How much do managers learn from the financial market? The decomposition of the investment-price sensitivity *

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September 30, 2023

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Abstract

Managers can learn information from the financial market, which can guide their investment decisions. However, to what extent do managers acquire information from stock prices? While prior literature provides evidence on the relationship between managers' investment decisions and learning from stock prices, this indirect evidence cannot precisely determine how much learning in the stock market contributes to the variations in investment-price sensitivity. This paper develops a model of managers' learning in the context of investment decisions to dissect the factors contributing to investment-price sensitivity. This paper builds a model with a noisy expectation framework, and managers and informed traders make optimal decisions based on the information signals they observe. Leveraging the model, this paper decomposes the investment-price sensitivity into two sources of covariance: internal learning (already known to managers) and market learning (new to managers). This paper calibrates the model by matching the moments to the empirical counterparts of S&P 500 firms. The findings are that roughly 54% of the investment-price sensitivity is attributed to managers' pre-existing internal information, while the remaining 46% arises from their learning in the stock market. The increase in investment-price sensitivity does not necessarily indicate more market learning. Furthermore, the analysis of the full disclosure scenario has implications for corporate disclosure policies, suggesting that an increase in disclosure could potentially hinder managers' learning from the financial market.

Keywords: Investment, Financial markets, Financial efficiency, Disclosure
JEL Codes: E22, G31, G14

*I thank Monica Tran-Xuan and Yun Pei for their invaluable advice and guidance. I am grateful for comments from Neel Rao, Justin Downs, and Sanghoon Kim, the participants at the University at Buffalo, 87th Annual Meeting of the Midwest Economics Association and AEA-CSWEP Ph.D. Mentoring Workshop.

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Introduction

The primary function of the financial market is the production and aggregation of information through trading. Both theoretical literature and empirical evidence have supported the learning hypothesis, suggesting that managers can acquire valuable information from the stock markets to inform their investment decisions. The rationale is that while a manager has a precise signal about her firm's prospects, she may be less informed about macroeconomic factors, industry competition, and growth opportunities. A body of literature has presented evidence in support of this hypothesis. For example, Chen et al. (2007) finds that investment is more sensitive to Tobin's q with more private information incorporated in the stock prices through trading. Foucault and Fresard (2014) shows that the firm learns from a peer's stock prices, and the learning effect is stronger when a firm's stock price informativeness is lower or when its manager is uninformed.

While previous literature offers evidence regarding the causal relationship between a manager's investment decisions and their learning from stock prices, the literature has been silent about how much managers can learn from the stock market (Edmans et al. (2017),Jayaraman and Wu (2018)). Moreover, previous studies cannot analyze how a manager's learning from stock prices responds to shocks in different information signals. A difficult task here is the decomposition of market-produced information from the firm-released information disclosed to the market in stock prices. This paper helps to understand the decomposition of investment-price sensitivity and how it responds to different shocks.

This paper assumes that managers process two types of information when making investment decisions: new and internal information. The new information is incorporated through speculative trading in the stock prices and then observed by managers. Managers can observe superior internal information, and the internal information is released through public disclosures and incorporated into the stock prices. This paper is interested in the portion of the investment-price sensitivity that is attributed to the new information (market learning) and the internal information (internal learning).

In this paper, I ask the following questions about the effect of managers' learning from stock prices on their investment decisions: (i) How much do managers learn from the information in stock prices incorporated through speculative trading and new to the managers (market learning)? How much information contained in the stock prices is already known to the manager (internal learning)? (ii) How do internal learning and market learning change with respect to changes in information signals (compare partial disclosure and full disclosure scenarios)? (iii) What's the effect of changing the precision of information in fundamental shocks on internal learning and market learning?[1] To answer these questions, following Bai et al. (2016), this paper develops a parsimonious model to decompose the investment-price sensitivity and identify different elasticity in response to various information resources. The focus of this paper is not to determine the optimal investment level but to determine how the elasticity of investment to stock prices changes when there are shocks to different information signals.

The theoretical model has three major players: managers, informed traders, and uninformed traders. The manager possesses superior (though not perfect) information about the firm's productivity. Informed traders can incorporate their private information into stock prices through speculative trading. In contrast, uninformed traders provide market liquidity due to their liquidity needs.[2] Public information is shared between traders through regular earnings announcements. Thus, the stock price is a mix of public information, private information, and noise. The manager is well-informed about her firm's profitability, earnings, and accounting information. However, she needs to learn more about market demand, industry competition, macroeconomic conditions, and other external prospects. Making investment decisions requires integrating internal and external information, often leading managers to rely on stock market data. Once the manager observes the stock prices and extracts relevant information, she selects the optimal investment level to maximize the firm's value. Therefore, the investment level correlates with the information managers can glean from stock prices.

In the model, informed traders maximize their mean-variance utility function to choose their demand. The market clears by equating the informed traders' demand and external liquidity supply, and then the equilibrium market price is determined by a mix of signals and noise. Regressing the investment on Tobin's Q (a normalized price measure), this paper gets the investment-price sensitivity, a standard measure to gauge how the investment reacts to

[1] Full disclosure means the market participants can observe all the internal information possessed by the manager.

[2] There is a noisy supply of uninformed traders, who do not trade on their information.

the stock prices. Leveraging the model, this paper decomposes the investment-price sensitivity into two sources of covariance: internal information (already known to managers) and manager's learning (new to managers). The first covariance arises from internal information, and if a manager receives a high precision signal of her firm's productivity, she relies more on her internal information. The investment-price sensitivity arises even if she does not learn much from the stock market. The second covariance arises from the manager's learned information from stock prices, and if the manager extracts more precise information about the firm's fundamentals, the price is more informative, and her investment decision is more sensitive to the stock price. In this way, this paper answers how much managers can learn new information from stock prices.

Based on the model, this paper finds that about 54% of the investment-price sensitivity is attributed to the manager's internal learning, and 46% is attributed to the market's learning. Moreover, this paper conducts a comparative statics analysis of how investment-price sensitivity, internal learning, market learning, and forecasting price efficiency change in response to the shocks of information signals, the noise in the trading, relative risk aversion, and the uncertainty of fundamentals.[3] The result shows that investment-price sensitivity will increase with an improvement in the precision of internal signals, a reduction in noise trading, lower relative risk aversion, and higher uncertainty in fundamentals. Market learning will increase as there is a lower precision of internal signal, higher precision of private signal, less noise in the trading, low relative risk aversion, and lower uncertainty in fundamentals. Forecasting price efficiency will increase as the manager has more precise internal information and private information of informed traders, much less noise in the trading, low relative risk aversion, and higher uncertainty in fundamentals.

The comparison between the baseline model (partial disclosure) and the full disclosure scenario finds that market learning declines even though investment-price sensitivity and forecasting price efficiency increase under the full disclosure scenario. Our finding echoes the result in Jayaraman and Wu (2018) that disclosure could reduce manager's ability to extract decision-relevant information from prices. These results have implications for policymakers when they consider reforming the firms' mandatory disclosure policy. Also, this paper sheds

[3]The distribution of uninformed traders, specifically, the variance of the distribution may be varied.

light on the changes in market learning, internal learning, and forecasting price efficiency when the firm faces a higher uncertainty in the fundamentals, especially when the economy is experiencing a downturn.

Related Literature This paper contributes to the strand of literature that studies the effect of market prices on corporate decisions (Luo (2005),Chen et al. (2007),Bennett et al. (2020), see Bond et al. (2012) and Goldstein (2022) for a survey). Chen et al. (2007) first examines the relationship between the sensitivity of investment to stock prices and price informativeness. The hypothesis is that when prices are more informative, corporate investments are more sensitive to stock prices because managers will levy more on the information in stock prices to optimize their investment decisions. They find that the sensitivity of investment to stock prices is positively related to price informativeness, which is consistent with the story that manager learns new information from stock prices when making investment decisions. Foucault and Frésard (2012) utilize the cross-listing to study the manager's learning from stock prices. The idea is that the precision of information conveyed by their stock price to managers is higher for the cross-listed firms than non-cross-listed firms, thus enhancing managers' reliance on stock prices.[4] This paper provides empirical evidence that the investment-to-price sensitivity of firms cross-listed on U.S. exchanges is significantly higher than that of non-cross-listed firms, which supports the manager's learning story. Edmans et al. (2017) uses the variation of the price informativeness created by staggered enforcement of insider trading laws across 27 countries. The regulatory change in enforcement of insider trading laws discourages managers' trading on their information but encourages more outsiders to acquire and trade on the outsider information, thus bringing more of the information that is not known to managers into the price. This causes managers to base their investment levels on their respective stock prices to a greater extent because there is more relevant information in stock prices for their investment decisions. Furthermore, recent literature extends this strand of literature by studying the effect of peer valuation on a firm's investment. Foucault and Fresard (2014) find that managers learn additional information about growth opportunities by looking at peer's stock prices. Thus, the firm's investment decision is influenced not only by its own stock price

[4] Cross-listing is when a firm lists its equity shares on one or more foreign stock exchanges in addition to its domestic exchange. To be cross-listed, a company must thus comply with the requirements of all the stock exchanges in which it is listed.

but also by the stock price of its peers.

To study the effect of price informativeness on corporate investment decisions, the challenge is that there is no accepted way to separate the private information in stock prices that is new to managers from that already known to managers. The concern about the previous finding is that if the information in stock prices is already known to managers without looking at stock prices, it automatically leads to a positive relation between the sensitivity of investment to stock price and price informativeness. Previous literature adopts several different strategies to circumvent this problem. For example, Chen et al. (2007) includes insider trading activities and earnings surprise to control for managerial information. They provide stronger support for their main finding that managers learn from the private information in stock prices about their own firms' fundamentals and incorporate this information in corporate investment decisions. However, the measures of managerial information are endogenous, and the validity of this result depends on the extent to which insider trading activities and earnings surprises are reasonable proxies for managerial information. Foucault and Frésard (2012) use a novel strategy that cross-listing enhances the price informativeness for those cross-listed stocks, which naturally creates an environment to study the effect of the amount of private information impounded into the price on corporate investment decisions. Edmans et al. (2017) utilized the regulatory shock to the amount of insider information impounded in the stock prices to isolate the effect of private information in stock prices on corporate investment decisions. In contrast, this paper utilizes the theoretical model and quantitative analysis, which provides a cleaner environment to separate the private information in stock prices from that already known to managers.

This paper also relates to the disclosure and real effect of stock prices on real decisions (e.g., investments). Goldstein and Yang (2019) build a theoretical model and study the effect of disclosure on real efficiency. They find that if the positive effect of providing more information dominates the negative effect of reducing new information learned by managers, then disclosure has a positive effect on the forecast quality of managers. Jayaraman and Wu (2018) use mandatory segment reporting in the United States as an exogenous shock to the disclosure to study the overall impact of disclosure. Their empirical evidence supports that the cost of lower learning from stock prices outweighs the benefit of lower information asymmetry, suggesting a net negative consequence of promoting the disclosure. Bird et al. (2020) utilized the staggered introduction of the EDGAR(Electronic Data Gathering, Analysis, and Retrieval) platform to test further the hypothesis that prices are less informative to managers due to the crowding out of external information gathering. The idea is that publicizing more internal information disincentivizes the outsider to acquire information and impound this fundamental relevance into stock prices. This paper utilizes the comparative statics analysis to analyze the economic consequences of disclosure on market learning, internal learning, and forecast price efficiency, which provide new evidence to this strand of literature.

The first contribution of the paper is to disentangle the new information from the information managers already know in stock prices. Based on the reduced form model, prior literature finds a positive relation between investment-price sensitivity and the amount of private information on stock prices. Due to the difficulty of observing the information set of managers, researchers have yet to investigate how much information managers can learn from stock prices. This paper fills this gap by decomposing the investment-price sensitivity from different information sources based on a simple structural model. Second, this paper can perform comparative statics analysis to examine the effect of regulations on firms or other shocks on investment decisions by impacting the manager's learning channel. Thus, this paper could provide some insights to regulators when they plan to make reforms to firms. Third, this paper also sheds light on the impact of disclosure on managers' investment decisions. This paper compares the market and internal learning channels between my baseline model (partial disclosure) and the full disclosure scenario. My finding that full disclosure reduces manager's market learning is consistent with previous findings.

The paper is organized as follows. Section 1 describes the information environment, sets up the equilibrium, and demonstrates how to decompose the investment-price sensitivity. Section 2 provides a quantitative analysis and the main quantitative results of the decomposition of two channels - internal learning and market learning. Section 3 conducts a comparative analysis, and Section 4 concludes.

1 A Model of The Manager's Market Learning

This paper presents a static model of a manager's market learning in the context of investment. The model has three major players: managers, informed traders, and uninformed traders. The manager's objective is to maximize the firm's value, and she chooses the optimal investment level based on her forecast about productivity shock. Informed traders actively participate in the stock trading market and choose the traded quantity to maximize their utility. Uninformed traders provide exogenous liquidity in the stock market and clear the market.

There are three dates, t= 0,1,2. At date 0, firms release a subset of internal information to the public through public disclosure.[5] Informed traders trade in the stock market based on their information about the firm's fundamentals, and the stock price is determined simultaneously. At date 1, after observing the stock prices, managers can extract some new information and choose the optimal capital level to maximize the firm's value based on their forecast of the fundamentals of the firm. At date 2, the productivity shock is realized, and all payoffs are received.

1.1 Environment

Production Technology The real side of the firm is characterized by a production technology that uses only capital, k. Per period output is given by $(1 + z)(\bar{k} + k)$, $\bar{k}$ is the assets in place, k is the investment in new capital, z is the true productivity shock which cannot be observed perfectly by managers or market participants in the stock market. The shock z follows a normal distribution with mean 0 and σ_z^2 variance:

$$z \sim N(0, \sigma_z^2) \tag{1}$$

Information Environment Following Bai et al. (2016), this paper models the information environment faced by players in the market. In the model, there is a productivity shock z. A manager can observe an imperfect signal about true productivity based on her internal information. Besides, she also could extract some information from the stock prices in the

[5] For example, a company shares information about a company's profitability through the yearly or quarterly earnings announcement.

financial market.

The internal information produced by the firm is summarized by:

$$\eta = z + \epsilon_\eta \tag{2}$$

where $\epsilon_\eta \sim N(0, \sigma_\eta^2)$. The precision of this signal η is denoted as $h_\eta = 1/\sigma_\eta^2$.

Informed traders can produce and incorporate private information about a firm's productivity into security prices. For example, a manager for a retailer such as JCPenney may obtain valuable information about the demand for the clothing line of a fledgling garment manufacturer Subrahmanyam and Titman (1999). A trader who closely follows the broader healthcare industry may possess information about industry dynamics and regulatory changes that could impact a Pharmacy company's prospects, but such information may not be readily available to the company's managers. In this sense, this diverse information is aggregated across many stock market investors, which provides a useful signal for managers.[6] The private information observed by the informed traders is summarized by:

$$s = z + \epsilon_s \tag{3}$$

where $\epsilon_s \sim N(0, \sigma_s^2)$. The precision of this signal s is denoted as $h_s = 1/\sigma_s^2$. I assume that ϵ_η and ϵ_s are independent.

Informed traders and managers also share common sources of information, most prominently through disclosure. For example, public firms release quarterly earnings statements. In this way, managers disclose part of their internal information to the public. This additional information observed by informed traders is summarized by:

$$\eta^{'} = \eta + \epsilon_{\eta^{'}} \tag{4}$$

where $\epsilon_{\eta^{'}} \sim N(0, \sigma_{\eta^{'}}^2)$ is orthogonal to ϵ_η and ϵ_s. The precision of this signal $\eta^{'}$ is denoted as $h_{\eta^{'}} = 1/(\sigma_\eta^2 + \sigma_{\eta^{'}}^2)$.

[6] In practice, it is hard to ideally separate informed from uninformed trades ex-ante since we generally do not know the traders' information sets.

Figure 1 illustrates how the information signals processed by different players interact. Managers have two information signals: the internal signal η and public information $\eta^{'}$. Informed traders also have two information signals: the private information s and the public information $\eta^{'}$. The public information $\eta^{'}$ is shared between managers and informed traders through public disclosure. Informed traders trade on their information to optimize their profits. As you can see in the graph, stock prices integrate all the information impounded, and there is a random supply of noise u.[7]

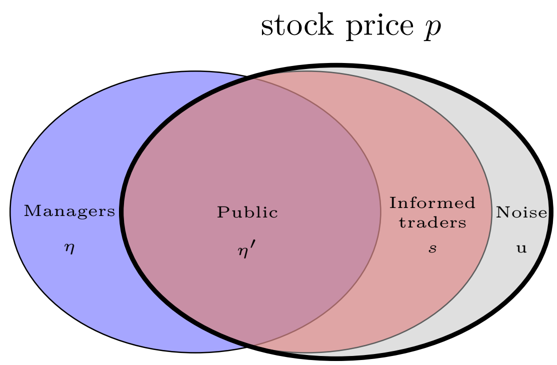

Figure 1: Information Set

Note: The Figure 1 summarizes the information set and describes how the information signal interacts. Managers' information set contains the internal signal η and public information $\eta^{'}$. Informed traders' information set contains the private information s and the public information $\eta^{'}$. The overlap between the manager's information set and informed traders' information set is the public information $\eta^{'}$. The stock price contains the public information $\eta^{'}$, informed traders' information s and the noise u.

Traders and stock market There is a number of n ex-ante identical informed traders in the stock markets. Informed traders acquire information about the firm's fundamentals and trade on their information to maximize their utility.[8] Each informed trader is endowed with two signals about the firms' fundamentals at date 0. The first signal is the private information s the informed traders observe. The second signal is the public information $\eta^{'}$ observed by all participants in the market. Each informed trader can buy or sell x shares of stocks in the market. They have a standard mean-variance expected utility with a coefficient of risk aversion ρ. The total benefit of purchasing or selling x shares of stocks is the product of the number

[7]See the details in the later section.

[8]This paper assumes that the manager does not trade in the stock market based on her information.

of trade shares x and the net expected payoff of trading one share (expected realized payoff conditional on her information minus the stock price). Then, the total benefit is adjusted by the risk aversion costs.

$$\max_{x} x\mathbb{E}[z-p|\eta^{'},s]-\frac{\rho}{2}x^{2}\mathbb{V}ar[z|\eta^{'},s] \tag{5}$$

The stock price is denoted by p. Following Goldstein et al. (2013), this paper assumes that informed traders do not observe the price when they trade in the market, and hence, they submit the market order, as in Kyle (1985). The simple setup is to capture the idea that managers have the stock price information that informed traders do not have when managers are making investment decisions.

Market clearing At date 0, conditional on his information set, each informed trader submits a market order to sell or buy a specific number of shares of stocks. Also, there is a noisy supply of uninformed traders who are subject to random shocks that force them to buy or sell the stock at any current price. The traditional interpretation of noisy supply is that a group of agents trade for exogenous reasons, such as liquidity or hedging needs. They don't trade on their information, and they will accept any current price of stocks. This noise ensures that the information extracted from stock prices is not a precise signal about information that other traders may know. The exogenous noisy supply of the stocks is as follows:

$$u \sim N(0,\sigma_u^2) \tag{6}$$

Firm's investment I consider a firm with ex-post fundamental value as follows:

$$v(z,k)=(1+z)(\bar{k}+k)-k-\frac{\gamma}{2\bar{k}}k^2 \tag{7}$$

where $\bar{k}$ is the assets in place, k is the investment in new capital, z is the productivity shock and γ is the adjustment cost parameter. Without loss of generality, here I assume that the firm purchases and sells capital at a price of one. And firm must incur a capital stock adjustment costs of $C=\gamma\bar{k}\left(\frac{k}{\bar{k}}\right)^2$. This cost can be considered as the extra cost of raising the capital, which is increasing in the rate of adjustment and the size of the new investment. [9]

[9] Charles C. Holt (1960) found a quadratic specification of adjustment costs to be a good approximation of hiring

The firm's total value is the value she captures from the output generated by the production technology minus her cost of raising capital. At date 1, the manager is endowed with two signals. The first signal is her internal information about the fundamental η. The second signal is the information extracted from the stock price $s^{'}$. [10]

$$s^{'} = s - \frac{\rho}{nh_s}u = z + \epsilon_s - \frac{\rho}{nh_s}u \tag{8}$$

It is important to emphasize that even if a manager has superior information about a firm's fundamentals, she still has an incentive to look at the stock prices and learn from the market, as traders in the market have other signals that she does not know. The manager chooses the investment level k^* to maximize the firm value conditional her information set $\mathcal{I}_m = \{\eta, s^{'}\}$:

$$k^* = argmax_k \mathbb{E}[v(z,k)|\mathcal{I}_m] \tag{9}$$

1.2 Equilibrium

Figure 2 describes the timeline of the events. There are three dates, t= 0,1,2. At date 0, firms disclose a subset of their internal information to the public. Simultaneously, the informed traders trade in their information about the firm's fundamentals with the uninformed traders, and the stock price is determined. At date 1, the managers observe the stock prices and extract a noisy signal about the firm's fundamentals. Then, they choose the optimal investment level to maximize the firm's value. At date 2, the productivity shock is realized, and all payoffs are received.

This paper is interested in the optimal capital allocation across firms, and I consider a large number of ex-ante identical firms (same k) that draw different signals about the fundamentals z. And I assume that each informed trader has the same utility form, but he draws different signals about the firm's fundamentals. Because the information obtained by the informed traders is diverse, the stock price aggregates any useful information across investors.

and layoff costs, overtime costs, inventory costs, and machine setup costs in the selected manufacturing industries. The costs of investment may also be related to the rate of adjustment with higher costs for more rapid changes, specified as $C = \gamma \bar{k} \left(\frac{k}{\bar{k}}\right)^2$

[10] The precision of this signal is denoted as $h_{s^{'}} = 1/(\sigma_s^2 + (\frac{\rho}{nh_s})^2 \sigma_u^2)$.

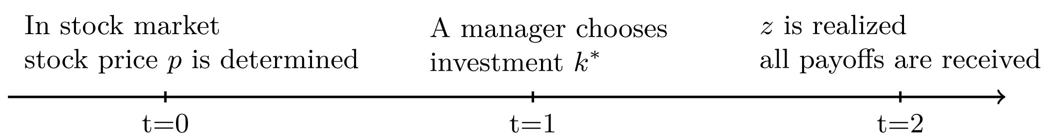

Figure 2: The Timeline of the Events

Note: The Figure 2 described the timeline of the events. There are three dates, t= 0,1,2. At each date, different player choose their actions to maximize their utility or profits.

Given the above equations, we now turn to the definition of the equilibrium.

Definition 1 *A equilibrium consists of a price level p, an investment policy k^* for the manager, strategies for informed traders x, such that*

- *Given p, informed traders choose their demand of shares x to solve a mean-variance utility-maximizing problem:*

$$\max_x x\mathbb{E}[z-p|\eta^{'}, s] - \frac{\rho}{2}x^2\mathbb{V}ar[z|\eta^{'}, s]$$

- *Given the price level p, a manager chooses the optimal investment k^* to solve firm value maximizing problem under her information set:*

$$k^* = argmax_k\mathbb{E}[v(z,k)|\mathcal{I}_m]$$

- *The market clearing condition is satisfied: $nx = u$*

1.3 The decomposition of investment-price sensitivity

In this section, this paper solves the equilibrium and demonstrates how to decompose the investment-price sensitivity.

Lemma 1 *In the equilibrium, this paper has the following:*

1. *Firm optimal investment is given by* [11]

$$k^* = \frac{\bar{k}}{\gamma} \cdot \frac{h_\eta \eta + h_{s'} s^{'}}{h_z + h_\eta + h_{s'}} \tag{10}$$

[11] h_z is the precision of the signal of fundamentals, and $h_z = \frac{1}{\sigma_z^2}$

2. *The equilibrium price in the stock market is given by*

$$p = \frac{h_s s + h_{\eta'} \eta' - \frac{\rho}{n} u}{h_z + h_s + h_{\eta'}} \tag{11}$$

3. *Forecasting price efficiency (FPE) is*

$$\mathbb{V}ar(\mathbb{E}[z|p]) = \frac{h_\pi}{h_\pi + h_z} h_z^{-1} \tag{12}$$

where

$$h_\pi = \frac{(h_s + h_{\eta'})^2}{h_s + h_{\eta'} + \frac{\rho^2}{n^2}\sigma_u^2}$$

4. *I decompose the investment-price sensitivity as follows:*

$$\beta_{\tilde{k},q} = \frac{cov(k^*, p)}{Var(p)} = \Delta\{\underbrace{h_\eta * cov(\eta, p)}_{\text{internal learning}} + \underbrace{h_{s'} * cov(s', p)}_{\text{market learning}}\} \tag{13}$$

where $\Delta = \frac{1}{\gamma Var(p)(h_z + h_\eta + h_{s'})(h_z + h_{\eta'} + h_s)}$

$$cov(\eta, p) = \left(h_s h_z^{-1} + h_{\eta'} h_z^{-1} + h_{\eta'} h_\eta^{-1}\right)$$

$$cov(s', p) = \left(h_s h_z^{-1} + h_{\eta'} h_z^{-1} + 1 + \frac{\left(\frac{\rho}{n}\right)^2 \sigma_u^2}{h_s}\right)$$

Proof. See Appendix A.2 for details. ■

The intuition is as follows. The optimal investment level k^* is proportional to the manager's conditional expectation of the investment return $\frac{\bar{k}}{\gamma}$. This expectation also depends partially on η, a signal of internal information with precision h_η. This expectation depends partially on s', an biased signal of s learned from the price p, which has precision $h_{s'}$.

The equilibrium price in the stock market is a mix of various sources of signals. The stock price integrated the signal of informed traders s, the public information signal η shared by all market participants, relative risk aversion of the informed traders $\frac{\rho}{n}$, and the noises brought by the unformed traders. It also depends on the uncertainty of the fundamentals.

Forecasting price efficiency (FPE) is the extent to which the security price can forecast its fundamental values. As the stock prices contain more total information, Forecasting price efficiency (FPE) increases, but it does not suggest that managers learn new information from the stock market. For example, if a manager of the firm releases more internal information, it could lead to an increase in forecasting price efficiency without increasing the market learning. [12] Similarly, the FPE depends on the signal of informed traders s, the public information signal $\eta^{'}$ shared by all market participants, relative risk aversion of the informed traders $\frac{\rho}{n}$, and the variance of noises σ_u brought by the unformed traders.

Generally, investment-price sensitivity arises from two sources of covariance between investment and the stock price and is weighted by the precision of the signals: internal learning (information already known to managers) given by $h_\eta * cov(\eta, p)$ and market learning (information new to managers) given by $h_{s'} * cov(s^{'}, p)$.

The first covariance arises from internal information, and if a manager receives a high-precision signal of her firm's productivity, she relies more on her internal information. The investment-price sensitivity arises through the internal learning channel even if the manager does not learn much from the stock market. The magnitude of the internal learning channel depends on the precision of the internal information h_η, the uncertainty of the fundamentals h_z^{-1}, the precision of informed traders' information h_s and the precision of the public information $h_{\eta'}$.

The second covariance arises from the manager's learned information from the stock market, and if the manager extracts more precise information about the firm's fundamentals, the price is more informative, and her investment decision is more sensitive to the stock price. The magnitude of the market learning channel depends on the precision of informed traders' information h_s, the uncertainty of the fundamentals h_z^{-1}, the precision of the public information $h_{\eta'}$, the relative risk aversion $\frac{\rho}{n}$ and the variance of noise trading σ_u^2.

2 Quantitative Analysis

In this section, I quantify investment-price sensitivity decomposition using calibrated parameters matching U.S. firm's data. Based on this quantitative analysis, I can assess the impor-

[12] See section 3 for the details.

tance of the two channels (i.e., internal learning and market learning) on manager's investment decisions.

2.1 Estimation of the investment-price sensitivity

To decompose the investment-price sensitivity, the first step is to estimate the magnitude of investment-price sensitivity. I obtain S&P 500 firms' data from the Compustat. The sample period is from 1985 to 2015. I exclude firms in the financial industries (SIC code 6000-6999) and utility industries (SIC code 4900-4990). I also drop firm-year observations with less than $10 million book value of equity. The final sample consists of 7,745 firm-year observations with 363 firms.

To get the estimation of investment-price sensitivity, I run cross-sectional regressions of future capital expenditures on current market prices:

$$\underbrace{\frac{CAPX_{i,t+1}}{Asset_{i,t}}}_{\text{Investment}} = \alpha + \beta \underbrace{\left(\frac{M_{i,t}}{Asset_{i,t}}\right)}_{\text{Price}} + \underbrace{\delta \left(\frac{CF_{i,t+1}}{Asset_{i,t}}\right) + \lambda \left(\frac{1}{Asset_{i,t}}\right)}_{\text{Controls}} + \underbrace{(e^s \mathbf{1}^s)}_{\text{Industry Effect}} + \underbrace{(e^t \mathbf{1}^t)}_{\text{Year Effect}} + \epsilon_{i,t} \tag{14}$$

As in Equation 14, the dependent variable is the investment of the firms. I use the capital expenditures scaled by beginning-of-year book assets to approximate the investments. I use the firm's Tobin's Q in our analysis as a normalized price measure. Tobin's Q is calculated as the market value of equity (price times shares outstanding from CRSP) plus the book value of assets minus the book value of equity (Item 6$-$Item 60), scaled by book assets, all measured at the end of year t. The main coefficient of interest is β, which measures the sensitivity of investment to stock prices. I also include several control variables to accommodate their effects on investments. The control variables ($Controls$) are as follows: $1/Asset_{i,t}$, $CF_{i,t}/Asset_{i,t}$. I include $1/Asset_{i,t}$ because both the dependent variable (I_{it}) and the price measure Q_{it} are scaled by the book assets in the previous year ($Asset_{i,t}$), which may induce the spurious correlation. Previous studies have documented the effect of cash flows ($CF_{i,t}$) on investments (e.g., Fazzari et al. (1988)), I include cash flows $CF_{i,t}/Asset_{i,t}$. We measure cash flows as the sum of net income before extraordinary items (Item 18), depreciation and amortization expenses (Item 14), and R&D expenses (Item 46), scaled by beginning-of-year book assets. I also control for the industry effect and year effect. Table 1 shows the estimation result. In my sample period, the investment-price sensitivity is about 0.005. The result shows that as the market evaluation increases by 1%, the investment will increase by 0.005%.[13]

Table 1: Estimation of the investment-price sensitivity

	Investment	
Tobin'Q	0.0106***	0.0052***
	(0.0011)	(0.0014)
1/Asset		1.0596**
		(0.4966)
Cash Flows		0.1360***
		(0.0190)
Observations	7,761	7,745
Industry Effect	YES	YES
Year Effect	YES	YES
Adj_R2	0.499	0.529

Note: The table 1 reports the regression coefficients and standard errors in parenthesis of a standardized price measure (Tobin'Q) with respect to the investment. The investment is the capital expenditures scaled by beginning-of-year book assets. Tobin's Q is calculated as the market value of equity (price times shares outstanding from CRSP) plus the book value of assets minus the book value of equity (Item 6−Item 60), scaled by book assets, all measured at the end of year t. Control variables are 1/Asset and Cash Flows. The cash flow is measured as the sum of net income before extraordinary items (Item 18), depreciation and amortization expenses (Item 14), and R&D expenses (Item 46), scaled by beginning-of-year book assets. I also control for the industry effect and time effect. * p<0.1, ** p< 0.05, *** p<0.001. Sources: Compustat, CRSP

2.2 Parameterization

To reduce the burden of estimation, I set a subset of parameters exogenously using data moments. Then, I estimate the rest of the parameters within the model. Table 2 summarizes these externally calibrated parameters.

The theory builds on the optimization of agents' behavior conditional on their information set. A group of important parameters is the precision of agents' information. Even though I cannot observe the managers' or the informed traders' information set directly, I could exploit the literature's advanced approach to estimate some of the information precision externally. Following Brogaard et al. (2022), I can identify and obtain the precision of public information and the noises from stock price movements based on a return variance decomposition model

[13] The price and investment measures are standardized and scaled by the book assets.

[14]. So, the precision of public information $h_{\eta'}$ is set to be 0.2096. The variance of noise trading σ_u^2 is chosen with a value of 3.88.

The model requires five parameters to be calibrated internally: the precision of productivity shock h_z, the precision of manager's information h_η, the precision of manager's learning from stock prices $h_{s'}$, the relative risk aversion $\frac{\rho}{n}$, the replacement costs γ. This paper jointly calibrates them to match five data moments. The moments for the data are (1) the precision of information of informed traders, (2) the forecasting price efficiency, (3) the investment-price sensitivity, (4) the variance of price measure, and (5) the variance of investment. [15]

Table 2: Externally Calibrated Parameters

Parameters	Description	Sources	Value
$h_{\eta'}$	the precision of public information	Brogaard et al. (2022)	0.2096
h_s	precision of private information	Brogaard et al. (2022)	0.2725
σ_u^2	the variance of noise trading	Brogaard et al. (2022)	3.88

Note: The table 2 describes the externally calibrated parameters, their values, and the data resources. All parameters cover the period of 1985-2015. Data sources: CRSP, Compustat, and Brogaard et al. (2022)

Table 3 summarizes the moment descriptions and values for the calibration. I obtain the forecasting price efficiency following Bai et al. (2016), who use the cross-sectional standard deviation in predicted earnings from investment as a measure of economic efficiency. If prices are totally uninformative, the ex-ante firms will all invest at the same level regardless of prices because they do not capture any useful information about their fundamentals from the stock prices. Otherwise, if the stock prices are informative, the cross-sectional dispersion will be larger because each firm invests at a different level based on the diverse signal they draw from the stock prices.[16]

This paper assumes the way that managers extract the information from the stock price using equation 8, and I calculate the variance of s'. Here, I can get the second moment. The investment-price sensitivity is the third moment, which is estimated by the regression in equation 14. The fourth moment is the variance of price, which is constructed by equation 11. I obtain the data moment from the S&P 500 firms I use in the regression 14. The last moment

[14]See Appendix A.3 for the details.

[15]See Appendix A.4 for the details.

[16]Here, this paper treats the predicted earnings as the realization of the fundamentals.

is the variance of the rate of investment, defined in the simulation as $k/\bar{k}$.

Table 3: Targeted Moments

Moment	Description	Sources	Value
$\mathbb{V}ar(\mathbb{E}[z\|p])$	Forecasting Price Efficiency	Bai et al. (2016)	5.76e-04
h_s	the relationship between manager's learned information and the signal of informed traders	Brogaard et al. (2022)	0.2725
$\beta_{\bar{k},q}$	the investment-price sensitivity	Equation 14	0.005
$\mathbb{V}ar(p)$	the variance of price	S&P 500 firms data	2.3738
$\mathbb{V}ar(k/\bar{k})$	the variance of the rate of investment	S&P 500 firms data	0.0039

Note: The table 3 describes the targets, their values, and the data sources. The forecasting price efficiency is the author's calculation based on Bai et al. (2016). The precision of informed traders' signal is obtained from Brogaard et al. (2022). The investment-price sensitivity is estimated by the regression. The variance of the price is the variance of Tobin'Q, which is obtained from the firm's data in the investment-price sensitivity regression. The variance of the rate of investment is also obtained from the firm's data in the investment-price sensitivity regression. Data sources: Bai et al. (2016), Brogaard et al. (2022), CRSP and Compustat.

2.3 Decompostion of the investment-price sensitivity

Table 5 presents the calibrated values and the proportion of internal learning and manager learning from decomposing the investment-price sensitivity.

The precision of productivity shock is about 3.5. The estimated precision of the unobserved manager's information is about 0.4668, consistent with my assumption, which is greater than the precision of public information 0.2096. The precision of the manager's learned signal from stock prices is about 0.0021, much lower than private information's precision of 0.2725. The relative risk aversion is about 2.76, and this number is comparable with the estimate in Kurlat and Veldkamp (2015) [17]. The replacement cost parameter is about 2.85. Compared to the results in Cooper and Haltiwanger (2006), this estimate is in a reasonable range.

Based on all the parameters mentioned above, the model generates two covariances: (i) the covariance between price and internal information signal, (ii) the covariance between price and manager's learned signal. The internal information covariance is about 0.2731, and the second manager's learning covariance is slightly lower, which is about 0.2301.

Furthermore, the result of the decomposition for two channels is that about 54% of the investment-price sensitivity comes from internal learning, and about 46% of the investment-

[17] Kurlat and Veldkamp (2015) gets the estimate for the relative risk aversion in the bond market, so my estimate in the stock market is greater than their estimate.

Table 4: Calibrated parameter values

Parameters	Description	Estimated Value
h_z	the precision of productivity shock	3.5493
h_η	the precision of manager's information	0.4668
$h_{s'}$	the precision of manager's learning from stock prices	0.0021
$\frac{\rho}{n}$	relative risk aversion	2.7594
γ	the replacement cost of capital	2.8549

Note: The table 4 describes the targets, their values, and the data sources. The forecasting price efficiency is the author's calculation based on Bai et al. (2016). The precision of informed traders' signal is obtained from Brogaard et al. (2022). The investment-price sensitivity is estimated by the regression. The variance of the price is the variance of Tobin'Q, which is obtained from the firm's data in the investment-price sensitivity regression. The variance of the rate of investment is also obtained from the firm's data in the investment-price sensitivity regression. Data sources: Bai et al. (2016), Brogaard et al. (2022), CRSP and Compustat.

Table 5: Calibrated Result

Parameters	Description	Estimated Value
$h_\eta * cov(\eta, p)$	the weighted covariance between price and internal signal	0.2731
$h_{s'} * cov(s^{'}, p)$	the weighted covariance between price and manager's learned signal	0.2301
Internal learning%	the fraction of investment-price sensitivity attributed to internal information	54.27%
Market learning%	tthe fraction of investment-price sensitivity attributed to managers' learning in stock markets	45.73%

Note: The table 5 reports the results using calibrated parameters. The internal learning proportion is calculated by the weighted covariance times the Δ divided by the investment-price sensitivity. The weighted covariance times the Δ divided by the investment-price sensitivity calculates the market learning proportion.

price sensitivity comes from the manager learning. In this way, I can assess these two channels' importance on the investment sensitivity to stock prices. Interestingly, the calibrated precision of the manager's learned signal is only 0.0021, significantly lower than internal information's precision. However, this biased signal leads to a larger component of market learning.

3 Effect of Disclosure and the Shock to Information on Market Learning

In this section, this paper studies the dynamics of investment-price sensitivity, internal learning, market learning, and forecasting price efficiency in response to the shocks of signals. Furthermore, I compare the baseline model (partial disclosure) with the full disclosure scenario to study the effect of disclosure policy on managers' market learning.

3.1 Shocks to internal information

Figure 3 demonstrates how investment-price sensitivity, internal learning, market learning, and forecasting price efficiency change when the precision of internal information changes. When the internal information is more precise, investment-price sensitivity is increasing. The intuition is that the public information is more precise, and the public information is impounded into the stock. Thus, more variations in the investments can be explained by the variations in the stock price. The improvement in internal information precision leads the manager to rely more on her internal information, and less on the stock-market learned information. As we can see from the second and third-panel graphs, internal learning is increasing, and market learning is decreasing at the same time. This implies that even though investment-price sensitivity increases, it does not necessarily mean that the manager's investment decision responds more to the impounded new information in stock prices. This result also explains the importance of isolating the internal learning channel from the market learning channel. Price reflects more on the fundamental information, so the forecasting price efficiency is increasing.

Under the full disclosure, investment-price sensitivity is higher than the baseline model.

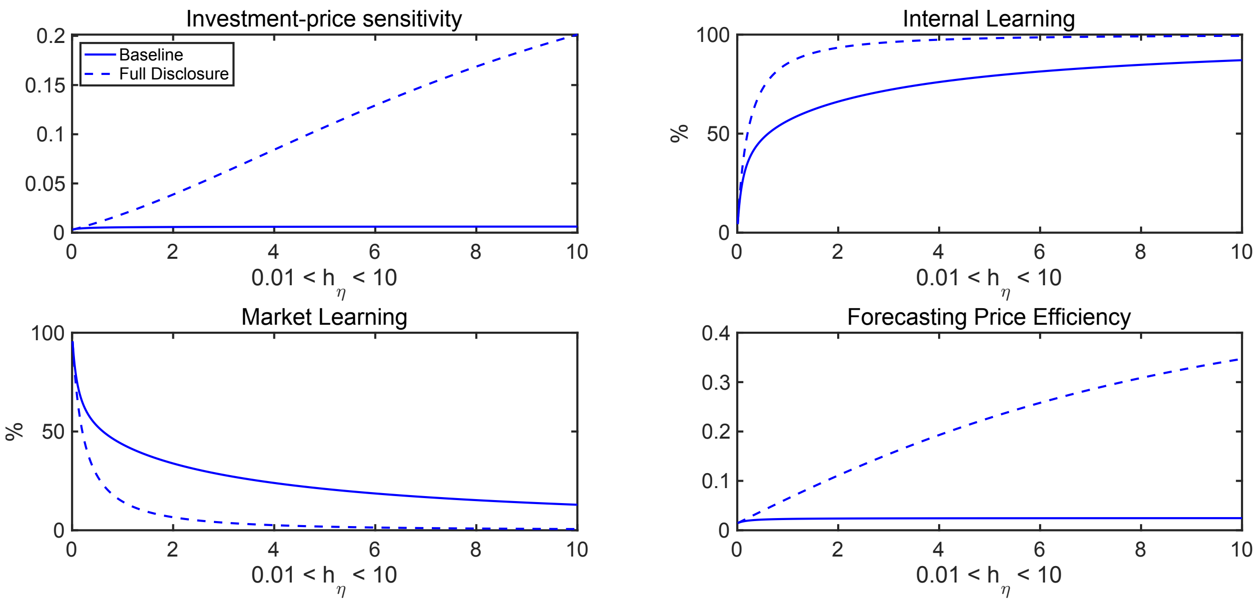

Figure 3: Dynamics when the precision of internal information changes

Note: The Figure 3 describes the dynamics of investment-price sensitivity, internal learning, market learning and forecast price efficiency in response to the change in the precision of internal information. The solid line is obtained from the baseline model(partial disclosure). The dashed line is obtained from the full disclosure scenario, which the market participants can observe all the internal information ($h_\eta = h_{\eta'}$).

Internal learning is higher than that in the baseline model, and market learning is lower than that in the baseline market. This results echoes the finding in Jayaraman and Wu (2018) that disclosure could reduce managers' ability to glean decision-relevant information from prices. Besides, full disclosure increases forecasting price efficiency because more disclosure will enhance price informativeness.

3.2 Shocks to informed traders' information

Figure 4 shows the dynamics of investment-price sensitivity, internal learning, market learning, and forecasting price efficiency when the precision of informed traders' signals changes. When the private information signal observed by informed traders is less precise (variance becomes larger), the investment-price sensitivity increases initially and then drops as the variance increases. There is a relatively higher proportion of market learning and a relatively lower proportion of internal learning when the private signal gets more precise. That is because when informed traders are more accurate about the fundamentals, managers will glean more relevant information from stock prices. Also, the forecasting price efficiency will increase as informed traders bring more useful information into stock prices.

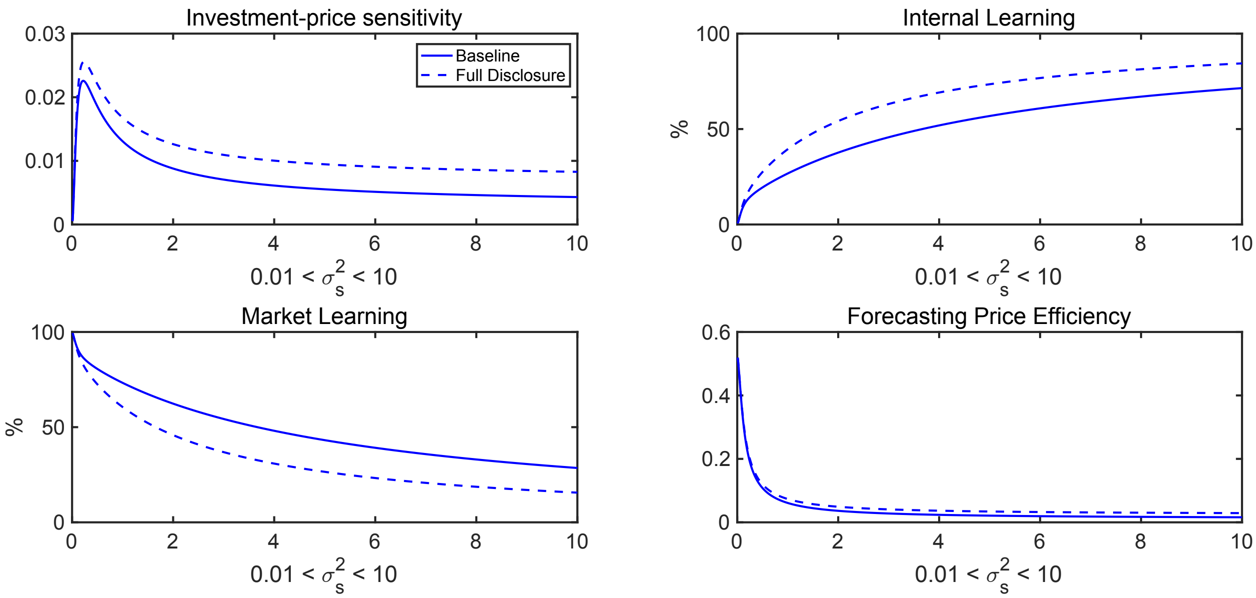

Figure 4: Dynamics when the precision of informed traders' information changes

Note: The Figure 4 describes the dynamics of investment-price sensitivity, internal learning, market learning and forecast price efficiency in response to the change in the precision of informed traders' information. The solid line is obtained from the baseline model(partial disclosure). The dashed line is obtained from the full disclosure scenario, which the market participants can observe all the internal information ($h_\eta = h_{\eta'}$).

The comparison between the baseline model and the full disclosure scenario shows higher investment-price sensitivity, forecasting price efficiency, and internal learning but lower market learning under full disclosure. This result is the same as what I find when the precision of internal information changes.

3.3 Noise trading

Figure 5 illustrates how investment-price sensitivity, internal learning, market learning, and forecasting price efficiency respond to the change in the variance of noise in stock prices. Due to the existence of noise traders, managers cannot have perfect information about what others know about the fundamentals. As the noises become larger, investment-price sensitivity decreases, market learning falls, and internal learning increases. The explanation is that the larger noises reduce the manager's ability to extract relevant information from stock prices so she will rely more on her internal information. And the noises reduce forecasting price efficiency.

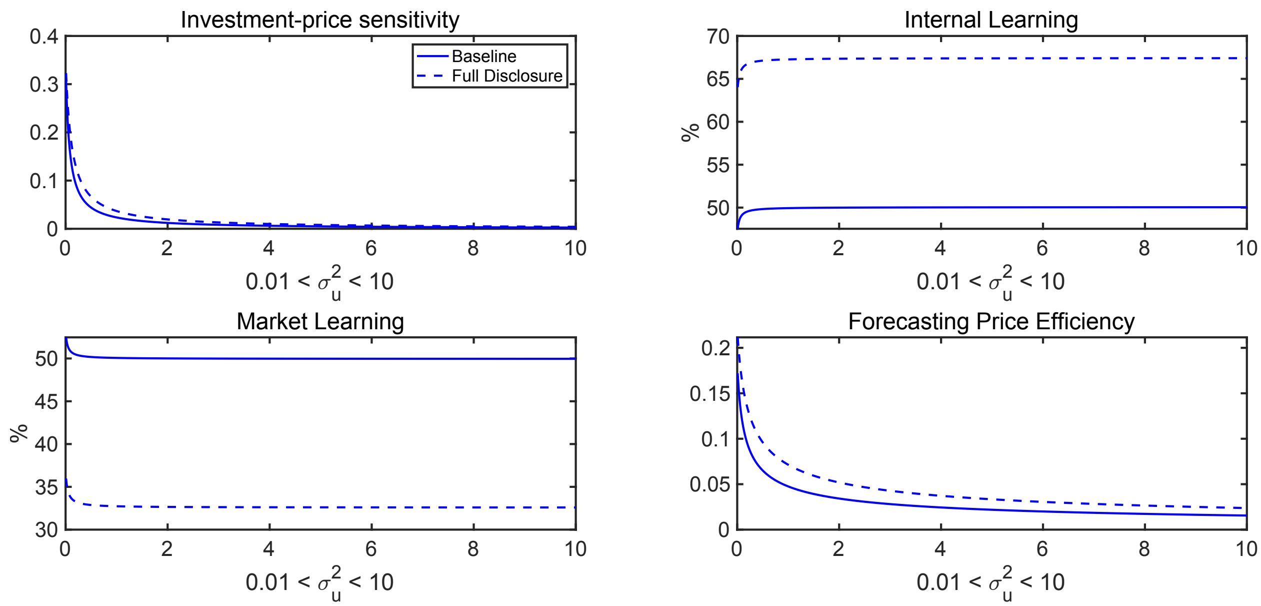

Figure 5: Dynamics when the precision of noise trading changes

Note: The Figure 5 describes the dynamics of investment-price sensitivity, internal learning, market learning, and forecast price efficiency in response to the change in the precision of noises. The solid line is obtained from the baseline model(partial disclosure). The dashed line is obtained from the full disclosure scenario, which the market participants can observe all the internal information ($h_\eta = h_{\eta'}$).

This result echoes the empirical finding in Dessaint et al. (2018) that a firm's investment response to the noise in its product market peers' stock prices by controlling for the effect of the firms' own stock price. This result also suggests that nonfundamental stock price shocks can harm investment efficiencies because they influence managers' beliefs about their growth opportunities.

The result of the comparison between the baseline model and the full disclosure model still holds.

3.4 Relative risk aversion

Figure 6 shows the dynamics of investment-price sensitivity, internal learning, market learning, and forecasting price efficiency when the relative risk aversion of informed traders changes. As the relative risk aversion increases, the investment-price sensitivity decreases, and the manager relies more on internal learning and less on market learning. Moreover, forecasting price efficiency decreases with the increase in relative risk aversion. A possible reason behind this is that as informed traders are more risk averse on average, they will be less active in acquiring and trading on private information. As a result, the forecasting price efficiency decreases, and the manager's market learning also declines.

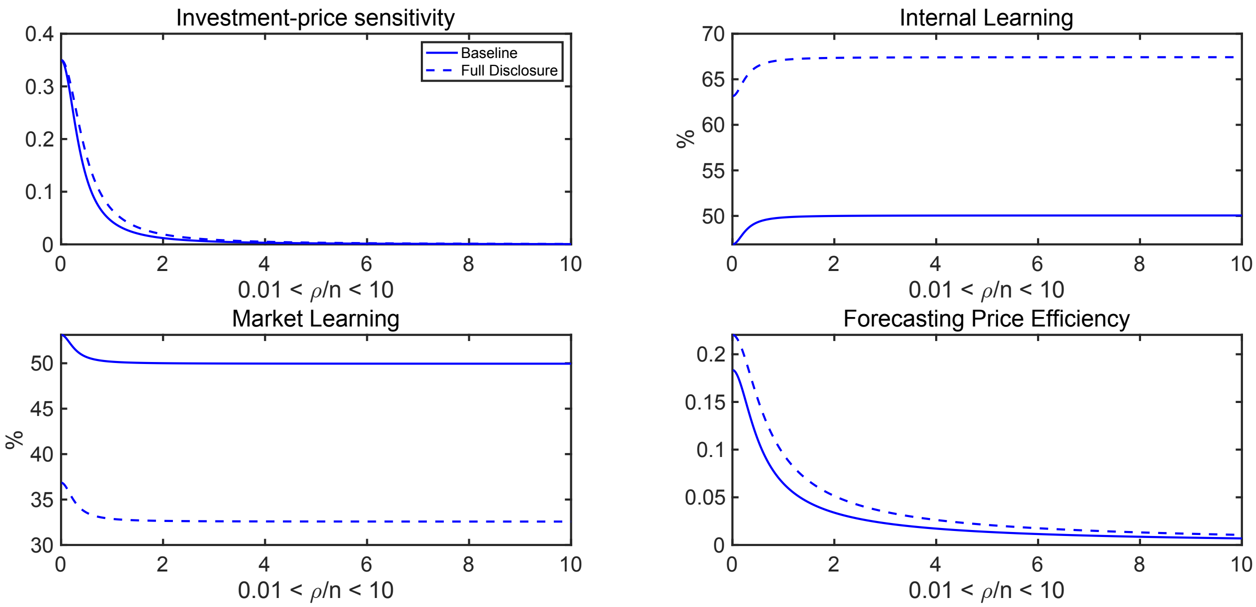

Figure 6: Dynamics when the relative risk aversion of informed traders changes

Note: The Figure 6 describes the dynamics of investment-price sensitivity, internal learning, market learning, and forecast price efficiency in response to the change in relative risk aversion. The solid line is obtained from the baseline model(partial disclosure). The dashed line is obtained from the full disclosure scenario, which the market participants can observe all the internal information ($h_\eta = h_{\eta'}$).

3.5 Uncertainy in the fundamentals

Figure 7 shows the analysis of the change in the investment-price sensitivity, internal learning, market learning, and forecasting price efficiency as the uncertainty of the fundamentals changes. The change in the uncertainty of the firm's fundamentals will have a non-negligible impact on the manager's investment decisions. As there is higher uncertainty about the fundamental, investment-price sensitivity increases, internal learning increases, but market learning decreases, forecasting price efficiency also increases. The intuition behind this is that the manager will put more confidence in her internal information when there is higher uncertainty about future payoffs. It is more profitable to acquire and trade on private information when people have a more diverse prediction about future fundamentals, so informed traders incorporate more information in the stock price and forecast price efficiency increases.

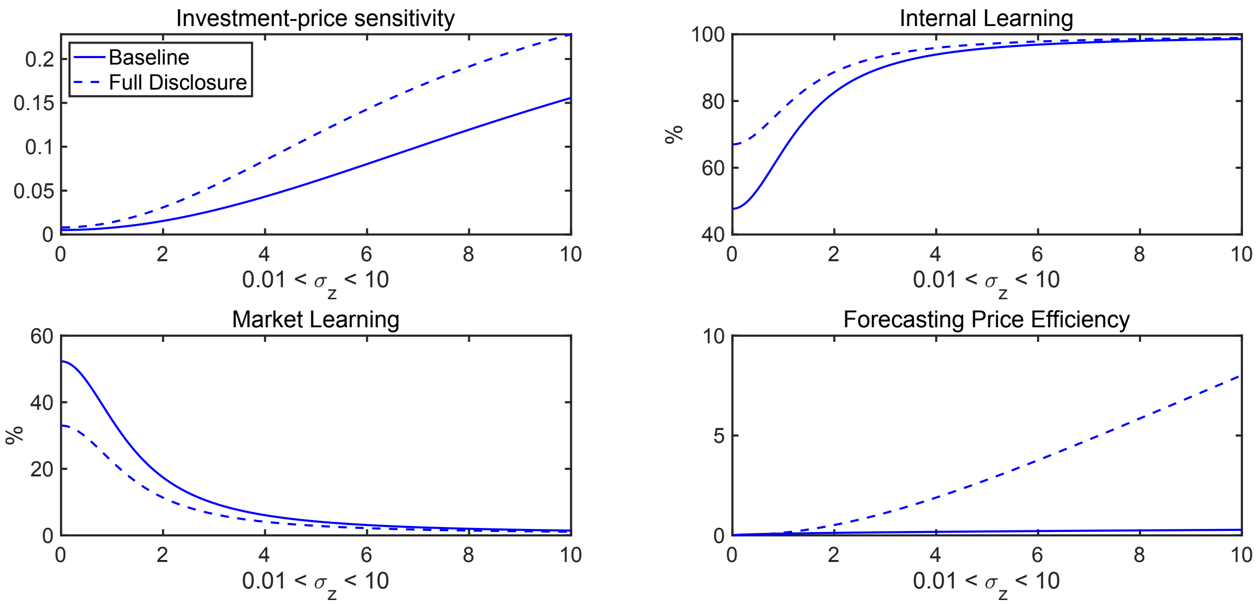

Figure 7: Dynamics when the uncertainty of the fundamentals changes

Note: The Figure 7 describes the dynamics of investment-price sensitivity, internal learning, market learning, and forecast price efficiency in response to the change in the precision of noises. The solid line is obtained from the baseline model(partial disclosure). The dashed line is obtained from the full disclosure scenario, which the market participants can observe all the internal information ($h_\eta = h_{\eta'}$).

For the comparison between the baseline and full disclosure models, there is higher investment-price sensitivity, forecasting price efficiency, and internal learning but lower market learning under full disclosure. This result is the same as what I found in the previous analysis.

4 Conclusion

This paper develops a manager's learning model in the context of investment decisions to decompose the investment-price sensitivity in order to measure how much managers can learn from stock prices. In this context, the manager optimizes her investment decision by making a forecast of the firm's future fundamentals based on her internal information and new information learned from stock prices. The stock price is a mix of various sources of information, so the investment-price sensitivity cannot tell us how much the importance of new information impounded in stock price is. This paper contributes to isolating the market learning channel (information new to the manager) from the internal learning channel (information already known to the manager) in the investment-price sensitivity. This main finding is that about 46% of the investment-price sensitivity comes from the manager's market learning, and about 54% comes from the manager's internal learning. The manager relies less on market learning if the firms disclose full information even though the investment-price sensitivity and forecasting price efficiency are higher. Moreover, a manager's market learning declines when the firm faces a higher uncertainty in the fundamentals. These results have implications for policymakers for designing disclosure policy when the economy is experiencing a downturn.

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A Appendix

A.1 Data

- Investment is the capital expenditures scaled by beginning-of-year book assets. Source: Compustat.
- Price is the Tobin's Q. Tobin's Q is calculated as the market value of equity (price times shares outstanding from CRSP) plus the book value of assets minus the book value of equity (Item 6−Item 60), scaled by book assets, all measured at the end of year t. Sources: Compustat and CRSP.
- Asset is the book asset of the firms. Source: Compustat.
- Cash flows are the sum of net income before extraordinary items (Item 18), depreciation and amortization expenses (Item 14), and R&D expenses (Item 46), scaled by beginning-of-year book assets. Source: Compustat

A.2 Characterization of the Equilibrium

There are n informed traders who choose their demand x to maximize a standard mean-variance objective:

Therefore, the demand of each trader is

$$x = \frac{1}{\rho}[h_s s + h_{\eta'}\eta' - p(h_z + h_s + h_{\eta'})] \tag{A.1}$$

We assume a random supply u of shares (equivalently noise traders), so the equilibrium condition is

$$nx = u \tag{A.2}$$

and we get the equilibrium price

$$p = \frac{h_s s + h_{\eta'}\eta' - \frac{\rho}{n}u}{h_z + h_s + h_{\eta'}} \tag{A.3}$$

Next, we want to understand what the manager learns. Since she knows η' she can observe

$$s' = s - \frac{\rho}{nh_s}u = z + \epsilon_s - \frac{\rho}{nh_s}u \tag{A.5}$$

Therefore her information set is in fact $\{\eta, s'\}$ and she sets

$$\gamma\frac{k^*}{\bar{k}} = \mathbb{E}[z|\mathcal{I}_m] = \frac{h_\eta \eta + h_{s'}s'}{h_z + h_\eta + h_{s'}} \tag{A.4}$$

where

$$h_{s'} = \frac{h_s}{1 + (\frac{\rho}{n})^2 h_s^{-1} \sigma_u^2} \tag{A.5}$$

To compute the efficiency of the economy, we obtain

$$\mathbb{E}[z|\mathcal{I}_m] = \frac{(h_\eta + h_{s'})z + h_\eta \epsilon_\eta + h_{s'}(\epsilon_s - \frac{\rho}{nh_s}u)}{h_z + h_\eta + h_{s'}} \tag{A.6}$$

and so aggregate efficiency is

$$\mathbb{V}ar(\mathbb{E}[z|\mathcal{I}_m]) = (\frac{h_\eta + h_{s'}}{h_z + h_\eta + h_{s'}})h_z^{-1} \tag{A.7}$$

Forecasting price efficiency (FPE) is

$$\mathbb{V}ar(\mathbb{E}[z|p]) = \frac{h_\pi}{h_\pi + h_z} h_z^{-1} \tag{A.8}$$

where

$$h_\pi = \frac{(h_s + h_{\eta'})^2}{h_s + h_{\eta'} + \frac{\rho^2}{n^2}\sigma_u^2}$$

As for Revelatory Price Efficiency, we have

$$\mathbb{V}ar(\mathbb{E}[z|\eta, \eta^{'}, s^{'}]) - \mathbb{V}ar(\mathbb{E}[z|\eta, \eta^{'}]) = \left(\frac{h_\eta + h_{s'}}{h_z + h_\eta + h_{s'}} - \frac{h_\eta}{h_z + h_\eta}\right) h_z^{-1} \tag{A.9}$$

From A.4, the optimal investment is as follows:

$$\gamma \frac{k^*}{\bar{k}} = \mathbb{E}[z|\mathcal{I}_m] = \frac{h_\eta \eta + h_{s'} s^{'}}{h_z + h_\eta + h_{s'}} \tag{A.10}$$

$$k^* = \frac{\bar{k}}{\gamma} \cdot \frac{h_\eta \eta + h_{s'} s^{'}}{h_z + h_\eta + h_{s'}}$$

We decompose the investment-price sensitivity as follows:

$$\beta_{\tilde{k}^* q} = \frac{cov(\tilde{k}^*, q)}{Var(q)} = \Delta\{\underbrace{h_\eta * cov(\eta, p)}_{\text{internal learning}} + \underbrace{h_{s'} * cov(s^{'}, p)}_{\text{manager's learning}}\} \tag{A.11}$$

where $\tilde{k}^* = \frac{k^*}{\bar{k}} = \frac{1}{\gamma}\frac{h_\eta \eta + h_{s'} s^{'}}{h_z + h_\eta + h_{s'}}$ and $\Delta = \frac{1}{\gamma Var(p)(h_z + h_\eta + h_{s'})(h_z + h_{\eta'} + h_s)}$

$$cov(\eta, p) = \left(h_s h_z^{-1} + h_\eta^{'} h_z^{-1} + h_{\eta'} h_\eta^{-1}\right)$$

$$cov(s^{'}, p) = \left(h_s h_z^{-1} + h_{\eta'} h_z^{-1} + 1 + \frac{\left(\frac{\rho}{n}\right)^2 \sigma_u^2}{h_s}\right)$$

A.3 Return Variance Decomposition

Consider the log of the observed price at time t, p_t, as the sum of two components:

$$p_t = m_t + s_t \tag{A.12}$$

where m_t is the efficient price and s_t is the pricing error.

m_t follows a random walk with drift μ and innovations w_t :

$$m_t = m_{t-1} + \mu + w_t \tag{A.13}$$

The stock return is

$$r_t = p_t - p_{t-1} = \mu + w_t + \Delta_{s_t} \tag{A.14}$$

The random-walk innovations,w_t , can then be decomposed into three parts:

$$w_t = \theta_{rm}\varepsilon_{rm,t} + \theta_x\varepsilon_{x,t} + \theta_r\varepsilon_{r,t} \tag{A.15}$$

Thus,

$$r_t = \underbrace{\mu}_{\text{discount rate}} + \underbrace{\theta_{rm}\varepsilon_{rm,t}}_{\text{market-wide info}} + \underbrace{\theta_x\varepsilon_{x,t}}_{\text{private info}} + \underbrace{\theta_r\varepsilon_{r,t}}_{\text{public info}} + \underbrace{\Delta_{s_t}}_{\text{noise}} \tag{A.16}$$

We estimate the components of Equation A.16 using a structural VAR with five lags to allow a full week of serial correlation and lagged effects:

$$\begin{aligned}
r_{m,t} &= \sum_{l=1}^{5} a_{1,l} r_{m,t-l} + \sum_{l=1}^{5} a_{2,l} x_{t-l} + \sum_{l=1}^{5} a_{3,l} r_{t-l} + \varepsilon_{rm,t} \\
x_t &= \sum_{l=0}^{5} b_{1,l} r_{m,t-l} + \sum_{l=1}^{5} b_{2,l} x_{t-l} + \sum_{l=1}^{5} b_{3,l} r_{t-l} + \varepsilon_{x,t} \\
r_t &= \sum_{l=0}^{5} c_{1,l} r_{m,t-l} + \sum_{l=1}^{5} c_{2,l} x_{t-l} + \sum_{l=1}^{5} c_{3,l} r_{t-l} + \varepsilon_{r,t}
\end{aligned}$$

where $r_{m,t}$ is the market return, x_t is the signed dollar volume of trading in the given stock (positive values for net buying and negative values for net selling), and r_t is the stock return.

A.4 Moment Conditions

$$h_s = h_{s'} * \left(1 + (\frac{\rho}{n})^2 h_s^{-1} \sigma_u^2\right) \tag{A.17}$$

$$\mathbb{V}ar(\mathbb{E}[z|p]) = \frac{h_\pi}{h_\pi + h_z} h_z^{-1} \tag{A.18}$$

where

$$h_\pi = \frac{(h_s + h_{\eta'})^2}{h_s + h_{\eta'} + \frac{\rho^2}{n^2}\sigma_u^2}$$

Define $\tilde{k} = k^*/\bar{k}$, where k^* is the optimal level of investment, $\bar{k}$ is the asset in place

$$\beta_{\tilde{k},q} = \frac{cov(\frac{k^*}{\bar{k}}, \frac{p}{\bar{k}})}{var(q)} = \frac{cov(k^*, p)}{var(p)} = \Delta\{h_\eta * cov(\eta, p) + h_{s'} * cov(s^{'}, p)\} \tag{A.19}$$

where $\Delta = \frac{1}{\gamma(h_z + h_{s'} + h_\eta)(h_z + h_s + h_{\eta'})var(q)}$

$$cov(\eta, p) = h_s h_z^{-1} + h_\eta^{'} h_z^{-1} + h_{\eta'} h_\eta^{-1}$$

$$cov(s^{'}, p) = h_s h_z^{-1} + h_{\eta'} h_z^{-1} + 1 + \frac{\rho^2}{n^2 h_s}\sigma_u^2$$

$$\mathbb{V}ar(p) = \frac{\left((h_s + h_{\eta'})^2 h_z^{-1} + h_s + h_{\eta'} + \frac{\rho^2}{n^2}\sigma_u^2\right)}{(h_z + h_s + h_{\eta'})^2} \tag{A.20}$$

$$\mathbb{V}ar(\frac{K^*}{\bar{K}}) = \frac{(h_\eta + h_{s'})^2 h_z^{-1} + h_\eta + h_s^{'}}{\gamma^2 (h_z + h_\eta + h_{s'})^2} \tag{A.21}$$