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Public opinion shaping: The impact of corporate digital transformation on analysts' optimistic forecast bias

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ABSTRACT

This study investigates the impact of digital transformation on analysts' optimistic forecast bias among listed firms, drawing on signaling theory. The findings indicate that the digital transformation is a high-value signal, thereby making analysts' forecasts more optimistic. Moreover, shaping public opinion through formal media channels can significantly strengthen this relationship, while employing online shills may undermine analysts' trust in the firm's real operating performance, thereby prompting more pessimistic forecasts. Overall, this research provides insights on enhancing the efficiency of signal conveyance in capital markets and bolstering investors' confidence in analysts.

1. Introduction

Digital transformation refers to the strategic and organizational changes firms implement by utilizing digital technologies (Hanelt et al., 2021). It enables firms to realize substantial business enhancements, boost customer experience, streamline operations, and develop innovative business models, thereby bolstering stakeholder confidence. In China, digital transformation is a critical imperative for firms. The unique business environment compels listed firms to accelerate their digital transformation efforts in order to remain competitive in the fast-paced digital age (Luo et al., 2023).

Moreover, research indicates that digital transformation not only boosts firms' revenues in product markets but also enhances their performance in capital markets. For example, digital transformation can attract investors who favor digital assets and mitigate the risk of stock price crashes (Jiang et al., 2022; Liu et al., 2023). However, in line with the efficient market hypothesis, capital market efficiency has its limitations. Investors can be deceived by firms' misleading advertising and may overreact upon its exposure (Wiles et al., 2010). In developed capital markets such as the United States and Europe, the channels for signal conveyance are highly diversified, encompassing traditional news media, financial news websites, social media platforms, and more. These channels are not only characterized by rapid information dissemination but also have a broad coverage, enabling the swift transmission of market information to investors. Moreover, developed capital markets are equipped with comprehensive legal frameworks and regulatory mechanisms. For instance, the SEC enforces strict supervision over market manipulations, insider trading, and other illegal activities.

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In contrast, signal conveyance channels in China are often chaotic, with online shills severely disrupting internet order and making investors more susceptible to misinformation. Analysts, who have access to more professional channels for obtaining corporate information, play a crucial role in reducing information asymmetry and enhancing investor confidence (Brown et al., 2015). Therefore, China has a greater need for analysts to bolster investor confidence. Examining analysts' optimism regarding corporate digital transformation and the impact of signal conveyance channels on them is vital for promoting the digital transformation of listed firms and encouraging investors' participation in the digital market.

The contributions of this study are as follows: First, this study underscores that digital transformation not only amplifies a firm's competitive edge within the product market but also functions as a conduit for transmitting positive signals to stakeholders. It elucidates the impetus behind firm managers employing digital transformation as a means to convey value signals to stakeholders, thereby broadening the application of signaling theory into the digital transformation domain. Second, this study diverges from the conventional transmission framework espoused by signaling theory. It uncovers that the efficacy of signal transmission is contingent upon the channels utilized. When signals are conveyed through channels that lack credibility in the eyes of stakeholders, the integrity and value of these positive signals are compromised, thereby inciting skepticism. This insight significantly extends the frontiers of signaling theory.

2. Literature review and hypotheses

2.1. Corporate digital transformation and analysts' forecasts

From the product market standpoint, firms primarily undertake digital transformation to adapt to the business ecosystem and address external pressures (Kohli and Melville, 2019). However, from the stock market perspective, digital transformation not only confers competitive advantages in operations but also acts as a signal of value to analysts. According to signaling theory, firms can convey signals about their future profitability to the market through specific actions. Digital transformation decisions reflect executives' innovative intent, optimized internal operations and management models, and reduced employee redundancy (Chen and Xu, 2023). This implies that firm managers possess a long-term vision, lower costs, and the capability to create long-term value for investors. As critical stakeholders of the firm, analysts are required to utilize their professional expertise to rigorously evaluate the firm's financial performance (such as profit margin and sales growth rate), operational performance (inventory turnover rate), and market performance (customer satisfaction, market share, etc.). When analysts become aware of the firm's inclination towards digital transformation, they will naturally assume that the firm will leverage digital technology to optimize its internal operations and management, enhance production efficiency, and reduce labor and material costs. Consequently, they are likely to assign higher ratings to the aforementioned performance. When firms' annual reports include more disclosures about digital transformation, analysts tend to adopt a more optimistic view of the firm's prospects. Based on this, we formulate the following hypothesis:

H1. Corporate digital transformation can increase analysts' optimistic forecast bias.

2.2. Public opinion shaping and analysts' forecasts

Digital transformation enables firms to convey signals of value to stakeholders; however, the channels through which stakeholders perceive and comprehend this signals are of paramount importance (Hensmans et al., 2021).On the one hand, the media have a broader reach and are more severe in their criticism of firms (Kölbel et al., 2017). Therefore, according to the theory of information asymmetry, media coverage has fewer information gaps with firms, and the credibility of media reports as a formal channel is significantly higher than that of informal channels. On the other hand, the resource-based view suggests that the high costs associated with promoting through formal channels, in terms of both time and money, are difficult to imitate and substitute (Barney, 1991). Such high-cost investments serve as a "signal" to stakeholders that the firm is willing to allocate resources to shape its image, which in turn enhances the credibility of the conveyed signals. Consequently, signals conveyed through formal channels, such as positive media coverage, are perceived as high-quality signals capable of bolstering analysts' confidence in the firm's future performance. By contrast, signals conveyed through informal channels, like online shills, may be regarded as low-quality signals that prompt analysts to doubt the firm's real operating performance. Based on this reasoning, we propose the following hypothesis:

H2a. Positive media coverage positively moderates the relationship between corporate digital transformation and analysts' optimistic forecast bias.

H2b. Online shills negatively moderate the relationship between corporate digital transformation and analysts' optimistic forecast bias.

3. Methodology

3.1. Variable definitions

3.1.1. Dependent variable: analysts' optimistic forecast bias

To investigate whether corporate digital transformation makes analysts' forecasts more optimistic, the dependent variable in this study is analysts' optimistic forecast bias (*Optim*). Following Jackson (2005), we measure analysts' optimistic forecast bias by comparing their earnings forecasts to the firm's actual earnings. Specifically, *Optim* is defined as the proportion of observations where analysts' earnings forecasts exceed the firm's actual earnings. The detailed calculation process is presented in Appendix A. A larger *Optim* value signifies a more optimistic forecast from analysts.

3.1.2. Independent variable: digital transformation

The digital transformation of firms encompasses innovations in software, infrastructure, or management, which are often intangible and typically disclosed to investors through annual reports (Porfírio, 2021). The disclosure of digital transformation in annual reports not only reflects a firm's business model and organizational culture but also serves as an important means of conveying future commitments to investors. Therefore, employing text analysis methods to identify words related to digital transformation in the annual reports of listed firms is deemed essential (Tetlock et al., 2008). Following the approach of Cui and Wang (2023), we use text analysis to extract keywords associated with digital transformation and then take the natural logarithm after adding one.

3.1.3. Moderator: public opinion shaping

Listed firms shape public opinion through various channels. Hensmans (2021) identifies politics, media, identity, education, and markets as key channels to enable investors to perceive and understand the truth. The markets channel reflects how firms leverage digital transformation to serve product markets, representing a substantive action. In contrast, the politics, media, identity, and education channels more effectively convey signals of value to investors indirectly. We categorize these into two types: formal and informal channels.

Formal channels are defined as the natural logarithm of the sum of positive and neutral news reports about the firm in a given year, plus one (*PNC*). We scanned over 500 Chinese news websites, including major platforms like CCTV News, Sina Finance, and Tencent News, to capture positive and neutral news related to the firm's collaborations. Negative reports are excluded as they do not align with the goal of conveying value through public opinion.

Informal channels are defined as the natural logarithm of the number of online shills employed by the firm in a given year, plus one (*OS*). We analyzed data from the discussion boards of listed firms on East Money, identifying posts as those made by online shills if the same account published highly similar content (over 70 % similarity) in multiple firm threads within 30 days.

Furthermore, this study also controls for other factors that may influence investor sentiment; for details, see Table 1.

3.2. Descriptive statistics

The sample for this study comprises Chinese A-share listed firms from 2012 to 2022. We excluded financial institutions and firms with missing financial data. Firm operating data were sourced from the CSMAR database, while media and online shills data were obtained from the CNRDS database. After 1 % tail trimming of the continuous variables to eliminate outliers, our final sample comprises 18,978 observations. For more details, refer to Table 2.

3.3. Research model

First, to examine whether firms' digital transformation can send positive signals to investors and thereby regulate investor sentiment, we establish the following model:

$$Optim_{i,t} = \alpha + \beta_1 Tech_{i,t} + \beta_2 Control_{i,t} + \sum Year + \sum Industry + \varepsilon_{i,t} \tag{1}$$

Table 1
Definition of variables.

Variable	Definition
Dependent variables	
Optim	*Optim* is analysts' optimistic forecast bias. Following Jackson (2005), we define *Optim* as the proportion of observations where analysts' earnings forecasts exceed the actual earnings of the firm. Please refer to Appendix A for the details.
Independent variable	
Tech	*Tech* is the firm's digital transformation, defined as the natural logarithm of the number of keywords related to digital transformation plus one.
Moderator variable	
OS	*OS* is defined as the natural logarithm of the number of online shills employed by the firm on China's East Money Stock Forum, plus one.
PNC	*PNC* is defined as the natural logarithm of one plus the number of positive and neutral news reports about the firm in a given year.
Control variables	
Lev	The total liabilities divided by total assets in a given year.
Size	The natural logarithm of the total assets of the firm.
ROA	Return on assets.
Growth	Sales growth rate of listed firm.
Tangibility	The proportion of fixed assets to total assets.
TOP1	Shareholding proportion of the largest shareholder.
Indep	The proportion of independent directors to the total number of directors.
Dual	$Dual = 1$ if the CEO and chairman of the board are the same person in the firm; otherwise, $Dual = 0$.
Age	The natural logarithm of the listed firm's age.

Table 2
Descriptive statistics.

VARIABLE	MEAN	STD	MIN	P25	MEDIAN	P75	MAX
Optim	0.7956	0.2946	0.0000	0.6667	0.9583	1.0000	1.0000
Tech	1.2222	1.3807	0.0000	0.0000	0.6931	2.0794	6.3008
OS	0.0901	0.3301	0.0000	0.0000	0.0000	0.0000	4.4067
PNC	2.6953	1.2869	0.0000	1.7918	2.5649	3.4657	9.2571
Lev	0.4333	0.1992	0.0500	0.2765	0.4271	0.5818	0.9241
Size	22.3966	1.2913	19.9142	21.4687	22.2152	23.1326	26.7103
ROA	0.0371	0.0642	−0.3679	0.0121	0.0351	0.0672	0.2566
Growth	0.1527	0.3951	−0.6718	−0.0357	0.0935	0.2477	4.0242
Tangibility	0.2142	0.1590	0.0016	0.0902	0.1821	0.3053	0.7341
TOP1	0.3443	0.1478	0.0845	0.2305	0.3212	0.4442	0.7802
Indep	0.3775	0.0539	0.3000	0.3333	0.3636	0.4286	0.6000
Dual	0.2676	0.4427	0.0000	0.0000	0.0000	1.0000	1.0000
Age	2.9630	0.3146	1.6094	2.7726	2.9957	3.1781	3.6109

where $Optim_{i,t}$ is investor sentiment, and $Tech_{i,t}$ is digital transformation. Year and industry fixed effects are included in Eq. (1). Then, to examine whether the way firms shape public opinion affects signal transmission, we establish the following model:

$$Optim_{i,t} = \alpha + \beta_1 Tech_{i,t} + \beta_2 Tech_{i,t} \cdot M_{i,t} + \beta_3 M_{i,t} + \beta_4 Control_{i,t} + \sum Year + \sum Industry + \varepsilon_{i,t} \tag{2}$$

where $M_{i,t}$ is the set of moderators, including $PNC_{i,t}$ *and* $OS_{i,t}$.

4. Empirical results

4.1. Baseline results

The results of the baseline analysis are presented in Table 3. Column (1) shows the results of Eq. (1), while Columns (2) and (3) present the results of Eq. (2). The findings indicate that the digital transformation of listed firms is a high-value signal, making analysts more optimistic about the firm's prospects. Moreover, shaping public opinion through formal channels can enhance this relationship. In contrast, informal channels, such as employing online shills, can reduce the value of the signals, causing analysts to doubt the firm's actual operating performance and leading to more pessimistic forecasts. These results support H1, H2a and H2b. Previously, Zhang and Yu (2024) explained how digital transformation alleviates the information asymmetry between firms and analysts and improves analysts' forecast quality from the perspective of the technological advantages brought by digital transformation. In contrast, we demonstrate that digital transformation itself is a high-value signal from the perspective of signaling theory. In addition to the aforementioned analyses, we also examine the two-way fixed effects and use cluster-robust standard errors. For more details, please refer to Appendix B.

4.2. Robustness test: alternative measure of main variable

In this subsection, we first substitute digital investment (Ho et al., 2011) for digital transformation as an alternative measure of the dependent variable (*Tech**). The corresponding results are displayed in columns (1) to (3) of Table 4. Next, we replace the number of online shills (*OS*) with the number of posts made by online shills (*OS**), with the results presented in column (4) of Table 4. Furthermore, we substitute the number of original positive and neutral news reports about the firm (*PNC**) for the total number of all positive and neutral news reports about the firm (*PNC*), with the results shown in column (5) of Table 4.[1] The aforementioned results align with the baseline findings. In addition, we conducted a test for negative reports, as detailed in Appendix C. We further conduct endogeneity tests using the number of digital economy patent applications at the city level as an instrumental variable. Additionally, we perform heterogeneity analyses by examining the moderating effects of institutional ownership and the level of real earnings management.

5. Conclusions

This study examines whether the digital transformation of firms influences analysts' optimistic forecast bias. The findings indicate that: (1) Digital transformation conveys positive signals to analysts, thereby rendering their forecasts more optimistic. (2) Shaping public opinion through formal channels, such as media coverage, reinforces the positive relationship between digital transformation and analysts' optimistic forecast bias. In contrast, when firms shape public opinion through informal channels, such as employing

[1] We further conduct endogeneity tests using the number of digital economy patent applications at the city level as an instrumental variable (Appendix D). Additionally, we perform heterogeneity analyses by examining the moderating effects of institutional ownership and the level of real earnings management (Appendix E).

Table 3
Results of baseline.

	(1)$Y = Optim$	(2)$Y = Optim$	(3)$Y = Optim$
Intercept	0.9402***	0.9546***	1.3077***
	(9.79)	(9.96)	(13.06)
Tech	0.0219***	0.0220***	0.0076**
	(6.69)	(6.72)	(2.31)
*Tech*OS*		−0.1862***	
		(−2.78)	
OS		1.1364***	
		(3.97)	
*Tech*PNC*			0.0040**
			(2.18)
PNC			0.0314***
			(8.20)
Lev	0.3645***	0.3659***	0.3600***
	(16.25)	(16.35)	(16.13)
Size	−0.0444***	−0.0451***	−0.0625***
	(−12.84)	(−13.05)	(−16.77)
ROA	1.1759***	1.1676***	1.1079***
	(16.75)	(16.66)	(15.84)
Growth	−0.0460***	−0.0478***	−0.0425***
	(−4.65)	(−4.85)	(−4.30)
Tangibility	−0.1129***	−0.1115***	−0.1304***
	(−4.18)	(−4.13)	(−4.83)
TOP1	−0.1955***	−0.1934***	−0.1955***
	(−8.59)	(−8.51)	(−8.61)
Indep	0.2936***	0.2878***	0.2605***
	(4.84)	(4.75)	(4.30)
Dual	0.0141*	0.0135*	0.0130*
	(1.86)	(1.78)	(1.72)
Age	−0.0152	−0.0151	−0.0135
	(−1.31)	(−1.30)	(−1.17)
Year FE	YES	YES	YES
Industry FE	YES	YES	YES
Adj R^2	39.20 %	39.31 %	39.68 %
Obs.	18,978	18,978	18,978

Noted: *, **, and *** denote statistical significance at the 10 %, 5 %, and 1 % levels, respectively.

Table 4
Results of robustness test.

	(1)$Y = Optim$ $X = Tech^*$	(2)$Y = Optim$ $X = Tech^*$ $M = OS$	(3)$Y = Optim$ $X = Tech^*$ $M = PNC$	(4)$Y = Optim$ $X = Tech$ $M = OS^*$	(5)$Y = Optim$ $X = Tech$ $M = PNC^*$
X	0.0115***	0.0119***	0.1231***	0.0196***	0.0063*
	(4.47)	(3.48)	(2.61)	(6.10)	(1.72)
*X*M*		0.9880***	0.0383***	−0.0146*	0.0041**
		(−3.27)	(2.61)	(−1.72)	(2.22)
M		0.5932**	0.0430***	0.2889***	0.0361***
		(2.35)	(11.88)	(5.97)	(9.23)
Year FE	YES	YES	YES	YES	YES
Industry FE	YES	YES	YES	YES	YES
Adj R^2	39.05 %	39.13 %	39.58 %	41.88 %	39.79 %
Obs.	18,874	18,874	18,874	18,978	18,978

Noted: Columns (1) present the regression results after the substitution of variables in Eq. (1), while columns (2)-(5) present the regression results after the substitution of variables in Eq. (2). *, **, and *** denote statistical significance at the 10 %, 5 %, and 1 % levels, respectively.

online shills, it can diminish the value of the signals conveyed. This may cause analysts to doubt the firm's real operating performance, resulting in more pessimistic forecasts.

Our research findings have the following policy implications: (1) The findings help capital markets transmit more accurate signals, aiding investors in making better decisions and improving market efficiency. (2) The findings stabilize analysts' forecast bias, enhancing investor trust in analysts and capital markets, and encouraging market participation. (3) Given that we found in the conclusion that listed firms' attempts to shape public opinion through online shills did not achieve the desired propaganda effect and even backfired, this can to some extent persuade listed firms to hire fewer online shills. When listed firms cease to employ online shills, the online environment and capital markets will be purified. This is conducive to Chinese internet information supervision departments in combating the disruption caused by misinformation, and is of great significance for maintaining the order of the internet and capital markets.

Ethical approval

This article does not contain any studies with human participants or animals performed by any of the authors.

Compliance with ethical standards

Disclosure of potential conflicts of interest: All authors declare that he has no conflict of interest.

Informed consent

Informed consent was obtained from all individual participants included in the study.

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CRediT authorship contribution statement

Cunzhi Guo: Methodology, Formal analysis, Data curation. **Kung-Cheng Ho:** Resources, Project administration, Formal analysis. **Yujing Gong:** Writing – original draft, Supervision, Software. **Jia-Qi Yu:** Writing – original draft, Supervision, Investigation, Formal analysis.

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Appendix A. Details of *Optim*'s definition

Drawing on the method of Jackson (2005), we define the optimistic forecast bias of analysts (*Optim*) by measuring the discrepancy between their earnings forecasts and the actual earnings of the company. First, the optimistic forecast bias is defined as:

$$Optimism_{i,j,t} = \frac{Forecast_{i,j,t} - Earning_{i,t}}{Price_i} \tag{A.1}$$

where $Forecast_{i,j,t}$ is the earnings per share forecast for firm i by analyst j in year t, $Earning_{i,t}$ is the actual earnings level of firm i in year t, and $Price_i$ is the closing price of firm i on the day before the analyst's earnings forecast is released. Then, we capture the observations where the analysts' earnings forecasts exceed the actual earnings of the firm. We denote the proportion of observations where $Optimism_{i,j,t}$ is greater than zero as the analysts' optimistic forecast bias (*Optim*). The larger the proportion of observations where forecast errors exceed zero, the more pronounced the optimistic forecast bias among firm' analysts.

Our dependent variable *Optim* differs somewhat from that of Jackson (2005). *Optim* measures the proportion of analysts who issue optimistic forecast biases, whereas Jackson (2005)'s definition encompasses both optimistic and pessimistic biases.

Appendix B. Two-way fixed effects and cluster-robust standard error

To further verify the robustness of the baseline results, we employ a two-way fixed effects model for testing. This model estimates the causal relationship by simultaneously controlling for year fixed effects and firm fixed effects, as both firms and years possess unique characteristics that may influence the dependent variable and are thus controlled as fixed effects in the model. The values in parentheses are cluster-robust standard errors at the firm level (Table B1).

Table B1
Two-way fixed effects and cluster-robust standard errors at the firm level.

	(1)*Y*=*Optim*	(2)*Y*=*Optim*	(3)*Y*=*Optim*
Intercept	1.4236*	1.1561**	2.1789*

(*continued on next page*)

Table B1 (*continued*)

	(1)*Y=Optim*	(2)*Y=Optim*	(3)*Y=Optim*
	(0.0031)	(0.0053)	(0.0036)
Tech	0.1012***	0.0588*	0.0421*
	(0.0048)	(0.0070)	(0.0062)
*Tech*OS*		−0.1786***	
		(0.0441)	
OS		0.8241***	
		(0.0968)	
*Tech*PNC*			0.0323***
			(0.0339)
PNC			0.1208***
			(0.0717)
Lev	−0.3336***	−0.0043***	−0.0039***
	(0.0450)	(0.0181)	(0.0095)
Size	0.3636***	0.2706***	0.3535***
	(0.0977)	(0.0849)	(0.0612)
ROA	2.1911***	−0.0305	1.5678***
	(0.0178)	(0.0007)	(0.0315)
Growth	−0.8104***	0.8359***	−1.0103***
	(0.0179)	(0.0094)	(0.0010)
Tangibility	−0.0011	−0.1943***	−0.0033**
	(0.0867)	(0.0004)	(0.0102)
TOP1	−2.0241***	0.4647***	−1.9206***
	(0.0159)	(0.0553)	(0.0004)
Indep	−0.0939	0.6144***	−0.6995***
	(0.0007)	(0.0418)	(0.0451)
Dual	−0.3064***	0.0694*	−0.2525***
	(0.0092)	(0.0148)	(0.0204)
Age	−0.0664	0.0886	0.2041
	(0.0004)	(0.0250)	(0.0138)
Year FE	YES	YES	YES
Firm FE	YES	YES	YES
Adj R^2	71.31 %	80.91 %	78.38 %
Obs.	18,978	18,978	18,978

Noted: *, **, and *** denote statistical significance at the 10 %, 5 %, and 1 % levels, respectively.

Appendix C. Negative reports

In Table C1, *NPNC* serves as an alternative measure to *PNC*, encompassing solely negative news reports. As illustrated in column (1), the coefficient of the interaction term is significantly positive, aligning with the baseline results and thereby affirming the robustness of our conclusions. However, given that negative reports fail to elucidate the motives behind a firm's public opinion shaping endeavors, *PNC* continues to be confined to positive and neutral reports exclusively.

Table C1
NPNC: Alternative measures of *PNC*.

	(1)*Y=Optim*
Intercept	1.6893***
	(4.22)
Tech	0.0543***
	(2.67)
*Tech*NPNC*	0.0072***
	(3.60)
NPNC	0.0925***
	(5.45)
Lev	−0.0195
	(−0.16)
Size	−0.3100
	(−0.91)
ROA	−0.1226***
	(−2.68)
Growth	0.5939**
	(1.98)
Tangibility	0.8784***
	(7.12)
TOP1	−0.4142***
	(−7.19)

(*continued on next page*)

Table C1 (*continued*)

	(1)Y=*Optim*
Indep	0.1734***
	(3.62)
Dual	−0.0853
	(−0.31)
Age	−0.0471***
	(−4.79)
Year FE	YES
Industry FE	YES
Adj R^2	29.44 %
Obs.	18,978

Noted: *, **, and *** denote statistical significance at the 10 %, 5 %, and 1 % levels, respectively.

Appendix D. Endogeneity: instrumental variable regressions

In this section, we follow the guidance of Keane and Neal (2023) and carefully consider the endogeneity that the instrumental variable regression alleviates and how endogeneity can lead to biased regression results in the model. Therefore, we select the natural logarithm of the number of digital economy patent applications at the city level as the instrumental variable. Niu et al. (2023) have already demonstrated a significant positive relationship between corporate digital transformation and digital innovation. The instrumental variable must satisfy the exogeneity assumption, and it is difficult for regional-level instrumental variables to be correlated with the investor characteristics of individual listed firms. Then, we establish the following model: (Table D1).

First stage:

$$Tech_{i,t} = \alpha_1 + \rho_1 DE_{i,t} + \rho_2 control_{i,t} + \sum Year + \sum Industry + \varepsilon_{i,t} \tag{3}$$

Second stage:

$$Optim_{i,t} = \alpha_2 + \gamma_1 \widehat{Tech}_{i,t} + \gamma_2 control_{i,t} + \sum Year + \sum Industry + \varepsilon_{i,t} \tag{4}$$

$$Optim_{i,t} = \alpha_2 + \gamma_1 \widehat{Tech}_{i,t} + \gamma_2 \widehat{Tech}_{i,t} \cdot M_{i,t} + \gamma_3 M_{i,t} + \gamma_4 control_{i,t} + \sum Year + \sum Industry + \varepsilon_{i,t} \tag{5}$$

Table D1
IV-2SLS model.

	First stage:	Second stage:		
	(1)*Tech*	(1)Y=*Optim*	(2)Y=*Optim*	(3)Y=*Optim*
$\widehat{Tech}$		0.0341**	0.0343**	−0.0175
		(2.53)	(2.55)	(−0.87)
$\widehat{Tech}$*OS*			−0.9354*	
			(−1.79)	
OS			−1.0955	
			(−0.53)	
$\widehat{Tech}$*PNC*				0.0228***
				(4.17)
PNC				0.0087
				(1.19)
DE	0.1419***			
	(29.07)			
Kleibergen-Paap rk LM	741.40			
	[0.00]			
Kleibergen-Paap rk Wald F	845.16			
	{16.38}			
Anderson-Rubin Wald test	83.09			
	[0.00]			
Controls	YES	YES	YES	YES
Year FE	YES	YES	YES	YES
Industry FE	YES	YES	YES	YES
Adj R^2	20.80 %	39.20 %	39.27 %	39.75 %
Obs.	18,101	18,101	18,101	18,101

Noted: *, **, and *** denote statistical significance at the 10 %, 5 %, and 1 % levels, respectively. The square brackets display the P-values of the Kleibergen-Paap-rk LM test and Anderson-Rubin Wald test. The curly brackets present the critical values of the Stock-Yogo weak ID test critical values.

Appendix E. Details of heterogeneity

Institutional Ownership (*Inst*): Defined as the ratio of shares held by institutional investors to the total number of shares outstanding.

Real earnings management (*REM*): The definition of real earnings management is consistent with Roychowdhury (2006). First, the expected cash flow from operating activities, expenses, and cost of goods sold for the firm in the current year are calculated. Then, abnormal cash flow from operating activities, abnormal expenses, and abnormal cost of goods sold are determined based on these expected values. Finally, the level of real earnings management is calculated as abnormal production costs minus abnormal cash flow from operating activities minus abnormal discretionary expenses. A higher value of real earnings management indicates a higher level of real earnings management activity.

In this section, we perform a heterogeneity analysis. Institutional investors are regarded as rational market participants. The higher the proportion of institutional ownership, the more likely analysts are to issue optimistic rating reports. Additionally, real earnings management suggests that managers have the motive to manipulate operating activities to influence financial reporting, potentially drawing additional attention from analysts to the firm's signals . We perform subsample regression based on institutional ownership levels and real earnings management levels (Roychowdhury, 2006). The results are presented in Table E1, Panels A and B. As expected, the interaction term is significant for high institutional ownership and high real earnings management..

Table E1
Results of heterogeneity.

	(1)$Y = Optim$	(2)$Y = Optim$	(3)$Y = Optim$	(4)$Y = Optim$	(5)$Y = Optim$	(6)$Y = Optim$
Panel A Institutional investor						
	High institutional ownership			Low institutional ownership		
Tech	0.0203***	0.0205***	−0.0004	0.0227***	0.0228***	0.0170**
	(4.28)	(4.32)	(−0.05)	(5.04)	(5.17)	(2.15)
*Tech*OS*		−0.1626**			−0.0170	
		(−2.10)			(−0.97)	
OS		0.9947***			0.3839***	
		(2.98)			(11.83)	
*Tech*PNC*			0.0059**			0.0010
			(2.38)			(0.35)
PNC			0.0220***			0.0377***
			(4.22)			(6.63)
Year FE	YES	YES	YES	YES	YES	YES
Industry FE	YES	YES	YES	YES	YES	YES
Adj R^2	38.19 %	38.30 %	38.55 %	39.35 %	45.32 %	43.30 %
Obs.	9687	9687	9687	9687	9687	9687
Panel B Real earnings management						
	High level of real earnings management			Low level of real earnings management		
Tech	0.0243***	0.0245***	0.0054	0.0184***	0.0163***	0.0059
	(4.86)	(4.89)	(0.60)	(3.92)	(3.54)	(0.71)
*Tech*OS*		−0.1251***			0.0101	
		(−2.88)			(0.80)	
OS		0.7522**			0.2934***	
		(2.05)			(11.79)	
*Tech*PNC*			0.0050*			0.0036
			(1.87)			(1.39)
PNC			0.0302***			0.0332***
			(5.32)			(6.01)
Year FE	YES	YES	YES	YES	YES	YES
Industry FE	YES	YES	YES	YES	YES	YES
Adj R^2	38.44 %	38.46 %	38.95 %	39.35 %	41.97 %	39.84 %
Obs.	8832	8832	8832	9058	9058	9058

Noted: *, **, and *** denote statistical significance at the 10 %, 5 %, and 1 % levels, respectively.

Data availability

Data will be made available on request.

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