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Mandatory disclosure of comment letters and analysts' forecasts

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ABSTRACT

Comment letters (CLs) have been adopted as the main supervision mechanism for information disclosure by the two main Chinese stock exchanges since 2013. Both CLs and firms' responses have been publicly disclosed since the end of 2014. Using nonfinancial listed firms from 2013 to 2019 as our sample, we investigate the impact of CLs and their mandatory disclosure on analysts' forecast quality. The results show that, in the pre-disclosure period, there is no significant relation between CLs and analysts' forecast quality. However, in the post-disclosure period, CLs are positively (negatively) correlated with analysts' forecast accuracy (optimism). The quality of analysts' forecasts is much higher when CLs contain more questions. In addition, the impact of CLs is larger for samples with a lower percentage of star analysts or samples with higher earnings volatility. CL recipients tend to disclose more information on their internal and external risks, which can offer additional information to analysts.

1. Introduction

The quality of analysts' forecasts is important for the efficiency of the capital market. Compared with individual investors, financial analysts have more professional knowledge. They collect, analyze, and evaluate the information of listed firms and then form their forecasts, which are expected to be useful for investors. The analyst's dual role of information user and information provider is indispensable in promoting the efficiency of the capital market (Francis & Soffer, 1997; Givoly & Lakonishok, 1979). The annual report is the key channel for analysts to obtain information about listed firms (Byard & Shaw, 2003; Lehavy, Li, & Kenneth, 2011). Authentic and reliable information in annual reports can help analysts understand firms' business prospects and make accurate forecasts (Hirst, Hopkins, & Wahlen, 2004). Therefore, establishing a sound regulatory mechanism of information disclosure to improve the quality of annual reports is critical for increasing the quality of analysts' forecasts and reducing the information asymmetry between internal and external investors.

In the past 30 years, the Chinese Securities Regulatory Commission and the two main Chinese stock exchanges, namely, the Shanghai Stock Exchange (SSE) and the Shenzhen Stock Exchange (SZSE), have been improving their supervision of the information disclosure of listed firms, step by step. To optimize the information disclosure of listed firms, SSE and SZSE introduced a profound reform of information disclosure in 2013. Prior to this reform, a listed firm could release its annual report to the public only after it had been approved by the supervisor at the stock exchange, who served as the "caretaker" of information disclosure for the listed firm. According to this reform, a listed firm is required to disclose its annual report first, which the stock exchange supervisor will then review. If there are flaws in the annual report, the supervisor will send a comment letter (CL) to the firm. The firm is then required to give a response within a given period, usually five to seven working days. Consequently, the supervision of information disclosure by the two exchanges has been shifted from the pre-disclosure to the post-disclosure period. Essentially, the role of the stock exchanges has switched from caretaker to "doctor."

The CLs from the two main Chinese stock exchanges focus on not only the integrity of financial information, but also forward-looking information, such as firms' business model, industry development, and business risks. After this question and answer process between the stock exchanges and CL recipients, both the quantity and quality of information are expected to increase. This, in turn, could help analysts make higher-quality forecasts, especially when the disclosure of the CLs and response letters is mandatory.

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The CL mechanism was initiated at the very beginning of 2013, but the comment and response letters were not mandated to be disclosed until the end of 2014. Since the end of 2014, the disclosure of comment and response letters on the exchanges' websites has been mandatory. The rationale for mandatory information disclosure is the theory of externality. Information disclosure has a positive externality and can reduce investors' cost of information collection. The information revealed through voluntary disclosure can be insufficient, since it is difficult for firms to internalize externalities while bearing the costs of disclosure. Thus, mandatory information disclosure is an effective way to protect investors (Coffee, 1984; Zingales, 2009).

A counterargument, however, is information overload. Given that a massive amount of information is disclosed during the annual report period, can the mandatory disclosure of CLs help information users improve the efficiency of their decisions? Information overload theory argues that investment decisions can be influenced by various cognitive biases on the part of investors, analysts, and others. For example, people are constrained by bounded rationality and, in an information overload environment, tend to have difficulties identifying the relevant information (Jacoby, 1977), ignore a large amount of information (Bawden & Robinson, 2009), lack perspective (Schick, Gorden, & Haka, 1990), and even make worse decisions (Paredes, 2003; Simon, 1995). Therefore, the effect of the mandatory disclosure of CLs is an empirical problem, and the Chinese setting offers an opportunity to test it.

Analysts have greater access to information than individual investors and even regulators do. Compared with the supervisors of exchanges, analysts have certain information advantages. For example, to maintain their independence, supervisors do not make site visits to firms as analysts usually do. Supervisors in stock exchanges usually have a professional background in finance or law, whereas, besides a financial background, many analysts have professional experience in the industry they are tracking. If the information contained in CLs and firms' responses has already been obtained by analysts through other channels, the CL mechanism will have no significant impact on their forecasts. To sum up, the CL mechanism is likely to provide more information for individual investors, but whether it offers significant incremental information for analysts to make more accurate forecasts remains an empirical issue.

In this paper, we use unique data from undisclosed CLs during 2013–2014 and disclosed CLs during 2015–2019 in the Chinese stock market to examine the importance of the mandatory disclosure of CLs. We find that, in the pre-disclosure period, there is no significant relation between CLs and analysts' forecast accuracy or forecast optimism. However, in the post-disclosure period, CLs are positively related to analysts' forecast accuracy and negatively associated with forecast optimism. These results show that the disclosure of CLs can offer incremental information, even to information users as sophisticated as financial analysts. For firms that receive CLs from stock exchanges, the quality of analyst forecasts is higher when the CLs contain more questions. In addition, because non-star analysts have less access to private information, the impact of CLs is larger for firms followed by a higher percentage of non-star analysts. The impact of CLs on the quality of analysts' forecasts is also larger for samples with higher earnings volatility than for samples with lower earnings volatility. Lastly, we test the specific channel through which CLs influence the quality of analysts' forecasts and find that CL recipients disclose more information on their internal and external risks after they are queried, which offers incremental information to analysts.

This paper makes several contributions to the literature. First, the CL mechanism is a supervision innovation and it transforms the traditional regulator's unilateral allegations into a bidirectional dialog between the regulator and public companies. This new regulatory style has important implications for future supervision reform to improve the efficiency of the capital market, especially emerging markets such as China, where the information environment is weaker. Second, we enrich the literature on the impact of mandatory information disclosure on the information environment of listed firms. Mandatory information disclosure through government intervention can relieve problems related to the insufficient supply and low quality of information disclosure and thereby improve the efficiency of the capital market (Christensen, Hail, & Leuz, 2016; Coffee, 1984; Zingales, 2009). By comparing the impact of CLs on analysts' forecasts between the CL pre-disclosure and post-disclosure periods, we provide additional evidence of the importance of mandatory information disclosure. Third, we enrich the literature on the effectiveness of CLs. A CL has a direct impact not only on the recipient, but also on its stakeholders. Prior research has found that institutional investors, auditors, creditors, other stakeholders, and regulators can adjust their expectations and decisions based on the information contained in CLs (Cassell, Cunningham, & Lei, 2019; Gietzmann & Isidro, 2013; Gietzmann & Pettinicchio, 2014; Hu, Xu, & Xue, 2022). This paper further investigates the influence of CLs on analysts' forecasting behavior. Fourth, by comparing the different effects of CLs between samples followed by higher and lower percentages of non-star analysts, we provide evidence of different information coverage among analysts. Finally, we expand the literature on the effect of the exchange as a front-line regulatory authority. Studies on the effectiveness of government regulation mainly focus on the effectiveness of supervision by the U.S. Securities and Exchange Commission (SEC; see Cassell et al., 2019; Gietzmann & Isidro, 2013; Gietzmann & Pettinicchio, 2014) or the China Securities Regulatory Commission (Chen, Jiang, Liang, & Wang, 2011; Chen & Yuan, 2004). This paper provides evidence of the effectiveness of first-line supervision by the two main exchanges in the Chinese capital market.

The reminder of the paper is as follows: Section 2 reviews the literature. Section 3 develops the hypotheses. Sections 4 and 5 describe the research design and empirical results, respectively. Section 6 presents our conclusions.

2. Literature review

2.1. Mandatory and voluntary information disclosure

Voluntary information disclosure system often leads to two problems. First, the supply of information is insufficient. Because of the cost of disclosure (e.g., the leakage of business secrets), firms usually lack motivation to disclose information. Second, the quality of the disclosed information is low. For example, self-interest can drive management to disclose more good news than bad news.

Most studies show that government intervention to mandate disclosure can effectively relieve these two problems (Bonaime, 2015; Horton, Serafeim, & Serafeim, 2013). Coffee (1984) discusses the effect of information disclosure on investor protection from the perspective of aggregate social wealth. The author argues that the information disclosed is a byproduct of firms' internal financial accounting system and that the marginal cost of information disclosure is very small. The mandatory information disclosure system can reduce investors' information search costs, resulting in a Pareto improvement of aggregate social wealth. This argument is supported by the literature on the Fair Disclosure Act (FD), the Sarbanes–Oxley Act, and the mandatory adoption of international accounting standards (i.e., International Financial Reporting Standards). Gintschel and Markov (2004) find that the implementation of the FD has been effective in curtailing selective disclosure. Bailey, Li, and Mao (2003) confirm that, after the FD, information leakage decreased while the divergence of analysts' forecasts increased. Cohen, Dey, and Thomas (2008) show that, after the promulgation of the Sarbanes–Oxley Act, the degree of accrual-based earnings management decreased and the quality of accounting information significantly increased. In addition, Horton et al. (2013) find that the mandatory adoption of International Financial Reporting Standards enhances the information environment by improving the quality of accounting information.

2.2. Impact of CLs on the information environment

The CL mechanism was adopted in the United States since 2005. Using U.S. firms as their sample, Johnston and Petacchi (2017) find that firms with historically poor reporting quality are more likely to receive CLs and that their information quality improves significantly afterward. Bens, Cheng, and Neamtiu (2016) find that the uncertainty of fair value estimations is reduced for the SEC's CL recipients, while Bozanic, Dietrich, and Johnson (2017) show that both the quantity and quality of information disclosure increase after CLs have been issued.

CLs impact not only the firms that receive them, but also the decisions of stakeholders. Gietzmann and Isidro (2013) find that institutional investors reduce their stock holdings of CL recipients. Gietzmann and Pettinicchio (2014) show that auditors ask for higher audit fees for CL recipients, while Hu et al. (2022) find that auditors tend to be more conservative with CL recipients. Cunningham, Schmardebeck, and Wei (2017) find that, after a firm receives a CL from the SEC, the bank charges higher interest. The interest rate is significantly higher if the CL results in a financial statement restatement, which suggests that material disclosure deficiencies have been identified in the CL. Kubick, Lynch, Mayberry, and Omer (2016) find that the SEC's CLs on taxes have a spillover effect on peer firms in the same industry.

In China, SSE and SZSE adopted the CL mechanism in 2013, but it was not until the end of 2014 that both the CLs and firms' responses were publicly disclosed. Previous studies have investigated the market reaction to CLs (Chen, Deng, & Li, 2018a) and the letters' impact on earnings management (Chen, Deng, & Li, 2019), stock price collapse (Zhang, Tang, & Li, 2018), and audit quality (Chen, Deng, & Li, 2018b). As far as we know, no study has focused on the consequences of the mandatory disclosure of CLs.

3. Hypothesis development

Issuing CLs on annual reports is an important supervision reform for the Chinese stock exchanges to improve the quality of firms' information disclosure. If the supervisor is unsatisfied with the response from the queried firm, the supervisor will continue to issue CLs. Thus, a firm that receives a CL can offer a high-quality response to reduce the probability of receiving another CL. In addition, the major investing and financing activities (e.g., seasoned equity offerings, mergers and acquisitions) of Chinese listed firms need to be approved by regulators, and a high-quality response will make a good impression on them. This, in turn, will facilitate firms' future investing or financing activities in the capital market. Firms' explanations, supplements, and corrections to the content of annual reports increase both the quantity and quality of the disclosed information.

The quality of analysts' forecasts can be evaluated based on the forecasts' accuracy and optimism. When firms disclose more information, analysts' forecasts become more accurate and less divergent (Lang & Lundholm, 1996). Byard and Shaw (2003) find that improved information disclosure significantly promotes analysts' understanding of public and private information, thereby increasing the accuracy of their forecasts. When a listed firm receives a CL, it will try to respond within the required time and provide more high-quality information (Bozanic et al., 2017; Johnston & Petacchi, 2017). These effects of CLs can reduce the cost for analysts to process and analyze information, which helps them make more accurate forecasts.

Analysts' forecasts tend to be optimistic. Previous studies confirm that earnings forecasts tend to be biased and higher than the actual earnings of listed firms (Francis & Philbrick, 1993; Michaely & Womack, 1999). Easterwood and Nutt (1999) find that analysts are generally unwilling to disclose firms' negative news but willing to issue more optimistic reports. There are various motivations for analysts' optimistic predictions, such as to please firms' executives to obtain private information (Lim, 2001; Zhao, Li, & Liu, 2013) and to gain more trading commissions (Gu, Li, & Yang, 2013; Jackson, 2005).

The issuance of a CL signals to the capital market that the recipients could have problems with accounting or corporate governance, which will negatively affect market expectations. If, after the letter, an analyst still chooses to release a forecast with an optimism bias, it will be easier for investors to challenge the analyst's forecast and damage the analyst's reputation. The higher the accuracy of analysts' forecasts, the more likely the analysts will move on to more famous securities firms or become star analysts in the future (Hong & Kubik, 2003). After considering their reputation and career development, analysts will more likely reassess the CL recipient's financial status and corporate governance, pay more attention to the potential impact of biased forecasts on their reputation, and thus integrate more negative information into earnings forecasts. In addition, the optimism bias of analysts is affected not only by rational factors such as the reputation mechanism, but also by irrational factors such as the sentiment of information users (Wu, Pan, & Hu, 2012). CLs are a negative signal to analysts and negatively affect their sentiment. Therefore, analysts' optimism bias will decrease.

Is the mandatory disclosure of CLs and firms' responses important to analysts' forecasts? CLs were not disclosed until the end of 2014 in China. In the pre-disclosure period (2013–2014), it was difficult for analysts to obtain the specific information of a CL or even know whether a letter had been issued. Of course, even then, the letters could have generated incremental information by prompting the recipients to make amendments or restatements to their annual reports (Cassell et al., 2019). In sum, the incremental information gained by analysts in the pre-disclosure period is less than that in the post-disclosure period, so CLs are expected to have a lesser impact on analysts' forecasts in the pre-disclosure period than in the post-disclosure period.

Based on the above discussion of CLs and the impact of their mandatory disclosure on analysts' forecasts, we propose the following hypothesis.

H1. **:** *When a firm is issued a CL, the accuracy of analysts' forecasts will be improved and optimism bias will be reduced. The positive impact of CLs on the quality of analysts' forecasts is stronger in the post-disclosure period than in the pre-disclosure period.*

The increase in the quantity and quality of public information can help analysts conduct in-depth information mining and analysis, which improves the accuracy of their predictions (Lang & Lundholm, 1996). CLs' impact on the accuracy of analysts' forecasts depends on the information quantity of the CLs, that is, the number of questions in the letters. When a CL asks more questions, analysts can obtain more incremental information. In addition to paying attention to the authenticity and completeness of financial information, supervisors usually keep track of forward-looking information such as corporate business models, industry prospect, and corporate risk disclosure. The disclosure of forward-looking information will change the expectations of firm analysts, thereby improving the quality of their earnings forecasts. Accordingly, we propose the following hypothesis.

H2. **:** *The number of questions contained in CLs is positively correlated with analysts' forecast accuracy and negatively correlated with analysts' forecast optimism.*

As an important information intermediary in the capital market, analysts base their predictions on both public and private information. Public information is available to all information users in the capital market and is an important information source for all analysts. Private information is held by individual analysts and not disclosed publicly. Previous studies have shown that, compared to non-star analysts, star analysts have superior information acquisition, especially via private information collection channels (Clement, 1999; Fang & Yasuda, 2014; Xu, Chan, Jiang, & Yi, 2013). A firm's response to a CL often contains information that has not been publicly disclosed prior to the disclosure of the response. When more information is publicly disclosed, information asymmetry among analysts will be reduced and the relative information advantage of star analysts will decline. Usually, more than one analyst is following a firm, so we use the percentage of star analysts to proxy for the average information advantage of analysts following a given firm. We expect that the disclosure of CLs and response letters is more helpful for the quality of analysts' forecasts of firms followed by a lower percentage of star analysts than of firms followed by a higher percentage of star analysts. Accordingly, we propose the following hypothesis.

H3. **:** *The disclosure of CLs is more helpful in improving the quality of analysts' forecasts for firms followed by a lower percentage of star analysts than for firms followed by a higher percentage of star analysts.*

A firm's earnings volatility will also have an impact on the relation between the CL mechanism and the quality of analysts' forecasts. Lower fluctuations in earnings indicate a better information environment and less information asymmetry. In this better information environment, the incremental information that analysts obtain from CLs tends to be limited. On the contrary, greater earnings fluctuations usually indicate a poorer information environment, so the information asymmetry faced by analysts will be greater. In this case, CLs provide more incremental information to analysts. We therefore expect that CLs will be more helpful to analysts conducting forecasts of firms with more volatile earnings than to analysts conducting forecasts of firms with less volatile earnings. Accordingly, we propose the following hypothesis.

H4. **:** *The disclosure of CLs is more helpful in improving the quality of analysts' forecasts following firms with higher earnings volatility than firms with lower earnings volatility.*

As discussed in the introduction, CLs might have no significant impact on analysts' forecasts for two reasons: First, analysts have an advantage in information collection and analysis, and CLs can thus offer them very marginal information. Second, the information in CLs can simply overload analysts, especially during annual report season, when a massive amount of information is available.

4. Research design

4.1. Empirical models and variable definitions

To test H1 and H2, we construct the following model:

$$AF_{i,t} = \alpha_1 + \alpha_2 {*} CL_{i,t}/LnQn_{i,t} + \alpha_3 {*} Control_{i,t} + Year/Ind + \varepsilon_{i,t} \tag{1}$$

where the dependent variable is analysts' forecasts (*AF*). We use two proxies to interpret the quality of analysts' forecasts. The first is the accuracy of analysts' forecasts (*AF_accuracy*), and the second is their optimism bias (*AF_optimism*). The variable *AF_accuracy* is defined as the opposite value of the error in analyst forecasts (*AF_error*) according to the following model:

$$AF\_accuracy_{i,t} = -AF\_error_{i,t} = -\frac{\text{Abs}\left[\text{Mean}\left(AF\_EPS_{i,t}\right) - EPS_{i,t}\right]}{Price_{i,t-1}} \tag{2}$$

where AF_EPS_t and EPS_t represent the earnings per share (EPS) forecasted by the analyst and the real EPS for firm *i* in year *t*, respectively; $Price_{t-1}$ is the stock price of firm *i* at the end of year *t* - 1; and *Abs* and *Mean* are the absolute value and the average value, respectively.

The variable $AF\_accuracy_{i,t} = -AF\_error_{i,t} = -\frac{\text{Abs}\left[\text{Mean}\left(AF\_EPS_{i,t}\right) - EPS_{i,t}\right]}{Price_{i,t-1}}$ *AF_optimism* is the difference between the mean of *AF_EPS* and *EPS* divided by the stock price of firm *i* at the end of year *t* - 1, as shown in the following model:

$$AF\_optimism_{i,t} = \frac{\text{Mean}\left(AF\_EPS_{i,t}\right) - EPS_{i,t}}{Price_{i,t-1}} \tag{3}$$

If the forecasted EPS (*AF_EPS*) are greater than the real EPS (*EPS*), this indicates that the analysts tend to be optimistic. The larger the value of *AF_optimism*, the more optimistic the analysts are.

Before defining the independent variables, we use Fig. A1 in Appendix A to illustrate the timeline of the annual report, the CL issuance, and the analyst forecast.

To test H1, we define *CL* in model (1) as equal to one if firm *i* is issued a CL in year *t* on its annual report of year *t* - 1, and zero otherwise. Then, to test H2, we define *LnQn* for CL recipients as the natural logarithm of the sum of the number of questions contained in the CL and one. We take firm-years with comment letters as our sample to test H2.

In H3 and H4, we expect the improvement of analysts' forecasts for CL recipients to be influenced by the analysts' ability to collect private information and by the firms' information environment, respectively. To test H3, we use the percentage of star analysts following firm *i* in year *t* to measure analysts' ability to collect private information. Specifically, *Lowstarp* equals one if the percentage of star analysts following firm *i* is lower than the median for all firms in the same industry, and zero otherwise. The appraisement of star analysts is made by *New Fortune*, a Chinese financial magazine. Star analysts are voted on annually by institutional investors, such as mutual funds, private equity funds, insurance asset management companies, social security funds, and other institutional buyers in the capital market, very similarly to the process in developed capital markets. To test H4, we use the volatility of a firm's earnings (*HighSdNP*) to measure the quality of the firm's information environment. The measure *HighSdNP* equals one if the standard deviation of the firm's return on assets from year *t* - 3 to year *t* - 1 is higher than the median for all firms in the same industry, and zero otherwise. We then split the total sample into two subgroups according to *Lowstarp* (*HighSdNP*) to test H3 (H4).

Following prior studies (Bozanic et al., 2017; Byard & Shaw, 2003; Johnston & Petacchi, 2017), we include the following firm's characteristics as control variables in model (1): the absolute value of discretionary accruals (*DA*), size (*Size*), leverage (*Lev*), the return on assets (*ROA*), operating cash flow (*OCF*), the annual stock return (*Yret*), the market-to-book ratio (*MB*), the shareholding ratio of institutional investors (*Inst*), the number of days between the forecast date and the annual report date (*Avlnday*), the internal control index (*IC*), whether a Big 4 auditor is employed (*Big4*), and the age (*Age*). The definitions of all the variables are listed in Appendix B.

We also include firm fixed effects in model (1) to control for unobservable characteristics that could affect the quality of analysts' forecasts. To avoid the influence of extreme observations, we winsorize all continuous variables at 1% and 99%.

4.2. Data

The two Chinese stock exchanges, that is, SSE and SZSE, implemented the CL mechanism in 2013, but the disclosure of CLs was not mandatory until the end of 2014. We obtained data on CLs issued in the pre-disclosure period (2013–2014) from one of the stock exchanges. This enables us to compare the effect of CLs on analysts' forecasts between the pre- and post-disclosure periods. We collected public data on CLs issued in the post-disclosure period (2015–2019) from the official websites of the two Chinese stock exchanges and then thoroughly read all of these CLs and recorded the number of questions each contained. We obtained analysts' forecasts and other financial data from the database of China Stock Market & Accounting Research, a leading financial data provider in China.

Specifically, our sample involves two parts: 1) the subsample for 2013–2014, which includes 1164 firm–years, 285 of which received CLs, and 2) the subsample for 2015–2019, which includes 7892 firm–years, 1268 of which received CLs. The sample distribution is presented in Table 1.

Table 1
Sample distribution.

	Pre-disclosure period	Post-disclosure period	Total
	2013–2014	2015–2019	2013–2019
Total sample	1164	7892	9056
Samples issued with CLs ($CL = 1$)	285	1268	1553

This table presents our sample distribution. Our sample includes two parts: 1) the sub-sample for 2013–2014, with 1164 firm–years, 285 of which received CLs, and 2) the sub-sample for 2015–2019, with 7892 firm–years, 1268 of which received CLs. In total, our sample for 2013–2019 includes 9056 firm–years, 1553 of which received CLs.

5. Empirical results

5.1. Descriptive statistics

Table 2 shows the descriptive statistics for all the variables in the main regressions. The means of *AF_accuracy* and *AF_optimism* are −0.016 and 0.012, respectively. The mean of *CL* is 0.171, suggesting that about 17.1% of the observations in our sample are issued CLs. The mean of *LnQn* is 2.326, indicating that the average number of questions in a CL is 9.24. The minimum number of questions is two and the maximum is 34, suggesting that the deviation of the number of questions in CLs is quite large. The averages of *DA*, *Size*, *Lev*, *ROA*, and *OCF* are 0.054, 22.83, 0.457, 0.038, and 0.049, respectively. The mean of *Yret* is 0.159, and the mean of *MB* is 3.383. The average of *Inst* is 0.076, indicating that the percentage of shares held by institutional investors is about 7.6%. The mean of *Avlnday* is 5.484, suggesting that analysts' forecasts are released 239.81 days before annual reports, on average. The mean of *Big4* is 0.085, indicating that 8.5% of the sample firms are audited by Big 4 audit firms. The average value of *Age* is 2.492, which indicates that, on average, the sample firms have been listed for 11.09 years.

5.2. CLs and the quality of Analysts' forecasts

Hypothesis 1 predicts that, after a firm is issued a CL, the accuracy of analysts' forecasts will increase and their optimism bias will decrease. Moreover, H1 predicts that the impact described above will be more significant in the post-disclosure period (2015–2019) than in the pre-disclosure period. There are 1553 CL recipients, of which 285 fall in 2013–2014 and 1268 fall in 2015–2019.

Table 3 presents the regression results for H1. Columns (1) and (2) exhibit the regression results of the first part of H1, where the sample period is from 2013 to 2019 and includes both the pre-disclosure and post-disclosure periods. In column (1), the coefficient of *CL* is 0.003, which is statistically significant at the 1% level. This indicates that, if a firm receives a CL, the forecast accuracy of its analysts will be significantly improved. In column (2), the coefficient of *CL* is −0.003, which is statistically significant at the 1% level. This suggests that, if a firm receives a CL, the forecast optimism of its analysts will be significantly decreased. The results in columns (1) and (2) confirm the first part of H1; that is, after a firm is issued a CL, the accuracy of analysts' forecasts will be improved and the optimism bias will be reduced.

The regression results for the second part of H1 are presented in columns (3) to (6) of Table 3. The sample period of columns (3) and (4) is 2013–2014, when CLs were not mandatorily disclosed. In both columns, the coefficients of *CL* are not statistically significant, indicating that, before CLs were mandatorily disclosed, they had no significant impact on analysts' forecast accuracy or forecast optimism. The sample period of columns (5) and (6) is 2015–2019, when CLs were mandatorily disclosed. In column (5), the coefficient of *CL* is 0.003 and statistically significant at the 1% level. This indicates that, in the post-disclosure period, if a firm received a CL, the forecast accuracy of its analysts was significantly improved. In column (6), the coefficient of *CL* is −0.003, also statistically significant at the 1% level. This suggests that, in the post-disclosure period, if a firm received a CL, the forecast optimism of its analysts was significantly decreased. The results in columns (3) to (6) confirm the second part of H1, that is, the impact of CLs on analysts is more pronounced in the post-disclosure period than in the pre-disclosure period.

In conclusion, the results in Table 3 imply that, if a firm is issued a CL, the accuracy of its analysts' forecasts is significantly improved and the analysts' optimism bias is significantly reduced. In addition, this impact is significant only in the mandatory disclosure period.

In terms of control variables, *ROA* is positively correlated with forecast quality, indicating that firms with good profitability are easier to forecast; *Inst* is positively correlated with forecast quality, meaning the shareholding ratio of institutional investors is positively correlated with analysts' forecast quality; and *IC* is positively correlated with forecast quality, indicating that firms with high-quality internal control are easier to forecast.

5.3. Information content of CLs and the quality of Analysts' forecasts

Hypothesis 2 predicts that the number of questions contained in CLs is positively correlated with analysts' forecast accuracy and negatively correlated with analysts' forecast optimism.

The regression results of H2 are shown in Table 4. In column (1), the coefficient of *LnQn* is 0.004 and statistically significant at the 5% level. This suggests that the more questions a CL contains, the more accurate the analysts' forecasts are. Specifically, if the number of questions increases by 100%, the forecast's accuracy will improve by 0.004. Given that the mean of *AF_accuracy* is −0.016, this means that the increase in forecast accuracy is economically significant. In column (2), the coefficient of *LnQn* is −0.003 and statistically significant at the 5% level. This indicates that, when CLs contain more questions, analysts' forecasts have less optimism bias. Specifically, if the number of questions increases by 100%, analysts' forecast optimism will decrease by 0.003. Given that the mean of *AF_optimism* is 0.012, this increase is also economically significant.[1]

In conclusion, the results in Table 4 are consistent with the idea that, when CLs contain more questions, more incremental information is released to the market. The improved information disclosure, in turn, helps analysts make higher-quality forecasts.

5.4. Information asymmetry, CLs, and the quality of Analysts' forecasts

5.4.1. Information asymmetry among analysts

We next explore the effect of the degree of information asymmetry on the relation between CLs and the quality of analysts' forecasts.

Analysts make their forecasts based on both public and private information. Public information is all of the information disclosed in the capital market and available to all analysts. Private information, however, is not publicly disclosed in the market and is held only by certain analysts. Private information is an important source for analysts when they make forecasts. Prior studies have shown that star analysts outperform non-star analysts in terms of information access, especially access to private information (Clement, 1999; Xu et al., 2013). CLs often involve information that was not previously disclosed to the public. When the incremental information contained in CLs is disclosed, the information advantage of star analysts declines. Therefore, the disclosure of CLs is expected to be more helpful in improving the forecast quality of firms followed by a lower percentage of star analysts than that of firms followed by a higher percentage of star analysts. To assess this,

[1] An alternative expression of the impact of *LnQn* is as follows: when *LnQn* changes by one standard deviation, *AF_accuracy* and *AF_optimism* will both change by 13.2%.

Table 2
Descriptive statistics.

Variables	N	mean	SD	p25	p50	p75	Min	Max
AF_accuracy	9056	−0.016	0.024	−0.018	−0.008	−0.003	−0.151	0
AF_optimism	9056	0.012	0.025	0	0.006	0.015	−0.037	0.148
CL	9056	0.171	0.377	0	0	0	0	1
LnQn	1553	2.326	0.528	1.946	2.303	2.708	1.099	3.555
Lowstarp	9056	0.666	0.472	0	1	1	0	1
HighSdNP	9056	0.438	0.496	0	0	1	0	1
DA	9056	0.054	0.057	0.017	0.037	0.071	0.001	0.329
Size	9056	22.83	1.271	21.92	22.65	23.59	19.61	26.14
Lev	9056	0.457	0.198	0.302	0.454	0.606	0.0580	0.955
ROA	9056	0.038	0.058	0.016	0.036	0.063	−0.406	0.190
OCF	9056	0.049	0.068	0.011	0.048	0.089	−0.196	0.239
Yret	9056	0.159	0.555	−0.225	0.008	0.387	−0.601	2.286
MB	9056	3.383	2.862	1.559	2.519	4.190	0.585	17.09
Inst	9056	0.076	0.078	0.018	0.050	0.107	0	0.395
Avlnday	9056	5.484	0.713	5.371	5.790	5.919	2.398	6.109
IC	9056	6.284	1.103	6.428	6.496	6.549	0	6.685
Big4	9056	0.085	0.279	0	0	0	0	1
Age	9056	2.492	0.521	2.079	2.565	2.944	0.693	3.258

This table presents the descriptive statistics for all the variables in the main regressions.

Table 3
CLs and Analyst Forecast Quality (H1).

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)
	2013–2019		2013–2014 (pre-disclosure period)		2015–2019 (post-disclosure period)	
	AF_accuracy	*AF_optimism*	*AF_accuracy*	*AF_optimism*	*AF_accuracy*	*AF_optimism*
CL	**0.003*****	**−0.003*****	**0.003**	**0.002**	**0.003*****	**−0.003*****
	(3.279)	**(−3.097)**	**(1.051)**	**(0.854)**	**(2.939)**	**(−2.869)**
DA	−0.041***	−0.007	−0.048**	0.010	−0.039***	−0.012*
	(−6.197)	(−1.300)	(−2.069)	(0.396)	(−5.563)	(−1.938)
Size	0.000	−0.000	0.008	−0.012**	−0.001	0.001
	(0.223)	(−0.162)	(1.346)	(−2.575)	(−0.897)	(0.821)
Lev	0.007*	−0.017***	0.011	−0.024	0.006	−0.016***
	(1.705)	(−4.412)	(0.579)	(−1.381)	(1.426)	(−3.970)
ROA	0.264***	−0.334***	0.465***	−0.608***	0.258***	−0.326***
	(23.379)	(−28.038)	(6.474)	(−7.911)	(21.869)	(−26.211)
OCF	−0.016***	−0.004	0.032	−0.050*	−0.017***	−0.002
	(−2.652)	(−0.668)	(1.428)	(−1.923)	(−2.641)	(−0.389)
Yret	−0.002**	−0.005***	−0.004*	−0.002	−0.002	−0.006***
	(−2.493)	(−6.285)	(−1.950)	(−0.895)	(−1.611)	(−6.902)
MB	−0.000	0.001***	0.002	−0.001	−0.000	0.001***
	(−0.957)	(3.983)	(1.346)	(−0.424)	(−1.318)	(4.311)
Inst	0.028***	−0.016***	0.004	−0.005	0.036***	−0.021***
	(5.986)	(−3.481)	(0.301)	(−0.296)	(6.611)	(−4.170)
Avlnday	−0.004***	0.004***	−0.003***	0.004***	−0.004***	0.004***
	(−11.819)	(11.809)	(−2.844)	(3.766)	(−11.064)	(10.598)
IC	0.001***	−0.001	0.003*	−0.003**	0.001***	−0.001
	(3.276)	(−1.447)	(1.729)	(−1.982)	(3.384)	(−1.441)
Big4	0.001	−0.003	0.010**	0.001	0.003	−0.004
	(0.272)	(−0.928)	(2.482)	(0.168)	(1.035)	(−1.605)
Age	0.001	−0.004	0.014	−0.002	−0.000	−0.006
	(0.218)	(−1.345)	(1.341)	(−0.138)	(−0.104)	(−1.402)
Constant	−0.024	0.030	−0.253**	0.339***	0.011	0.009
	(−0.808)	(1.026)	(−1.966)	(2.991)	(0.377)	(0.321)
Observations	9056	9056	1164	1164	7892	7892
R-Squared	0.3689	0.4317	0.3452	0.4061	0.3939	0.4601
Firm/Year	Fixed	Fixed	Fixed	Fixed	Fixed	Fixed
F	70.80	81.00	6.550	14.90	72.76	84.77

This table presents the regression results for H1. The sample period for columns (1) and (2) is 2013–2019, which includes both the pre-disclosure and post-disclosure periods. The sample period for columns (3) and (4) is 2013–2014, when CLs were not mandatorily disclosed. The sample period for columns (5) and (6) is 2015–2019, when CLs were mandatorily disclosed. The variable definitions are provided in Appendix B. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively (two tailed for all *t*-statistics).

we split the sample into a group followed by a higher percentage of star analysts (*Lowstarp* = 0) and a group followed by a lower percentage of star analysts (*Lowstarp* = 1) and run model (1).

Table 5 presents the results for H3. Columns (1) and (2) show the results for *AF_accuracy*. The regression results in column (1) are for the group followed by more star analysts, and the coefficient of *CL* is 0.002 and not statistically significant. In contrast, the coefficient of *CL* for the group followed by fewer star analysts, shown in column (2), is 0.004 and statistically significant at the 1% level. This means that, as hypothesized, the disclosure of CLs is more helpful in improving the accuracy of analysts' forecasts for firms followed by fewer star analysts. The difference between these two coefficients is significant at the 10% level (p = 0.083). In column (3), the coefficient of *CL* for the group followed by more star analysts is not statistically significant. The coefficient of *CL* for

Table 4
Information Content of CLs and Analyst Forecast Quality (H2).

VARIABLES	(1)	(2)
	2015–2019	2015–2019
	AF_accuracy	*AF_optimism*
LnQn	**0.004****	**−0.003****
	(2.148)	**(−2.233)**
DA	−0.040**	−0.002
	(−2.100)	(−0.173)
Size	0.005	−0.001
	(1.170)	(−0.175)
Lev	−0.037**	0.016*
	(−2.165)	(1.934)
ROA	0.238***	−0.269***
	(9.882)	(−13.836)
OCF	−0.049**	0.038**
	(−2.210)	(2.322)
Yret	−0.009**	−0.001
	(−2.315)	(−0.596)
MB	0.002*	0.000
	(1.726)	(0.081)
Inst	0.017	0.027*
	(0.837)	(1.807)
Avlnday	−0.002*	0.002**
	(−1.781)	(2.528)
IC	0.001	−0.001
	(1.422)	(−1.599)
Big4	−0.020	−0.003
	(−1.552)	(−0.498)
Age	−0.024	−0.010
	(−1.318)	(−0.606)
Constant	−0.054	0.043
	(−0.578)	(0.475)
Observations	1268	1268
R-Squared	0.5025	0.5597
Firm/Year	Fixed	Fixed
F	13.22	24.24

This table presents the regression results of H2, which predicts that the number of questions contained in CLs are positively correlated with analysts' forecast accuracy and negatively correlated with analysts' forecast optimism. The variable *LnQn* is the logarithm of the sum of the number of questions contained in the CL and one. The other variable definitions are provided in Appendix B. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively (two tailed for all *t*-statistics).

Table 5
Lower versus Higher Percentage of Star Analysts (H3).

VARIABLES	(1)	(2)	(3)	(4)
	2015–2019		2015–2019	
	Lowstarp = 0	*Lowstarp* = 1	*Lowstarp* = 0	*Lowstarp* = 1
	AF_accuracy	*AF_accuracy*	*AF_optimism*	*AF_optimism*
CL	**0.002**	**0.004*****	**0.003**	**−0.004*****
	(0.790)	**(3.148)**	**(1.285)**	**(−3.353)**
DA	−0.042***	−0.034***	−0.010	−0.007
	(−2.873)	(−3.900)	(−0.737)	(−0.907)
Size	−0.003	−0.000	0.004	0.001
	(−0.863)	(−0.136)	(1.320)	(0.346)
Lev	0.015	0.002	−0.029***	−0.011**
	(1.500)	(0.499)	(−3.473)	(−2.260)
ROA	0.183***	0.283***	−0.281***	−0.346***
	(5.694)	(21.935)	(−7.640)	(−25.592)
OCF	−0.027*	−0.017**	−0.012	0.004
	(−1.855)	(−2.208)	(−0.795)	(0.594)
Yret	−0.003	−0.001	−0.012***	−0.004***
	(−1.415)	(−1.240)	(−6.624)	(−3.922)
MB	−0.000	−0.000	0.002***	0.001**
	(−0.811)	(−1.068)	(3.800)	(2.029)
Inst	0.040***	0.033***	−0.010	−0.023***
	(3.834)	(4.652)	(−1.069)	(−3.275)
Avlnday	−0.003***	−0.004***	0.003***	0.004***
	(−3.743)	(−9.230)	(3.932)	(9.315)
IC	0.003**	0.001***	−0.001	−0.001
	(2.139)	(2.637)	(−0.820)	(−1.367)
Big4	0.001	0.003	−0.000	−0.006
	(0.121)	(1.374)	(−0.023)	(−1.444)
Age	−0.020*	0.005	0.004	−0.008
	(−1.816)	(0.958)	(0.419)	(−1.506)
Constant	0.083	−0.017	−0.063	0.021
	(1.108)	(−0.514)	(−0.988)	(0.570)
t	**3.01* (p = 0.083)**		**5.50** (p = 0.019)**	
Observations	2693	5199	2693	5199
R-Squared	0.2113	0.4639	0.3533	0.5200
Firm/Year	Fixed	Fixed	Fixed	Fixed
F	9.119	69.04	15.17	81.64

This table presents the results for H3. We split the sample into a group followed by a higher percentage of star analysts (*Lowstarp* = 0) and a group followed by a lower percentage of star analysts (*Lowstarp* = 1) and run model (1). Columns (1) and (2) show the results for *AF_accuracy*. Columns (3) and (4) show the results for *AF_optimism*. The variable definitions are provided in Appendix B. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively (two tailed for all *t*-statistics).

the group followed by fewer star analysts, in column (4), is significant at the 1% level, indicating that, when a firm receives a CL, the optimistic forecast bias of the group followed by fewer star analysts is significantly decreased. The difference between the two coefficients is significant at the 5% level ($p = 0.019$). The regression results in Table 5 are consistent with the expectation of H3.

5.4.2. Firms' information environment

Dichev and Tang (2009) show that firms with higher earnings volatility will increase information asymmetry in the market. The mandatory disclosure of CLs could alleviate the information asymmetry that results from earnings volatility. Hypothesis 4 proposes that the disclosure of CLs will be more helpful in improving the quality of analysts' forecasts for firms with higher earnings volatility than for firms with lower earnings volatility.

Table 6 presents the results for H4. In column (1), the coefficient of *CL* for the sample with low earnings volatility is 0.002 and statistically significant at the 10% level. In column (2), the coefficient of *CL* for the sample with high earnings volatility is 0.004 and statistically significant at the 5% level. The difference between the two coefficients is significant at the 5% level (p = 0.019), which means that the disclosure of CLs is more helpful in improving the accuracy of analysts' forecasts for firms with a higher degree of information asymmetry. In column (3), the coefficient of *CL* for the sample with low earnings volatility is −0.002 and statistically significant at the 5% level. The coefficient of *CL* for the sample with high earnings volatility, in column (4), is −0.004 and statistically significant at the 5% level. The absolute value of the coefficient of *CL* is significantly larger in column (4) than in column (3) at the 5% level ($p = 0.032$). This means the disclosure of CLs is more helpful in reducing the optimistic forecast bias of analysts who follow firms with higher earnings volatility, which supports H4.

To sum up, the results of H3 and H4 indicate that the disclosure of CLs will improve the quality of analysts' forecasts more significantly in settings where information asymmetry is more severe.

5.5. Do firms increase information disclosure after receiving CLs?

In this section, we run an additional test to determine how CLs affect the recipients' information disclosure and then the quality of analysts' forecasts. It is obvious that receiving a CL is negative news for the firm's investors (Dechow, Lawrence, & Ryans, 2016; Gietzmann & Isidro, 2013). To alleviate the market's mistrust and avoid further CLs, the CL recipient can disclose more information, such as details about risks. In practice, the supervisors at SSE and SZSE will also focus on risk issues. Therefore, we expect that, when a firm receives a CL, it will disclose more risk factors to reduce the probability of further inquiries.

We obtain risk data from Chinese Research Data Services. In this database, the risk factors are classified into internal and external risks.

Table 6
High versus Low Earnings Volatility (H4).

VARIABLES	(1)	(2)	(3)	(4)
	2015–2019		2015–2019	
	HighSdNP = 0	*HighSdNP* = 1	*HighSdNP* = 0	*HighSdNP* = 1
	AF_accuracy	*AF_accuracy*	*AF_optimism*	*AF_optimism*
CL	**0.002***	**0.004****	**−0.002****	**−0.004****
	(1.887)	**(2.221)**	**(−2.136)**	**(−2.167)**
DA	−0.006	−0.065***	−0.011*	0.002
	(−0.919)	(−5.918)	(−1.723)	(0.257)
Size	−0.002	−0.000	−0.001	0.002
	(−1.127)	(−0.038)	(−0.504)	(1.059)
Lev	0.008	−0.001	−0.020***	−0.013**
	(1.630)	(−0.141)	(−3.781)	(−2.008)
ROA	0.230***	0.234***	−0.397***	−0.307***
	(8.391)	(17.641)	(−12.890)	(−21.623)
OCF	−0.000	−0.013	−0.000	−0.009
	(−0.065)	(−1.077)	(−0.021)	(−0.730)
Yret	−0.001	−0.002	−0.005***	−0.009***
	(−0.571)	(−1.146)	(−4.373)	(−5.584)
MB	−0.000	0.000	0.001***	0.001**
	(−1.047)	(0.329)	(4.019)	(2.577)
Inst	0.018***	0.041***	−0.016***	−0.009
	(3.968)	(3.895)	(−3.068)	(−0.947)
Avlnday	−0.003***	−0.005***	0.003***	0.004***
	(−9.334)	(−7.983)	(8.396)	(6.705)
IC	0.001	0.001*	−0.001	−0.000
	(1.564)	(1.691)	(−1.160)	(−0.378)
Big4	0.000	0.013**	−0.003	−0.016**
	(0.162)	(2.428)	(−0.867)	(−2.557)
Age	0.001	−0.011	−0.000	−0.008
	(0.351)	(−1.178)	(−0.070)	(−0.882)
Constant	0.018	0.019	0.048	−0.014
	(0.580)	(0.352)	(1.287)	(−0.272)
t	**5.47** (p = 0.019)**		**4.59** (p = 0.032)**	
Observations	4409	3483	4409	3483
R-Squared	0.1578	0.4171	0.2082	0.5106
Firm/Year	Fixed	Fixed	Fixed	Fixed
F	23.51	47.17	24.88	58.39

This table presents the results for H4. We split the sample into a group with a lower standard deviation of the return on assets (*HighSdNP* = 0) and a group with a higher standard deviation (*HighSdNP* = 1) and run model 1). Columns (1) and (2) show the results for *AF_accuracy*. Columns (3) and (4) show the results for *AF_optimism*. The variable definitions are provided in Appendix B. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively (two tailed for all *t*-statistics).

Internal risks cover seven factors: operational risk, financial risk, human resources risk, production risk, technological risk, losses, and other internal risks. External risks also cover seven factors: competition risk, the price risk of production, the risk of raw materials, industry risk, macroeconomic risk, policy risk, and other external risks. Each factor is a dummy that equals one if a firm discloses the corresponding risk, and zero otherwise. We define *Firisk* as the sum of all seven internal risk factors and *Ferisk* as the sum of all seven external risk factors. A third variable, *Frisk*, is the sum of all 14 risk factors. Thus, the maximum value for both *Firisk* and *Ferisk* is seven, and the minimum value is zero. The maximum value of *Frisk* is 14, and the minimum value is zero. The greater *Frisk* is, the more risks the firm discloses.

Panel A of Table 7 reports the regression results of the impact of CLs on the total risk information disclosure (*Frisk*) of firms in the following year. In column (1), the coefficient of *CL* for the pre-disclosure period is 0.001 and not statistically significant. This suggests that CLs will not cause firms to disclose more information on their risks in the pre-disclosure period. In column (2), the coefficient of *CL* for the post-disclosure period is 0.052 and statistically significant at the 1% level. This suggests that, in the post-disclosure period, if a firm receives a CL, it will disclose more risk factors in the following year. The additional disclosure of risk factors could provide analysts with more information, which would help them improve the quality of their forecasts. Panels B and C present the results of the impact of CLs on internal and external risk disclosures, respectively. The results are similar to those in Panel A.

Table 7
CLs and the Disclosure of Risk Information.

Panel A: CLs and the Disclosure of Risk Information

VARIABLES	(1)	(2)
	2013–2014	2015–2018
	Frisk	*Frisk*
CL	**0.001**	**0.052*****
	(0.025)	**(2.773)**
Control variables	Control	Control
Observations	966	6293
Wald χ^2	12.86 (p = 0.538)	256.57 (p = 0.000)
Firm/Year	Fixed	Fixed

Panel B: CLs and the Disclosure of Internal Risk Information

VARIABLES	(1)	(2)
	2013–2014	2015–2018
	Firisk	*Firisk*
CL	**−0.046**	**0.061*****
	(−0.546)	**(2.798)**
Control variables	Control	Control
Observations	888	6145
Wald χ^2	22.80 (p = 0.064)	109.17 (p = 0.000)
Firm/Year	Fixed	Fixed

Panel C: CLs and the Disclosure of External Risk Information

VARIABLES	(1)	(2)
	2013–2014	2015–2018
	Ferisk	*Ferisk*
CL	**0.034**	**0.043***
	(0.538)	**(1.749)**
Control variables	Control	Control
Observations	940	6055
Wald χ^2	4.38 (p = 0.993)	286.70 (p = 0.000)
Firm/Year	Fixed	Fixed

This table presents the regression results for the impact of CLs on the risk information of firms in year $t+1$. The dependent variables, *Frisk, Firisk,* and *Ferisk* in Panels A to C, respectively, are the total risk, internal risk, and external risk factors disclosed in year $t+1$. The variables *Frisk*, *Firisk*, and *Ferisk* are count variables and obey the Poisson distribution; therefore, the results reported in this table are for Poisson regressions with fixed effects. While the latest available risk factors are for 2019, the sample period in column (2) is from 2015 to 2018. The variable definitions are provided in Appendix B. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively (two tailed for all *t*-statistics).

5.6. Endogeneity

Since the two exchanges might not issue CLs randomly, we adopt the propensity score matching (PSM) method to alleviate the impact of endogeneity. Cassell, Dreher, and Myers (2013) find that the probability of receiving a CL is mainly influenced by a firm's internal control (*IC*), material restatements (*Restate*), size (*Size*), age (*Age*), losses (*Loss*), sales growth rate (*Growth*), and audit quality (*Big4*). Thus, we select *IC*, *Restate*, *Size*, *Age*, *Loss*, *Growth*, and *Big4* as matching factors. Each firm–year observation with a CL is matched with a firm–year observation without a CL based on these matching factors in the same year.

Panel A of Table 8 presents the regression results of the PSM. In column (1), where the dependent variable is *AF_accuracy*, the coefficient of *CL* is 0.003 and statistically significant at the 5% level. In column (2), where the dependent variable is *AF_optimism*, the coefficient of *CL* is −0.004 and statistically significant at the 1% level. Thus, the results of

Table 8
Endogeneity consideration.

Panel A: PSM Method

VARIABLES	(1)	(2)
	2015–2019	2015–2019
	AF_accuracy	*AF_optimism*
CL	**0.003****	**−0.004*****
	(2.094)	**(−2.802)**
Control variables	Control	Control
Constant	0.023	−0.004
	(0.412)	(−0.066)
Observations	2536	2536
R-Squared	0.5190	0.5713
Firm/Year	Fixed	Fixed
F	68.17	84.20

Panel B: PSM-DID Method

VARIABLES	(1)	(2)
	2015–2019	2015–2019
	AF_accuracy	*AF_optimism*
CLall	−0.000	0.001
	(−0.402)	(1.622)
Post	0.000	−0.000
	(0.487)	(−0.283)
CLall_Post	**0.002****	**−0.003*****
	(2.066)	**(−3.053)**
Control variables	Control	Control
Constant	0.020**	−0.025***
	(2.316)	(−2.808)
Observations	5548	5548
R-Squared	0.3857	0.4130
Firm/Year	Fixed	Fixed
F	30.89	34.00

This table presents the regression results of endogeneity tests. Panel A presents the regression results of PSM. Panel B presents the regression results of PSM–DID. The variable *CLall* equals one if a firm receives at least one CL during the post-disclosure period from 2015 to 2019, and zero otherwise; *Post* equals one if the firm has received a CL in a previous year, and zero otherwise; and *CLall_Post* is the interaction of *CLall* and *Post*, or *CLall*×*Post*. The other variable definitions are provided in Appendix B. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively (two tailed for all *t*-statistics).

PSM confirm the robustness of our main conclusions.

To further alleviate the endogeneity problem, we carry out a PSM–difference-in-differences (PSM–DID) test. First, we construct a treatment variable, *CLall*, that equals one if a firm receives at least one CL during the post-disclosure period, from 2015 to 2019, and zero otherwise. Then, we define *Post*, which equals one if the firm received a CL in the previous years, and zero otherwise. The variable *CLall_Post* is the interaction of these two variables, or *CLall*×*Post*. We still select *IC*, *Restate*, *Size*, *Age*, *Loss*, *Growth*, and *Big4* as the matching factors. Each treatment observation is matched with an observation whose firm was never issued a CL during 2015–2019.

Panel B of Table 8 reports the regression results of the PSM–DID test. In column (1), where the dependent variable is *AF_accuracy,* the coefficient of *CLall_Post* is 0.002 and statistically significant at the 5% level. In column (2), where the dependent variable is *AF_optimism*, the coefficient of *CLall_Post* is −0.003 and statistically significant at the 1% level. The results in Panel B indicate that, compared with the forecast quality of firms that never received a CL, the forecast quality of firms that received at least one CL is significantly improved. Therefore, the results of the PSM–DID tests confirm the robustness of our main conclusions.

5.7. Additional tests

We conduct robustness tests to examine whether our conclusions still hold at the analyst–firm level. We obtain 36,592 observations at the analyst–firm level, 3293 of which were issued CLs by their exchanges. Panel A of Table 9 reports the regression results at the analyst–firm level. The results in columns (1) and (3) show that CLs help improve the quality of analysts' forecasts in the post-disclosure period, which confirms H1. Columns (2) and (4) show that the more information the CLs contain, the greater the improvement in analysts' forecast quality. These results support H2.

In another robustness test, we redefine the dependent variables of the change in forecast accuracy (*Change_AFaccuracy*) and the change in forecast optimism (*Change_AFoptimism*) before and after the firm has received a CL. After selecting observations that received CLs in year *t* but did not receive any in year *t* - 1, we are left with a sample of 6367 observations. Panel B of Table 9 presents the regression results for changes in analysts' forecast quality. The results in columns (1) and (2) again confirm that CLs can increase analysts' forecasting quality.

6. Conclusion

Alleviating information asymmetry is one of the most important topics in capital markets. The CL mechanism is a unique way to alleviate information asymmetry, at least in the following two aspects. On the one hand, public companies are traditionally required to disclose information according to the rules issued by regulators. Such routine disclosure

Table 9
Additional tests.

Panel A: Results at the Analyst–Firm Level

VARIABLES	(1)	(2)	(3)	(4)
	2015–2019		2015–2019	
	AF_accuracy	*AF_accuracy*	*AF_optimism*	*AF_optimism*
CL	**0.004*****		**−0.003*****	
	(9.082)		**(−5.329)**	
LnQn		**0.006*****		**−0.007*****
		(3.174)		**(−3.727)**
Control variable	Control	Control	Control	Control
Constant	−0.122***	−0.086	0.087***	0.177
	(−5.938)	(−0.777)	(4.514)	(1.428)
Observations	36,592	3293	36,592	3293
R-Squared	0.2568	0.4493	0.4356	0.4807
A-F/Year	Fixed	Fixed	Fixed	Fixed
F	155.9	14.57	283.4	23.84

Panel B: Results for the Difference of Analyst Forecast Quality

VARIABLES	(1)	(2)
	Change_AFaccuracy	*Change_AFoptimism*
CL	**0.004*****	**−0.007*****
	(2.847)	**(−3.598)**
Control variable	Control	Control
Constant	0.089	−0.154**
	(1.451)	(−2.142)
Observations	6367	6367
R-Squared	0.2706	0.2797
Firm/Year	Fixed	Fixed
F	52.06	50.12

This table presents the results for two additional tests. Panel A presents the regression results at the analyst–firm level. We obtain 36,592 observations at the analyst–firm level, 3293 of which were issued CLs by the exchanges. Panel B presents the regression results for changes of analysts' forecast accuracy ($Change\_AFaccuracy = AF\_accuracy_t - AF\_accuracy_{t-1}$) and changes of analysts' forecast optimism ($Change\_AFoptimism = AF\_optimism_t - AF\_optimism_{t-1}$). In the regression of Panel B, we only keep observations that received a CL in year *t* but did not receive one in year *t* - 1. Thus, the number of observations in Panel B is 6367. The variable definitions are provided in Appendix B. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively (two tailed for all *t*-statistics).

lacks interaction between companies and regulators. The CL mechanism is a regulation innovation that transforms the traditional regulator's unilateral *allegations* into a bidirectional dialog between the regulator and public companies. This question and answer mechanism enables regulators to prompt companies to disclose detailed information on issues that are important for the specific company, industry, or event. Thus, the CL mechanism is a more flexible instrument for the regulator to tailor questions according to the market, conditional on management behaviors. On the other hand, because high-quality information disclosure is a way to reduce information asymmetry, mandatory information disclosure has always been critical to the development of capital markets. Mandatory information disclosures can be split into two categories: information disclosed in accordance with the requirements of unified regulations and information disclosed according to the regulator's specific request. This paper focuses on the latter. Since the end of 2014, CLs have been mandatorily disclosed in the Chinese capital market. The information in these letters is usually firm specific. We investigate whether Chinese CLs and their mandatory disclosure significantly reduce the information asymmetry between firms and analysts.

Our findings are as follows. First, CLs have no significant impact on the forecast quality of analysts in the pre-disclosure period. For CL recipients during the post-disclosure period, however, the accuracy of analysts' forecasts improves significantly and the optimism bias in analysts' forecasts decreases significantly. This implies that only through disclosure can CLs reduce the degree of information asymmetry. Second, among firms that receive CLs, the more questions the CLs contain, the higher the quality the analysts' forecasts will be. Third, the CLs' effect on improving the quality of analysts' forecasts is more pronounced in the group followed by a lower percentage of star analysts than in the group followed by a higher percentage of star analysts. Fourth, firms with higher earnings volatility have a poorer information environment than firms with lower earnings volatility. The positive impact of CLs on analysts' forecasts is larger in samples with higher earnings volatility. Fifth, firms choose to disclose more risk factors to the market after receiving a CL. These disclosures are likely to provide incremental information and reduce the degree of information asymmetry.

The theoretical contributions of this paper lie in several dimensions. First, we find that the new regulatory approach involving CLs, which allows a bidirectional dialog between the regulator and public companies, can improve the quality of analysts' forecasts and, thus, the efficiency of the capital market. Second, this paper enriches the literature on the impact of mandatory information disclosure. By comparing the impact of CLs on the quality of analysts' forecasts between the pre- and post-disclosure periods, we find that mandatory information disclosure can provide incremental information to the market and effectively reduce the degree of information asymmetry. Third, our findings enrich the literature on the impact of CLs on the quality of information disclosure. Specifically, this paper confirms the information content of CLs by showing their impact on the forecasting efficiency of analysts. The fourth contribution is that we observe a heterogeneous impact of CLs on the forecast quality of star and non-star analysts, which implies that star analysts have more private information. Finally, this paper provides empirical evidence of the effectiveness of front-line supervision by the stock exchanges.

Author statement

I have made substantial contributions to the conception or design of the work; or the acquisition, analysis, or interpretation of data for the work; AND.

I have drafted the work or revised it critically for important intellectual content; AND.

I have approved the final version to be published; AND.

I agree to be accountable for all aspects of the work in ensuring that questions related to the accuracy or integrity of any part of the work are appropriately investigated and resolved.

All persons who have made substantial contributions to the work reported in the manuscript, including those who provided editing and writing assistance but who are not authors, are named in the Acknowledgments section of the manuscript and have given their written permission to be named. If the manuscript does not include Acknowledgments, it is because the authors have not received substantial contributions from nonauthors.

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Appendix A

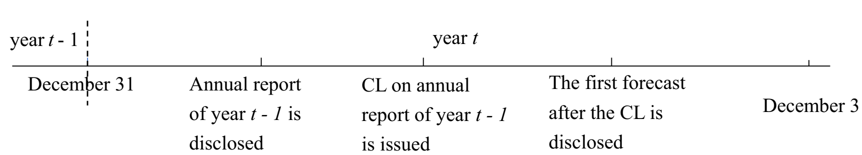

Fig. A1. Event Timeline of the Annual Report, CL, and Analyst Forecast.

Appendix B

B.1. Variable definitions

Variables	Code	Definition
Analyst forecast accuracy	*AF_accuracy*	The opposite number of *AF_error*, where *AF_error* equals the absolute value of the difference between the mean of the forecasted EPS and the real EPS, divided by the stock price at the end of year t - 1.
Analyst optimism	*AF_optimism*	The difference between the mean of the forecasted EPS and the real EPS, divided by the stock price at the end of year t - 1.

(*continued on next page*)

(*continued*)

Variables	Code	Definition
Analyst change of forecast accuracy	*Change_AFaccuracy*	The change of *AF_accuracy* between year *t* - 1 and year *t*, which equals $AF\_accuracy_t$ minus $AF\_accuracy_{t-1}$.
Analyst change of optimism	*Change_AFoptimism*	The change of *AF_optimism* between year *t* - 1 and year *t*, which equals $AF\_optimism_t$ minus $AF\_optimism_{t-1}$.
Comment letter	*CL*	Equals 1 if the firm receives a CL on its annual report in year *t* - 1, and 0 otherwise.
Quantity of the information in the CL	*LnQn*	The logarithm of the number of questions in the CL plus 1.
Percentage of star analysts following	*Lowstarp*	Equals 1 if the percentage of star analysts following firm *i* is lower than the industry median, and 0 otherwise.
Earnings volatility	*HighSdNP*	Equals 1 if the standard deviation of *ROA* during year *t* - 3 to year *t* - 1 is higher than the industry median, and 0 otherwise.
Discretionary accruals	*DA*	The absolute value of discretionary accruals calculated by the modified Jones model.
Firm size	*Size*	The logarithm of total assets.
Firm leverage	*Lev*	Total liabilities divided by total assets.
Firm profitability	*ROA*	Earnings divided by total assets.
Firm cash flow	*OCF*	Net cash flow from operations divided by total assets.
Firm yearly return	*Yret*	Stock return in year *t* - 1.
Firm market-to-book ratio	*MB*	Price per share divided by net assets per share.
Firm's institutional shareholding	*Inst*	The ratio of shares held by institutional investors.
The timelessness of forecasts	*Avlnday*	The logarithm of the number of days between the forecast report date and the annual report date.
Firm internal control	*IC*	The logarithm of the internal control index released by the DIB Internal Control and Risk Management database.
Auditor	*Big4*	Equals 1 if the auditor is one of the Big 4 firms, and 0 otherwise.
Firm age	*Age*	The logarithm of firm age.
Disclosure of risk information	*Frisk*	The sum of all 14 risk factors in year *t* + 1.
Disclosure of internal risk information	*Firisk*	The sum of seven internal risk factors in year *t* + 1.
Disclosure of external risk information	*Ferisk*	The sum of seven external risk factors in year *t* + 1.
Firm restatement	*Restate*	Equals 1 if the annual report of year *t* is restated, and 0 otherwise.
Firm loss	*Loss*	Equals 1 if the earnings in year *t* are negative, and 0 otherwise.
Firm sales growth	*Growth*	Sales in year *t* minus sales in year *t* - 1, divided by sales in year *t* - 1

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