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Stock dividend and analyst optimistic bias in earnings forecast☆

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ABSTRACT

Abundant research has found optimistic bias in analysts' earnings forecasts. Using a sample of Chinese listed companies from 2008 to 2017, this paper investigates how stock dividend affects analyst's optimistic bias in earnings forecast. We find that analysts bias their earnings forecasts optimistically after stock dividends. Further study demonstrates that the influence of stock dividend on analyst's optimistic bias is more significant when the company has less institutional stock holdings or when the analyst is in a small brokerage firm. The bias is moderated when the forecast is issued by a star analyst in a bull market. Mechanism analysis reveals that analysts issue optimistic forecasts for the interests of their own rather than unconsciously. The findings of this study indicate that self-interest motivates analysts to issue biased earnings forecasts, which ultimately reduces the efficiency of the capital market.

1. Introduction

As an information intermediary of the capital market, analysts can improve market efficiency and alleviate the information asymmetry between companies and investors through information exploration and interpretation. By making buy-sell recommendations and issuing various forecasts, among which earnings forecasts have attracted the most attention, analysts can send signals to the market. The accuracy of analysts' earnings forecasts is not only affected by analysts' ability to acquire information, but also greatly depend on analysts' integrity and independence. Researchers have found that analysts may intentionally bias their earnings forecasts optimistically to repair their relationship with management (Francis & Philbrick, 1993), please managers (Das, Levine, & Sivaramakrishnan, 1998), encourage trading (Irvine, 2004) and facilitate personal career development (Hong & Kubik, 2003). Meanwhile, some other scholars argue that the optimistic bias in analysts' earnings forecasts may be unintentional (De Bondt & Thaler, 1990; Abarbanell & Bernard, 1992; Kang, O'Brien, & Sivaramakrishnan, 1994; McNichols & O'Brien, 1997; Easterwood & Nutt, 1999; Heaton & Lucas, 2000). Therefore, investigating and exploring the antecedents of analysts' optimistic bias in their earnings forecasts are essential to understanding the logic of analysts' behavior and provides implications for improving the pricing efficiency of the market and protecting the interests of investors.

Stock dividend and stock split are cosmetic transactions that should have no effect on firm value in perfect capital markets (Muscarella & Vetsuypens, 1996). Yet vast amount of literature has documented that stock prices increase with the announcement of

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stock dividend or stock split (Grinblatt, Masulis, & Titman, 1984; Ikenberry & Ramnath, 2002). One possible explanation for the positive market response to stock dividend is that the change in shares' nominal price can alter the decision of investors (Baker, Greenwood, & Wurgler, 2009) and create a "nominal price illusion", that is to say, investors may overestimate the room to grow for low-priced stocks and take lottery-like bets in these stocks (Birru & Wang, 2016). On the other side, unlike small investors that have limited information and bounded rationality, analysts have access to more information and are more sophisticated and rational in interpreting information and making decisions. Whether they are also affected by stock dividend and the nominal price illusion is therefore an interesting question to study. Analysts' decisions are affected by their incentives to generate trading commissions (Hayes, 1998), so they may seek to maximize trading volume through issuing optimistic earnings forecasts. However, issuing intentionally biased earnings forecast is not without cost. Forecast errors tarnish the reputation of analysts and may impair their ability to generate trade in the future (Beyer & Guttman, 2011). Therefore, analysts must trade off the short-term commissions generated from lying and the long-term gains from building reputation (Jackson, 2005). We argue in this paper that stock dividend creates nominal price illusion in the market, increases investors' tolerance for over-estimation of companies' future earnings and reduces analysts' cost of issuing optimistic earnings forecast. Analysts thereby utilize the opportunity created by stock dividends and issue optimistically biased earnings forecast to encourage trading and acquire more trading commissions.

We test the above proposition using a sample of Chinese A-share listed companies during 2008–2017. The Chinese companies create an ideal setting to conduct this study for three reasons. First, stock dividend is becoming increasingly popular in the Chinese market in recent years. The number of announcements of stock dividends increased from 220 in 2008 to 582 in 2017. These stock dividend announcements have generated extensive consequences in the capital market and raised a lot of discussion in both the academia and the practice. Therefore, Chinese analysts certainly pay close attention to such events and react accordingly. Second, although the capital market in China has been developing rapidly in the past three decades, its structure is yet imbalanced. According to the data provided by China Securities Depository and Clearing Corporation Limited (CSDC), by the end of 2017, the number of investors in China amounted to 133.983 million, of which 133.6221 million were individual investor, accounting for as high as 99.7% of the total number. With regard to the share of market capitalization, according to the data from the WIND database, shares held by individual investors comprise about 52% of the total market value at the end of 2017. This ratio is higher than that held by institutional investors and much higher than it in the developed markets. As individual investors are disadvantageous in getting access to information, they lack the ability to fully identify the motivation of analyst forecasts (Malmendier & Shanthikumar, 2007) and tend to rely more on analysts' reports than institutional investors. Therefore, the specific structure of the investors in the Chinese market provides analysts with good opportunities to encourage trading through sending signals in their reports. Third, the information disclosure of Chinese listed companies is relatively opaque. Individual investors can hardly obtain accurate information of listed companies, making information intermediaries (such as analysts) important references to small and medium-sized investors in their decision making. Thus, the influence of analysts' behavior on the market is also reinforced (Pacelli, 2019) and worth study. All these features of the Chinese market constitute an excellent background for us to investigate the possible impact of stock dividend on analyst's optimistic bias in earnings forecast.

The results of the empirical tests reveal that stock dividends lead to optimistic biases in analysts' earnings forecasts. Further examination shows that this effect is more pronounced when listed companies have less institutional shareholdings or when analysts are in smaller brokerage firms. Moreover, the optimistic biases led by stock dividends are mitigated by star analysts in bull market. In addition, we find that optimistically biased earnings forecasts issued after stock dividends indeed result in more trading volume. The above findings together indicate that self-interest motivates analysts to issue biased earnings forecast and ultimately reduces the efficiency of the market.

The contributions of this study may lie in the following aspects. First, the findings of this paper supplement the line of research on the antecedents of the biases in analyst earnings forecasts. By proposing that the stock dividend may induce analysts to optimistically bias their earnings forecasts, we provide new evidence supporting the theory that analysts issue intentionally biased forecasts to encourage trading and obtain more trading commissions. Second, most existing studies on the impact of stock dividend and stock split directly examine the responses of the investors. We switch to a new perspective by investigating how stock dividend affects analysts' behavior in issuing earnings forecast. As an important information intermediary, analysts are able to send signals to the market and influence the decision making of investors. The optimistic forecasts issued by analysts after stock dividend announcements can in turn lead to high stock prices. Therefore, our study not only broadens the scope of researches on stock dividend by expanding it to the analyst angle, but also provides a new explanation for how stock dividend indirectly affects stock prices through analysts. Third, analysts are generally regarded as an important information intermediary that are able to mitigate the information asymmetry in the market. However, we demonstrate that analysts' self-interests may motivate them to distort the information they receive. This finding has implications to the supervision of the analyst profession and the protection of investors' welfare.

2. Hypothesis development

Stock dividends are in essence split of stocks and are merely number transfers between different categories of shareholders' equity that should not have any impact on the fundamentals of companies' financial situation. Yet abundant research has found evidence that stock dividends can generate positive market responses (Grinblatt et al., 1984; Ikenberry & Ramnath, 2002). This phenomenon is explained in previous literature with three main theories: the liquidity theory, the signaling theory and the catering theory. The liquidity theory presents that stock dividends increase the liquidity of stocks (Lin, Singh, & Yu, 2009) and generate abnormal returns thereby (Muscarella & Vetsuypens, 1996). The signaling theory argues that through stock dividends or stock splits, management send positive signals to the market. Company management propose stock dividend or stock split only when they are confident about

companies' future earnings and want to send this information to the market (Asquith, Healy, & Palepu, 1989; Brennan & Copeland, 1988; McNichols & Dravid, 1990). The market receives this signal and reacts positively, causing share price to increase. These two theories are both based on the assumption that market participants are rational. However, based on these two theories, stock dividend should not result in a significant change in analysts' earnings forecast. As there is indeed no change in companies' financial situation after issuing stock dividend, their future earnings should not be affected in the short-term only given that the liquidity of stocks has increased. Meanwhile, the signals sent by stock dividend should neither cause a significant change in analysts' forecast. Because analysts have access to more private information than the public, they place more weights on their private information when forecasting earnings (Chen & Jiang, 2006). Fischer and Stocken (2010) predict in their model that when there is a change in the amount of publicly available information, analysts either gather more precise information to increase decision-maker's responsiveness to their information or simply leave the market. Therefore, it is unlikely that analysts modify their earnings forecasts for the public signals sent by stock dividend, not to mention that they over-react to these signals and bias their earnings forecasts optimistically.

The reasons and consequences of issuing stock dividend are also discussed with behavioral finance theories. For example, Baker and Wurgler (2004a, 2004b) propose that while company management are rational and investors are irrational, management cater to investors by making dividend policies according to investor preferences. Li and Lie (2006) also find that management change dividend policy for catering incentives. Baker et al. (2009) find that firms may try to cater to investor preferences via price targeting and define this behavior as "catering through nominal share prices". Weld, Michaely, Thaler, and Benartzi (2009) also document a nominal price puzzle, as they find the prices of U.S. shares remained quite constant and stable in nominal terms since the Great Depression while the general price level in the U.S. economy has risen more than tenfold. Based on the discovery of that investors make decisions based on the nominal prices of shares, Birru and Wang (2016) incorporate psychological theories into the investigation of this phenomenon and provide evidence that investors suffer from "nominal price illusions". With nominal price illusions, investors tend to overestimate the value of low-priced stocks relative to high-priced stocks. This nominal price illusion also explains the positive market response to stock dividend.

Unlike individual investors that have limited information and limited rationality, analysts not only have access to public information, but can also obtain private information through visiting the sites or maintaining good relationship with management etc. In addition, they have professional knowledge and skills that enable them to better interpret the information they obtain. Thus, they should be less disturbed by the noises and illusions in the market when making forecasts. However, a great number of studies still find that the earnings forecasts of analysts are generally optimistic (O'brien, 1988). Various reasons have been discovered for analysts' optimistic bias in earnings forecasts, such as overreaction of analysts (De Bondt & Thaler, 1990; Abarbanell & Bernard, 1992; Easterwood & Nutt, 1999), incentive motivations and cognitive biases (Kang, O'Brien, & Sivaramakrishnan, 1994; McNichols & O'Brien, 1997; Heaton & Lucas, 2000). While these earlier studies assume that analysts are irrational and unintentional when making biased forecasts, later research explains the causes of optimistic biases assuming that analysts are rational and intentionally make optimistic biases in earnings forecasts. The latter line of research proposes that analysts issue optimistic earnings forecasts to obtain higher commissions (Hayes, 1998; Irvine, 2004; Jackson, 2005; Cowen, Groysberg, & Healy, 2006; Beyer & Guttman, 2011; Dambra, Field, Gustafson, & Pisciotta, 2018), to satisfy the requirement of the investment banks (Michaely & Womack, 1999; Dechow, Hutton, & Sloan, 2000; Lin & McNichols, 1998), to cater to the management (Lim, 2001; Soltes, 2014) and for the promotions of their own career (Hong & Kubik, 2003).

Although analysts are expected to alleviate the information asymmetry in the market and act with independence and integrity, the fact that they are mostly employed by brokerage firms that operate both brokerage services and investment banking services may bring conflict of interests and induce them to behave in a self-interested manner. On one hand, analysts' compensation is directly related to the brokerage commissions they help generate, so they obviously have incentives to encourage trading. Irvine (2004), Jackson (2005), and Cowen et al. (2006) have all documented that trading incentive can affect analysts' choice in earnings forecasts and recommendations. On the other hand, reports and studies have found that a significant proportion of analysts' compensation is influenced by analysts' "helpfulness" to the investment banking department (Lin & McNichols, 1998; Michaely & Womack, 1999). To maintain a good business relationship with their clients and boost revenue from underwriting services, the investment banking department may exert pressure on analysts to publish favorable research reports about these clients (Michaely & Womack, 1999; Dugar & Nathan, 1995; Lin & McNichols, 1998; Ljungqvist, Marston, Starks, Wei, & Yan, 2007). Therefore, issuing optimistic earnings forecast is one of the efficient tools to accomplish both tasks of analysts: helping generate brokerage commissions and helping with the investment banking service of their employers. However, issuing biased forecast is costly. Biased earnings forecast may destroy the reputation of analysts and impair their ability to generate trading volume in the future (Beyer & Guttman, 2011). Therefore, analysts have to trade-off between obtaining short-term commissions by issuing biased forecasts and maintaining long-term reputation by issuing accurate forecasts (Jackson, 2005).

In the capital markets such as that in China, where the market is dominated by individual investors, optimistically biased forecasts can even bring more benefits to analysts. When companies issue stock dividends, individual investors are easily trapped in nominal price illusions and trigger an optimistic mood in the market (Wu, Pan, Hu, & Jiang, 2012). Optimistically biased forecasts can generate more trading in such environment and bring more commissions to analysts. Moreover, the nominal price illusion caused by stock dividend also reduces analyst' cost of issuing optimistically biased forecasts.

When companies issue stock dividends, nominal price illusions are created, leading to an optimistic mood among investors, especially individual investors. When they are in optimistic mood, investors tend to make optimistic predictions about companies' future performance (Brown, 1999; Gervais & Odean, 2001; Statman, Thorley, & Vorkink, 2006). Therefore, the optimistic earnings forecasts issued by analysts are just consistent with investors' expectations and are less likely to impair the reputation of analysts even if they are biased. The cost of issuing optimistically biased earnings forecast is thus greatly reduced, providing analysts with excellent

opportunity to encourage trading and obtain trading commissions through issuing earnings forecasts with optimistic bias.

To summarize our arguments above, we propose our hypothesis:

H1. *Ceteris paribus*, stock dividend escalates analyst's optimistic bias in earnings forecast.

3. Research design

We use the following OLS regression model to investigate the effect of stock dividend on analysts' optimistic bias in earnings forecast:

$$Fopt_{i,t} = \beta_0 + \beta_1 Sat_{i,t-1} + \beta_2 Controls_{i,t-1} + Fixed\ effects + \varepsilon \quad (1)$$

In this model, $Fopt_{i,t}$ refers to analyst optimism on firm i for year t. Following Huyghebaert and Xu (2016), we first define an analyst's forecast bias $Fopt_{j,i,t}$ as $(FEPS_{j,i,t} - AEPS_{i,t})/|AEPS_{i,t}|$, where $FEPS_{j,i,t}$ is the earnings per share forecasted by analyst j on firm i for year t. $AEPS_{i,t}$ is the reported earnings per share by firm i for year t. Analyst optimism $Fopt_{i,t}$ is calculated as the average of all analysts' forecasting biases for firm i in year t.

$Sat_{i,t-1}$ is an indicator variable that equals one if firm i pays stock dividends in year $t-1$. We include a number of control variables and time and industry fixed effects. H1 implies that $Sat_{i,t-1}$ has a significantly positive coefficient.

Following Hong and Kacperczyk (2010), we include the following indicators as control variables in our model. *Size* is the natural logarithm of firm's total assets. *Lev* is debt-to-assets ratio, defined as firm's total liabilities divided by total assets. *Roa* is firm profitability, calculated as the ratio of net income to the book value of total assets. *Mb* is firm's market value of assets divided by the book value. *Big4* is an indicator variable that equals one if the firm is audited by an international Big 4 audit firm and zero otherwise. *Soe* is an indicator variable that equals one if Chinese state is in ultimate control of the firm and zero otherwise. *Largest* is the ownership percentage of the largest shareholder. *Num* is the natural logarithm of one plus the number of analysts. *Horizon* is the natural logarithm of the average days elapsed from the earnings forecast date to the earnings announcement date of all analysts. *Loss* is an indicator

Table 1
Sample selection and distribution.

Panel A: Sample Selection Procedures	
Total firm-year observations of non-financial listed firms available on CSMAR from 2008 to 2017	23,741
Delete observations that undergo IPO within one year	(1,942)
Delete observations that are under ST/PT	(1,301)
Delete observations with missing data	(5,653)
Final sample	14,845

Panel B: Sample Distribution by Industry	No. of Obs.	% of sample
Agriculture, forestry and fishing	185	1.25
Mining	467	3.14
Manufacturing	9,016	60.73
Utilities	584	3.93
Construction	380	2.56
Wholesale trade	843	5.68
Transportation	556	3.74
Accommodation and catering	72	0.49
Information and technology	1,042	7.02
Real estate	741	4.99
Services	328	2.21
Management	219	1.48
Education	26	0.18
Health work	61	0.41
Entertainment	224	1.51
Conglomerates	101	0.68
Total	14,845	100

Panel C: Sample Distribution by Year	No. of Obs.	% of sample
2008	910	6.13
2009	1,030	6.94
2010	1,154	7.77
2011	1,346	9.07
2012	1,463	9.86
2013	1,653	11.14
2014	1,749	11.78
2015	1,928	12.99
2016	1,938	13.05
2017	1,674	11.27
Total	14,845	100

variable that equals one if firm's net income is negative and zero otherwise. *Sigma* is the variance of daily raw returns. *Growth* is defined as the growth ratio of revenue. *Abnret* is firm's abnormal annual stock return (adjusted by value-weighted market return). *Age* is the natural logarithm of firm age. *Inhold* is the ownership percentage of institutional investors. In addition, we control for year-fixed effects and industry-fixed effects. We winsorize all continuous variables at 1% and 99% to deal with outliers. Following Petersen (2009), we cluster standard errors by firm to address the problem caused by potential correlations between residuals. Details of variable definitions are presented in Appendix 1.

4. Empirical results and discussion

4.1. Data and sample

Our sample comprises A-share firms listed on the Shanghai Stock Exchange and Shenzhen Stock Exchange from 2008 to 2017. The data on stock dividends, analysts and accounting variables are obtained from the China Stock Market and Accounting Research database (CSMAR). The data on institutional investors and the data of brokerage firm size are from Wind information. Considering that quarterly earnings forecasts are scarcely disclosed in China, we only include the cases of stock dividend issuance with annual report to match analysts' EPS forecasts for the annual reports. As done in prior research (Hong & Kacperczyk, 2010), we retain the latest forecast for each analyst in the current fiscal year. Specifically, if one analyst produces earnings forecasts respectively for a parent company and its group, we deem the situation as the analyst issue two forecasts. Our initial sample consists of 23,741 non-financial publicly listed firm-year observations for the period 2008–2017. As China began to adopt the current set of accounting standards in 2007, we start our sample period from 2008 to ensure the consistency of accounting indicators. We remove 1,942 observations that undergo IPO within one year. We further exclude 1,301 observations under special treatment(ST) or particular transfer(PT), as they are regulated with different rules with other companies. We also delete 5,653 observations with missing values for the calculation of other control variables. Our final sample comprises 14,845 observations. The selection procedure is presented in Panel A of Table 1. Panel B and Panel C of Table 1 report the sample distributions by industry and year.

Table 2 presents the descriptive statistics of analyst optimistic bias and other variables for our main analyses. Panel A reports the results of the full sample. The average optimistic bias is 88.3% and the median is 25.0%, suggesting that analysts' forecasts are generally biased in optimism. The average $Sat_{i,t-1}$ is 20.0%, suggesting that during the sample period, an average of 20.0% of the firms paid stock dividends. The mean value of *Num* and *Horizon* are 2.010 and 5.517, respectively. The mean values of *Soe* is 0.431, suggesting that 43.1% of the sample companies are state-owned. The mean and median of *Lev* are 0.438 and 0.437, respectively. The mean values of *Roa* and *Mb* are 0.047 and 2.111. The mean of *Big4* is 0.069, indicating that about 7% of audits are performed by international Big 4 audit firms. The mean of *Loss* is 0.055, implying that 5.5% companies report negative profits. These descriptive statistics are generally comparable to values reported in prior studies. Panel B and Panel C report the descriptive statistics for companies that issue stock dividends and companies that do not issue stock dividends, respectively. The mean of *Fopt* for dividend-issuing companies is 1.172, and the mean for non-dividend-issuing companies is 0.811, which is consistent with our prediction that analysts are more optimistic in earnings forecast when companies issue stock dividends.

4.2. Baseline results

Table 3 reports multivariate regression results for the test of hypothesis H1. We first present the results for the mean optimism with just $Sat_{i,t-1}$ in column (1), and include industry-fixed effects and control variables in column (2); year-fixed effects and control variables in column (3), and industry-fixed effects, year-fixed effects and control variables altogether in column (4). The estimated coefficients on $Sat_{i,t-1}$ are all significantly positive and significant at the 1% level (0.321, t = 6.87, Column (1); 0.451, t = 10.17, Column (2); 0.423, t = 9.53, Column (3); and 0.430, t = 9.67, Column (4)). This result supports our hypothesis that when firms issue stock dividends, analysts' earnings forecasts are more optimistic. And a number of control variables come in significantly in the regression. The coefficient on *Num*, *Soe*, *Loss* are all significantly negative, suggesting that the average optimistic bias in company' s earnings forecasts is less when the company has more following analysts, is state-owned or is loss-making. The coefficient on *Horizon* and *Mb* are significantly positive, showing that there is more optimistic bias in company's earnings forecasts when there is a longer period between earnings announcement date and earnings forecast date and when the market-to-book value is higher.

4.3. Robustness checks

4.3.1. Different measure of stock dividend and analyst optimism variables

We use two alternative methods to recalculate analysts' optimistic bias. According to Hong and Kacperczyk (2010), we calculate $Fopt1_{j,i,t} = (FEPS_{j,i,t} - AEPS_{i,t})$/year-end stock price of t-1. And following Jackson (2005), we calculate $Fopt2_{j,i,t} = (FEPS_{j,i,t} - AEPS_{i,t})$/ stock price of the day before earnings forecast. These findings are respectively presented in column (1) and column (2) of Table 4. To replace the original stock dividend variable, following Li, Yu, Lu, and Xu (2014), we use a dummy variable equaling one if the ratio of stock dividend is more than 0.5 in column (3) and the ratio of stock dividends in column (4). The key coefficients on stock dividend measures are all positive and significant at the 1% level, which is consistent with our previous finding.

Table 2
Descriptive statistics.

Variables	n	Mean	Median	Std.Dev	Q1	Q3
Panel A: Full Sample						
Fopt	14,845	0.883	0.250	2.056	0.029	0.866
Sat	14,845	0.200	0.000	0.400	0.000	0.000
Num	14,845	2.010	2.079	0.883	1.386	2.708
Horizon	14,845	5.517	5.529	0.262	5.384	5.679
Soe	14,845	0.431	0.000	0.495	0.000	1.000
Lev	14,845	0.438	0.437	0.204	0.275	0.599
Roa	14,845	0.047	0.042	0.046	0.020	0.071
Mb	14,845	2.111	1.694	1.275	1.287	2.445
Size	14,845	22.240	22.063	1.277	21.314	22.987
Big4	14,845	0.069	0.000	0.253	0.000	0.000
Largest	14,845	0.364	0.349	0.150	0.243	0.471
Loss	14,845	0.055	0.000	0.228	0.000	0.000
Sigma	14,845	0.031	0.029	0.010	0.023	0.036
Growth	14,845	0.224	0.141	0.442	0.009	0.316
Abnret	14,845	0.113	−0.007	0.501	−0.197	0.279
Age	14,845	2.634	2.708	0.408	2.398	2.944
Inhold	14,845	0.413	0.422	0.235	0.216	0.599
Panel B: Companies Issue Stock Dividends						
Fopt	2,968	1.172	0.467	2.256	0.176	1.119
Num	2,968	2.234	2.303	0.866	1.609	2.944
Horizon	2,968	5.536	5.544	0.235	5.413	5.673
Soe	2,968	0.258	0.000	0.438	0.000	1.000
Lev	2,968	0.374	0.359	0.197	0.213	0.513
Roa	2,968	0.065	0.057	0.043	0.035	0.087
Mb	2,968	2.336	1.922	1.342	1.444	2.742
Size	2,968	21.879	21.712	1.113	21.047	22.548
Big4	2,968	0.034	0.000	0.180	0.000	0.000
Largest	2,968	0.352	0.338	0.140	0.241	0.446
Loss	2,968	0.011	0.000	0.105	0.000	0.000
Sigma	2,968	0.031	0.029	0.009	0.024	0.036
Growth	2,968	0.319	0.213	0.467	0.082	0.413
Abnret	2,968	0.226	0.079	0.578	−0.160	0.465
Age	2,968	2.532	2.565	0.432	2.303	2.833
Inhold	2,968	0.399	0.401	0.238	0.194	0.585
Panel C: Companies Do Not Issue Stock Dividends						
Fopt	11,877	0.811	0.193	1.996	0.007	0.773
Num	11,877	1.954	1.946	0.879	1.099	2.639
Horizon	11,877	5.512	5.525	0.268	5.375	5.680
Soe	11,877	0.474	0.000	0.499	0.000	1.000
Lev	11,877	0.454	0.456	0.203	0.296	0.614
Roa	11,877	0.043	0.037	0.046	0.016	0.066
Mb	11,877	2.055	1.642	1.251	1.258	2.374
Size	11,877	22.331	22.160	1.299	21.389	23.090
Big4	11,877	0.077	0.000	0.267	0.000	0.000
Largest	11,877	0.367	0.352	0.153	0.244	0.477
Loss	11,877	0.066	0.000	0.249	0.000	0.000
Sigma	11,877	0.030	0.028	0.010	0.023	0.036
Growth	11,877	0.200	0.124	0.433	−0.004	0.293
Abnret	11,877	0.085	−0.023	0.476	−0.204	0.239
Age	11,877	2.659	2.708	0.398	2.398	2.944
Inhold	11,877	0.416	0.427	0.234	0.222	0.602

4.3.2. *Propensity score matching*

To exclude the possibility that our finding is driven by the inherent differences between companies issuing and not-issuing stock dividend, we adopt propensity score matching (PSM) advocated by Rosenbaum and Rubin (1984) to address potential selection bias in paying stock dividends. We would like to compare firms that are identical in every aspect except for the issuance of stock dividends. We first construct a logit model for the whole sample, where the likelihood of issuing stock dividends is based on a number of attributes of firms including ultimate controller, market-to-book ratio, the ownership percentage of largest shareholder, the audit firm status, the loss dummy, abnormal stock returns, the size, the profitability, the growth ratio of revenue, the debt-to-assets ratio, the industry, the age of firm, the volatility of stock returns and the ownership percentage of institutional investors.[1] We then use the propensity score

[1] We have checked the balance of our matched sample. Untabulated results show that the treated and the control group are insignificantly different on these variables after matching.

Table 3
The effect of stock dividend on analyst optimistic bias in earnings forecast: Baseline analyses.

	Fopt(1)	Fopt(2)	Fopt(3)	Fopt(4)
Intercept	1.122***	−6.227***	−8.646***	−8.248***
	(5.67)	(-10.28)	(-12.96)	(-11.35)
Sat	0.321***	0.451***	0.423***	0.430***
	(6.87)	(10.17)	(9.53)	(9.67)
Num		−0.219***	−0.198***	−0.219***
		(-9.02)	(-8.28)	(-8.95)
Horizon		1.520***	1.547***	1.532***
		(21.46)	(21.43)	(21.29)
Soe		−0.108**	−0.167***	−0.164***
		(-2.49)	(-3.88)	(-3.62)
Lev		0.331**	0.005	0.139
		(2.55)	(0.04)	(1.04)
Roa		−5.746***	−6.419***	−6.120***
		(-9.55)	(-10.23)	(-9.78)
Mb		0.114***	0.139***	0.135***
		(5.08)	(5.77)	(5.52)
Size		−0.006	0.059**	0.059**
		(-0.28)	(2.46)	(2.33)
Big4		−0.123**	−0.152**	−0.160***
		(-2.10)	(-2.47)	(-2.73)
Largest		−0.165	−0.192	−0.182
		(-1.23)	(-1.44)	(-1.36)
Loss		−0.235**	−0.218**	−0.246**
		(-2.17)	(-2.02)	(-2.27)
Sigma		−5.181***	9.511***	6.561*
		(-2.69)	(2.69)	(1.77)
Growth		−0.024	−0.046	−0.040
		(-0.60)	(-1.14)	(-1.00)
Abnret		−0.066	−0.094**	−0.083*
		(-1.53)	(-2.02)	(-1.78)
Age		−0.080*	−0.016	0.017
		(-1.78)	(-0.35)	(0.36)
Inhold		−0.255***	−0.263***	−0.250***
		(-2.78)	(-2.83)	(-2.71)
Year-fixed effects	Yes	No	Yes	Yes
Industry-fixed effects	Yes	Yes	No	Yes
Adj. R^2	0.016	0.087	0.088	0.092
Observations	14,845	14,845	14,845	14,845

Notes: ***, **, * The coefficients are significant at the 0.01, 0.05, and 0.10 levels, respectively, based on two-tailed statistical tests.

estimated by the logit model to match each observation issuing stock dividends with one or two observation that does not. The findings are presented in Panel A of Table 5. The coefficients on $Sat_{i,t-1}$ are both positive and significant, suggesting that after controlling for the potential selection bias, our findings supporting H1 are robust.

4.3.3. Difference-in-differences

Simply comparing the difference in the optimism of analysts' earnings forecasts between companies issuing and not issuing stock dividend may not rule out the difference between the two groups of companies before they issue stock dividends; and simply comparing the difference in the optimism of analysts' earnings forecasts before and after companies issue stock dividend may fail to exclude the time-varying factors. Therefore, we adopt a difference-in-differences approach (DID) to address both issues and more reliably isolate the effect of stock dividends on analysts' optimistic forecasts. We exclude firms that issued stock dividends for more than once in the sample period. Following Bertrand and Mullainathan (2003), we construct Eq (2) and use the whole sample and the PSM sample respectively to conduct the tests:

$$Fopt_{i,t} = \beta_0 + \beta_1 After_{i,t-1} + \beta_2 Controls_{i,t-1} + Fixed\ effects + \varepsilon \quad (2)$$

$After_{i,t-1}$ takes the value of one at or after the time when firm i pays stock dividends and zero otherwise. The control variables are the same as those in Eq (1). We also control for firm and year fixed effects and the coefficient β_1 is expected to be significantly positive. As reported in Panel B of Table 5, the coefficients on $After_{i,t-1}$ are both significantly positive at the 1% level with the full sample and the PSM subsample. These findings confirm to our hypothesis that analysts' forecasts are more optimistic after firms issue stock dividends.

4.3.4. An alternative time-window

Different analysts generate earnings forecasts based on different standards of calculating shares around stock dividend issuance, which implies that some optimistic biases observed after stock dividend issuance are in fact not caused by stock dividends but by the biases themselves. To alleviate this endogenous problem, we drop firm-year observations whose earnings announcement date is not the

Table 4
Robustness check: Different measures of analyst optimism and stock dividends.

	Fopt1(1)	Fopt2(2)	Fopt(Hsat)(3)	Fopt(Satratio)(4)
Intercept	−0.124***	−0.133***	−8.200***	−8.199***
	(-15.14)	(-16.58)	(-11.34)	(-11.32)
Sat	0.002***	0.003***	0.563***	0.636***
	(7.58)	(9.74)	(10.55)	(11.03)
Num	−0.003***	−0.003***	−0.221***	−0.224***
	(-12.72)	(-13.19)	(-9.07)	(-9.18)
Horizon	0.019***	0.018***	1.517***	1.514***
	(22.69)	(22.89)	(21.11)	(21.06)
Soe	−0.002***	−0.002***	−0.158***	−0.156***
	(-3.86)	(-4.55)	(-3.51)	(-3.45)
Lev	0.011***	0.011***	0.165	0.163
	(7.80)	(7.57)	(1.23)	(1.22)
Roa	−0.006	−0.002	−5.938***	−5.942***
	(-1.14)	(-0.47)	(-9.55)	(-9.53)
Mb	−0.000**	−0.000**	0.142***	0.142***
	(-2.19)	(-2.15)	(5.83)	(5.84)
Size	0.002***	0.002***	0.060**	0.061**
	(6.54)	(8.12)	(2.39)	(2.40)
Big4	−0.004***	−0.004***	−0.164***	−0.160***
	(-4.68)	(-4.83)	(-2.77)	(-2.72)
Largest	−0.005***	−0.006***	−0.185	−0.191
	(-3.20)	(-4.35)	(-1.38)	(-1.43)
Loss	0.002*	0.002*	−0.241**	−0.235**
	(1.73)	(1.69)	(-2.23)	(-2.18)
Sigma	−0.005	0.031	6.297*	6.370*
	(-0.13)	(0.80)	(1.70)	(1.72)
Growth	0.000	−0.000	−0.047	−0.049
	(0.16)	(-0.16)	(-1.19)	(-1.22)
Abnret	−0.002***	−0.002***	−0.093**	−0.101**
	(-6.66)	(-6.13)	(-2.01)	(-2.17)
Age	−0.001*	−0.001**	0.021	0.021
	(-1.84)	(-2.26)	(0.43)	(0.44)
Inhold	−0.003***	−0.002*	−0.241***	−0.241***
	(-2.91)	(-1.82)	(-2.61)	(-2.61)
Year-fixed effects	Yes	Yes	Yes	Yes
Industry-fixed effects	Yes	Yes	Yes	Yes
Adj. R^2	0.126	0.133	0.094	0.094
Observations	14,845	14,845	14,845	14,845

Notes: ***, **, * The coefficients are significant at the 0.01, 0.05, and 0.10 levels, respectively, based on two-tailed statistical tests.

same as announcement date of stock dividends and restrict the date analysts produce earnings forecasts to the period between earnings announcement date and the fiscal year-end of that year. The result of re-conducting model (1) regression with this more restricted sample is reported in column (1), Panel C of Table 5. The coefficient on $Sat_{i,t-1}$ is significantly positive at the 1% level, suggesting that our findings supporting H1 are still robust.

To further reduce the bias brought from different calculation of shares by each analyst that discussed above, we adjust the reported earnings per share with the shares at the end of the quarter when analysts issue forecasts. Specifically, adjusted earnings per share is reported earnings per share divided by the ratio of shares at the end of the quarter when analysts issue forecasts to the shares reported in earning announcement to which the forecast relates. The regression result after such adjustment is presented in column (2), Panel C of Table 5. The coefficient on $Sat_{i,t-1}$ still remains significantly positive.

4.3.5. Organizing data in terms of analyst-firm-year

We conduct a robustness test in terms of analyst-firm-year and still use model (1) to estimate the effect of stock dividends on analyst optimism. As reported in Panel D of Table 5, the first regression only contains a set of firm characteristic variables and the coefficient on $Sat_{i,t-1}$ is significantly positive. Column (2) presents the regression results after controlling for analyst characteristics that can affect analysts' forecast optimism such as analysts' experience in issuing forecasts (*Expe*), analysts' firm-specific experience (*Fexp)*, the number of firms that one analyst cover (*Cover*), the brokerage firm size that analyst works for (*Top3*) and whether the analyst is selected as star analyst or not (*Anastar*). As reported, we find the coefficient $\beta 1$ still significantly positive at the 1% level, suggesting consistent results with our key conclusions.

4.3.6. Fixed-effect model and cash dividend

Although we have controlled for variables commonly found in previous studies, there is still possibility that some uncontrolled variables may affect the relationship between company's issuance of stock dividends and analysts' earnings forecast bias. Therefore, we further conduct a test controlling for firm fixed-effects. The results are shown in column (1) of Panel E in Table 5.

Table 5
Robustness checks: Propensity score matching, difference-in-differences.

Panel A: Propensity Score Matching		
	1:1 Matching (1)	1:2 Matching(2)
Intercept	−9.587***	−8.629***
	(-7.70)	(-8.04)
Sat	0.449***	0.436***
	(7.81)	(8.89)
Control variables	Yes	Yes
Year-fixed effects	Yes	Yes
Industry-fixed effects	Yes	Yes
Adj. R^2	0.125	0.116
Observations	4,661	6,762
Panel B: Difference-in-differences		
	DID(1)	*PSM* + *DID*(2)
Intercept	−3.464	−6.853
	(-1.27)	(-1.32)
After	0.685***	0.800***
	(7.79)	(5.38)
Control variables	Yes	Yes
Year fixed effects	Yes	Yes
firm-fixed effects	Yes	Yes
Within. R^2	0.054	0.076
Observations	9,274	4,212
Panel C: Re-sampling and Adjusting for Capital Stocks		
	Re-sampling(1)	Adjusting for Capital Stocks(2)
Intercept	−5.578***	−7.201***
	(-8.99)	(-10.59)
Sat	0.202***	0.196***
	(5.36)	(5.01)
Control variables	Yes	Yes
Year fixed effects	Yes	Yes
Industry fixed effects	Yes	Yes
Adj. R^2	0.074	0.083
Observations	13,569	14,845
Panel D: Re-organizing Data in Terms of Analyst-firm-year		
	(1)	(2)
Intercept	0.849*	−8.701***
	(1.95)	(-14.75)
Sat	0.285***	0.278***
	(9.79)	(10.26)
Top3		0.017
		(1.37)
Anastar		0.029***
		(2.72)
Num		−0.258***
		(-14.60)
Horizon		1.679***
		(23.27)
Cover		−0.002***
		(-7.94)
Expe		0.033***
		(6.27)
Fexp		0.024**
		(2.56)
Control variables	Yes	Yes
Year fixed effects	Yes	Yes
Industry fixed effects	Yes	Yes
Adj. R^2	0.056	0.113
Observations	146,868	146,868
Panel E: Firm Fixed Effects and Cash Dividend		
	Fopt(1)	*Fopt*(2)
Intercept	−10.904***	−8.257***
	(-6.00)	(-11.36)
Sat	0.449***	0.435***
	(9.43)	(9.88)

(*continued on next page*)

Table 5 (*continued*)

Panel A: Propensity Score Matching		
	1:1 Matching (1)	1:2 Matching(2)
Year fixed effects	Yes	Yes
Industry fixed effects	No	Yes
Firm-fixed effects	Yes	No
Adj. R^2	0.065	0.098
Observations	14,845	14,016

Notes: ***, **, * The coefficients are significant at the 0.01, 0.05, and 0.10 levels, respectively, based on two-tailed statistical tests.

Moreover, many companies are likely to pay cash dividends when they issue stock dividends. To control for the potential influence of cash dividend payments, we further include a control variable indicating cash dividend payment (*Div*), and as shown in column (2) of Panel E, the results remain robust.

5. Test for trading incentive

In an ideal setting, we should test directly how trading incentive of analysts affects the relationship between stock dividend and analyst optimistic bias. However, analysts' "incentive" to encourage trading can hardly be observed and measured directly given the limited available data, so we apply three indirect methods to test the effect of trading incentives. First, we conduct a series of cross-sectional tests to see if the relationship between stock dividend and analyst optimistic bias is more significant when analysts' trading incentive is stronger. Second, we test whether analysts' optimistic earnings forecast issued after stock dividend announcement indeed encourages trading and the results show that the trading volume indeed becomes larger when analysts produce optimistic earnings forecasts. Third, we also test whether the cost of making optimistically biased forecast is lower after companies issue stock dividends.

5.1. Cross-sectional analyses

5.1.1. Institutional shareholdings

Compared with individual investors, institutional investors are more professional and rational. For example, Brandt, Brav, Graham, and Kumar (2010) find that companies with less institutional shareholdings are more speculative. If our arguments above are in line with reality, nominal price illusion mainly affects individual investors who have limited information and limited rationality, but can hardly influence institutional investors who have access to more information and are more rational. Therefore, issuing optimistically biased earnings forecasts can generate more trading volume from the speculativeness of individual investors but can hardly drive institutional investors to participate in trading. In addition, as institutional investors are more professional, they may easily detect the motivation of analysts to issue biased forecasts (Ljungqvist et al., 2007). Hence, analysts are more inclined to generate optimistic earnings forecasts after firms with less institutional shareholdings issue stock dividends.

To test this proposition, we use two methods to measure the shareholdings of institutional investors. Following Chen, Hong, and Stein (2002), the first measure, *Inhold*, is the percentage of shares owned by institutional investors. The second measure, *Inhold1*, is the number of institutional investors. We then define a dummy variable $Inst_{i,t-1}$ which equals one when *Inhold* or *Inhold1* of firm *i* in year *t-1* is greater than the year-median and zero otherwise. After including $Inst_{i,t-1}$ and its interaction term with $Sat_{i,t-1}$ in model (1), we obtain the results reported in Panel A of Table 6. The coefficients on $Sat_{i,t-1}$*$Inst_{i,t-1}$ are both significantly negative with two measures of institutional shareholdings, suggesting that the positive effect of stock dividends on analyst optimistic bias is more pronounced when companies have less proportion of shares held by institutional investors. That is, the proportions of institutional and individual investors matter in the process of analysts' forecast making. Catering to irrational sentiment of individual investors, analysts have a tendency to produce earnings forecasts that are more biased in optimism when individual investors hold more shares of the company, which leads to the negative coefficient on the interaction term $Sat_{i,t-1}$*$Inst_{i,t-1}$.

5.1.2. Brokerage firm size

The size of the brokerage firms where analysts work can influence the forecasts of analysts. Brown, Hagerman, Griffin, and Zmijewski (1987) and Clement (1999) both find a positive correlation between brokerage firm size and analyst forecast accuracy. Jacob, Lys, and Neale (1999) discover that larger brokerage firms can provide more resources and supports to their analysts, which add to the accuracy of analysts' forecasts. On the other hand, large brokerage firms lose more if they are penalized, so they in turn pose stricter supervision on their analysts. Meanwhile, the analysts of larger brokerage firms have higher status in the profession and receive more compensations, so they are less motivated to trigger trading volume through intentional lying. Therefore, the relationship we find between stock dividend and analyst optimism should be less significant when analysts work for larger brokerage firms, i.e. the positive relationship should be more pronounced in small brokerage firms.

We define a dummy variable *Top3* to measure the size of brokerage firms. Specifically, we rank all brokerage firms by the number of analysts they have and their revenues, respectively. If a brokerage firm ranks among the top 3, then *Top3* equals one, and zero otherwise. As a company may be covered by more than one analyst, we further define a dummy $Bigbroker_{i,t}$ which equals one if a company is covered by more analysts from top 3 brokerage firms than the year-median, and zero otherwise. $Bigbroker_{i,t}$ and its interaction term with $Sat_{i,t-1}$ are incorporated into model (1). Results of the regressions are reported in Panel B of Table 6. Consistent

Table 6
Cross-sectional analyses.

Panel A: Institutional Shareholdings

	Fopt (Inhold)	*Fopt* (Inhold1)
	(1)	(2)
Intercept	−8.127***	−7.850***
	(-11.23)	(-10.71)
Sat	0.494***	0.556***
	(7.80)	(8.06)
Inst	−0.068	0.074
	(-1.63)	(1.59)
Sat Inst*	−0.141*	−0.258***
	(-1.69)	(-2.99)
Control variables	Yes	Yes
Year fixed effects	Yes	Yes
Industry fixed effects	Yes	Yes
Adj. R^2	0.092	0.092
Observations	14,845	14,845

Panel B: Brokerage Firm Size

	Fopt (Ranking based on analyst number)(1)	*Fopt* (Ranking based on revenue)(2)
Intercept	−8.247***	−8.251***
	(-11.32)	(-11.34)
Sat	0.534***	0.570***
	(7.35)	(7.63)
Bigbroker	0.021	0.042
	(0.54)	(1.00)
Sat Bigbroker*	−0.195**	−0.261***
	(-2.21)	(-2.95)
Control variables	Yes	Yes
Year fixed effects	Yes	Yes
Industry fixed effects	Yes	Yes
Adj. R^2	0.092	0.092
Observations	14,845	14,845

Panel C: Analyst Reputation and Market Situation

	Fopt(Full sample)(1)	*Fopt*(Bull market)(2)	*Fopt*(Bear market)(3)
Intercept	−8.064***	−7.633***	−8.548***
	(-10.91)	(-5.87)	(-10.35)
Sat	0.476***	0.617***	0.418***
	(6.92)	(4.86)	(5.19)
Star	−0.015	0.181**	−0.088**
	(-0.42)	(2.31)	(-2.11)
Sat Star*	−0.104	−0.375**	0.013
	(-1.20)	(-2.34)	(0.13)
Control variables	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes
Adj. R^2	0.092	0.084	0.095
Observations	14,845	4,312	10,533

Panel D: Short Selling and Conflict of Interests

	Fopt	*Fopt*
Intercept	−8.332***	−8.269***
	(-11.07)	(-11.38)
Sat	0.464***	
	(9.20)	
Short-List	0.015	
	(0.28)	
Sat Short-List*	−0.182*	
	(-1.91)	
SEO		−0.127
		(-1.19)
Sat SEO*		0.726**
		(2.43)
Control variables	Yes	Yes
Year fixed effects	Yes	Yes
Industry fixed effects	Yes	Yes
Adj. R^2	0.091	0.092
Observations	14,845	14,845

Notes: ***, **, * The coefficients are significant at the 0.01, 0.05, and 0.10 levels, respectively, based on two-tailed statistical tests.

with the prediction, the coefficients on $Sat_{i,t-1}$*$Bigbroker_{i,t}$ are significantly negative, suggesting that the positive effect of stock dividends on analyst optimism is less pronounced for analysts from large brokerage firms than for analysts from small firms.

5.1.3. Analyst reputation and market situation

Stickel (1992) demonstrates that the forecasts made by star analysts are more accurate than those made by non-star analysts. This is proved by Fang and Yasuda (2009), who add to the finding by showing that analysts are more aware of their reputations, and that the reputation mechanism relieves the negative consequences brought by conflicts of interests. When companies issue stock dividends, star analysts weigh more on their long-term reputations and are less likely to be driven by short-term interests and intentionally bias their forecasts. Meanwhile, market situation also affects forecast accuracy of analysts (Becchetti, Hasan, Santoro, & Anandarajan, 2007). Specifically, non-star analysts are more likely to cater to investors' high mood in a bull market and issue optimistically biased earnings forecasts while star analysts are more likely to maintain their independence and integrity. In a bear market, however, the return for issuing optimistic forecast is low, as investors are more precautious then, both star analysts and non-star analysts become less motivated to issue optimistic forecast. Therefore, we predict that the relationship between stock dividend and analyst optimistic bias is more pronounced with non-star analysts in bull market.

We define a dummy $Star_{i,t}$ which equals one if company i is covered by more star analysts than the year-median in year t, and zero otherwise. Regression results reported in Panel C of Table 6 demonstrate a significantly negative coefficient on the interaction term in the bull market. In the bear market, the coefficient becomes insignificant. These findings confirm that analyst's personal constraint of reputation plays a crucial role in earnings forecast. Specifically, this constraint takes effect only in the bull market.

In short summary, the above findings prove that the relationship between stock dividend and analyst optimistic bias is more significant when analysts' trading incentive is stronger, i.e., when the company has less institutional stock holdings, when the analyst is in a small brokerage firm or when the earnings forecast is issued by non-star analyst in a bull market, which supports our argument.

5.1.4. Short selling mechanism

The implementation of a short selling mechanism can change the costs and benefits of analysts' forecasts, thus affecting analysts' optimism in forecasting. Previous studies have shown that short sellers are important information traders in capital markets, as they are able to identify negative information about firms and transmit it to the market through short selling transactions (Boehmer, Jones, Wu, & Zhang, 2020; Christophe, Ferri, & Hsieh, 2010). Hence, after the short selling constraint is relaxed, analysts may face significant losses in their personal reputation if they still issue biased, especially optimistically biased earnings forecasts, thus changing the costs and benefits of analysts' forecasting behavior. As a result, analysts' optimism in response to companies issuing stock dividends may be lower after the implementation of the short selling mechanism. China officially launched securities margin trading on March 31, 2010, and expanded the scope of the underlying stocks twice in 2011 and 2013. In this paper, we define a short-sale dummy variable *Short_List* which equals one if the company is among the list of the securities margin trading in that year, and zero otherwise. The coefficient of *Sat* Short_List* is −0.182 and is significant at the 10% level, indicating that after the implementation of the short selling mechanism, analysts' optimistic bias in response to companies' issuance of stock dividends significantly decreases.

5.1.5. Analysts' conflict of interests

Analysts' conflicts of interests can cause analysts to behave in a self-interested manner. Numerous studies have shown that analysts' behavior is more likely to be influenced by self-interest motives when they are from brokerage firms with which the company has a business relationship (Dugar & Nathan, 1995; Lin & McNichols; 1998; Mola & Guidolin, 2009). Therefore, we look at the conflicts of interests faced by analysts to verify whether analysts' optimistic bias in forecasts when companies pay stock dividends is "intentional" or "unintentional". We distinguish between analysts who are from the company's refinancing underwriters and those who are not. If the underwriter's analysts exhibit a higher forecast optimistic bias after the company issues stock dividend, it is more likely that the optimistic bias in the analysts' earnings forecasts is "intentional" rather than "unintentional". The results are reported in column (2) of Panel D in Table 6. *SEO* indicates whether analysts are influenced by the relationship between the brokerage firm and the company, which is designated one if the company has made seasoned equity offerings in the year and at least one of the analysts forecasting the company is from the underwriter, otherwise it is zero. The coefficient of *Sat*SEO* is significantly positive, indicating that the relationship between analysts and underwriters significantly influences analysts' optimism when the company issues stock dividends. This result suggests that the optimistic bias in analysts' earnings forecasts is more likely to be "intentional".

5.2. Test of trading volume after optimistic earnings forecasts

As discussed above, trading incentive can affect analysts' earnings forecasts and lead analysts to produce biased earnings forecasts especially in optimism. Following Dambra et al. (2018), we use stock turnover as a proxy for brokerage trading revenue. Based on the hypothesis of positive association between analyst compensation and stock turnover via trading commissions, we think stock turnover is a reasonable, albeit imperfect, proxy for trading revenue. Thus, driven by the incentives to generate more trading commissions, analysts have a tendency to produce optimistic earnings forecasts and theoretically, stock turnover is positively related to these optimistic earnings forecasts.

We empirically examine whether analysts' optimistic earnings forecasts lead to a larger stock turnover or not and the presence of trading incentive. We use the following OLS regression and the coefficient on the interaction term is expected to be positive:

$$Turnover_{i,t} = \beta_0 + \beta_1 Sat_{i,t-1} + \beta_2 Foptdummy_{i,t} + \beta_3 Sat_{i,t-1}{*}Foptdummy_{i,t} + \beta_4 Controls_{i,t-1} + Fixed\ effects + \varepsilon \quad (3)$$

where $Turnover_{i,t}$ is stock turnover of firm i in year t; $Foptdummy_{i,t}$ is an indicator variable that equals one when average analyst optimism of firm i in year t is greater than the year-median and zero otherwise. We then control for a series of variables that may affect stock turnover and include industry and year fixed effects.

Column (1) of Table 7 presents the result of the regression to examine the effect of stock dividends on turnover. The coefficient on $Sat_{i,t-1}$ is significantly positive at the 1% level, suggesting that stock turnover is positively related to stock dividends. When firms issue stock dividends, investors react positively, which leads to larger turnover. Column (2) of Table 7 presents the regression result after adding $Foptdummy_{i,t}$ and the interaction term $Sat_{i,t-1}$*$Foptdummy_{i,t}$. As reported, the coefficient on interaction term is significantly positive at the 1% level, suggesting that the trading volume indeed becomes larger when analysts produce optimistic earnings forecasts, which in turn supports analysts' trading-inducing incentive to some extent.

5.3. Test for the reputational costs after issuing optimistic forecasts

We argue that analysts make optimistic earnings forecasts based on a trade-off between their own costs and benefits. In section 5.2, we examine the benefit of analysts after issuing optimistic forecasts. To further support our idea, we make an additional test of the reputational costs faced by analysts after issuing optimistic earnings forecasts.

Specifically, we investigate whether analysts who make optimistic forecasts face lower reputational costs when companies issue stock dividends. We follow Hong, Kubik, and Solomon (2000) to include analysts leaving the industry as a cost variable for their reputation damage and thus dismissal. We argue that analysts are less likely to be penalized for optimistic forecasts when companies issue stock dividends because even if analysts send optimistic signals to investors, this signal is consistent with investors' illusion of low stock prices and investors are less likely to believe that the optimistic forecasts issued by analysts are intentional, reducing the penalty for analysts. We therefore expect the reputational damage of analysts issuing optimistic forecasts to be lower after stock dividends.

If analyst j issues earnings forecast in year t-1 and does not issue any earnings forecast in year t and thereafter, we define the analyst

Table 7
Additional analyses: Test of Trading Incentives.

	Turnover(1)	Turnover(2)
Intercept	28.554***	29.582***
	(29.41)	(27.59)
Sat	0.864***	0.432***
	(12.51)	(3.83)
Foptdummy		0.086
		(1.56)
Sat Foptdummy*		0.502***
		(3.49)
Amplitude	2.498***	2.734***
	(4.19)	(4.10)
Sizeflow	0.349***	0.535***
	(3.33)	(4.93)
Soe	−0.179**	−0.058
	(-2.53)	(-0.75)
Lev	−0.033	−0.298
	(-0.16)	(-1.35)
Roa	−3.375***	−4.729***
	(-4.46)	(-5.63)
Mb	−0.592***	−0.635***
	(-20.34)	(-19.09)
Size	−1.055***	−1.102***
	(-24.50)	(-23.50)
Largest	−0.023***	−0.024***
	(-10.53)	(-10.74)
Loss	−0.332***	−0.137
	(-3.13)	(-1.05)
Sigma	149.494***	141.767***
	(25.57)	(21.84)
Growth	0.098*	0.128**
	(1.94)	(2.20)
Abnret	0.109*	0.173***
	(1.85)	(2.78)
Age	−0.330***	−0.198**
	(-3.62)	(-2.15)
Year fixed effects	Yes	Yes
Industry fixed effects	Yes	Yes
Adj. R^2	0.446	0.467
Observations	19,939	15,005

Notes: ***, **, * The coefficients are significant at the 0.01, 0.05, and 0.10 levels, respectively, based on two-tailed statistical tests.

as having left the industry in year *t* and the variable *Ana_Turnover* takes the value of one. Otherwise, *Ana_Turnover* takes the value of zero. Also following Hong et al. (2000), we construct for each analyst a measure of relative optimism as our measure of analyst optimism. The calculation formula is as follows.

$$Score_{j,i,t} = 100 - \left[\frac{rank - 1}{analysts - 1}\right] * 100$$

$Score_{j,i,t}$ is the optimism score of analyst *j*'s forecast for company *i* in year *t*. *Rank* is the ranking of analyst *j*'s optimism bias for company *i* in year *t*. If analyst *j* makes the most optimistic forecast for company *i* in year *t*, it is ranked the first. *Analysts* is the number of analysts following company *i* in year *t*. After averaging each analyst's $Score_{j,i,t}$, we use the optimism score $Score_{j,t}$ of analyst *j* in year *t* as a measure of analyst *j*'s optimism. We define another variable $Ana\_Sat_{j,t-1}$, which takes the value of one if one of the companies followed by analyst *j* issues stock dividend in year *t-1*, and zero otherwise. We construct the following logit regression model to conduct the test. The interaction term $Ana\_Sat_{j,t-1} * Score_{j,t}$ should be significantly negative if the cost of reputational damage for analysts issuing optimistic forecasts decreases after a company issues stock dividends. The results presented in Table 8 show that the coefficient of $Ana\_Sat_{j,t-1} * Score_{j,t}$ is significantly negative, which further supports our argument.

$$Ana\_Turnover_{j,t} = \beta_0 + \beta_1 Ana\_Sat_{j,t-1} + \beta_2 Score_{j,t} + \beta_3 Ana\_Sat_{j,t-1} * Score_{j,t} + \beta_4 Controls_{j,t-1} + Fixed\ effects + \varepsilon \quad (4)$$

6. Conclusions and implications

The information intermediary role of sell-side analysts is especially important in emerging market where information asymmetry is severe. However, optimistic biases widely exist in analysts' earnings forecasts. Analysts are self-interest driven and sometimes even contribute to the inefficient pricing of the market. Inspired by this situation, this paper investigates the effect of stock dividend on analyst optimistic bias in earnings forecast from the perspective of analysts' incentives to encourage trading. Our study finds that the announcement of stock dividend leads to increased optimistic bias in analysts' earnings forecasts. Further study reveals that this phenomenon is especially significant when companies have less institutional shareholdings, when analysts are in small brokerage firms and when earnings forecasts are issued by non-star analysts in bull market. These findings are all consistent with our argument that analysts intentionally generate optimistically biased earnings forecasts after stock dividend issuance to trigger more trading volume and obtain trading commissions. In addition, we find that the optimistic bias in analysts' earnings forecasts indeed lead to more trading volumes.

The findings of this paper have important practical implications. Whereas the supervision over analysts in developed markets is effective, it is yet weak in emerging markets. Therefore, reinforcing the external supervision on analysts and improving the professional ethics of them are both necessary.

Table 8
Test of reputational cost.

	Ana_Turnover
	(1)
Intercept	−5.205***
	(-24.14)
Ana_Sat	0.549**
	(2.08)
Score	0.021***
	(9.12)
*Ana_Sat * Score*	−0.010**
	(-2.32)
Top3	0.004
	(0.03)
Anastar	−0.896***
	(-7.90)
Cover	−0.035***
	(-7.87)
Expe	1.687***
	(29.77)
Fexp	0.061
	(1.13)
Year fixed effects	Yes
Pseudo R^2	0.170
Observations	8,336

Notes: ***, **, * The coefficients are significant at the 0.01, 0.05, and 0.10 levels, respectively, based on two-tailed statistical tests.

Author statement

Lixin Huang: Software, Data curation. **Wei Li:** Conceptualization, Methodology, Writing-Reviewing and Editing. **Hong Wang:** Writing- Original draft preparation. **Liansheng Wu:** Supervision.

APPENDIX 1

Variable Definitions

Variables	Definitions
Dependent variables	
Fopt	We first define an analyst's forecast bias $Fopt_{j,i,t} = (FEPS_{j,i,t} - AEPS_{i,t})/\mid AEPS_{i,t}\mid$, where $FEPS_{j,i,t}$ is the forecast of earnings per share by analyst *j* on firm *i* for year *t*. $AEPS_{i,t}$ is the reported earnings per share by firm *i* for year *t*. Second, analyst optimism $Fopt_{i,t}$ is calculated as the average of all analysts' forecasting biases for firm *i* in year *t*. $Fopt_{i,t}$ captures the consensus mean bias among all analysts covering the identical firm.
Turnover	Total shares traded of firm *i* in year *t* divided by average shares outstanding.
Key independent variables	
Sat	Indicator variable, which equals one if one firm pays stock dividends in a given year and zero otherwise.
Hsat	Indicator variable, which equals one if the ratio of stock dividends is more than 0.5 in a given year and zero otherwise.
Satratio	The ratio of stock dividends.
Control variables	
Size	Natural logarithm of a company's total assets in a given year.
Lev	Debt-to-assets ratio of a company in a given year.
Soe	Indicator variable, which equals one if the firm is controlled ultimately by Chinese state and zero otherwise.
Mb	The market value of asset divided by the book value of asset.
Roa	The net income divided by the company's total assets.
Big4	Indicator variable, which equals one if the firm is audited by an international Big 4 audit firm in a given year and zero otherwise.
Largest	The ownership percentage of the largest shareholder.
Num	Natural logarithm of one plus the number of analysts covering the company in a given year.
Horizon	Natural logarithm of mean days elapsed from all of the analysts' latest earnings forecasts date to the earnings announcement date.
Growth	Revenue growth in year *t* divided by revenue in year *t-1*.
Top3	Indicator variable, which equals one if one analyst works for one of top three brokerage firms and zero otherwise.
Anastar	Indicator variable, which equals one if one analyst is selected as star analyst by *New Fortune* magazine and zero otherwise.
Cover	Number of firms covered by one analyst.
Expe	

(*continued on next page*)

(*continued*)

Variables	Definitions
	Natural logarithm of one plus the number of years since the analyst began to provide earnings forecasts (for any company).
Fexp	Natural logarithm of one plus the number of years since the analyst began to issue earnings forecasts for the company
Amplitude	Difference between highest stock price and lowest stock price divided by the average stock price in a given year.
Sizeflow	We calculate $Sizeflow_{i,t} = \frac{Q_i - \overline{Q}}{\sigma_Q}$, where Q_i is mean outstanding shares of firm i at the end of year t. $\overline{Q}$ is mean outstanding shares of all of firms at the end of year t. σ_Q is standard deviation of outstanding shares of all firms at the end of year t.
Age	Natural logarithm of the age of the company
Loss	Indicator variable, which equals one if the net income is negative in year t and zero otherwise.
Abnret	Abnormal annually stock return during the year t of the firm i(adjusted by value-weighted market return).
Sigma	Variance of daily raw returns of the firm i during the year t.
Inhold	The ownership percentage of institutional investors.
Foptdummy	Indicator variable, which equals one if average analyst optimism of firm i in year t is greater than annual sample median and zero otherwise.
Inst(Inhold)	Indicator variable, which equals one if the ownership percentage of institutional investors of firm i at the end of year t is greater than the annual sample median and zero otherwise.
Inst(Inhold1)	Indicator variable, which equals one if the number of institutional investors of firm i at the end of year t is greater than the annual sample median and zero otherwise.
Bigbroker	Indicator variable, which equals one if the ratio of top-three analysts covering the firm i in year t is greater than the annual sample median and zero otherwise.
Star	Indicator variable, which equals one if the ratio of star analysts covering the firm i in year t is greater than the annual sample median and zero otherwise.

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