Market Feedback: Evidence from the Horse's Mouth

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Abstract

We surveyed all Chinese public firms in 2019 and 2022 to examine the real effects of financial markets. The response rates were close to 100%. More than 90% of firms reported that they care about the stock market for the purposes of learning information to guide real investment decisions and of accessing external financing. These findings provide direct evidence for the wide existence of market feedback through a learning channel and a financing channel. We analyze firms' responses and how they relate to firm characteristics and actions, and provide direct evidence about what firms learn from the stock prices. We also show what firms do is highly consistent with what they report by exploring their actions on trading suspensions. Overall, our analysis suggests that financial markets are not only a side show, but instead, do affect the real economy.

Key words: Market feedback, corporate investment, learning, financing

JEL number: G14, G31, D25

1. INTRODUCTION

Financial markets are not just a sideshow and can feed back into the real economy, either through providing capital or through proving useful information to real decision-makers such as firm managers and creditors. In the primary market,[1] the well-functioning of financial markets helps to facilitate the companies' access to external capital, thereby allowing them to tap into good investment opportunities. The literature sometimes labels it as the "capital budgeting" channel (e.g., Brogaard, Ringgenberg, and Sovich, 2019; Goldstein, Yang, and Zuo, 2022), and we call it the "financing channel" throughout the paper. In the secondary market, the financial market aggregates useful information from various market participants, who trade on their private information, and this information can guide the decision of real decision-makers. This channel is often labeled as an "informational feedback effect" in the literature (See Bond, Edmans, and Goldstein (2012) and Goldstein (2023) for surveys on this effect). We term it the "learning channel" throughout the paper.

It is difficult to identify the real effects of financial markets partly because of various endogeneity considerations. For instance, the information sets of market participants and real decision-makers are unobservable, and hence it is particularly challenging to test the informational feedback effect. Even some basic conceptual questions remain debatable: Do firm managers really learn information from the financial market given that they are supposed to be the most informed players? If so, what information do they learn? The existing literature has used two main strategies to draw inferences on whether real decision-makers learn information from financial markets.[2] One strategy relies on analyzing the investment-to-price sensitivity and whether it is correlated with variables indicating an active informational role. The other strategy relies on shocks that affect prices for non-fundamental reasons. However, these inferences, at their best, are only indirect and suggestive. In addition, the literature largely remains silent on what information managers extract from asset prices, if they indeed learn. Given these challenges in identifying the real effects of financial markets, in this paper we

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[1] By "primary market," we refer to the marketplace in which securities are created. It includes both the initial public offering (IPO) (creating shares of a private corporation to the public in a new stock issuance) and the seasoned equity offering (SEO) (creating new shares by an already publicly traded company).

[2] See Goldstein (2023) for a detailed discussion on these two strategies. A partial list of studies adopting one of these two strategies includes Luo (2005), Chen, Goldstein, and Jiang (2007), Bakke and Whited (2010), Edmans, Goldstein, and Jiang (2012), Foucault and Frésard (2012, 2014), Dessaint, Foucault, Frésard, and Matray (2019), and Jayaraman and Wu (2020), among others.

consider a direct approach and ask firms themselves *whether* and *why* they care about stock prices, and if they indeed learn information from prices, *what* kind of information they attempt to learn.

Specifically, we collaborated with the China Securities Regulatory Commission (CSRC), which is China's counterpart of the U.S. Securities and Exchange Commission (SEC), and conducted two rounds of surveys in June 2019 and June 2022 to elicit the opinions of Chinese public firms about market feedback. In the 2019 survey, we asked all 3,628 firms listed on the Shanghai and Shenzhen stock exchanges whether they pay attention to the stock market, and the reasons if they care about their own stock prices. In the 2022 survey, besides these two questions of whether and why, we also asked all 4,732 public firms what information they learn if they do say that they learn information from their stock prices.

The response rates were close to 100%—specifically, 3,626 (99.99%) firms in the 2019 survey and 4,641 (98.1%) firms in the 2022 survey responded—and thus, our study avoids the sampling bias problem that is common to other surveys. The information we collected from the surveys is reliable because (1) the information typically was provided by top executives or by teams specializing in capital market affairs, who are all highly knowledgeable about their firms' operations; and (2) the respondents were unlikely to hide their true opinions as we carefully asked plain, purely academic questions without "correct" answers and implemented a strict "limited use" policy in the surveys. We indeed find highly consistent responses between surveys, among respondents of different ranks, and across industries, which partly confirms the validity of our responses. We believe that China's financial markets are a good place to study market feedback, given that their information efficiency has increased substantially in recent years, as documented by Carpenter, Lu, and Whitelaw (2021).

In response to the question of whether they pay attention to the stock market, firms are given a few options of what prices they might care about. We find that in both surveys more than 90% of firms say that they care about their own or their peers' stock prices. Specifically, among the 4,641 responding firms in the 2022 survey, 121 (2.6%) firms reported that they only care about their own stock prices; 72 (1.6%) firms reported that they only care about peer firms' stock prices; 4,299 (92.6%) firms reported that they care about both prices; and 44 (0.9%) firms reported that they only care about the market index. Taken together, 97.7% of Chinese public firms reported that they pay attention to the stock market. This result holds across different positions of respondents and across different industries. Responses from the 2019 survey are very similar, and 93.7% of the 3,626 responding firms reported that they care about stock prices.

Among those firms reporting that they care about their own stock prices, they were then given a few non-exclusive options as to why they care about their stock prices. The most common reasons point to a learning channel and a financing channel. Specifically, in the 2022 survey, among the 4,420 firms saying caring about their own stock prices, 3,553 (80.4%) reported that they care about stock prices for learning new information that is relevant for real investment decisions; 3,038 (68.7%) firms reported that they care about stock prices because prices would impact refinancing. The third important reason that firms care about their stock prices is pressure from boards and shareholders, and 1,519 (34.4%) firms pointed to this reason. Other reasons, such as incentive pay and avoiding being acquired, were not very prevalent among responding firms, probably because these practices are not very popular yet in the Chinese market. Results from the 2019 survey are also very consistent—the most frequently picked reasons are learning investment information (75.2%), considering financing opportunities (66.1%), and board and shareholder pressures (35.6%).

In the 2022 survey, we asked the 3,553 firms, who say that they care about their own stock prices for learning information regarding investments, what kind of information they attempt to learn from stock prices. We find that the most important information that firms learn about is macro and industry information (90.2% of the firms affirm this statement), followed by policy and regulatory information (86.3%) and information about the company's competitive position (84.9%). Other important information firms learn about includes cost of capital (61.9%), customers' demand (59.5%), technologies (54.7%), and the company's potential acquisitions (53.1%). Our results are consistent with the theoretical reasoning in the literature which argues that firms are expected to rely on prices to extract information about the state of the macro economy, their product market competitive positions, and their customers' demand for firms' products (e.g., Goldstein and Yang, 2019; Goldstein, 2023). Overall, the information that is produced outside the firm, alien to the managers, and costly for them to collect on their own is most valuable to firms.

We then go on to analyze firms' responses and how they relate to firms' characteristics and actions. This exercise serves to validate the survey responses and to gain additional insights as to which firms care about the market for what reasons. Our analysis is based on the 2022 survey, since the results are highly consistent across the two rounds of surveys and the 2022 survey reflects the most recent information. Regarding the response to the learning channel, our premise is that if a firm thinks that its stock price contains a great deal of information that is new to its manager, it will report that it pays attention to its stock price for learning new information about investments. Based on this premise, we predict that a firm is more likely to report the learning channel if (1) its investors are more informed; (2) its manager is less informed; (3) its analysts are less informed; (4) its manager is more sophisticated; or (5) it perceives its stock price to be more informative. Our regression analysis generally confirms these predictions.

In addition, we also follow Chen, Goldstein, and Jiang (2007) and conduct an investment-to-price sensitivity analysis to provide indirect evidence on the learning channel and examine the interactions between investment-to-price sensitivity and firms' responses regarding the learning channel. The idea of Chen, Goldstein, and Jiang (2007) is that if investments are more sensitive to prices when prices are informative, this indicates that the information in the price is used for the investment decisions, providing indirect evidence for the learning channel. We find that this is the case in our sample for three price informativeness measures that are commonly adopted in the literature, namely, price nonsynchronicity (e.g., Roll, 1988; Durnev, Morck, and Yeung, 2004), adjusted probability of informed trading (Duarte and Young, 2009) and price delay (Hou and Moskowitz, 2005). Interestingly, this result on investment-to-price sensitivity is primarily driven by the subsample composed of those firms who report that they care about stock prices for the learning purpose.

Regarding the response to the financing channel, our regression results suggest that firms' choice of the financing channel depends on the benefits of financing. Specifically, financially constrained firms with large capital demand are more likely to monitor their stock prices for financing opportunities. In addition, managerial sophistication matters for the financing channel, as we find well-educated managers with backgrounds in professional services may better find and take advantage of the opportunities revealed by their stock prices.

We also find that firms indeed exploit financing opportunities revealed by their stock prices to determine follow-on equity financing. Firms observing higher Tobin's Q, which is a price-based proxy for firm valuation and financing cost, raise more capital through SEOs in the future. This pattern is more pronounced among firms reporting the financing channel than among the non-reporting firms. In a placebo test on bond financing, we do not find similar results because signals revealed by the stock prices are less relevant in this case.

Finally, we connect firms' responses (what they say) to their actions (what they do) by exploring the responding firms' active trading suspensions, which is a unique feature of the Chinese stock market. We find that those firms, who say that they learn information from stock prices, are less likely to suspend their trading. This is consistent with the idea that these firms think the information in the price is valuable and hence they do not want to suppress it. On the other hand, those firms, who say that they care about the price because of the financing channel, are more likely to suspend trading when faced with large price drops. This is consistent with the idea that the primary consideration for these firm is to prevent the price from falling further, since this will hurt their financing opportunities.

Our paper is closely related to two strands of literature. First, it contributes to the literature on the real effects of financial markets, in particular, on the informational feedback effect. As mentioned above, the existing literature uses regression analysis to make indirect inferences on the informational feedback effect (e.g., Chen, Goldstein, and Jiang, 2007; Foucault and Frésard, 2012, 2014; Carpenter, Lu, and Whitelaw, 2021). The most recent literature tries to overcome the endogeneity issues by exploring various settings (e.g., Foucault and Frésard, 2012, 2014; Dessaint, Foucault, Frésard, and Matray, 2019). Still, the evidence is indirect and suggestive. By contrast, our paper provides direct evidence for the real consequences of financial markets, both through the informational feedback effect of the secondary market and through the capital budgeting channel of the primary market, and further identifies when these channels are important. More importantly, we also provide direct evidence on what kind of information firms attempt to learn from stock prices, which is largely an open but fundamental question in the existing literature.

Second, our paper contributes to the growing literature that uses surveys to identify and measure the importance of various economic channels. Graham and Harvey (2001) and Graham, Harvey, and Rajgopal (2005) use survey data to examine the cost of capital, capital budgeting, capital structure, and corporate financial reporting. Glaser and Weber (2007) and Dorn and Sengmueller (2009) have used survey data to study the excessive trading puzzle. Choi and Robertson (2020) rely on survey data to compare many factors that may affect investment decisions. Giglio, Maggiori, Stroebel, and Utkus (2021a, 2021b) employ survey-based expectations to analyze people's belief dynamics. Edmans, Gosling and Jenter (2021) survey directors and investors on how they set CEO pay in practice and find a number of departures from mainstream academic theories. Liu, Peng, Xiong, and Xiong (2022) propose a new approach to combining subjective survey responses with observational data to study behavioral biases of investors in the Chinese stock market. Our paper offers the first study to examine the real effects of financial markets, and our survey data is comprehensive and does not suffer the sampling bias that is commonly seen in other survey studies.

2. THE SURVEYS

2.1 *Questionnaires*

Starting from 2017, the PBC School of Finance at Tsinghua University and the China Securities Regulatory Commission (CSRC) have jointly surveyed Chinese public firms every six months to collect opinions on the macro economy and a variety of topics that may be of interest to the policymakers and academia. Every public firm in the Chinese stock market is invited by the CSRC to respond to the surveys, which are designed by researchers from both the PBC school and the CSRC, and later distributed by the regulator.

In June 2019 and June 2022, we conducted two rounds of surveys about the real effects of the stock market. In both rounds, we asked public firms *whether* they care about stock prices, and if so, then *why*. In the 2022 survey, we also asked those firms, who say that they learn from their stock prices for investment information, *what* information they attempt to learn from the prices. Specifically, we asked the following questions:

I. How does your company pay attention to the stock market? (Select one answer) (Included in both surveys)

A. Only care about the price of your own company's stock;

B. Only care about the prices of other similar companies' stocks;

C. Both A and B;

D. Only care about the composite stock index;

E. Do not care about the stock market at all.

II. If you choose A or C in I: Which of the following is the reason that your company cares about the stock price of your own company? (Select all that apply) (Included in both surveys)

A. Stock price contains information that is new for investment decisions;

B. Stock price would impact refinancing (SEO/bond issuance/bank loan);

C. Compensation of management is linked to the stock price, or they hold stocks or options;

D. Pressure from the board and shareholders;

E. Avoiding being acquired or merged;

F. Others, please specify:_______________.

III. If you choose A in II: When learning from the market, what kind of information can the company's own stock price be useful for? (For each possibility, choose your opinion (strongly agree, agree, neutral, disagree, or strongly disagree)) (Included only in the 2022 survey)

A. Information about the state of the macro economy or the industry;

B. Information about policies and regulations related to the company's business;

C. Information about the company's competitive position relative to competitors;

D. Information about customers' demand for the company's products/services;

E. Information about developments in technologies the company may employ;

F. Information about the cost of capital;

G. Information about the prospects of the company's potential acquisitions of other companies, assets, or technologies;

H. Information about the impact of COVID-19 on the company's business;

I. There is no information to learn from the stock price;

J. There is other information to learn from the stock price. Please specify:________________.

Firms were asked to respond to Question I by selecting a single choice; to Question II by selecting multiple choices; and to Question III by rating their agreements with each statement (ratings include "strongly agree", "agree", "neutral", "disagree", and "strongly disagree").

We designed our questions based on the existing indirect evidence on the real effects of the stock market. Question I elicits firms' opinions on whether they pay attention to the stock market at all and if yes, to what prices. Choice A reflects those studies documenting firm managers extract information from their own stock prices (e.g., Luo, 2005; Chen, Goldstein, and Jiang, 2007). Choice B reflects those studies suggesting firm managers also keep an eye on peer firms' stock prices (e.g., Foucault and Frésard, 2014).

Question II attempts to collect firms' opinions on the reasons that they care about their own stock prices, conditional on that they say that they pay attention to their own firms' stock prices in the first place (choose A or C in Question I). Answers to this question reveal information about the specific channels of market feedback. Choice A is based on studies that find managers learn information to guide real investment decisions (e.g., Chen, Goldstein, and Jiang, 2007), which is the "learning channel." Choice B is based on studies showing that managers pay attention to stock prices for financing opportunities (e.g., Giammarino, Heinkel, Hollifield, and Li, 2004; Goldstein, Yang, and Zuo, 2020). This choice could also be related to the learning channel in a case in which the decision makers are creditors, but it covers the capital-budgeting in the primary market and so we connect Choice B to the "financing channel." Choice C is based on studies linking stock prices and managerial incentives (e.g., Kang and Liu, 2008; Bond, Edmans, and Goldstein, 2012), and we term it the "compensation channel." Choice D is based on studies on the substitution effect between market monitoring and board monitoring, because market monitoring is more powerful with informative stock prices (e.g., Ferreira, Ferreira, and Raposo, 2011). We term it the "monitoring channel." Choice E is based on the notion that firm prices can affect the likelihood that the firms become a target of merger and acquisition, and we term it the "M&A channel." Choice F allows respondents to specify other reasons which are not documented in the literature.

Question III aims to collect opinions about what kind of information firms extract from the financial market when they report they learn investment information from their own firms' stock prices (choose A in Question II). As pointed out by Goldstein (2023), the existing literature is almost silent on this question, and most discussions are conducted at the level of theoretical reasoning.[3] For example, Goldstein and Yang (2019) argue that markets have a comparative advantage in providing information that needs to be aggregated from many sources and thus firms are expected to learn information that needs such aggregation (e.g., information about product market competition). Following the same logic, Goldstein (2023) suggests that firms may want to learn information about their products and the prospects of their growth options, as well as the macro economy and its effect on the firms. Liu and Tian (2021) borrow the Chemmanur and Fulghieri (1994) model and suggest the information learned by VC investors is startup firms' IPO probability.

We take advantage of the 2022 survey and attempt to fill this gap with direct evidence, by asking firms to rate their agreements with statements about the types of information they extract. The information we list includes the state of the economy and industry (Choice A), policy and regulatory environment (Choice B), competitive position (Choice C), customers' demand (Choice D), technologies the firm may adopt (Choice E), cost of capital (Choice F), acquisition opportunities (Choice G), and the impact of COVID-19 (Choice H). Additionally, Choice I covers the possibility that there is no information contained in stock prices; and Choice J allows respondents to specify other information we omit in the choices.

Besides the above questions, we also asked the public firms to provide information on the positions of the respondents who are assigned by the firms to fill in the questionnaires. The identities of the responding firms were also recorded, enabling us to combine the survey data and public information to perform further analyses.

2.2 *Responses*

The questionnaires were distributed to public firms by the CSRC via its electronic survey system.

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[3]Two recent empirical studies have explored the question of what information firms learning from the stock market. Aretz, Ilyas, and Kankanhalli (2023) find that firm managers learn information about technological progress from market prices. Gao and Xiao (2023) suggest that managers learn from the information impounded by nonlocal investors when making investment decisions.

The 2019 survey questionnaire (containing Questions I and II) was distributed in June 2019, and the 2022 survey questionnaire (containing all three questions) was distributed in June 2022. The key advantage of collaborating with the CSRC is that we avoid the nonresponse bias (i.e., some subjects refuse to respond, or the survey is unable to reach every respondent). We managed to collect responses from 3,626 out of the 3,628 Chinese public firms at the survey date in the 2019 survey, representing a response rate of 99.99%; and collect responses from 4,641 out of 4,732 public firms in the 2022 survey, representing a response rate of 98.1%. So, our surveys cover nearly all public firms in the Chinese market and hence our analysis does not suffer the representativeness issue commonly seen in survey studies.

We also believe that the results of the joint surveys are reliable and unlikely to suffer the response bias (i.e., the survey results are different from the actual opinions or facts held by the respondents). Although the questionnaires were distributed to the firms by the CSRC, the respondents had no incentives to provide biased information to cater to the CSRC's preferences because (1) we carefully asked plain, purely academic questions that cannot be used to directly judge a firm's behavior (that is, there are no "correct" answers to these questions); and (2) in the surveys, we formally declared that the responses and other relevant information would be used only in policy and academic research in a large sample. The respondents knew that there will be no information released or reported about individual firms over the previous rounds of surveys since 2017.

In addition, we believe that the respondents understand the survey questions and their firms' operations, so that their opinions are informative about their firms. Figure 1 shows that, for the 2019 survey, in 413 (11.4%) of the 3,626 responding firms, the respondents take on important managerial positions including chairperson of the board, director, chief executive officer (CEO), chief financial officer (CFO), and other executives. In another 2,265 (62.5%) firms, the answers are prepared by the board secretary, who also belongs to top executives. In the remaining 948 (26.1%) firms, responses are prepared by other related functions (e.g., the office of investor relations, which is a specialized team in charge of capital market affairs led by the board secretary). For the 2022 survey, the pattern is similar: in 282 (6.1%) of the 4,641 responding firms, the answers are prepared by the chairperson, director, CEO, CFO and other executives; in 2,411 (52.0%) firms they are prepared by the board secretary; and in the remaining 1,948 (42.0%) firms they are prepared by other related functions.

[Figure 1 about Here]

Note that in Chinese public firms, the board secretary is an important member of the top management. Besides handling affairs about the board, shareholder meetings, and liaison with the regulators, the board secretary is also responsible for functions about the capital market, including information disclosure, investor relations, and raising capital. This observation explains why most respondents (62.5% in the 2019 survey and 52.0% in the 2022 survey) are board secretaries.

In the following analysis, we divide the respondents into three groups according to their position levels: (i) a high-ranking group including chairperson, CEO, director, CFO and other executives; (ii) a medium-ranking group including board secretary; and (iii) a low-ranking group including other functions. When presenting the survey results, along with the full sample results we also report statistics in different groups to check (1) whether our findings are driven by board secretaries and (2) whether low-ranking respondents are sufficiently informed about the questions similar to their high-ranking peers.

2.3 *Summary Statistics of Responding Firms*

In Table 1, we provide summary statistics for the firms responding to our two surveys. Information on stock prices and firm characteristics is as of 2018 for the 2019 survey, and as of 2021 for the 2022 survey. The data is retrieved from the China Stock Market & Accounting Research Database (CSMAR). Given that the responding sample contains more than 98% of Chinese public firms, we are essentially summarizing the population of Chinese public firms.

[Table 1 about Here]

Taking respondents to the 2022 survey as an example, we find that, as of 2021, 30% of the public firms are ultimately owned by the state in the Chinese stock market (and in our survey), and that short-selling is allowed in 48% of these firms. On average, a public firm is about 21.8 years old since its establishment. It has a total asset of 12.6 billion RMB (1.8 billion in US dollars), and its market capitalization is 13.4 billion RMB (2.0 billion in US dollars). The average firm is moderately levered with a leverage ratio of 42.3%. The valuation of the firm is comparable to that in the U.S. market, and its Tobin's Q is around 2.6. It is also reasonably profitable with a return on assets (ROA) of 5.5%. Its capital expenditure and R&D expenses account for 5.3% and 2.8% of the total assets. On average, there are 6.7 sell-side analysts following each public firm. Meanwhile, 35.6% of the firm's outstanding shares are held by institutional investors including mutual funds, insurance companies, pension funds, investment banks, and trust firms. The reported insiders' trading activities are relatively thin, as their trading volume only accounts for 0.02% of the total shares outstanding. The level of the average firm's stock price informativeness, measured by $1\text{-}R^2$, is around 0.8.

3. DIRECT EVIDENCE FOR MARKET FEEDBACK

In this section, we summarize firms' responses to our questions to provide direct evidence on market feedback. Throughout the analysis, we refer to a firm's behavior of caring about the stock market, in particular, caring about its own or its peers' prices, as market feedback effect (i.e., Choices A – D in Question I). We also employ the learning channel and financing channel mentioned in Introduction and Subsection 2.1 to refer to the practices of monitoring own stock prices for investment and financing purposes (i.e., Choices A and B in Question II). Besides reporting survey results in the full sample, we also summarize responses across industries to explore the heterogeneity in firms' behaviors.

3.1 *Prevalence of Market Feedback*

Our first question ("*I. How does your company pay attention to the stock market?"*) concerns the existence of general market feedback, or whether firms care about stock prices at all. We report the responses in Figure 2. According to Panel A, among the 4,641 firms responding to the 2022 survey (the full sample), 121 (2.6%) firms responded that they only care about their own stock prices (Choice A); 72 (1.6%) firms responded that they only care about peer firms' stock prices (Choice B); 4,299 (92.6%) firms responded that they pay attention to both their own and peer firms' stock prices (Choice C); and 44 (0.9%) firms responded that they only care about the overall market conditions (Choice D). Only 105 (2.3%) firms indicated that they do not care about the stock market at all (Choice E). In other words, 97.7% of the responding firms monitor stock prices for some reasons (Choices

A+B+C+D). Considering 98.1% of the Chinese public firms responded to the 2022 survey, we find that nearly all Chinese public firms do pay attention to the stock market. The 2019 survey results show very similar patterns: 3,399 (93.7%) of the 3,626 responding firms say they care about stock prices in some forms, and 3,049 (84.1%) firms pay attention to both their own and peer firms' stock prices, suggesting market feedback is also persistent across years in the Chinese stock market.

Panels B, C, and D respectively report survey results in different groups of respondents. Regardless of the respondents' ranks in the firms, their opinions are highly consistent and point to the existence of market feedback. For example, in the 2022 survey, 90.4% of the high-ranking group (chairperson, CEO, director, CFO, and other executives, N=282) reported they pay attention to both their own and peer firms' stock prices (Choice C). The figures for the medium-ranking group (board secretary, N=2,411) and the low-ranking group (other positions, N=1,948) are 92.6% and 93.0%, respectively. In the high-ranking group, 95.4% of firms care about stock prices (Choices A+B+C+D), which is comparable to that of the medium-ranking group (98.0%) and the low-ranking group (97.8%). Again, the results from the 2019 survey are qualitatively the same. The above results suggest that our findings are consistent among respondents from various positions, and not driven by the reports from medium-ranking board secretaries.

[Figure 2 about Here]

This direct survey evidence on the prevalence of market feedback in the Chinese stock market is consistent with the indirect evidence provided by Chen and Liu (2018), who follow the methodology of Chen, Goldstein, and Jiang (2007) and find a positive relation between price informativeness and investment-to-price sensitivity among the Chinese public firms. Taken together, our findings strongly support that it is a common practice for Chinese public firms to closely monitor the stock market.

3.2 *Channels for Market Feedback*

Our second question ("*II. If you choose A or C in I: Which of the following is the reason that you care about the stock price of your own company?"*) explores why the firms care about their own stock prices. The 3,320 firms choosing A or C in question I in the 2019 survey and the 4,420 firms doing so in the 2022 survey were asked to respond. We report the summary of their answers in Figure 3. As the firms can choose more than one answer to this question, these frequency counts of each choice do not necessarily add up to the number of firms.

[Figure 3 about Here]

Panel A reports the results in the full sample. The most important reasons for firms to monitor their own stock prices are to learn information for investments (the learning channel, Choice A) and to finance investment opportunities (the financing channel, Choice B). Specifically, in the 2022 survey, 3,553 (80.4%) and 3,038 (68.7%) of the 4,420 firms caring about their own stock prices pick Choice A and Choice B, respectively. Similarly, in the 2019 survey, the factions of firms choosing Choice A and B are 75.2% and 66.1%. The third important reason underlying market feedback is pressure from boards and shareholders (the monitoring channel, Choice D), and 34.4% (35.6%) of the firms agree with this statement in the 2022 (2019) survey. The compensation channel (Choice C) is not chosen by many firms (16.6% in the 2022 survey and 11.3% in the 2019 survey), probably because equity-linked compensations such as managerial shareholding or stock options are not very popular among Chinese public firms due to relatively strict regulations.[4] The M&A channel (Choice E) is the least frequently chosen reason (8.3% in the 2022 survey and 10.2% in the 2019 survey), as hostile takeovers are rarely observed in the Chinese stock market due to higher ownership concentration in public firms.

Again, Panels B, C, and D show that the opinions are highly consistent across different groups of respondents. For example, in the 2022 survey, around 80% of the respondents in the high- (78.9%), medium- (80.6%), and low-ranking (80.3%) groups picked the learning channel (Choice A). The fractions picking the financing channel (Choice B) for high-, medium-, and low-ranking groups are 66.3%, 67.8%, and 70.3%. The 2019 survey results also demonstrate firms' preferences towards choices A and B across different respondent groups. Overall, the results suggest that the primary reasons for firms to care about their own stock prices are the learning and financing channels.

3.3 *Heterogeneity across Industries*

We now summarize the responses by industry. We include the results of the 2022 survey in the

[4]As of the end of 2021, on average the management team (excluding members from the board of directors and the board of supervisors) holds 0.55% of these public firms' outstanding shares. During the period from 2006 to 2021, fewer than 45% of these firms have ever implemented managerial incentive plans in terms of stock options, restricted stocks, and stock appreciation rights.

main text and those of the 2019 survey in Appendix A to save space. Panel A of Table 2 ranks the 31 industries from high to low by the percentage of firms in that industry picking Choices A, B, C, or D (i.e., care about the stock market in general). We find the market feedback effect is prevalent across industries. Among them, the composite industry has the lowest ratio of firms paying attention to the stock market, but this ratio is still quite high at 90.0%. Industries that are most likely to care about the stock market include coal (100.0%), utilities (100%), media (99.3%), light industry (99.3%), and transportation (99.2%).

[Table 2 about Here]

Panel B presents the summary of reasons for firms caring about their own stock prices, categorized by industries. For each channel, we rank industries from high to low by the percentage of firms in that industry selecting Choice A (i.e., the learning channel). Food and beverage (88.4%) and agriculture (85.1%) have the highest fractions of firms picking the learning channel, which might reflect the relatively high uncertainty in investments in these industries. Banking (94.1%) and construction (80.8%) have the highest propensity to select Choice B (i.e., the financing channel), probably because these industries are short of capital and have strong financing needs. Beauty (25.9%) and telecommunication (23.8%) have the largest fraction of firms picking the compensation channel. Computer (46.6%) and media (44.7%) are industries subject to the most intensive monitoring from the boards and shareholders (i.e., the monitoring channel). Lastly, for the M&A channel, telecommunication (14.3%) and computer (13.1%) have the largest fraction of firms monitoring the stock market to protect them from takeovers. In contrast, in the banking industry, no firms worry about this specific threat. Taken together, our analysis regarding the existence of market feedback is highly consistent across both rounds of surveys, different position groups of respondents, and different industries.

In the subsequent sections, we connect the survey responses to firm characteristics and behaviors to explore the channels underlying market feedback (Sections 4 and 5) and further validate our main argument (Section 6). Unless otherwise specified, the data on firm characteristics and behaviors are obtained from the CSMAR and Wind database. We conduct the analysis based on the 2022 survey, since the results are highly consistent across two rounds of surveys and the 2022 survey reflects the most recent information about the subject of interest. As mentioned in Subsection 2.2, there were 4,641 responding firms in the 2022 survey. We exclude firms that are financially distressed, listed for less than 6 months, in the process of delisting, suspended for trading, in the financial industry, or with missing key information, leaving a sample of 4,171 firms for the empirical analysis.

4. THE LEARNING CHANNEL

In this section, we use regression analysis to investigate the learning channel in detail. Our analysis serves to validate the survey results and gain additional insights as to which firms learn from prices and what information they learn from prices. First, we present a theoretical framework that guides our specification that links the firms' responses to their characteristics. Second, we test these predictions on investor information, analyst information, and managerial characteristics. Third, we examine the role of price informativeness and in particular, conduct an analysis similar to Chen, Goldstein, and Jiang (2007) regarding the indirect evidence on market feedback. Finally, we provide direct evidence on what information managers learn from prices, which we collected from the 2022 survey.

4.1 *Theoretical Framework and Testing Methodology*

We make our predictions on the learning channel based on the general premise that a firm will select choice A in question II, "Stock price contains information that is new for investment decisions," if the firm thinks that the price is a useful information source so that it will put a meaningful weight on the price signal in its investment decisions. In Appendix B, we develop a stylized model to formalize the following predictions:

Hypothesis 1 (*Learning Channel*). *A firm is more likely to report that it pays attention to its stock price for the learning purpose (select Choice A in Question II) if (1) its investors' information precision level is higher; (2) its manager's private information precision level is lower; (3) its analysts' information precision level is lower; (4) its firm manager's sophistication level is higher; or (5) it perceives its stock price to be more informative.*

First, the private information of investors increases the amount of information in the stock price that is new to firm managers and thus the extent to which managers rely on the price when they make their investment decisions (see, Grossman and Stiglitz, 1980; Easley and O'Hara, 1987), which underlies Prediction (1). Second, when firm managers have more private information on their own, they are expected to rely less strongly on the stock price in their investment decisions (e.g., Chen, Goldstein, Jiang, 2007; Goldstein and Yang, 2019), which explains Prediction (2).

Third, in principle, analysts' information precision can have two opposite effects on the extent that firm managers rely on the price. On the one hand, if the information produced by analysts and impounded into the price is new to firm managers, more precise analyst information increases the likelihood that managers think the price to be an important source of information. On the other hand, if analysts mainly help to communicate information from managers to the markets (e.g., Bailey, Li, Mao, and Zhong, 2003; Agrawal, Chadha, and Chen, 2006), information released by analysts will lower the reliance of investors on their own private information, which therefore reduces price informativeness. Chen, Goldstein, and Jiang (2007) finds that in the U.S. market, this second effect dominates, and so we also take this view and predict that firms rely less on the price when analysts' information is more precise (Prediction (3)).

Fourth, if firm managers are more sophisticated, they understand the market better and so are more likely to use the price as a useful signal to guide their investments (Prediction (4)). Finally, for whatever reason, if firm managers perceive the price to be more informative, they will rely more strongly on the price in their investment decisions (Prediction (5)).

We test the above five predictions on the learning channel that drives market feedback based on the 2022 survey. We construct a dummy variable, *Learn*, about the learning channel, which equals one if a firm chooses A in question II. *Learn* indicates that the firm cares about its own stock price for investment information, and zero otherwise. We then employ the following specification to explore factors influencing market feedback via the learning channel:

$$Learn = a + b*Factor + c*Controls + \varepsilon, \quad (1)$$

where *Factor* denotes factors such as the informational environment, manager sophistication, and other market or firm characteristics that may affect a firm's behavior of monitoring the stock prices. Across regressions, we also include the natural logarithm of firm market capitalization (*Size*), firm leverage (*Leverage*), listing history (*History*), state-owned enterprise dummy (*SOE*), and annual stock return (*Ret*) and volatility (*Vola*) to control for the influences of size, capital structure, experience as a public firm, state ownership, and stock performance. In addition, the respondent position, industry, and province fixed effects are included to absorb any influences varying only with the respondent's rank in the firm, industry, and the firm's geographical location. All independent variables are constructed with information as of 2021, and the definitions are included in Table A2 in Appendix A. Since *Learn* is a binary choice variable, we run Probit regressions to estimate equation (1).

4.2 *Investor Information, Analyst Information, and Managerial Characteristics*

In this subsection, we test Predictions (1) – (4) of Hypothesis 1 and defer the tests surrounding price informativeness, Prediction (5) of Hypothesis 1 and the replication exercise of Chen, Goldstein, and Jiang (2007), to the next subsection.

Investor Information

We use institutional ownership (*InsShares*) to measure investor information contained in stock prices, assuming institutional shareholders possess superior information about the firm and capitalize it by trading (e.g., Daniel, Grinblatt, Titman, and Wemers, 1997; Boone and White, 2015). Our second measure of investor information is *Short*, a short-selling dummy that equals one if short-selling is allowed for the stock, and zero otherwise. Short-sellers are effective information producers, and actively contribute (negative) information to prices by trading (e.g., Boehmer, Jones, and Zhang, 2008; Engelberg, Reed, and Ringgenberg, 2012).

We replace *Factor* with the investor information proxies in equation (1) and focus on coefficient *b*. Columns (1) and (2) of Table 3 report the Probit regression results. The marginal effects of *InsShares* and *Short* are 0.0248 and 0.0261, which are statistically significant at the 5% level. Regarding the economic impact, a one-standard-deviation increase in *InsShares* leads to an increase of 0.6% in the probability of learning; the probability of learning for firms for which short-selling is allowed is 2.6% higher than that for firms for which short-selling is prohibited. Taken together, the above results are consistent with our Prediction (1) that a firm manager is more likely to learn from her stock price if the latter contains more precise investor information.

[Table 3 about Here]

Managerial Information

We use two proxies to measure managerial private information. The first proxy is insider trading (*Insider*), which is defined as the number of transactions by insiders scaled by the total number of transactions in 2021. To the extent that corporate insiders, including firm managers, may trade on their private information for excessive returns (e.g., Finnerty, 1976), variable *Insider* can reflect the private information possessed by the manager. The second proxy for managerial information is earning surprise (*ERC*), defined as the average of the absolute stock returns over the four quarterly earnings announcement periods (day –5 to day 5). If *ERC* is high, there is information in earnings that was not made public and incorporated into the price. Because the manager has the access to the accounting data and thus knows the earnings before announcements, *ERC* is increasing in the manager's private information (e.g., Chen, Goldstein, and Jiang, 2007; Gomes, Gorton, and Madureira, 2007).

We regress the learning channel dummy *Learn* on *Insider* and *ERC* following equation (1), and report the Probit regression results in columns (3) and (4) of Table 3. Indeed, consistent with Prediction (2), we find that the manager is less likely to learn investment information from her stock price if she has precise private information: the marginal effects of *Insider* and *ERC* are negative and statistically significant at the 5% level. A one-standard-deviation increase in *Insider* (*ERC*) decreases the probability of learning by 4.2% (1.2%).

Analyst Information

We use the number of analysts following a firm (*NAnalysts*) and the number of earning forecasts produced in 2021 (*NForecasts*) to measure analyst information. According to Prediction (3), if analysts mainly transfer information from managers to the market, then analyst information is negatively correlated to the manager's choice of the learning channel.

We regress *Learn* on the analyst information proxies and report the Probit regression results in columns (5) and (6). The marginal effects of *NAnalysts* and *NForecasts* are -0.0007 and -0.0007, which are statistically significant at the 1% level, suggesting that more analysts following a firm are associated with the firm's lower probability of collecting information from its stock prices for the investment purpose. Regarding the economic significance, a one-standard-deviation increase in *NAnalysts*

(*NForecasts*) leads to a decrease of 0.9% (1.6%) in the probability of learning.

Managerial Sophistication

We use two proxies, *Professional* and *Degree*, to measure managerial sophistication at the firm level (See Guiso and Sodini (2013) for a discussion on the influences of education and backgrounds on financial decision-making). For each member of the management team, we define a background dummy that equals one if she has backgrounds in professional services including business, accounting, finance, management, and law, and zero otherwise. Then we calculate *Professional* at the firm level by averaging the background dummy among the management team, to measure managerial sophistication. We construct variable *Degree* in a similar manner. For each member, we measure her education level with the following scheme: 1 for high (or vocational) school diploma or below, 2 for junior college diploma, 3 for bachelor's degree, 4 for master's degree, and 5 for PhD. We then calculate *Degree* at the firm level by averaging the education variable.

We regress *Learn* on *Professional* and *Degree* in equation (1), and report the Probit regression results in columns (7) and (8). The marginal effects of *Professional* and *Degree* are 0.1343 and 0.0301, which are statistically significant at the 1% and 10% levels, respectively. With respect to the economic magnitude, a one-standard-deviation increase in *Professional* (*Degree*) leads to an increase of 2.0% (1.5%) in the probability of learning. These results are consistent with Prediction (4).

4.3 *Price Informativeness and Managerial Learning*

In this subsection, we conduct two tests surrounding price informativeness. First, we test the role of price informativeness in determining the firms' choices in the learning channel (i.e., Prediction (5) of Hypothesis 1). Second, we borrow the indirect approach by Chen, Goldstein, and Jiang (2007) to further examine the learning channel and validate the survey results.

4.3.1 *Price Informativeness and Survey Responses: Testing Prediction (5) of Hypothesis 1*

When firms *perceive* their stock prices to be more informative, they will naturally rely more on prices to guide investment decisions. Although it is difficult to find proxies for firms' perceived price informativeness, the literature has come up with proxies to measure the equilibrium level of private information in price based on the resulting price and trading behaviors. In our test, we take these measures, and the premise is that other things being equal, when the prices contain more information, the firms also perceive so. Of course, these measures are imperfect. For instance, it is possible that in some scenarios, although these measures indicate that prices contain a great deal of information, the firm managers might be overconfident and think that the prices are very noisy and so ignore price information in investment decisions. In the next subsection where we replicate Chen, Goldstein, and Jiang (2007), we indeed find some preliminary evidence for this possibility.

In testing Prediction (5), we consider three price informativeness measures that have been commonly used in previous studies examining market feedback, including (1) 1-R^2, the R^2-based price nonsynchronicity measure by Roll (1988) and Durnev, Morck, and Yeung (2004); (2) *AdjPIN*, the adjusted probability of informed trading measure by Duarte and Young (2009); and (3) *PriceDelay*, the price delay measure by Hou and Moskowitz (2005). The measures of 1-R^2 and *AdjPIN* are positively associated with price informativeness, while the measure *PriceDelay* is negatively associated with price informativeness.

[Table 4 about Here]

We regress *Learn* on the three informativeness measures in equation (1), and report the Probit regression results in Table 4. The marginal effects of 1-R^2 and *PriceDelay* are 0.0742 and -0.0023 in columns (1) and (3), which are statistically significant at the 1% and 5% levels, indicating in general the manager is more likely to monitor her stock price for investment information when the price is informative. The marginal effects of *AdjPIN* are positive but statistically insignificant in column (2). Thus, the results are generally consistent with our Prediction (5).

4.3.2 *Investment-to-Price Sensitivity: Replication of Chen, Goldstein, and Jiang (2007)*

In this subsection, we replicate the analysis in Chen, Goldstein, and Jiang (2007) in different samples. The goal is twofold. First, we want to verify that the learning channel is also supported through the investment-to-price sensitivity approach by Chen, Goldstein, and Jiang (2007). Second, we wish to explore the interactions between firms' responses and the investment-to-price sensitivity.

Our testing sample spans from 2012 to 2021,[5] and the following three samples are used in our analysis: (1) all responding firms in the 2022 survey (the *Full* sample), (2) the subsample of firms selecting the learning channel in question II (the *Learn* subsample), and (3) the subsample of firms not selecting the learning channel (the *NoLearn* subsample). We include the two subsamples to consider the interactions between firms' responses and the investment-to-price sensitivity.

Following Chen, Goldstein, and Jiang (2007), we run the regression at the firm-year level:

$$Capxrnd_{i,t+1} = a_i + b_t + c{*}Q_{i,t}{*}Info_{i,t} + d{*}Q_{i,t} + e{*}Info_{i,t} + Controls_{i,t} + \varepsilon_{i,t}, \qquad (2)$$

where *Capxrnd* denotes a firm's capital expenditure plus R&D expenses, scaled by the beginning-of-year assets; *Q* denotes Tobin's Q; and *Info* denotes price informativeness measures at the firm-year level, including $1\text{-}R^2$, *AdjPIN*, and *PriceDelay*. *Controls* is a vector of control variables including net free cash flows from operation divided by book assets (*CF*), stock return in the recent three months (*Ret3*), and the inverse of book assets (*InvAst*). We also include the firm and year fixed effects in regressions to absorb any influence varying only with firm and time. According to Chen, Goldstein, and Jiang (2007), a significant estimate for coefficient *c* in equation (2) provides indirect evidence in favor of informational feedback from the stock market to real investments.

Columns (1), (4) and (7) of Table 5 report the OLS regression results in the full sample. The coefficient estimates on the variables of interest, $Q{*}(1\text{-}R^2)$, *Q*AdjPIN* and *Q*PriceDelay*, have signs consistent with theory predictions and are statistically significant at the 1% and 5% levels. Indeed, we find indirect evidence that Chinese public firms learn information from the stock market to guide real investment decisions, which is consistent with the literature and shows how the learning manager utilizes the price signal.

[Table 5 about Here]

Interestingly, results in the *Learn* and *NoLearn* subsamples show different patterns. The coefficient estimate on $Q{*}(1\text{-}R^2)$ is 0.0059 and significant in the *Learn* subsample, while the estimate is -0.0018 and insignificant in the *NoLearn* subsample. The difference in the estimate (0.0078) in the two subsamples is significant at the 5% level. The coefficient estimate on *Q*AdjPIN* is 0.0461 and

[5] We use a shorter sample period (ten years) in our analysis, because firms' responses in our survey can only reflect their opinions in recent years. In remote years, firm fundamentals and manager characteristics could be very different.

significant in the *Learn* subsample, and the estimate is -0.0027 and insignificant in the *NoLearn* subsample. The difference in the estimate (0.0489) is significant at the 10% level. The results with *PriceDelay* as the informativeness measure are qualitatively the same though statistically insignificant. In sum, based on the indirect investment-to-price sensitivity approach, those firms selecting the learning channel indeed consider the price signals in making investment decisions, while those firms not selecting the learning channel ignore prices in investment decisions.

We also compare the price-informativeness levels across the two subsamples and find insignificant differences. For example, the mean of $1\text{-}R^2$ is 0.5471 in the *Learn* subsample, and 0.5434 in the *NoLearn* subsample. The difference (0.0037) is statistically insignificant. The results on *PriceDelay* and *AdjPIN* are similar. These results are consistent with the idea that in the *NoLearn* subsample, although the prices contain information, firms perceive the prices not to be informative and thus neglect the prices in their investment decisions (and honestly report that they do not pay attention to stock prices for the learning purpose).

4.4 *What Information Do Managers Learn from Prices?*

In this subsection, we answer the question of what kind of information firms learn from stock prices when the learning channel is most relevant. To shed direct evidence on this question, we include question III in the 2022 survey and ask the firms to choose their opinions ("strongly disagree", "disagree", "neutral", "agree", and "strongly agree") on statements about the information contents they extract from their stock prices, and firms selecting the learning channel in question II were asked to respond (see Subsection 2.1 for details on the question and choices).

[Figure 4 about Here]

Figure 4 presents the survey results. We say that a firm affirms a statement if it chooses "Strongly agree" or "Agree" for the statement. Panel A shows, regarding the contents of information contained in their stock prices, information about the state of the macro economy and the industry (Choice A) is the most useful for the learning manager: 3,204 (90.2%) of the 3,553 firms selecting the learning channel (i.e., select Choice A in question II) affirm the corresponding statement. The second and third most useful information is information about policies and regulations related to the company's business (Choice B, affirmation rate = 86.3%) and information about the company's competitive position relative to competitors (Choice C, affirmation rate = 84.9%).

Other information we list is also meaningful to the responding firms, including cost of capital (Choice F, affirmation rate = 61.9%), customers' demand for the company's products/services (Choice D, affirmation rate = 59.5%), developments in technologies the company may employ (Choice E, affirmation rate = 54.7%), and the prospects of the company's potential acquisitions of other companies, assets, or technologies (Choice G, approval rate = 53.1%). It is worthy of noting that, very few (0.8%) of the learning firms strongly agree with Choice L, "There is no information to learn from the stock price," suggesting their responses are consistent across questions.

These results are very consistent with the theoretical reasoning in the literature. For instance, Goldstein and Yang (2019) and Goldstein (2023) argue that firms are expected to rely on prices to extract information about the state of the macro economy, their product market competitive positions, and their customers' demand for firms' products. In addition, our survey result on developments in technologies the company may employ squares with the recent empirical evidence by Aretz, Ilyas, and Kankanhalli (2023), who find that firm managers learn information about technological progress from market prices. Overall, our results suggest that the information that is produced outside the firm, alien to the managers, and costly for them to collect (e.g., the macro, industry, regulatory, and competition information), is particularly useful to the learning firms.

[Table 6 about Here]

We also report survey results in high-, medium-, and low-ranking respondents in Panels B, C, and D (See Subsection 2.2 for the definition of respondent groups). The patterns are highly consistent with those in the full sample – the manager puts her top priority on the macro, industry, regulatory, and competition information contained in her stock price. Table 6 summarizes the responses by industry, and the results stay qualitatively the same across industries.

5. THE FINANCING CHANNEL

In this section, we examine market feedback via the financing channel, i.e., the financial market helps to facilitate the companies' access to external capital in the primary market, thereby allowing them to tap into good investment opportunities. We conduct two exercises. First, we investigate how financial constraints, capital demands, and managerial sophistication affect firms' survey responses regarding the financing channel. Second, following the similar spirit as Subsection 4.3.2 which connects firms' investment activities to their responses to the learning channel, we link firms' real equity financing activities to their responses to the financing channel.

5.1 *Financial Constraints, Capital Demand, and Managerial Sophistication*

Regarding firms' response to the financing channel, we make the following predictions:

Hypothesis 2 (*Financing Channel*). *A firm is more likely to report that it pays attention to its stock price for the financing purpose (select Choice B in Question II) if (1) it is more financially constrained; (2) its capital demand is higher; or (3) its firm manager's sophistication level is higher.*

These predictions are intuitive. First, financially constrained firms benefit more from equity financing, and are thus more likely to monitor their stock price for such opportunities. Second, firms with larger capital needs are more likely to monitor stock prices for the financing purpose. Third, more sophisticated firm managers understand the market better and thus are more likely to care about the stock prices for financing opportunities.

We follow the same empirical methodology as in Section 4 to test these predictions. Specifically, we construct a dummy variable, *Fin*, about the financing channel, which equals one if a firm chooses B in question II. *Fin* indicates that the firm monitors its own stock price for financing opportunities, and zero otherwise. We then run Probit regression on equation (1) and report the results in Table 7.

[Table 7 about Here]

Financial Constraints

We employ two proxies for financial constraints. The first proxy is the KZ score (*KZ*) suggested by Kaplan and Zingales (1997). The second proxy comes from one of our survey questions. Specifically, in the 2022 survey, we asked firms about factors affecting their investment plans at the survey date, and one factor they can choose is short of capital. So, we define a short-of-capital dummy, *LackCap*, which equals one if the responding firm reports it lacks capital, and zero otherwise. We then regress the financing channel dummy *Fin* on the financial-constraints proxies in equation (1). In regressions with *KZ* as an independent variable, we exclude firm leverage *(Leverage)* as a control variable because it is considered in the construction of *KZ*.

We find that the marginal effect of *KZ* is positive and significant at the 1% level in column (1) of Table 7. In column (2) of Table 7, we also observe that *LackCap*, a variable positively measuring financial constraints, is positively and significantly associated with *Fin*. These results support Prediction (1) of Hypothesis 2.

Capital Demand

We construct two proxies for capital demand. The first measure is *AmtSEO*, defined as the amount of seasoned equity offerings (in 2021), scaled by book assets. The second measure is based on one of our survey questions in the 2022 survey, which asked firms about their investment plans in 2022 compared to 2021. We then construct measure *ChgBudget*, defined as a firm's expectation on increases in capital expenditure in 2022 based on firms' response to this survey question.[6] These two variables respectively capture a firm's investment intensity in the past and in the future and thus represent the firm's capital needs.

Columns (3) and (4) of Table 7 report results regressing the financing channel dummy *Fin* on capital demand variables and other controls, based on the specification in equation (1). Column (3) shows that *AmtSEO* is positively and significantly correlated to *Fin*. That is, firms raising more capital in the past are more likely to monitor their own stock prices for the financing purpose. Testing results based on the expected financing demand, *ChgBudget*, is qualitatively the same: in column (4), the marginal effects of *ChgBudget* are positive and significant. These results support Prediction (2) of Hypothesis 2.

Managerial Sophistication

We regress *Fin* on the two managerial sophistication measures, *Professional* and *Degree* (see Subsection 4.2 for variable definitions) based on equation (1), and report Probit regression results in columns (5) and (6) of Table 7. The marginal effects of *Professional* and *Degree* are 0.0601 and 0.0737,

[6] We assigned different values to *ChgBudget* according to firms' responses as follows: -2 denotes "large decrease"; -1 denotes "small decrease"; 0 denotes "no change"; 1 denotes "small increase"; and 2 denotes "large increase".

and statistically significant at the 1% and 5% levels. Hence, a well-educated manager with backgrounds in professional services is indeed more likely to understand the financing opportunities (e.g., cost of capital) reflected by her stock price, and monitors the price for the financing purpose, which is consistent with Prediction (3) of Hypothesis 2.

5.2 *Financing Channel and Seasoned Equity Offerings*

In this subsection, we conduct an analysis in the similar spirit to Section 4.3.2 and connect firms' seasoned equity offerings (SEOs) with their responses to the financing channel. We use the following three samples in our tests: (1) the *Full* sample, (2) the *Fin* subsample reporting the financing channel in question II, and (3) the *NoFin* subsample not reporting the financing channel. We then run the following regression at the firm-year level:

$$SEO_{i,t+1} = a_i + b_t + c^*Q_{i,t} + Controls_{i,t} + \varepsilon_{i,t}, \quad (3)$$

where *SEO* denotes the amount (*AmtSEO*) or number (*NSEO*) of a firm's SEOs in a year. The independent variable of interest is Tobin's Q, which proxies for firm valuation and cost of capital. We control for firm free cash flow (*CF*), recent stock return (*Ret3*), asset size (*Asset*), and firm and year fixed effects in regressions. In this setting, a significant and positive estimate for coefficient *c* in equation (3) suggests the manager monitors the stock market and make equity financing decisions.

[Table 8 about Here]

Panel A of Table 8 reports the OLS regression results. Columns (1) and (4) present the results in the full sample. The coefficient estimates on *Q* are positive and statistically significant at the 1% and 5% levels, respectively. We also find significant results in subsample tests in columns (2), (3), (5), and (6). The results indicate that in general the manager is responsive to financing opportunities revealed by her stock price. As a result, she is motived to monitor the stock price for the financing purpose.

In addition, we find results in the *Fin* subsample are more pronounced than those in the *NoFin* subsample. For the *AmtSEO* regressions, the coefficient estimate on *Q* is 0.1594 in the *Fin* subsample, while that in the *NoFin* subsample is 0.0478. The difference (0.1116) is significant at the 10% level. The results of the *NSEO* regressions are qualitatively similar. Similar to the rationale discussed in Subsection 4.3.2, the difference in results in the two subsamples may be explained by the firms' perception about the usefulness of stock markets in financing investment opportunities.

We also run a placebo test on bond financing and report the results in Panel B of Table 8. In contrast to our findings on equity financing, the amount (*AmtBond*) and number (*NBond*) of bond issues are not significantly correlated to financing opportunities revealed by the stock market. Though the financing opportunities mentioned in Choice B in question II cover both equity and bond financing, apparently investment opportunity information carried by stock prices is more relevant to equity financing. The results of the placebo tests further strengthen our argument about the financing channel.

6. TRADING SUSPENSION: WHAT FIRMS SAY, WHAT FIRMS DO

We have argued that respondents are unlikely to provide untruthful information in our surveys, because of the academic nature of the questions and the trust relationship we have built over time (see Subsection 2.2 for detailed discussion). In this section, we further strengthen this argument by providing another validation test that connects firms' responses (what they say) to their actions (what they do). Specifically, we examine firms' active management on trading suspensions that may influence price informativeness and price levels, which provides further evidence that firms do care about the stock market by directly intervening in the trading process.

6.1 *Trading Suspensions in the Chinese Stock Market*

In the Chinese stock market, the Shanghai and Shenzhen stock exchanges allow public firms to suspend their stocks' trading for multiple reasons, including (1) shareholder meeting, (2) important matters, (3) company reports, (4) abnormal transactions, (5) M&A/restructuring, (6) major risks, (7) media reports, and (8) financing activities, among many others.[7] Some of the reasons, in particular, the reason of important matters, are sufficiently flexible to offer public firms the discretion to strategically suspend the trading of their stocks. In practice, firms can easily apply for suspensions for "important matters," in which it is unnecessary for them to disclose the true reasons to the market.

[Table 9 about Here]

[7] Source: http://www.sse.com.cn/lawandrules/sselawsrules/stock/main/listing/c/c_20210128_5311968.shtml.

We collect the trading suspension data for each Chinese public firm from the CSMAR database, including suspension dates, horizons, and reasons. Our sample period spans from January 2020 to October 2022. Table 9 reports summary statistics on trading suspensions of the 4,641 responding firms in the 2022 survey. During the period, there were 1,483 suspensions in total (0.11 suspension per firm in one year), and on average a suspension lasts for 11.5 trading hours. 998 (67.3%) suspensions are longer than 4 trading hours (one trading day, i.e., 9:30am to 11:30am and 1:00pm to 3:00pm). The most frequently used reason is indeed "important matters" (50.6%), followed by "transaction related" (32.1%) and "major risk" (8.7%).

6.2 *Active Management of Trading Suspensions*

We attempt to connect public firms' trading suspensions (what firms do) to their responses about market feedback in the 2022 survey (what firms say), and confirm whether respondents provide meaningful opinions. First, public firms can actively use trading suspensions to influence the information contained in their stock prices, because suspended trading stops traders from incorporating information into prices. We expect that those firms who care about prices for the learning purpose are less likely to suspend trading, because trading suspension shrinks the firms' information set by one signal, the stock price.[8] Second, in bad market circumstances, public firms can also suspend trading to avoid extreme price drops (e.g., Huang, Shi, and Zhao, 2019), which hurts their capacity of raising capital from the market. Thus, we hypothesize that if the stock price drops a lot and firms care about the stock prices for the financing purpose, they will suspend trading more frequently. Formally, we have the following hypothesis:

Hypothesis 3 (*Trading Suspension*). *(1) Those firms, who say that they learn information for stock prices, are less likely to suspend the trading of their stocks. (2) Those firms, who say that they care about the stock prices because of the financing channel, are more likely to suspend trading when faced with large price drops.*

In testing the above predictions, we follow Liu, Trzcinka, and Zhao (2021) and exclude suspensions shorter than one day (4 trading hours) to construct the testing sample. We only include

[8] A counter argument is that if stock prices are very noisy, the shutdown of trading may increase price informativeness in the long run. We do not think Chinese stock prices are so noisy, because we follow Bai, Philippon, and Savov (2016) and Carpenter, Lu, and Whitelaw (2021) and show prices can forecast future cash flows at least in the short run in China in unreported analysis.

trading suspensions with the reason "important matters" since firms have the most discretion power on suspension by using this reason (suspensions with other reasons, e.g., transaction related, may be compulsory according to the exchanges' rules). We then estimate the following Probit regression at the firm-month level:

$$Susp_{i,t} = b_t + c*Feedback_i*PriceDrop_{i,t} + d*Feedback_i + e*PriceDrop_{i,t} + Controls_i + \varepsilon_{i,t}, \quad (4)$$

where $Susp_{i,t}$ is a dummy variable indicating whether firm *i* suspends trading for the "important matters" reason in month *t*. $Feedback_i$ represents the dummy variables about the learning and financing channels (*Learn* and *Fin*) defined in Sections 4 and 5. $PriceDrop_{i,t}$ captures large price declines, which is a dummy variable that equals one if firm *i*'s stock return in month *t* ranks in the bottom tercile among all firm-months (the cutoff value for the bottom tercile is -5.1%), and zero otherwise. *Controls* includes all the firm-level control variables as in equation (1). In addition, we include the year-month, position, industry, and province fixed effects across regressions.

[Table 10 about Here]

We report the regression results in Table 10. Columns (1) and (2) use *Learn* as the independent variable. In column (1), the marginal effect of *Learn* is -0.13% and significant at the 5% level. Hence, for public firms reporting the learning channel in the 2022 survey, the probability of suspending trading in each month is 0.13% lower than those non-learning firms. Considering the unconditional suspension probability being 0.92% in our sample, this impact is sizable. In column (2), we insert *Feedback*PriceDrop* into the regression. The marginal effect of *Learn* remains significantly negative, and the marginal effect of the interaction term is positive and marginally significant at the 10% level. So, if firms care about stock prices for learning investment information, they also try to avoid extreme price movements. Overall, these results are consistent with Prediction (1) of Hypothesis 3.

Columns (3) and (4) of Table 10 report the regression results with *Fin* being the independent variable. Column (3) shows that in general firms reporting monitoring stock prices for the financing purpose do not suspend trading frequently, as the marginal effect of *Fin* is insignificant. However, the marginal effect of *Fin*PriceDrop* is positive and statistically significant at the 5% level in column (4), suggesting that if stock prices drop a lot and firms care about prices for financing opportunities, they suspend more frequently to maintain the price levels. Again, these results confirm Prediction (2) of Hypothesis 3.

7. CONCLUSION

In this paper, we take a survey approach to examining the real effects of financial markets. Our two surveys conducted in 2019 and 2022 are comprehensive, covering nearly all Chinese public firms and featuring response rates of 99.99% and 98.1%. We find that more than 90% of firms pay attention to the stock market and that the most salient reasons for them to care about stock markets are to learn information from prices and to access external financing. These findings provide direct evidence for the wide existence of market feedback through a learning channel and a financing channel.

The learning channel is more pronounced when prices are more informative and managers are more sophisticated. Specifically, firms are more likely to pay attention to their stock prices for the learning purpose when their investors are more informed, their managers are less informed, they are covered by fewer analysts, and their managers have better educations or more relevant backgrounds. Our survey evidence suggests the macro, industry, policy, regulatory, and competition information, which is costly for managers to produce by themselves, is the most important information that firms learn from the financial market. The financing channel is more pronounced when firms benefit more from financing and the manager is more sophisticated. Financially constrained firms with large capital demand are more likely to select the financing channel. Well-educated managers with backgrounds in professional services are also likely to select this channel.

We also find what firms do is highly consistent with what they report in our survey by exploring their active management of informativeness via trading suspension. Firms selecting the learning channel are less likely to suspend trading to keep information production, and those firms selecting the financing channel are more likely to suspend trading in case of large price drops to maintain certain price levels. Overall, our analysis highlights the prevalence and mechanisms of market feedback.

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FIGURES

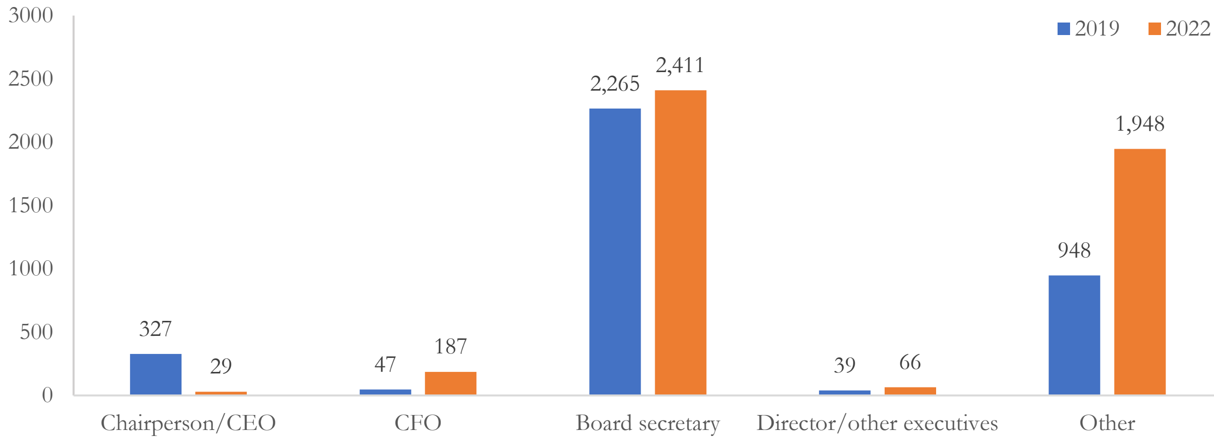
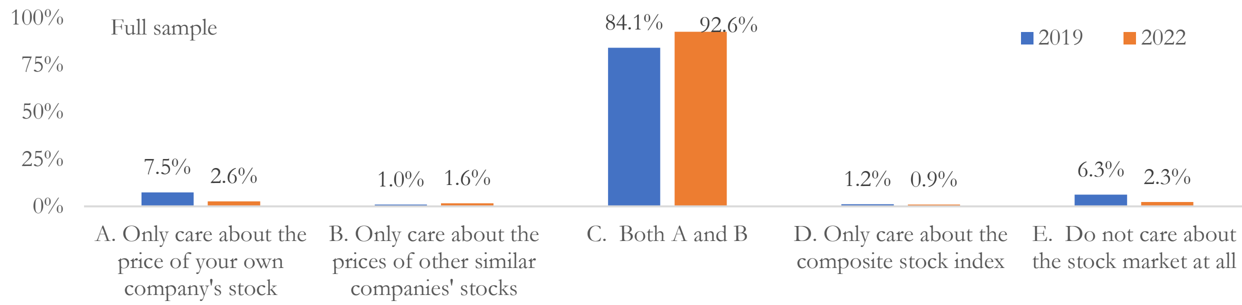
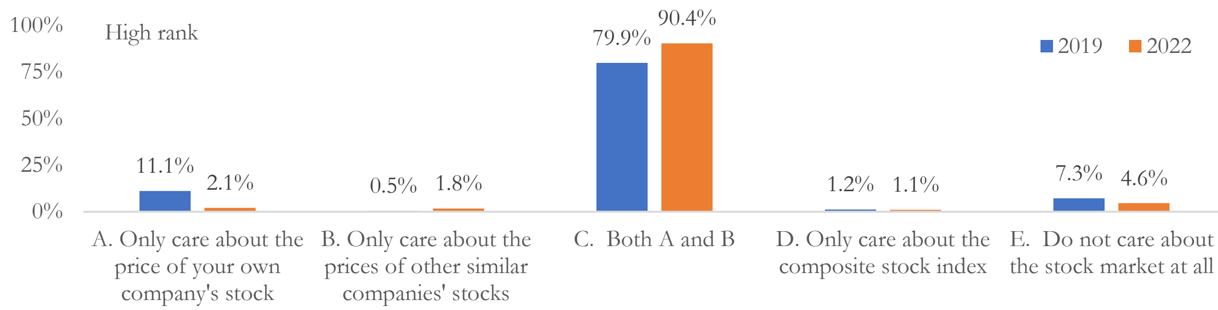


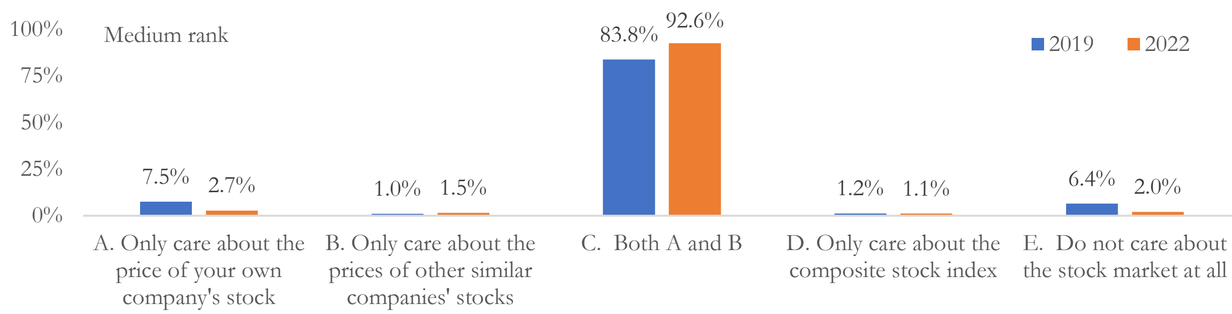
Figure 1: Distribution of respondents' positions in their firms. This figure plots the distribution of the positions of the respondents that were assigned by their firms to respond to our 2019 and 2022 market feedback surveys. 3,626 Chinese public firms listed on the Shanghai and Shenzhen Stock Exchanges responded to the 2019 survey, and 4,641 firms responded to the 2022 survey.



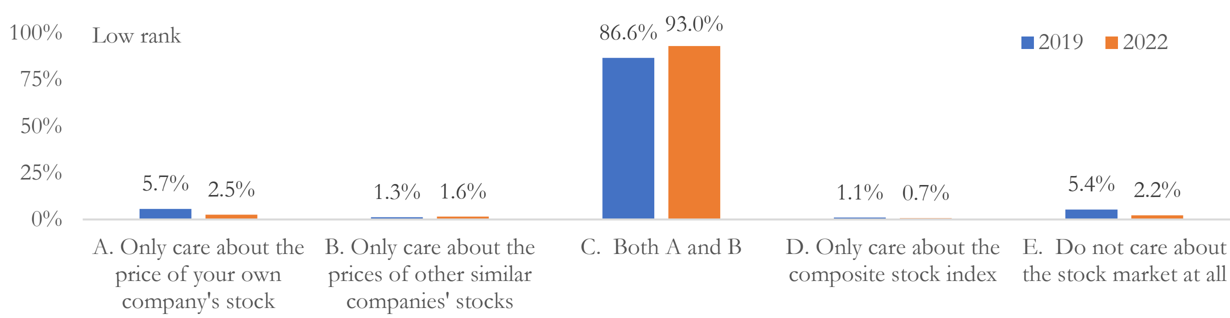
Panel A: Full sample (2019 survey N=3,626; 2022 survey N=4,641)



Panel B: Chairperson, CEO, Director, CFO, and other executives (2019 survey N=413; 2022 survey N=282)

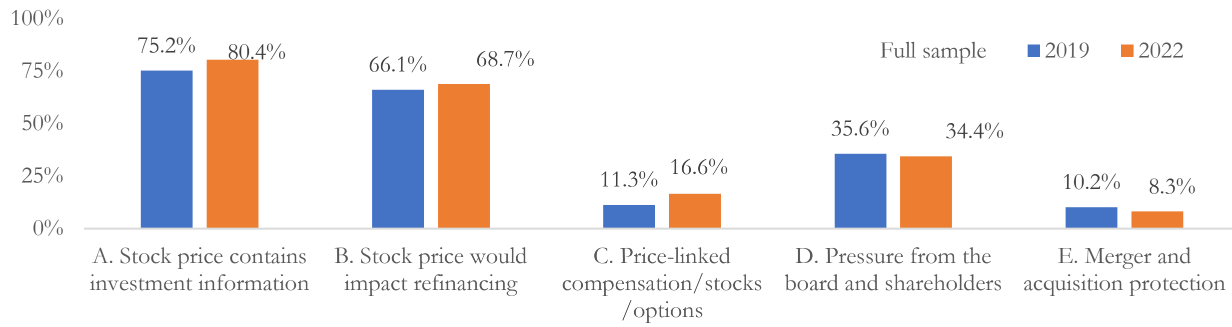


Panel C: Board secretary (2019 survey N=2,265; 2022 survey N=2,411)

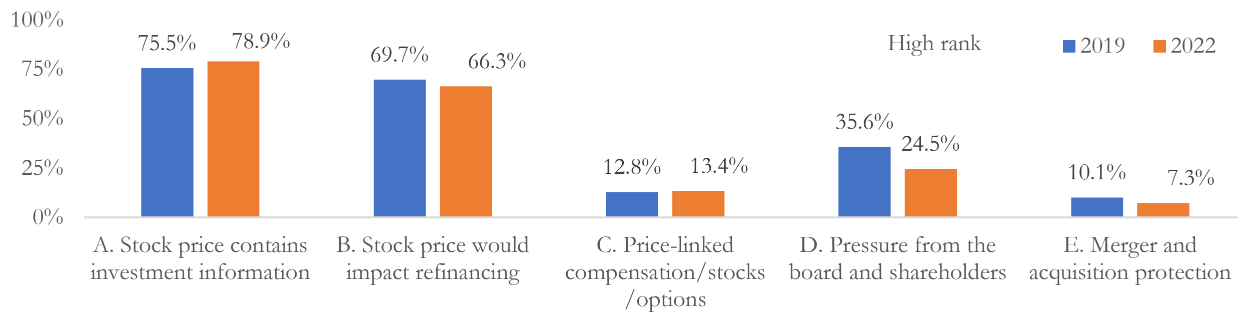


Panel D: Other positions (2019 survey N=948; 2022 survey N=1,948)

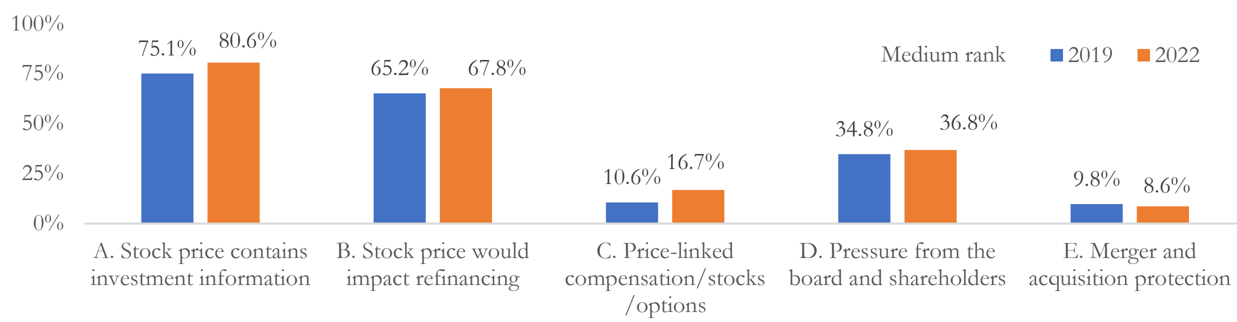
Figure 2: Responses to survey question I. This figure plots the frequencies for each choice by the responding firms in survey question I ("*How does your company pay attention to the stock market?*"). Panel A presents results in the full sample. Panel B, C, and D present results in high-, medium-, and low-ranking respondents, respectively.



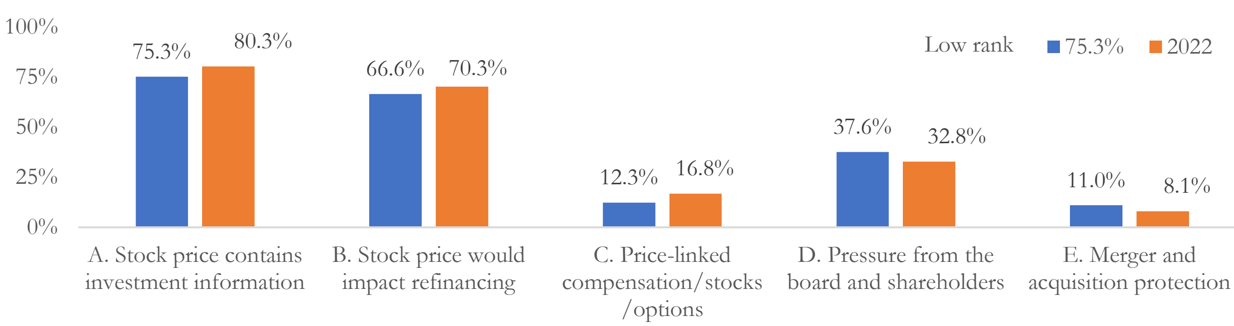
Panel A: Full sample (2019 survey N=3,320; 2022 survey N=4,420)



Panel B: Chairperson, CEO, Director, CFO, and other executives (2019 survey N=376; 2022 survey N=261)

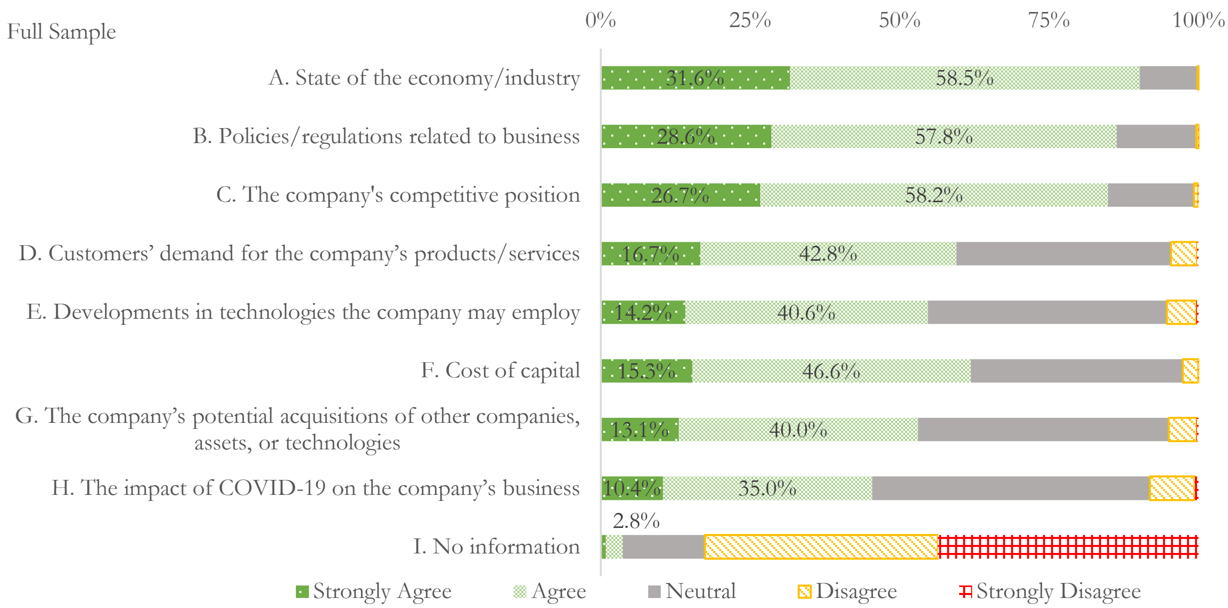


Panel C: Board secretary (2019 survey N=2,069; 2022 survey N=2,299)

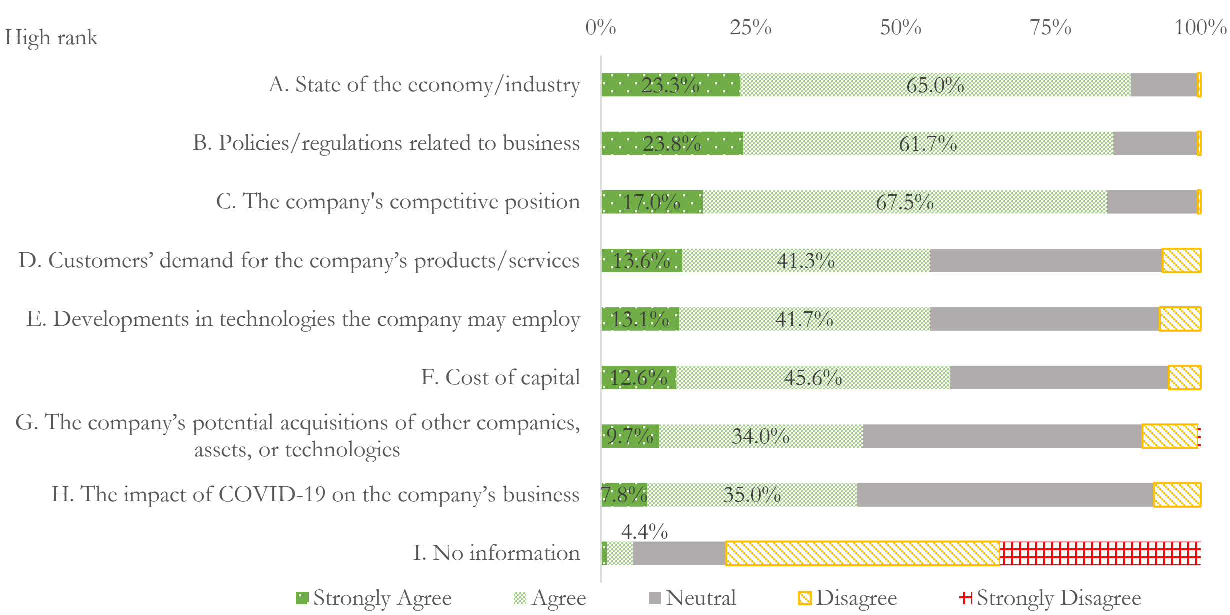


Panel D: Other positions (2019 survey N=875; 2022 survey N=1,860)

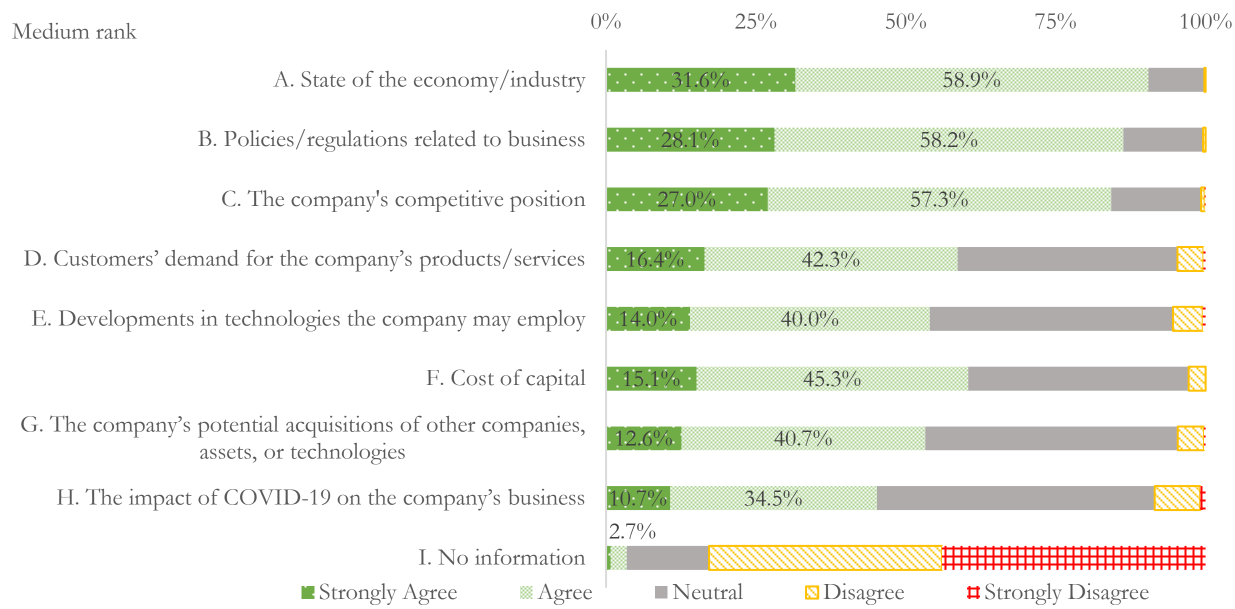
Figure 3: Responses to survey question II. This figure plots the frequencies for each choice by the responding firms in survey question II (*"If you choose A or C in I: Which of the following is the reason that your company cares about the stock price of your OWN company?"*). Panel A presents results in the full sample. Panel B, C, and D present results in high-, medium-, and low-ranking respondents, respectively.



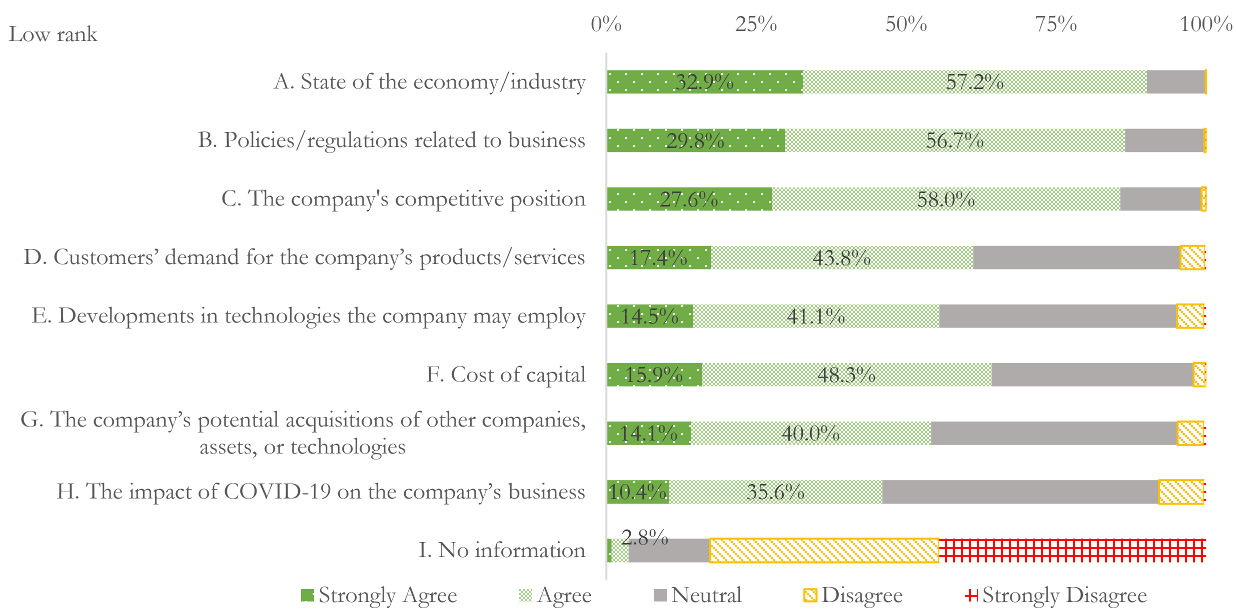
Panel A: Full sample (2022 survey N=3,553)



Panel B: Chairperson, CEO, Director, CFO and other executives (2022 survey N=206)



Panel C: Board secretary (2022 survey N=1,853)



Panel D: Other positions (2022 survey N=1,494)

Figure 4: Responses to survey question III. This figure plots the frequencies for each choice by the responding firms in survey question III (*"If you choose A in II: When learning from the market, what kind of information can the company's own stock price be useful for?"*) in the 2022 survey. Panel A presents results in the full sample. Panels B, C and D present results in high-, medium-, and low-ranking respondents, respectively.

TABLES

Table 1: Summary statistics for the responding firms

This table reports summary statistics for the 3,626 Chinese public firms responding to the 2019 survey, and the 4,641 firms responding to the 2022 survey. Firm information is as of 2018 for the 2019 survey, and 2021 for the 2022 survey, respectively.

	2019 Survey (N=3,626)			2022 Survey (N=4,641)		
	Mean	Median	STD	Mean	Median	STD
Firm Age (year)	20.14	20.05	5.01	21.84	21.74	5.41
Total Assets (billion RMB)	11.71	4.12	18.82	12.57	3.89	21.29
Market Cap. (billion RMB)	7.56	4.07	8.22	13.38	6.43	16.47
Capital Expenditure (%)	4.75	3.12	4.84	5.26	3.40	5.41
R&D Expense (%)	2.21	1.87	1.81	2.80	2.39	2.23
ROA (%)	4.91	5.20	6.79	5.47	5.48	6.76
Tobin's Q	1.80	1.50	0.91	2.62	2.09	1.65
Leverage (%)	43.52	42.26	20.22	42.66	41.35	20.83
No. Analysts	7.59	2.00	11.01	6.66	1.00	10.59
Short Indicator	0.27	0.00	0.44	0.48	0.00	0.50
Insider Trading (%)	0.14	0.00	0.31	0.02	0.00	0.06
Institutional Ownership (%)	37.47	38.20	23.03	35.58	35.64	23.35
1-R^2	0.52	0.50	0.18	0.79	0.84	0.16
SOE	0.32	0.00	0.47	0.30	0.00	0.46

Table 2: Responses to survey questions I and II in the 2022 survey by industry

This table summarizes the responses to questions I and II in the 2022 survey by industry. There are 4,641 responses to question I, and 4,420 responses to question II. The fraction of firms in an industry selecting each choice is reported.

Panel A: I. *How does your company pay attention to the stock market?* N=4,641

Industry	N. firms	A. Own stock	B. Peers' stocks	C. Both A and B	D. Comp. index	E. Don't care
Coal	37	5.4%	0.0%	94.6%	0.0%	0.0%
Utilities	119	3.4%	1.7%	94.1%	0.8%	0.0%
Media	145	2.1%	1.4%	95.2%	0.7%	0.7%
Light industry	136	4.4%	2.2%	92.6%	0.0%	0.7%
Transportation	129	1.6%	0.0%	97.7%	0.0%	0.8%
Pharmaceutical	433	1.2%	0.9%	96.3%	0.5%	1.2%
Construction	151	4.6%	0.7%	92.1%	1.3%	1.3%
Chemical	358	3.4%	2.0%	91.6%	1.7%	1.4%
Machinery	466	2.4%	2.4%	92.3%	1.5%	1.5%
Real estate	125	7.2%	1.6%	88.8%	0.8%	1.6%
Automobile	235	3.4%	0.9%	93.2%	0.9%	1.7%
Telecommunication	110	2.7%	2.7%	92.7%	0.0%	1.8%
Oil	47	2.1%	0.0%	93.6%	2.1%	2.1%
Nonferrous metals	132	2.3%	0.8%	93.9%	0.8%	2.3%
Computer	297	2.4%	0.7%	92.9%	1.7%	2.4%
Electrical equipment	281	2.1%	3.2%	91.1%	1.1%	2.5%
Food and beverage	117	0.0%	0.9%	95.7%	0.9%	2.6%
Construction materials	77	3.9%	3.9%	88.3%	1.3%	2.6%
Electronics	371	1.9%	1.1%	93.0%	1.3%	2.7%
Defense	118	2.5%	3.4%	89.8%	0.8%	3.4%
Environment	116	1.7%	2.6%	92.2%	0.0%	3.4%
Commerce	103	1.9%	1.9%	91.3%	1.0%	3.9%
Steel	45	6.7%	0.0%	88.9%	0.0%	4.4%
Textile	112	0.9%	2.7%	90.2%	1.8%	4.5%
Home appliance	81	0.0%	0.0%	93.8%	1.2%	4.9%
Agriculture	99	4.0%	0.0%	90.9%	0.0%	5.1%
Social service	74	1.4%	2.7%	90.5%	0.0%	5.4%
Banking	18	0.0%	0.0%	94.4%	0.0%	5.6%
Beauty	29	6.9%	0.0%	86.2%	0.0%	6.9%
Non-banking finance	50	2.0%	0.0%	90.0%	0.0%	8.0%
Composite	30	10.0%	3.3%	76.7%	0.0%	10.0%

Panel B: II. *Which of the following is the reason that your company cares about the stock price of your OWN company?* N=4,420

Industry	N. firms	A. Learning	B. Financing	C. Compensation	D. Monitoring	E. M&A protect
Food and beverage	112	88.4%	45.5%	16.1%	36.6%	8.0%
Agriculture	94	85.1%	75.5%	14.9%	29.8%	9.6%
Composite	26	84.6%	57.7%	0.0%	26.9%	3.8%
Machinery	441	83.7%	63.7%	15.9%	29.3%	8.8%
Chemical	340	82.9%	69.4%	15.6%	31.2%	9.7%
Pharmaceutical	422	82.7%	68.7%	20.6%	37.9%	9.0%
Textile	102	82.4%	58.8%	10.8%	42.2%	9.8%
Real estate	120	81.7%	60.8%	8.3%	42.5%	7.5%
Defense	109	81.7%	69.7%	16.5%	34.9%	6.4%
Home appliance	76	81.6%	46.1%	13.2%	25.0%	5.3%
Beauty	27	81.5%	55.6%	25.9%	33.3%	7.4%
Light industry	132	81.1%	71.2%	16.7%	34.8%	8.3%
Automobile	227	81.1%	66.5%	18.9%	28.2%	7.0%
Social service	68	80.9%	60.3%	10.3%	33.8%	8.8%
Electronics	352	80.7%	70.7%	19.0%	32.1%	8.0%
Construction materials	71	80.3%	67.6%	14.1%	36.6%	7.0%
Electrical equipment	262	79.8%	72.5%	15.3%	32.1%	8.8%
Media	141	79.4%	62.4%	16.3%	44.7%	7.1%
Telecommunication	105	79.0%	73.3%	23.8%	41.0%	14.3%
Computer	283	78.8%	75.3%	22.6%	46.6%	13.1%
Utilities	116	78.4%	75.0%	13.8%	31.9%	3.4%
Transportation	128	78.1%	73.4%	21.9%	33.6%	3.9%
Nonferrous metals	127	77.2%	74.0%	15.0%	23.6%	6.3%
Steel	43	76.7%	69.8%	14.0%	39.5%	2.3%
Construction	146	76.0%	80.8%	15.1%	36.3%	8.2%
Commerce	96	75.0%	66.7%	11.5%	31.3%	7.3%
Environment	109	73.4%	78.0%	17.4%	37.6%	11.0%
Coal	37	73.0%	78.4%	5.4%	24.3%	2.7%
Oil	45	71.1%	75.6%	8.9%	33.3%	2.2%
Non-banking finance	46	65.2%	71.7%	10.9%	28.3%	6.5%
Banking	17	52.9%	94.1%	5.9%	35.3%	0.0%

Table 3: Information, managerial characteristics, and market feedback

This table reports the Probit regression results on firms' choice of the learning channel. The sample consists of firms responding to the 2022 survey. The dependent variable is a dummy variable that equals one if a firm chooses A in question II in the 2022 survey, and zero otherwise. The independent variables of interest are investor, managerial, analyst information measures, and managerial sophistication measures. The respondent position, industry, and province fixed effects are included. See Table A2 in Appendix A for variables definitions. Marginal effects are reported. Standard errors reported in parentheses are adjusted for heteroscedasticity and clustering at the respondent position level. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

	Investor Info.		Managerial Info.		Analyst Info.		Managerial Sophistication	
Y = Learn	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Info =	*InsShares*	*Short*	*Insider*	*ERC*	*NAnalysts*	*NForecasts*	*Professional*	*Degree*
Info	0.0248**	0.0261**	-5.7234**	-0.1953**	-0.0007***	-0.0007***	0.1343***	0.0301*
	(0.0125)	(0.0110)	(2.8983)	(0.0961)	(0.0003)	(0.0002)	(0.0275)	(0.0166)
Size	0.0148***	0.0101*	0.0232***	0.0193***	0.0235***	0.0273***	0.0184***	0.0107
	(0.0048)	(0.0059)	(0.0039)	(0.0062)	(0.0041)	(0.0058)	(0.0058)	(0.0078)
Leverage	-0.0163	-0.0094	-0.0029	-0.0260	-0.0154	-0.0152	-0.0279*	0.0064
	(0.0177)	(0.0150)	(0.0187)	(0.0158)	(0.0172)	(0.0171)	(0.0165)	(0.0284)
History	-0.0008	-0.0010	-0.0003	-0.0005	-0.0008	-0.0008	-0.0011	-0.0013***
	(0.0007)	(0.0006)	(0.0013)	(0.0008)	(0.0007)	(0.0007)	(0.0007)	(0.0004)
SOE	-0.0424***	-0.0416***	-0.0561***	-0.0458***	-0.0417***	-0.0430***	-0.0387***	-0.0336*
	(0.0056)	(0.0046)	(0.0109)	(0.0052)	(0.0038)	(0.0042)	(0.0039)	(0.0181)
Ret	0.0192	0.0307**	0.0531***	0.0288*	0.0189	0.0177	0.0207	0.0252
	(0.0172)	(0.0128)	(0.0093)	(0.0156)	(0.0162)	(0.0162)	(0.0169)	(0.0159)
Vola	0.2026	-0.1374	-1.3401***	-0.4718	0.0614	0.0440	0.1152	-0.2478
	(0.6565)	(0.7598)	(0.3669)	(0.4649)	(0.6972)	(0.7073)	(0.6906)	(0.3841)
FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	4,171	4,171	3,373	3,941	4,171	4,171	4,171	3,355
Pseudo R^2	0.0171	0.0166	0.0223	0.0176	0.0166	0.0169	0.0181	0.0227

Table 4: Price informativeness and market feedback

This table reports the Probit regression results on firms' choice of the learning channel. The sample consists of firms responding to the 2022 survey. The dependent variable is a dummy variable that equals one if a firm chooses A in question II in the 2022 survey, and zero otherwise. The independent variables of interest are stock price informativeness measures. The position, industry, and province fixed effects are included. See Table A2 in Appendix A for definitions of variables. Marginal effects are reported. Standard errors reported in parentheses are adjusted for heteroscedasticity and clustering at the respondent position level. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Y = Learn	(1)	(2)	(3)
Informativeness =	*1-R^2*	*AdjPIN*	*PriceDelay*
Informativeness	0.0742***	0.3053	-0.0023**
	(0.0093)	(0.4013)	(0.0011)
Size	0.0275***	0.0241***	0.0198***
	(0.0037)	(0.0049)	(0.0030)
Leverage	-0.0049	-0.0090	-0.0052
	(0.0143)	(0.0163)	(0.0152)
History	-0.0000	-0.0001	-0.0002
	(0.0013)	(0.0013)	(0.0013)
SOE	-0.0484***	-0.0471***	-0.0477***
	(0.0086)	(0.0074)	(0.0086)
Ret	0.0474***	0.0410***	0.0460***
	(0.0172)	(0.0136)	(0.0146)
Vola	-1.7798***	-0.9360	-1.0699
	(0.2861)	(0.8037)	(0.6752)
FEs	Yes	Yes	Yes
N	3,606	3,776	3,770
Pseudo R^2	0.0205	0.0186	0.0189

Table 5: Price informativeness, learning, and firm investments

This table reports the OLS regression results about firm investments following Chen, Goldstein, and Jiang (2007). The *Full* sample consists of all firms responding to the 2022 survey; and the *Learn (NoLearn)* subsample includes firms reporting (not reporting) the learning channel in question II. The sample period is from 2012 to 2021. The dependent variable is capital expenditure plus R&D expenses. The firm and year fixed effects are included. See Table A2 in Appendix A for definitions of variables. Standard errors reported in parentheses are adjusted for heteroscedasticity and clustering at the firm level. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Y =*Capxrnd*	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Info =		*1- R2*			*AdjPIN*			*PriceDelay*	
Sample =	*Full*	*Learn*	*NoLearn*	*Full*	*Learn*	*NoLearn*	*Full*	*Learn*	*NoLearn*
*Q*Info*	0.0040***	0.0059***	-0.0018	0.0349***	0.0461***	-0.0027	-0.0002**	-0.0002**	-0.0002
	(0.0015)	(0.0017)	(0.0035)	(0.0133)	(0.0157)	(0.0223)	(0.0001)	(0.0001)	(0.0001)
Q	0.0006	0.0003	0.0018	-0.0006	-0.0011	0.0010	0.0031***	0.0039***	0.0007
	(0.0010)	(0.0011)	(0.0021)	(0.0014)	(0.0017)	(0.0023)	(0.0006)	(0.0007)	(0.0011)
Info	-0.0174***	-0.0220***	-0.0040	-0.1505***	-0.1638***	-0.1043	0.0004**	0.0003*	0.0005
	(0.0047)	(0.0052)	(0.0100)	(0.0352)	(0.0412)	(0.0646)	(0.0002)	(0.0002)	(0.0004)
*CF*Info*	0.0736*	0.0554	0.1513*	0.6741**	0.6906**	0.6008	0.0017	0.0019	0.0016
	(0.0401)	(0.0457)	(0.0826)	(0.2726)	(0.3152)	(0.5282)	(0.0013)	(0.0016)	(0.0022)
CF	0.0232	0.0245	0.0079	-0.0016	-0.0097	0.0270	0.0728***	0.0662***	0.0943***
	(0.0219)	(0.0250)	(0.0447)	(0.0279)	(0.0319)	(0.0555)	(0.0105)	(0.0121)	(0.0208)
Ret3	-0.0044***	-0.0043***	-0.0048**	-0.0042***	-0.0041***	-0.0045**	-0.0044***	-0.0043***	-0.0049**
	(0.0009)	(0.0010)	(0.0019)	(0.0009)	(0.0010)	(0.0020)	(0.0009)	(0.0010)	(0.0019)
InvAst	16.2617***	14.0921***	20.6742***	17.5939***	16.6777***	19.5131***	18.2522***	17.8786***	19.3115***
	(3.7880)	(4.6869)	(5.9830)	(3.6792)	(4.4554)	(6.2454)	(3.6845)	(4.4607)	(6.2442)
Cons.	0.0494***	0.0514***	0.0446***	0.0544***	0.0547***	0.0542***	0.0379***	0.0363***	0.0431***
	(0.0031)	(0.0035)	(0.0065)	(0.0040)	(0.0048)	(0.0070)	(0.0020)	(0.0024)	(0.0038)
FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	15,729	11,949	3,780	16,136	12,256	3,880	16,143	12,262	3,881
R^2	0.5547	0.5605	0.5422	0.5479	0.5531	0.5371	0.5465	0.5509	0.5370
Diff in Coef.		0.0078**			0.0489*			-0.0000	

Table 6: Responses to question III in the 2022 survey by industry

This table summarizes the responses to survey question III (*"If you choose A in II: When learning from the market, what kind of information can the company's own stock price be useful for?"*) in the 2022 survey by industry. There are 3,553 responses to the question. The affirmation rate, defined as the fraction of firms choosing "*Strongly agree*" or "*Agree*", is reported.

Industry	A. Econ. /ind. state	B. Policies /regulation	C. Compet. position	D. Custom. demand	E. Technology	F. Cost of capital	G. Potential acquisition	H. COVID impact	L. No info.
Real estate	95.9%	92.9%	79.6%	57.1%	27.6%	62.2%	0.6%	40.8%	2.0%
Home appliance	95.2%	91.9%	87.1%	67.7%	58.1%	51.6%	0.8%	50.0%	3.2%
Nonferrous metals	94.9%	93.9%	87.8%	61.2%	53.1%	66.3%	0.7%	38.8%	3.1%
Defense	94.4%	87.6%	88.8%	60.7%	49.4%	61.8%	0.7%	40.4%	3.4%
Computer	92.8%	90.6%	87.0%	58.3%	63.7%	65.9%	0.3%	53.4%	1.8%
Electronics	92.6%	85.6%	87.7%	61.6%	60.2%	68.3%	0.2%	39.1%	4.2%
Coal	92.6%	100.0%	85.2%	55.6%	40.7%	48.1%	1.8%	18.5%	3.7%
Environment	92.5%	88.8%	87.5%	62.5%	57.5%	71.3%	0.9%	47.5%	1.3%
Utilities	92.3%	90.1%	87.9%	58.2%	49.5%	64.8%	0.7%	40.7%	5.5%
Construct. materials	91.2%	91.2%	82.5%	66.7%	47.4%	59.6%	1.0%	36.8%	1.8%
Chemical	91.1%	87.6%	82.3%	56.7%	53.5%	59.6%	0.2%	40.8%	3.5%
Social service	90.9%	89.1%	85.5%	74.5%	61.8%	72.7%	1.3%	78.2%	10.9%
Food and beverage	90.9%	80.8%	87.9%	66.7%	43.4%	53.5%	0.5%	53.5%	1.0%
Telecommunication	90.4%	81.9%	84.3%	55.4%	57.8%	61.4%	0.7%	43.4%	4.8%
Machinery	90.0%	83.7%	83.5%	56.6%	58.3%	60.2%	0.2%	41.5%	2.7%
Electrical equipment	90.0%	89.0%	85.2%	60.3%	59.8%	63.2%	0.3%	36.8%	4.3%
Light industry	89.7%	87.9%	84.1%	55.1%	47.7%	61.7%	0.6%	41.1%	3.7%
Pharmaceutical	89.7%	85.7%	85.1%	61.6%	58.7%	62.2%	0.2%	53.9%	3.4%
Transportation	89.0%	84.0%	85.0%	57.0%	46.0%	68.0%	0.7%	65.0%	2.0%
Banking	88.9%	88.9%	88.9%	55.6%	66.7%	77.8%	8.6%	44.4%	0.0%
Agriculture	88.8%	83.8%	87.5%	63.8%	51.3%	62.5%	0.8%	38.8%	7.5%
Construction	88.3%	90.1%	90.1%	63.1%	61.3%	62.2%	0.6%	46.8%	4.5%
Automobile	86.4%	84.2%	84.2%	59.2%	61.4%	57.6%	0.3%	41.8%	3.3%

Beauty	86.4%	81.8%	81.8%	50.0%	40.9%	54.5%	2.5%	59.1%	9.1%
Composite	86.4%	90.9%	86.4%	50.0%	54.5%	72.7%	3.3%	40.9%	4.5%
Commerce	86.1%	79.2%	76.4%	54.2%	36.1%	55.6%	0.8%	55.6%	0.0%
Steel	84.8%	78.8%	72.7%	48.5%	45.5%	60.6%	1.8%	24.2%	0.0%
Media	84.8%	79.5%	84.8%	61.6%	58.9%	56.3%	0.5%	47.3%	5.4%
Oil	84.4%	78.1%	81.3%	50.0%	46.9%	65.6%	2.1%	46.9%	18.8%
Textile	83.3%	79.8%	82.1%	56.0%	46.4%	53.6%	0.6%	57.1%	4.8%
Non-banking finance	76.7%	80.0%	73.3%	60.0%	50.0%	53.3%	1.8%	43.3%	6.7%

Table 7: Capital budgeting, managerial characteristics, and market feedback

This table reports the Probit regression results on firms' choice of the financing channel. The sample consists of firms responding to the 2022 survey. The dependent variable is a dummy variable that equals one if a firm chooses B in question II in the 2022 survey, and zero otherwise. The independent variables of interest are financial constraints and capital demand measures, and managerial sophistication measures. The respondent position, industry, and province fixed effects are included. See Table A2 in Appendix A for variables definitions. Marginal effects are reported. Standard errors reported in parentheses are adjusted for heteroscedasticity and clustering at the respondent position level. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

	Financial Constraints		Capital Demand		Managerial Sophistication	
Y = Fin	(1)	(2)	(3)	(4)	(5)	(6)
Budget =	*KZ*	*LackCap*	*AmtSEO*	*ChgBudget*	*Professional*	*Degree*
Budget	0.0023***	0.1122***	1.1516***	0.0240***	0.0601***	0.0737**
	(0.0001)	(0.0427)	(0.1457)	(0.0031)	(0.0081)	(0.0308)
Size	0.0218*	0.0174**	0.0081	0.0096	0.0114	-0.0006
	(0.0122)	(0.0082)	(0.0102)	(0.0103)	(0.0102)	(0.0035)
Leverage		0.4899***	0.5454***	0.5505***	0.5383***	0.5620***
		(0.0130)	(0.0131)	(0.0144)	(0.0130)	(0.0140)
History	0.0005	-0.0012	-0.0011	-0.0009	-0.0012	-0.0009
	(0.0015)	(0.0016)	(0.0015)	(0.0016)	(0.0016)	(0.0012)
SOE	-0.0362***	-0.0532***	-0.0579***	-0.0663***	-0.0610***	-0.0863***
	(0.0081)	(0.0068)	(0.0095)	(0.0099)	(0.0100)	(0.0134)
Ret	-0.0050	0.0257	0.0136	0.0153	0.0201	0.0199
	(0.0490)	(0.0325)	(0.0343)	(0.0340)	(0.0348)	(0.0336)
Vola	3.0219*	1.3230	1.6555*	1.3926	1.5586	1.4853
	(1.5716)	(1.0573)	(0.9957)	(1.0426)	(1.0329)	(1.0021)
FEs	Yes	Yes	Yes	Yes	Yes	Yes
N	3,864	4,171	4,171	4,171	4,171	3,355
Pseudo R^2	0.0363	0.0603	0.0582	0.0568	0.0557	0.0610

Table 8: Financing opportunities, the financing channel, and seasoned equity offerings

This table reports the OLS regression results about SEOs. The *Full* sample consists of all firms responding to the 2022 survey; and the *Fin (NoFin)* subsample includes firms reporting (not reporting) the financing channel in question II. The sample period is from 2012 to 2021. The dependent variables include SEO and bond financing number and amount in Panels A and B, and the key independent variable of interest is Tobin's Q. The firm and year fixed effects are included. See Table A2 in Appendix A for definitions of variables. Standard errors reported in parentheses are adjusted for heteroscedasticity and clustering at the firm level. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Equity financing

Y =		*AmtSEO*			*NSEO*1000*	
	(1)	(2)	(3)	(4)	(5)	(6)
Sample =	*Full*	*Fin*	*NoFin*	*Full*	*Fin*	*NoFin*
Q	0.1221***	0.1594***	0.0478***	0.1296**	0.1776**	0.0329***
	(0.0409)	(0.0603)	(0.0147)	(0.0542)	(0.0802)	(0.0067)
CF	1.8740	2.6355	0.2419*	1.4532*	2.0504	0.1773**
	(1.2185)	(1.7831)	(0.1388)	(0.8554)	(1.2508)	(0.0841)
Ret3	0.0091	0.0153	-0.0047	0.0213	0.0311	-0.0043
	(0.0098)	(0.0144)	(0.0040)	(0.0154)	(0.0210)	(0.0045)
Asset	-0.0018	-0.0028	0.0001	0.0000	-0.0000	0.0004***
	(0.0018)	(0.0027)	(0.0003)	(0.0006)	(0.0009)	(0.0001)
Constant	-0.3298**	-0.4246**	-0.1091**	-0.3421**	-0.4705**	-0.0594***
	(0.1471)	(0.2103)	(0.0431)	(0.1653)	(0.2382)	(0.0205)
FEs	Yes	Yes	Yes	Yes	Yes	Yes
N	16,156	10,794	5,362	16,156	10,794	5,362
R^2	0.1618	0.1648	0.2174	0.1803	0.1848	0.2218
Diff in Coef.		0.1116*			0.1447*	

Panel B: Bond financing						
Y =		*AmtBond*			*NBond*1000*	
	(1)	(2)	(3)	(4)	(5)	(6)
Sample =	*Full*	*Fin*	*NoFin*	*Full*	*Fin*	*NoFin*
Q	0.0002	0.0004	-0.0002	0.0008	0.0012	0.0002
	(0.0008)	(0.0012)	(0.0004)	(0.0013)	(0.0018)	(0.0007)
CF	-0.0287***	-0.0289***	-0.0274***	-0.0443***	-0.0431***	-0.0465***
	(0.0065)	(0.0087)	(0.0081)	(0.0124)	(0.0161)	(0.0175)
Ret3	0.0006	0.0001	0.0018**	0.0015	-0.0003	0.0056**
	(0.0005)	(0.0006)	(0.0008)	(0.0012)	(0.0014)	(0.0025)
Asset	0.0002***	0.0003***	0.0001***	0.0003***	0.0003***	0.0002***
	(0.0000)	(0.0000)	(0.0001)	(0.0000)	(0.0001)	(0.0001)
Constant	0.0111***	0.0108***	0.0114***	0.0207***	0.0209***	0.0197***
	(0.0019)	(0.0028)	(0.0012)	(0.0031)	(0.0045)	(0.0023)
FEs	Yes	Yes	Yes	Yes	Yes	Yes
N	16,156	10,794	5,362	16,156	10,794	5,362
R^2	0.3358	0.3027	0.4476	0.3225	0.3061	0.3719
Diff. Coef.		0.0006			0.001	

Table 9: Summary of trading suspensions

This table reports summary statistics for trading suspensions by firms responding to the 2022 survey from January 2020 to October 2022.

	Full sample		≥ 1 day (4 hours)	
Reason	N. Suspension	Duration (hours)	N. Suspension	Duration (hours)
All	1483	11.5	998	16.8
- Important matters	750	16.6	747	16.6
- Transaction related	476	0.7	7	22.3
- Major risk	129	4.0	129	4.0
- M&A/restructure	101	34.1	101	34.1
- Financing/Shareholder meeting/Media report	19	6.6	6	20.7
- Unknown/others	8	18.5	8	18.5

Table 10: Market feedback and trading suspensions

This table reports the Probit regression results about the effects of the learning and financing channels on firms' trading suspensions. The sample covers trading suspensions by firms responding to the 2022 survey from January 2020 to October 2022. The dependent variable is a dummy variable indicating whether a firm suspends the trading of its stock in a month. The independent variables of interest include dummy variables indicating whether the firm reports the learning/financing channels in our survey. The year-month, position, industry, and province fixed effects are included. See Table A2 in Appendix A for definitions of variables. Marginal effects are reported. Standard errors reported in parentheses are adjusted for heteroscedasticity and clustering at the year-month level. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Y = Susp	(1)	(2)	(3)	(4)
Feedback =	*Learn*		*Fin*	
Feedback	-0.0013**	-0.0017***	0.0000	-0.0004
	(0.0005)	(0.0006)	(0.0004)	(0.0004)
PriceDrop		-0.0014		-0.0014
		(0.0009)		(0.0008)
*Feedback*PriceDrop*		0.0016*		0.0015**
		(0.0010)		(0.0008)
Size	-0.0004*	-0.0004*	-0.0004*	-0.0004*
	(0.0002)	(0.0002)	(0.0002)	(0.0002)
Leverage	0.0035***	0.0034***	0.0034***	0.0034***
	(0.0011)	(0.0011)	(0.0011)	(0.0011)
History	0.0002***	0.0002***	0.0002***	0.0002***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
SOE	0.0002	0.0002	0.0003	0.0002
	(0.0005)	(0.0005)	(0.0006)	(0.0006)
FEs	Yes	Yes	Yes	Yes
N	124,407	124,407	124,407	124,407
Pseudo R^2	0.0516	0.0521	0.0506	0.0511

APPENDIX A: ADDITIONAL TABLES

Table A1: Responses to survey questions I and II in the 2019 survey by industry

This table summarizes the responses to questions I and II in the 2019 survey by industry. There are 3,626 responses to question I, and 3,320 responses to question II. The fraction of firms in an industry selecting each choice is reported.

Panel A: I. *How does your company pay attention to the stock market?* N=3,626

Industry	N. firms	A. Own stock	B. Peers' stocks	C. Both A and B	D. Comp. index	E. Don't care
Utilities	102	11.8%	2.0%	78.4%	7.8%	0.0%
Media	128	2.3%	0.8%	89.1%	7.8%	0.0%
Telecommunication	91	8.8%	0.0%	83.5%	7.7%	0.0%
Environment	64	6.3%	0.0%	87.5%	6.3%	0.0%
Electrical equipment	176	6.3%	1.1%	86.4%	6.3%	0.0%
Construction materials	82	7.3%	0.0%	86.6%	6.1%	0.0%
Defense	73	11.0%	2.7%	83.6%	2.7%	0.0%
Oil	33	9.1%	3.0%	84.8%	3.0%	0.0%
Social service	53	18.9%	1.9%	77.4%	1.9%	0.0%
Home appliance	59	3.4%	0.0%	93.2%	3.4%	0.0%
Composite	51	7.8%	2.0%	84.3%	5.9%	0.0%
Nonferrous metals	111	6.3%	1.8%	87.4%	4.5%	0.0%
Chemical	314	8.6%	1.0%	84.7%	5.4%	0.3%
Automobile	176	7.4%	0.6%	83.0%	8.5%	0.6%
Real estate	130	7.7%	0.8%	80.0%	10.8%	0.8%
Construction	130	6.2%	3.1%	83.8%	6.2%	0.8%
Commerce	103	8.7%	1.0%	78.6%	10.7%	1.0%
Food and beverage	94	7.4%	0.0%	84.0%	7.4%	1.1%
Agriculture	89	7.9%	1.1%	86.5%	3.4%	1.1%
Electronics	234	9.8%	0.9%	81.6%	6.4%	1.3%
Computer	211	4.7%	0.9%	89.1%	3.8%	1.4%
Transportation	112	11.6%	0.0%	80.4%	6.3%	1.8%
Light industry	97	2.1%	4.1%	84.5%	7.2%	2.1%
Pharmaceutical	289	4.8%	0.0%	87.9%	5.2%	2.1%
Machinery	342	9.6%	0.3%	82.2%	5.6%	2.3%
Steel	37	10.8%	2.7%	75.7%	8.1%	2.7%
Banking	32	0.0%	3.1%	90.6%	3.1%	3.1%
Textile	96	6.3%	1.0%	81.3%	8.3%	3.1%
Non-banking finance	71	1.4%	0.0%	84.5%	8.5%	5.6%
Coal	35	17.1%	2.9%	62.9%	11.4%	5.7%
Beauty	11	0.0%	0.0%	90.9%	0.0%	9.1%

Panel B: II. *Which of the following is the reason that your company cares about the stock price of your own company?* N=3,320

Industry	N. firms	A. Learning	B. Financing	C. Compensation	D. Monitoring	E. M&A Protect
Telecommunication	84	83.3%	11.9%	61.9%	17.9%	13.1%
Pharmaceutical	268	81.7%	10.1%	65.7%	39.6%	13.4%
Light industry	84	81.0%	11.9%	65.5%	34.5%	14.3%
Beauty	10	80.0%	20.0%	30.0%	10.0%	0.0%
Media	117	77.8%	9.4%	66.7%	41.9%	5.1%
Electronics	214	77.6%	16.8%	69.2%	37.9%	10.3%
Defense	69	76.8%	11.6%	66.7%	29.0%	5.8%
Computer	198	76.8%	20.2%	67.7%	33.8%	11.1%
Construction materials	77	76.6%	6.5%	67.5%	39.0%	10.4%
Social service	51	76.5%	9.8%	68.6%	41.2%	15.7%
Agriculture	84	76.2%	3.6%	71.4%	36.9%	8.3%
Chemical	293	76.1%	11.3%	61.4%	34.5%	10.2%
Automobile	159	76.1%	9.4%	67.3%	28.9%	10.7%
Home appliance	57	75.4%	12.3%	57.9%	38.6%	10.5%
Non-banking finance	61	75.4%	9.8%	70.5%	34.4%	4.9%
Construction	117	75.2%	14.5%	74.4%	36.8%	10.3%
Environment	60	75.0%	13.3%	65.0%	28.3%	6.7%
Coal	28	75.0%	10.7%	67.9%	35.7%	3.6%
Real estate	114	74.6%	7.0%	66.7%	36.0%	3.5%
Food and beverage	86	74.4%	14.0%	51.2%	30.2%	12.8%
Electrical equipment	163	74.2%	12.3%	68.7%	33.7%	11.0%
Commerce	90	73.3%	8.9%	64.4%	42.2%	14.4%
Machinery	314	73.2%	11.5%	67.2%	38.5%	10.5%
Banking	29	72.4%	13.8%	58.6%	37.9%	0.0%
Transportation	103	71.8%	6.8%	65.0%	29.1%	6.8%
Utilities	92	70.7%	5.4%	68.5%	33.7%	13.0%
Composite	47	70.2%	10.6%	53.2%	38.3%	10.6%
Oil	31	67.7%	9.7%	54.8%	45.2%	12.9%
Nonferrous metals	104	66.3%	6.7%	73.1%	32.7%	10.6%
Textile	84	64.3%	15.5%	71.4%	48.8%	10.7%
Steel	32	53.1%	3.1%	62.5%	40.6%	3.1%

Table A2: Variable definitions.

Variables are constructed with information during the year of or by the end of 2021 for cross-sectional regressions and with annual information for panel regressions, unless otherwise specified.

Variable	Definition
Learn	A dummy variable that equals one if a firm chooses A in survey question II, and zero otherwise.
Fin	A dummy variable that equals one if a firm chooses B in survey question II, and zero otherwise.
Size	The natural logarithm of a firm's total market capitalization in million RMB.
Leverage	The ratio of a firm’s total debt over its total assets.
History	A firm’s listing history in years since its listing on the stock exchanges.
SOE	A dummy variable that equals to one if a firm is owned by the state, and zero otherwise.
Ret	Annual stock return.
Vola	The standard deviation of daily stock returns in a year.
InsShares	The fraction of shares outstanding held by institutional investors, including mutual fund, securities firms, insurance companies, the social security fund, pensions, trust firms, financial firms, private equity funds, non-financial entities, and foreign institutional investors.
Short	A dummy variable that equals one if short-selling is allowed for a stock, and zero otherwise.
Insider	The number of stock transactions by corporate insiders, scaled by the total number of transactions.
ERC	The average of the absolute stock returns over the four quarterly earnings announcement periods (day –5 to day 5).
NAnalysts	The number of analysts following a firm.
NForecasts	The number of earning forecasts produced.
Professional	The average of the professional service dummy among the management team, where the professional service dummy indicates whether a manager has backgrounds in professional services including business, accounting, finance, management, and law.
Degree	The average of the education levels among the management team. A manager’s education takes the value of 1 for high (or vocational) school diploma or below, 2 for junior college diploma, 3 for bachelor’s degree, 4 for master’s degree, and 5 for Ph.D.
Capxrnd	A firm’s capital expenditure plus R&D expenses, scaled by the beginning-of-year assets.
$1\text{-}R^2$	One minus R^2 is from regressing daily stock returns on market and industry returns over a year.
AdjPIN	The adjusted PIN measure proposed by Duarte and Young (2009).
PriceDelay	The price delay measure D3 proposed by Hou and Moskowitz (2005).

Q	Tobin's Q, calculated as (market value of total equity + book value of assets - book value of equity)/(book value of assets)
CF	The ratio of net cash flows from operations divided by beginning-of-year book assets.
Ret3	Stock return in the recent three months.
KZ	The five-variable KZ score for financial constraints constructed according to Kaplan and Zingales (1997).
LackCap	A dummy variable that equals one if a firm reports it lacks capital in the 2022 survey, and zero otherwise.
AmtSEO	The amount of seasoned equity offerings in a year, scaled by total assets.
ChgBudget	A firms' expectation on capital expenditure in 2022, compiled with information from the 2022 survey. -2 denotes "large decrease"; -1 denotes "small decrease"; 0 denotes "no change"; 1 denotes "small increase"; and 2 denotes "large increase".
NSEO	The number of seasoned equity offerings in a year, scaled by total assets.
AmtBond	The amount of bond issues in a year, scaled by total assets.
NBond	The number of bond issues in a year, scaled by total assets.
Asset/InvAst	Total book value of assets in billion RMB/the inverse of total assets.
Susp	A dummy variable that equals one if a firm suspends trading for the "important matters" reason, and zero otherwise.
PriceDrop	A dummy variable that equals one if a firm's monthly stock return ranks in the bottom tercile among all firm-months, and zero otherwise.

APPENDIX B: A THEORETICAL FRAMEWORK FOR FIRMS' RESPONSE TO THE LEARNING QUESTION

In this appendix, we provide a stylized model to illustrate the main predictions regarding the firms' responses to the learning question. The general idea is that a firm will select choice A, "Stock price contains information that is new for investment decisions," in question II, if the firm thinks that its asset price is a useful information source so that it will put a meaningful weight on the price signal in its investment decisions.

Let us consider a representative firm. The firm has a growth option, whose value is realized at the end of the model and given by $\tilde{\theta}K - 0.5K^2$, where K is the capital investment, and $\tilde{\theta}$ is a productivity shock. We assume that $\tilde{\theta}$ has an improper prior (i.e., $\tilde{\theta}$ is normally distributed with mean 0 and variance ∞). This assumption is without loss of generality in the sense that $\tilde{\theta}$ can admit any mean and variance. The firm is operated by a manager, who chooses K to maximize the expected value of the growth option given her information.

The model has two periods, $t = 0$ and 1. On $t = 0$, investors trade a risky asset and the asset price is formed. Investors have information and thus, the asset price aggregates information. On $t = 1$, the firm manager observes the price and makes real investment decisions. The firm manager will extract information from the asset price, but as discussed below, she might be subject to a dismissiveness bias so that she may ignore part or all of the information in the asset price.

We assume that the asset payoff is given by $\tilde{\theta} + \tilde{\delta}$, where $\tilde{\delta} \sim N(0, \tau_\delta^{-1})$ with $\tau_\delta \in (0, \infty)$ and $\tilde{\delta}$ is independent of $\tilde{\theta}$. The idea is that $\tilde{\theta}$ is the learnable element while $\tilde{\delta}$ is not learnable. There is a representative investor, who derives constant-absolute-risk-aversion (CARA) utility over her wealth at the end of the model. For simplicity, let us normalize the investor's risk aversion coefficient as 1. The investor observes a private signal, $\tilde{s}_T = \tilde{\theta} + \tilde{\varepsilon}_T$, where $\tilde{\varepsilon}_T \sim N(0, \tau_T^{-1})$ with $\tau_T \in (0, \infty)$ and $\tilde{\varepsilon}_T$ is independent of the other shocks. At the date-0 asset market, there is also noise demand, $\tilde{z} \sim N(0, \tau_z^{-1})$ with $\tau_z \in (0, \infty)$. As usual, noise trading is introduced to perturb information aggregation in the asset price.

The firm manager observes a private signal about $\tilde{\theta}$: $\tilde{s}_M = \tilde{\theta} + \tilde{\varepsilon}_M$, where $\tilde{\varepsilon}_M \sim N(0, \tau_M^{-1})$ with $\tau_M \in (0, \infty)$. Suppose that part of the manager's information is communicated to the market by sell-side analysts. We model this communication as a public announcement $\tilde{y}$, which is a garbled version of the manager's private information; that is, $\tilde{y} = \tilde{s}_M + \tilde{\eta}$, where $\tilde{\eta} \sim N\left(0, \tau_\eta^{-1}\right)$ with $\tau_\eta \in (0, \infty)$. The underlying random variables $\{\tilde{\theta}, \tilde{\delta}, \tilde{\varepsilon}_T, \tilde{\varepsilon}_M, \tilde{\eta}, \tilde{z}\}$ are mutually independent.

We now derive the asset price. The CARA-normal structure implies the investor's demand function is as follows:

$$D(\tilde{s}_T, \tilde{y}, \tilde{p}) = \frac{E\left(\tilde{\theta} + \tilde{\delta} \middle| \tilde{s}_T, \tilde{y}\right) - \tilde{p}}{Var\left(\tilde{\theta} + \tilde{\delta} \middle| \tilde{s}_T, \tilde{y}\right)} = \frac{\dfrac{\tau_T \tilde{s}_T + \frac{\tau_M \tau_\eta}{\tau_M + \tau_\eta} \tilde{y}}{\tau_T + \frac{\tau_M \tau_\eta}{\tau_M + \tau_\eta}} - \tilde{p}}{\dfrac{1}{\tau_T + \frac{\tau_M \tau_\eta}{\tau_M + \tau_\eta}} + \dfrac{1}{\tau_\delta}},$$

where we obtain the second equality by applying the Bayes' rule to compute the two conditional moments. Using the market-clearing condition, $D(\tilde{s}_T, \tilde{y}, \tilde{p}) + \tilde{z} = 0$, we can compute the price function as follows:

$$\tilde{p} = \frac{\tau_T \tilde{s}_T + \frac{\tau_M \tau_\eta}{\tau_M + \tau_\eta} \tilde{y}}{\tau_T + \frac{\tau_M \tau_\eta}{\tau_M + \tau_\eta}} + \left(\frac{1}{\tau_T + \frac{\tau_M \tau_\eta}{\tau_M + \tau_\eta}} + \frac{1}{\tau_\delta} \right) \tilde{z}.$$

We next examine how the firm manager uses price information in making real investment decisions. The manager's information set includes her private information $\tilde{s}_M$ and public information $\{\tilde{y}, \tilde{p}\}$. Using the above price function, the public information $\{\tilde{y}, \tilde{p}\}$ is equivalent to the following signal to the firm manager in predicting $\tilde{\theta}$:

$$\tilde{s}_p \equiv \frac{\tilde{p} - \dfrac{\frac{\tau_M \tau_\eta}{\tau_M + \tau_\eta}}{\tau_T + \frac{\tau_M \tau_\eta}{\tau_M + \tau_\eta}} \tilde{y}}{\dfrac{\tau_T}{\tau_T + \frac{\tau_M \tau_\eta}{\tau_M + \tau_\eta}}} = \tilde{s}_T + \left[\frac{1}{\tau_T} + \frac{1}{\tau_\delta} \left(1 + \frac{1}{\tau_T} \frac{\tau_M \tau_\eta}{\tau_M + \tau_\eta} \right) \right] \tilde{z}.$$

So, the price partially transmits the investor's information $\tilde{s}_T$ to the manager. The effectiveness of this transmission is related to the variance of the noise term, $\left[\frac{1}{\tau_T}+\frac{1}{\tau_\delta}\left(1+\frac{1}{\tau_T}\frac{\tau_M\tau_\eta}{\tau_M+\tau_\eta}\right)\right]\tilde{z}$. To capture the idea that the manager may not fully understand the asset market, we assume that the manager may perceive a lower precision level of noise trading $\tilde{z}$. That is, in the manager's mind, the noise trading's distribution is $\tilde{z} \sim N\left(0, \frac{1}{\phi\tau_z}\right)$. Parameter $\phi \in [0,1]$ captures the manager's sophistication level in understanding the financial market. When $\phi = 1$, the manager is fully rational. By contrast, when $\phi = 0$, the manager believes that market is too noisy so that she completely neglects the information in the price.

Formally, by the definition of $\tilde{s}_p$, the manager perceives that the price signal $\tilde{s}_p$ is a signal about $\tilde{\theta}$ with precision given by

$$\tau_p = \frac{1}{\frac{1}{\tau_T}+\left[\frac{1}{\tau_T}+\frac{1}{\tau_\delta}\left(1+\frac{\frac{\tau_M\tau_\eta}{\tau_M+\tau_\eta}}{\tau_T}\right)\right]^2\frac{1}{\phi\tau_z}}.$$

Clearly, τ_p increases with ϕ, and when $\phi = 0$, we have $\tau_p = 0$. Now, the manager's problem is $\max_K E\left(\tilde{\theta}K - 0.5K^2 \middle| \tilde{s}_M, \tilde{s}_p\right)$. Solving this problem, we obtain the optimal investment as follows:

$$K^* = E\left(\tilde{\theta}\middle|\tilde{s}_M, \tilde{s}_p\right) = \frac{\tau_M}{\tau_M+\tau_p}\tilde{s}_M + \frac{\tau_p}{\tau_M+\tau_p}\tilde{s}_p.$$

The weight $\tau_p/(\tau_M+\tau_p)$ captures how important the price information is in the manager's real decision, and it is essentially Kalman's gain. If this weight is above a threshold, say, if $\tau_p/(\tau_M+\tau_p) \geq \alpha$, where α is an exogenous fraction, then the firm will think that price information is important and meaningful, and thus, it will select choice A in question I. Otherwise, the firm thinks that the price information is immaterial and will not select choice A.

By simple algebra, we obtain the following proposition which forms the basis for our five predictions of Hypothesis 1 in testing the learning channel.

Proposition. *The firm is more likely to report that it pays attention to asset prices for the learning purpose if (1) the investor's information precision* τ_T *is higher; (2) the analyst information precision* τ_η *is lower; (3) the manager's private information precision* τ_M *is lower; (4) the manager's sophistication level* ϕ *is higher; or (5) its perceived price informativeness* τ_p *is higher;.*