary independent variable, industry valuation, is proxies by the equal-weighted average Tobin's Q of public firms in the three-digit SIC industry that the private firm belongs to ($Industry\_Q_{i,t}$). In Table 2, I report results corresponding to the estimation of Equation (21). Consistent with Hypothesis 1 of my model, the sensitivity of private firms' investment to the industry valuation is significantly positive.

I control for firm and industry characteristics known to affect investment decisions. The sensitivity remains significantly positive when in Column (2), private firm's own lagged cash flow ($CashFlow_{i,t-1}$) and size ($Ln(Asset)_{i,t-1}$) are controlled for, and in Column (3), the average cash flow and size of all private peers, as well as the average cash flow of public firms are further controlled for. The economic magnitude is considerable: a one standard deviation increase in the industry valuation is associated with a 1.4% increase in the capital expenditure (scaled by the beginning-of-year fixed assets) of private firms ($\beta \times SD(Ind\_Q) = 0.23 \times 0.6 = 1.4\%$), which is about 7% of the average investment-to-fixed asset ratio in my sample. This effect is obtained after controlling for the unobserved time-varying shocks common to all firms (by using the year fixed effects), and the unobserved heterogeneity at the firm-level (by using the firm fixed effects).

My results are robust to how industry valuation is measured. In Column (4) to (6), I replace the equal-weighted industry valuation with value-weighted average ($Industry\_Q\_vw_{i,t}$), the results still hold. The results are also robust to how investment is measured. In unreported tables, I change the dependent variable from $Capx/K$, which is capital expenditures scaled by the beginning-of-period capital to ΔK, which is the annual change of capital scaled by the beginning-of-period capital, the sensitivity of private firms' investment to the industry valuation is still positive. The difference between the two measures is that ΔK accounts not only for fixed assets invested internally, but also for fixed assets acquired externally through mergers and acquisitions. But since mergers and acquisitions among private firms are not as active as that in public firms, the sensitivity of the two measures to the industry valuation do not have material difference.

4.2 Information Spillover from Minor-Segment Industry Leaders

4.2.1 Minor-Segment Industry Valuation and Private Firms' Investment

As has been discussed in previous sections, since we are dealing with unobservable signals to the manager, biases may arise. It is possible that some unobserved factors affecting firm's investment behavior co-exist in the manager's private information set and the industry price signal, but cannot be perfectly controlled by the firm and industry characteristics. In this case, we may find $\beta > 0$ even under the "No Learning" scenario. To isolate the effect, I essentially plug Equation (17), which is a transformation of the conditional expectation under the "Learning" hypothesis (Equation (14)), into the optimal investment policy, and test Hypothesis 1b that private firm's investment responds to the noise term in the industry average stock price under the "learning" scenario. Intuitively, the stock prices of public firms contains both information related to private firms in the same industry and information unrelated ("noise") to private firms. If the manager of a private firm does not learn from the stock price, but observes this "noise" directly from other channels such as golf clubs, she would not adjust the investment decision in response to the false signal. If, instead, she learns from the stock prices of the public firms and cannot completely separate the relevant information from the "noise", then *ex post* the investment of her firm will be sensitive to the stock prices as well as the "noise" in the price signal. Therefore, my model implies that, if private firm managers pay attention to stock prices and cannot separate the fundamental information from non-fundamental information, then investment decisions will be sensitive to the noise in the industry average stock price.[19]

[19]This implication is consistent with the "false" signal theory in Morck, Shleifer and Vishny (1990).

I explore the valuation of industry leaders' unrelated minor-segment industries as the "noise" in the price signal for a private firm in the industry leaders' major-segment industry because it satisfies two conditions crucial for testing the "learning" hypothesis. Firstly, it is unrelated to the fundamental investment opportunities for private firms which are operating in the industry leaders' major-segment industry. Industry leaders' are usually large public firms with many lines of business. Sometimes, the minor segments are in industries unrelated to industry of their major segment, thereby unrelated to the private firms in their major segments industries. If the private firms do not learn from the industry valuation, then their investment will not respond to the valuation of industries in which the public leaders have *unrelated* minor segments, as such valuation is irrelevant to the investment opportunity of private firms in the public leaders' major segment industry. Therefore, the room for a spurious relationship between the investment of private firms and industry valuation of public firms is squeezed in my design as private firms are not expected to react to the investment opportunities of unrelated minor-segment industries.

The second condition the "noise" strategy relies on requires that the decision maker cannot completely filter out the unrelated information. Otherwise, even if there is learning, the investment will not be sensitive to the "noise". The stock valuation of conglomerate firms reflects information in both their major and minor segments. As suggested by existing studies, it is indeed difficulty to be filtered out the unrelated minor-segment industry valuation from the (major-segment) industry valuation. Investors and equity analysts have bounded rationality and may price small firms based on returns of large firms. Therefore, industry leaders, which are usually large in size, may lead the pure players (which are usually small firms) in stock returns.Hou (2007) finds that within the same industry, leaders lead followers in stock returns. Cen et al. (2013) further document a strong contemporaneous and a lead-lag relation in stock returns between firms from industry leaders' unrelated minor-segment industries and pure players in the industry leaders' major-segment industry, which is consistent with the information diffusion hypothesis that the less sophisticated investors price industry pure players based on the industry leaders' returns without being able to distinguish between the major and minor segment fundamentals. Therefore, even if the private firms learn from the stock prices of pure players in their industry, the price may still contains "noise" about the industry leaders' minor segments.

I obtain the segment industry code and financials of public firms from the Worldscope database, which reports information on product segments for international public firms from 1980 and have sufficient coverage after 1990. I use the two-digit segment SIC code in each year to determine to which industry a product segment belongs.[20] When the segment SIC code is missing, I replace it by the most recent non-missing SIC code of the segment. I identify the "industry leaders" as firms whose major-segment industry 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. If a firm does not have any such segment, its major-segment industry is regarded as missing. I also identify "industry pure players" as firms that are not industry leaders and generate all the sales from the major-segment industry. As industry leaders are usually larger firms, many of them have product segments in other two-digit SIC industries. These are defined as the "minor-segment industry", while the leaders in the minor-segment industry are called "minor-segment industry leaders". I require that there be five industry leaders and at least five pure players in each two-digit SIC industry.[21]

I use the average valuation of the "minor-segment industry leaders" as an instrument for the noise term in the industry valuation, and estimate whether the investment of private firms responds positively to this piece of variation.

$$I_{i,t} = \alpha + \beta \times Minor\_Q_{i,t} + \lambda \times X_{i,t-1} + \theta \times Industry\_X_{i,t-1} + \kappa_i + \delta_t + \epsilon_{i,t} \tag{22}$$

To make sure that the results I obtain are, to the largest extent, from minor-segment industries

[20]Product segments defined by a different four-digit or three-digit SIC code may belong to the same two-digit SIC segment industry in my sample.

[21]My results are not sensitive to the number of industry leaders and pure players.

that are unrelated to the industries of private firms, I exclude industry pairs where the leaders of two industries have minor segments in each other. Furthermore, I exclude those minor-segment industries that the private firms may also have business in or are likely to have supplier or customer relationships with. My model predicts $\beta = 0$ when the private firm managers does not learn from the stock market, and $\beta > 0$ when she learns from the stock market. The test is novel in the sense that no "mislearning" shall be found if there were no learning, as the noise captures part of the price signal that is orthogonal to private firms' investment opportunities.

I first measure the unrelated minor-segment industry valuation with the average beginning-of-period Tobin's Q of minor-segment industry leaders for a two-digit SIC industry ($Minor\_Leader\_Q_{i,t}$), and then by the average beginning-of-period Tobin's Q of all public firms in the unrelated minor-segment industries ($Minor\_Industry\_Q_{i,t}$). I find that investment of private firms in the industry leaders' major-segment industry reacts strongly to the valuation of industry leaders' unrelated minor-segment industries: a one standard deviation increase in minor-segment industry valuation is associated with a 0.5% increase in the capital expenditure (scaled by the beginning-of-year fixed assets) of private firms in the major segments ($\beta \times SD(Minor\_Leader\_Q) = 0.0083 \times 0.61 = 0.5\%$), about 2.3% of the average investment-to-fixed assets ratio. The results are robust if I also control for firm-level and industry-level characteristics that affect investment behavior.

Industry valuation movements caused by the unrelated minor-segment industry valuation are unlikely to be correlated with private firm's fundamentals because such movements are due to less sophisticated investors' lack of ability to decompose the valuation of industry leaders, who usually have fairly complicated business segments, to the part that is related to its major-segments industry and the part that is driven by the fundamentally unrelated minor-segment industries. The evidence suggests that managers of private firms are also subject to this "limited attention" bias because otherwise, their investment would not be responsive to the spurious information driven by unrelated minor-segments of the industry leader. The findings suggest that the private firm mangers exhibit "Learning" behavior and cannot filter out irrelevant information from the industry valuation.

4.2.2 Placebo Tests: Irrelevant Industry Valuation and Private Firms' Investment

One alternative explanation for the results in 4.2.1 is that the results I claim to be the information spillover effect may simply reflect common factors in the stock prices of all industries or some industries with unobserved links. To address this concern, I conduct placebo tests by constructing average valuation measures of random irrelevant industries. I replace each minor segment of the industry by a randomly selected "irrelevant" industry, that is, an two-digit SIC industry that does not belong to the minor-segment industries nor share any minor-segment industries with the major-segment industry leaders. The idea is that if the co-movements can explain the findings, even with the "irrelevant" industries, I would still observe $\beta > 0$, while under the "learning" framework, using the "irrelevant" industries will produce $\beta == 0$.

I randomly choose the "irrelevant" industries for 500 times and estimate Equation (23) as follows:

$$I_{i,t} = \alpha + \beta \times Random\_Q_{i,t} + \lambda \times X_{i,t-1} + \theta \times Industry\_X_{i,t-1} + \kappa_i + \delta_t + \epsilon_{i,t} \tag{23}$$

where $Random\_Q_{i,t}$ is the average beginning-of-period market-to-book of all leaders (or all firms) in the "random irrelevant" industries that are selected to replace the true minor-segment industries.

As shown in Table 4, the result does not hold for the "irrelevant" industries. Once I substitute the average valuation of minor-segment industry leaders (or all firms) with the corresponding valuation from "irrelevant" industries, the relationship between private firms' investment and the market-to-book of the minor-segment industries completely vanishes. This result suggests that the mechanism is through the information spillover from minor-segment industries to the major-segment industry leaders' stock prices: the valuation of "irrelevant" industries do not affect the major-segment industry valuation, thereby are not learnt by the private firms' managers.

4.2.3 Robustness Tests: Economically Unlinked Private Firms

Another concern with the analysis is that private firms may also have minor segments in the same set of industries as the public industry leaders in the major-segment industry. If this is the case, then the average valuation of the minor-segment industries may simply reflect the fundamentals in minor-segment industries within which private firms' also have minor segments, and the investment-to-valuation of minor segments is essentially caused by the economic links rather than the information spillovers. In addition, it is possible that the industry leaders' minor-segment industries have supplier or customer relationships with private firms in the industry leaders' major-segment industry, thereby have correlated fundamentals with the private firms in the major-segment industry. In this section, I establish the results by excluding the possible economic links in a number of ways.

I retrieve the secondary SIC code of private firms from FAME.[22] As firms are required to report not only the SIC codes for their business segments, but also for all the other industries that they operate, I exclude to the largest extent any common business segments shared by private firms and public industry leaders. I first exclude the firm-year observations for which a possible economic links could be found, then exclude the firms' entire data points if a possible economic links could be found in any year over the sample period. My results are robust as reported in Panel A of Table 5. I also exclude the minor-segment industries that potentially have supplier or customer relationship with the major-segment industries. My results still stand as reported in column (5) and (6) of Panel B. Moreover, my results are robust if I exclude minor-segment industries that potentially have supplier and customer relationships with the major-segment industries, where supplier and customer industries are defined using the 2012 U.S. Input-Output Tables provided by the Bureau of Economic Analysis. Therefore, the common minor-segment industries of private firms and public industry leaders or supplier and customer relationships cannot alone account for the documented investment responses to the valuation of minor-segment industries.

[22]Worldscope, from which I obtain the segment SIC code of public firms, does not cover private firms

4.3 Cross-sectional Tests

My model also provides cross-sectional implications to test the learning hypothesis. In this section, I first examine how the informativeness of the industry price signal affect the investment-to-industry valuation sensitivity (Hypothesis 2), and later examine the how industry competition structure affect this sensitivity (Hypothesis 3).

4.3.1 Price Informativeness

I first test Hypothesis 2 and examine how the informativeness (precision) of the industry price signal affects the investment-to-industry valuation sensitivity. I use three measures for the industry price informativeness. The first is number of *public* firms in the same three-digit SIC industry ($H\_\#Public$), which is a dummy equals to 1 if the logarithm of 1 plus the number of public firms of the industry is above the 70th percentile, and equals to 0 if it is below the 30th percentile. As in Chemmanur, He and Nandy (2010), the more firms already listed in a industry, the easier it is for outsiders to evaluate firms in that industry. The outsides include unsophisticated investors, sophisticated investors, financial analysts and market makers. Therefore, if there are more public firms in the industry, the industry price is more precise.

For similar reason, I use is $\%Public$, which is the fraction of number of public firms to all firms in a three-digit SIC industry, as the second measure for price informativeness. As argued in Badertscher, Shroff and White (2013), the faction of public to all firms in a industry affect the information environment, and thereby, the (price) and investment efficiency.

The third measure is price non-synchronocity ($H\_Nonsynchronisity$), which is a dummy equals to 1 if the $Nonsynchronisity$ of a three-digit SIC industry is above the 70th percentile, and equals to 0 if it is below the 30th percentile. As in many other papers (Durnev, Morck and Yeung (2004), Chen, Goldstein and Jiang (2007), and Foucault and Frésard (2014)), I use the price non-synchronicity (or firm-specific return variation) as the measure for individual price informativeness.[23] I then construct the dummy from the average price non-synchronicity in an industry.

As shown in Table 6, I find that in industries where the stock prices are more informative about future fundamentals, private firms' investment responds more to the industry average valuation, consistent with Hypothesis 2. The economic magnitude of the investment-price sensitivity in those industries increases substantially: a one standard deviation increase in industry valuation is associated with approximately 3.4% increase in private firms' capital expenditure (scaled by the beginning-of-year capital) in industries with high price informativeness, about 16% of the average investment-to-capital ratio.

4.3.2 Common Shocks

I then test Hypothesis 3. As predicted by my model, the sensitivity of private firms' investment to the average stock price are expected to be stronger when the common demand (or productivity) shock is more important to firms relative to the firm-specific shock.

I use three measures for how likely firms are facing common demand shocks: (i) number of firms in the three-digit SIC industry ($H\_\#Firms$), which is a dummy equals to 1 if the logarithm of 1 plus the number of all firms of the industry is above the 70th percentile, and equals to 0 if it is below the 30th percentile; (ii) the (inverse of) Herfindahl-Hirschman Index of a three-digit SIC industry (L_HHI), which a dummy equals to 1 if HHI in a three-digit SIC industry is below the 30th percentile, and equals to 0 if it is above the 70th percentile; and (iii) market share of the top 4 firms in a three-digit SIC industry (L_Top4_Shares), which a dummy which equals to 1 if the market share of the top 4 firms in a three-digit SIC industry is below the 30th percentile, and equals 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 (Hart (1983), Giroud

[23] I regress public firm i's weekly stock returns on the market portfolio returns and the industry portfolio returns, obtain the $R^2_{i,t}$ and define firm-specific return variation as $1 - R^2_{i,t}$. Weekly return data are from Worldscope.

and Mueller (2011)).

As shown in Table 7, I find that in industries where firms are more likely to face common shocks, private firms' investment responds more to the industry average valuation, consistent with Hypothesis 3. The economic magnitude of the investment-price sensitivity in those industries increases substantially: a one standard deviation increase in industry valuation is associated with approximately 3.3% increase in private firms' capital expenditure (scaled by the beginning-of-year capital) in more competitive industries, about 16% of the average investment-to-capital ratio.

The results also help rule out an alternative hypothesis that competition between public firms and private firms generate the investment-valuation relationship in absence of learning. Such alternative mechanism stretches on the strategic interactions between firms such that private firms may adjust investment in response to public firms' investment instead of stock prices. However, the competition argument predicts that the effect be stronger for concentrated industries in which strategic behaviors are more predominant, which is the opposite to the findings. Moreover, the optimal behavior of private firms under Cournot competition is expected to be negative, which again contradicts the findings. Therefore, the results suggest that the spillover effect I document here cannot be fully explained by competitions between public and private firms.

4.4 Public Firms' Investment

My model predicts that when there is high uncertainty to future systematic productivity (or demand), and firms do not receive perfect signals, private firms always have higher sensitivity to the industry average stock price than public firms based on the learning framework. I do not aim to find supporting evidence for Hypothesis 4, simply because public firms' investment may be sensitive to the stock market valuation for many other reasons than "Learning". The most prominent channels documented in existing literature are the "equity financing channel" and the catering channel. The former suggests that equity issuance and capital investment of public firms be affected by stock prices because the effective cost of external equity of public firms can diverge from the cost of other forms of capital due to movements of the irrational element contained in stock prices (Keynes (1936), Morck, Shleifer and Vishny (1990), Stein (1996) and Baker, Stein and Wurgler (2003), among others). The latter, as in Polk and Sapienza (2009), argues that managers of public firms may try to boost short-run share prices by catering current sentiment, especially for managers with shorter shareholder horizon. Furthermore, Asker, Farre-Mensa and Ljungqvist (2015) suggest that public firms investment are less responsive to changes in investment opportunities due to managerial myopia. Therefore, the purpose of this section is to test the difference in investment response between public and private firms to the industry valuation, and see to what extent public firms investment deviates from the optimal investment behavior suggested by the "Learning" framework.

I use caliper-based nearest-neighbor match with replacement adapted to a panel setting following Asker, Farre-Mensa and Ljungqvist (2015). Stating from 1993, I match private firms with public firms from the same three-digit industry and closest in size. I require that the ratio of their total assets is less than 2. If no match can be formed, I drop the observation and look for a match in the following year. Once a match is found, it is kept in subsequent years. The panel structure of the data allows us to estimate the within-firm sensitivity of investment to the industry valuation. Since one public firm could be matched to different private firms, I end up with more private observations (76,738) than public ones (8,135).

I estimate the baseline regression on investment and financing policies for matched sample of private and public firms as shown in Equation (24).

$$Y_{i,t} = \alpha + \beta \times Industry\_Q_{i,t} + \beta_2 \times Industry\_Q_{i,t} \times Public_i + \lambda \times X_{i,t-1} + \theta \times X_{i,t-1} \times Public_i + \kappa_i + \delta_t + \epsilon_{i,t} \tag{24}$$

The results are presented in Table 8. The dependent variables in Column (1) and (2) are $Capx/K$, which is the annual capital expenditure (scaled by lagged capital), and ΔK, which is the annual change of capital (scaled by lagged capital), respectively. A notable finding is that while the private firms have statistically insignificant difference from public firms in the response of $Capx/K$ to industry valuation, they exhibit significantly lower sensitivity of their investment in fixed assets to the industry valuation. This difference is possibly due to fixed assets acquired through mergers and acquisitions which are associated much more with public firms since they can involve intensively in equity acquisition than can private firms.

I further turn to the comparison of financing policies. I construct $Equity\ Issue$ and $Debt\ Issue$ variables using balance sheet items following Dasgupta, Noe and Wang (2011). Column (3) and (4) report the results when the dependent variables are the annual change of Book Equity minus the annual change of Retained Earnings (scaled by lagged fixed assets), and the annual change of Book Debt (scaled by lagged capital), respectively. It shows that public firms' equity financing responds much more sensitively to industry valuation, which is consistent with earlier view that public firms rely much more heavily on equity than do private firms (Brav (2009)). Surprisingly, their debt issuance not only responds less sensitively than private firms, but even *negatively* to industry valuation. This substitution of debt with equity is in line with the market timing literature that high returns trigger equity issuance(Baker, Stein and Wurgler (2003), Alti and Sulaeman (2012), among others). Therefore, due to other incentives for manager to adjust investment in response to stock prices, public firms' investment cannot be fully justified a "learning" framework.

5 Conclusion

Whether the stock market affects the real economy through its role of producing and aggregating information has long been the interests of finance studies. While previous studies have documented ample evidence on the relationship of stock prices and public firms' investment, it is challenging to attribute the effect to managerial learning due to the econometricians' inability to observe corporate managers' private information set when making investment decisions.

In this paper, I examine privately held companies. Using a large panel data set for the United Kingdom, I find that investment of private firms responds positively to the valuation of public firms in the same industry. The sensitivity is stronger in industries where stock prices are more informative or firms are more likely to face common demand shocks. To rule out the possibility that unobserved factors drive both private firms' investment and the industry valuation and generate a spurious relationship even in the absence of learning, I further show that the investment of private firms in the industry leaders' major-segment industry responds strongly to the valuation of industry leaders' unrelated minor-segment industries.

"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" (Hayek (1945)). In this paper, I show that private firms behave in such a way. Private firm managers exploit information contained in the stock prices, but cannot completely filter out the information related to the multisegment public leaders but unrelated to themselves.

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A Stock Prices and Public Firms' Investment

In this appendix, I derive the investment policy of a public firm under two scenarios: (i) the public firm's manager uses information conveyed in the firm's own stock price p_i; and (ii) the public firm's manager utilizes all the information possible including the information embedded in the industry average stock price, information in the firm's own stock price, and the manager's private signal.

A.1 Learning from own stock price

If public firm i's manager ($i = 1, \ldots, N$) makes use of i's own stock price, but ignores the average stock price (i.e., $\Omega_i = [p_i, m_i]$) [24], the expectations of the shocks can be derived as

$$\mathrm{E}\left(v_i \mid p_i, m_i\right) = \left(1 - \gamma_{Pub}^{Narrow} - \lambda_{Pub}^{Narrow}\right)\mu_\Phi + \gamma_{Pub}^{Narrow} p_i + \lambda_{Pub}^{Narrow} m_i \tag{25}$$

where

$$\gamma_{Pub}^{Narrow} = \frac{\sigma_\varepsilon^2\left(\sigma_\Phi^2 + \sigma_\eta^2\right)}{\sigma_\varepsilon^2\left(\sigma_\Phi^2 + \sigma_\eta^2\right) + \sigma_\omega^2\left(\sigma_\Phi^2 + \sigma_\eta^2 + \sigma_\varepsilon^2\right)} \tag{26}$$

$$\text{and} \qquad \lambda_{Pub}^{Narrow} = \frac{\sigma_\omega^2\left(\sigma_\Phi^2 + \sigma_\eta^2\right)}{\sigma_\varepsilon^2\left(\sigma_\Phi^2 + \sigma_\eta^2\right) + \sigma_\omega^2\left(\sigma_\Phi^2 + \sigma_\eta^2 + \sigma_\varepsilon^2\right)} \tag{27}$$

A.2 Learning from own and average stock price

Furthermore, when i's manager complements her private signal with both i's own stock price and the industry average stock price (i.e., $\Omega_i = [\bar{p}, p_i, m_i]$) [25], the conditional expectations of the shocks can be derived as

$$\mathrm{E}\left(v_i \mid \bar{p}, p_i, m_i\right) = \left(1 - \beta_{Pub}^{Learn} - \gamma_{Pub}^{Learn} - \lambda_{m_i}^{Learn}\right)\mu_\Phi + \beta_{Pub}^{Learn}\bar{p} + \gamma_{Pub}^{Learn} p_i + \lambda_{Pub}^{Learn} m_i \tag{28}$$

where

$$\beta_{Pub}^{Learn} = \frac{1}{\Lambda}\sigma_\varepsilon^2\left[\sigma_\Phi^2\sigma_\omega^2 - \sigma_{\bar{\omega}}^2\left(\sigma_\Phi^2 + \sigma_\eta^2\right)\right] \tag{29}$$

$$\gamma_{Pub}^{Learn} = \frac{1}{\Lambda}\sigma_\eta^2\sigma_\varepsilon^2\left(\sigma_\Phi^2 + \sigma_{\bar{\omega}}^2\right) \tag{30}$$

$$\lambda_{Pub}^{Learn} = \frac{1}{\Lambda}\left[\sigma_\Phi^2\sigma_\eta^2\sigma_\omega^2 + \sigma_{\bar{\omega}}^2\left(\sigma_\omega^2 - \sigma_{\bar{\omega}}^2\right)\left(\sigma_\Phi^2 + \sigma_\eta^2\right)\right] \tag{31}$$

and

$$\Lambda = \sigma_\Phi^2\sigma_\eta^2\sigma_\varepsilon^2 + \sigma_\eta^2\left(\sigma_\Phi^2\sigma_\omega^2 + \sigma_\varepsilon^2\sigma_{\bar{\omega}}^2\right) + \left(\sigma_\omega^2 - \sigma_{\bar{\omega}}^2\right)\left[\sigma_\Phi^2\sigma_\varepsilon^2 + \sigma_{\bar{\omega}}^2\left(\sigma_\Phi^2 + \sigma_\eta^2 + \sigma_\varepsilon^2\right)\right] \tag{32}$$

[24] Such scenario is similar to the "narrow learning" results examined in Foucault and Frésard (2014).

[25] This is similar to the "learning from peers" case in Foucault and Frésard (2014). However, since Foucault and Frésard (2014) do not have firm-specific shock, the implication about firms' response to industry average stock price may be different from my results.

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

$$\begin{aligned}
\beta_{Pub}^{Learn} &= \frac{\sigma_{\varepsilon}^2\sigma_{\omega}^2}{\Lambda}\left[(1-\rho)\,\sigma_{\Phi}^2 - \rho\sigma_{\eta}^2\right] && (33)\\
\gamma_{Pub}^{Learn} &= \frac{\sigma_{\eta}^2\sigma_{\varepsilon}^2}{\Lambda}\left(\sigma_{\Phi}^2 + \rho\sigma_{\omega}^2\right) && (34)\\
\lambda_{Pub}^{Learn} &= \frac{\sigma_{\omega}^2}{\Lambda}\left[\sigma_{\Phi}^2\sigma_{\eta}^2 + \rho\,(1-\rho)\,\sigma_{\omega}^2\left(\sigma_{\Phi}^2 + \sigma_{\eta}^2\right)\right] && (35)
\end{aligned}$$

where

$$\Lambda = \sigma_{\Phi}^2\sigma_{\eta}^2\sigma_{\varepsilon}^2 + \sigma_{\eta}^2\sigma_{\omega}^2\left(\sigma_{\Phi}^2 + \rho\sigma_{\varepsilon}^2\right) + (1-\rho)\,\sigma_{\omega}^2\left[\sigma_{\Phi}^2\sigma_{\varepsilon}^2 + \rho\sigma_{\omega}^2\left(\sigma_{\Phi}^2 + \sigma_{\eta}^2 + \sigma_{\varepsilon}^2\right)\right] \qquad (36)$$

For all possible values of ρ, we have

$$\Lambda > 0, \quad \gamma_{Pub}^{Learn} > 0, \text{ and } \quad \lambda_{Pub}^{Learn} > 0$$

The sign of β_{Pub}^{Learn}, however, depends on the value of ρ and $f = \frac{\sigma_{\Phi}^2}{\sigma_{\Phi}^2+\sigma_{\eta}^2}$:

(1) when $\rho = 0$, meaning that $\bar{p}$ is a perfect signal of the common shock, $\beta_{Pub}^{Learn} > 0$;

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

(3) when $\rho = 1$, meaning that the noise term in the average stock price is as volatile as in the individual price, $\beta_{Pub}^{Learn} < 0$.

B Variable Definitions

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

B.1 Firm-level variables

Total Assets is the balance sheet item Total Asset reported in 2005 constant million pounds;

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

Capx/K is the cash flow statement item Capital Expenditures scaled by the beginning-of-period capital;

ΔK is the annual change of capital scaled by the beginning-of-period capital;

Ln(Asset) is the logarithm of Total Assets;

CashFlow is the cash flow of the period scaled by the beginning-of-period Total Assets, where cash flow is the sum of the profit & loss account items Profit (Loss) for the Period and Depreciation;

ΔSales is the annual change of sales scaled by the beginning-of-period Total Assets, where sales corresponds to the profit & loss account item Turnover;

ΔCash is the annual change of cash holdings scaled by the beginning-of-period Total Assets, where cash holdings is the sum of the balance sheet items Bank & Deposits and Investment;

Tangibility is the sum of the balance sheet items Land & Buildings, Fixtures & Fittings, and Plant & Vehicles, scaled by the beginning-of-period Total Assets;

Leverage is defined as the Book Debt plus Trade Creditors, scaled by the beginning-of-period Total Assets;

Equity Issue is the annual change of Book Equity minus the annual change of Retained Earnings, scaled by the beginning-of-period capital, where Book Equity is constructed using the balance sheet items and is the sum of Shareholders Fund and Deferred Tax, and Retained Earnings is defined as the balance sheet item profit & loss account;

Debt Issue is the annual change of Book Debt scaled by the beginning-of-period capital, where Book Debt is constructed using the balance sheet items and is defined as Long Term Debt plus Short Term Loans & Overdrafts minus Group Loans;

Market-to-book for public firms is the market-to-book ratio of assets, where the market value of assets is defined as Total Assets $-$ Book Equity $+$ stock price at the end of fiscal year $\times$ number of shares outstanding;

Own_Q for public firms is the beginning-of-period *Market-to-book*;

B.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_Q_vw is the value-weighted average of the beginning-of-period *Market-to-book* of public firms in a three-digit SIC industry, where the weight is the Total Assets;

Industry_CashFlow is the average $CashFlow$ of all firms in a three-digit SIC industry;

Private_CashFlow is the average *CashFlow* of private peers in the three-digit SIC industry;
Private_Ln(Asset) is the average *Ln(Asset)* of private peers in the three-digit SIC industry;
Public_CashFlow is the average *CashFlow* of public firms in a three-digit SIC industry;
Public_Ln(Asset) is the average *Ln(Asset)* of public firms in a three-digit SIC industry;
Minor_Leader_Q is the average beginning-of-period *Market-to-book* of all minor-segment industry leaders for a two-digit SIC industry;

Minor_Industry_Q is the average beginning-of-period *Market-to-book* of all minor-segment industries for a two-digit SIC industry;

Random_Leader_Q is the average beginning-of-period *Market-to-book* of all leaders in the "random irrelevant" industries that are selected for the private firm;

Random_Industry_Q is the average beginning-of-period market-to-book of the "random irrelevant" industries that are selected for the private firm;

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

H_#Public is a dummy which equals to 1 if *#Public* of the industry is above the 70th percentile, and equals to 0 if it is below the 30th percentile;

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

Nonsynchronisity is estimated by the $1 - R^2$ from running weekly firm return on the market return and three-digit SIC industry return;

H_Nonsynchronisity is a dummy which equals to 1 if the $Nonsynchronisity$ of a three-digit SIC industry is above the 70th percentile, and equals to 0 if it is below the 30th percentile;
#Firms is the logarithm of 1 plus the number of all firms in a three-digit SIC industry;

H_#Firms is a dummy which equals to 1 if the $\#Firms$ of a three-digit SIC industry is above the 70th percentile, and equals to 0 if it is below the 30th percentile;

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

L_HHI is a dummy which equals to 1 if HHI in a three-digit SIC industry is below the 30th percentile, and equals to 0 if it is above the 70th percentile;

Top4_Share is the market share of the top 4 firms in a three-digit SIC industry;

L_Top4_Share is a dummy which equals to 1 if the $Top4\_Share$ in a three-digit SIC industry is below the 30th percentile, and equals to 0 if it is above the 70th percentile;

Table 1: **Summary Statistics**

This table reports the descriptive statistics of the main variables used in the analysis. The sample period is from 1993 to 2010. All variables are defined in Appendix B. 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 are also from Worldscope. I restrict the sample to limited liability companies to which the Companies Act applies, and keep only the consolidated financial statements to mitigate the impact of inter-company dividends on my results. I also exclude the small firms as defined by the Companies House to prevent large number of missing data, and exclude firm-year observations that do not satisfy the auditing requirements. I also exclude financial, insurance, and real estate firms (US SIC code 6000-6900), utilities (US SIC code 4900-4999), and public sector firms (US SIC code above 8999), and any firm-year observation that has missing book value of asset, sales, or shareholders' equity. I further require each firm have 5 consecutive years of data. All pound values are converted to 2005 constant million pounds using the U.K consumer price index from the WDI. Firm characteristics are winterized separately for public and private firms at 1% level at both tails. Firm-level variables are presented in Panel A. Industry characteristics (firm-year average) are presented in Panel B. Reported statistics include number of observations (Obs.), mean, median and standard deviation (SD).

Panel A. Firm Characteristics

	Private Firms				Public Firms			
	Obs.	Mean	Median	SD	Obs.	Mean	Median	SD
$Capx/K$	69,962	0.216	0.095	0.453	12,177	0.174	0.100	0.242
ΔK	109,154	0.119	-0.018	0.676	12,177	0.267	0.025	0.978
$Ln(Asset)$	110,292	2.720	2.506	1.487	12,178	4.563	4.313	2.053
$CashFlow$	110,114	0.055	0.051	0.134	12,177	0.074	0.081	0.149
$\Delta Sales$	110,294	0.114	0.045	0.570	12,178	0.132	0.059	0.425
$\Delta Cash$	99,573	0.013	0.000	0.110	12,146	0.019	0.001	0.139
$Tangibility$	108,722	0.276	0.215	0.237	12,178	0.277	0.228	0.232
$Leverage$	106,295	0.392	0.371	0.266	12,158	0.322	0.305	0.198
$Equity\ Issue$	109,454	0.046	-0.003	0.513	12,177	0.280	-0.001	1.558
$Debt\ Issue$	109,512	0.058	0.000	1.500	12,177	0.084	0.000	0.587
Own_Q					11,480	1.809	1.425	1.245

Panel B. Industry Characteristics

	Private Firms				Public Firms			
	Obs.	Mean	Median	SD	Obs.	Mean	Median	SD
Industrt_Q	110,294	1.674	1.566	0.596	12,178	1.804	1.655	0.668
Industry_Q_vw	110,294	1.619	1.511	0.602	12,178	1.767	1.584	0.743
Minor_Leader_Q	77,565	1.816	1.652	0.609	8,356	1.840	1.706	0.603
Minor_Industry_Q	79,853	1.758	1.698	0.393	8,498	1.725	1.685	0.383
#Public	110,294	2.225	1.946	0.917	12,178	2.427	2.197	0.997
%Public	110,294	0.101	0.063	0.094	12,178	0.310	0.212	0.291
Nonsynchronicity	110,294	0.705	0.724	0.145	12,178	0.727	0.766	0.154
#Firms	110,294	4.797	4.700	1.057	12,178	3.918	3.932	1.374
HHI	110,294	0.131	0.072	0.144	12,178	0.241	0.165	0.217
Top4_Share	110,294	0.483	0.449	0.225	12,178	0.648	0.657	0.248

Table 2: **Industry Valuation and Private Firms' Investment**

This table presents the results from estimating Equation (21) for private firms as shown below:

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

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 in column (1) to (3) is $Industry\_Q_{i,t}$, the equal-weighted average of the beginning-of-period market-to-book ratio of public firms in the three-digit SIC industry that the private firm belongs to, and in column (4) to (6) is $Industry\_Q\_vw_{i,t}$, which is the value-weighted average. Column (2), (3), (5), and (6) control for private firm's own lagged $CashFlow$ and $Ln(Asset)$. In addition, column (3) and (6) control for $Private\_CashFlow$, $Private\_Ln(Asset)$, $Public\_CashFlow$, $Public\_Ln(Asset)$, which are the average cash flow and size for all private peers and public firms at the beginning-of-period, respectively. All the variable constructions are described in Appendix B. All the 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 to be conservative. Coefficients significant at the 10%, 5%, and 1% levels are marked with *, **, and ***, respectively.

	(1) $Capx/K$	(2) $Capx/K$	(3) $Capx/K$	(4) $Capx/K$	(5) $Capx/K$	(6) $Capx/K$
$Industry\_Q_{i,t}$	0.028***	0.024***	0.022***			
	(3.33)	(3.22)	(3.11)			
$Industry\_Q\_vw_{i,t}$				0.023***	0.018**	0.016*
				(2.95)	(2.11)	(1.94)
$CashFlow_{i,t-1}$		0.629***	0.625***		0.630***	0.625***
		(18.20)	(18.03)		(18.22)	(18.08)
$Ln(Asset)_{i,t-1}$		-0.156***	-0.159***		-0.156***	-0.158***
		(-13.01)	(-13.87)		(-12.94)	(-13.85)
Year FE & Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Other Controls	No	No	Yes	No	No	Yes
Obs.	69,962	64,748	64,747	69,962	64,748	64,747
$Adj.R^2$	0.193	0.220	0.220	0.193	0.219	0.220

Table 3: **Minor-Segment Industry Valuation and Private Firms' Investment**

This table presents the results from estimating Equation (22) for private firms as shown below:

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

The dependent variable investment $I_{i,t}$ is $Capx/K$, which is Capital Expenditures scaled by the lagged capital. The primary independent variable $Minor\_Q_{i,t}$ in model (1) to (3) is $Minor\_Leader\_Q_{i,t}$, which is the average beginning-of-period market-to-book of all minor-segment industry leaders for the two-digit SIC industry that the private firm belongs to; in model (4) to (6) is the $Minor\_Industry\_Q_{i,t}$, which is the average beginning-of-period market-to-book of all minor-segment industries for a two-digit SIC industry that the private firm belongs to. Column (2), (3), (5), and (6) control for private firm's own lagged $Ln(Asset)$ and $CashFlow$, and the average value of all private peers, and that of public firms. In addition, column (3) and (6) control for $Private\_CashFlow$, $Private\_Ln(Asset)$, $Public\_CashFlow$, $Public\_Ln(Asset)$, which are the average cash flow and size for all private peers and public firms at the beginning-of-period, respectively. All the variable constructions are described in Appendix B. All the regression models are estimated with firm-fixed effects and year-fixed effects. 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.

	(1) $Capx/K$	(2) $Capx/K$	(3) $Capx/K$	(4) $Capx/K$	(5) $Capx/K$	(6) $Capx/K$
$Minor\_Leader\_Q_{i,t}$	0.008**	0.008**	0.007**			
	(2.32)	(2.56)	(2.31)			
$Minor\_Industry\_Q_{i,t}$				0.021**	0.016**	0.014*
				(2.45)	(2.01)	(1.84)
$CashFlow_{i,t-1}$		0.637***	0.627***		0.630***	0.620***
		(16.43)	(16.83)		(16.58)	(16.70)
$Ln(Asset)_{i,t-1}$		-0.146***	-0.149***		-0.150***	-0.153***
		(-10.39)	(-11.48)		(-10.23)	(-11.21)
Year FE & Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Other Controls	No	No	Yes	No	No	Yes
Obs.	48,756	45,279	45,279	50,713	46,773	46,773
$Adj.R^2$	0.193	0.221	0.222	0.195	0.219	0.220

Table 4: **Random Irrelevant Industry Valuation and Private Firms' Investment**

This table presents the results from estimating Equation (23) for private firms as shown below:

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

Each minor-segment industry used to estimate Equation (22) is replaced by a randomly selected irrelevant industry, that is, an two-digit SIC industry that does not belong to the minor-segment industries nor share any minor-segment industries with the major-segment industry leaders. The dependent variable investment $I_{i,t}$ is $Capx/K$, which is Capital Expenditures scaled by the lagged capital. The primary independent variable $Random\_Leader\_Q_{i,t}$ in model (1) and (2) is the average beginning-of-period market-to-book of all leaders in the "random irrelevant" industries that are selected for the private firm; in model (3) and (4) is the $Random\_Industry\_Q_{i,t}$, which is the average beginning-of-period market-to-book of the "random irrelevant" industries that are selected for the private firm. I control for private firm's own lagged $Ln(Asset)$ and $CashFlow$, and the average value of all private peers, and that of public firms. All the variable are described in Appendix B. All the regression models are estimated with firm-fixed effects and year-fixed effects. The reported estimates are the cross-simulation average of the coefficients from 500 simulations. 95% confidence intervals are included in brackets and coefficients are marked with *** if 95% confidence intervals do not span zero.

	(1) $Capx/K$	(2) $Capx/K$	(3) $Capx/K$	(4) $Capx/K$
$Random\_Leader\_Q_{i,t}$	-0.0001	-0.0001		
	[-0.0007, 0.0004]	[-0.0006, 0.0004]		
$Random\_Industry\_Q_{i,t}$			-0.0015***	-0.0016***
			[-0.002, -0.001]	[-0.002, -0.001]
$CashFlow_{i,t-1}$	0.644***	0.636***	0.645***	0.637***
	[0.644, 0.645]	[0.636, 0.036]	[0.644, 0.646]	[0.637, 0.638]
$Ln(Asset)_{i,t-1}$	-0.147***	-0.149***	-0.147***	-0.149***
	[-0.147, -0.147]	[-0.149, -0.149]	[-0.147, -0.147]	[-0.149, -0.149]
Year FE & Firm FE	Yes	Yes	Yes	Yes
Other Controls	No	Yes	No	Yes
Obs.	56,296	56,296	55,303	55,302
$Adj.R^2$	0.225	0.225	0.225	0.226

Table 5: **Robustness Tests**

This table presents the results from estimating Equation (22) for private firms that are economically unlinked to the industry leaders. In panel A, I first exclude the firm-year observations if a private firm share one or more minor-segment industries with the industry leaders in that year (results are presented in column (1) and (2)), and then exclude the private firms if they share one or more minor-segment industries with the industry leaders in any time over the sample period (results are presented in column (3) and (4)). In panel B, I first exclude the minor-segment industries shared by industry leaders and the private firms in the industry leaders' major-segment industries (results are presented in column (5) and (6)), and then exclude the minor-segment industries that potentially have supplier or customer relationship with the major-segment industries (results are presented in column (7) and (8)). I define private firms' segments as secondary SIC industries reported in the private firm's accounts. Supplier and customer industries are defined using the 2012 U.S. Input-Output Tables provided by the Bureau of Economic Analysis. The dependent variable investment $I_{i,t}$ is $Capx/K$, which is Capital Expenditures scaled by the lagged capital. The primary independent variable $Minor\_Leader\_Q_{i,t}$ in column (1), (3), (5) and (7) is the average beginning-of-period market-to-book of all minor-segment industry leaders for the two-digit SIC industry that the private firm belongs to; in column (2), (4), (6) and (8) is the $Minor\_Industry\_Q_{i,t}$, which is the average beginning-of-period market-to-book of all minor-segment industries for a two-digit SIC industry that the private firm belongs to. I control for private firm's own lagged $Ln(Asset)$ and $CashFlow$, and the average value of all private peers, and that of public firms. All the variable constructions are described in Appendix B. All the regression models are estimated with firm-fixed effects and year-fixed effects. 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.

Panel A. Excluding potential economic linked observations

	Excluding private firm-years sharing the same minor segments with industry leaders		Excluding private firms sharing the same minor segments with industry leaders	
	(1)	(2)	(3)	(4)
	$Capx/K$	$Capx/K$	$Capx/K$	$Capx/K$
$Minor\_Leader\_Q_{i,t}$	0.009***		0.007*	
	(2.63)		(1.78)	
$Minor\_Industry\_Q_{i,t}$		0.015*		0.022***
		(1.92)		(2.66)
$CashFlow_{i,t-1}$	0.634***	0.625***	0.625***	0.612***
	(15.58)	(15.51)	(14.27)	(14.36)
$Ln(Asset)_{i,t-1}$	-0.151***	-0.155***	-0.144***	-0.149***
	(-10.87)	(-10.65)	(-10.75)	(-10.12)
Year FE & Firm FE	Yes	Yes	Yes	Yes
Other Controls	Yes	Yes	Yes	Yes
Obs.	42,275	43,802	37,183	38,491
$Adj.R^2$	0.222	0.220	0.216	0.216

Panel B. Excluding potential economic linked minor-segment industries

	Excluding minor-segment industries shared by private firms and leaders		Excluding minor-segment industries in supplier or customer industries	
	(1)	(2)	(3)	(4)
	$Capx/K$	$Capx/K$	$Capx/K$	$Capx/K$
$Minor\_Leader\_Q_{i,t}$	0.009**		0.007**	
	(2.47)		(2.22)	
$Minor\_Industry\_Q_{i,t}$		0.019**		0.016**
		(2.23)		(2.02)
$CashFlow_{i,t-1}$	0.632***	0.664***	0.625***	0.620***
	(13.46)	(15.90)	(16.47)	(16.70)
$Ln(Asset)_{i,t-1}$	-0.157***	-0.169***	-0.147***	-0.153***
	(-15.51)	(-12.65)	(-11.46)	(-11.21)
Year FE & Firm FE	Yes	Yes	Yes	Yes
Other Controls	Yes	Yes	Yes	Yes
Obs.	42,198	36,253	45,055	46,773
$Adj.R^2$	0.228	0.228	0.221	0.220

Table 6: **Private Firms' Investment and the Informativeness of Industry Stock Price**

This table presents the results from estimating Equation (21) adding an interaction term of $Industry\_Q_{i,t}$ (or $Industry\_Q\_vw_{i,t}$) with the measures for $informativeness$ of firm i's industry stock price at the beginning-of-period. The dependent variable is $Capx/K$, which is Capital Expenditures scaled by the beginning-of-period capital. $Industry\_Q_{i,t}$ is the average of the beginning-of-period market-to-book ratio of public firms in the three-digit SIC industry that the private firm belongs to, and $Industry\_Q\_vw_{i,t}$ is the value-weighted average. I also control for private firm's own lagged $Ln(Asset)$ and $CashFlow$, and the average value of all private peers, as well as the average value of public firms. Measures for $Informativeness$ include: (i) $H\_\#Public$, a dummy equals to 1 if the logarithm of 1 plus the number of public firms of the industry is above the 70th percentile, and equals to 0 if it is below the 30th percentile; (ii) $\%Public$, the fraction of number of public firms to all firms in a three-digit SIC industry; and (iii) H_Nonsynchronisity, a dummy equals to 1 if the $Nonsynchronisity$ of a three-digit SIC industry is above the 70th percentile, and equals to 0 if it is below the 30th percentile. All the variable constructions are described in Appendix B. All the regression models are estimated with firm-fixed effects and year-fixed effects. 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.

Informativeness Measures:	$H\_\#Public$		% Public		H_Nonsynchronisity	
	(1)	(2)	(3)	(4)	(5)	(6)
	$Capx/K$	$Capx/K$	$Capx/K$	$Capx/K$	$Capx/K$	$Capx/K$
$Industry\_Q_{i,t}$	0.011		0.010		0.021*	
	(1.04)		(1.25)		(1.93)	
$Industry\_Q_{i,t} \times Informativeness_{i,t-1}$	0.047***		0.111**		0.029**	
	(3.32)		(2.29)		(2.12)	
$Industry\_Q\_vw_{i,t}$		0.011		-0.001		0.010
		(1.02)		(-0.11)		(0.93)
$Industry\_Q\_vw_{i,t} \times Informativeness_{i,t-1}$		0.026*		0.136***		0.023*
		(1.78)		(2.93)		(1.65)
Year FE & Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Other Controls	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	35,194	35,194	64,696	64,696	35,810	35,819
$Adj.R^2$	0.230	0.230	0.220	0.220	0.228	0.225

Table 7: **Private Firms' Investment and Industry Common Shocks**

This table presents the results from estimating Equation (21) and (**??**) adding an interaction term of $Industry\_Q_{i,t}$ (or $Industry\_Q\_vw_{i,t}$) with the measures for the *competitiveness* of firm i's industryat the beginning-of-period. The dependent variable is $Capx/K$, which is Capital Expenditures scaled by the beginning-of-period capital. $Industry\_Q_{i,t}$ is the average of the beginning-of-period market-to-book ratio of public firms in the three-digit SIC industry that the private firm belongs to, and $Industry\_Q\_vw_{i,t}$ is the value-weighted average. I also control for private firm's own lagged $Ln(Asset)$ and $CashFlow$, and the average value of all private peers, as well as the average value of public firms. Measures for *competitiveness* of the industry include: (i) $H\_\#Firms$, a dummy equals to 1 if the logarithm of 1 plus the number of all firms of the industry is above the 70th percentile, and equals to 0 if it is below the 30th percentile; (ii) L_HHI, a dummy equals to 1 if HHI in a three-digit SIC industry is below the 30th percentile, and equals to 0 if it is above the 70th percentile; and (iii) L_Top4_Shares, a dummy which equals to 1 if the market share of the top 4 firms in a three-digit SIC industry is below the 30th percentile, and equals to 0 if it is above the 70th percentile. All the variable constructions are described in Appendix B. All the regression models are estimated with firm-fixed effects and year-fixed effects. 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.

Competitive Industry Measures:	$H\_\#Firms$		L_HHI		L_Top4_Shares	
	(1)	(2)	(3)	(4)	(5)	(6)
	$Capx/K$	$Capx/K$	$Capx/K$	$Capx/K$	$Capx/K$	$Capx/K$
$Industry\_Q_{i,t}$	0.002		0.017*		0.011	
	(0.18)		(1.81)		(1.30)	
$Industry\_Q_{i,t} \times Competitive_{i,t-1}$	0.038***		0.022*		0.027**	
	(2.90)		(1.77)		(2.16)	
$Industry\_Q\_vw_{i,t}$		-0.003		0.010		0.013
		(-0.36)		(1.09)		(1.43)
$Industry\_Q\_vw_{i,t} \times Competitive_{i,t-1}$		0.022*		0.015		0.020*
		(1.74)		(1.26)		(1.67)
Year FE & Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Other Controls	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	35,986	35,986	40,087	40,087	39,144	39,144
$Adj.R^2$	0.045	0.233	0.228	0.228	0.225	0.225

Table 8: **Comparison of Public and Private Firms on Matched Sample**

This table presents the results from estimating Equation (24) for matched sample of private and public firms:

$$Y_{i,t} = \alpha + \beta \times Industry\_Q_{i,t} + \beta_2 \times Industry\_Q_{i,t} \times Public_i + \lambda \times X_{i,t-1} + \theta \times X_{i,t-1} \times Public_i + \kappa_i + \delta_t + \epsilon_{i,t}$$

The dependent variable in model (1) is $Capx/K$, which is Capital Expenditures scaled by lagged capital, in model (2) is ΔK, which is the annual change of capital scaled by lagged capital, in model (3) is $Equity\ Issue$, which is the annual change of Book Equity minus the annual change of Retained Earnings, scaled by lagged capital, and in model (4) is $Debt\ Issue$, which is the annual change of Book Debt, scaled by lagged capital. Thus, the financing variables are defined with balance sheet items. The main independent variable $Industry\_Q_{i,t}$ is the average of the beginning-of-period market-to-book ratio of public firms in the three-digit SIC industry, and its interaction with the dummy *Public* which equals to 1 if it is a public firm and 0 if private. I also control for public firm's own beginning market-to-book, private firm's own lagged $Ln(Asset)$ and $CashFlow$ and their interactions with *Public*. All the variable constructions are described in Appendix B. I use caliper-based nearest-neighbor match adapted to a panel setting following Asker, Farre-Mensa and Ljungqvist (2015). Stating from 1993, I match private firms with public firms from the same three-digit industry and closest in size. I require that the ratio of their total assets is less than 2. If no match can be formed, I drop the observation and look for a match in the following year. Once a match is found, it is kept in subsequent years to ensure the panel structure of the data. All the regression models are estimated with firm-fixed effects and year-fixed effects. t-statistics in parentheses are adjusted using the Huber-White estimator allowing within firm clusters. Coefficients significant at the 10%, 5%, and 1% levels are marked with *, **, and ***, respectively.

	Investment		Financing	
	(1)	(2)	(3)	(4)
	$Capx/K$	ΔK	$Equity\ Issue$	$Debt\ Issue$
$Industry\_Q_{i,t}$	0.024***	0.019**	0.029***	0.028*
	(3.87)	(2.30)	(4.33)	(1.66)
$Industry\_Q_{i,t} \times$ Public	0.001	0.094***	0.083*	-0.045**
	(0.08)	(3.32)	(1.87)	(-2.19)
$Own\_Q_{i,t}$	0.036***	0.191***	0.250***	0.070***
	(9.22)	(8.13)	(6.71)	(5.82)
$CashFlow_{i,t-1}$	0.626***	0.688***	-0.195***	0.477***
	(20.12)	(18.90)	(-6.22)	(5.88)
$Ln(Asset)_{i,t-1}$	-0.158***	-0.305***	-0.085***	-0.389***
	(-17.61)	(-27.61)	(-9.89)	(-16.91)
$CashFlow_{i,t-1} \times$ Public	-0.396***	0.150	-0.257	-0.082
	(-9.17)	(0.87)	(-0.93)	(-0.70)
$Ln(Asset)_{i,t-1} \times$ Public	0.089***	0.018	-0.253***	0.262***
	(8.83)	(0.62)	(-6.03)	(9.92)
$Constant$	0.524***	0.777***	0.286***	0.887***
	(19.88)	(16.89)	(4.01)	(10.28)
Obs.	52,111	77,092	77,333	77,361
$Adj.R^2$	0.244	0.076	0.116	0.001