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Market feedback: Evidence from the horse's mouth

Itay Goldstein [a], Bibo Liu [b], Liyan Yang [c,*]

[a] The Wharton School, University of Pennsylvania, 3620 Locust Walk, PA 19104-6367, Philadelphia, United States
[b] PBC School of Finance, Tsinghua University, 43 Chengfu Road, Haidian District, Beijing, 100084, China
[c] Rotman School of Management, University of Toronto, 105 St. George Street, Toronto, ON M5S3E6, Canada

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A B S T R A C T

We surveyed all Chinese public firms in 2019 and 2022 to examine the real effects of financial markets. Over 90% of firms say they actively monitor the stock market, and the most common reasons they provide are that they learn new information from the price and that they depend on the price for financing. Focusing on the learning channel, we examine how the responses relate to firm characteristics and actions. Firms that indicate learning have characteristics that suggest greater benefit from market information. They also exhibit higher investment-to-price sensitivity. We provide results on what dimensions of information firms learn about.

1. Introduction

Stock markets capture huge attention, but whether they are just a sideshow or they affect the real economy, and how they might do so, remains a hotly debated issue. Several channels have been proposed for a possible real effect of stock markets. In their review, Bond et al. (2012) put forward two main channels: the financing channel and the learning channel. The first one operates in primary markets, where firms actively issue securities through Initial Public Offerings (IPOs) or through Seasoned Equity Offerings (SEOs). Changes in security prices can then directly affect the amount of capital they can raise and hence their investments. The second one occurs in the secondary market, when firms are not actively raising capital. It comes from the fact that the stock market is a powerful source of information as it aggregates trading across many market participants, who follow their private signals. The existence of such information in the market then reasonably implies that decision makers, such as managers, will rely on the stock price to update their beliefs before they make decisions on the real side, such as corporate investment decisions. This is sometimes referred to as the "feedback effect" due to the informational feedback that the market provides to managers.

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Empirical literature has provided evidence across these two channels. For example, Brogaard et al. (2019) and Goldstein et al. (2023) demonstrate the importance of the financing channel for the real effects of financial markets. Since most trading occurs in secondary markets, understanding the learning channel is especially important. Indeed, this channel has attracted substantial empirical research and is the most controversial, lying at the heart of debates concerning the real effects of financial markets (e.g., Chen et al., 2007; Bakke and Whited, 2010; Goldstein, 2023). Identifying this channel in the data is always a challenge as the information sets of market participants and real decision makers are unobservable. Goldstein (2023) discusses how the literature relies on two key strategies to indirectly infer the learning channel from the data.[1] But despite the progress that has been made, the issues remain under controversy because of the indirect nature of the evidence and some skepticism about the channel, given strong priors in the finance literature that key decision makers in the real side should be very well informed already.

The goal of this paper is to supplement the existing empirical studies and provide evidence for market feedback from a different perspective relying on a different approach, namely survey evidence. For this purpose, 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 the way they are affected by the stock market in general, and about the learning channel in particular.[2] The big advantage of conducting this survey in China is the collaboration with the CSRC, which implied a response rate that is very close to 100% among all public firms listed on the Shanghai and Shenzhen stock exchanges (3,628 in 2019 and 4,732 in 2022). Thus, our study does not feature the selection bias problem that is common to other surveys. The responses were given by top executives or by teams specializing in capital market affairs, who are all highly knowledgeable about their firms' operations. Hence, it is clear overall that conducting a survey of such scope and depth is a rare opportunity. Moreover, given that the information efficiency of China's financial markets has increased substantially in recent years (see, Carpenter et al., 2021), China appears to be a good place to study the real effects of financial markets.

The first question we asked in both rounds of the survey was whether the firms pay attention to (monitor) the stock market, and respondents were given a few options of what prices they might monitor. We find that in both surveys more than 90% of firms say that they monitor both their own stock prices and their peers' stock prices. Before exploring the channels, this establishes at a basic level that firms indeed care about the market.

The second question in both rounds of the survey was designed to go into the channels. Those firms reporting that they monitor their own stock prices (either in addition to the peers' stock prices or not) were presented with a few non-exclusive options as to why they monitor their stock prices. We gave them five different possible channels motivated by arguments in the literature. Interestingly, the ones they chose most frequently are the two mentioned above: the learning channel and the financing channel. Specifically, in the 2022 survey, 80.4% of the firms that were asked this question reported that they pay attention to stock prices for learning new information that is relevant for real investment decisions, and 68.7% of the firms reported that they monitor stock prices because prices would impact refinancing. The other three possibilities received significantly less support: pressure from boards and shareholders, incentive pay, and avoiding being acquired. Results from the 2019 survey were highly consistent with this pattern. As described below, after establishing this basic evidence, the paper continues to dive into the learning channel with much more analysis, motivated by the active debate in the literature that surrounds it.[3]

One piece of evidence comes from a question we added in the 2022 survey, which was motivated by comments we received when presenting the original version of the paper. The firms who replied that they learn from the market for making real-investment decisions were asked what kind of information they attempt to learn from stock prices. This is an important dimension to add to the informational feedback literature, since for the most part empirical evidence thus far could not tell what dimensions managers are looking to learn about. Firms were given eight non-exclusive options, covering eight areas of uncertainty that are important for investment decisions (including one related to Covid that was a top concern at the time).

The three dimensions that firms stated most frequently that they learn about were: macro and industry information (90.2% of the firms affirm this statement), policy and regulatory information (86.3%), and information about the company's competitive position (84.9%). Other areas of uncertainty that received less support, but still significant support, were the cost of capital (61.9%), customers' demand (59.5%), technologies (54.7%), and the company's potential acquisitions (53.1%). The literature highlighted that market feedback should be particularly important in areas where the information is external to the firm and where there is greater benefit to aggregation across different market participants (e.g., Goldstein and Yang, 2019; Goldstein, 2023). Our results shed light on what these dimensions of information may be. Intuitively, macro-, policy-, and competition-related uncertainties indeed seem to be dimensions on which aggregation of external information will be particularly valuable. It is perhaps less clear that information about customer demand is less valuable. Exploring these dimensions further can be a very fruitful direction for future empirical research.

Other evidence we bring on the learning channel revolve around relating firms' responses to their characteristics and actions. This helps validating that the responses do not represent just noise, which is a common concern with surveys, and also to gain more insights on the nature of learning from prices. Towards this goal, we develop two sets of predictions regarding firms' responses about the learning channel. The first set uses firm characteristics to explain their decision on whether to learn from stock prices, based on theoretical reasoning about the perceived benefit of learning. We predict that a firm is more likely to report they learn from stock prices if its investors are more informed and its manager is less informed. We indeed confirm these in regression analyses based on measures of investor information and managerial information. Another variable that is important is the availability of other sources of information, and we look at analysts. Here, the prediction is more nuanced, but we find in the data that firms with more analysts' coverage report learning from the market less prominently. This is consistent with Chen et al. (2007), who argued that analysts do not bring new information to the market but rather channel managerial information to the market. Managerial background may also be important, as managers with higher levels of education and professional experience may be more prone to realize the benefits of the market and to attempt to learn from it. We find evidence along these lines as well.

[1] 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), Zuo (2016), Dessaint, Foucault, Frésard, and Matray (2019), and Jayaraman and Wu (2020), among others.

[2] We completed the first draft of the paper based on the survey in June 2019 and presented it in several conferences and seminars. After collecting comments from these presentations, we decided to conduct another round of survey for two reasons. First, in this second round of survey, we can ask additional questions inspired by the comments. Second, we can check the consistency of responses across the two rounds of survey, which helps to evaluate the validity of our survey approach.

[3] In the Online Appendix, we also provide supplementary results on the financing channel.

Finally, we bring in measures of price informativeness from the literature and predict that firms indicating that they are learning might do so because they think their prices are informative and contain information new to them. We find statistically significant results for two of the three measures we use, providing new insights into what these measures capture.

In the second set of predictions, we link firms' real investments to their responses regarding whether they learn from stock prices and what dimension of information they learn about. We begin by comparing the investment-to-price sensitivity of learning firms to that of non-learning firms. If survey respondents provide truthful information, we expect firms that report learning from stock prices to rely more on stock prices in their investment decisions. The results provide strong evidence consistent with this prediction: Investment-to-price sensitivity is positive and significant for firms that affirm they learn from prices, but insignificant for those that report they do not. Similarly, if a firm reports learning about a specific type of information from its stock price, we expect it to rely more heavily on the price for investment decisions. The regression results confirm this prediction: Investment-to-price sensitivity is significantly higher for firms that report learning a great deal along specific informational dimensions than for those that do not.

After establishing these results on investment-to-price sensitivity, we next examine whether firms that report learning from the market subsequently enhance shareholder value. Given that a decision not to learn could reflect particular managerial background or attitude, such a decision can be suboptimal, and so we may expect learning firms to show better performance on some dimensions. Answering such a question requires us to look at particular managerial actions and their consequences, and so we focus on the context of mergers and acquisitions (M&As). From the third question in the survey, we can differentiate between firms who say that they learn from the market about potential M&A opportunities and those who say they do not. We show that firms in the former group conduct more attempts of acquisitions and succeed more often in such attempts. In addition, their stocks perform better following such attempts, both in the long run (12 months after the completion of the deal) and around the announcement of the deal (day −1 to 1). This provides indication that learning from prices on a particular dimension does help firms make decisions on this dimension, resulting in better performance.

Finally, we validate our survey responses by exploiting a unique aspect of the Chinese stock market: trading suspensions. Firms in China have the ability to suspend trading in their stock for some time even without specifying a concrete reason for doing so. We find that those firms, who say that they learn information from stock prices, are less likely to suspend their trading. This provides another validation to the results of our survey, as one would expect that firms who think that the information in the price is valuable would not want to suppress this signal. In contrast, firms that report monitoring prices for financing reasons are more likely to suspend trading, particularly during large price drops. This result aligns with their response that they care about stock prices because of their worry about access to capital.

Our paper contributes to two strands of literature. First is the literature on the real effects of financial markets, in particular on the informational feedback effect. As mentioned above, the existing literature uses different approaches to indirectly infer from the data that such informational feedback affects managerial decision making (e.g., Chen et al., 2007; Bakke and Whited, 2010; Foucault and Frésard, 2012, 2014; Dessaint et al., 2019; Carpenter et al., 2021). The survey evidence here cannot substitute these approaches but certainly complement them by asking managers directly what they do, and so we bring evidence from an important different angle that managers care to learn from the price.[4] In addition, we relate to these studies by linking managerial responses to the firms' characteristics and actions. This provides validation to the reliability of the responses and also at times sheds new light on circumstances and characteristics that are associated with greater tendency to learn. Finally, we also provide evidence, based on managers' responses, on what managers wish to learn. This is a dimension that the empirical literature has not tackled much before with indirect inferences.

It should be noted that a typical concern that people have with survey evidence is that respondents might not say what they really think or do, either they do not pay much attention to their responses, or maybe they worry about saying the truth. We described above how different strategies in the paper—conducting two rounds of the survey, and more importantly, relating the responses to firms' characteristics and actions—help alleviate the concerns. As we also mentioned, the scope of the survey and the lack of selection bias make it more credible than usual. In addition, it should be noted that our questions were designed to be purely academic questions that should not trigger concerns among respondents to think that any answer could be problematic. Moreover, our surveys were part of the series of surveys conducted through collaboration between the PBC School of Finance at Tsinghua University and the CSRC, and this ongoing relationship strictly implements a policy of limited use of the responses. Hence, respondents came to expect that these will not be used beyond academic purposes and that their identity will not be revealed. It is interesting to note that the state-owned enterprises (SOEs), who might be more susceptible to try and please in their responses, were consistently responding less in favor of the learning and financing hypotheses, as we report in the paper. This pattern is consistent with theoretical reasoning, as these firms naturally care less about the market, and it also further removes concerns of biased responses.

The second strand of the literature that our paper contributes to is the growing literature that uses surveys in finance. Graham and Harvey (2001) and Graham et al. (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) explore 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 et al. (2021a, 2021b) employ survey-based expectations to analyze people's belief dynamics. Liu et al. (2022) propose a new approach to combining subjective survey responses with observational data to study behavioral biases of investors in the Chinese stock market. Edmans et al. (2023) survey directors and investors on how they set CEO pay in practice and find several departures from mainstream academic theories. 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 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

[4] In the Online Appendix, we confirm that the finding based on the indirect approach of Chen, Goldstein, and Jiang (2007) holds in the Chinese market and is, in fact, primarily driven by the subsample of firms that indicate that they learn from the price.

and the CSRC and later distributed by the regulator.

In the two rounds of surveys conducted in June 2019 and June 2022, we include a set of questions about the real effects of the stock market. In both rounds, we asked public firms *whether* they monitor stock prices, and if so, then *why*. In the 2022 survey, we also asked those firms, who say that they learn information from their stock prices to guide real investments, *what* information they attempt to learn from the prices. As we mentioned in Footnote 2 of the Introduction, we wrote the first version of the paper based on the first round of survey. After presenting that earlier version in conferences/seminars and collecting comments, we decided to conduct another round of survey, which allows us to ask an important question we did not ask in the first round ("What information do firms learn from stock prices?") and to check the consistency of responses across the two rounds of surveys.

Specifically, we asked the following questions about the real effects:

I. How does your company pay attention to the stock market? (Select one answer) (Included in both surveys)
A. Only pay attention to the price of your own company's stock;
B. Only pay attention to the prices of other similar companies' stocks;
C. Both A and B;
D. Only pay attention to the composite stock index;
E. Do not pay attention to the stock market at all.

II. If you choose A or C in I: Which of the following is the reason that your company pays attention to the stock price of your own company? (Select all that apply) (Included in both surveys)
A. Stock price contains information that is new for real 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 (monitor) 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 et al., 2007; Bakke and Whited, 2010). 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 monitor 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 for the real effects. Choice A is based on those studies that find managers learn information to guide real investment decisions (e.g., Chen et al., 2007), which is the "learning channel" and the focus of our subsequent analysis in Sections 4 and 5. We also note that, when phrasing Choice A, we make it explicit that the information in prices is about real investments as opposed to about financial investments, to avoid any potential confusion by respondents about these two types of investments. Choice B is based on those studies showing that managers pay attention to stock prices for financing opportunities (e.g., Giammarino et al., 2004; Goldstein et al., 2023). 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 primarily to the "financing channel." Choice C is based on those studies linking stock prices and managerial incentives (e.g., Kang and Liu, 2008; Bond et al., 2012), and we term it the "compensation channel." Choice D is based on those studies on the substitution effect between market monitoring and board monitoring, because market monitoring is more powerful with informative stock prices (e.g., Ferreira et al., 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 M&A, and we term it the "M&A channel." Choice F allows respondents to specify other reasons which are not highlighted in the literature.

Question III aims to collect opinions about what kind of information firms extract from financial markets 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.[5] 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. Subrahmanyam and Titman (1999) posit that managers glean information about their cost of capital from the stock market. Liu and Tian (2022) borrow the Chemmanur and Fulghieri (1999) 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),[6] 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

[5] Several recent empirical studies have explored the question of what information firms learning from the stock market. Gao and Xiao (2023) suggest that managers learn from the information impounded by nonlocal investors when making investment decisions. Aretz, Ilyas, and Kankanhalli (2024) find that firm managers learn information about technological progress from market prices. Dessaint, Gondhi, and Peress (2025) find that in M&A transactions managers learn information about discount rates rather than cashflows from target stock prices.

[6] Choice B of Question II (the financing channel) and Choice F of Question III (learning about the cost of capital) are clearly related, as both pertain to a firm's financing behavior. However, they capture distinct concepts. It is important to note that Question III, Choice F is posed specifically to firms that report monitoring their stock prices for a learning purpose. Choice B of Question II, in contrast, could be selected by a firm that already has a clear understanding of its investment opportunities and is thus not learning from the price, but is simply issuing shares to raise cash for a predetermined investment.

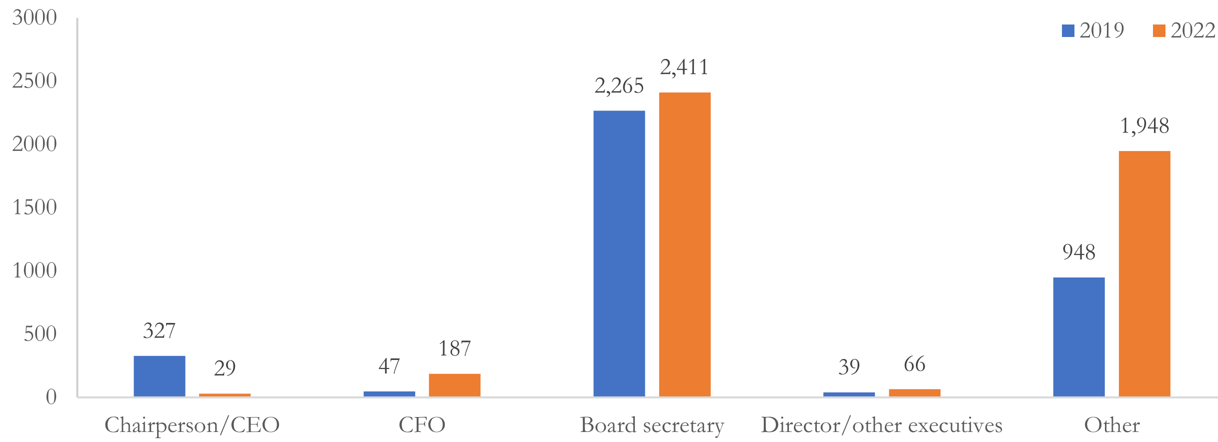


Figure 1. Distribution of respondents' positions in their firms. This figure plots the distribution of the positions of the respondents that were assigned by their firms to respond to our 2019 and 2022 market feedback surveys. 3,626 Chinese public firms listed on the Shanghai and Shenzhen Stock Exchanges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

prices; and Choice J allows respondents to specify other information we omit in the choices.[7]

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 recorded, enabling us to combine the survey data and public information to perform further analyses.

2.2. Responses

The 2019 survey questionnaire (containing Questions I and II) was distributed to public firms by the CSRC via its electronic survey system 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 99.9%; 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 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.

We also believe that the respondents understand the survey questions and their firms' operations, so that their opinions are informative about their firms. Fig. 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.

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 addition, we believe respondents carefully read and consider our questions and don't simply pick the choices that appear first (e.g., A or B), so that the ordering of choices is unlikely to affect their answers and bias our results. We check the distribution of choices for the four questions with the largest number of choices (nine or ten, from A to I/J) among all questions asked in the 2022 survey, and find Choices F (22.8%), E (18.2%) and H (15.7%) appear late but are also frequently picked. These frequencies are comparable to that of the most popular choice (B, 29.1%).

In the following analysis, we divide the respondents into three groups according to their position levels: (1) a high-ranking group including chairperson, CEO, director, CFO, and other executives; (2) a medium-ranking group including board secretary; and (3) 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.

[7] When designing Question III, we aimed to understand what information firms learn from their own stock prices as opposed to from the prices of peer firms or the prices of indices, because learning from own stock prices is more subtle and debatable than learning from the stock prices of peers or the stock indices in many cases. For instance, it is more natural and receivable that a firm learns macro information from the aggregate stock index, but it becomes less clear and more controversial whether a firm can learn such macro information from its own stock price.

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 is as of 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

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.

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 42.7%. 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-R^2, is around 0.8.

3. Direct evidence for the real effects of financial markets

This section summarizes firms' responses to our survey questions to provide direct evidence on the real effects of financial markets. In Subsection 3.1, we define a firm's monitoring of the stock market—including its own stock price, the prices of its peers, and the overall stock index—as constituting real effects (corresponding to Choices A – D in Question I). Subsection 3.2 describes the various channels through which the stock market affects the real economy (Question II). Subsection 3.3 then focuses specifically on the learning channel, reporting what information managers learn from their own stock prices (Question III). Finally, Subsection 3.4 presents the correlations between responses and discusses their variations across industries and over time. Overall, this section aims to provide a broad picture of the real effects of financial markets. In the subsequent two sections (Sections 4 and 5), we will sharpen our focus to the learning channel, as this is the channel that the literature primarily views with skepticism.

3.1. *Prevalence of real effects*

Our first question ("*I. How does your company pay attention to the stock market?*") concerns the existence of real effects, or whether firms monitor stock prices at all. We report the responses in Fig. 2. According to Panel A, among the 4,641 firms in the full sample of the 2022 survey, 97.7% of the responding firms monitor the stock market (Choices $A + B + C + D$), and 95.2% of the firms monitor their own stock prices (Choices $A + C$). 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, suggesting the real effects are 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 real effects. For example, in the 2022 survey, 92.5% of the high-ranking group (chairperson, CEO, director, CFO, and other executives, $N = 282$) reported they pay attention to their own stock prices (Choice $A + C$). The figures for the medium-ranking group (board secretary, $N = 2{,}411$) and the low-ranking group (other positions, $N = 1{,}948$) are 95.3% and 95.5%, respectively. 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. These findings establish at a basic level that firms indeed care about the stock market, not yet establishing the channels.

3.2. *Channels for real effects*

Our second question ("*II. If you choose A or C in I: Which of the following is the reason that you pay attention to the stock price of your own company?*") goes into the channels and explores why the firms monitor 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 Fig. 3. As the firms can choose more than one answer to this question, the sum of these frequency counts of each choice exceeds the total number of firms.

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 monitoring 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%, respectively. The third important reason behind firms' monitoring of their own stock prices is pressure from boards and shareholders (the monitoring channel, Choice D), and 34.4% (35.6%) of the firms affirm 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.[8] The M&A channel (Choice E)

[8] 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.

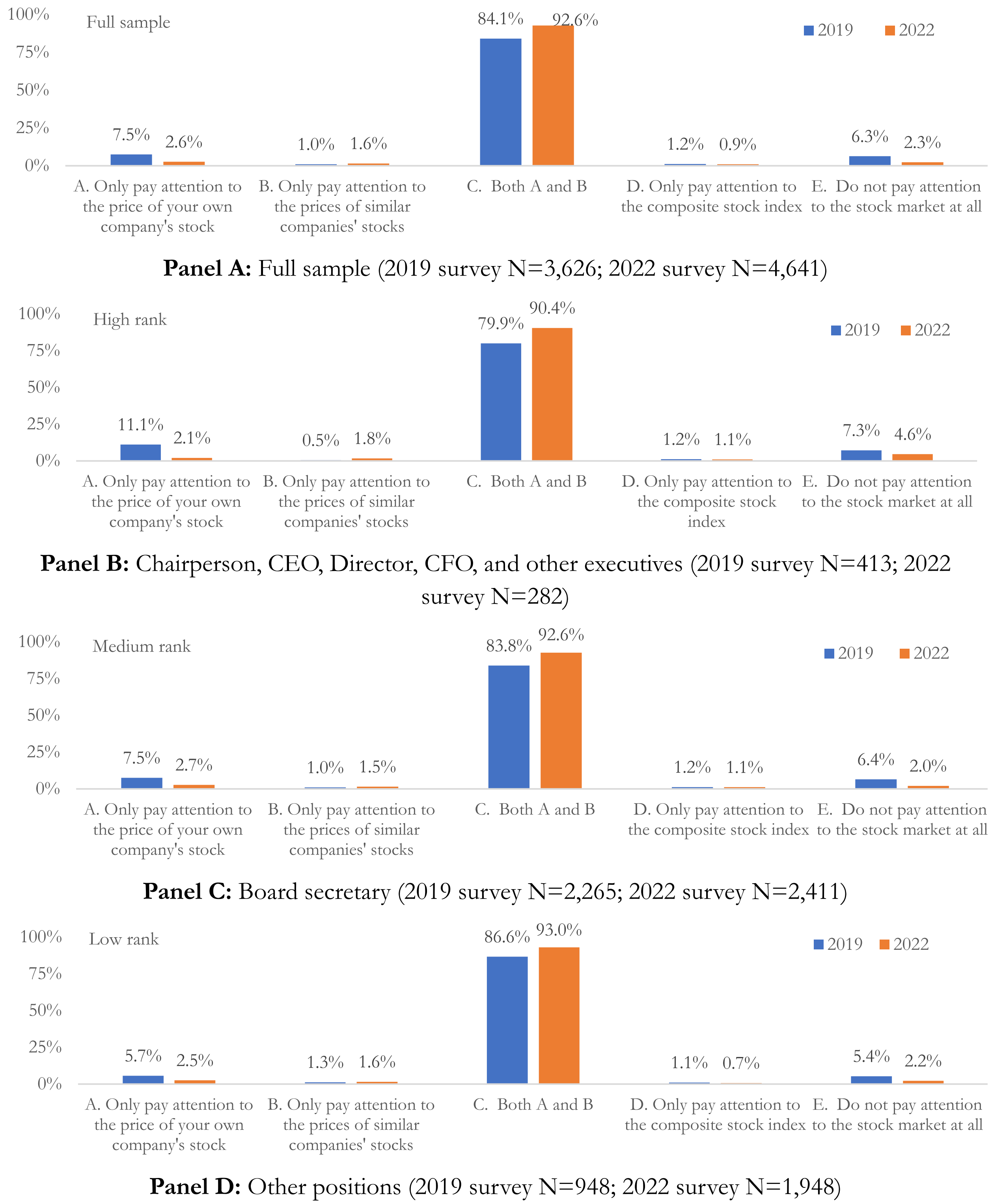
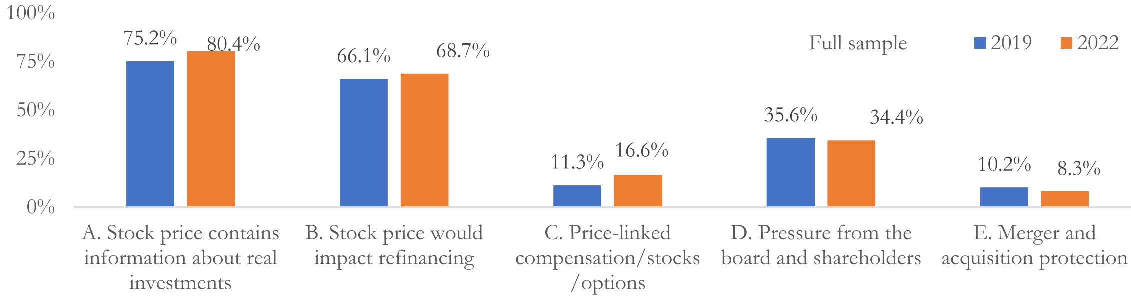


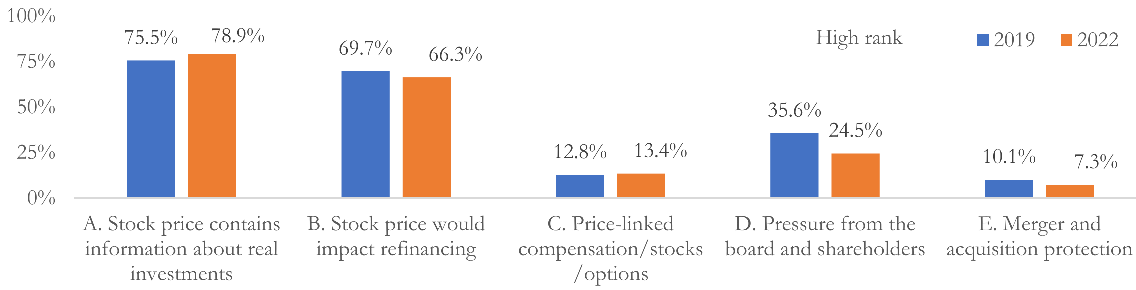
Figure 2. Responses to Question I. This figure plots the frequencies for each choice by the responding firms in survey Question I ("*How does your company pay attention to the stock market?*"). Panel A presents results in the full sample. Panel B, C, and D present results in high-, medium-, and low-ranking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

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 among public firms.

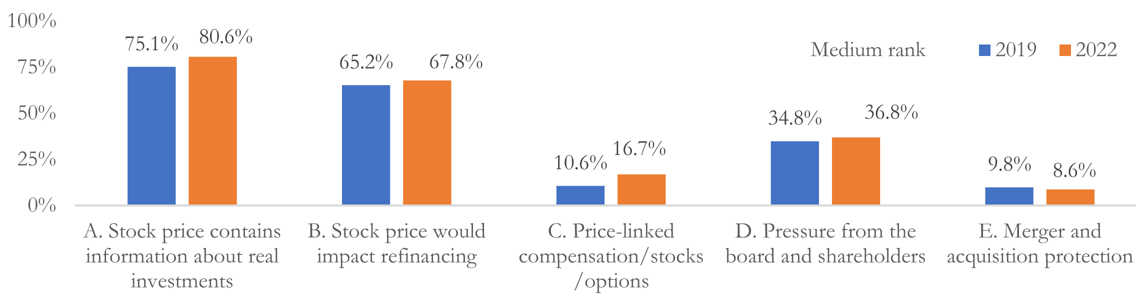
Again, Panels B, C, and D show that the opinions are highly consistent across different groups of respondents. For example, in the 2022 survey, around 80% of the respondents in the high- (78.9%), medium- (80.6%), and low-ranking (80.3%) groups picked the learning channel (Choice A). The fractions picking the financing channel (Choice B) for high-, medium-, and low-ranking groups are 66.3%, 67.8%, and 70.3%, respectively. The 2019 survey results also demonstrate firms' similar preferences toward Choices A and B across different respondent groups.



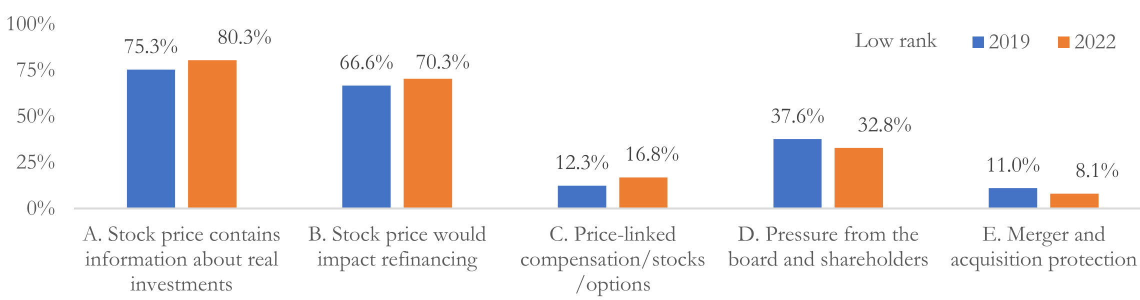
Panel A: Full sample (2019 survey N=3,320; 2022 survey N=4,420)



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)



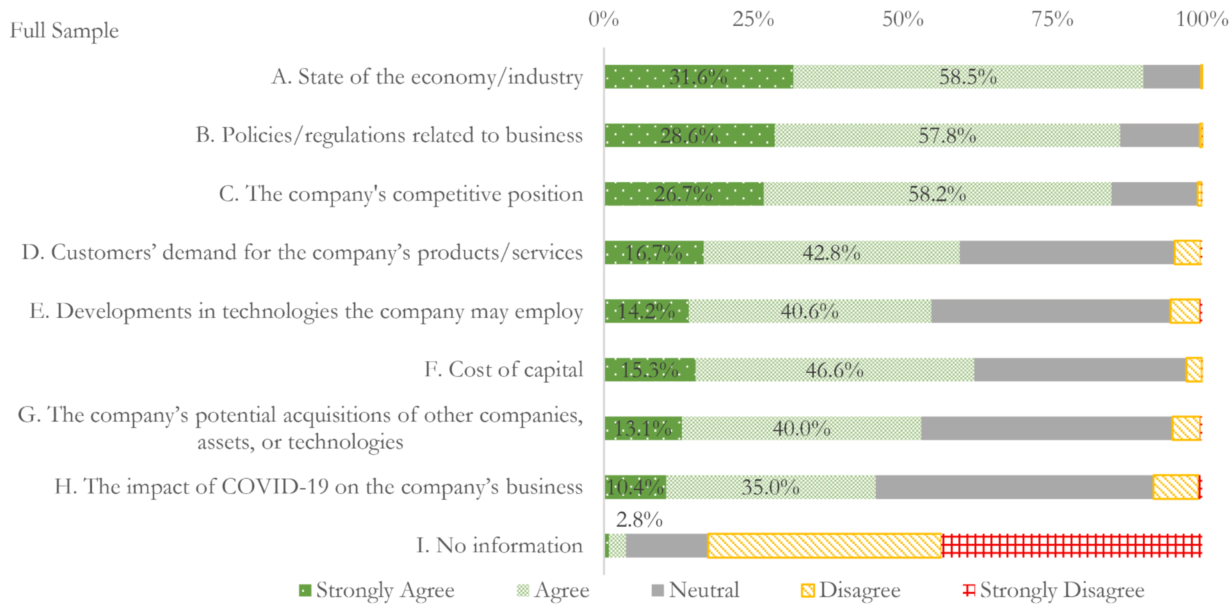
Panel D: Other positions (2019 survey N=875; 2022 survey N=1,860)

Figure 3. Responses to Question II. This figure plots the frequencies for each choice by the responding firms in Question II (*"If you choose A or C in I: Which of the following is the reason that your company pays attention to 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.

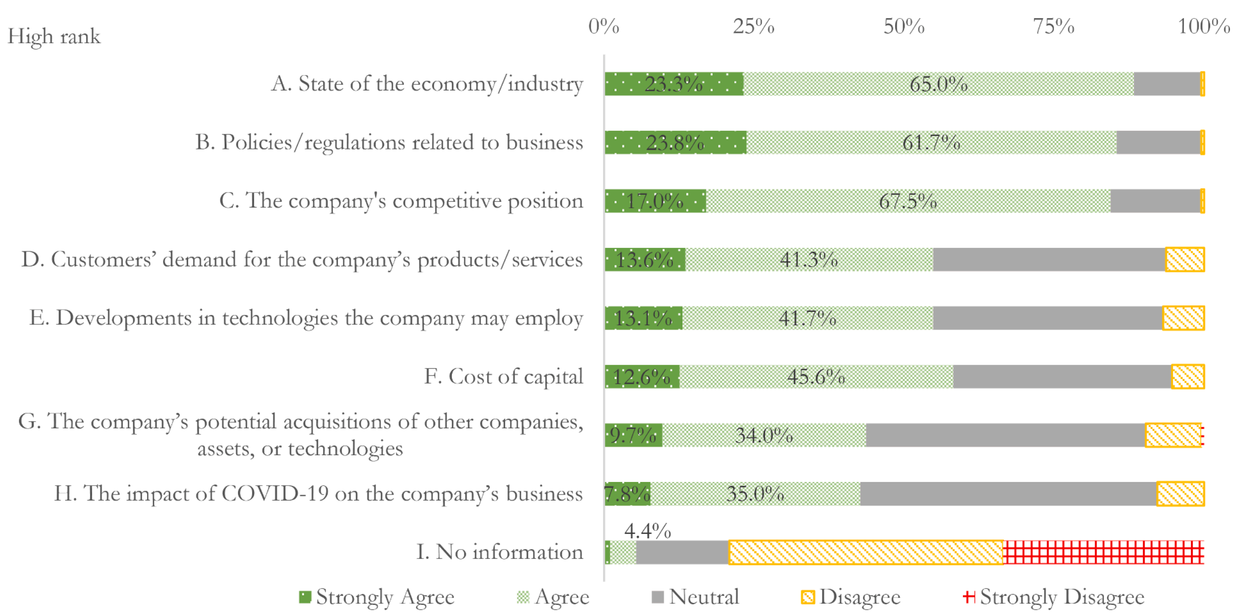
3.3. *What information do managers learn from prices?*

In this subsection, we answer the question of what kind of information firms learn from stock prices when the learning channel is most relevant, which is an important dimension to add to the informational feedback literature. To provide direct evidence, 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 (i.e., select Choice A in Question II) were asked to respond (see Subsection 2.1 for details on the question and choices).

Fig. 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 affirm the corresponding statement. The second and third most useful information is information about policies and regulations related to the company's



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



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

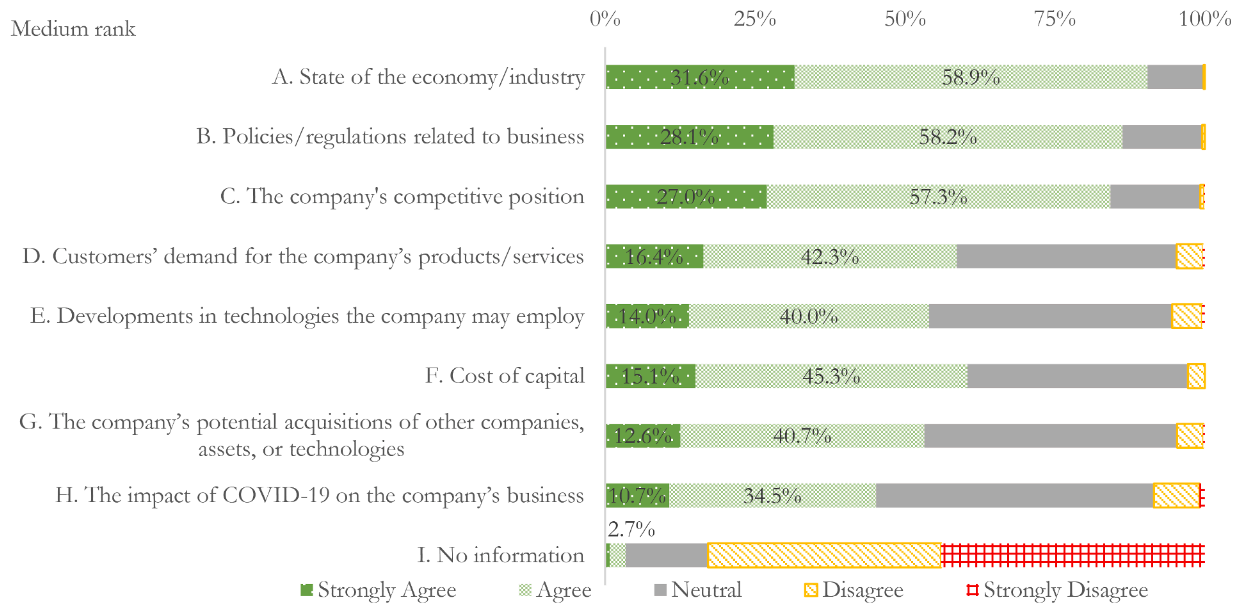
Figure 4. Responses to Question III. This figure plots the frequencies for each choice by the responding firms in Question III (*"If you choose A in II: When learning from the market, what kind of information can the company's own stock price be useful for?"*) in the 2022 survey. Panel A presents results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

business (Choice B, affirmation rate = 86.3%) and information about the company's competitive position relative to competitors (Choice C, affirmation rate = 84.9%).

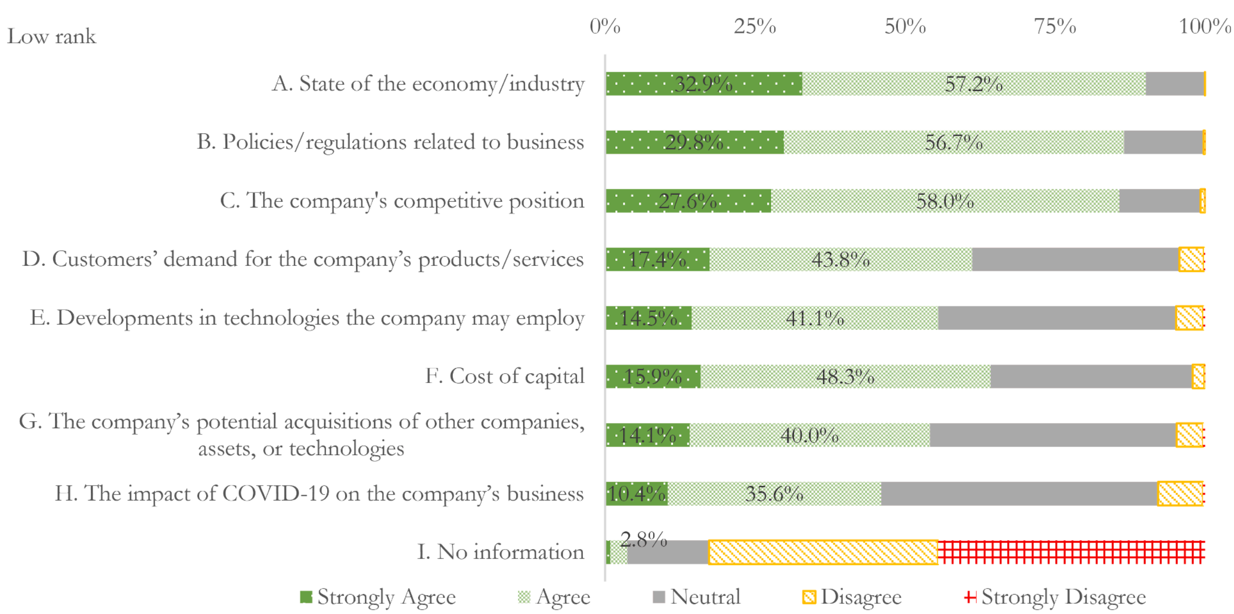
Other information we list is also meaningful to the responding firms, including the cost of capital (Choice F, affirmation rate = 61.9%), customers' demand for the company's products/services (Choice D, affirmation rate = 59.5%), developments in technologies the company may employ (Choice E, affirmation rate = 54.7%), and the prospects of the company's potential acquisitions of other companies, assets, or technologies (Choice G, affirmation rate = 53.1%). Our result on the cost of capital aligns with Dessaint et al. (2025), who provide evidence that managers learn about discount rates from stock prices in M&A settings. In addition, it is worth noting that, very few (0.8%) of the learning firms strongly agree with Choice I, "There is no information to learn from the stock price," suggesting their responses are consistent across questions.

We also report survey results in high-, medium-, and low-ranking respondents in Panels B, C, and D. The patterns are highly consistent with those in the full sample, that is, the manager puts her top priority on the macro, industry, regulatory, and competition information contained in her stock price.

The literature highlighted that the informational feedback should be particularly important in areas where the information to be learned is



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



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

Figure 4. (*continued*).

external to the firm and where there is greater benefit to information aggregation across different market participants (e.g., Goldstein and Yang, 2019; Goldstein, 2023). Our results shed light on what these dimensions of information from stock prices may be. Intuitively, macro-, policy-, and competition-related uncertainties indeed seem to be dimensions on which aggregation of external information will be particularly valuable. It is perhaps less clear that information about customer demand is less valuable. Exploring these dimensions further can be a very fruitful direction for future empirical research.

3.4. Additional analysis

In this subsection, we compute the correlations between responses and examine their variation across industries and over time to further our understanding of market feedback.

3.4.1. Correlations between responses

We first compute the correlations between market feedback channels reported in Question II for both surveys. We denote the learning, financing, compensation, monitoring, and M&A channels with dummy variables *Learn, Finance, Compensation, Monitor*, and *M&A*. A dummy variable equals one if the corresponding channel is chosen in responses to Question II, and zero otherwise. As shown in Panels A and B of Table 2, the correlations across channels are very low, suggesting they capture distinct motives for firms monitoring the stock market.

We then explore the correlations between the types of information

Table 2
Correlations between responses.
This table reports the correlations between channels of market feedback based on responses to Question II ("If you choose A or C in I: Which of the following is the reason that your company pays attention to the stock price of your OWN company?") and the correlations between information contents firms expect to learn about based on responses to 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?"). The channel indicators (*Learn, Finance, Compensation, Monitor*, and *M&A*) equal one if they are chosen by the respondent, and zero otherwise. The information content indicators (*Macro, Policy, Competition, Demand, Technology, Cost, Acquisition, Covid*) take the value of 2 if the respondent chooses "strongly agree" for the corresponding information type, 1 for "agree", 0 for "neutral", −1 for "disagree", and −2 for "strongly disagree". ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Market feedback channels (2019 Survey, N = 3,320)

	Learn	*Finance*	*Compensation*	*Monitor*	*M&A*
Learn	1.0000	−0.1616***	0.0310*	−0.1141***	0.0153
Finance		1.0000	0.0569***	0.0632***	0.0977***
Compensation			1.0000	0.1259***	0.1668***
Monitor				1.0000	0.1581***
M&A					1.0000

Panel B: Market feedback channels (2022 Survey, N = 4,420)

	Learn	*Finance*	*Compensation*	*Monitor*	*M&A*
Learn	1.0000	−0.0812***	−0.0083	−0.1332***	0.0327**
Finance		1.0000	0.1587***	0.0421***	0.0504***
Compensation			1.0000	0.1800***	0.1245***
Monitor				1.0000	0.1525***
M&A					1.0000

Panel C: Information contents for learning firms (2022 Survey, N = 3,553)

	Macro	*Policy*	*Competition*	*Demand*	*Technology*	*Cost*	*Acquisition*	*Covid*
Macro	1.0000	0.7664***	0.5915***	0.4166***	0.3979***	0.3825***	0.3211***	0.2921***
Policy		1.0000	0.6087***	0.4670***	0.4464***	0.3956***	0.3487***	0.3036***
Competition			1.0000	0.5572***	0.4728***	0.4307***	0.3889***	0.3343***
Demand				1.0000	0.6744***	0.4683***	0.4395***	0.4348***
Technology					1.0000	0.4935***	0.4935***	0.4669***
Cost						1.0000	0.5695***	0.411***
Acquisition							1.0000	0.5050***
Covid								1.0000

firms expect to learn, based on responses to Question III in the 2022 survey. For firms choosing the learning channel, we define indicators for different information contents (*Macro, Policy, Competition, Demand, Technology, Cost, Acquisition, Covid*). These indicators take a value of 2 if the respondent chooses "strongly agree" for the corresponding information type, 1 for "agree", 0 for "neutral", −1 for "disagree", and −2 for "strongly disagree". Panel C reports the pairwise correlations between these indicators, which range from 0.29 to 0.77. Some correlations are higher than others, consistent with theoretical reasoning. For instance, the correlation between macro and policy information is higher than that between macro and acquisition information, as both macro and policy relate to the aggregate economy, while acquisition is more firm-specific.

3.4.2. Industry variation in responses

We also analyze the industry and time variation of firms' responses. First, as shown in Appendix A1, we find the real effects of financial markets are prevalent across industries, but with significant variations. For example, Panel A of Table A2 shows, across all industries, the fraction of firms monitoring the stock market varies from 90% to 100%, according to the 2022 survey. Panel B shows, albeit the leading reason for doing so is for the learning purpose, its prevalence also differs: In the food/beverage and agriculture industries, over 85% firms choose the learning channel; in contrast, in the financial industries (including banking and non-banking finance), less than 66% firms choose that reason. Similarly, Table A3 shows the information contents firms extract from their stock prices also vary across industries. For example, 75% firms in the social service industry affirm the information about customer demand is useful, while in the steel industry only 49% firms believe so.

3.4.3. Time variation in responses

Untabulated results suggest that firms did not change their responses significantly between the two survey rounds, which may be attributed to the short three-year interval. In particular, firms' attitudes toward the learning channel (Choice A in Question II) were very consistent. Among the 3,626 firms that responded to the 2019 survey, the majority (2,228 firms, or 61.4%) did not change their response. Of the remaining 38.6% of firms, 773 (21.3%) switched from not affirming to affirming the learning channel, while 625 (17.2%) switched from affirming to not affirming it.

4. Managerial learning

Given that the skepticism in the literature on the real effects of financial markets mainly concerns the existence of the learning channel, we concentrate on this channel in the subsequent sections. A concern about survey evidence in general is that respondents might not pay much attention to their answers and so their answers might not reflect what they actually think or do. In the following analysis, we study how firms' responses about the learning channel relate to firms' characteristics and actions for firmer validation. Unless otherwise specified, the data on firm characteristics and actions are obtained from the CSMAR and Wind databases. 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.

4.1. Hypothesis development

In this subsection, we develop two sets of predictions regarding firms' responses on the learning channel in Questions II and III. The first set aims to explain these responses using firm characteristics, while the second set seeks to assess the veracity of these responses.

When developing the first set of firm-characteristic-based predictions, we hold the general premise that a firm will select Choice A in Question II, "Stock price contains information that is new for real 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. Specifically, in the Online Appendix, we provide a stylized model to formalize the following hypothesis:

Hypothesis 1. *(Explaining the 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 (a) its investors' information precision level is higher; (b) its manager's private information precision level is lower; (c) its analysts' information precision level is lower; (d) its firm manager's sophistication level is higher; or (e) it perceives its stock price to be more informative.*

These five predictions correspond respectively to five parts in Proposition OA in the Online Appendix. 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 Hypothesis 1 (a). 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 et al., 2007; Goldstein and Yang, 2019), which explains Hypothesis 1(b).

Third, the predictions on analyst's information precision and managerial sophistication (Hypothesis 1(c) and Hypothesis 1(d)) are more nuanced and subtle. 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 et al., 2003; Agrawal et al., 2006), information released by analysts will lower the reliance of investors on their own private information, which therefore reduces price informativeness. Chen et al. (2007) find that in the U.S. market, this second effect dominates. Albeit we take the second view when modeling analyst information and predict that firms rely less on the price when analysts' information is more precise (Hypothesis 1(c)), we take this prediction more as an empirical question. Additionally, regarding managerial characteristics, we postulate 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 real investments (Hypothesis 1(d)).

Finally, Hypothesis 1(e) presents a prediction based on price informativeness. Intuitively, what matters for managers learning from prices is the amount of new information in stock prices. Therefore, if firms perceive their stock prices to be informative and to contain new information, they are more likely to report paying attention to stock prices for the learning purpose. Of course, this perceived price informativeness is related to other firm characteristics such as investor information, analyst coverage, and managerial sophistication.

We next develop a second set of predictions to validate the learning channel. The core idea is to link firms' real actions—specifically, investment—to their survey responses. Our methodology tests whether learning firms demonstrate greater investment-to-price sensitivity and superior investment performance compared to non-learning firms. We propose the following specific predictions:

Hypothesis 2. (*Validating the learning channel*). *Other things being equal, (a) the investment-to-price sensitivity is higher among those firms reporting that they pay attention to their stock prices for the learning purpose (*i.e.*, they select Choice A in Question II) than that among those non-learning firms; (b) the investment-to-price sensitivity is higher among those firms affirming that they learn information from their stock prices (*i.e.*, they select "strongly agree" or "agree" in a choice of Question III) than that among those non-affirming firms; and (c) the investment performance of learning firms is higher than that of non-learning firms.*

Hypothesis 2(a) aims to validate firms' answers in Question II regarding whether they learn from their stock prices. We predict that firms affirming they learn from prices will use these price signals in their investment decisions, thus exhibiting higher investment-to-price sensitivity than firms that do not. Hypothesis 2(b) turns to firms' answers in Question III concerning what specific information they learn. We expect that if firms learn a great amount of information on certain dimensions from stock prices, they will rely more on prices for investment decisions, leading to higher investment-to-price sensitivity. Hypothesis 2(c) addresses the consequences of learning. Specifically, we predict that firms which report learning from the market will consequently enhance their investment performance and shareholder value.

4.2. Explaining the learning channel: Testing Hypothesis 1

In this subsection, we test the five predictions of Hypothesis 1 using the 2022 survey data. Hypothesis 1 aims to understand firms' responses regarding whether to pay attention to stock prices for the learning purpose.

4.2.1. Methodology

We use the dummy variable *Learn* constructed in Subsection 3.4 to indicate the learning channel, which equals one if a firm chooses A in Question II, and zero otherwise. We then employ the following specification to explore factors influencing the real effects via the learning channel:

$$Learn = a + b^{*}Factor + c^{*}Controls + \varepsilon, \tag{1}$$

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 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, history 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, the firm's industry, and the firm's geographical location.[9] All independent variables are constructed with information as of 2021, and the definitions are included in Appendix A2. Since *Learn* is a binary choice variable, we run Probit regressions to estimate Eq. (1).

4.2.2. Investor information

We use institutional ownership (*InsShares*) as the first measure for investor information contained in stock prices, assuming institutional shareholders possess superior information about the firm and capitalize it by trading (e.g., Daniel et al., 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

[9] There could be some unobservable industry-, location-, or position-specific factors that may influence managers' responses about learning. For example, managers from investment-intensive industries (e.g., telecommunication) are more likely to learn and report so; managers residing in provinces closer to Beijing might be more political and attempt to cater to the CSRC's preference by reporting learning; and managers ranking high in their firms are better connected to the regulator and are likely to take similar actions.

Table 3
Information, firm characteristics, and the learning channel.
This table reports the Probit regression results on firms' choice of the learning channel following Eq. (1). The sample consists of 4,171 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, managerial sophistication, and price informativeness measures. The respondent position, industry, and province fixed effects are included. See Appendix A2 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.

$Y = Learn$	Investor Info.		Managerial Info.		Analyst Info.		Manag. Sophistication		Price Informativeness		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
Info =	*InsShares*	*Short*	*Insider*	*ERC*	*NAnalysts*	*NForecasts*	*Professional*	*Degree*	*1-R*^{2}	*AdjPIN*	*PriceDelay*
Info	0.0248**	0.0261**	−5.7234**	−0.1953**	−0.0007***	−0.0007***	0.1343***	0.0301*	0.0742***	0.3053	−0.0023**
	(0.0125)	(0.0110)	(2.8983)	(0.0961)	(0.0003)	(0.0002)	(0.0275)	(0.0166)	(0.0093)	(0.4013)	(0.0011)
Size	0.0148***	0.0101*	0.0232***	0.0193***	0.0235***	0.0273***	0.0184***	0.0107	0.0275***	0.0241***	0.0198***
	(0.0048)	(0.0059)	(0.0039)	(0.0062)	(0.0041)	(0.0058)	(0.0058)	(0.0078)	(0.0037)	(0.0049)	(0.0030)
Leverage	−0.0163	−0.0094	−0.0029	−0.0260	−0.0154	−0.0152	−0.0279*	0.0064	−0.0049	−0.0090	−0.0052
	(0.0177)	(0.0150)	(0.0187)	(0.0158)	(0.0172)	(0.0171)	(0.0165)	(0.0284)	(0.0143)	(0.0163)	(0.0152)
History	−0.0008	−0.0010	−0.0003	−0.0005	−0.0008	−0.0008	−0.0011	−0.0013***	−0.0000	−0.0001	−0.0002
	(0.0007)	(0.0006)	(0.0013)	(0.0008)	(0.0007)	(0.0007)	(0.0007)	(0.0004)	(0.0013)	(0.0013)	(0.0013)
SOE	−0.0424***	−0.0416***	−0.0561***	−0.0458***	−0.0417***	−0.0430***	−0.0387***	−0.0336*	−0.0484***	−0.0471***	−0.0477***
	(0.0056)	(0.0046)	(0.0109)	(0.0052)	(0.0038)	(0.0042)	(0.0039)	(0.0181)	(0.0086)	(0.0074)	(0.0086)
Ret	0.0192	0.0307**	0.0531***	0.0288*	0.0189	0.0177	0.0207	0.0252	0.0474***	0.0410***	0.0460***
	(0.0172)	(0.0128)	(0.0093)	(0.0156)	(0.0162)	(0.0162)	(0.0169)	(0.0159)	(0.0172)	(0.0136)	(0.0146)
Vola	0.2026	−0.1374	−1.3401***	−0.4718	0.0614	0.0440	0.1152	−0.2478	−1.7798***	−0.9360	−1.0699
	(0.6565)	(0.7598)	(0.3669)	(0.4649)	(0.6972)	(0.7073)	(0.6906)	(0.3841)	(0.2861)	(0.8037)	(0.6752)
FEs	Yes	Yes	Yes	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	3,606	3,776	3,770
Pseudo R^2	0.0171	0.0166	0.0223	0.0176	0.0166	0.0169	0.0181	0.0227	0.0205	0.0186	0.0189

contribute (negative) information to prices by trading (e.g., Boehmer et al., 2008; Engelberg et al., 2012).

We replace *Factor* with the investor information proxies in Eq. (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; and 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 Hypothesis 1(a) that a firm manager is more likely to learn from her stock price if the latter contains more precise investor information.

4.2.3. 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. 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 market-model abnormal 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 et al., 2007; Gomes et al., 2007).

We regress the learning channel dummy *Learn* on *Insider* and *ERC* following Eq. (1) and report the Probit regression results in columns (3) and (4) of Table 3. Indeed, consistent with Hypothesis 1(b), 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%).

4.2.4. 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. We then 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. So, in the Chinese market, firms with more analysts' coverage report learning from the market less prominently, consistent with Hypothesis 1(c). As explained before, this prediction is derived under the assumption that analysts help to communicate information from managers to the markets and reduce price informativeness, which has received supporting evidence in the U. S. market (e.g., Bailey et al., 2003; Chen et al., 2007).

4.2.5. 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 Eq. (1) and report the Probit regression results in columns (7) and (8). As suggested by Hypothesis 1(d), 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.

4.2.6. Price informativeness

To test Hypothesis 1(e), we take the premise that other things being equal, when the prices contain more information, the firms also perceive so and thus we proxy for perceived informativeness using standard measures of price informativeness that have been used in previous studies: (1) 1-R^2, the R^2-based price nonsynchronicity (or firm-specific return variation) measure by Roll (1988) and Durnev et al. (2004). This measure is based on the return information, and reflects private information incorporated to stock prices through the trading activity of speculators; (2) *AdjPIN*, the adjusted probability of informed trading measure by Duarte and Young (2009). It is constructed with both the stock return and order information, and measures the amount of private information in stock prices from informed traders; and (3) *PriceDelay*, the price delay measure by Hou and Moskowitz (2005). It is based on stock returns and measures the average delay with which a firm's stock price responds to information, reflecting the information efficiency of stock prices. By construction, the measures of 1-R^2 and *AdjPIN* are positively associated with price informativeness, while the measure *PriceDelay* is negatively associated with price informativeness.

In testing Hypothesis 1(e), we regress *Learn* on the three informativeness measures. The Probit regression results are reported in columns (9), (10), and (11). The marginal effects of 1-R^2 and *PriceDelay* are 0.0742 and −0.0023 in columns (9) and (11), 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 (10). Thus, the results are generally consistent with our Hypothesis 1(e).

Note that the results in columns (9) to (11) can be alternatively interpreted as using survey evidence to evaluate empirical proxies for price informativeness. This is particularly relevant given the lack of a consensus in the literature on a well-accepted measure.[10] That is, if one trusts our survey data, then these results suggest that 1-R^2 and *PriceDelay* are more robust price-informativeness measures than *AdjPIN* in the Chinese context.

4.2.7. SOE

Among all the control variables, we observe that the coefficient on variable *SOE* is significantly negative across all regressions. These firms, which, given their close connection with the government and their political considerations, might be more susceptible to try and please in their responses, were actually responding less in favor of the learning channel. This pattern is consistent with theoretical reasoning and further validates our survey approach. Intuitively, SOEs assume certain social responsibilities and so their objective puts a smaller weight on profitability. As a result, they rely less on stock prices to extract information that is useful for enhancing investment profitability.

4.3. Validating the learning channel: Testing Hypothesis 2

We begin by examining the association between investment-to-price sensitivity and firms' survey responses to test Hypotheses 2(a) and 2(b), which connect firms' decisions on whether to learn from prices and what to learn to their real investment decisions. Subsequently, we use M&A settings to test Hypothesis 2(c), which concerns the consequences of learning from stock prices.

4.3.1. Investment-to-price sensitivity and survey responses: Testing Hypotheses 2(a) and 2(b)

We first describe the testing methodology. To test Hypotheses 2(a) and 2(b), we first define different testing samples. The *Full* sample spans from 2012 to 2021,[11] and includes all 4,171 sample responding firms in the 2022 survey. In testing Hypothesis 2(a), we divide the *Full* sample into two subsamples based on firms' responses to Question II: The *Learn* subsample includes firms selecting the learning channel, and the *NoLearn* subsample contains firms not selecting the learning channel. In testing Hypothesis 2(b), we utilize responses to Question III to define subsamples based on types of information firms extract from their stock prices. Specifically, for each statement about the information contents (See Subsection 2.1 for details about these statements), a firm falls into the *Affirm* subsample if it chooses "strongly agree" or "agree"; otherwise, the firm falls into the *NoAffirm* subsample. That is, the *Affirm* subsample contains firms that are more likely to learn from stock prices on specific dimensions of information, relative to the *NoAffirm* subsample firms.

Table 4

Investment-to-price sensitivity conditional on whether to learn.

This table reports the OLS regression results about firm investments following Eq. (2). The *Full* sample includes 4,171 responding firms in the 2022 survey. The *Learn (NoLearn)* subsample includes firms selecting (not selecting) the learning channel in Question II in the 2022 survey. 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 Appendix A2 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* *Sample* =	(1) *Full*	(2) *Learn*	(3) *NoLearn*
Q	0.0030***	0.0038***	0.0007
	(0.0006)	(0.0007)	(0.0011)
CF	0.0741***	0.0674***	0.0963***
	(0.0106)	(0.0121)	(0.0213)
Ret3	−0.0043***	−0.0042***	−0.0048**
	(0.0009)	(0.0010)	(0.0020)
InvAst	17.6647***	16.9093***	19.3833***
	(3.6817)	(4.4597)	(6.2245)
Cons.	0.0382***	0.0369***	0.0430***
	(0.0020)	(0.0024)	(0.0038)
FEs	Yes	Yes	Yes
N	16,156	12,273	3,883
R^2	0.5454	0.5498	0.5356
Diff in Coef.		0.0031**	

[10] For example, Dasgupta, Gan, and Gao (2010) suggest that a rapid incorporation of information into the stock prices decreases 1-R^2; Duarte and Young (2009) find that only the PIN component related to illiquidity is priced and propose the *AdjPIN* measure; and Griffin, Kelly, and Nardari (2010) show that *PriceDelay* may be misleading because they observed smaller delay in emerging markets.

[11] 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, managerial opinions, firm fundamentals and manager characteristics could be very different.

We next employ the following specification at the firm-year level to consider the association between firms' responses and the investment-to-price sensitivity:

$$Capxrnd_{i,t+1} = a_i + b_t + c^*Q_{i,t} + Controls_{i,t} + \varepsilon_{i,t}, \tag{2}$$

where *Capxrnd* denotes a firm's capital expenditure plus R&D expenses, scaled by the beginning-of-year assets; *Q* denotes Tobin's Q; *Controls* is a vector of control variables including net free cash flows from operation divided by book assets (*CF*), stock return in the next three years (*Ret3*), and the inverse of book assets (*InvAst*); all at the firm-year level. We also include the firm and year fixed effects in regressions to absorb any influence varying only with firm and time. We compare *c* in different subsamples to test Hypotheses 2(a) and 2(b).

In testing Hypothesis 2(a), we compare the investment-to-price sensitivity between firms that report the learning channel in Question II and those that do not. Table 4 reports the OLS regression results following Eq. (2). In the *Full* sample, the coefficient estimate on *Q* is positive and significant at the 1% level (column (1)), suggesting in general firms are responsive to investment signals revealed by their stock prices. More importantly, the positive effect only exists in the *Learn* subsample (column(2)); in contrast, the coefficient estimate is statistically insignificant in the *NoLearn* subsample (column(3)). The difference in coefficients between the two subsamples is positive and significant at the 5% level. The above results are consistent with Hypothesis 2(a), validating our survey results by showing learning firms do act on what they say in the survey.

Table 5 tests Hypothesis 2(b) by comparing the investment-to-price sensitivities of firms that affirm learning about specific information types in Question III with those that do not. The results reveal distinct patterns between the *Affirm* and *NoAffirm* subsamples for nearly every information type listed. Specifically, we make two key observations. First, investment-to-price sensitivities are consistently higher in the *Affirm* subsamples than in the *NoAffirm* subsamples for every information type. The difference is statistically significant at the 1% level for all types except Covid-related information. Second, the sensitivities in the *Affirm* subsamples are statistically significant (at the 1% or 5% levels) for all information types. In contrast, the sensitivities in the *NoAffirm* subsamples are insignificant for several types (e.g., macro, policy, competitive position, and product demand). These results provide strong support for Hypothesis 2(b) and validate that firms seek to extract the types of information listed in Question III to guide their real investments.

4.3.2. *Value enhancement by learning in the case of M&As: Testing Hypothesis 2(c)*

In this subsection, we test Hypothesis 2(c) and address the question of whether firms who say they learn from the market indeed enhance shareholder value. Given that a decision not to learn could reflect particular managerial background or attitude, such a decision can be suboptimal, and so we may expect learning firms to show better performance on some dimensions. To answer such a question, we focus on the context of M&As. Specifically, we expect that if learning is value-creating, acquiring firms that learn information about potential M&A

Table 5
Investment-to-price sensitivity conditional on what to learn about.
This table reports the OLS regression results about firm investments following Eq. (2). For each information type in Question III, a firm falls into the *Affirm* subsample if it chooses "strongly agree" or "agree"; otherwise, the firm falls into the *NoAffirm* subsample. 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 Appendix A2 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)**
Info =	***Macro***		***Policy***		***Competition***		***Demand***	
Sample =	***Affirm***	***NoAffirm***	***Affirm***	***NoAffirm***	***Affirm***	***NoAffirm***	***Affirm***	***NoAffirm***
Q	0.0043***	0.0004	0.0044***	0.0006	0.0044***	0.0005	0.0054***	0.0011
	(0.0008)	(0.0009)	(0.0008)	(0.0009)	(0.0008)	(0.0009)	(0.0010)	(0.0007)
CF	0.0703***	0.0829***	0.0622***	0.0983***	0.0708***	0.0810***	0.0699***	0.0782***
	(0.0131)	(0.0177)	(0.0131)	(0.0178)	(0.0138)	(0.0160)	(0.0162)	(0.0137)
Ret3	−0.0047***	−0.0035**	−0.0046***	−0.0034**	−0.0044***	−0.0042***	−0.0056***	−0.0033***
	(0.0011)	(0.0017)	(0.0011)	(0.0016)	(0.0011)	(0.0016)	(0.0013)	(0.0012)
InvAst	16.6759***	19.1900***	14.1341***	23.0760***	16.2964***	19.5643***	21.7721***	14.6705***
	(4.5353)	(5.9928)	(4.6952)	(5.6693)	(4.8752)	(5.3312)	(5.9489)	(4.3146)
Cons.	0.0358***	0.0435***	0.0368***	0.0410***	0.0357***	0.0431***	0.0322***	0.0431***
	(0.0025)	(0.0034)	(0.0025)	(0.0034)	(0.0026)	(0.0031)	(0.0032)	(0.0024)
FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	11,040	5,116	10,591	5,565	10,405	5,751	7,178	8,978
R^2	0.5547	0.5294	0.5485	0.5438	0.5452	0.5492	0.5482	0.5465
Diff in Coef.	0.0039***		0.0038***		0.0039***		0.0043***	

Y* =*Capxrnd	**(9)**	**(10)**	**(11)**	**(12)**	**(13)**	**(14)**	**(15)**	**(16)**
Info =	***Technology***		***Cost of Capital***		***Acquisition***		***Covid***	
Sample =	***Affirm***	***NoAffirm***	***Affirm***	***NoAffirm***	***Affirm***	***NoAffirm***	***Affirm***	***NoAffirm***
Q	0.0051***	0.0017**	0.0044***	0.0019**	0.0048***	0.0018**	0.0042***	0.0024***
	(0.0011)	(0.0007)	(0.0009)	(0.0008)	(0.0010)	(0.0007)	(0.0011)	(0.0007)
CF	0.0717***	0.0762***	0.0786***	0.0705***	0.0979***	0.0582***	0.0917***	0.0658***
	(0.0176)	(0.0131)	(0.0158)	(0.0143)	(0.0190)	(0.0121)	(0.0186)	(0.0128)
Ret3	−0.0048***	−0.0042***	−0.0053***	−0.0036***	−0.0037**	−0.0049***	−0.0052***	−0.0039***
	(0.0015)	(0.0011)	(0.0014)	(0.0011)	(0.0015)	(0.0011)	(0.0016)	(0.0011)
InvAst	17.6897***	17.8215***	14.4373**	20.4397***	16.7639***	17.7030***	12.8295**	19.8795***
	(5.9677)	(4.5414)	(5.8220)	(4.6259)	(6.0244)	(4.5420)	(5.8807)	(4.6638)
Cons.	0.0333***	0.0411***	0.0380***	0.0383***	0.0324***	0.0423***	0.0369***	0.0389***
	(0.0033)	(0.0025)	(0.0033)	(0.0026)	(0.0035)	(0.0024)	(0.0035)	(0.0025)
FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	6,422	9,734	7,381	8,775	6,493	9,663	5,507	10,649
R^2	0.5551	0.5411	0.5547	0.5377	0.5388	0.5521	0.5500	0.5437
Diff in Coef.	0.0033***		0.0024**		0.0030**		0.0017	

opportunities from their stock prices should be better informed, and outperform their non-learning counterparts.

We retrieve information on M&A deals from 2018 to 2022 in the Chinese market from the CSMAR database. We measure a firm's acquiring performance (*MA*) using the following four proxies: (1) *NAnnounce*, the number of merger proposals announced by the firm in the sample period, in which it acts as the acquirer; (2) *NCompletion*, the number of mergers that are completed successfully by the firm; (3) *BHAR*, the buy-and-hold abnormal return, adjusted by industry, size, and book-to-market ratio, in the 12 months following the completion of the merger; and (4) *CAR*, the cumulative abnormal return from day −1 to +1 around the announcement date of the merger proposal, estimated with the market model.

We develop a proxy (*LearnAcq*) to measure to what extent a firm learns information about M&A opportunities based on its opinion on Choice G, Question III in the 2022 survey (see Subsection 2.1 for the survey question and Subsection 3.3 for an analysis of the responses). *LearnAcq* takes the value of 2 if a firm chooses "strongly agree" for the statement "*Information about the prospects of the company's potential acquisitions of other companies, assets, or technologies can be useful when learning from the market*"; and it takes the value of 1 for "agree", 0 for "neutral", −1 for "disagree", and −2 for "strongly disagree". It also takes the value of −2 if a firm doesn't learn (doesn't choose Choice A in Question II) or doesn't monitor its stock price at all (doesn't choose A or C in Question I).

To test the effect of learning on firms' acquiring performance, we run the following regression:

$$MA = a + b^{*}LearnAcq + Controls + \varepsilon, \tag{3}$$

where *MA* and *LearnAcq* are defined as above and *Controls* includes *Size, Leverage, History*, and *SOE*. The respondent position, industry, and province fixed effects are included in the *NAnnounce* and *NCompletion* regressions; and the year fixed effects are further included in the *BHAR* and *CAR* regressions.

Table 6

The learning channel and merger performance.

This table reports the OLS regression results on the effects of learning on firms' merger performance following Eq. (3). The sample consists of M&A transactions from 2018 to 2022 in which firms responding to the 2022 survey are acquirers. The dependent variables include the number of M&A announcements, the number of completed mergers, the buy-and-hold abnormal return during the 12 months following the completion, and the cumulative abnormal return from day −1 to day 1 around the announcement. The independent variable is the degree to which a manager learns information about potential M&A opportunities according to the 2022 survey. The respondent position, industry, and province fixed effects are included in columns (1) and (2); and the year fixed effects are further included in columns (3) and (4). See Appendix A2 for variables definitions. Standard errors reported in parentheses are adjusted for heteroscedasticity and clustering at the industry level. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Y=	(1) *NAnnounce*	(2) *NCompletion*	(3) *BHAR*	(4) *CAR*
LearnAcq	0.0531***	0.0167**	0.0140***	0.0011**
	(0.0158)	(0.0063)	(0.0033)	(0.0005)
Size	0.1412***	0.0252*	−0.0075	0.0001
	(0.0267)	(0.0136)	(0.0098)	(0.0013)
Leverage	0.9316***	0.4857***	0.1575***	0.0016
	(0.2012)	(0.0482)	(0.0222)	(0.0049)
History	0.0241***	0.0050***	−0.0014*	0.0002
	(0.0037)	(0.0013)	(0.0007)	(0.0002)
SOE	−0.1246	−0.0830***	−0.0038	0.0019
	(0.0788)	(0.0200)	(0.0134)	(0.0014)
Constant	−0.4585**	0.0553	0.0099	0.0001
	(0.1609)	(0.1046)	(0.0767)	(0.0100)
FEs	Yes	Yes	Yes	Yes
Observations	4,166	4,166	1,997	5,093
R^2	0.0900	0.0337	0.0512	0.0241

Table 6 reports the OLS regression results. The coefficient estimates on *LearnAcq* are 0.0531 and 0.0167 in columns (1) and (2), which are statistically significant at the 1% and 5% levels. This suggests firms learning M&A information bid for other firms or assets more frequently and manage to complete the deal in more cases. With respect to the economic magnitude, the number of proposals (*NAnnounce*, mean=1.40) and completed deals (*NCompletion,* mean=0.51) increase by 3.8% and 3.2%, if *LearnAcq* increases by 1 (for example, the opinion on learning acquisition information moves from "neutral" to "agree"). Columns (3) reports results on the post-merger performance for the successfully completed deals. The coefficient estimate on *LearnAcq* is 0.0140 and significant at the 1% level, suggesting relative to acquiring firms not learning the M&A information, learning acquirers are better at target selection and post-merger integration, and create more value for shareholders. This effect is quite sizable: If *LearnAcq* increases by 1, the acquirer's stock performance in 12 months following the merger (*BHAR*, mean=0.75%) would increase by 17.3% relative to the sample mean. Similarly, we find *LearnAcq* is positively and significantly correlated to the stock market reaction around the announcements of those merger proposals, pointing to a value-enhancing effect.

Overall, our results support the view that learning from stock prices is value-enhancing in the context of M&As. If an acquirer intensively learns information about potential M&A opportunities from its stock price, it is more likely to bid for other firms or assets and has a higher probability of completing the deal successfully. More importantly, its stock performs better both in the long run and around the announcement, suggesting learning do enhance shareholder value.

5. 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). We have also validated the survey responses regarding the learning channel by linking firms' responses to their characteristics and real investments in Section 4. 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) for the learning channel. Similar testing results for the financing channel are also presented as a comparison. 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.

5.1. 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 risk, (7) media reports, and (8) financing activities, among many others.[12] 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 a concrete reason.

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 2020 to 2022. Table 7 reports summary statistics on trading suspensions of the 4,641 responding firms in the 2022 survey. During the period, there were 1,532 suspensions in

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

Table 7
Summary of trading suspensions.
This table reports summary statistics for trading suspensions by firms responding to the 2022 survey from 2020 to 2022.

	Full sample		*≥ 1 day (4 trading hours)*	
Reason	N. Suspension	Duration (trading hours)	N. Suspension	Duration (trading hours)
All	1532	11.8	1047	17.1
- Important matters	791	16.5	788	16.6
- Transaction related	484	0.8	10	21.6
- Major risk	130	6.4	130	6.4
- M&A/restructure	105	34.1	105	34.1
- Financing/Shareholder meeting/Media report	8	18.5	8	18.5
- Unknown/others	14	9.7	6	20.7

Table 8
Real effects and trading suspensions.
This table reports the Probit regression results about the effects of the learning and financing channels on firms' trading suspensions following Eq. (4). The sample covers trading suspensions by firms responding to the 2022 survey from 2020 to 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 Appendix A2 for definitions of variables. Marginal effects are reported. Standard errors reported in parentheses are adjusted for heteroscedasticity and clustering at the year level. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Y = Susp	(1)	(2)	(3)	(4)
Feedback =	*Learn*		*Fin*	
Feedback	−0.0012***	−0.0015***	0.0000	−0.0002
	(0.0004)	(0.0005)	(0.0005)	(0.0006)
PriceDrop		−0.0012		−0.0012
		(0.0010)		(0.0010)
*Feedback*PriceDrop*		0.0011***		0.0012***
		(0.0002)		(0.0004)
Size	−0.0005	−0.0005	−0.0005	−0.0005
	(0.0004)	(0.0004)	(0.0004)	(0.0004)
Leverage	0.0038***	0.0038***	0.0038***	0.0038***
	(0.0005)	(0.0005)	(0.0006)	(0.0005)
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
	(0.0003)	(0.0003)	(0.0003)	(0.0002)
FEs	Yes	Yes	Yes	Yes
N	133,463	133,463	133,463	133,463
Pseudo R^2	0.0438	0.0441	0.0428	0.0431

total (0.11 suspension per firm in one year), and on average a suspension lasts for 11.8 trading hours. 1,047 (68.3%) 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" (51.6%), followed by "transaction related" (31.6%) and "major risk" (8.5%).

5.2. Active management of trading suspensions

We attempt to connect public firms' trading suspensions (what firms do) to their responses about the real effects 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 affirming the learning channel are less likely to suspend trading, because trading suspension shrinks the firms' information set by one signal, the stock price. Second, in adverse market circumstances, public firms can also suspend trading to avoid extreme price drops (e.g., Huang et al., 2019), which hurts their capacity of raising capital from the market. Thus, we conjecture that if the stock price drops a lot and firms affirm the financing channel, they will suspend trading more frequently. Formally, we have the following hypothesis:

Hypothesis 3. (*Trading Suspension*). *(a) Those firms, who respond that they learn information for stock prices, are less likely to suspend the trading of their stocks. (b) Those firms, who respond that they monitor 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 et al. (2021) and exclude suspensions shorter than one day (4 trading hours) to construct the testing sample. We only include 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:

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

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*, which equals one if a firm chooses A in Question II, and zero otherwise; *Fin*, which equals one if a firm chooses B in Question II, and zero otherwise. $PriceDrop_{i,t}$ 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 quartile among all firm-months (the cutoff value for the bottom quartile is −7.6%), and zero otherwise. *Controls* includes all the firm-level control variables as in Eq. (1). In addition, we include the year, month, position, industry, and province fixed effects across regressions.

We report the regression results in Table 8. Columns (1) and (2) use *Learn* as the independent variable. In column (1), the marginal effect of *Learn* is −0.12% and significant at the 1% level. Hence, for public firms reporting the learning channel in the 2022 survey, the probability of suspending trading in each month is 0.12% lower than those non-learning firms. Considering the unconditional suspension probability being 0.57% 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. The negative regression coefficients on *Learn* in columns (1) and (2) align with Hypothesis 3(a). We also find that the marginal effect of the interaction term in column (2) is positive and significant, suggesting that firms monitoring prices for investment information suspend trading more frequently following large stock price declines. While the exact mechanism underlying this result remains unclear, one potential explanation is that severe price drops may reduce price informativeness, for instance, by triggering margin calls or panic selling.

Columns (3) and (4) 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 1% level in column (4), suggesting that if stock prices drop a lot and firms monitor prices for the financing purpose, they suspend more frequently to maintain the price levels. Again, these results confirm Hypothesis 3(b).

6. Conclusion

In this paper, we take a survey approach to examine 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 99.9% and 98.1%, respectively. Our survey reveals that more than 90% of firms monitor the stock market, with the two primary motivations being learning from prices and securing financing. Our analysis focuses on the learning channel because its existence is the primary point of skepticism in the literature. Our survey evidence suggests that the macro, industry, policy, regulatory, and competitiveness information, which is external to the firm and with greater benefit to aggregation across different market participants, is the most important information that firms learn from financial markets. These findings provide direct evidence for the wide existence of the real effects of financial markets through a learning channel.

We study how the survey responses relate to firms' characteristics and actions to explain and validate the survey results. We find that firms are more likely to monitor their stock prices for learning purposes when their investors are more informed, their managers are less informed, they are covered by fewer analysts, their managers are better educated or have more relevant backgrounds, and their stock prices are more informative. We also find a higher investment-to-price sensitivity among firms that affirm the learning channel. Furthermore, our results indicate that learning from stock prices enhances value in the context of M&As.

Finally, by examining firms' decisions to suspend trading, we find a high consistency between their reported motivations and their actions. Firms that affirm the learning channel are less likely to suspend trading, thereby preserving information production. In contrast, firms that affirm the financing channel are more likely to suspend trading following large price drops to maintain certain price levels. Taken together, our analysis highlights the prevalence of market feedback, particularly through an informational learning channel that connects financial markets to the real economy.

CRediT authorship contribution statement

Itay Goldstein: Writing – review & editing, Writing – original draft, Validation, Supervision, Resources, Project administration, Methodology, Investigation, Formal analysis, Conceptualization. **Bibo Liu:** Writing – review & editing, Writing – original draft, Visualization, Validation, Software, Resources, Project administration, Methodology, Formal analysis, Data curation, Conceptualization. **Liyan Yang:** Writing – review & editing, Writing – original draft, Validation, Supervision, Resources, Project administration, Methodology, Investigation, Funding acquisition, Formal analysis, Conceptualization.

Declaration of competing interest

Itay Goldstein has no conflicts of interest to disclose.

Bibo Liu has no conflicts of interest to disclose.

Liyan Yang has received financial support from Bank of Canada Fellowship and Social Sciences and Humanities Research Council (SSHRC) for the research described in this article. There are no other conflicts of interest to disclose.

Supplementary materials

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.jfineco.2026.104255.

Appendix. Industry analysis and variable definitions

Appendix A1. Survey Responses by Industry

Table A1
Responses to 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 %	0.0 %	7.8 %
Media	128	2.3 %	0.8 %	89.1 %	0.0 %	7.8 %
Telecommunication	91	8.8 %	0.0 %	83.5 %	0.0 %	7.7 %
Environment	64	6.3 %	0.0 %	87.5 %	0.0 %	6.3 %
Electrical equipment	176	6.3 %	1.1 %	86.4 %	0.0 %	6.3 %
Construction materials	82	7.3 %	0.0 %	86.6 %	0.0 %	6.1 %
Defense	73	11.0 %	2.7 %	83.6 %	0.0 %	2.7 %
Oil	33	9.1 %	3.0 %	84.8 %	0.0 %	3.0 %
Social service	53	18.9 %	1.9 %	77.4 %	0.0 %	1.9 %
Home appliance	59	3.4 %	0.0 %	93.2 %	0.0 %	3.4 %
Composite	51	7.8 %	2.0 %	84.3 %	0.0 %	5.9 %
Nonferrous metals	111	6.3 %	1.8 %	87.4 %	0.0 %	4.5 %
Chemical	314	8.6 %	1.0 %	84.7 %	0.3 %	5.4 %
Automobile	176	7.4 %	0.6 %	83.0 %	0.6 %	8.5 %
Real estate	130	7.7 %	0.8 %	80.0 %	0.8 %	10.8 %
Construction	130	6.2 %	3.1 %	83.8 %	0.8 %	6.2 %
Commerce	103	8.7 %	1.0 %	78.6 %	1.0 %	10.7 %

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Table A1 (*continued*)

Food and beverage	94	7.4 %	0.0 %	84.0 %	1.1 %	7.4 %
Agriculture	89	7.9 %	1.1 %	86.5 %	1.1 %	3.4 %
Electronics	234	9.8 %	0.9 %	81.6 %	1.3 %	6.4 %
Computer	211	4.7 %	0.9 %	89.1 %	1.4 %	3.8 %
Transportation	112	11.6 %	0.0 %	80.4 %	1.8 %	6.3 %
Light industry	97	2.1 %	4.1 %	84.5 %	2.1 %	7.2 %
Pharmaceutical	289	4.8 %	0.0 %	87.9 %	2.1 %	5.2 %
Machinery	342	9.6 %	0.3 %	82.2 %	2.3 %	5.6 %
Steel	37	10.8 %	2.7 %	75.7 %	2.7 %	8.1 %
Banking	32	0.0 %	3.1 %	90.6 %	3.1 %	3.1 %
Textile	96	6.3 %	1.0 %	81.3 %	3.1 %	8.3 %
Non-banking finance	71	1.4 %	0.0 %	84.5 %	5.6 %	8.5 %
Coal	35	17.1 %	2.9 %	62.9 %	5.7 %	11.4 %
Beauty	11	0.0 %	0.0 %	90.9 %	9.1 %	0.0 %

Panel B: II. *Which of the following is the reason that your company pays attention to the stock price of your own company?* $N = 3{,}320$

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

Table A2

Responses to 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 %

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Table A2 (*continued*)

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 pays attention to the stock price of your OWN company?* $N = 4{,}420$

Industry	N. firms	A. Learn	B. Finance	C. Compensation	D. Monitor	E. M&A
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 A3

Responses to Question III in the 2022 survey by industry.

This table summarizes the responses to 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/ regulations	C. Compet. position	D. Custom. demand	E. Technology	F. Cost of capital	G. Potential acquisition	H. COVID impact	I. 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 %

(*continued on next page*)

Table A3 (*continued*)

Industry	A. Econ./ind. state	B. Policies/ regulations	C. Compet. position	D. Custom. demand	E. Technology	F. Cost of capital	G. Potential acquisition	H. COVID impact	I. No info.
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 %

Appendix A2. Variable definitions

Table A4
Variable definitions.
This table provides the definitions of those variables used in Sections 4 and 5. 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 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 market-model abnormal 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.
1-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).
Capxrnd	A firm's capital expenditure plus R&D expenses, scaled by the beginning-of-year assets.
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 next three years.
NAnnounce	The number of merger proposals announced by a firm in the sample period, in which it acts as the acquirer.
NCompletion	The number of M&A deals completed by a firm in the sample period, in which it acts as the acquirer.
BHAR	The industry, size, and book-to-market ratio adjusted buy-and-hold abnormal return in the 12 months following the completion of the merger.
CAR	The cumulative abnormal return from day −1 to +1 around the announcement date of the merger proposal, estimated with the market model.
LearnAcq	The degree to which a firm learns information about M&A opportunities based on its opinion on Choice G, question III in the 2022 survey. It takes the value of 2 if a firm chooses "strongly agree" for the statement "*Information about the prospects of the company's potential acquisitions of other companies, assets, or technologies can be useful when learning from the market*"; and it takes the value of 1 for "agree", 0 for "neutral", −1 for "disagree", and −2 for "strongly disagree". It also takes the value of −2 if a firm doesn't learn (doesn't choose Choice A in question II) or doesn't monitor its stock price at all (doesn't choose A or C in question I).
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 quartile among all firm-months, and zero otherwise.

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