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Digital Technology Innovation, Surplus Management and Analyst Forecast Bias

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Abstract

With the rapid development of digital economy, digital technology, as its technical support, has an important impact on market information environment and analysts' forecast deviation. Using the data of listed companies from 2007 to 2021, this paper investigates the impact of corporate digital technology innovation on analyst forecast bias. We find that enterprise digital technology innovation has a restraining effect on analyst forecast bias, and this conclusion is still valid after a series of robustness tests. Heterogeneity analysis shows that this effect is more obvious in firms with low media attention, investor attention and institutional ownership. Mechanism analysis shows that digital technology innovation inhibits firms' earnings management behavior, thus reducing analyst forecast bias. These results are consistent with the logic that digital technology innovation enables managers to use visual earnings management to suppress earnings manipulation and reduce analyst forecast bias. The conclusion of this paper expands the research scope of the economic effect of technological innovation in the digital era, and has certain significance for enterprises to optimize digital innovation strategy and improve market transparency.

Keywords

Digital Technology Innovation; Surplus Management; Analyst Forecast Bias.

1. Introduction

Over the past four decades, China's economy has grown rapidly and its financial market development has attracted worldwide attention. Digital innovation has played a central role in this process and has thrived with it. From e-commerce to mobile payments, and from smart manufacturing to artificial intelligence, Chinese companies have actively explored and used digital technologies to drive economic transformation and financial innovation. Among them, remarkable achievements have been made in digital technology innovation in ICT, big data and cloud computing. As China's National Development and Reform Commission pointed out in its report, "the digital economy is a strategic driver of future development and an important force for high-quality, efficient and high- quality development." However, while digital innovation brings great potential and contribution to China's economy, it also contains potential risks. Excessive pursuit of digital technology innovation by enterprises may lead to problems such as inadequate risk prevention and management, or even immature technology and non-standard application. In order to ensure the stability of the financial market, it is necessary to pay attention to the impact of digital technology innovation on the profitability and financial status of enterprises and prevent possible risks. Therefore, in order to ensure the stability of the financial market and promote the development of the real economy and the high-quality growth of the national economy, it is necessary to conduct in-depth research on the impact of enterprises' digital technology innovation on the economy. At present, the academic community is extensively studying the digital economy, which is regarded as a transformative force that has profoundly changed the form of business operation and management not only through business model innovation, but also by improving efficiency, innovation and competitiveness. Therefore, digital economy is regarded as an important research field, which is widely used in academic research, theoretical discussion and practical application, providing more possibilities for the future development of enterprises and the construction of capital markets.

The academic community has studied the impact of digital transformation on enterprises from different perspectives, but there are few studies on digital technology innovation. Khan et al. (2022) argued that big data analysis technology and digital platform capabilities can improve the agility and innovation ability of enterprises; Wu et al. (2021) found that digital transformation of enterprises can significantly improve stock liquidity; Zhao et al. (2021) believed that digital technology can improve the total factor productivity of enterprises. These studies help to better understand the positive impact of enterprise digital transformation. However, the current discussion on the economic impact of digital technology innovation in enterprises is not in-depth enough. Based on previous literature, this paper focuses on the impact of digital technology innovation on analyst forecast bias.

The impact of digital technology innovation on analyst forecast bias is controversial. On the one hand, digital technology innovation helps to reduce analyst forecast bias. Luo et al. (2021) argued that the digital transformation of enterprises is likely to improve their internal data mining and analysis capabilities, thus increasing the transparency of accounting information and enhancing the supervisory role of management. The improvement of accounting information quality can effectively alleviate the information asymmetry between analysts and enterprises, strengthen the effectiveness of management supervision, and thus reduce the over-reaction of management and the forecast deviation of analysts. On the other hand, the digital technology innovation of enterprises may increase the difficulty of analysts' prediction and exacerbate the forecast bias. Li Shufang (2019) argued that business complexity and the resulting organizational complexity will increase the complexity of a company's accounting information. Li Min (2022) argued that the complexity of accounting information will affect the quality of the company's accounting information disclosure, leading to a decline in the accuracy of analysts' forecasts.

However, there is little literature research on the impact and mechanism of enterprise digital technology innovation on analyst forecast bias. Therefore, using the panel data and related data of A-share listed companies from 2007 to 2021, this paper confirms the inhibitory effect of corporate digital technology innovation on analyst forecast bias. In addition, this effect is more obvious in the samples with low media attention, investor attention and institutional ownership. At the same time, this paper confirms that digital technology innovation can inhibit earnings management. Therefore, this paper empirically concludes that digital technology innovation can reduce analyst forecast bias by inhibiting firm earnings management.

The main contributions of this paper are reflected in three aspects. First, this paper broadens the research on the economic consequences of corporate digital innovation. The existing literature discusses the impact of enterprise digital transformation comprehensively. For example, digital transformation promotes traditional enterprises to develop in the direction of informatization, digitalization and intelligence (Qi and Xiao, 2020), and also promotes the transformation and upgrading of enterprises. In contrast, there are relatively few studies on the economic effects of digital technology innovation. Therefore, this paper further focuses on the field of digital technology innovation and explores its impact on analyst forecast bias from the perspective of economic consequences. Secondly, this paper broadens the research scope of the influencing factors of analyst forecast bias. The current literature mainly studies the influencing factors of analyst forecast bias at the analyst, firm and information levels. For example, the study by Zhang Zongxin et al. (2017) emphasizes that an analyst's professional experience in China's financial market directly affects his/her ability to forecast earnings. Fang Junxiong (2011) pointed out that there is a significant positive correlation between firm size and stock concentration and analysts' forecast bias. The research of Gu Wenlin et al. (2015) shows that there is a positive correlation between the improvement of information quality and the accuracy of analysts' forecasts. With the advent of the era of digital economy, the importance of digital technology innovation in the development of enterprises has become increasingly prominent. However, the research on the relationship between digital innovation and analyst forecast bias is still limited. Therefore, it is necessary to further explore the mechanism of digital innovation influencing analyst forecast and identify the potential impact path. Thirdly, this paper can provide policy makers with in-depth insights into digital technology innovation of enterprises, which can provide new insights for optimizing digital economy policies and developing incentives. Understanding how digital technology innovation affects analysts' forecast bias will enable governments and regulators to more accurately evaluate performance and value, formulate more scientific and reasonable regulatory policies, maintain market stability and fairness, and realize the synergy effect between digital technology innovation and enterprise development.

The structure of this paper is as follows: the second part is the literature review, the third part is the research hypothesis, the fourth part is the empirical design, the fifth part is the empirical results and analysis, the sixth part is the further heterogeneity analysis and mechanism verification, and the seventh part is the conclusion.

2. Literature Review

2.1. Digital Technology Innovation

At the beginning of the research, this paper first needs to clarify the definition of digital technology innovation. Digital technology innovation is the process of combining digital and physical components to create innovative results such as new products, new services and new business models. Subsequent research has deepened and broadened the connotation of digital technology innovation. From a broader perspective, digital technology innovation refers to the process and result of companies and organizations creating new products, processes, organizations and business models based on digital technology (Yoo et al., 2012; Nambisan et al., 2017). In this definition, digital technology refers to information, computing, communication and connectivity technologies and their combination, including artificial intelligence, big data, cloud computing and blockchain (Vial, 2019), while the term innovation refers to innovation processes and innovation outcomes, which are embodied in patent output in most studies. At the same time, this definition emphasizes three characteristics of digital technology innovation: first, the combination, that is, the innovation process emphasizes the use of information, computing, communication and connectivity technology combination, rather than a single technology; The second is growth, that is, digital innovation can be continuously improved and modified due to the characteristics of data homogeneity and recodibility of digital technology (Yoo et al., 2012; Ciriello et al., 2018); Third, convergence: digital innovation can break the boundaries of industries, organizations, departments and even products, making various boundaries blurred (Nambisan et al., 2017; Liu et al., 2020).

Compared with the research on digital technology innovation, the focus of existing academic research is to explore the impact of digital transformation on enterprises themselves, mainly focusing on the application of digital technology in business areas such as production and operation (Wang, 2021). Digital transformation refers to the development of digital technologies and supporting capabilities to create dynamic digital business models. At the micro level, the application of digital technology can improve the data collection, storage and analysis capabilities of enterprises, reduce the information asymmetry between enterprises, and help enterprises create more value (Jiao, 2020); It can reduce operational risks, ease financial constraints and reduce agency costs caused by default risks (Wang et al., 2022). The

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above research mainly deals with the positive impact of digital transformation, which may also bring negative impact to enterprises. The introduction of digital technology will lead to the disruption of the overall system of the enterprise, and the related costs will increase with the number and type of digital technology introduced (Qi and Xiao, 2020).

From the macro perspective, digital transformation has a certain impact on the performance of enterprises in the capital market. The digital transformation of enterprises can effectively improve the liquidity of stocks (Wu et al., 2021), reduce the synchronization of stock prices (Lei et al., 2022), and inhibit the risk of stock price crash (Lin, 2022), which has certain reference significance for further improving the efficiency of capital market and information transmission efficiency.

Digital technology innovation is different from digital transformation. The former focuses on new breakthroughs and changes in digital technology itself, while the latter focuses on the application of digital technology, that is, the application of digital technology to create new products, improve production processes, change organizational forms and innovate business models (Yoo et al., 2012; Bharadwaj et al., 2013; Liu et al., 2020). Therefore, digital technology can be regarded as the technical foundation of digital transformation, and its innovation process plays an important role in the effectiveness of digital transformation. Many previous literatures on digital transformation regard digital technology as an established fact and do not distinguish the concepts of digital technology innovation and digital transformation. Therefore, the impact of digital technology innovation is not clearly distinguished theoretically and empirically, so the impact of the two is not distinguished. For example, some literature discusses the impact of digital transformation on auditors' risk decisions (Zhu et al., 2023) and the quality of accounting information (Luo et al., 2023).

In addition, although the literature analyzing the impact of digital technology innovation on enterprises has gradually increased in recent years, which provides useful supplementary information for the research in the field of digital technology innovation, there are still obvious research gaps. In the existing literature, case studies and text analysis are mainly used to study the impact of digital technology innovation. For example, digital technology innovation can promote enterprises to reduce the information asymmetry between organizational departments, improve the ability of resource integration, and enhance the operational efficiency and financial performance of enterprises (Svahn et al., 2017). Innovating products and processes through digital technology can improve customer satisfaction and thus enhance customer loyalty (Balci, 2021). However, there are still some gaps in the research on the impact of digital technology innovation. First, in terms of research paradigms, the current academic views are mainly based on cases and theoretical analysis, and there are few empirical studies with large samples to explore the consequences of the impact of digital technology innovation. Second, in terms of measurement indicators, most literature relies on the annual report of enterprises to describe the degree of their digital transformation and application of digital technology (Wu et al., 2021; Zhao et al., 2021; Zhang et al., 2021). However, the description of digital technology in the annual report of enterprises is limited, the text information may be deliberately tamper with by the management, and the phenomenon of "saying but not doing" makes it difficult to accurately measure the level of digital technology innovation of enterprises. To sum up, there are still relatively few empirical studies on the impact of digital technology innovation.

2.2. Analyst Forecast Bias

Analysts play an important role in information intermediaries and capital markets. The most important job of analysts is to evaluate the value of companies and make appropriate investment recommendations to investors. Compared with ordinary retail investors, analysts have professional financial knowledge, can obtain market information efficiently and timely,

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and accurately interpret market information. Through the collection and evaluation of disclosed and undisclosed information, analysts analyze the future potential of listed companies, predict accounting earnings, and provide suggestions on stock trading or holding on this basis.

Analysts' work should first be based on complete information, and the quality of information disclosure has an important impact on the prediction results. From the perspective of public information, the information disclosed by listed companies has a direct impact on the accuracy of analysts' forecasts. Wang et al. (2017) used text analysis to quantify risk disclosure in annual reports, and found empirical evidence that the higher the frequency of risk disclosure, the higher the accuracy of analysts' forecasts. In addition, the complexity of business, accounting policies, audit quality and earnings management will affect the content and quality of corporate information disclosure, and thus affect the analyst forecast. Wu Xihao and Hu Guoliu et al. (2015) found that the conservatism of accounting information has a significant impact on analysts' earnings forecasts. The research of Dong et al. (2017) confirmed that internal control quality has a positive effect on analysts' earnings forecast.

Second, analysts themselves directly affect the quality of their reports. The existing research results show that the process of analysts producing analysis reports is also the process of information processing, which is affected by the overall ability of analysts, including the way of thinking, cognitive level, professional experience and knowledge reserve. Fang and Yasuda's (2009) research shows that analysts with good reputation do not distort research reports for their own interests, but tend to publish independent research reports to increase the prediction accuracy. The research of Bradley et al. (2022) confirmed that analyst reputation has a certain inhibitory effect on the forecast bias caused by conflicts of interest. The existing literature shows that analysts not only obtain private information from public sources, but also obtain private information through communication with company management and on-site research. Clement (1999) regarded private communication between analysts and management as a favorable condition for obtaining potential information.

Macro environment plays an important role in corporate information environment and is an important scene of analysts' work and life. Its possible impact on analysts' cognitive habits, emotional fluctuations and behavioral decisions cannot be ignored. In the context of global corporate information disclosure, many studies have focused on analysts' earnings forecasting. Tan et al. (2021) found that the application of international accounting standards has improved the forecast accuracy of foreign analysts. Related literature on China's financing and securities system points out that the lifting of short sale constraints has prompted analysts to make optimistic forecasts (Wang and Luo, 2017). Chu (2019) and other scholars also verified the above conclusions and confirmed the "correction effect" of short sale mechanism on analysts' earnings forecast bias. In addition, some researchers believe that macroeconomic factors such as the development of the Internet, the opening of high-speed trains, media attention, external audit, bond market credit rating and economic policy uncertainty have a positive effect on the improvement of the overall information environment of enterprises.

2.3. Literature Review

The existing literature pays more attention to the economic impact of digital transformation on small and micro enterprises, which is mainly reflected in business model, economic performance and innovation performance. Although some researchers have linked enterprise digital transformation with comparability of accounting information in recent years, they believe that enterprise digital transformation can improve the quality of accounting information (Luo Xiying et al., 2023) and effectively alleviate the decision risk of auditors (Zhu Guanping et al., 2023). However, there is still a lack of literature on the impact of enterprise digital technology innovation on analyst forecast bias.

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At the same time, since enterprise digital technology innovation is the technical support of digital transformation, most of the previous literature on digital transformation does not distinguish between digital technology innovation and digital transformation, and fails to clearly separate the impact of digital technology innovation on analyst forecast bias at the theoretical and empirical levels. Therefore, it is necessary to conduct independent analysis on the impact of digital technology innovation. On this basis, this paper investigates the impact of digital technology innovation on analyst forecast bias and its underlying mechanism, thereby broadening the micro-level research on the operation of digital economy and providing new insights for firms to formulate digital technology innovation strategies.

3. Research Hypotheses

The existing literature shows that the quality of accounting information has a significant impact on analyst forecast bias. Digital technology innovation can improve the quality of accounting information by improving the quality of internal control, inhibiting earnings management and improving information asymmetry, thus affecting the analyst forecast bias to a certain extent.

First of all, digital technology innovation improves the quality of internal control of enterprises and provides internal basic conditions for improving the quality of accounting information (Wang et al.,2023). The internal control system of enterprises has five aspects, namely risk assessment, control target design, control activities, information, communication and supervision mechanism, which play an important role in meeting the needs of enterprise risk management, financial reporting and compliance. Enterprise digital technology innovation connects every link in enterprise management with the system, and realizes the internal intelligent management of the enterprise with the data sharing and evaluation of the internal control node of each link in the system, improves the quality and efficiency of the internal management of the enterprise (Sun Lingrong,2023), and effectively realizes the informatization and digitalization of enterprise operation. Constitute the fundamental condition for the quality of enterprise accounting information to be effectively improved.

Secondly, enterprise digital technology innovation can inhibit enterprise earnings management behavior, and provide supervision and management guarantee for improving enterprise information comparability. (Luo, 2022) Chinese scholars define earnings management as the behavior that enterprise management, on the basis of following accounting standards, chooses supervisors through accounting policies and accounting estimates to achieve the purpose of increasing or decreasing earnings and maximize the interests of the subject. Based on principal-agent theory, managers may choose earnings management to whitewash financial data for their own interests, thus reducing the quality of accounting information (Ye and Wang, 2022). The innovation of digital technology has led to drastic changes in the enterprise ecosystem and fundamental changes in the decision-making of the stakeholders who work closely with the enterprise.

Third, enterprise digital technology innovation can improve information asymmetry and create a good information environment for improving the quality of accounting information (Du, 2023). Enterprise digital technology innovation involves a wide range of areas and mainly goes through four stages: R&D, supply, production and sales. Digital technology has realized the transformation of information in all links to standardized data, making enterprise business processes more standardized, standardized and transparent, and improving enterprise information asymmetry. Once the problem of information asymmetry is solved, information providers will no longer use information advantages to affect the normal disclosure of accounting information (Nie et al., 2022), and the quality of accounting information will no longer be affected by poor information.

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The forecast of securities analysts is mainly based on the accounting information of listed companies (Gu et al., 2015). The improvement of accounting information disclosure quality will reduce the deviation of analysts' forecast (Wu et al., 2016). In terms of earnings management, Liu Huiqin (2020) argued that high-quality information disclosure, especially the readability of annual reports, can reduce the deviation of analysts' earnings forecasts. In terms of the impact of performance forecast, the higher the quality of corporate accounting information disclosure is, the more accurate information can be provided to financial analysts to reduce the analyst's own performance forecast bias (Fang, 2007). From the perspective of sample stock price prediction, Dai et al. (2011) found that firms with better information readability generally have better analyst forecast quality, and the risk of stock market crash caused by information opacity is lower. Therefore, improving the quality of accounting information can effectively reduce the analyst forecast bias.

Based on the above analysis, this paper proposes Hypothesis H1a:

H1a: Digital technology innovation helps to reduce analyst forecast bias.

However, digital technology innovation can also bring a series of adverse effects to the organization, such as system imbalance and data security problems. These adverse effects will make it difficult for analysts to predict, which will increase the deviation of analysts' prediction.

Digital technology innovation will cause overall systemic disruption and increase the complexity of a company's business. At the same time, the related costs will increase with the number and type of digital technologies deployed (Qi and Xiao, 2020), and the company's financial stability will weaken, making analysts' prediction more difficult. Digital technology innovation can also lead to security and privacy issues (Ragesh and Baskaran, 2016). For example, as the connectivity between systems and organizations increases, there are threats to data security (Ren and Zhang, 2022). These security and privacy issues increase operational risks and uncertainty for enterprises, making it more difficult for analysts to make predictions.

Digital innovation will also pose a challenge to organizational performance. Leveraging emerging digital platforms can bring benefits to organizations, but this first-mover advantage needs to be built on the basis of benefiting the organization. For example, while developing business models, the digitalization process also increases management costs and labor costs (Ren and Dai, 2015), which may offset each other in terms of performance. In this way, the dual effect of digital technology innovation may make it difficult for analysts to predict, and the forecast deviation will increase accordingly.

Based on the above analysis, this paper proposes Hypothesis H1b.

H1b: Digital technology innovation will increase analysts' forecast bias.

4. Empirical Design

4.1. Model Setting

In order to test the impact of enterprise digital technology innovation on analysts' forecast bias, the following regression model is set with reference to Wang et al. (2022) and Liu (2022):

$$\boldsymbol{FERROR_{i,t} = \beta_0 + \beta_1 DIG_{i,t} + \beta_2 Controls_{i,t} + \sum YEAR + \sum IND + \varepsilon_{i,t}} \quad (1)$$

Among them, the explained variable represents the deviation of earnings forecast made by analysts for company i in year t, and the explanatory variable represents the degree of enterprise digital technology innovation.

*FERRORi,tDIGi,t*According to the previous literature, this paper controls other factors that may affect analysts' forecast bias, and the specific variables are defined in Table 1. *Controls* In addition, this paper also controls the influence of industry fixed effect () and year fixed effect ().

$INDYEAR$In order to control the potential cross-section correlation, the standard errors are clustered by the company dimension in all regressions. $\beta 1$ We focus on the estimated regression coefficients. If the estimated value is significantly positive, it indicates that enterprise digital technology innovation will increase analyst forecast bias; If the estimated value is negative, it indicates that enterprise digital technology innovation has a restraining effect on analyst forecast bias.

4.2. Variable Setting

1) Explained variable -- analyst forecast deviation$FERROR$

Forecast bias refers to the difference between the consensus analyst forecast for earnings and the actual earnings. However, there is a time lag between the expected period and the actual period during which the equity may be adjusted. In order to ensure the comparability between the forecast value of earnings and the forecast value of actual earnings, the mean of the most recent earnings per share forecast of each securities analyst for the current year is selected as the analyst's forecast value of earnings, so as to minimize the time difference between the forecast period and the actual period.$Mean(FEPS)$.

After the change of share capital, the model still has the problem of over-dependence on the stock price.

Therefore, referring to the practice of Wu (2016) and Chu (2019), the initial stock price () of the company is used to further adjust the model. $PRICE$ Finally, the magnification is 100 times to visualize the regression results.

$FERROR$The final indicators are as follows:

$$\boldsymbol{FERROR} = \frac{\boldsymbol{Mean(FEPS) - MEPS}}{\boldsymbol{PRICE}} \times \mathbf{100} \tag{2}$$

Where, is the average of the latest earnings per share forecast of each securities analyst in the current year; $Mean(FEPS)MEPS$Is actual earnings per share; $PRICE$ Is the company's initial stock price.

2) Explanatory variable: enterprise digital technology innovationDIG

This paper uses the number of authorized digital technology patents to measure enterprise digital technology innovation. Patents have the ability to directly reflect the level of technological innovation of enterprises. The authorized digital technology patents have the characteristics that can be directly applied to the next stage, which is more objective and accurate in measuring the enterprise digital technology innovation. This paper uses the Derwent Innovation platform as a patent retrieval and analysis tool. The platform collects high-quality patent information from 156 countries or regions around the world. In terms of keywords, this paper selects five core technologies involved in the new infrastructure, namely artificial intelligence, blockchain (parallel chain, relay chain, Ethereum and other blockchains), cloud computing, big data, Internet (mobile Internet, industrial Internet, cloud platform, Internet of Things), etc. (Teece et al., 2018; Chen et al., 2022).

Finally, this paper obtains the number of digital technology patent applications newly added by enterprises every year, and then measures the scale of digital technology innovation of enterprises. Compared with using text analysis to mine the word frequency of annual reports, it is more direct and effective to judge the level of digital technology innovation by the technical field of the patent.

3) Control variables$Controls$

In addition to the firm digital technology innovation that this paper focuses on, there are some firm and analyst characteristics that affect analyst forecast bias. Referring to the existing

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research of Wang Haifang et al. (2022), the specific control variables selected in this paper are: company size (), asset-liability ratio (), return on assets (), company growth (), ownership concentration (), job integration (), audit quality (), analyst attention (), annual stock return (), annual stock turnover rate (), and Tobin's Q().
$Size LEV ROA Growth TOP Dual Audit AUM YTD TOY Tobin\ Q YEAR$And represent that this paper controls year and industry fixed effects, respectively. IND See Table 1 for detailed definitions.

Table 1. Variable definition and description1

Variable symbols	Variable name	Variable description
FERROR	Analyst forecast bias	(Mean of each security analyst's most recent EPS forecast for the year - Actual earnings per share)/company's stock price at the beginning of the period *100
DIG	Enterprise digital technology innovation	ln(number of new applications for five digital technology patents authorized by enterprises +1)
Size	Enterprise size	Natural logarithm of total assets
LEV	Asset-liability ratio	Total liabilities/total assets
ROA	Return on assets	Net profit/total assets
Growth	Growth of the company	Growth rate of operating income
TOP	Ownership concentration	Shareholding ratio of the largest shareholder
Dual	Two in one	The combination of chairman and general manager is equal to 1, otherwise it is equal to 0
Audit	Quality of audit	1 if audited by a top ten accounting firm, 0 otherwise
AUM	Analyst attention	Log of the number of analysts followed
YTD	Annual individual stock returns	The return on investment of individual stocks held within a year
TOY	Annual turnover rate of stocks	The ratio of the number of shares traded in a year to the number of shares outstanding
Tobin Q	Tobin Q	(Total market capitalization + total liabilities)/total assets
YEAR	Year	The duration of the enterprise
IND	Industry	CSRC 2012 Industry classification

4.3. Sample Interpretation and Data Sources

This paper takes China's A-share listed companies as the research object, based on the panel data and related data of A-share listed companies from 2007 to 2021. The data of digital technology innovation of enterprises in this paper come from Derwent Innovation Platform, and the rest of the data are* from CSMAR database. Excluding the enterprises with missing data and fewer than 3 analysts, a total of 16,964 observations were obtained. In order to avoid the extreme value of the data, the sample variables were winsorized by 1%.

4.4. Descriptive Statistics

The descriptive statistics of the main variables in this paper are shown in Table 2. $FERROR$ The mean, maximum and minimum values of are 2.378, -2.278 and 15.35, respectively, indicating that the analyst forecast error is large, and the optimistic forecast bias is common. $FERROR$The standard deviation of is 2.481, indicating that there is a significant difference in analyst forecast bias among enterprises. DIGThe value range is 0 to 4.554, and the standard deviation is 0.979, indicating that there are great differences in the degree of digital technology innovation among non-financial listed companies. DIGThe mean value of is 0.627, indicating that the overall

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degree of digital technology innovation of non-financial listed companies in China is low. In terms of control variables, there is no obvious abnormal skewness, which is within a reasonable range.

Table 2. Descriptive statistics of main variables2

Variables	Sample size	Mean	Standard deviation	Minimum	Maximum
FERROR	16964	2.378	2.481	2.278	15.350
DIG	16964	0.627	0.979	0.000	4.554
Dual	16964	0.267	0.442	0.000	1.000
Growth	16964	0.326	0.809	0.623	5.471
TOP	16964	35.860	15.260	8.860	75.050
Size	16964	22.590	1.348	20.240	26.660
Audit	16964	0.091	0.288	0.000	1.000
LEV	16964	0.431	0.198	0.056	0.853
ROA	16964	0.057	0.050	0.104	0.217
TobinQ	16964	2.148	1.366	0.869	8.476
AUM	16964	2.324	0.749	1.099	3.871
YTD	16964	0.242	0.679	0.689	3.010
TOY	16964	3.295	2.357	0.313	11.700

5. Empirical Results and Analysis

5.1. Analysis of Benchmark Regression Results

Table 3. Benchmark regression results3

Variables	(1)	(2)	(3)	(4)
	FERROR	*FERROR*	*FERROR*	*FERROR*
DIG	0.231 * * *	0.215 * * *	0.203 * * *	0.197 * * *
	(9.967)	(8.035)	(8.934)	(7.776)
Size			0.029	0.008
			(1.074)	(0.281)
LEV			0.693 * * *	0.734 * * *
			(4.477)	(4.665)
ROA			21.901 * * *	23.186 * * *
			(25.890)	(27.849)
TOP			0.002	0.002
			(1.347)	(1.499)
Dual			0.127 * * *	0.053
			(2.700)	(1.175)
Growth			0.092 * * *	0.094 * * *
			(2.768)	(3.201)
Audit			0.239 * *	0.212 * *
			(2.423)	(2.304)
AUM			0.087 * * *	0.092 * * *
			(2.804)	(2.950)
YTD			0.345 * * *	0.031
			(10.203)	(0.688)
TOY			0.011	0.001
			(1.044)	(0.137)
TobinQ			0.007	0.091 * * *
			(0.356)	(4.514)
Intercept term	2.523 * * *	2.507 * * *	2.659 * * *	3.744 * * *
	(77.143)	(9.666)	(4.533)	(5.762)
Sample size	16964	16964	16964	16964
R^2	0.008	0.107	0.218	0.300
Industry & Year	Not controlled	Control	Not in control	Control

Note: ***, ** and * indicate significance at the levels of 1%, 5% and 10%, respectively. The figures in parentheses are t val ues adjusted by robust standard errors.

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Table 3 shows the benchmark regression results of this paper. Columns (1), (2) and (3) of Table 3 show that the coefficient of enterprise digital technology innovation is significantly negative at the level of 1% under the condition of no control variables and fixed effects, only fixed industry and year effects, and only control variables respectively, which initially indicates that enterprise digital technology innovation is significantly negatively correlated with analyst forecast bias. However, column (4) controls variables and fixed effects at the same time, and the cross-industry and cross-time differences are eliminated, and some factors affecting analyst forecast bias are absorbed. Under this premise, the coefficient of enterprise digital technology innovation is still significantly negative at the level of 1%, which further indicates that enterprise digital technology innovation has a significant inhibitory effect on analyst forecast bias, and the hypothesis is verified. $H1a$.

5.2. Robustness Test

1) Change the explained variable

Referring to the research of Chu et al. (2019) and Li et al. (2018), the explained variable () is replaced by analyst earnings forecast bias () and analyst forecast optimism bias (), and the calculation method is as follows: Equations (3) and (4). $FERRORAPEAOE$After replacing the explained variable, the original model is used to re- test the regression. Table 4 shows that the research conclusion remains unchanged, indicating that the regression of this study is highly robust.

$$\boldsymbol{APE = \frac{|Mean(FEPS) - MEPS|}{PRICE} \times 100} \tag{3}$$

$$\boldsymbol{AOE = \frac{Mean(FEPS) - MEPS}{EPS} \times 100} \tag{4}$$

Table 4. Regression results of replacing explained variables4

	(1)	(2)
Variables	APE	AOE
DIG	0.213 * * *	0.102 * * *
	(8.343)	(3.966)
$Size$	0.072 * *	0.082 * * *
	(2.506)	(2.928)
LEV	0.906 * * *	0.125
	(5.869)	(0.708)
ROA	18.530 * * *	20.698 * * *
	(21.696)	(30.895)
TOP	0.003 * *	0.001
	(2.115)	(0.524)
$Dual$	0.024	0.125 * *
	(0.546)	(2.525)
$Growth$	0.050 *	0.053
	(1.804)	(1.633)
$Audit$	0.192 * *	0.026
	(2.159)	(0.335)
AUM	0.043	0.071 * *
	(1.363)	(2.147)
YTD	0.246 * * *	0.488 * * *
	(5.417)	(12.126)
TOY	0.038 * * *	0.018
	(3.442)	(1.450)
$Tobin\ Q$	0.006	0.293 * * *
	(0.289)	(12.319)
Intercept term	1.547 * *	4.560 * * *
	(2.359)	(6.811)
Sample size	16964	16963
R^2	0.285	0.170
Industry & Year	Control	Control over

2) Change the explanatory variables

Some scholars believe that the original measure of the explanatory variable, the number of patents granted by enterprises, has a certain lag. Therefore, this paper uses the application data of digital technology invention patent () and digital technology utility model patent () respectively to replace the explanatory variables. $DPIPTI$As shown in the regression results in Table 5, no matter how the level of enterprise digital technology innovation is measured, the estimated results are consistent with the results of the benchmark regression, that is, the benchmark regression in this paper is robust.

Table 5. Regression results of changing explanatory variables5

	(1)	(2)
Variables	$FERROR$	$FERROR$
DTI	0.224 * * *	
	(7.343)	
PTI		0.153 * * *
		(4.449)
$Size$	0.006	0.020
	(0.211)	(0.688)
LEV	0.727 * * *	0.747 * * *
	(4.620)	(4.707)
ROA	23.209 * * *	23.129 * * *
	(27.865)	(27.719)
TOP	0.002	0.002
	(1.542)	(1.370)
$Dual$	0.052	0.049
	(1.166)	(1.093)
$Growth$	0.093 * * *	0.099 * * *
	(3.153)	(3.337)
$Audit$	0.207 * *	0.220 * *
	(2.250)	(2.367)
AUM	0.090 * * *	0.080 * *
	(2.907)	(2.564)
YTD	0.029	0.034
	(0.652)	(0.773)
TOY	0.001	0.001
	(0.081)	(0.130)
$Tobin\ Q$	0.093 * * *	0.087 * * *
	(4.571)	(4.272)
Intercept term	3.709 * * *	4.026 * * *
	(5.694)	(6.193)
Sample size	16964	16964
R^2	0.299	0.297
Industry & Year	Control	Control

3) Change the regression sample

The sample used above is firms with at least three analysts following them. In order to avoid sample bias, this paper selects four samples with at least 4, 5, 6 and 7 analyst followers () for regression. $AnaAttention$ The regression results are shown in Table 6, indicating that the conclusions of this paper are robust.

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Table 6. Regression results of changing regression samples6

	(1)	(2)	(3)	(4)
Variables	$FERROR$	$FERROR$	$FERROR$	$FERROR$
	4 or higher	5 or more	6 or higher	7 or higher
DIG	0.212 * * *	0.204 * * *	0.206 * * *	0.201 * * *
	(9.336)	(8.802)	(8.883)	(8.322)
$Size$	0.037	0.029	0.035	0.038
	(1.311)	(1.009)	(1.178)	(1.239)
LEV	0.661 * * *	0.688 * * *	0.630 * * *	0.637 * * *
	(4.178)	(4.187)	(3.750)	(3.629)
ROA	20.926 * * *	20.147 * * *	19.161 * * *	18.461 * * *
	(23.917)	(22.151)	(20.421)	(18.977)
TOP	0.002	0.001	0.001	0.001
	(1.159)	(0.756)	(0.842)	(0.511)
$Dual$	0.114 * *	0.116 * *	0.079	0.078
	(2.404)	(2.429)	(1.634)	(1.540)
$Growth$	0.097 * * *	0.105 * * *	0.113 * * *	0.117 * * *
	(2.958)	(3.150)	(3.238)	(3.253)
$Audit$	0.243 * *	0.209 * *	0.188 *	0.194 *
	(2.410)	(2.024)	(1.767)	(1.755)
AUM	0.067 * *	0.082 * *	0.076 *	0.087 *
	(1.997)	(2.179)	(1.871)	(1.921)
YTD	0.313 * * *	0.309 * * *	0.307 * * *	0.252 * * *
	(9.197)	(8.713)	(8.748)	(7.157)
TOY	0.016	0.017	0.015	0.011
	(1.524)	(1.566)	(1.345)	(0.868)
$Tobin\ Q$	0.005	0.006	0.000	0.011
	(0.243)	(0.341)	(0.019)	(0.597)
Term of intercept	2.487 * * *	2.528 * * *	2.403 * * *	2.201 * * *
	(4.125)	(4.092)	(3.823)	(3.392)
Sample size	15496	14098	12842	11639
R^2	0.215	0.212	0.210	0.205
Industry & Year	Control	Control	Control	Control

5.3. Endogeneity Test: Instrumental Variable Method

The research samples in this paper may be affected by unobserved causal relationships or exogenous variables, which may cause bias problems. Therefore, in order to further control the endogenous sources, the instrumental variable method is used to deal with this problem. Referring to the research of Wang et al. (2023), this paper uses the enterprise digital technology innovation level () based on the industry average as the instrumental variable to conduct a two-stage regression on analyst forecast bias. DIG_IND Because companies in the same industry often face similar industrial characteristics and external environment, their digital technology innovation level will be affected by other companies. However, there is no correlation between the level of digital technology innovation based on the industry average and the analyst forecast deviation, which meets the conditions of instrumental variable correlation and exogeneity. The first-stage regression results in Column (1) of Table 7 show that the coefficient of the industry average based digital innovation level () is significantly positive at the level of 1%, that is, there is a strong correlation between the instrumental variable and the endogenous explanatory variable.

DIG_INDDIG_INDDIG Column (2) shows the regression results of the second stage, the level of enterprise digital technology innovation () is significantly negatively correlated with analyst forecast bias (), and there is no weak instrumental variable and unidentifiable problem, which is consistent with the main regression.

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$DIGFERROR$Therefore, the research conclusion is still robust after controlling the endogeneity effect.

Table 7. Endogeneity test results7

	(1)	(2)
Variables	DIG	$FERROR$
IND	1.006 * * *	
	(22.552)	
DIG		0.267 * * *
		(2.762)
$Size$	0.123 * * *	0.000
	(6.757)	(0.005)
LEV	0.044	0.732 * * *
	(0.516)	(4.592)
ROA	0.140	23.184 * * *
	(0.542)	(27.787)
TOP	0.001	0.002
	(1.353)	(1.539)
$Dual$	0.037	0.055
	(1.328)	(1.217)
$Growth$	0.014	0.093 * * *
	(1.234)	(3.153)
$Audit$	0.047	0.209 * *
	(0.839)	(2.255)
AUM	0.094 * * *	0.099 * * *
	(5.969)	(3.045)
YTD	0.033 * *	0.029
	(2.250)	(0.643)
TOY	0.005	0.002
	(0.985)	(0.157)
$Tobin\ Q$	0.020 * *	0.093 * * *
	(1.966)	(4.550)
Intercept term	2.816 * * *	3.544 * * *
	(7.111)	(4.924)
Sample size	16964	16964
R^2	0.374	0.296
Industry & Year	Control	Control

6. Further Analysis

6.1. Heterogeneity Analysis

1) Media Attention

News media plays a role in discovering, interpreting and disseminating company information. The research shows that the news media can effectively improve the information content of capital market by quickly mining and transmitting private information, and reduce the information collection cost of capital market participants. (Bloomfield, 2012) Secondly, Luo (2012) believed that higher media attention can reduce the double agency cost of a company and improve its own governance level accordingly. It can be seen that the increase of media attention can improve the corporate governance level and the quality of accounting information, thus reducing the analyst forecast bias. Digital technology innovation also has an inhibitory effect on analyst forecast bias by inhibiting earnings management. Therefore, we expect that digital technology innovation has a more significant inhibitory effect on analyst forecast bias in firms with low media attention.

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Referring to the method of Luo (2012), this paper uses the number of news articles obtained by CNRDS as the measure of media attention of each company, and divides them into high and low groups according to the annual median of the industry. Column (1) and column (2) of Table 8 are the high and low media attention groups, respectively. The regression results are significantly different between the two groups by Chow test. According to the regression results, the inhibition effect of digital technology innovation on analyst forecast bias is more obvious in companies with low media attention, which is in line with the above expectations.

Table 8. Regression on heterogeneity of media attention8

	(1)	(2)
Variables	$FERROR$	$FERROR$
	high	low
DIG	0.184 * * *	0.203 * * *
	(5.649)	(5.696)
$Size$	0.003	0.065
	(0.075)	(1.467)
LEV	0.872 * * *	0.484 * *
	(3.878)	(2.457)
ROA	21.053 * * *	25.684 * * *
	(19.200)	(22.221)
TOP	0.002	0.002
	(0.773)	(1.133)
$Dual$	0.093	0.015
	(1.369)	(0.278)
$Growth$	0.175 * * *	0.029
	(3.812)	(0.772)
$Audit$	0.281 * *	0.069
	(2.556)	(0.431)
AUM	0.003	0.171 * * *
	(0.057)	(4.301)
YTD	0.008	0.063
	(0.136)	(0.998)
TOY	0.000	0.007
	(0.011)	(0.484)
$Tobin\ Q$	0.082 * * *	0.102 * * *
	(3.095)	(3.599)
Intercept term	4.297 * * *	4.445 * * *
	(4.684)	(4.572)
Sample size	8202	8762
R^2	0.297	0.321
Industry & Year	Control	Control
Chow test	2.28 * * *	

2) Investor attention

A large amount of investor attention will affect the judgment of corporate management and analysts. The research of Duan Shunling (2021) pointed out that the increase of investor attention will improve the risk awareness of enterprise management and inhibit the level of earnings management. Xu et al. (2021) found that investors' online search activities can provide market participants with additional information about stock market risks, which helps market participants better identify and predict the risk of stock price crash. And corporate digital technology innovation can also reduce analysts' forecast bias by inhibiting management earnings manipulation. Therefore, this paper predicts that the improvement of investors'

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attention can increase the risk awareness of enterprise management, alleviate the information asymmetry between enterprises and analysts, and reduce the analyst's forecast bias.

Based on the research of Zhang Wenfei et al. (2022), this paper obtains the search times of stock codes through China Research Data Service Platform (CNRDS), and then quantizes investor attention, which is divided into two groups according to the annual median of the industry. Column (1) and column (2) of Table 9 are the groups with high and low investor attention respectively. The regression passes the Chow test, and there are significant differences in the results between the two groups. According to the regression results, when investors' attention is low, the negative effect of corporate digital innovation on analyst forecast bias is more obvious, which verifies the above hypothesis.

Table 9. Heterogeneity regression of investor attention9

	(1)	(2)
Variables	$FERROR$	$FERROR$
	high	low
DIG	0.183 * * *	0.219 * * *
	(5.145)	(6.716)
$Size$	0.012	0.065 *
	(0.247)	(1.758)
LEV	0.859 * * *	0.691 * * *
	(3.244)	(3.903)
ROA	26.445 * * *	20.842 * * *
	(21.72)	(20.305)
TOP	0.006 * *	0.001
	(2.352)	(0.675)
$Dual$	0.073	0.039
	(0.942)	(0.809)
$Growth$	0.147 * * *	0.057 *
	(2.708)	(1.712)
$Audit$	0.228 *	0.183
	(1.803)	(1.560)
AUM	0.123 * *	0.091 * *
	(2.375)	(2.456)
YTD	0.045	0.103 *
	(0.620)	(1.851)
TOY	0.007	0.018
	(0.390)	(1.205)
$Tobin\ Q$	0.061 *	0.093 * * *
	(1.783)	(4.017)
Intercept term	3.563 * * *	4.701 * * *
	(3.139)	(5.567)
Sample size	6995	9969
R^2	0.337	0.282
Industry & Year	Control over	Control
Chow test	3.35 * * *	

3) Percentage of institutional ownership

Many scholars believe that institutional investors have a certain regulatory effect, which can improve the quality of corporate information disclosure and provide more reliable information for analysts' forecasts. Kong et al. (2017) believed that institutional investors can reduce the optimism of analysts' forecasts by exerting supervision effect. Qi (2019) believed that institutional investors constrained the company's operation and management and played the

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role of external supervision, thus reducing the deviation of analysts' forecasts. It can be seen that institutional investors can play the role of external supervision in corporate governance, restrict the speculation of corporate management, improve the transparency of accounting information, and thus create good conditions for analysts to forecast. From the perspective of inhibiting earnings management, digital technology innovation can reduce analysts' forecast bias. Therefore, we expect that the dampener effect of digital technology innovation on analyst forecast bias will be more obvious in firms with higher institutional ownership.

Referring to the research of Wang (2023), this paper divides the high (low) institutional ownership groups by the annual median of the industry, and then conducts regression and Chow test. Column (1) and column (2) are the groups with high and low institutional ownership, respectively. It can be seen from Table 10 that the inhibitory effect of corporate digital technology innovation on analyst forecast errors is more obvious in the group with low institutional ownership than in the group with low institutional ownership. The results pass the Chow test, and there are significant differences between the two groups of regression results. In conclusion, institutional investors play a regulatory role in companies, which promotes the improvement of corporate governance and accounting information quality, and is conducive to analysts' earnings prediction, which is consistent with the expectation of this paper.

Table 10. Heterogeneous regression of institutional ownership10

	(1)	(2)
Variables	$FERROR$	$FERROR$
	high	low
DIG	0.176 * * *	0.229 * * *
	(5.766)	(6.410)
$Size$	0.039	0.046
	(1.071)	(1.200)
LEV	0.621 * * *	0.851 * * *
	(3.107)	(3.962)
ROA	20.393 * * *	25.713 * * *
	(18.908)	(23.010)
TOP	0.002	0.003
	(0.990)	(1.470)
$Dual$	0.008	0.103 *
	(0.134)	(1.673)
$Growth$	0.075 * *	0.113 * *
	(1.986)	(2.571)
$Audit$	0.176	0.261 *
	(1.589)	(1.920)
AUM	0.003	0.223 * * *
	(0.077)	(5.172)
YTD	0.036	0.071
	(0.657)	(1.002)
TOY	0.004	0.012
	(0.275)	(0.874)
$Tobin\ Q$	0.102 * * *	0.072 * *
	(4.267)	(2.372)
Intercept term	2.787 * * *	4.374 * * *
	(3.364)	(4.953)
Sample size	8229	8735
R^2	0.294	0.317
Industry & Year	Control	Control
Chow test	2.33 * *	

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6.2. Mechanism Analysis

The above basic regression and a series of robustness tests confirm that enterprise digital technology innovation helps to reduce analysts' forecast bias, but this paper has not explored the specific mechanism between the two. According to the above theoretical deduction, considering that under the high agency problem, managers are prone to myopic and self-interested behaviors, and may whitewash financial data and hide negative news through earnings management, which damages the robustness of accounting information (Tong, Yao, 2023). The innovation of enterprise digital technology enables the management to conduct transparent earnings management on financial statements through digital, intelligent and visual methods, thus avoiding earnings manipulation (Qiu, 2022). Therefore, this paper argues that digital technology innovation may reduce analysts' forecast bias by inhibiting firms' earnings management behavior.

Based on the research of Li and Zhang (2018), this paper establishes the following model to test the mechanism of corporate earnings management. This paper uses DD model (), nonlinear manipulative profit () and modified Jones model () to measure the degree of earnings management. $DDMNLGFDisAcc$The higher the values of these three variables are, the higher the degree of earnings management is. As shown in columns (1), (2) and (3) of Table 11, after introducing digital technology innovation and earnings management behavior into the model, digital technology innovation has a negative impact on enterprises' earnings management, and it is significant at the levels of 10%, 5% and 1%, respectively. It can be seen that corporate earnings management is a major mechanism for digital innovation to affect analysts' forecast bias. The results show that digital technology innovation reduces analysts' forecast bias by inhibiting firms' earnings management behavior.

Table 11. Mechanism analysis of earnings management11

	(1)	(2)	(3)
Variables	DDM	$NLGF$	$DisAcc$
DIG	0.002 *	0.002 * * *	0.003 * * *
	(1.760)	(3.483)	(3.168)
$Size$	0.005 * * *	0.001 * *	0.001
	(3.533)	(2.065)	(0.788)
LEV	0.039 * * *	0.001	0.005
	(4.624)	(0.318)	(0.835)
ROA	0.191 * * *	0.685 * * *	0.490 * * *
	(6.361)	(47.214)	(21.652)
TOP	0.000	0.000 * *	0.000 * *
	(1.180)	(2.406)	(2.115)
$Dual$	0.005 * *	0.002	0.003 *
	(2.307)	(1.491)	(1.672)
$Growth$	0.010 * * *	0.004 * * *	0.007 * * *
	(4.420)	(5.980)	(5.084)
$Audit$	0.005	0.009 * * *	0.016 * * *
	(1.384)	(4.256)	(5.905)
AUM	0.006 * * *	0.002 * * *	0.001
	(3.700)	(2.986)	(1.084)
YTD	0.014 * * *	0.004 * * *	0.001
	(5.109)	(3.732)	(0.837)
TOY	0.003 * * *	0.001 * * *	0.001
	(6.076)	(4.157)	(1.531)
$Tobin\ Q$	0.005 * * *	0.004 * * *	0.004 * * *
	(4.471)	(7.376)	(4.250)
Intercept term	0.076 * *	0.013	0.001
	(2.459)	(0.826)	(0.051)
Sample size	14752	15201	16559
R^2	0.023	0.353	0.159
Industry & Year	Control	Control	Control

7. Conclusion

With the high penetration of digital technology under the new round of industrial revolution, digital technology innovation enabling enterprises to transform has become an important focus of China's high-quality economic development. Based on the sample data of A-share listed companies from 2007 to 2021, this paper empirically examines the impact of corporate digital technology innovation on analyst forecast bias. The results show that enterprise digital technology innovation can reduce analyst forecast bias, which is still valid after a series of robustness tests. Further mechanism analysis shows that digital technology innovation enables management to manage corporate earnings transparantly through visual means, inhibits earnings management behavior, and provides a supervision guarantee for enterprises to improve the comparability of accounting information, thus reducing analysts' forecast bias. At the same time, the impact of enterprise digital technology innovation on analyst forecast bias is heterogeneous, and the inhibitory effect of enterprise digital technology innovation on analyst forecast bias is more obvious in enterprises with lower media attention, investor attention and institutional ownership. The conclusions of this paper have important practical significance and enlightenment for giving full play to the role of analysts as information intermediaries and promoting the healthy development of the capital market.

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