International Review of Financial Analysis 89 (2023) 102775

Contents lists available at ScienceDirect

International Review of Financial Analysis

journal homepage: www.elsevier.com/locate/irfa

Performance commitments and the properties of analyst earnings forecasts: Evidence from Chinese reverse merger firms

Yu Liu[a], Lingxuan Yang[b,*], Lu Xiong[c]

[a] School of Economics and Business Administration, Chongqing University, Chongqing, China
[b] School of Accounting, Henan University of Economics and Law, Zhengzhou, China
[c] Department of Mathematical Sciences, Middle Tennessee State University, TN, USA

ARTICLE INFO

JEL classification:
G34
G38
M41

Keywords:
Performance commitment
Analyst earnings forecast
Reverse merger
Information

ABSTRACT

We investigate whether the performance commitments in Chinese reverse merger (RM) transactions affect the properties of analyst earnings forecasts. All RM firms in China are required to make performance commitments for a limited number of years after being publicly listed. As performance commitment is an important piece of public information, it can influence analysts' understanding of firms and their efforts to forecast earnings. Using manually assembled information on RM transactions, we find that, in comparison to the control firms, RM firms exhibit an increase in analyst forecast error and dispersion after the end of performance commitment. This effect is more pronounced in firms with lower levels of information transparency. We also document that the public information contents of analyst forecasts decrease and forecast revisions increase in the post-commitment period, while the private information content of analyst forecasts and the number of their firm visits remain unchanged. Overall, our findings suggest that analysts rely greatly on public information; they have important implications for academics and policymakers in understanding how performance commitments in RM transactions affect the market information environment.

1. Introduction

Analysts play a crucial role in the information environment of the capital market. By assessing firm fundamentals and disseminating information to investors through earnings forecasts, they reduce information asymmetry and improve resource allocation efficiency (Dambra, Field, Gustafson, & Pisciotta, 2018; Frankel & Li, 2004; Roulstone, 2003). As Schipper (1991) notes, analysts use both public and private information to make earnings forecasts, and public information in particular is an important source for analyst earnings forecasts because of its low collection cost. The literature documents many kinds of public information considered by analysts when performing assessments, such as audit reports (Behn, Choi, & Kang, 2008), tax planning (Francis, Neuman, & Newton, 2019), and internal control disclosure (Ji, Lu, Qu, & Richardson, 2019), among other factors. In this study, we extend this line of research by focusing on a special type of public information arising from Chinese reverse merger (RM) transactions.[1] We explore the consequences of the performance commitments made by RM transactions and, more importantly, examine their effects on the properties of analyst earnings forecasts.

As a piece of public information, performance commitment disclosures in RM transactions are the consequence of the regulation of Chinese capital market. RM transactions have long been criticized by stock investors as a potential source of problems such as insider trading and market manipulation. To alleviate information asymmetry and protect the interests of the minority shareholders of formerly listed firms, the China Securities Regulatory Commission (CSRC) revised the *Measures for the Administration of Material Assets Reorganization of Listed Firms* in 2008. According to this regulation, the private firm (also referred to as the acquiree) must sign a performance commitment to the formerly listed firm (also referred to as the acquirer) if an RM transaction is priced using the discounted future earnings method. This performance commitment is an essential component of the RM transaction, and if the performance targets are not met, the controlling shareholder of the

* Corresponding author at: School of Accounting, Henan University of Economics and Law, N0.180 Jinshui East Road, Jinshui District, Zhengzhou 450000, China
E-mail addresses: yuliu@cqu.edu.cn (Y. Liu), lxyang@huel.edu.cn (L. Yang), lu.xiong@mtsu.edu (L. Xiong).

[1] Due to the strict IPO censorship regime in China, the RM has become a popular method for private firms to go public in recent years. In an RM transaction, also referred to as a "backdoor listing" or "shortcut", a private firm is merged into a listed firm and the controlling shareholder of the private firm takes over control of the combined listed firm (Lee et al., 2017).

https://doi.org/10.1016/j.irfa.2023.102775
Received 10 December 2022; Received in revised form 15 April 2023; Accepted 27 June 2023
Available online 30 June 2023
1057-5219/

acquiree is required to pay a large amount of compensation to the investors of the acquirer. To avoid such losses, the controlling shareholder of the acquiree is motivated to manipulate firm performance, thus making it a common phenomenon for RM firms to just meet and beat performance targets (Hou, Jin, Yang, Yuan, & Zhang, 2015). This phenomenon makes performance commitments an excellent reference for analyst earnings forecasts. However, the performance commitment period typically lasts only three years following the firm's listing.[2] Subsequently, because the acquiree no longer needs to meet particular performance targets, analysts lose an important piece of public information for their assessments. This also means that in the post-commitment period, analysts need to collect other substitute information to make up for the loss of public information.

Analysts use their expertise and knowledge to assess firms' earning potential (Ji et al., 2019; Weiss, 2010), and there are at least two reasons to expect that analyst forecast error and dispersion could increase in the post-commitment period. First, performance commitments usually contain a clear accounting target for the accounting performance of the acquiree. Clear accounting targets are highly readable public information that can reduce the cost of collecting information for analysts and make it easier for them to assess it (Lehavy, Li, & Merkley, 2011). Second, the phenomenon of most acquirees just "meet and beat" their accounting targets improves the utility of performance commitments for analysts. Analysts can make earnings forecasts by referring to performance commitments and thus issue more accurate and less dispersed earnings forecasts in the commitment period. However, this public information with high readability and utility will not be consistently available for analysts in the post-commitment period. As a result, it could be difficult for analysts to mitigate the information gap and maintain the desirable properties of earnings forecasts.

To investigate whether analyst earnings forecasts deteriorate in the post-commitment period, we manually collect a sample of firms that are publicly listed via RM transactions in China from 2011 to 2016. To better estimate the causal treatment effect, we use the matching approach to identify a control group of firms that go public via the initial public offering (IPO) process and are most similar to the treatment group (i.e., RM firms). We further adopt a difference-in-differences (DID) research design around the end of the commitment period by comparing the properties of the analyst earnings forecasts of both the treatment and matched control groups.[3] Consistent with our expectation, we find that the analyst forecast error and dispersion of RM firms increase in the three-year period after the end of performance commitments. These results are economically significant: RM firms exhibit an increase in analyst forecast error of 39.72% and in forecast dispersion of 35.29 percnet after the end of the performance commitment period. Our results are robust to the application of placebo tests, dynamic approach, different matching strategies, and different fixed effects to control for unknown characteristics that may affect analyst earnings forecasts.

In additional analyses, we conduct cross-sectional tests to examine whether the relationship between analyst forecast properties and performance commitments is heterogeneous across firms with different levels of information transparency. We find that the analyst forecast error and dispersion experience a greater increase in the post-commitment period when the firms have lower earnings management, transparency ratings and media coverage. These results suggest that the above-mentioned relationship is more pronounced in firms with lower information transparency, which is consistent with the literature showing that public information could be more valuable for analyst earnings forecasts when they assess firms with opaque information (Chen and Jiang, 2006).

We also perform several additional tests to corroborate our main findings. First, we explore the relationship between analyst forecast properties and whether the performance commitments are achieved. Prior studies (e.g., Hou et al., 2015) note that controlling shareholders will just "meet and beat" performance targets through the means of earnings management. If analysts rely on performance commitments in their assessments, they may make more accurate forecasts for firms that meet performance targets than for firms that do not. Our results are consistent with this conjecture that the achievement of performance targets is positively associated with analyst forecast error and dispersion.

Second, using the empirical proxy developed by Barron, Kim, Lim, and Stevens (1998), we examine the public and private information components of analyst earnings forecasts after they lose the performance commitments. We find that the public information component of the forecasts significantly decreases after the end of performance commitments; however, the private information component is unchanged. These results suggest that analyst earnings forecasts contain less public information when the information environment deteriorates because of the lack of performance commitments. However, this circumstance does not incentivize analysts to collect private information, resulting in no change in the private information component in their earnings forecasts.

Third, we conduct more analyses to examine analysts' reactions to the lack of public information. We document that analysts revise earnings forecasts more frequently after the end of the commitment period. This result is consistent with the prediction that the fraction of analysts revising their forecasts increases following changes in the public information environment (Kross & Suk, 2012). In addition, we examine whether analysts obtain private information through firm visits. Face-to-face communication with firm management can furnish analysts with private information and produce new insights into a firm (Han, Kong, & Liu, 2018). However, we find no evidence that analysts conduct more firm visits in the post-commitment period. These findings further suggest that analysts rely greatly on public information and have less incentive to collect private information even after losing performance commitments.

Our study extends the literature on the relationship between performance commitments and analyst earnings forecasts in two key dimensions. First, we identify performance commitments as an important determinant of analyst earnings forecast assessment. Prior studies document that public information is of great importance to analysts (Chen & Jiang, 2006; Tan, Wang, & Welker, 2011). Such public information includes audit reports, management earnings forecasts, tax planning, and nonfinancial disclosures (Behn et al., 2008; Bratten, Gleason, Larocque, & Mills, 2016; Dhaliwal, Radhakrishnan, Tsang, & Yang, 2012; Francis et al., 2019; Kim & Song, 2015; Libby, Tan, & Hunton, 2006; Muslu, Mutlu, Radhakrishnan, & Tsang, 2017; Xie, Zhang, & Zhou, 2012). In contrast to those studies, we show that performance commitments affect the properties of analyst earnings forecasts and document a significant increase in analyst forecast error and dispersion once they can no longer benefit from expired performance commitments. However, such analysts have little incentive to collect substitute information, whether public or private, despite the expiration of performance commitments. This effect is incremental to analysts' reliance on public information (Kross & Suk, 2012) and usage of private information (Han et al., 2018), which deepens our understanding of analysts' earnings forecast assessment and decision-making.

Second, our paper extends the literature on the value of performance commitments (Hou et al., 2015; Lee, Li, & Zhang, 2015; Lee, Qu, & Shen, 2019; Wu, Xu, & Jin, 2022). In recent years, regulators have often implemented performance commitment regimes in reverse merger

[2] The *Measures for Administration of Material Assets Reorganization of Listed Firms* does not specify the length of the performance commitment period. Based on our manually collected data on Chinese RM transactions from 2011 to 2016, around 87.8% of RM firms have a performance commitment period of three years. Besides, around 8.7% of RM firms have a two-year performance commitment.

[3] As IPO firms do not have performance commitments, we compare the properties of analyst earnings forecasts of IPO firms from the first three years and four to six years after their listing.

transactions to improve information transparency and protect the interests of retail investors. Due to the accounting targets set in performance commitments, RM firms have achieved excellent performance after being publicly listed (Lee et al., 2015; Qu, Wu, & Shen, 2018). In contrast, some researchers find that performance commitments incentivize RM firms to engage in more aggressive earnings management, which increases firm risk and harms firm performance in the long run (Hou et al., 2015; Li, Guo, & Wei, 2019; Wu et al., 2022). These mixed findings have drawn particular attention to whether performance commitments affect the operation of RM firms. Our study focuses on the information environment implications of performance commitments. We provide evidence that performance commitments provide clear guidance for analyst earnings forecasts and affect analysts' information collection process, which is consistent with the notion that performance commitments improve the information environment in the capital market.

As information intermediaries, analysts play an important role in alleviating information asymmetry in the capital market, especially in emerging economies with weak institutional environments and severe insider trading problems (Demmer, Pronobis and Yohn, 2019; Tan et al., 2011). The findings in our paper suggest that even though public information is important for analysts, they cannot rely on public information alone. Private information can be used as a supplement to public information and remain integral for analysts' assessments. Thus, our findings from the Chinese RM transaction setting have general implications for other emerging economies.

The rest of this paper proceeds as follows. Section 2 discusses the institutional background, related literature and develops our hypotheses. Section 3 describes the research design, construction of the variables, and sample selection process. Section 4 reports the main empirical results and the results of robustness tests. Section 5 presents the results of additional tests. Finally, Section 6 concludes this paper.

2. Institutional background, related literature, and hypothesis development

2.1. RM transaction and performance commitment

Firms usually have two ways of entering the stock market. Most choose to go public via IPOs, which entails undergoing the tedious process of review and adjudication by regulators. Others, however, choose to go public via RM transactions. An RM transaction is also referred to as a "backdoor listing" or a "shortcut". This generally refers to a series of asset and equity transactions between a listed firm ("shell" firm or acquirer) and a private firm (acquiree), which enable the private firm to enter the stock market (Gleason, Rosenthal, & Wiggins, 2005; Lee, Qu, & Shen, 2017). In practice, the acquirer purchases assets from the acquiree by issuing additional shares, and the controlling shareholder of the acquiree takes over control of the acquirer through asset restructuring. In developed economies, such as the U.S., an RM transaction is a way for smaller, less profitable, and generally riskier firms to become publicly listed. However, in China, the lengthy IPO review process and frequent occurrence of IPO suspension make this process arduous, which has incentivized many firms to explore RM transactions as an alternative way to access the domestic capital market. As noted by Lee et al. (2019), firms generally engage in RM transactions in China to avoid the notoriously long IPO waiting period and the uncertainty associated with government policy rather than because of failure to meet IPO thresholds.[4]

RM transactions involve a change in the fundamentals of the acquirers and are accompanied by dramatic stock price revaluation. To protect the interests of small shareholders and alleviate information asymmetry, the CSRC revised the *Measures for Administration of Material Assets Reorganization of Listed Firms* in 2008. According to this new measure, if the RM transaction price is estimated using the present value of earnings method, the controlling shareholder of the acquiree is required to make a commitment regarding accounting performance for approximately three years after the completion of the transaction.[5] The performance targets set by firms vary, as they may be measured in terms of net income, cumulative net income, or pre-tax income. If the firm fails to meet the performance target, the controlling shareholder must pay a large amount of cash and equity compensation to the acquirer. Therefore, to avoid losses, the controlling shareholders of acquirees have a strong incentive to manipulate their accounting performance, and it has become common for RM firms to just meet and beat performance targets (Hou et al., 2015). We compile statistics on the performance target completion ratio of firms listed via RM transactions from 2011 to 2016.[6] As shown in Fig. 1, the completion ratio is significantly clustered on the right side of 1. Specifically, 49.9% of firms have a completion ratio between 1 and 1.1; however, only 5.9% of firms have a completion ratio between 0.9 and 1. This phenomenon reflects RM firms' strong tendency toward earnings management, which increases the information asymmetry of the capital market. A typical example is STO Express (stock code: 002468), which was merged and acquired by Eddy West in 2016, through a backdoor listing. The controlling shareholder of STO Express committed itself to achieve net profits of RMB 1.17 billion, 1.4 billion and 1.6 billion, respectively over the next three years. As expected, STO Express just met its performance targets, achieving net profits of RMB 1.18 billion, 1.45 billion, and 1.69 billion in 2016, 2017, and 2018, respectively, whereas STO Express's net profit was only RMB 1.34 billion in 2019 and slid to −0.03 billion in 2020. Therefore, market participants generally consider performance commitments to be a double-edged sword: they can protect minority shareholders' interests in RM transactions, but also trigger earnings management.

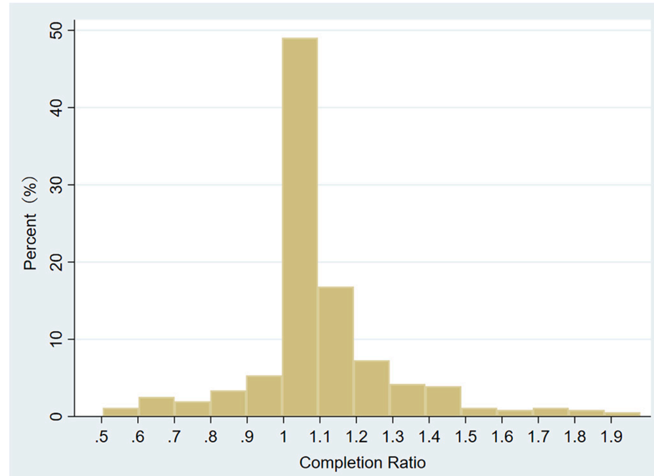


Fig. 1. Completion ratio of performance target.
Note: This figure presents the completion ratio of the performance target. The completion ratio is measured as the real performance divided performance target.

[4] As most firms listed in the U.S. via RMs do not meet IPO standards, their shares are traded in the over-the-counter market. In contrast, firms listed in China via RMs are subject to the same regulatory standards as IPO firms. Thus, their shares are traded in the main board.

[5] For a more detailed interpretation of the RM transaction process and performance commitment, please refer to Appendix B.

[6] Following Yuan et al. (2021), the completion ratio of the performance target is measured as the real performance divided by the performance target.

2.2. Related literature

The information asymmetry inherent in the capital market means that stock investors are often under-informed or misled. As market information intermediaries, analysts can reduce information asymmetry and improve the efficiency of resource allocation (Altınkılıç & Hansen, 2009; Chen & Jiang, 2006; Dambra et al., 2018). Specifically, analysts assess the future performance of listed firms based on public and private information and deliver their assessments to the capital market by issuing earnings forecasts. In this process, analysts need to make trade-offs between the cost of information collection and the benefit of improved forecasting (O'Brien & Tan, 2015). For analysts, the public information released by firm management involves almost zero marginal cost of access, in contrast to private information. Because of the strict scrutiny of regulators, public information offers more extensive content than private information available to analysts. Consequently, extensive and inexpensively acquired public information may reduce analysts' need for private information. As a result, public information becomes a major component of the analyst's information set (Schipper, 1991). Prior studies document that public information disclosure, such as management earnings forecasts (Kim & Song, 2015), corporate social responsibility disclosure (Dhaliwal et al., 2012; Muslu et al., 2017), and internal control reports (Ji et al., 2019), enhance the accuracy of analyst earnings forecasts. Hirshleifer and Teoh (2003) show that because of limited analyst attention, the information provided by other market participants can affect analysts' behavior. Consistent with this theory, the literature finds that audit reports (Behn et al., 2008; Xie et al., 2012) and credit ratings (Batta, Qiu, & Yu, 2016) are positively associated with desirable properties of analyst earnings forecasts.

As users of information, analysts need to invest more effort to interpret low-quality information (Brown, Call, Clement, & Sharp, 2015; Muslu et al., 2017). Lobo, Song, and Stanford (2012) find that high levels of accounting accruals lead to greater analyst forecast error and this impact can be mitigated by an increase in private information. Francis et al. (2019) show that tax planning, as measured by auditor-provided tax services, reduces analysts' forecast accuracy because analysts may have difficulty understanding the effects of tax planning. Lehavy et al. (2011) find that analysts require more effort to interpret less readable financial reports, resulting in lower analyst forecast accuracy, greater dispersion, and greater overall uncertainty.

Despite evidence of the role of public information in analyst assessments, the impact of performance commitments in RM transactions on the properties of analyst earnings forecasts remains largely unexplored. Specifically, we know little about analysts' behavior after the end of the performance commitments period. By focusing on analysts' reliance on public information, our study investigates whether performance commitments affect analyst forecast properties.

2.3. Hypothesis development

Two commonly studied analyst forecast properties are forecast accuracy and dispersion. Forecast accuracy measures how far the analyst consensus is from actual earnings. Forecast dispersion measures the uncertainty associated with a firm's information environment (Ji et al., 2019). The literature shows that the information environment has a decisive impact on the properties of analyst earnings forecasts. Specifically, higher quality, availability and reliability, or lower uncertainty of information are closely related to an increase in forecast accuracy and a decrease in forecast dispersion (Behn et al., 2008; Bratten et al., 2016; Huang, Lin, & Zang, 2022; Muslu et al., 2017).

Given that performance commitment is an important piece of public information disclosed in RM transactions, we posit that it influences the properties of analyst earnings forecasts. On the one hand, controlling shareholders of the acquiree commit to achieving a clear performance target as part of the deal in the RM transaction. For analysts, the targets in performance commitments can reduce the cost of information collection and the difficulty of interpreting information. In particular, such targets reduce the uncertainty of the information because they are presented in explicit accounting figures; this could lead to more accurate forecasts and less dispersion. On the other hand, the phenomenon in which shareholders just "meet and beat" the performance targets increases the value of performance commitments as a reference for analyst forecasts. Because the performance commitment is the controlling shareholder's estimate of future performance, this reduces the potential for estimation error, making the information more valuable for analysts (Lobo et al., 2012). To avoid economic losses after the commitment period, the controlling shareholders have strong incentives to improve firms' performance in various ways and most RM firms just meet their performance targets (Hou et al., 2015). Therefore, performance commitment provides a precise estimate of a firm's future performance, which improves analyst forecast accuracy and reduces forecast dispersion.

In an RM transaction, performance commitment is an estimation of the future performance of the acquiree. However, even the shareholders of the acquiree find it difficult to accurately estimate long-term firm profitability. Thus, the performance commitment period usually lasts for three years, which means that analysts can use the information in performance commitments for only a limited time. In the post-commitment period, analysts lose a piece of highly reliable public information and are forced to make forecasts based on other sources of public and private information. Specifically, the public information that analysts can use includes, for example, annual reports and corporate social responsibility reports. Although the literature (e.g., Behn et al., 2008; Dhaliwal et al., 2012) documents that such public information sources help analysts to make forecast earnings, these sources contain mainly historical information, which has weak relevance to firms' future performance. In contrast with the clear performance targets in performance commitments, the historical information in other sources of public information is less useful for analysts to assess firms' future performance, and this leads to an increase in forecast error and dispersion. Analysts can also use private information, such as visits to firms, to compensate for the expiration of performance commitments. Interacting with firm management enables analysts to better evaluate firms' actual state of development and reach new views of or insights into firms' performance. However, accessing private information comes at an extra cost.[7] As noted by O'Brien and Tan (2015), analysts need to make a trade-off between cost and benefit when making earnings forecasts. Given the benefit of earnings forecasts, the higher level of cost could disincentivizes analysts from collecting private information. Because of this, analysts only conduct firm visits occasionally, and their private information is insufficient to completely substitute for the expired performance commitments. As a result, analysts may have difficulty maintaining their earnings forecasts at a high-performance level in the post-commitment period. Based on the above discussion, we propose the following hypotheses:

H1a. Analyst earnings forecast accuracy declines after the end of the performance commitment period.

H1b. Analyst earnings forecast dispersion increases after the end of the performance commitment period.

3. Research design

3.1. Sample and data

We select all of the firms that go public via RM from 2011 to 2016 in China as the initial sample. Our sample begins in 2011 because a new

[7] For example, in our interviews with analysts, we learned that analysts need to spend more time and effort to access private information, cover travel expenses and pay more salary to research staff when engaging in firm visits.

version of the *Decision on Material Asset Reorganization and Financing of Listed Firms* came into effect in 2011, which brought RM firms into the same regulatory system as IPO firms. This regulation requires RM firms to disclose information comparable to that required of IPO firms in addition to following the specific disclosure requirements for RM firms (i.e., performance commitment). In this study, we need to examine analyst earnings forecast behavior for the next six years (i.e., three years during the commitment period and three years after that) after the firms are publicly listed, and we can only obtain data up to 2021. To ensure that firms have data within the six-year window, thus our RM firm sample ends in 2016. Accordingly, the observations in the empirical test are from 2011 to 2021.

Specifically, we begin with a sample of RM firms from the China Stock Market and Accounting Research (CSMAR) database. We then manually check each RM proposal from the Wind database and identify RM transactions by following the CSRC criteria of a change in the control rights of the listed firm and a transaction value larger than the book value of the total assets of the listed firm before the transaction. If both conditions are met, the transaction is regarded as an RM. As 87.2% of RM firms' performance commitment periods are three years, we retain these firms and exclude RM firms with all other performance commitment periods from the initial sample.[8] Performance commitment data are manually collected from the RM transaction proposals. All of the analyst's forecast data and firm financial information used in our empirical analysis are collected from the CSMAR database.

To empirically examine the properties of analyst earnings forecasts for RM firms during and after the performance commitment period, we need to have a control sample for benchmarking. Following Chen, Cheng, Lin, Lin, and Xiao (2016), Lee et al. (2017) and Lee et al. (2019), we pair each of the 116 RM firms with a matched IPO firm (without replacement); the latter is defined as the IPO firm in the same trading venue (Shenzhen or Shanghai Stock Exchange), year, industry, and that is closest in size (i.e., total assets), based on financial information from the fiscal year immediately before the public listing.[9] We use the data from the six-year window after the RM and IPO firms are publicly listed to examine the properties of analyst forecasts.[10] After excluding observations with fewer than four analysts following each year, observations in the financial industry, and observations with other missing data, our final sample includes 630 firm-year observations.

3.2. Measures of analyst forecast properties

Following the literature (Dhaliwal et al., 2012; Ji et al., 2019; Muslu et al., 2017), our measure for analyst forecast error (*FERROR*) is defined as the absolute difference between the actual annual earnings per share (EPS) and the mean value of all the analysts' most recent forecasted EPS before the fiscal year-end, scaled by the stock price at the beginning of the year.

$$FERROR_{i,t} = \frac{\left| mean(FEPS)_{i,t} - EPS_{i,t} \right|}{P_{i,t}} \tag{1}$$

The forecast dispersion (*FDISP*) is defined as the standard deviation of all the analysts' most recent forecasted EPS before the fiscal year-end, scaled by the stock price at the beginning of the year.

$$FDISP_{i,t} = \frac{sd(FEPS)_{i,t}}{P_{i,t}} \tag{2}$$

3.3. Model specification

To test H1a and H1b, we estimate the following ordinary least squares (OLS) regression models[11]:

$$\begin{aligned} FERROR_{i,t} =& \beta_0 + \beta_1 RM_i{*}POST_{i,t} + \beta_2 POST_{i,t} + \sum CONTROLS_{i,t} \\ &+ \sum YEAR\ Dummy + \sum FIRM\ Dummy + \varepsilon_{i,t} \end{aligned} \tag{3}$$

$$\begin{aligned} FDISP_{i,t} =& \gamma_0 + \gamma_1 RM_i{*}POST_{i,t} + \gamma_2 POST_{i,t} + \sum CONTROLS_{i,t} \\ &+ \sum YEAR\ Dummy + \sum FIRM\ Dummy + \varepsilon_{i,t} \end{aligned} \tag{4}$$

The dependent variables in Eqs. (3) and (4) are *FERROR* and *FDISP*, respectively, as defined above. The independent variable *RM* is an indicator variable that equals one for treatment (RM) firms, and zero for control (IPO) firms. *POST* is an indicator variable taking the value of one for the post-commitment period of RM firms (years $t+3$, $t+4$, and $t+5$ of IPO firms), and zero for the in-commitment period of RM firms (years t, $t+1$, and $t+2$ of IPO firms).[12] The coefficient on *RM**POST* (β_2 and γ_2) captures the change in analyst forecast properties for treatment firms relative to the change for control firms after the performance commitment has ended.

Following the literature (Bratten et al., 2016; Dhaliwal et al., 2012; Huyghebaert & Xu, 2016; Tehranian, Zhao, & Zhu, 2014), we control for other variables that potentially affect analyst forecast properties. For firm characteristics, we include an indicator for firms that are audited by Big 10 auditors in China (*BIG10*), ownership of the largest shareholder (*FIRST*), an indicator for firms that are ultimately controlled by the Chinese government (*SOE*), firm size (*SIZE*), financial leverage (*LEV*), firm profitability (*ROA*), and market-to-book ratio (*MTB*). For analyst characteristics, we include analyst coverage (*ANUM*), which is the natural logarithm of the number of unique analysts following the firm during the year. We also control for forecast horizon (*HORIZON*), measured as the length of days between the forecasting date and the annual reports announcement date. For all regressions, we include year and firm fixed effects (*YEAR* and *FIRM*) to control for time-specific effects and time-invariant firm characteristics, respectively. All variables are defined in Appendix A. We winsorize all continuous variables at the 1st and 99th percentiles to mitigate the influence of outliers. In addition, we use robust standard errors clustered by the firm for all of our analyses to mitigate concerns about heteroscedasticity and serial correlation in the error term (Petersen, 2009).

[8] More specifically, in all the RM firms, 0.9% of the firms' performance commitment periods are one year. 8.5% of the firms' performance commitment periods are two years. 87.2% of the firms' performance commitment periods are three years. 1.7% of the firms' performance commitment periods are four years. The other 1.7% of the firms' performance commitment periods are five years.

[9] Consistent with the literature (e.g., Chen et al., 2016; Lee et al., 2017; Lee et al., 2019), we do not use a propensity score matching (PSM) in our main analysis. In robustness test, we employ a PSM analysis to further alleviate the selection bias problem in our sample.

[10] As mentioned above, we keep RM firms with three-year performance commitments and pair each RM firm with a matched IPO firm for our empirical analyses. To maintain balance in the number of observations during and after the performance commitment period, we use the data from the six-year window after these firms are publicly listed.

[11] Year and firm fixed effects are included in Eqs. (3) and (4). Hence, we use the fixed effects estimator in all the regressions. In robustness tests, we also use Driscoll-Kraay standard errors to address cross-sectional dependence and grouped fixed effects to address grouped pattern of heterogeneity. Our untabulated results are all consistent with the primary results. Notwithstanding that the approaches used in our paper are in line with the mainstream accounting literature and allow us to address the potential endogeneity to the maximum extent possible, we concede that it is impossible to completely rule out endogeneity and construct a perfect econometrics model.

[12] For convenience, we use t to denote the first year in which the firms are publicly listed.

Table 1
Descriptive statistics.

Panel A: Descriptive statistics								
Variables	N	Mean	S.D.	Min	Q1	Median	Q3	Max
FERROR	630	0.028	0.058	0.000	0.003	0.008	0.022	0.353
FDISP	630	0.016	0.025	0.000	0.004	0.008	0.016	0.156
RM	630	0.484	0.500	0.000	0.000	0.000	1.000	1.000
POST	630	0.462	0.499	0.000	0.000	0.000	1.000	1.000
BIG10	630	0.631	0.483	0.000	0.000	1.000	1.000	1.000
FIRST	630	0.379	0.158	0.066	0.249	0.358	0.510	0.704
SOE	630	0.188	0.391	0.000	0.000	0.000	0.000	1.000
SIZE	630	22.663	1.169	20.390	21.952	22.560	23.178	26.523
LEV	630	0.458	0.212	0.076	0.292	0.450	0.615	0.972
ROA	630	0.050	0.102	−0.560	0.028	0.053	0.092	0.305
MTB	630	1.584	1.393	0.143	0.764	1.190	1.961	8.544
ANUM	630	2.829	0.864	1.386	2.079	2.773	3.466	4.727
HORIZON	630	4.794	0.625	3.895	4.428	4.836	5.235	6.904

Panel B: Distribution by industry			
Code	Industry	Obs.	%
B	Mining	24	3.81
C1	Food and beverage manufacturing, textiles, and apparel	21	3.33
C2	Paper and printing, petrochemicals, and medicine and biological products	104	16.51
C3	Machinery, metals and non-metals, and electronics manufacturing	170	26.98
C4	Other manufacturing	18	2.86
D	Electric power, gas production, and tap water	48	7.62
E	Construction	33	5.24
F	Wholesale and retail trade	25	3.97
G	Transportation	13	2.06
I	Information technology	63	10.00
K	Real estate	21	3.33
L	Leasing and business services	27	4.29
M	Scientific research and integrated technological services	9	1.43
N	Public facilities and services	16	2.54
R	Cultural, sports, and entertainment	38	6.03
Total		630	100

This table presents the descriptive statistics for the variables used in our main analysis and the sample distribution by industry. All continuous variables are winsorized at the 1% and 99% levels. All variables are defined in Appendix A. Industry group is based on the China Securities Regulatory Commission (CSRC) industry classification.

Table 2
Difference-in-differences comparison.

Panel A: Difference-in-differences comparison of *FERROR*						
	(1) During		(2) Post		Diff	Diff-in-Diff
Variable	N	Mean	N	Mean	(2)–(1)	(Merger-IPO)
RM	156	0.011	148	0.061	0.050***	0.045***
IPO	184	0.017	142	0.022	0.005	

Panel B: Difference-in-differences comparison of *FDISP*						
	(1) During		(2) Post		Diff	Diff-in-Diff
Variable	N	Mean	N	Mean	(2)–(1)	(Merger-IPO)
RM	156	0.011	148	0.025	0.015***	0.012***
IPO	184	0.010	142	0.013	0.003*	

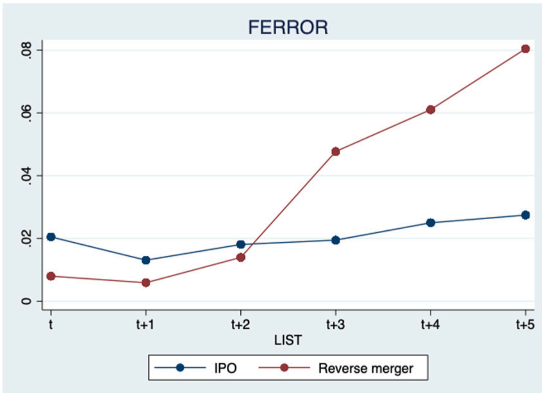
This table presents difference-in-differences comparisons of analyst forecast properties between the treatment (RM firms) and control firms (IPO firms). Panel A reports the mean values of analyst forecast error (*FERROR*) for both the treatment and control firms during and after the commitment period. Panel B reports the mean values of analyst forecast dispersion (*FDISP*) for both the treatment and control firms during and after the commitment period. See Appendix A for variable definitions. The superscripts ***, **, and * indicate two-tailed statistical significance at the 1%, 5%, and 10% levels, respectively.

4. Main empirical results

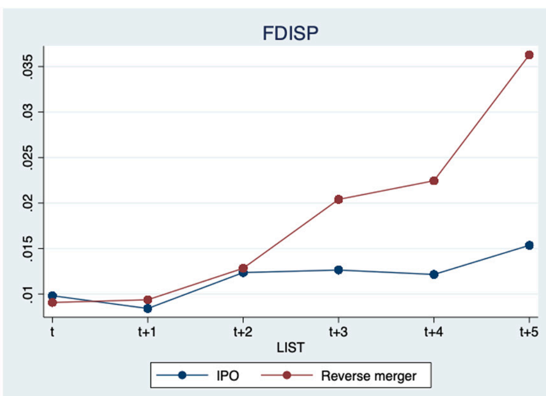
4.1. Descriptive statistics

Table 1 presents the descriptive statistics for the sample and the sample distribution by industry. Panel A presents the descriptive statistics of the variables used in our main analyses. For the dependent variables, the mean (median) value of *FERROR* is 0.028 (0.008), indicating that analysts' mean (median) scaled EPS forecasts are within 2.8% (0.8%) of actual EPS. The mean (median) value of *FDISP* is 0.016 (0.008), indicating that analysts' mean (median) forecast dispersions are 1.6% (0.8%). For the independent variable, the mean value of *RM* is 0.484, which suggests that about 48.4% of the observations are RM firms. Moreover, the mean value of *BIG10* is 0.631, indicating that more than half of the observations are audited by Big 10 auditors. On average, the percentage of shares of the largest shareholder (*FIRST*) is 37.9%. About 18.8% of the observations are from state-owned enterprises. The value of firm size (*SIZE*) is 22.663 on average, which is equivalent to about RMB 6.95 billion. The mean leverage (*LEV*) is 0.458 and the mean market-to-book ratio (*MTB*) is 1.584. Our sample has an average 5% return on assets (*ROA*). The mean values of *ANUM* and *HORIZON* are 2.829 and 4.794, which are equivalent to 17 analysts and 121 days, respectively.

The sample distribution by industry is presented in Panel B of Table 1. Within our sample, the number of observations varies substantially across industry groups based on the China Security Regulatory Commission (CSRC) industry classification. For example, the industry group consisting of machinery, metals and non-metals, and electronics



Panel A: Analyst forecast error (*FERROR*) during and after the commitment period



Panel B: Analyst forecast dispersion (*FDISP*) during and after the commitment period

Fig. 2. Graphical evolution of analyst earnings forecast properties.
Note: This figure presents the graphical evolution of analyst forecast error and dispersion of both control and treatment firms during and after the performance commitment period. Panel A presents analyst forecast error (*FERROR*) during and after the commitment period. Panel B presents analyst forecast dispersion (*FDISP*) during and after the commitment period.

manufacturing has the most observation in our sample (26.98%), followed by the industry group of paper and printing, petrochemicals, and medicine and biological products (16.51%). Whereas only 9 observations (1.43%) in the scientific research and integrated technological services industry and 13 observations (2.06%) in the transportation industry.[13]

Table 2 presents the difference-in-differences comparisons of analyst forecast error and dispersion between the treatment and control firms. We present the *t*-statistics for the mean tests of the differences during and after the commitment period for both the treatment and control firms. In Panel A, the difference between columns (1) and (2) indicates that analysts' forecast errors for the treatment (RM) firms increase significantly after the end of the commitment period. The last column of Panel A shows a test of differences in forecast error across the treatment and control firms between the commitment and post-commitment periods. The result shows significant differences in aggregate and average forecast error across the treatment and control firms between the periods. In Panel B, we similarly find that the differences in analysts' forecast dispersion across the treatment and control firms between the commitment and post-commitment periods are also significant.

The above test results are confirmed by Panels A and B of Fig. 2, in

[13] When we exclude observations from the scientific research and integrated technological services industry and the transportation industry, our empirical results remain unchanged.

Table 3
Pearson correlation matrix.

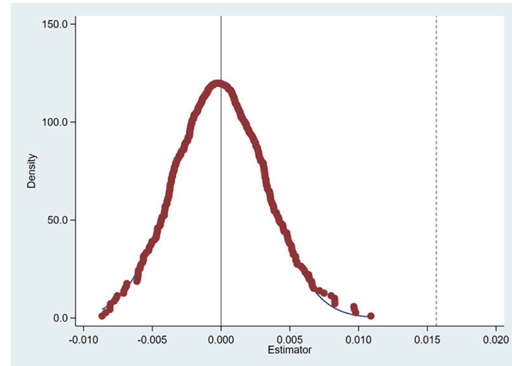
Variable	*FERROR*	*FDISP*	*RM*	*POST*	*SOE*	*BIG10*	*FIRST*	*SIZE*	*LEV*	*ROA*	*BTM*	*ANUM*	*HORIZON*
FERROR	1.000												
FDISP	0.623***	1.000											
RM	0.122***	0.050**	1.000										
POST	0.254***	0.221***	0.055	1.000									
SOE	0.040	0.070*	0.003	0.016	1.000								
BIG10	−0.157***	−0.143***	−0.146***	0.011	−0.035	1.000							
FIRST	−0.112***	−0.048	−0.226***	−0.105***	0.145***	0.075*	1.000						
SIZE	−0.005	0.134***	0.178***	0.311***	0.126***	0.189***	0.145***	1.000					
LEV	0.323***	0.219***	0.186***	0.123***	0.051	0.023	0.057	0.433***	1.000				
ROA	−0.451***	−0.239***	−0.044	−0.235***	−0.052	0.091**	0.087**	0.023	−0.430***	1.000			
BTM	−0.161***	−0.147***	−0.034	−0.016	−0.171***	0.056	−0.059	−0.344***	−0.427***	0.222***	1.000		
ANUM	−0.107***	0.066*	−0.053	0.287***	−0.169***	0.141***	−0.006	0.360***	0.067*	0.165***	0.111***	1.000	
HORIZON	0.367***	0.177***	−0.057	0.424***	0.127***	−0.095**	−0.117***	−0.040	0.073*	−0.392***	−0.152***	−0.007	1.000

This table presents the Pearson correlation coefficients among the main test variables for the sample of 630 firm-year observations in our study. See Appendix A for variable definitions. The superscripts ***, **, and * indicate two-tailed statistical significance at the 1%, 5%, and 10% levels, respectively.

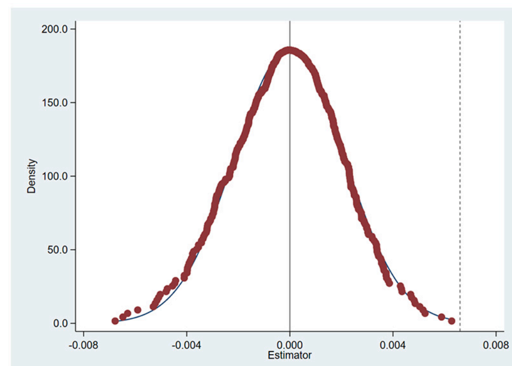
Table 4
Performance commitments and the properties of analyst earnings forecasts.

Variable	*FERROR*	*FDISP*	*FERROR*	*FDISP*
	(1)	(2)	(3)	(4)
POST	−0.0087	−0.0016	−0.0012	−0.0006
	(−0.999)	(−0.428)	(−0.211)	(−0.177)
RM POST*	**0.0360*****	**0.0082*****	**0.0155*****	**0.0066****
	(3.258)	**(2.635)**	**(2.790)**	**(1.995)**
BIG10			−0.0078	−0.0070**
			(−1.148)	(−2.578)
FIRST			0.0380	0.0231
			(1.472)	(1.296)
SOE			0.0173*	0.0018
			(1.912)	(0.249)
SIZE			−0.0169*	−0.0027
			(−1.805)	(−0.878)
LEV			0.1025***	0.0143
			(2.744)	(1.314)
ROA			−0.3033***	−0.0342***
			(−8.430)	(−2.830)
MTB			0.0057**	0.0016*
			(2.080)	(1.648)
ANUM			−0.0110***	0.0003
			(−2.739)	(0.155)
HORIZON			0.0037*	0.0034*
			(1.837)	(1.670)
CONSTANT	−0.0181	0.0071	0.3293	0.0780
	(−1.038)	(0.469)	(1.653)	(1.126)
YEAR FE	Yes	Yes	Yes	Yes
FIRM FE	Yes	Yes	Yes	Yes
N	630	630	630	630
R^2	0.251	0.231	0.682	0.287
Adj. R^2	0.238	0.016	0.671	0.048

This table presents the regression results of the impact of performance commitments on analyst forecast properties. The dependent variable is analyst forecast error (*FERROR*) and dispersion (*FDISP*). See Appendix A for variable definitions. Our sample includes 630 firm-year observations. Year and firm fixed effects are included. The *t*-statistics based on robust standard errors clustered by firms are presented in parentheses beneath each estimate. ***, **, and * indicate two-tailed statistical significance at the 1%, 5%, and 10% levels, respectively.



Panel A. The estimated coefficients of *RM*POST* when the dependent variable is *FERROR*.



Panel B. The estimated coefficients of *RM*POST* when the dependent variable is *FDISP*.

Fig. 3. Placebo tests.
Note: This figure presents the placebo test results. We randomly assign RM firms and IPO firms to observation without replacement 500 times. Panel A presents the estimated coefficients of *RM*POST* when the dependent variable is *FERROR*. Panel B presents the estimated coefficients of *RM*POST* when the dependent variable is *FDISP*.

which we present graphical evolutions of the analysts' forecast error and dispersion for the treatment and control firms by the number of years after listing. Panels A and B show that the analysts' forecast error and dispersion have a constant trend in the two samples during the commitment period (years t, $t+1$, and $t+2$), suggesting that our study meets the requirement of a parallel trend when using the difference-in-differences approach. In addition, the trends in the two samples show significant differences in the post-commitment period (years $t+3$, $t+4$, and $t+5$). The forecast error and dispersion increase drastically for RM firms in the post-commitment period, suggesting that the lack of performance commitment harms analyst forecast accuracy and dispersion.

Table 3 presents the Pearson correlation coefficients among the main test variables for the full sample. Notably, the correlation coefficients between *FERROR* and *POST*, and *FDISP* and *POST* are positive and significant. The pairwise correlations indicate that both analyst forecast error and dispersion increase over time. *FERROR* and *FDISP* are also positively and significantly correlated with *RM*, suggesting that analyst forecast error and dispersion are higher in our treatment firms (i.e., RM firms) than in control firms (i.e., IPO firms) during our sample period, which is consistent with the results in Table 2. We next turn on multivariate regression analyses for specific hypothesis testing.

4.2. Performance commitments and the properties of analyst earnings forecasts

Table 4 reports the estimates of our regression models regarding the impact of performance commitment on the properties of analyst earnings forecasts. In columns (1) and (2), we regress analyst forecast properties (*FERROR* and *FDISP*) on the interaction term of RM firms and the post-commitment indicator (*RM*POST*) without control variables. The estimated coefficients on *RM*POST* are 0.0360 and 0.0082, which are both statistically significant at the 1% level, respectively. When we include control variables in columns (3) and (4), the estimated coefficients on *RM*POST* are 0.0155 and 0.0066, which are statistically significant at the 1% and 5% levels, respectively. The effect of performance commitment on analyst forecast properties is not only statistically significant but also economically large. For example, in columns (3) and (4), compared with the control firms, the forecast error increased by 39.72% and dispersion increased by 35.29% for RM firms in the three years after the end of the commitment period. These results suggest that RM firms experience a decrease in analyst forecast accuracy and an increase in forecast dispersion after the commitment period. The results from columns (1) to (4) are consistent with H1a and H1b.

Many of the included control variables are statistically significant. For example, in Columns (3) and (4) of Table 4, the coefficients on *ROA* are both negative and significant at the 1% level, indicating that profitability has a positive impact on earnings forecast properties. The coefficients on *MTB* are both positive and significant, suggesting that high-growth firms increase the difficulty of analysts' forecasts. The coefficients on *HORIZON* are both significantly positive, indicating that the difficulty of analyst forecasts increases with the time between the forecast and earnings announcement. These results are consistent with the prior literature (Han et al., 2018; Hu, Xu, & Xue, 2022; Ni, Jin, Hu, & Zhang, 2023).

4.3. Robustness tests

In our baseline model, we construct a difference-in-differences

Table 5
Dynamic analysis.

Variable	*FERROR*	*FDISP*
	(1)	(2)
RM^*Y^{+1}	0.0115	0.0054
	(1.314)	(1.012)
$RM^*\ Y^{+2}$	0.0124	0.0050
	(1.084)	(0.934)
$RM^*\ Y^{+3}$	**0.0297****	**0.0101***
	(2.069)	**(1.860)**
$RM^*\ Y^{+4}$	**0.0326*****	**0.0112***
	(2.714)	**(1.873)**
$RM^*\ Y^{+5}$	**0.0406*****	**0.0149****
	(2.686)	**(2.299)**
Y^{+1}	0.0026	0.0030
	(0.512)	(0.770)
Y^{+2}	0.0158**	0.0107**
	(2.271)	(2.350)
Y^{+3}	0.0288***	0.0172***
	(3.267)	(3.112)
Y^{+4}	0.0285***	0.0147**
	(2.862)	(2.292)
Y^{+5}	0.0318***	0.0209***
	(2.675)	(2.771)
CONTROLS	Yes	Yes
CONSTANT	0.4022*	0.1004
	(1.851)	(1.411)
YEAR FE	Yes	Yes
FIRM FE	Yes	Yes
N	630	630
R^2	0.688	0.300
Adj. R^2	0.674	0.051

This table presents the regression results of the dynamic analysis. The dependent variable is analyst forecast error (*FERROR*) and dispersion (*FDISP*). See Appendix A for variable definitions. Our sample includes 630 firm-year observations. Year and firm fixed effects are included. The *t*-statistics based on robust standard errors clustered by firms are presented in parentheses beneath each estimate. ***, **, and * indicate two-tailed statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 6
Controlling for matching-pair fixed effects.

Variable	*FERROR*	*FDISP*
	(1)	(2)
RM	0.0016	0.0002
	(0.280)	(0.060)
POST	−0.0014	−0.0019
	(−0.225)	(−0.487)
*RM*POST*	**0.0147****	**0.0070****
	(2.107)	**(2.048)**
BIG10	−0.0079	−0.0069***
	(−1.620)	(−3.157)
FIRST	0.0134	0.0180**
	(0.610)	(2.181)
SOE	0.0120	0.0034
	(1.137)	(0.937)
SIZE	−0.0034	−0.0009
	(−0.943)	(−0.544)
LEV	0.0578**	0.0016
	(2.120)	(0.198)
ROA	−0.3066***	−0.0375***
	(−8.110)	(−3.194)
MTB	0.0036*	0.0014
	(1.666)	(1.471)
ANUM	−0.0053**	0.0008
	(−2.059)	(0.546)
HORIZON	0.0036	−0.0022
	(0.813)	(−1.192)
CONSTANT	0.0458	0.0828*
	(0.562)	(1.808)
YEAR FE	Yes	Yes
MATCHING-PAIR FE	Yes	Yes
N	630	630
R^2	0.676	0.503
Adj. R^2	0.621	0.408

This table presents the regression results controlling for matching-pair fixed effects. The dependent variable is analyst forecast error (*FERROR*) and dispersion (*FDISP*). See Appendix A for variable definitions. Our sample includes 630 firm-year observations. Year and matching-pair fixed effects are included. The *t*-statistics based on robust standard errors clustered by firms are presented in parentheses beneath each estimate. ***, **, and * indicate two-tailed statistical significance at the 1%, 5%, and 10% levels, respectively.

approach and document an increase in analyst forecasts error and dispersion of RM firms in the post-commitment period, our results may suffer from endogeneity concerns regarding firms' listing choices. Although we add a variety of control variables in the baseline model, we are still concerned that omitted variables impacting firms' listing choices would make our estimation model misspecified.

4.3.1. Placebo test

To alleviate endogeneity concerns, following Li, Lu, and Wang (2016), we first use a non-parametric permutation test to make a statistical inference by comparing the actual estimated coefficients with the distribution of placebo coefficients estimated when RM firms' identities are randomly assigned to observations. To conduct this test, we randomly assign RM firms and IPO firms to observations without replacement 500 times. We then estimate the regression of Eqs. (1) and (2) using each of the 500 randomly drawn placebo assignments. In Panels A and B of Fig. 3, we plot the distribution of the estimated coefficients on *RM*POST* when the dependent variables are *FERROR* and *FDISP*, respectively, from the 500 sets of regressions and determine the location of the coefficient from the actual dataset. As expected, the distribution of placebo coefficients is centered around zero, and none of the estimates is more positive than our real estimates. The results indicate that the actual estimated effect is unlikely to be owing to firms' listing choice.

4.3.2. Dynamic analysis

Following Chen, Hung, and Wang (2018), we use the dynamic approach to assess the validity of the parallel trend assumption underlying our DID research design. We replace *POST* in the regression models with year indicators that track the effect of a performance commitment before and after its expiration.[14] Then, we incorporate two variables, Y^{+1} and Y^{+2}, for the commitment period of RM firms (years $t+1$ and $t+2$ of IPO firms) and three variables, Y^{+3}, Y^{+4}, and Y^{+5}, for the post-commitment period of RM firms (years $t+3$ to $t+5$ of IPO firms). Next, we interact these five timing dummy variables with *RM*. The results are reported in Table 5. The coefficients on RM^*Y^{+1} and RM^*Y^{+2} are not significant, suggesting that there are no significant differences in either forecast error or dispersion between the treatment (RM) firms and control (IPO) firms during the commitment period. The coefficients on RM^*Y^{+3}, RM^*Y^{+4}, and RM^*Y^{+5} are positive and statistically significant, suggesting that our observed increase in analyst forecast error and dispersion for RM firms occurs after the end of the commitment period. These results support the parallel trend assumption of our difference-in-differences approach.

4.3.3. Controlling for matching-pair fixed effects

As an alternative to firm fixed effects in our main tests, we augment the regression models with matching-pair fixed effects to remove potential contamination by any unobservable time-invariant matching-pair-specific characteristics as omitted variables (Xin, Zhou, & Hu, 2018). The regression results are reported in columns (1) and (2) of

[14] As we use the data from the six-year window after the RM and IPO firms are publicly listed to examine the properties of analyst forecasts, we set five dummy variables (Y^{+1} to Y^{+5}) to proxy for years $t+1$ to $t+5$ in which the firms are listed. We use the first year (year *t*) in which the firms are listed as the benchmark year.

Table 7
Additional controls.

Variable	*FERROR*	*FDISP*	*FERROR*	*FDISP*
	(1)	(2)	(3)	(4)
POST	−0.0013	−0.0010	−0.0039	−0.0017
	(−0.236)	(−0.279)	(−0.712)	(−0.457)
*RM*POST*	**0.0157*****	**0.0069****	**0.0152*****	**0.0067***
	(2.822)	**(2.099)**	**(2.733)**	**(1.925)**
BIG10	−0.0077	−0.0067**	−0.0075	−0.0067**
	(−1.136)	(−2.456)	(−1.087)	(−2.382)
FIRST	0.0386	0.0244	0.0411	0.0221
	(1.511)	(1.371)	(1.561)	(1.206)
SOE	0.0176*	0.0027	0.0139	0.0014
	(1.974)	(0.373)	(1.385)	(0.177)
SIZE	−0.0171*	−0.0031	−0.0166	−0.0039
	(−1.809)	(−1.033)	(−1.551)	(−1.158)
LEV	0.1021***	0.0133	0.0896**	0.0107
	(2.733)	(1.219)	(2.355)	(0.916)
ROA	−0.3027***	−0.0324***	−0.3048***	−0.0353**
	(−8.423)	(−2.671)	(−7.406)	(−2.514)
MTB	0.0057**	0.0015	0.0054*	0.0014
	(2.069)	(1.552)	(1.834)	(1.356)
ANUM	−0.0109***	0.0006	−0.0143***	−0.0003
	(−2.697)	(0.306)	(−3.147)	(−0.125)
HORIZON	0.0038	−0.0031	0.0077**	0.0016
	(0.859)	(−1.505)	(1.995)	(0.729)
MF	−0.0015	−0.0041*	0.0017	0.0044
	(−0.421)	(−1.658)	(0.403)	(1.565)
ACC			0.0025	0.0056
			(0.140)	(0.646)
CONSTANT	0.3307	0.0827	0.3075	0.0935
	(1.654)	(1.195)	(1.380)	(1.247)
YEAR FE	Yes	Yes	Yes	Yes
FIRM FE	Yes	Yes	Yes	Yes
N	630	630	588	588
R^2	0.682	0.292	0.707	0.287
adj. R^2	0.670	0.052	0.695	0.020

This table presents the regression results using additional controls. The dependent variable is analyst forecast error (*FERROR*) and dispersion (*FDISP*). See Appendix A for variable definitions. Year and firm fixed effects are included. The *t*-statistics based on robust standard errors clustered by firms are presented in parentheses beneath each estimate. ***, **, and * indicate two-tailed statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 6. The coefficients on the interaction term *RM*POST* are both positive and statistically significant at the 5% level, consistent with our primary findings.

4.3.4. Additional controls

Our main tests in Table 3 show that performance commitments, as a type of important public information used in analysts' assessments, influence the properties of analyst earnings forecasts. However, it is still unclear whether performance commitment affects the properties of analyst earnings forecasts that are incremental to the effects of other critical public information, such as management earnings forecasts, and information quality, as with discretionary accruals (Chen & Jiang, 2006; Kim & Song, 2015; Lobo et al., 2012). We add two additional controls, *MF* and *ACC*, to the baseline model in Eqs. (3) and (4). Specifically, *MF* is an indicator that equals one if the management issues earnings forecasts before the fiscal year-end, and zero otherwise. *ACC* is the absolute value of discretionary accruals, which is estimated from the Jones model as modified in Kothari, Leone, and Wasley (2005). In columns (1) and (2) of Table 7, we include *MF* as an additional control variable in the regressions and find that the coefficients on *RM*POST* are positive and statistically significant. We then include *ACC* as an alternative variable in the regression models; as shown in columns (3) and (4), the coefficients on *RM*POST* remain positive and significant. The results in Table 7 are consistent with the predictions of H1a and H1b.

4.3.5. Different matching strategies

To control for observed differences between RM firms and IPO firms, we match each RM firm to the IPO firm in the same trading venue, year, and industry that is closest in size. This approach may result in some firm pairs that are closest in size but may still have large differences. In this subsection, we adopt three alternative matching strategies to limit these differences and construct the treatment and control groups. First, we pair each RM firm with a matched IPO firm in the same trading venue, year, and industry that is within 20% of scale in terms of firm size (*SIZE*). Second, we pair each RM firm with a matched IPO firm in the same trading venue, year, and industry that is within 20% of scale in accounting performance (*ROA*). Third, we employ the propensity score matching (PSM) approach to control for observed differences between RM and IPO firms. We run a logit regression to estimate the likelihood of a firm choosing to go public via RM transactions, then construct a one-to-one match using a caliper distance of 0.05 from IPO firms to form the control group.[15] Table 8 presents the regression results of Eqs. (1) and (2) using the different matching strategies. Our main results continue to hold.

4.3.6. Alternative measures of analyst earnings forecasts

We use the alternative definition to measure analyst forecast error and dispersion. Following Han et al. (2018), analyst forecast error (*FERROR*) and dispersion (*FDISP*) are similar to the definitions in the baseline empirical model but use actual EPS instead of the stock price at the beginning of the year as the dominator. The regression results using these alternative measures of analyst forecast error and dispersion are presented in Table 9. The coefficients on *RM*POST* are both significantly positive in columns (1) and (2), which are consistent with our primary findings.

4.3.7. Regression results using analyst-firm-year sample

To draw reliable inferences about the relationship between performance commitments and analyst earnings forecast properties, following previous studies (e.g., Lehavy et al., 2011), we use an alternative sample consisting of analyst-firm-year observations. The sample size is thus increased from 630 firm-year observations to 15,391 analyst-firm-year observations. Based on Eq. (3), we use *FERROR_I* to proxy for analyst forecast error at the individual level, which is measured as the absolute difference between the actual annual earnings per share (EPS) and the analyst's most recent forecasted EPS before the fiscal year-end, scaled by the stock price at the beginning of the year.[16] In addition to all of the control variables used in our main model in Eq. (3), we include three variables to control for individual analyst characteristics, i.e., analyst gender (*GENDER*), educational background (*EDUCATION*), and professional experience (*EXPERIENCE*).[17] Table 10 presents the regression results. The coefficient on *RM*POST* is positive and significant at the 5% level. Our main results continue to hold for the analyst-firm-year sample.

5. Further analyses

Our primary findings suggest that analysts exhibit a large increase in forecast error and dispersion after the end of the performance

[15] Following Lee et al. (2015) the control variables used in calculating the propensity score are *BIG10*, *FIRST*, *SOE*, *SIZE*, *LEV*, *ROA*, and *MTB*. Please see Appendix A for variable definitions.

[16] Note that analyst forecast dispersion (*FDISP* in the primary models) is based on the standard deviation of all the analysts' forecast at the firm level, which cannot be measured at the individual analyst level. Thus, in this section, we only examine the impact of performance commitments on analyst forecast error using analyst-firm-year observations.

[17] *GENDER* is an indicator variable which equals one if an analyst is female, and zero otherwise. *EDUCATION* is an indicator variable which equals one if an analyst has a Bachelor's degree or higher, and zero otherwise. *EXPERIENCE* is measured as the logarithm of the number of years an analyst has been in the profession. Please see Appendix A for variable definitions.

Table 8
Different matching strategies.

Variable	*SIZE* within 20%		*ROA* within 20%		PSM	
	FERROR	*FDISP*	*FERROR*	*FDISP*	*FERROR*	*FDISP*
	(1)	(2)	(3)	(4)	(5)	(6)
POST	−0.0042	0.0025	−0.0051	−0.0079**	−0.0050	−0.0035
	(−0.717)	(0.593)	(−0.869)	(−2.259)	(−0.745)	(−0.640)
*RM*POST*	**0.0231*****	**0.0085****	**0.0122***	**0.0059***	**0.0140***	**0.0048****
	(3.798)	**(2.231)**	**(1.905)**	**(1.744)**	**(1.892)**	**(2.242)**
BIG10	−0.0056	−0.0045	0.0003	0.0023	−0.0120	−0.0001
	(−0.775)	(−1.453)	(0.048)	(0.837)	(−1.300)	(−0.035)
FIRST	0.0460	0.0212	0.0966***	0.0247	−0.0217	0.0021
	(1.395)	(0.926)	(2.705)	(1.121)	(−0.231)	(0.069)
SOE	0.0195	−0.0019	0.0102	−0.0017	0.0098	−0.0047
	(1.645)	(−0.188)	(1.035)	(−0.254)	(1.072)	(−0.458)
SIZE	−0.0156*	−0.0076**	−0.0179*	−0.0011	−0.0276***	−0.0055
	(−1.710)	(−2.325)	(−1.905)	(−0.334)	(−3.402)	(−1.475)
LEV	0.1029**	0.0278**	0.0797**	0.0061	0.0303	0.0085
	(2.456)	(2.226)	(2.512)	(0.505)	(0.855)	(0.693)
ROA	−0.2716***	−0.0193	−0.3336***	−0.0415**	−0.4471***	−0.0530***
	(−7.097)	(−1.422)	(−4.522)	(−2.429)	(−7.557)	(−2.973)
TOBINQ	−0.0060*	−0.0020*	−0.0019	−0.0003	−0.0032	−0.0014
	(−1.858)	(−1.738)	(−0.526)	(−0.238)	(−1.465)	(−1.382)
ANUM	−0.0136***	0.0009	−0.0099**	0.0042**	−0.0028	−0.0007
	(−3.180)	(0.416)	(−2.209)	(2.166)	(−0.817)	(−0.469)
HORIZON	0.0033	−0.0043*	0.0137***	0.0030	0.0012	0.0065***
	(0.702)	(−1.804)	(2.691)	(1.476)	(0.248)	(2.715)
CONSTANT	0.2996	0.1797**	0.2855	−0.0270	0.6369***	0.1303
	(1.548)	(2.353)	(1.415)	(−0.347)	(3.406)	(1.540)
YEAR FE	Yes	Yes	Yes	Yes	Yes	Yes
FIRM FE	Yes	Yes	Yes	Yes	Yes	Yes
N	566	566	404	404	366	366
R^2	0.668	0.296	0.605	0.270	0.658	0.360
Adj. R^2	0.655	0.050	0.583	0.013	0.638	0.124

This table presents the regression results using different matching strategies. The dependent variable is analyst forecast error (*FERROR*) and dispersion (*FDISP*). In columns (1) and (2), we pair each RM firm with a matched IPO firm in the same trading venue, year, and industry that is within 20% scale in *SIZE*. In columns (3) and (4), we pair each RM firm with a matched IPO firm in the same trading venue, year, and industry that is within 20% scale in *ROA*. In columns (5) and (6), we pair each RM firm with a matched IPO firm using the PSM approach. See Appendix A for variable definitions. The *t*-statistics based on robust standard errors clustered by firms are presented in parentheses beneath each estimate. ***, **, and * indicate two-tailed statistical significance at the 1%, 5%, and 10% levels, respectively.

commitment period for RM firms. In this section, we perform several additional tests designed to provide evidence that corroborate the results from our primary analyses.

5.1. The effect of information transparency on analyst earnings forecasts

We investigate whether the relationship between performance commitment and analyst earnings forecast properties is heterogeneous across different types of firms. In particular, we study whether this relationship varies with the level of firms' information transparency. For example, prior studies (e.g., Bratten et al., 2016; Francis et al., 2019; Libby et al., 2006) document that high information transparency of a firm fosters a better information environment, given that analysts benefit from transparent firm information, which helps them make more accurate forecasts. Hence, the clear performance targets in performance commitments could be more valuable for analyst earnings forecasts when firms have lower information transparency. Therefore, we expect that analysts' forecast error and dispersion increase more in the post-commitment period for firms with lower levels of information transparency.

Three settings are used to examine the effect of information transparency on analyst earnings forecasts. First, following Lobo et al. (2012), we use discretionary accruals to measure information transparency. Based on the median of discretionary accruals, the full sample is partitioned into two groups: low transparency (LOW) and high transparency (HIGH). Second, the Shanghai and Shenzhen stock exchanges conduct annual assessments on the transparency of information disclosure of listed firms and publish the rating results. We therefore also perform a different partitioning of the sample into firms rated level 1 in these assessments (HIGH) and firms with all other rating levels (LOW). Third, as noted by Bradshaw, Lock, Wang, and Zhou (2020), firm-specific media coverage decreases information asymmetry and is informative for analyst earnings forecasts. Thus, we finally partition the sample into two groups based on the median of firm-specific media coverage (HIGH and LOW). We re-examine the main models using these three alternative partitioning criteria.

The regression results are presented in Panels A, B, and C of Table 11, respectively. We find that the coefficients on *RM*POST* are significant and positive in all the LOW information transparency groups, but not significant in the HIGH information transparency groups. In summary, the findings in Table 11 are consistent with our expectation that performance commitments are more valuable to analysts when assessing firms with lower information transparency.

5.2. Performance commitment achievement and analyst earnings forecasts

In all of the tests above, we argue that analysts rely on performance commitment in their assessments and their forecast properties decline significantly after they lose this important public information. As failure to meet performance commitments will result in large economic losses for the controlling shareholders of acquirees, they are highly incentivized to achieve performance targets. Importantly, to avoid suffering losses, controlling shareholders are likely to engage in earnings management to just meet and beat performance targets (Hou et al., 2015; Yuan, Gao, & Shi, 2021). Therefore, if a firm can achieve the performance target, such information from the performance commitment would become the best reference for analysts. Conversely, if a firm fails to meet its target, then analysts relying on performance commitments could produce more inaccurate forecasts. Given these reasons, we can

Table 9
Alternative measures of analyst earnings forecasts.

Variable	*FERROR*	*FDISP*
	(1)	(2)
POST	−1.5249**	0.0875
	(−2.017)	(0.214)
*RM*POST*	**1.6058****	**1.0814****
	(2.231)	**(1.999)**
BIG10	0.4554	−0.6273*
	(0.736)	(−1.940)
FIRST	0.9378	−0.2686
	(0.230)	(−0.443)
SOE	0.6859	0.7898*
	(0.857)	(1.681)
SIZE	−0.2125	−0.2054*
	(−0.493)	(−1.943)
LEV	0.4524	2.5598***
	(0.243)	(2.914)
ROA	−0.8829	−1.3532
	(−0.404)	(−1.265)
MTB	0.0199	0.0961
	(0.169)	(1.121)
ANUM	−1.4735**	0.3210
	(−2.369)	(1.524)
HORIZON	1.2920***	0.5922*
	(2.742)	(1.793)
CONSTANT	0.7122	0.6008
	(0.068)	(0.212)
YEAR FE	Yes	Yes
FIRM PAIR FE	Yes	Yes
N	630	630
R^2	0.123	0.081
Adj. R^2	0.093	0.047

This table presents the regression results of Eqs. (3) and (4) using alternative measures of analyst earnings forecasts. *FERROR* is defined as the absolute difference between the actual EPS and the mean value of the analyst's most recent forecasted EPS before the fiscal year-end, scaled by the actual EPS. *FDISP* is defined as the standard deviation of analysts' most recent forecasted EPS before the fiscal year-end, scaled by the actual EPS. See Appendix A for other variable definitions. Year and firm fixed effects are included. The *t*-statistics based on robust standard errors clustered by firms are presented in parentheses beneath each estimate. ***, **, and * indicate two-tailed statistical significance at the 1%, 5%, and 10% levels, respectively.

expect analyst forecast error and dispersion to be lower if firms achieve their performance targets.

To conduct these analyses, we use a sample consisting of RM firm observations during the performance commitment period.[18] We set an indicator variable, *ACHIEVE*, that equals one if the firm achieves its performance target in a given year, and zero otherwise. The regression results are presented in Table 12. In columns (1) and (2), we find a significantly negative association between *ACHIEVE* and *FERROR*, and in columns (3) and (4), we also find a significantly negative association between *ACHIEVE* and *FDISP*. These findings support our prediction that analysts rely on performance commitments in their assessments and that forecast error and dispersion are lower when firms achieve their performance targets.

5.3. Information components of analyst forecasts in the post-commitment period

As an important type of public information, performance commitments can be shared by all analysts at almost zero marginal costs. However, after the expiration of the performance commitment, analysts

Table 10
Regression results using analyst-firm-year sample.

Variable	*FERROR_I*	
	Coefficient	*t*-statistics
	(1)	(2)
POST	−0.0115**	−2.411
*RM*POST*	**0.0167****	**2.031**
BIG10	−0.0106**	−1.980
FIRST	−0.0064	−0.361
SOE	−0.0026	−0.283
SIZE	0.0003	0.132
LEV	0.0154	0.791
ROA	−0.4249***	−4.464
MTB	0.0029	1.604
HORIZON	0.0118**	2.207
GENDER	0.0007	0.386
EDUCATION	0.0001	0.053
EXPERIENCE	0.0001	1.438
CONSTANT	−0.0307	−0.493
YEAR FE	Yes	
FIRM FE	Yes	
ANALYST FE	Yes	
N	15,391	
R^2	0.428	
Adj. R^2	0.426	

This table presents regression results using analyst-firm-year sample. The dependent variable is analyst forecast error (*FERROR_I*) at the analyst level. See Appendix A for variable definitions. Year, firm, and analyst fixed effects are also included in the regression. The full sample includes 15,391 analyst-firm-year observations. The *t*-statistics based on robust standard errors clustered by firms are presented in column (2). ***, **, and * indicate two-tailed statistical significance at the 1%, 5%, and 10% levels, respectively.

are forced to collect and use private information due to the absence of valuable public information. If analysts rely less on performance commitments, they can be expected to collect more private information in the post-commitment period, which will result in a decline in the public information component and an increase in the private information component in their earnings forecasts. We use the Barron et al. (1998) model to measure the relative amounts of public and private information components in analyst forecasts. The model proposes that private information (*PRIVATE*) can be measured as a ratio with dispersion in the numerator and one minus the number of analysts multiplied by the dispersion plus the squared mean forecast error in the denominator. Public information (*PUBLIC*) can be measured as a ratio with the squared mean forecast error less the ratio of dispersion to the number of analysts in the numerator and the same denominator as *PRIVATE*.

Table 13 reports the regression results. In column (1), the coefficient on the interaction term *RM*POST* is negative and significant at the 5% level when the dependent variable is *PUBLIC*. However, in column (2), the coefficient on the interaction term *RM*POST* is not significant when the dependent variable is *PRIVATE*. The results suggest that analysts incorporate a smaller public information component in their forecasts because of the absence of performance commitment; however, the private information component is unchanged. Because of the extra effort required to collect private information, analysts have less incentive to increase their collection of private information after the end of the performance commitment.

5.4. Analyst reactions in the post-commitment period

Table 13 documents a significant decline in the public information component in analyst forecasts in the post-commitment period. It is still unclear how analysts react under circumstances where public information is inadequate. Therefore, we next push our research forward to analyzing analysts' reactions to RM firms in the post-commitment period.

First, the literature documents that after the information

[18] During the performance commitment period, RM firms are required to hire auditors each year to conduct a special audit on the achievement of the performance targets. We check, by each year, whether the RM firms met their performance targets based on the manually collected special audit reports.

Table 11
The effect of information transparency on analyst earnings forecasts.

Panel A: Discretionary accruals

Variable	*FERROR*		*FDISP*	
	LOW	*HIGH*	*LOW*	*HIGH*
	(1)	(2)	(3)	(4)
POST	−0.0059	−0.0026	−0.0020	0.0064
	(−1.406)	(−0.247)	(−0.529)	(0.848)
RM POST*	**0.0165*****	0.0110	**0.0080****	0.0021
	(3.380)	(0.940)	**(2.352)**	(0.311)
CONTROLS	Yes	Yes	Yes	Yes
CONSTANT	0.3113***	0.1524	0.1093	−0.0359
	(2.637)	(0.338)	(1.383)	(−0.259)
YEAR FE	Yes	Yes	Yes	Yes
FIRM FE	Yes	Yes	Yes	Yes
N	316	314	316	314
R^2	0.491	0.773	0.440	0.283
Adj. R^2	0.456	0.757	0.108	0.352

Panel B: Transparency ratings

Variable	*FERROR*		*FDISP*	
	LOW	*HIGH*	*LOW*	*HIGH*
	(1)	(2)	(3)	(4)
POST	−0.0009	−0.0006	−0.0024	0.0058
	(−0.132)	(−0.110)	(−0.536)	(1.069)
RM POST*	**0.0194*****	0.0114	**0.0085****	0.0001
	(2.919)	(1.447)	**(2.182)**	(0.008)
CONTROLS	Yes	Yes	Yes	Yes
CONSTANT	0.5032*	0.4291***	0.0602	0.0976
	(1.751)	(3.590)	(0.733)	(0.883)
YEAR FE	Yes	Yes	Yes	Yes
FIRM FE	Yes	Yes	Yes	Yes
N	508	122	508	122
R^2	0.701	0.580	0.298	0.389
Adj. R^2	0.682	0.487	0.049	0.028

Panel C: Media coverage

Variable	*FERROR*		*FDISP*	
	LOW	*HIGH*	*LOW*	*HIGH*
	(1)	(2)	(3)	(4)
POST	−0.0116	0.0017	−0.0062	0.0066
	(−1.511)	(0.231)	(−1.085)	(1.122)
RM POST*	**0.0167****	0.0064	**0.0109****	0.0014
	(2.341)	(0.950)	**(2.027)**	(0.248)
CONTROLS	Yes	Yes	Yes	Yes
CONSTANT	0.0074	−0.0006	−0.0032	−0.0028
	(0.863)	(−0.098)	(−0.822)	(−0.955)
YEAR FE	Yes	Yes	Yes	Yes
FIRM FE	Yes	Yes	Yes	Yes
N	312	318	312	318
R^2	0.827	0.522	0.339	0.164
Adj. R^2	0.812	0.479	0.076	0.410

This table presents the regression results of the effect of information transparency on analyst earnings forecasts. We use discretionary accruals, transparency ratings from the Shanghai and Shenzhen stock exchanges, and media coverage to proxy for the firm's information transparency in Panels A, B, and C, respectively. The dependent variable is analyst forecast error (*FERROR*) and dispersion (*FDISP*). See Appendix A for variable definitions. Year and firm fixed effects are included. The *t*-statistics based on robust standard errors clustered by firms are presented in parentheses beneath each estimate. ***, **, and * indicate two-tailed statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 12
Performance commitment achievement and analyst earnings forecasts.

Variable	*FERROR*		*FDISP*	
	(1)	(2)	(3)	(4)
ACHIEVE	**−0.0506****	**−0.0059***	**−0.0109***	**−0.0082***
	(−2.003)	**(−1.763)**	**(−1.784)**	**(−1.922)**
BIG10		−0.0010		0.0023
		(−0.272)		(0.677)
FIRST		0.1469***		−0.0616
		(3.335)		(−1.364)
SIZE		−0.0117**		−0.0121*
		(−2.535)		(−1.781)
LEV		0.0447**		0.0182
		(2.312)		(0.663)
ROA		−0.2333***		0.0282
		(−5.266)		(1.003)
MTB		0.0023		−0.0023
		(0.982)		(−0.973)
ANUM		0.0056*		0.0082
		(1.664)		(1.202)
HORIZON		0.0034		0.0019
		(1.460)		(0.635)
CONSTANT	0.0682**	0.1811*	0.0202***	0.2689*
	(2.624)	(1.788)	(3.999)	(1.765)
YEAR FE	Yes	Yes	Yes	Yes
FIRM FE	Yes	Yes	Yes	Yes
N	156	156	156	156
R^2	0.130	0.816	0.029	0.081
Adj. R^2	0.099	0.795	0.023	0.018

This table presents the regression results of performance commitment achievement on analyst earnings forecasts. The dependent variable is analyst forecast error (*FERROR*) and dispersion (*FDISP*). See Appendix A for variable definitions. Year and firm fixed effects are included. The *t*-statistics based on robust standard errors clustered by firms are presented in parentheses beneath each estimate. ***, **, and * indicate two-tailed statistical significance at the 1%, 5%, and 10% levels, respectively.

environment changes, analysts revise their earnings forecasts based on the new information (Bradshaw et al., 2020). We expect that during the performance commitment period, analysts do not need to revise earnings forecasts frequently because they can make assessments based on performance commitments. In contrast, in the post-commitment period, analysts must increase the frequency of forecast revisions to avoid deviations due to the absence of performance commitments. Following the literature (Altınkılıç & Hansen, 2009; Kim & Song, 2015), we use *REVISION*, which is measured as the number of forecast revisions divided by the number of analysts, to proxy for revision frequency. A higher *REVISION* indicates a higher frequency of forecast revision. In column (1) of Table 14, the interaction term *RM*POST* is positive and statistically significant at the 1% level, which suggests that analysts adopt a higher revision frequency to compensate for the absence of performance commitments after the end of the commitment period.

Second, in-person communication between analysts and firm management helps analysts to gain private information, which enables them to better evaluate the firms' operation and issue more accurate earnings forecasts (Han et al., 2018). Nevertheless, as shown in Table 13, we find no changes in the private information component of analyst forecasts for RM firms in the post-commitment period. Thus, we expect that analysts have less incentives to acquire private information via private communications with firm managers because they are highly reliant on public information. To conduct this analysis, we use two variables, *VISIT_DUM* and *VISIT*, to proxy for analysts' firm visits. Specifically, *VISIT_DUM* is an indicator variable that takes the value of one if the firm is visited by analysts in a given year, and zero otherwise. *VISIT* is measured as the logarithm of one plus the number of analyst visits for the firm. In columns (2) and (3) of Table 14, the values of the interaction term *RM*POST* are insignificant, which is consistent with our argument that analysts have little incentive to collect extra private information through firm visits. Taken together, the results in Table 14 suggest that analysts conduct more frequent forecast revisions in the post-commitment period, but the number of firm visits is unchanged. Moreover, these

Table 13
Information components of analyst forecasts in the post-commitment period.

Variable	*PUBLIC*	*PRIVATE*
	(1)	(2)
POST	−4.2113*	8.9102**
	(−1.709)	(2.253)
*RM*POST*	**−5.3808****	2.1273
	(−2.070)	(0.488)
BIG10	−2.3196	0.8841
	(−0.875)	(0.231)
FIRST	−1.8562	−24.2819
	(−0.233)	(−1.484)
SOE	−6.7998	3.3984
	(−1.502)	(0.362)
SIZE	−3.3655	4.8128
	(−1.550)	(1.331)
LEV	4.1479	−13.9642
	(0.492)	(−0.915)
ROA	−11.8151	21.4629*
	(−1.593)	(1.746)
MTB	0.2260	0.0571
	(0.396)	(0.054)
ANUM	3.6980**	−6.3403**
	(2.154)	(−2.368)
HORIZON	−4.9121***	2.4528
	(−2.834)	(0.896)
CONSTANT	75.1744	−48.6700
	(1.525)	(−0.583)
YEAR FE	Yes	Yes
FIRM FE	Yes	Yes
N	630	630
R^2	0.102	0.112
Adj. R^2	0.071	0.082

This table presents regression results of information components of analyst forecasts in the post-commitment period. The dependent variable is the public information component (*PUBLIC*) and private information component (*PRIVATE*) of analyst earnings forecasts. See Appendix A for variable definitions. Our sample includes 630 firm-year observations. Year and firm fixed effects are included. The *t*-statistics based on robust standard errors clustered by firms are presented in parentheses beneath each estimate. ***, **, and * indicate two-tailed statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 14
Analysts' reactions in the post-commitment period.

Variable	*REVISION*	*VISIT_DUM*	*VISIT*
	(1)	(2)	(3)
POST	−0.1579	−1.4415*	−0.3607**
	(−1.592)	(−1.875)	(−2.182)
*RM*POST*	**0.4295*****	0.4158	0.2045
	(4.210)	(0.649)	(1.099)
BIG10	0.0230	−0.5351	−0.0969
	(0.293)	(−1.092)	(−0.657)
FIRST	−0.4292	−0.4503	0.1233
	(−0.993)	(−0.083)	(0.216)
SOE	−0.1463	0.2290	0.0713
	(−1.180)	(0.177)	(0.168)
SIZE	0.1549**	1.2620**	0.2568
	(2.003)	(2.177)	(1.430)
LEV	0.3338	0.3372	−0.2545
	(0.960)	(0.182)	(−0.399)
ROA	0.6639**	1.2829	0.2242
	(1.993)	(0.656)	(0.338)
MTB	0.0526	0.2698	0.0451
	(1.652)	(1.396)	(1.202)
ANUM	0.0522	0.2032	0.2904***
	(0.891)	(0.532)	(2.666)
CONSTANT	−1.6667	–	−5.1872
	(−1.018)	–	(−1.330)
YEAR FE	Yes	Yes	Yes
FIRM FE	Yes	Yes	Yes
N	630	270	630
R^2	0.342	–	0.081
Adj. R^2	0.320	–	0.051
Pseudo. R^2	–	0.148	–

This table presents regression results of analysts' reactions in the post-commitment period. The dependent variable is the frequency of analyst earnings forecasts (*REVISION*), firm visit indicator (*VISIT_DUM*), and the number of firm visits (*VISIT*). Our sample includes 630 firm-year observations. Year and firm fixed effects are included. The *t* (*z*)-statistics based on robust standard errors clustered by firms are presented in parentheses beneath each estimate. ***, **, and * indicate two-tailed statistical significance at the 1%, 5%, and 10% levels, respectively.

findings further support analysts' reliance on public information, as they have less incentive to collect private information even after losing the information from performance commitments.

6. Conclusion

While the literature discussed public information and private information the analysts incorporate in their assessments, there is little evidence of how performance commitment affects the properties of analyst earnings forecasts. Our study addresses this gap in the literature. We focus on the setting of Chinese reverse merger transactions and examine whether performance commitments affect analyst forecast properties and whether analysts' behavior changes in the post-commitment period. According to the RM regulations, shareholders of the acquirees are required to sign a performance commitment for approximately three years after being publicly listed. Analysts can rely on this performance commitment to forecast firm performance during this period but lose this information in the post-commitment period. In this setting, we find significant increases in analyst forecast error and dispersion for RM firms after the end of the commitment period in comparison to the control sample of IPO firms. This increase is more pronounced for firms with lower information transparency. Furthermore, RM firms that achieve performance targets are positively associated with desirable properties of analyst earnings forecasts. Moreover, the public information component of analyst forecasts declines, and analyst forecast revisions increase in the post-commitment period, while the private information component in analyst forecasts and analyst firm visits remains unchanged. Overall, our findings suggest that performance commitments play an important role in analysts' assessments and that analysts rely greatly on the information from performance commitments and have less incentive to collect private information in the post-commitment period.

Our findings have implications for analysts in other emerging economies who are attempting to improve the quality of their earnings forecasts. Cost-saving and reliable public information helps analysts issue high-quality earnings forecasts. However, analysts cannot rely solely on such public information; they must also improve their ability to interpret as well as collect a wide range of public and private information.

Declaration of Competing Interest

None.

Data availability

The authors do not have permission to share data.

Acknowledgement

We thank Shiyang Hu, Julia Junxia Liu, Qingquan Xin, Xiaofei Zhang and seminar participants at the Hang Seng University of Hong Kong and Central University of Finance and Economics for comments and suggestions. Yu Liu and Lingxuan Yang acknowledge financial support from the National Natural Science Foundation of China under Project No. 71232004 and 71872022 and Henan Provincial Universities Philosophy and Social Science Innovation Team Support Program No. 2023-CXTD-07. Any errors and omissions are our own.

Appendix A. Variable definitions

Variable	Definition
Dependent variables	
FERROR	The absolute difference between the actual annual earnings per share (EPS) and the mean value of all the analysts' most recent forecasted EPS before the fiscal year-end, scaled by the stock price at the beginning of the year.
FDISP	The standard deviation of all the analysts' most recent forecasted EPS before the fiscal year-end, scaled by the stock price at the beginning of the year.
FERROR_I	Analyst forecast error at the individual level, measured as the absolute difference between the actual annual earnings per share (EPS) and the analyst's most recent forecasted EPS before the fiscal year-end, scaled by the stock price at the beginning of the year.
PUBLIC	The ratio with the squared mean forecast error less the ratio of dispersion to the number of analysts in the numerator and one minus the number of analysts multiplied by dispersion plus the squared mean forecast error in the denominator.
PRIVATE	The ratio with dispersion in the numerator and one minus the number of analysts multiplied by dispersion plus the squared mean forecast error in the denominator.
REVISION	The number of forecast revisions divided by the number of analysts.
VISIT_DUM	An indicator variable which equals 1 if the firm is visited by analysts, and 0 otherwise.
VISIT	The natural logarithm of 1 plus the number of analyst visits for the firm.
Independent variables	
RM	An indicator variable which equals 1 for treatment (RM) firms, and 0 for control (IPO) firms
POST	An indicator variable, taking the value of 1 for the post-commitment period of RM firms (years $t+3$, $t+4$, and $t+5$ of IPO firms), and 0 for the pre-commitment period of RM firms (years t, $t+1$, and $t+2$ of IPO firms). We use t to denote the first year in which a firm is publicly listed.
ACHIEVE	An indicator variable which equals 1 if the RM firm achieves its performance target in a given year, and 0 otherwise.
Control variables	
BIG10	An indicator variable which equals 1 if the audit firm is a Big 10 audit firm in China, and 0 otherwise.
FIRST	The percentage of shares held by the top one shareholder.
SOE	An indicator variable which equals 1 if the firm is ultimately controlled by the government, and 0 otherwise.
SIZE	The natural logarithm of the firm's total assets at fiscal year-end.
LEV	Total liabilities divided by the total assets of the firm.
ROA	Net income divided by the total assets of the firm.
MTB	The market value of equity divided by the book value of equity.
ANUM	The natural logarithm of the number of unique analysts following the firm during the year.
HORIZON	The average length of days between the forecasting date and the annual reports announcement date
MF	An indicator variable which equals one if management issues a forecast before the fiscal year-end, and zero otherwise.
ACC	The absolute value of discretionary accruals, which is estimated from the Jones model as modified in Kothari et al. (2005)
GENDER	An indicator variable which equals one if an analyst is female, and zero otherwise.
EDUCATION	An indicator variable which equals one if an analyst has a Bachelor's degree or higher, and zero otherwise.
EXPERIENCE	The logarithm of the number of years an analyst has been in the profession.

Appendix B. RM transaction process

According to the new version of the *Decision on Material Asset Reorganization and Financing of Listed Firms* issued by the China Security Regulatory Committee (CSRC) in 2011, two conditions must be met for an RM transaction (backdoor listing). First, the control rights of the formerly listed firm (i.e., acquirer or "shell" firm) must be changed after the completion of the RM transaction. Second, the total assets of the private firm (i.e., acquiree) need to be greater than those of the acquirer. Therefore, we require the RM firms in our study to meet both conditions. In practice, the RM transaction process is divided into the following six steps.

Step 1	The acquirer reaches a preliminary agreement on an RM transaction with the acquiree and issues a stock trading suspension announcement.
Step 2	The acquirer needs to carry out due diligence, audit, evaluation, profit forecast, review, etc. in conjunction with the acquiree. On this basis, both parties to the RM transaction create a preliminary transaction proposal covering key matters. The acquirer releases the preliminary transaction proposal and resumes stock trading.
Step 3	The acquirer submits the preliminary transaction proposal to the CSRC for review and then, revises the proposal according to the feedback and comments from the CSRC.
Step 4	The acquirer resubmits the revised proposal to the CSRC. This proposal is reviewed by the CSRC's M&A committee for listed firms.
Step 5	After the review and approval, the acquirer officially releases the transaction proposal.
Step 6	The acquirer issues additional shares to purchase the acquiree. When the deal is done, the acquirer holds an extraordinary shareholders' meeting to reorganize the board of directors, and the acquiree finally takes ownership of the acquirer.

The key point of an RM transaction is the issuance of shares by the acquirer to purchase the assets of the acquiree. The valuation of the acquiree's assets determines the number of shares issued by the acquirer. In practice, to obtain a higher valuation, the acquiree usually adopts the discounted future earnings method to assess its assets, which depends on the level of predicted future earnings. To prevent the acquiree from exaggerating the forecasted earnings and obtaining excessive valuation, the CSRC issued the revised version of the *Measures for Administration of Material Assets Reorganization of Listed Firms* in 2008, which requires the acquiree to make a performance commitment for approximately three years after listing. The acquiree is also required to hire an auditor to issue an annual special audit opinion on the achievement of the performance commitment. If the actual performance does not meet the performance target, the acquiree must compensate the shareholders of the acquirer. A common form of compensation is for the acquiree to repurchase and cancel a portion of its shares, along with cash compensation. Furthermore, a failure to meet the performance commitment can also undermine the market's confidence in the acquiree, which damages its reputation and leads to a decline in stock price.

References

Altınkılıç, O., & Hansen, R. S. (2009). On the information role of stock recommendation revisions. *Journal of Accounting and Economics, 48*(1), 17–36.

Barron, O. E., Kim, O., Lim, S. C., & Stevens, D. E. (1998). Using analysts' forecasts to measure properties of analysts' information environment. *Accounting Review*, 421–433.

Batta, G. E., Qiu, J., & Yu, F. (2016). Credit derivatives and analyst behavior. *The Accounting Review, 91*(5), 1315–1343.

Behn, B. K., Choi, J. H., & Kang, T. (2008). Audit quality and properties of analyst earnings forecasts. *The Accounting Review, 83*(2), 327–349.

Bradshaw, M. T., Lock, B., Wang, X., & Zhou, D. (2020). Soft information in the financial press and analyst revisions. *The Accounting Review, 96*(5), 107–132.

Bratten, B., Gleason, C. A., Larocque, S. A., & Mills, L. F. (2016). Forecasting taxes: New evidence from analysts. *The Accounting Review, 92*(3), 1–29.

Brown, L. D., Call, A. C., Clement, M. B., & Sharp, N. Y. (2015). Inside the "black box" of sell-side financial analysts. *Journal of Accounting Research, 53*(1), 1–47.

Chen, K.-C., Cheng, Q., Lin, Y. C., Lin, Y.-C., & Xiao, X. (2016). Financial reporting quality of Chinese reverse merger firms: The reverse merger effect or the weak country effect? *The Accounting Review, 91*(5), 1363–1390.

Chen, Q., & Jiang, W. (2006). Analysts' weighting of private and public information. *The Review of Financial Studies, 19*(1), 319–355.

Chen, Y.-C., Hung, M., & Wang, Y. (2018). The effect of mandatory CSR disclosure on firm profitability and social externalities: Evidence from China. *Journal of Accounting and Economics, 65*(1), 169–190.

Dambra, M., Field, L. C., Gustafson, M. T., & Pisciotta, K. (2018). The consequences to analyst involvement in the IPO process: Evidence surrounding the JOBS act. *Journal of Accounting and Economics, 65*(2–3), 302–330.

Demmer, M., Pronobis, P., & Yohn, T. L. (2019). Mandatory IFRS adoption and analyst forecast accuracy: The role of financial statement-based forecasts and analyst characteristics. *Review of Accounting Studies, 24*(3), 1022–1065.

Dhaliwal, D. S., Radhakrishnan, S., Tsang, A., & Yang, Y. G. (2012). Nonfinancial disclosure and analyst forecast accuracy: International evidence on corporate social responsibility disclosure. *The Accounting Review, 87*(3), 723–759.

Francis, J. R., Neuman, S. S., & Newton, N. J. (2019). Does tax planning affect analysts' forecast accuracy? *Contemporary Accounting Research, 36*(4), 2663–2694.

Frankel, R., & Li, X. (2004). Characteristics of a firm's information environment and the information asymmetry between insiders and outsiders. *Journal of Accounting and Economics, 37*(2), 229–259.

Gleason, K. C., Rosenthal, L., & Wiggins, R. A. (2005). Backing into being public: An exploratory analysis of reverse takeovers. *Journal of Corporate Finance, 12*(1), 54–79.

Han, B., Kong, D., & Liu, S. (2018). Do analysts gain an informational advantage by visiting listed companies? *Contemporary Accounting Research, 35*(4), 1843–1867.

Hirshleifer, D., & Teoh, S. H. (2003). Limited attention, information disclosure, and financial reporting. *Journal of Accounting and Economics, 36*(1), 337–386.

Hou, Q., Jin, Q., Yang, R., Yuan, H., & Zhang, G. (2015). Performance commitments of controlling shareholders and earnings management. *Contemporary Accounting Research, 32*(3), 1099–1127.

Hu, N., Xu, J., & Xue, S. (2022). Mandatory disclosure of comment letters and analysts' forecasts. *International Review of Financial Analysis, 84*, Article 102426.

Huang, A. H., Lin, A.-P., & Zang, A. Y. (2022). Cross-industry information sharing among colleagues and analyst research. *Journal of Accounting and Economics*, 101496.

Huyghebaert, N., & Xu, W. (2016). Bias in the post-IPO earnings forecasts of affiliated analysts: Evidence from a Chinese natural experiment. *Journal of Accounting and Economics, 61*(2–3), 486–505.

Ji, X., Lu, W., Qu, W., & Richardson, V. J. (2019). Changes in internal control disclosure and analyst forecasts around mandatory disclosure required by the China SOX. *Accounting Horizons, 33*(3), 43–68.

Kim, Y., & Song, M. (2015). Management earnings forecasts and value of analyst forecast revisions. *Management Science, 61*(7), 1663–1683.

Kothari, S. P., Leone, A. J., & Wasley, C. E. (2005). Performance matched discretionary accrual measures. *Journal of Accounting and Economics, 39*(1), 163–197.

Kross, W. J., & Suk, I. (2012). Does regulation FD work? Evidence from analysts' reliance on public disclosure. *Journal of Accounting and Economics, 53*(1–2), 225–248.

Lee, C. M. C., Li, K. K., & Zhang, R. (2015). Shell games: The long-term performance of Chinese reverse-merger firms. *The Accounting Review, 90*(4), 1547–1589.

Lee, C. M. C., Qu, Y., & Shen, T. (2017). *Reverse mergers, shell value, and regulation risk in Chinese equity markets* (Working paper).

Lee, C. M. C., Qu, Y., & Shen, T. (2019). Going public in China: Reverse mergers versus IPOs. *Journal of Corporate Finance, 58*, 92–111.

Lehavy, R., Li, F., & Merkley, K. (2011). The effect of annual report readability on analyst following and the properties of their earnings forecasts. *The Accounting Review, 86* (3), 1087–1115.

Li, J., Guo, Y., & Wei, M. (2019). Performance commitment in M&as and stock price crash risk. *China Journal of Accounting Studies, 7*(3), 317–344.

Li, P., Lu, Y., & Wang, J. (2016). Does flattening government improve economic performance? Evidence from China. *Journal of Development Economics, 123*, 18–37.

Libby, R., Tan, H. T., & Hunton, J. E. (2006). Does the form of Management's earnings guidance affect analysts' earnings forecasts? *The Accounting Review, 81*(1), 207–225.

Lobo, G. J., Song, M., & Stanford, M. (2012). Accruals quality and analyst coverage. *Journal of Banking & Finance, 36*(2), 497–508.

Muslu, V., Mutlu, S., Radhakrishnan, S., & Tsang, A. (2017). Corporate social responsibility report narratives and analyst forecast accuracy. *Journal of Business Ethics, 154*(4), 1119–1142.

Ni, J., Jin, S., Hu, Y., & Zhang, L. (2023). Informative or distracting: CSR disclosure of peer firms and analyst forecast accuracy. *International Review of Financial Analysis, 87*, Article 102575.

O'Brien, P. C., & Tan, H. (2015). Geographic proximity and analyst coverage decisions: Evidence from IPOs. *Journal of Accounting and Economics, 59*(1), 41–59.

Petersen, M. A. (2009). Estimating standard errors in finance panel data sets: Comparing approaches. *Review of Financial Studies, 22*(1), 435–480.

Qu, Y., Wu, W., & Shen, T. (2018). IPO or RM: What influence the listing choice of Chinese firms? *Management World, 34*(09), 130–142+192 (in Chinese).

Roulstone, D. T. (2003). Analyst following and market liquidity. *Contemporary Accounting Research, 20*(3), 552–578.

Schipper, K. (1991). Analysts' forecasts. *Accounting Horizons, 5*(4), 105.

Tan, H., Wang, S., & Welker, M. (2011). Analyst following and forecast accuracy after mandated IFRS adoptions. *Journal of Accounting Research, 49*(5), 1307–1357.

Tehranian, H., Zhao, M., & Zhu, J. L. (2014). Can analysts analyze mergers? *Management Science, 60*(4), 959–979.

Weiss, D. (2010). Cost behavior and Analysts' earnings forecasts. *Accounting Review, 85* (4), 1441–1471.

Wu, K., Xu, M., & Jin, Z. (2022). *Do performance commitment clauses protect M&A bidders?*. Working paper.

Xie, Y., Zhang, Y., & Zhou, J. (2012). National level, city level auditor industry specialization and analyst forecast properties. *International Journal of Auditing, 16*(3), 248–267.

Xin, Q., Zhou, J., & Hu, F. (2018). The economic consequences of financial fraud: Evidence from the product market in China. *China Journal of Accounting Studies, 6*(1), 1–23.

Yuan, H., Gao, C., & Shi, H. (2021). Failure in performance commitment and goodwill impairment: Evidence from M&As. *Journal of Accounting Research, (04), 60-77* (in Chinese).