Mandatory Disclosure, Investment Efficiency, and Learning: Evidence from China

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Abstract

Mandatory disclosure could increase price informativeness by crowding in the manager's unknown information into the price. By learning from the price, the manager increases the firm's investment efficiency. In this study, we use the mandatory disclosure regulation of company visits as an exogenous shock to test the learning channel. We find that there is a positive learning effect in the Chinese market. Consistent with the learning theory, we show that the effect is determined by the information types of disclosure. In addition, a higher disclosure precision will amplify this effect: firms that disclose more precise information exhibit a stronger learning effect. Overall, we add to the existing literature novel empirical evidence on the learning channel of mandatory disclosure and its real effect.

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JEL: G10, G30, M41

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1. Introduction

The economic implications of mandatory disclosure for investments have attracted increasing attention in the literature (Bond et al., 2012; Bai et al., 2016; Goldstein and Yang, 2019). In particular, prior studies have demonstrated that stock prices contain valuable information from which investors will learn (Hayek, 1945; Carpenter et al., 2021; Goldstein et al., 2021). Later, the existing theory underscores the critical role of the information types: Disclosing information that managers already possess could always improve price informativeness and real efficiency, whereas the impact of disclosing information such as firm competition, which managers are interested in but may not understand as thoroughly as outsiders, may be ambiguous (Goldstein and Yang, 2019). Despite this significant finding, current research has offered limited empirical evidence for it, mainly due to the challenges in measuring information type from disclosure. Our goal is to fill this gap by constructing proxies that are consistently available and comparable to support the theory.

We first utilize the Chinese stock market to test the overall learning effects of disclosure. On July 17, 2012, the Shenzhen Stock Exchange (SZSE) mandated listed firms to disclose corporate site visits within two trading days, resulting in 48,985 disclosures from 2012 to 2021.[1] In contrast, companies listed on the Shanghai Stock Exchange (SSE) were not subject to this policy. Consequently, only 9 disclosures occurred during the same period. This discrepancy serves as an exogenous regulatory shock, allowing us to assess the causal impact of mandatory disclosure by comparing firms listed in SZSE and SSE.[2]

Specifically, we adopt an investment-to-price framework as used in Edmans et al. (2017) and Jayaraman and Wu (2019). We find that the investment-q sensitivity for SZSE firms (affected) is substantially greater than its counterpart for SSE firms

[1]The information is disclosed through an official online platform called "*Hu Dong Yi*" (Easy-communications), see example in Appendix A.1

[2]The SZSE and SSE are independently operated but under the same regulations of "The Chinese Securities Regulatory Commission (CSRC)".

(unaffected) after the mandatory disclosure regulation. The results demonstrate a crowding-in effect of disclosure and illustrate the presence of the firm's learning behavior. We also find that firms do not learn information that has already been reflected in the past stock price: the falsification test shows that the sensitivity of cash flows is insignificant, and prices do not predict past investments.

Next, we use the textual analysis method to directly identify the information type of disclosure. We follow Loughran and McDonald (2011) and use a dictionary-based method to count the proportion of f and a in the firm's disclosure. Following Goldstein and Yang (2019), a is about the firm's fundamental information, and f is information about the firm's competition (e.g., information about future and prospective). Goldstein and Yang (2019) shows that disclosing a type information could always lead to a positive crowding-in learning effect. If managers disclose more of this type of information to the market after the regulation, the learning effect should be more pronounced and firms will also benefit from it and improve their investment-q sensitivity. Indeed, our empirical tests show consistent results to the learning theory: we find that the crowding-in learning effect exists and the overall effect in terms of investment efficiency depends on the proportion of each type of information firms disclose.

Our findings hold up in a variety of robustness tests: one concern is that a firm may not disclose any a information. One reason could be that the firm does not operate functionally, which is likely to have abnormal investment and stock prices. If information type matters, not disclosing any a information would not bring any crowding-in learning effect. To test it, we compare firms with zero proportion of a type information (zero-info firms) with Non-zero a ones (non-zero-info firms) in the SZSE sample. The difference in investment-q sensitivity between these two groups is significant after the regulation. This result supports the theory of the importance of information type. We also test the difference between these non-zero-info firms and firms in the SSE sample. Since firms in the SSE sample do not disclose more due to the mandatory disclosure regulation, the learning effect from disclosure should be limited for these two groups. Consistently, we show that the difference in investment-q sensitivity between these two groups is insignificant, which further supports our result that information types matter in the learning channel for the increased investment-q sensitivity. Second, dictionary-based textual analysis methods require the manual selection of relevant words, making them potentially subjective. Following Li et al. (2021), we instead utilize machine learning technology and employ word embedding methods to identify the most relevant words in the disclosure objectively. We find that the results from robustness tests align with our main findings.

Finally, we investigate how increasing disclosure precision affects learning. We follow Wang et al. (2023) and Huang et al. (2014) and construct two variables, *Certainty* and *Commonly*, to measure disclosure precision. Disclosure with higher *Certainty* has more definite words (e.g., extreme, very) than undefined words (e.g., -ish, insufficiently), and disclosure with higher *Commonly* has a higher proportion of commonly used words. Since increasing information precision is beneficial to improving the stock market information environment (Diamond, 1985; Diamond and Verrecchia, 1991; Balakrishnan et al., 2014; Bowen et al., 2018; Yang et al., 2020), increasing the precision of disclosure is therefore beneficial to amplify the market feedback, enhancing the learning effect and improving the investment efficiency. Consistent with this, we find that firms with a higher level of *Certainty* and a higher level of *Commonly* have a higher investment-q efficiency for *a* type of disclosure. Both of these results are consistent with our main findings.

Our study contributes to existing literature in two aspects. First, we contribute to the literature on disclosure. Prior studies focus on the market effects of company visit events (Han et al., 2018; Cheng et al., 2019), whereas our study focuses on the real effects of financial markets. The stock market is not just a sideshow but can significantly influence real economic activity (Bond et al., 2012). Our findings demonstrate that the feedback effect from market prices resulting from more disclosure significantly impacts the firm's investment-q sensitivity in the Chinese market. Previous studies have paid limited attention to this distinction, instead emphasizing information acquisition channels such as analysts' forecasts, earnings forecast accuracy, and analysts' visit preferences (Yang et al., 2020; Cheng et al., 2016). We find this distinction rather important, as it yields a significant difference before and after the disclosure regulation around visits.

Second, our work also relates to recent work about the emerging learning theory. Despite the topic's importance, Previous research primarily focused on exploring the learning effect theoretically (Bond et al., 2012; Goldstein and Yang, 2019) or empirically relies on an indirect measurement: the investment-to-price framework (Edmans et al., 2017; Jayaraman and Wu, 2019; Carpenter et al., 2021). Our paper extends and complements these earlier efforts by employing state-of-the-art textual analysis techniques to identify specific types of information and directly test the learning effect. Our study also provides one of the first attempts to empirically test the learning effect of disclosure in China. We show that a positive crowding-in effect of learning is significant in the Chinese market after the mandatory disclosure regulation. The results complement Goldstein and Yang (2019)'s theory and can jointly explain the real effect of disclosure. In addition, we show that increasing disclosure precision could enhance the learning effect. We identify that the crowding-in learning effect is more pronounced for firms with higher precision and for financially unconstrained firms as well as firms with more private information. Our study thus broadens the economic consequences of mandatory disclosure and provides the political implication for creating disclosure policies in developing markets.

The rest of this paper proceeds as follows. Section 2 discusses the empirical strategy, data, and samples, Section 3 presents the empirical results. Finally Section 4 concludes.

2. Empirical strategy, data and sample selection

In this section, we discuss the empirical strategy and the data used in our analysis.

2.1. Mandatory disclosure and the learning effect

Following Edmans et al. (2017) and Jayaraman and Wu (2019), we use a difference-in-differences (DID) method to test for the effects of the mandatory disclosure regulation. The DID method compares changes in investment-q sensitivity between treated firms listed in the SZSE, which are affected by the adoption of mandatory disclosure requirements, and control firms listed in the SSE which are unaffected.

Specifically, we run a firm-level regression that interacts the investment-q sensitivity with the implementation of mandatory disclosure as follows:

$$\begin{aligned}
Invstment_{i,t+1} &= \alpha_i + \gamma_t + \beta_1 q_{i,t} + \beta_2 Cash_{i,t} + \beta_3 Treat_i * Post_t + \beta_4 q_{i,t} * Treat_i \\
&+ \beta_5 q_{i,t} * Post_t + \beta_6 q_{i,t} * Treat_i * Post_t + \beta_7 Cash_{i,t} * Treat_i + \beta_8 Cash_{i,t} * Post_t \\
&+ \beta_9 Cash_{i,t} * Treat_i * Post_t + \tilde{\theta} Controls_{i,t} + \varepsilon_{i,t},
\end{aligned} \tag{1}$$

where α_i denotes firm-fixed effects, γ_t captures year fixed effects and $Invstment_{i,t+1}$ is the dependent variable, defined as firm i's capital expenditures in year $t+1$ scaled by the total assets as of year t. $Treat_i$ is a dummy variable that equals 1 if firm i is listed in the SZSE and 0 if this firm is listed in the SSE. $Post_t$ is a dummy variable that equals 1 on and after the disclosure regulation was implemented and 0 otherwise.

In our model, q denotes Tobin's q, which is constructed using the ratio of a firm's market value over its book value. The coefficient of the interaction term $q * Treat * Post$, i.e. β_6, is the focus of our empirical analysis. Note that this is different from a standard difference-in-differences framework, which studies the effect of an event on a level variable. In our model, this would correspond to the impact of the mandatory disclosure on investment, i.e. β_3. In contrast, here we are interested in the investment-q sensitivity, which is a slope coefficient. A positive sign of the coefficient of the interaction term $q * Treat * Post$ indicates that the investment-q sensitivity increases for firms in SZSE due to the enforcement of the disclosure regulation.

We include cash flows ($Cash$) as a non-price measure (Edmans et al., 2017), which is equal to revenue plus depreciation and amortization, scaled by assets. We interact $Cash$ with the disclosure regulation as what we have done to q. This allows us to compare our main results for q against $Cash$. We also control for firm size ($Size$), measured by the natural logarithm of total assets, the number of years a firm is listed in the stock market ($Listage$), the change of a firm's annual market value ($Return$), and a firm's leverage level ($Leverage$), which is measured by a firm's total debt divided by total assets. $\tilde{\theta}$ is a vector of coefficients for control variables. We cluster standard errors at the industry level. To mitigate potential outliers, we winsorize all continuous variables at 1% and 99% levels.

2.2. Type of disclosure information

To test the role of information type, we follow Wang et al. (2023) and Huang et al. (2014) and employ a textual analysis method to process the content of disclosures to create two variables that capture information about a and f factors respectively. Specifically, we extract the meeting content, which includes questions from company visitors and answers from managers, from each disclosure and cut the sentences using a widely used Chinese textual analysis package ("jieba") for text segmentation. We then identify words that relate to information of type a or f. According to Goldstein and Yang (2019), hard facts such as firm revenues, profits, or corporate events are related to the a factor (firm fundamentals); on the other hand, information such as forecasts for a firm's future performance aligns with the f factor.

- a words include "*xiao shou qing kuang*"(sales), "*gai kuang*"(general information), "*cheng guo*"(achievement), "*bu ju*"(business arrangement and organizational structures), and "*ying li mo shi*"(profitable activities).
- f words include "*wei lai*"(future), "*jiang lai*"(future), "*ji hua*"(plan), "*zhi hou*"(after), and "*ying xiang*"(influence).

We apply the word frequency method proposed by Jegadeesh and Wu (2013) to measure the amount of a and f type information contained in each disclosure.

This is done by computing a ratio that divides the number of a (f) words by the total number of words for a disclosure. Then, we average the two ratios across all disclosures released by firm i in year t to construct $a_{i,t}$ and $f_{i,t}$ respectively. Ideally, it would be better if we could compare individual disclosures to access the impacts of disclosing different types of information to the public on the investment-q sensitivity. However, given that we only have access to annual investment data, integrating the information data to the annual level is the only way to proceed with our analysis.

With the two variables constructed previously, we explore how disclosing different types of information affects investment-q sensitivity, using a fixed-effects model as follows:

$$Investment_{i,t+1} = \tilde{\alpha}_i + \tilde{\gamma}_t + \tilde{\beta}_1 q_{i,t} + \tilde{\beta}_2 q_{i,t} * a_{i,t} + \tilde{\beta}_3 q_{i,t} * f_{i,t} + \tilde{\theta} Controls + \varepsilon_{i,t}, \quad (2)$$

where α_i is the firm fixed effect and γ_t is the year fixed effect. The two interaction terms $q * a$ and $q * f$ are of interest for our analysis. We include cash flows, firm size, the change of a firm's market value, the number of years a firm is listed in the stock market, and a firm's leverage as controls in the regression.

2.3. Precision of disclosure information

We construct two variables $Certainty$ and $Common$ to test the role of information precision. Specifically, we follow Wang et al. (2023) and apply a dictionary-based textual analysis method. We use HowNet Vocabulary as our word dictionary. The HowNet dictionary is one of the most commonly used sentiment dictionaries involving Chinese text. We assign a word as carrying either a positive or negative emotion and rank the strength of emotion into 6 categories. Ranging from the most definite "over / super", "extreme / most", "very", to undefined "more", "-ish", "insufficiently". Disclosure with higher precision has more positive words (e.g., extreme, very) than negative words (e.g., -ish, insufficiently). The variable $Certainty$ is then computed as the difference of the frequency between positive and negative words, adjusted by the total number of emotional words in the disclosure.

Our second proxy *Common* is the ratio of commonly used words. Similarly, we use a dictionary-based method to identify words using 56,064 commonly used Chinese words.[3] The ratio of these common words in the disclosure is calculated to measure the extent of their usage and gauge the precision of the text. Alternatively, we restrict *Certainty* and *Common* to appear only in the same sentence as the identified "a-words" and "f-words" to gauge the precision more accurately.

We run a fixed-effects model of future investment over q and its interaction with the information types and precision as follows:

$$\begin{aligned} Investment_{i,t+1} = \gamma_1 q_{i,t} + \gamma_2 q_{i,t} * a_{type} * precision + \gamma_3 q_{i,t} * f_{type} * precision \\ + \gamma_4 Controls + \alpha_i + \gamma_t + \varepsilon_{i,t}, \end{aligned} \tag{3}$$

where α_i is the firm fixed effect and γ_t is the year fixed effect. The two interaction terms $q * a_{type} * precision$ and $q * f_{type} * precision$ are of interest for our analysis. $precision$ is the precision measure we constructed before and control variables are the same as in the main regression.

2.4. Sample and variables

The firm-level data used in this study is from the China Stock Market and Accounting Research Database (CSMAR) and Wind databases. Our sample covers the period between 2007 and 2017, that is, 5 years before and after the introduction of the disclosure requirement, respectively. To address the high debt issue in their operational activities, we exclude all financial companies from our sample. Additionally, we eliminate specially treated firms. The financial data are obtained from consolidated annual reports. Table 1 presents the descriptive statistics of our samples: From 2007 to 2017, the dataset comprises 14,797 observations. The average investment rate is 6%, with an average Tobin's q of 2.13.

[3]See https://books.google.com.hk/books?id=KpzxPgAACAAJ

Table 1: Descriptive statistics

Variable	Obs.	Mean	SD	Min	Median	Max
$Treat$	14,797	0.536	0.499	0	1	1
$Post$	14,797	0.625	0.484	0	1	1
$Investment$	14,797	0.06	0.068	0	0.039	0.483
q	14,797	2.13	2.111	0.098	1.537	22.333
$Cash$	14,797	0.699	0.48	0.041	0.597	3.049
$Size$	14,797	22.181	1.379	18.666	22.025	27.467
$Return$	14,797	0.3	0.841	-0.838	0.057	6.503
$Leverage$	14,797	0.488	0.228	0.04	0.487	3.569
$Listage$	14,797	2.114	0.827	0	2.398	3.219
a_{type}	14,797	0.023	0.08	0	0	1.515
f_{type}	14,797	0.155	0.335	0	0	5.669

3. Empirical results

3.1. Effect of mandatory disclosure on investment-q sensitivity

In this section, we evaluate whether the sensitivity of investment to stock price increases after the disclosure regulation.

The left panel in Table 2 presents our main results for the real effect of mandatory disclosure regulation. Column (1) shows the baseline estimation result without the treatment effects, where future investment is regressed on our main explanatory variable, Tobin's q. The coefficient on q is positive and significant, indicating that a firm's stock price has an impact on this firm's future investment. The coefficient estimate for $Cash$ is also positive and significant, with a magnitude much smaller than that for q. In column (2), we interact q with $Treat$ and $Post$ to investigate the effect of the disclosure regulation. The positive and significant coefficient of 0.351 on $q * Treat * Post$ suggests an increase of 0.351 in the investment-q sensitivity for companies in the treatment group after the mandatory disclosure regulation. This result suggests that managers rely more on stock prices when making investment decisions after the mandatory disclosure requirement is implemented.

The full specification of our model is shown in column (3), where we introduce

$Cash$ and its interactions with $Post$ and $Treat$ in the regression. The coefficient on $Cash * Treat * Post$ is negative and insignificant. Note that the inclusion of Cash-based interactions affects neither the significance nor the magnitude of the coefficient estimate on $q*Treat*Post$. This result suggests that the learning channel is working through the firm's stock price instead of other non-price investment opportunities. Overall, the empirical results show strong support that the mandatory disclosure requirement increases firms' investment-q sensitivity.

Table 2: Investment-q sensitivity after disclosure regulation

	Future Investment			Past Investment		
	(1)	(2)	(3)	(4)	(5)	(6)
q	0.489***	0.522***	0.516***	0.085	-0.001	-0.002
	(0.063)	(0.099)	(0.103)	(0.059)	(0.058)	(0.057)
$Cash$	0.638***	0.626***	0.461	-0.686**	-0.709**	-0.904**
	(0.211)	(0.206)	(0.485)	(0.261)	(0.278)	(0.335)
$Treat * Post$		-0.003	-0.000		0.002	0.003
		(0.004)	(0.006)		(0.002)	(0.004)
$q * Treat$		-0.247**	-0.243**		-0.072	-0.072
		(0.099)	(0.099)		(0.048)	(0.047)
$q * Post$		-0.059	-0.052		0.211**	0.215**
		(0.099)	(0.099)		(0.075)	(0.075)
$q * Treat * Post$		0.351***	0.346***		-0.053	-0.057
		(0.084)	(0.083)		(0.080)	(0.080)
$Cash * Treat$			-0.043			0.232
			(0.527)			(0.331)
$Cash * Post$			0.564			0.264
			(0.505)			(0.203)
$Cash * Treat * Post$			-0.387			-0.188
			(0.544)			(0.258)
$Size$	-0.005***	-0.005***	-0.005***	0.003	0.003	0.003
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
$Return$	0.005***	0.005***	0.005***	-0.007***	-0.007***	-0.007***
	(0.002)	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)
$Leverage$	-0.035***	-0.034***	-0.034***	-0.003	-0.001	-0.001
	(0.008)	(0.009)	(0.009)	(0.003)	(0.003)	(0.003)
$Listage$	-0.021***	-0.023***	-0.023***	-0.011***	-0.012***	-0.012***
	(0.003)	(0.004)	(0.004)	(0.001)	(0.001)	(0.001)
Constant	Yes	Yes	Yes	Yes	Yes	Yes
Clustering	Industry	Industry	Industry	Industry	Industry	Industry
Fixed effects	F, Y	F, Y	F, Y	F, Y	F, Y	F, Y
Adj. R^2	0.463	0.464	0.464	0.498	0.500	0.500
Obs.	14,705	14,705	14,705	14,697	14,697	14,697

Notes: The dependent variable for columns (1)-(3) is future investment, while that for columns (4)-(6) is past investment. Robust standard errors are clustered by industry (in brackets). ***, **, and * indicate the significance at the 1%, 5%, and 10% levels. The sample period is 2007–2017 and firm and year-fixed effects (F, Y) are included for all regressions. Following Edmans et al. (2017), we multiply the coefficient on any term containing q and $Cash$ by 100.

Our analysis so far relies on the assumption that firms' future investment decisions are affected by information contained in stock prices. To test this assumption, we follow Jayaraman and Wu (2019) to conduct a falsification test. We use past investment (one year before q) as the dependent variable in our regression. The results are shown in the right panel, columns (4)-(6), of Table 2. The investment-q sensitivity is insignificant across all specifications. More importantly, in contrast with the left panel, the coefficient on $q * Treat * Post$ is statistically insignificant, which confirms that past investment decisions are not affected by future stock prices.

3.2. Parallel trend test

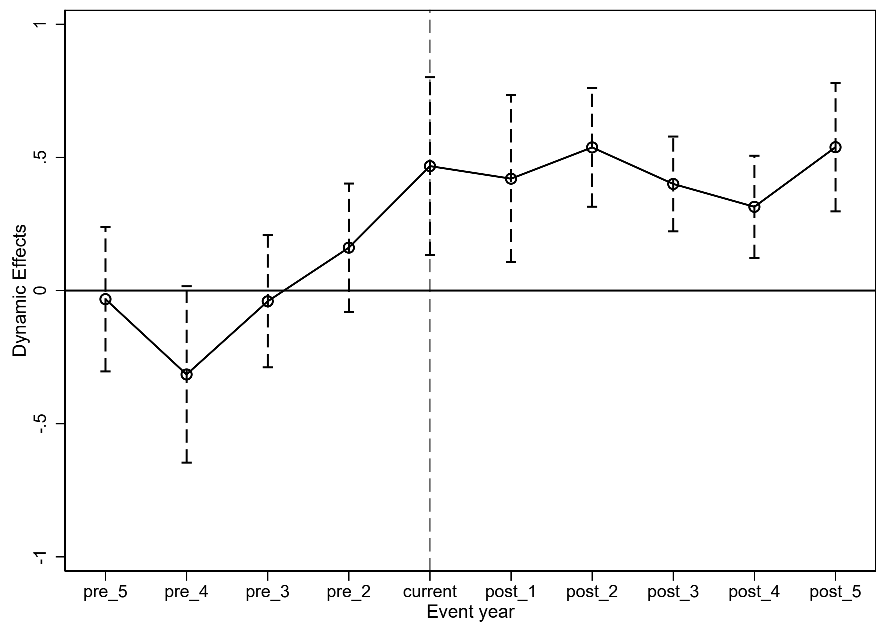

Figure 1: The parallel trend test

Notes: The figure plots the event-study DID estimates. The x-axis denotes the year from 2007 to 2017 where we use pre_1 (2011) as the base year for comparison. The y-axis plots the difference of the investment-q sensitivity coefficient for each event year.

We address the endogeneity issue of our model by testing for the time trend on the sensitivity of investment to q. We regress the outcome variable on a binary indicator for the treatment group and a time trend variable. Figure 1 presents the graphical evidence for the incremental effect of the disclosure regulation on the affected firms. The interaction terms are insignificant from 0 before the policy launch, suggesting similar investment-q sensitivities before the launch of mandatory disclosure regulation. However, the interaction terms change to be positive and significantly different from 0 for 2012 and persistent thereafter. The result again proves that the disclosure improves the investment-q sensitivity after the regulation is launched. After the 2012 regulation (current), the investment-q sensitivity for SZSE firms has increased and become higher than SSE firms, indicating a significant influence due to the regulation.

3.3. Randomly generated treated status

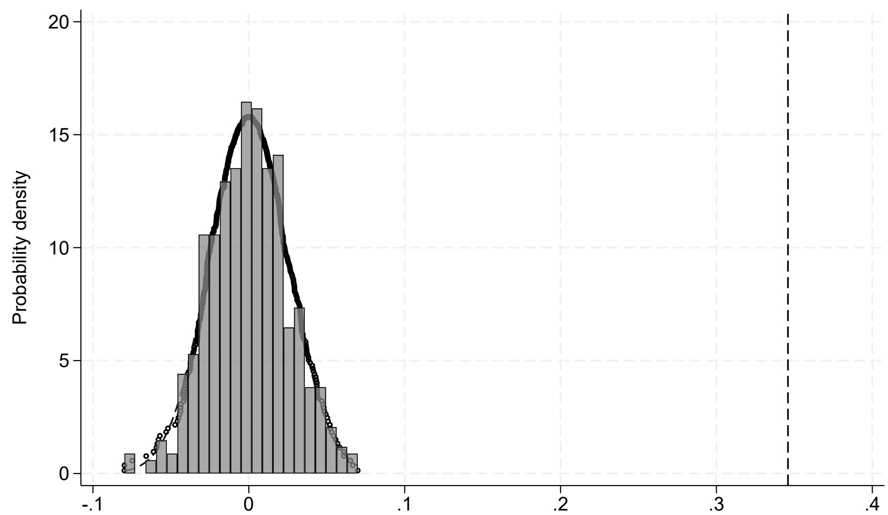

Figure 2: The permutation test

Notes: The figure displays the cumulative distribution density of the estimated coefficients from 500 simulations where the treat status was randomly assigned to firms. The vertical line corresponds to the result of column (3) in Table 2.

To further test the robustness of our main regression, we follow Li et al. (2016) and run a placebo test by randomly assigning the adoption of mandatory disclosure regulation to firms. Specifically, we utilize a permutation inference to repeatedly randomize the treatment assignment vector. Using this false treatment variable, a placebo DID estimation is conducted using the specification in column (3) in Table 2. Given the random data generation process, the permutation inference should not yield any significant estimate. To enhance the identification power of this placebo test, it is repeated 500 times.

Figure 2 illustrates the distribution of these estimates. The distribution of estimates is centered around zero, with a standard deviation of 0.253, indicating an insignificant effect with a randomly constructed regulation. Moreover, the benchmark estimate, 0.346 from column (3) in Table 2, lies outside the entire distribution. These findings collectively indicate the robustness of our DID results, and that the positive and significant effect of the mandatory disclosure regulation on investment-q sensitivity is not influenced by some unobserved factors.

3.4. Effect of disclosure information type

The results in the previous section demonstrate that the overall investment-q sensitivity is higher for firms in SZSE than those in SSE after the mandatory disclosure requirements are implemented. In this section, we further test whether the type of information disclosed by firms has an impact on the investment-q sensitivity.

Table 3 presents the estimation results from running the fixed effects model 2. Column (1) includes only the interaction of q and a_{type} as the key explanatory variable. The coefficient on this interaction term is positive and statistically significant, implying that there is a positive relationship between the amount of a type information released in firms' disclosures and firms' investment-q sensitivity over time.

Column (2) and Column (3) present another dimension of information. The interaction term of Tobin's q with f_{type} are both insignificant in Column (2) and Column (3). The coefficient of $q * a_{type}$ in Column (3) is higher than that in Column (1), which further proves that the crowding-in effect learning channel exists in the market. The negative coefficient of $q * f_{type}$ in Column (3) partially shows the negative crowding-out effect, however, this effect is not significant, possibly due to a lack of sample data.[4] Overall, the disclosure from the learning channel exhibits a positive

[4] It could be that firms disclose more about the "known" information rather than "unknown" information.

effect in the market, potentially due to the dominating proportion of a types of information in the firm's disclosure.

Table 3: Impact of disclosure information type

	Future Investment			Past Investment		
	(1)	(2)	(3)	(4)	(5)	(6)
q	0.479***	0.497***	0.481***	0.048	0.038	0.037
	(0.050)	(0.044)	(0.044)	(0.070)	(0.071)	(0.073)
$q * a_{type}$	0.568***		0.578***	0.100		0.040
	(0.147)		(0.125)	(0.159)		(0.153)
$q * f_{type}$		0.024	-0.010		0.063	0.061
		(0.091)	(0.086)		(0.046)	(0.045)
$Cash$	0.655**	0.676***	0.655**	-0.691**	-0.684**	-0.686**
	(0.229)	(0.226)	(0.232)	(0.256)	(0.264)	(0.262)
$Size$	-0.004*	-0.004*	-0.004*	0.002	0.002	0.002
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
$Return$	0.004***	0.004***	0.004***	-0.007***	-0.007***	-0.007***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
$Leverage$	-0.032***	-0.032***	-0.032***	0.003	0.003	0.003
	(0.008)	(0.008)	(0.008)	(0.003)	(0.003)	(0.003)
$Listage$	-0.027***	-0.027***	-0.027***	-0.013***	-0.013***	-0.013***
	(0.004)	(0.004)	(0.004)	(0.002)	(0.002)	(0.002)
Constant	Yes	Yes	Yes	Yes	Yes	Yes
Clustering	Industry	Industry	Industry	Industry	Industry	Industry
Fixed effects	F, Y	F, Y	F, Y	F, Y	F, Y	F, Y
Adj. R^2	0.463	0.463	0.463	0.487	0.487	0.487
Obs.	7,902	7,902	7,902	7,898	7,898	7,898

Notes: The sample period is 2007–2017 and firm and year-fixed effects (F, Y) are included for all regressions. Robust standard errors are clustered by industry (in brackets). ***, **, and * indicate the significance at the 1%, 5%, and 10% levels. Following Edmans et al. (2017), we multiply the coefficient on any term containing q and $Cash$ by 100.

3.5. Samples with zero information proportion

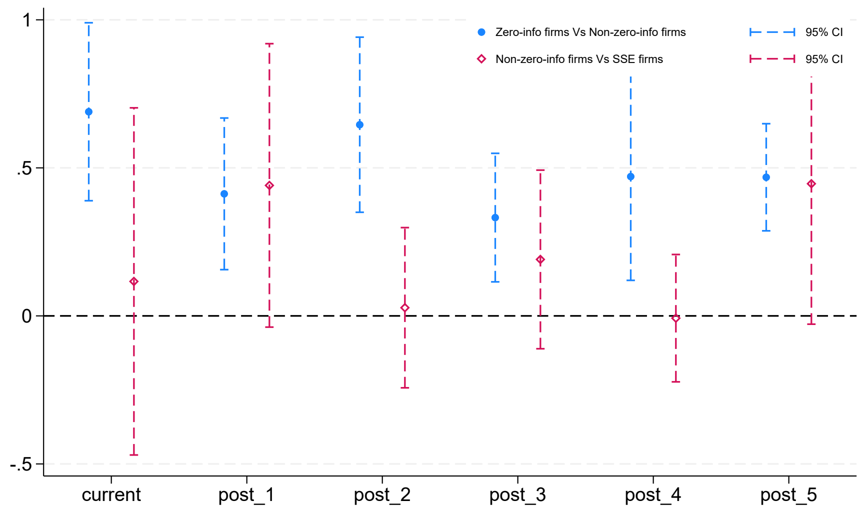

Figure 3: Samples with zero information proportion

Notes: The figure plots the event-study estimates based on model 2. The x-axis denotes the year from 2012 to 2017 after the disclosure regulation. The y-axis plots the difference of the investment-q sensitivity coefficient for each event year. Specifically, the dashed line shows the difference between zero-info firms and non-zero-info firms. The solid line shows the difference between non-zero-info firms and SSE firms.

3.6. The precision of disclosure

So far, we have seen that mandatory disclosure is overall beneficial and can improve a firm's investment efficiency from the learning channel. In this section, we will explore whether this effect will change when disclosure precision increases. To see the effect of disclosure precision more precisely, we focus on the interaction term between q, information type, and precision measures.

The results for model 3 are shown in Table 4 and Table 5. We can see a positive and significant coefficient for each proxy for a_{type} information. The evidence is consistent with the learning theory that a more precise disclosure with firm fundamental information will increase investment efficiency Goldstein and Yang (2019). The effect is significantly enhanced in column (2) of Table 5 when a more detailed measure of text precision is introduced, and it continues to show a positive and significant effect with the *Certainty* measure as in column (1).

Table 4: Impact of disclosure information precision

	Future Investment		Past Investment	
	(1)	(2)	(3)	(4)
q	0.484***	0.481***	0.040	0.038
	(0.045)	(0.044)	(0.074)	(0.073)
$q * f_{type} * Certainty$	-0.027		0.101	
	(0.097)		(0.066)	
$q * a_{type} * Certainty$	1.191***		-0.023	
	(0.270)		(0.372)	
$q * f_{type} * Common$		-0.000		0.001
		(0.001)		(0.001)
$q * a_{type} * Common$		0.007***		0.000
		(0.001)		(0.002)
Control	Yes	Yes	Yes	Yes
Constant	Yes	Yes	Yes	Yes
Clustering	Industry	Industry	Industry	Industry
Fixed effects	F, Y	F, Y	F, Y	F, Y
Adj. R^2	0.463	0.463	0.487	0.487
Obs.	7,902	7,902	7,898	7,898

Notes: The dependent variable is investment 1 year after . Robust standard errors are clustered by industry (in brackets). ***, **, and * indicate the significance at the 1%, 5%, and 10% levels. The sample period is 2007–2017 and firm and year-fixed effects (F, Y) are included for all regressions. Following Edmans et al. (2017), we multiply the coefficient on any term containing q by 100. All models include control variables and are the same as Equation (1). Only the relevant coefficients are tabulated for parsimony.

Table 5: Impact of disclosure information precision (sentence)

	Future Investment		Past Investment	
	(1)	(2)	(3)	(4)
q	0.484***	0.497***	0.038	0.052
	(0.046)	(0.049)	(0.073)	(0.070)
$q * f_{type} * Certainty$	-0.026		0.093	
	(0.126)		(0.069)	
$q * a_{type} * Certainty$	0.891***		0.059	
	(0.223)		(0.245)	
$q * f_{type} * Common$		-0.047		-0.014
		(0.072)		(0.046)
$q * a_{type} * Common$		0.847**		0.126
		(0.368)		(0.612)
Control	Yes	Yes	Yes	Yes
Constant	Yes	Yes	Yes	Yes
Clustering	Industry	Industry	Industry	Industry
Fixed effects	F, Y	F, Y	F, Y	F, Y
Adj. R^2	0.463	0.463	0.487	0.487
Obs.	7,902	7,902	7,898	7,898

Notes: The dependent variable is investment 1 year after . Robust standard errors are clustered by industry (in brackets). ***, **, and * indicate the significance at the 1%, 5%, and 10% levels. The sample period is 2007–2017 and firm and year-fixed effects (F, Y) are included for all regressions. Following Edmans et al. (2017), we multiply the coefficient on any term containing q by 100. All models include control variables and are the same as Equation (1). Only the relevant coefficients are tabulated for parsimony.

3.7. Generated words using word embedding

One concern is that the f and a types of information are often disclosed subtly. Industry-specific jargon, abbreviations, and idioms may be present in a disclosure, which can be understood only within a specific context. For example, one might recognize "Gallium Nitride" as a material used in the production of semiconductor chips during a company visit, but even a finance expert may find it challenging to identify this specific phrase from the millions of isolated words in firm disclosure.

Secondly, classifying words into either f or a can be challenging. For instance, two individuals may make different choices when categorizing a word. Even for a single person, she may assign a word to different categories at different times. In other words, it is challenging for humans to consistently and objectively categorize each word. Furthermore, it is impractical to assume that one could develop a dictionary that is capable of accommodating all words. As technologies and industries evolve, new words and phrases enter the business vocabulary while others phase out. For instance, a dictionary created in the 2000s might not recognize a term like "blockchain."

To alleviate these concerns and to ensure the robustness of the results, we use a machined-generated word list to replace our a-words and f-words. Instead of manually selecting the most relevant a words and f words, we follow Li et al. (2021) and use word-embedding techniques to select the most relevant a and f words directly from disclosures.[5]

Specifically, we first use the a words and f words in our main test as a baseline word list. Then, we use the pre-trained word embedding model proposed by Song et al. (2018) to conduct vectorization.[6] The word embedding model is a novel machine learning-based method for textual analysis. It has been largely used in both computer science literature (e.g., word2vec) and finance literature recently (Mikolov et al., 2013). In contrast to traditional dictionary-based approaches, word embedding utilizes a neural network to incorporate contextual information and acknowledge inter-word dependencies. Therefore, the word embedding methods can offer us an unbiased word list.

After vectorization, the similarity between each word pair in the disclosure is computed using the cosine similarity method. Subsequently, we select the 100 most similar words through sorting. For example, for the word "Future" in the f-words list, we match 100 words for it. All these 100 words are from disclosure. Finally, we manually review the generated words and eliminate any irrelevant ones.[7] Then we employ a similar method to construct a_{type}, f_{type}, and $Certainty$ and rerun model 2

[5]As noted by Li et al. (2021), dictionary-based methods treat words as independent tokens, assuming that their order and context are not significant.

[6]The pre-trained model can be downloaded at `https://ai.tencent.com/ailab/nlp/en/embedding.html`

[7]See Appendix D for generated words.

and model 3. The results are presented in Table 6.

Table 6: Robustness for generated words using word embedding

	Future Investment				
	(1)	(2)	(3)	(4)	(5)
q	0.450***	0.484***	0.460***	0.461***	0.450***
	(0.047)	(0.042)	(0.042)	(0.047)	(0.046)
$q * a_{type}$	0.398***		0.458***		
	(0.087)		(0.065)		
$q * f_{type}$		0.033	-0.034		
		(0.048)	(0.045)		
$q * a_{type} * Certainty$				0.642***	
				(0.125)	
$q * a_{type} * Common$					0.005***
					(0.001)
Control	Yes	Yes	Yes	Yes	Yes
Constant	Yes	Yes	Yes	Yes	Yes
Clustering	Industry	Industry	Industry	Industry	Industry
Fixed effects	F, Y	F, Y	F, Y	F, Y	F, Y
Adj. R^2	0.464	0.463	0.464	0.464	0.464
Obs.	7,902	7,902	7,902	7,902	7,902

Notes: The dependent variable is investment 1 year after . Robust standard errors are clustered by industry (in brackets). ***, **, and * indicate the significance at the 1%, 5%, and 10% levels. The sample period is 2007–2017 and firm and year-fixed effects (F, Y) are included for all regressions. Following Edmans et al. (2017), we multiply the coefficient on any term containing q by 100. All models include control variables and are the same as Equation (1). Only the relevant coefficients are tabulated for parsimony.

As shown in Table 6, the effect of disclosure on investment efficiency is consistent with the main regression, and disclosure with more precise a type information contributes a higher positive effect.

4. Conclusion

The mandatory disclosure of company visit regulations is beneficial not only in the informational channels but also in the learning channels in the Chinese market. The real effect of mandatory disclosure depends on the information it contains. The disclosures contain more manager "known" information and exhibit a crowding-in effect in the learning channel. Nevertheless, the mandatory disclosure regulation is effective and enhances the learning effect in the Chinese market. The empirical evidence presents a result of an increase in the sensitivity of investment to price because of more revelatory information on prices.

Our study contributes to the existing learning-related literature. By exploiting the setting of a mandatory change in company visits disclosure regulation in China, we find increased investment-q sensitivity for firms that are required to disclose. Consistent with the literature, this increase in investment-q sensitivity is concentrated in firms with more private information, and more financially unconstrained.

Our research further adds to the list of mandatory disclosure literature by identifying the effect of increasing precision in a learning setting. We find that firms with higher disclosure precision have a higher level of investment efficiency.

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Appendix A. Sample disclosure file

Securities code: 000651 Securities abbreviation: Gree Electric

Zhuhai Gree Electric Appliance Co., Ltd.

Investor Relations Activity Record Form

Number: 2020-001

Investor relations activities category	☐Research on specific objects ☐Analyst meeting ☐Media interview ☑ Performance briefing ☐Press conference ☐Roadshow ☐Visit on site ☐Others
Participatants	A total of 1,233 online institutional and individual investors
Time	May 14, 2020 (Thursday) 15:00 PM
Location	China Fund News-jihiubao Online Roadshow Center (www.jhbshow.com)
Managerment attentend	Ms. Dong Mingzhu, Chairman and President Mr. Huang Hui, Director and CEO Mr. Wang Jingdong, Director, Vice President, Chief Financial Officer Mr. Zhang Wei, Secretary of the Board of Directors Mr. Wang Xiaohua, Independent Director
Meeting content	**Question 1:** Please talk about the changes in Gree's online and offline channels and the development of small household appliances. **Answer:** Gree Electric started with air conditioners, but its strategic layout is not limited to air conditioners. Judging from the current operating conditions, air-conditioning occupies a dominant position in all industries, accounting for about 80%, but Gree Electric's industrial layout in the field of home appliances has been very complete, ranging from air-conditioners, refrigerators, washing machines to small home appliances. Also, we are fully prepared for our "smart home" business. **Question 2:** Please talk about the reason why this year's dividend profit is lower than in previous years, do you consider periodic dividends? **Answer:** This year's dividend is lower than in previous years, and the company is not incapable of sharing it. In the face of natural disasters such as the epidemic, we cannot assess and control what lies behind. When considering this dividend, the company must also consider the company's subsequent development issues, ensure sufficient cash flow, and balance the short-term interests of shareholders and the company with long-term development. Whether to distribute dividends in the second half of the year needs to be determined according to the operating conditions. The company will do its best to do a good job in the next production and operation, such as the rapid and effective start of the peak season, the company's business recovery, and the half-year dividend.

Figure Appendix A.1: Investor relation record

Appendix B. Institutional background

The Chinese market has had two independently operated domestic stock exchanges since 1990: the Shanghai Stock Exchange and the Shenzhen Stock Exchange. Even though the two stock exchanges are independently operated, they are under similar regulations of "The Chinese Securities Regulatory Commission (CSRC)". The regulation of private in-house meetings is most relevant to the regulations of inside trading, which was developed in the early 1990s in China (Han et al., 2018). Later, a more detailed regulation was introduced in the "Chinese Securities Law (1999)" and was updated in 2006 (Tong et al., 2013). These regulations apply to both SZSE and SSE, mandating that companies disclose their information fairly and transparently.

The company onsite visit or in-house meeting belongs to the category of investor relations. The suggestions for disclosing investor relationships go back to 2003 in the "guidance on investor relationship management for firms listed on the SZSE". Starting from August 10, 2006, the SZSE encouraged its listed firms to disclose the company visit information in their annual reports. The official file is called "guidance on fair disclosure for firms listed on the SZSE". Firms are free to hold private in-house meetings in China. The 2006 guidance has encouraged firms to hold more private in-house meetings (Han et al., 2018). While information leakage prevailed at that time, "the 2006 guidance" prohibits firms from disclosing nonpublic information to attendees during company visits and meetings. Later, The SZSE revised the guidance twice in 2008 and 2012 and required firms to disclose more detailed information to the public.

After 2009, listed companies are required to provide more specific information in their annual reports as a result of the 2008 change. The detail criterion includes the information on participants' dates, locations, and general questions discussed. However, the firm's disclosures under "the 2009 requirement" are delayed and not detailed enough.[8] In 2012, the SZSE released new requirements for disclosing company onsite

[8]For example, we do not know who visits and asks questions and how firms respond to these questions.

visits in "the 41st memo of information disclosure requirements — investor relationship management and its disclosure (the 41st memo)". The requirement is unique because other stock markets do not have this kind of regulation, even not in the SSE (Yang et al., 2020). Under the 41st memo, firms listed on SZSE are required to disclose each visit within 2 trading days after the meeting. Moreover, more detailed information is required to provide: For example, firms need to provide the names and identities of insider attendees, the names and titles of managers who attend the meeting, and the managers' responses to the questions asked in the meeting. Questions in the company site visits usually relate to firms' operations, stock performance, and company performance information (Han et al., 2018; Yang et al., 2020).

Once published, outside investors can see this information through an official online platform called "*Hu Dong Yi*" (Easy-communications).[9] An example of company onsite visit disclosure according to the 41st memo requirement is provided in Appendix A.1. The firm's disclosure due to the mandatory regulation can be categorized into 9 types of questions, including routine operations, payout policies, stock performance, stock issuance and ownership structures, asset operations, company debts, corporate governance, top management teams, and detailed company performance information. Most content of the disclosure is related to a firm's hard facts: 40.8% of the disclosure relates to firms' routine operations, 10.2% relates to stock issuance and ownership structures, and 21% relates to company performance information.

[9] https://irm.cninfo.com.cn

Appendix C. The learning theory

The learning theory focuses on the information flows from investors to managers (Jayaraman and Wu, 2019). In this theory, the stock price aggregates information from traders with private information. Consequently, managers benefit from the new information embedded in the stock price and use it to guide their future investments.[10] Bond et al. (2012) formally propose that it is "revelatory price efficiency" (RPE), which is the information that manager can learn and guide for their investment, that matters for the real efficiency. The idea differs from total information contained in price, which Bond et al. (2012) terms as "forecasting price efficiency" (FPE), which emphasizes the information already known to the manager.

To illustrate, suppose that there are only two types of information in disclosure: information managers know better $a_m > a_t$ (e.g., firm's fundamental information), and information outsiders know better $f_t > f_m$ (e.g., firm's industry prospectus where outsiders have a comparative informational advantage). The information set for manager and outsider traders are $\mathcal{I}_m = a_m + f_m$ and $\mathcal{I}_t = a_t + f_t$. If the manager discloses a_m, traders will put more weight on a_m (rather than a_t) when pricing the firm's stock price. Since traders will use all information $\mathcal{I}_t$ to maximize their profits, and will rely more on a_m rather than a_t, their assessment of a firm performance will rely more on f_t. The manager's unknown private information (f_t) is then incorporated into the price (price informativeness increase). On the contrary, if the information manager discloses is complementary to traders (f_m), it can crowd out f_t, resulting in a decrease in price informativeness (Goldstein and Yang, 2019; Gao and Liang, 2013). As a result, the investment efficiency of a firm's disclosure can decrease if too much f information is disseminated by firms.

[10] e.g., Outside informed traders, such as institutional investors, may know better about the prospects of the industry. By trading, they incorporated this information into the price. As a result, managers can use the stock prices to acquire new private information and steer their future investments.

Appendix D. Automated generated words

Table D.1: Generated *a* words

销路(Sales)	销价(Selling price)
中间业务(Intermediate Business)	批发价格(Wholesale Prices)
整合营销(Integrated Marketing)	商品价格(Commodity prices)
定价(Pricing)	概述(Overview)
滞销产品(Lagging Products)	赢利(Profitability)
成果(Results)	布局(Layout)
售量(Sales Volume)	简史(Brief History)
生产量(Production Volume)	进货价格(Purchase Price)
产品质量(Product Quality)	投入产出(Inputsand Outputs)
重大进展(Significant Progress)	市场化(Marketability)
地理位置(Geographical Location)	构架(Structure)
布置(Layout)	简况(Profile)
规划(Plan)	市场占有率(Market Share)
产品产量(Product Output)	详细资料(Detailed Information)
名称(Names)	增长点(Growth Points)
价格水平(Price Levels)	赢利点(Profitability)
概况(Overview)	盈利性(Profitability)
盈利(Profitability)	发货量(Shipment Volume)
核心内容(Core Content)	发展史(Development History)
具体内容(Specific Information)	供货量(Supply Quantity)
历史背景(Historical Background)	简介(Introduction)
样式(Styles)	订单数(Number of Orders)
佣金制(Commission System)	研究成果(Research Results)
回报(Returns)	去化(De-inventory)
盈利模式(Profitability Pattern)	销出(Sell Out)
业务流程(Business Process)	现金流(Cash Flow)
现状(Status)	畅销品(Best Sellers)
市场策略(Market Strategy)	卖价(Selling Price)

Table D.2: Generated f words

成果(Outcome)	负面影响(Negative Impact)
成为(Become)	相信(Believe)
可能(May)	再说(Besides)
一旦(Once)	否则(Otherwise)
消极影响(Negative Impact)	难保(Hard to Guarantee)
谋划(Plan)	造成(Cause)
不良影响(Negative Impact)	结果(Result)
设想(Envisage)	要不然(Otherwise)
行动计划(Action Plan)	憧憬(Vision)
若是(If)	后来(After)
乃至(Even)	可行(Feasible)
必然(Necessarily)	想来(Think)
未必(Not Necessarily)	即将(Upcoming)
既然(Since)	安排(Future Arrangement)
若真(If True)	三年计划(Three-year Plan)
最终(Eventually)	益处(Benefit)
之后(After)	说不定(Maybe)
将来(Future)	方针(Direction)
想法(Idea)	明天(Tomorrow)
关系不大(Not Very Important)	接下来(Next)
今后(Future)	对策(Solution)
等到(After)	如若(If)
尔后(After)	前程(Future)
拟定(Proposed)	早有计划(Plan Ahead)
恐怕(Afraid)	形势(Situation)
有用吗(Does it work?)	担忧(Worry)
希望(Hope)	想将来(In Future)
而后(Then)	按计划(As Plan)
短期计划(Short-term Plan)	接着(Next)
弄不好(Mess it up)	猜测(Guess)
意见(Opinion)	作战方案(Plan)
不良后果(Adverse Consequences)	计划表(Plan)
下任(Next)	终于(Finally)
随后(Followed)	假以时日(In Time)

Continued on next page

随即(Followed)	过后(After)
永远(Forever)	也许(Maybe)
有利(Beneficial)	来后(After)
哪一天(Which Day)	即便(Even)
就算(Even If)	副作用(Side Effects)
那样的话(In That Case)	前景(Prospect)
战争(War)	长期(Long-term)
将要(Will)	那会(In that time)
局势(Situation)	搞不好(Not Good Enough)
的话(In That Case)	变动(Change)
预言(Prediction)	下一代(Next Generation)
要是(If)	万一(In Case)
打算(Plan)	到来(Come)
年度计划(Annual Plan)	收购计划(Acquisition Plan)
五年计划(Five-year Plan)	没准(Maybe)
此后(After)	这样的话(In That Case)
以后(After)	总之(In Short)
到时候(By Then)	计划书(Plan)
前途(Future)	短期内(Short Term)
很快(Soon)	方略(Strategy)
带来不利(Causes harm to)	不然的话(Otherwise)
后果(Consequences)	下次(Next Time)
然后(Then)	计划(Plan)
引起(Cause)	不然(Otherwise)
一年计划(Year Plan)	意图(Intention)
承诺(Promise)	势必(Be bound to)
理想(Ideal)	一会(Once)
规划(Plan)	预计(Expected)
真要(If)	目标(Goal)
国运(National Future)	就(On)
幅射(Radiation)	明年(Next Year)
总有一天(One Day)	倘若(If)
即使(Even)	导致(Cause)
方案(Plan)	最后(Finally)

Continued on next page

事后(After)	有朝一日(Someday)
筹划(Plan)	不久(Soon)
长远(Future)	没过多久(Not Long)
影响(Influence)	定下(Decide)
第二天(Next day)	最起码(At least)
不见得(Not Necessary)	未来(Future)
构想(Plan)	早有打算(Plan in Advance)
十年规划(10 Years Plan)	日后(After)
迟早(Sooner or Later)	将会(Will)
战略目标(Plan)	後(After)
期待(Expect)	利弊(Pros and Cons)
想必(Think)	开发计划(Development Plan)
成就(Achievement)	美好未来(Good Future)
政策(Policy)	潜力(Potential)
或许(Perhaps)	关联(Associated)
假如(If)	继而(Following)
布署(Deployment)	一段时间(In a While)
后(After)	那时(Then)
况且(Besides)	必定(Must)
幻想(Fantasy)	其后(Then)

Appendix E. Variable definitions

Table E.1: Variable definitions

Variable	Definition
Dependent and independent variables	
Investment$_{i,t+1}$	The firm i's capital expenditures in year $t+1$ divided by total assets.
$q_{i,t}$	The Tobin's q, defined as the firm's market value divided by total assets.
Variables regarding disclosure regulation	
$Treat_{i,t}$	Equals 1 for firms in the Shenzhen Stock Exchange (SZSE) and 0 otherwise.
$Post_{i,t}$	Equals 1 after the mandatory disclosure regulation in 2012, and
Firm characteristics	
$Size_{i,t}$	The natural logarithm of total asset.
$Cash_{i,t}$	The firm's cash flows and is defined as revenue plus depreciation and amortization and divided by total assets.
$Listage_{i,t}$	The listed year and is defined as the nature logarithm of the number of years listed in the stock market.
$Return_{i,t}$	The change in the market value of the firm over that prior year.
$Leverage_{i,t}$	The sum of the book value total debt divided by the asset.

Appendix F. Heterogeneity

We have shown that increasing the precision of disclosure is beneficial for firms to get a higher investment efficiency. In this section, we will test the heterogeneity of this effect based on factors that are commonly studied in the learning literature.

Specifically, we investigate how increasing disclosure precision affects the crowding-in effect of learning. First, we focus on a types of information and divide the sample based on the level of private information. Following Chen et al. (2007) and Foucault and Frésard (2012), we construct VPIN, the probability of informed trading, to measure private information. As a robustness check as in Carpenter et al. (2021), we divide firms into SOEs and Non-SOEs to verify whether SOEs demonstrate lower informativeness in their stock price. We find that the crowding-in effect of increasing precision is more pronounced for firms with higher VPIN and in the Non-SOEs sample.

Second, we split our samples based on the level of the firm's financial constraints. It is well documented that financially unconstrained firms are more flexible in adjusting their cash flow for investment, thus displaying a higher investment sensitivity to the stock price (Jayaraman and Wu, 2019; Bakke and Whited, 2010; Edmans et al., 2017; Chen et al., 2007). Following Lamont et al. (2001) and Hadlock and Pierce (2010), we construct the KZ-index and the SA-index to proxy the firm-level financial constraints. Similarly, we split our sample based on the median value of these two indices and rerun the investment-q regression. The empirical results also show a positive crowding-in learning effect when disclosure precision increases.

Private information

The first commonly studied factor is private new information (Chen et al., 2007; Foucault and Frésard, 2012). According to the previous literature, managers will learn from private information in stock prices to conduct their investment decisions and the learning effect is more pronounced for firms with more private information. Following this logic, we expect to see a greater effect on investment-q sensitivity for firms with more private information as disclosure precision improves. We start by splitting our sample based on the level of private new information.

Specifically, we follow Jayaraman and Wu (2019) and Easley et al. (2012) and use VPIN to proxy firms' private information. The volume-synchronized probability of informed trading (VPIN) captures the probability of informed trading for a particular stock. High VPIN firms have more private information compared to low VPIN firms. Therefore, high VPIN firms should present a more significant learning effect. The key parameters are described in the following equations and in Easley et al. (2012).

$$V_\tau^B = \sum_{i=t(\tau-1)+1}^{t(\tau)} V_i * Z\left(\frac{P_i - P_{i-1}}{\sigma_{\Delta P}}\right) \tag{F.1}$$

$$V_\tau^s = \sum_{i=t(\tau-1)+1}^{t(\tau)} V_i * Z\left[1 - Z\left(\frac{P_i - P_{i-1}}{\sigma_{\Delta P}}\right)\right] = V - V_\tau^B \tag{F.2}$$

$$VPIN = \frac{\sum_{\tau=1}^{n} \left|V_\tau^B - V_\tau^S\right|}{nV} \tag{F.3}$$

Where $t(\tau)$ is the index of the last time bar included in the τ volume bucket, i means the smallest time interval, for which we choose 1 min. V_i is the transaction volume at the moment i. P_i presents the price at the moment, and $\sigma_{\Delta P}$ is the standard derivation of price changes. Z presents the cumulative distribution function, and n is the number of baskets. We choose a basket of 50 and construct our daily VPIN in the Chinese market. Finally, we aggregate this proxy into year frequency and get our VPIN index.

We also split our sample based on SOEs and non-SOEs as a comparison. As highlighted by Carpenter et al. (2021), SOEs may prioritize alternative goals, such as maximizing employment and GDP, instead of solely concentrating on profit maximization. Moreover, after 2009, the government utilized economic stimulus packages to allocate funds to SOEs to bolster investment. As a result, SOEs often demonstrate less informativeness in their stock prices (Harrison et al., 2019; Chen et al., 2020). We therefore argue the Non-SOEs sample should exhibit a higher and more significant result. Table F.1 shows the regression result for these sub-samples.

Table F.1: Cross-sectional evidence with different information level

	Low VPIN	High VPIN	SOE	Non-SOE
	(1)	(2)	(3)	(4)
q	0.523***	0.456***	0.203	0.545***
	(0.110)	(0.082)	(0.121)	(0.065)
$q * a_{type} * Certainty$	0.061	1.266***	1.390**	1.181***
	(0.646)	(0.282)	(0.584)	(0.368)
Control	Yes	Yes	Yes	Yes
Constant	Yes	Yes	Yes	Yes
Clustering	Industry	Industry	Industry	Industry
Fixed effects	F, Y	F, Y	F, Y	F, Y
Adj. R^2	0.509	0.545	0.495	0.456
Obs.	3,711	4,008	2,480	5,422

Notes: The dependent variable is investment 1 year after . Robust standard errors are clustered by industry (in brackets). ***, **, and * indicate the significance at the 1%, 5%, and 10% levels. The sample period is 2007–2017 and firm and year-fixed effects (F, Y) are included for all regressions. Following Edmans et al. (2017), we multiply the coefficient on any term containing q by 100. All models include control variables and are the same as Equation (1). Only the relevant coefficients are tabulated for parsimony.

In Column (2) of Table F.1, we can see a positive and significant coefficient for $q * a_{type} * Certainty$ for high VPIN firms, but an insignificant one in Column (1) for low VPIN firms. These results can be interpreted as the positive effect on investment efficiency from an increasing disclosure precision is more pronounced in firms with more private information. Firms with greater VPIN are more likely to engage in informed trading and may have more private information; thus, the coefficient in the High VPIN sample is positive and significant, whereas it is not significant in the Low VPIN sample. Column (3) and Column (4) present a consistent result. The investment-q relationship in SOEs is less significant compared to non-SOEs, as well as the positive impact of improved disclosure accuracy on the learning effect.

Financial constraints

The second test we conduct is to split the sample based on financial constraints. Previous literature has identified that firms with more capital can adjust their investment against price more easily and the learning effect is more pronounced in these firms (Edmans et al., 2017; Jayaraman and Wu, 2019). Therefore, with the increase in disclosure precision, we expect to see are stronger increase for financially unconstrained firms than financially constrained firms.

To do so, we use KZ-index and SA-index to proxy the level of financial constraints (Lamont et al., 2001; Hadlock and Pierce, 2010). We split our sample based on the median value of each proxy and rerun the previous regression based on the new sub-samples. Table F.2 presents the empirical result.

Table F.2: Cross-sectional evidence with different financial constraints

	Unconstrained	Constrained	Unconstrained	Constrained
	(1)	(2)	(3)	(4)
q	0.462***	0.535**	0.497***	0.388**
	(0.080)	(0.194)	(0.102)	(0.164)
$q * a_{type} * Certainty$	1.468***	-0.194	1.847**	0.170
	(0.278)	(0.905)	(0.736)	(0.711)
Control	Yes	Yes	Yes	Yes
Constant	Yes	Yes	Yes	Yes
Clustering	Industry	Industry	Industry	Industry
Fixed effects	F, Y	F, Y	F, Y	F, Y
Adj. R^2	0.464	0.463	0.454	0.456
Obs.	4,958	2,944	4,022	3,880

Notes: The dependent variable is investment 1 year after . Columns (1) and (2) use the KZ index to measure financial constraint while Columns (3) and (4) use the SA index. Robust standard errors are clustered by industry (in brackets). ***, **, and * indicate the significance at the 1%, 5%, and 10% levels. The sample period is 2007–2017 and firm and year-fixed effects (F, Y) are included for all regressions. Following Edmans et al. (2017), we multiply the coefficient on any term containing q by 100. All models include control variables and are the same as Equation (1). Only the relevant coefficients are tabulated for parsimony.

Table F.2 presents our empirical result. As expected, the positive effect of increasing disclosure precision is more pronounced in unconstrained firms. The coefficient for financially unconstrained firms is not only more significant but higher than for financially constrained firms.

Appendix G. The effect on green innovation performance

One way to test a firm's investment efficiency is to evaluate its innovation performance. In this section, we take the firm's green innovation performance as an example and show how learning from stock price could affect the firm's green innovation performance. We construct a firm-level measurement, RPE, to proxy the learning effect. Specifically, we adopt Keane and Neal (2020)'s method of Mean-OLS and decompose the investment-q regression to capture the firm-level investment-q sensitivity. This measurement enables us to capture the heterogeneous learning effect not only at the temporal level but also individually. Using this proxy, we show that firms with more RPE have a better green innovation performance. The results further support the idea of the learning effect and its real effect on investment efficiency.

Revelatory price efficiency

Efficient financial markets can facilitate real decision-making. In the secondary markets, prices aggregate information and guide managerial decisions. Since the decision maker will use their information regardless of its reflection in the price, it may not be the entirety of the information in prices (FPE) that matters in real decision-making, but rather the information not already possessed by the decision maker. Bond et al. (2012) termed this concept as Revelatory Price Efficiency (RPE) and argued that RPE is what matters for efficient allocation.

RPE captures the learning effect we tested in the main regression. So far, we have shown that the mandatory disclosure regulation exhibits a positive effect through learning channels in the Chinese market. The effect is associated with the type of information and will be higher for disclosure with a higher level of precision. In this section, we decompose this learning effect into firm level using a decomposition method proposed by Keane and Neal (2020) and test whether firms with more learning effect (in terms of RPE) are associated with more green activities.

Decomposition

To do so, we first need to calculate the firm-specific RPE. Consider the following simplified investment-q framework:

$$Inv_{i,t+h} = a_{t,h} + b_{t,h} q_{it} + \varepsilon_{it,h},$$

The RPE is then defined as:

$$RPE_{t,h} = b_{t,h} \times \sigma_t(q).$$

Where, $q_{i,t}$ and $Inv_{i,t}$ are Tobin's q and investment of firm i in period t. RPE in period t at horizon h is the forecasting coefficient $b_{t,h}$ multiplied by $\sigma_t(q)$, the cross-sectional standard deviation of the forecasting variable q in period t. This predicted variation is a measure of RPE, the amount of information about future investment contained in prices. It is increasing in two quantities, the cross-sectional standard deviation of the investment forecast variable q and the investment responsiveness coefficient b_t. Intuitively, the greater the dispersion in q across firms and the more sensitive investments are to this variable, the greater the forecasting power of stock price. This forecasting power or RPE is what we tested before as the learning channel.

The RPE above captures only time-varying characteristics. To decompose this learning effect into firm-level, we draw on the Mean-OLS (Mean Observation OLS) method proposed by Keane and Neal (2020). We therefore capture both firm-specific and time-specific heterogeneity. In specific, consider the following general model with variable coefficients in time and space:

$$y_{it} = \beta'_{it} x_{it} + u_{it}.$$

where $\beta'_{it} = (\beta_{0it}, \beta_{1it}, \cdots, \beta_{Kit})'$ is a $(K+1) \times 1$ coefficient vector, and these coefficients vary with individuals and periods. To obtain a consistent estimate of β_{it}, the Mean-OLS method first decomposes the model into the following three feasible regression models:

Pooled regression:

$$y_{it} = x_{it}'\beta + v_{it},$$

$$v_{it} = x_{it}'\lambda_i + x_{it}'\theta_t + u_{it}.$$

Time-specific regression:

$$y_{it} = x_{it}'\left(\beta + \theta_t\right) + v_{it} = x_{it}'\beta_t + v_{it},$$

$$v_{it} = x_{it}'\lambda_i + u_{it}.$$

Unit-specific regression:

$$y_{it} = x_{it}'\left(\beta + \lambda_i\right) + v_{it} = x_{it}'\beta_i + v_{it},$$

$$v_{it} = x_{it}'\theta_t + u_{it}.$$

Then, construct a preliminary estimate of β_{it}:

$$\beta_{it}^{\text{Prel}} = \hat{\beta}_i + \hat{\beta}_t - \hat{\beta}.$$

The idea of Mean-OLS methods is to run pooled, i-specific, and t-specific regression separately for multiple times. Then iterating the subtracting process for each result to reduce the bias and get a consistent estimator of the coefficient of interest. The original deviation of $\hat{\beta}_{it}^{\text{Prel}}$ is eliminated by iteration, and finally a consistent estimate of $\hat{\beta}_{it}^{\text{Prel}}$ is obtained:

$$\begin{aligned}\hat{\boldsymbol{\beta}}_{it} = &\hat{\boldsymbol{\beta}}_i + \hat{\boldsymbol{\beta}}_t - \hat{\boldsymbol{\beta}} + \sum_{\ell=0}^{L}(-1)^{\ell+1}\left(Q_{xx,N}^{-1}\frac{1}{N}\sum_{i=1}^{N} x_{it}x_{it}'\Gamma_{1,\ell} + Q_{xx,T}^{-1}\frac{1}{T}\sum_{t=1}^{T} x_{it}x_{it}'\Gamma_{2,\ell}\right.\\ &\left.-Q_{xx,NT}^{-1}\frac{1}{NT}\sum_{i=1}^{N}\sum_{t=1}^{T}\left(x_{it}x_{it}'\Gamma_{1,\ell} + x_{it}x_{it}'\Gamma_{2,\ell}\right)\right)\end{aligned}$$

where $\Gamma_{1,\ell} = Q_{xx,T}^{-1}\left(\frac{1}{T}\sum_{t=1}^{T} x_{it}x_{it}'\Gamma_{2,\ell-1}\right), \Gamma_{2,\ell} = Q_{xx,N}^{-1}\left(\frac{1}{N}\sum_{i=1}^{N} x_{it}x_{it}'\Gamma_{1,\ell-1}\right)$.

Therefore, we extend the coefficients $b_{t,h}$ into $b_{it,h}$ to construct the measurement of RPE with both spatial and temporal heterogeneity as follows:

$$RPE_{it,h} = b_{it,h} \times \sigma_{it}(q).$$

Firm-level evidence

$RPE_{it,h} = b_{it,h}$ capture how much each firm learn from price. Following Carpenter et al. (2021), we take the model to the data on equity market value, investment, and asset book value from the China Stock Market and Accounting Research Database (CSMAR) from 2007 to 2017. Using these data, we construct firm-level RPE with a horizon of 1 and 3 years (h=1,3).

Then we test whether a higher RPE triggers firms to make more environmental responses. Firms with higher RPE are more likely to learn from price. These are the firms often with higher precision of growth-related disclosure (see Section 2). Disclosure on social responsibility is one of these types of information. Here, we focus on testing the firm's environmental performance. According to Jackson et al. (2020), stakeholders will be more effective in rewarding environmentally responsible corporate activities. Therefore, we argue that a firm with a higher level of RPE is expected to have a higher level of green innovation performance. Table G.1 present the firm-level results:

Table G.1: Cross-sectional evidence for RPE and green innovation performance

	Green Innovation (GI)				
	(1)	(2)	(3)	(4)	(5)
$RPE3$	3.897***	0.772**	0.997**		
	(5.313)	(2.450)	(2.497)		
$RPE1$				2.679***	3.234***
				(2.988)	(3.245)
Control	No	No	Yes	No	Yes
Constant	Yes	Yes	Yes	Yes	Yes
Clustering	Industry	Industry	Industry	Industry	Industry
Fixed effects	F	F, Y	F, Y	F, Y	F, Y
Adj. R^2	0.757	0.765	0.770	0.755	0.759
Obs.	12,778	12,778	12,644	14,446	14,298

Notes: The dependent variable GI is the firm's green innovation performance, measured as the number of green patents. green patent is identified using the green patent list from WIPO and matched using the IPC classification code. $RPE3$ and $RPE1$ are firm-level RPE with horizons of 1 and 3 years ($h = 1, 3$). The subsidy is included as a control variable, which is aggregated from subsidy information from the annual reports and financial statement notes. All other control variables are the same as the main regression. Robust standard errors are clustered by industry (in brackets). ***, **, and * indicate the significance at the 1%, 5%, and 10% levels. The sample period is 2007–2017. firm (F) and year-fixed effects (Y) are included in different columns. Only the relevant coefficients are tabulated for parsimony.

As shown in Table G.1, firms with higher levels of RPE have greater green innovation performance. The effect is significant in a 3-year horizon, but it is more pronounced in a 1-year horizon.

Appendix H. Other robustness tests

Table H.1: Full sample tests

	Future Investment (Inv_{t+1})				
	(1)	(2)	(3)	(4)	(5)
q	0.514***	0.516***	0.514***	0.515***	0.514***
	(0.103)	(0.103)	(0.104)	(0.103)	(0.103)
$Cash$	0.005	0.005	0.005	0.005	0.005
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
$Treat * Post$	-0.000	-0.000	-0.000	-0.000	-0.000
	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)
$q * Treat * Post$	0.323***	0.363***	0.344***	0.322***	0.323***
	(0.086)	(0.090)	(0.093)	(0.086)	(0.086)
$q * Treat$	-0.240**	-0.244**	-0.241**	-0.239**	-0.240**
	(0.099)	(0.099)	(0.099)	(0.099)	(0.099)
$q * Post$	-0.051	-0.053	-0.052	-0.052	-0.051
	(0.099)	(0.099)	(0.100)	(0.099)	(0.099)
$Cash * Treat$	-0.000	-0.001	-0.001	-0.000	-0.000
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
$Cash * Post$	0.006	0.006	0.006	0.006	0.006
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
$Cash * Treat * Post$	-0.004	-0.004	-0.004	-0.004	-0.004
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
$q * Treat * Post * a_{type}$	0.392**		0.456***		
	(0.145)		(0.137)		
$q * Treat * Post * f_{type}$		-0.050	-0.074		
		(0.082)	(0.082)		
$q * Treat * Post * Certainty$				0.861***	
				(0.283)	
$q * Treat * Post * Common$					0.005**
					(0.002)
Control	Yes	Yes	Yes	Yes	Yes
Constant	Yes	Yes	Yes	Yes	Yes
Clustering	Industry	Industry	Industry	Industry	Industry
Fixed effects	F, Y	F, Y	F, Y	F, Y	F, Y
Adj. R^2	0.464	0.464	0.464	0.464	0.464
Obs.	14,705	14,705	14,705	14,705	14,705

Notes: This table uses full sample data to test the effect of information types and precision. The dependent variable is investment 1 year after (Inv_{t+1}). Robust standard errors are clustered by industry (in brackets). ***, **, and * indicate the significance at the 1%, 5%, and 10% levels. The sample period is 2007–2017 and firm and year-fixed effects (F, Y) are included for all regressions. Following Edmans et al. (2017), we multiply the coefficient on any term containing q by 100. All models include control variables and are the same as Equation (1). Only the relevant coefficients are tabulated for parsimony.

Table H.2: Cross-sectional evidence with different information level

	Low VPIN	High VPIN	SOE	Non-SOE
	(1)	(2)	(3)	(4)
q	0.364***	0.585***	0.400	0.563***
	(0.108)	(0.161)	(0.241)	(0.079)
$Cash$	0.006	0.006	0.005	0.002
	(0.006)	(0.005)	(0.006)	(0.004)
$Treat * Post$	-0.000	0.002	-0.019*	0.012
	(0.007)	(0.008)	(0.011)	(0.008)
$q * Treat * Post$	0.496**	0.403**	0.600*	0.186*
	(0.195)	(0.145)	(0.289)	(0.104)
$q * Treat$	-0.216	-0.251	-0.422	-0.117
	(0.162)	(0.145)	(0.259)	(0.093)
$q * Post$	-0.044	-0.196	0.012	-0.114
	(0.101)	(0.126)	(0.168)	(0.119)
$Cash * Treat$	0.003	-0.002	-0.011	0.007
	(0.007)	(0.006)	(0.010)	(0.006)
$Cash * Post$	0.001	0.009	0.005	0.009
	(0.004)	(0.006)	(0.007)	(0.007)
$Cash * Treat * Post$	-0.005	-0.007	0.006	-0.010
	(0.006)	(0.007)	(0.006)	(0.009)
$q * Treat * Post * Certainty$	0.007	0.899**	0.317	1.090***
	(0.579)	(0.374)	(0.544)	(0.345)
Control	Yes	Yes	Yes	Yes
Constant	Yes	Yes	Yes	Yes
Clustering	Industry	Industry	Industry	Industry
Fixed effects	F, Y	F, Y	F, Y	F, Y
Adj. R^2	0.505	0.547	0.494	0.450
Obs.	7,225	7,155	6,215	8,490

Notes: This table uses full sample data for the heterogeneity tests. The dependent variable is investment 1 year after (Inv_{t+1}). Robust standard errors are clustered by industry (in brackets). ***, **, and * indicate the significance at the 1%, 5%, and 10% levels. The sample period is 2007–2017 and firm and year-fixed effects (F, Y) are included for all regressions. Following Edmans et al. (2017), we multiply the coefficient on any term containing q by 100. All models include control variables and are the same as Equation (1). Only the relevant coefficients are tabulated for parsimony.

Table H.3: Cross-sectional evidence with different financial constraints

	Unconstrained	Constrained	Unconstrained	Constrained
	(1)	(2)	(3)	(4)
q	0.609**	0.536***	0.526*	0.497***
	(0.238)	(0.117)	(0.267)	(0.074)
$Cash$	0.012	0.001	0.011	0.002
	(0.010)	(0.004)	(0.008)	(0.005)
$Treat * Post$	-0.008	0.003	-0.017**	0.011
	(0.010)	(0.009)	(0.007)	(0.007)
$q * Treat * Post$	0.475**	0.397	0.271***	0.381*
	(0.185)	(0.237)	(0.076)	(0.199)
$q * Treat$	-0.246	-0.401**	-0.267	-0.306
	(0.169)	(0.186)	(0.211)	(0.178)
$q * Post$	-0.294	0.043	0.145	-0.176*
	(0.192)	(0.216)	(0.118)	(0.094)
$Cash * Treat$	-0.005	0.001	-0.010	0.005
	(0.011)	(0.009)	(0.009)	(0.007)
$Cash * Post$	0.006	0.006	-0.001	0.008
	(0.008)	(0.007)	(0.006)	(0.005)
$Cash * Treat * Post$	-0.007	-0.003	0.007	-0.009
	(0.010)	(0.006)	(0.008)	(0.006)
$q * Treat * Post * Certainty$	1.237***	-0.421	1.449*	0.102
	(0.278)	(0.858)	(0.711)	(0.822)
Control	Yes	Yes	Yes	Yes
Constant	Yes	Yes	Yes	Yes
Clustering	Industry	Industry	Industry	Industry
Fixed effects	F, Y	F, Y	F, Y	F, Y
Adj. R^2	0.480	0.447	0.450	0.465
Obs.	7,862	6,843	6,039	8,666

Notes: This table uses full sample data for the heterogeneity tests. The dependent variable is investment 1 year after (Inv_{t+1}). Robust standard errors are clustered by industry (in brackets). ***, **, and * indicate the significance at the 1%, 5%, and 10% levels. The sample period is 2007–2017 and firm and year-fixed effects (F, Y) are included for all regressions. Following Edmans et al. (2017), we multiply the coefficient on any term containing q by 100. All models include control variables and are the same as Equation (1). Only the relevant coefficients are tabulated for parsimony.

Eliminate zero information sample

In this section, we remove sample firms if the disclosure has no a_{type} information using f-words as used in the model 2. This procedure also removes firms that do not have any disclosure after the regulation, which is likely to be abnormally operated. For example, the company is facing bankruptcy and does not care about investor relations anymore. We rerun our baseline regression and report the result in Table H.4. The result in Columns (1) to (3) for the interaction term is consistent with our main regression, which further enhanced the robustness of our result.

Table H.4: Robustness for eliminating information sample

	Future Investment (Inv_{t+1})		
	(1)	(2)	(3)
q	0.536***	0.573***	0.568***
	(0.078)	(0.100)	(0.104)
$Cash$	0.006**	0.006**	0.005
	(0.003)	(0.003)	(0.005)
$Treat * Post$		0.000	0.003
		(0.003)	(0.006)
$q * Treat$		-0.132	-0.127
		(0.103)	(0.106)
$q * Post$		-0.080	-0.074
		(0.106)	(0.106)
$q * Treat * Post$		0.337***	0.333***
		(0.100)	(0.101)
$Cash * Treat$			-0.001
			(0.007)
$Cash * Post$			0.006
			(0.005)
$Cash * Treat * Post$			-0.004
			(0.005)
Control	Yes	Yes	Yes
Constant	Yes	Yes	Yes
Clustering	Industry	Industry	Industry
Fixed effects	F, Y	F, Y	F, Y
Adj. R^2	0.508	0.509	0.509
Obs.	11,754	11,754	11,754

Notes: The dependent variable is investment 1 year after (Inv_{t+1}). Robust standard errors are clustered by industry (in brackets). ***, **, and * indicate the significance at the 1%, 5%, and 10% levels. The sample period is 2007–2017 and firm and year-fixed effects (F, Y) are included for all regressions. Following Edmans et al. (2017), we multiply the coefficient on any term containing q by 100. All models include control variables and are the same as Equation (1). Only the relevant coefficients are tabulated for parsimony.