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Article

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Firms' digital transformation and management earnings forecasts: Evidence from China

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Abstract

This paper examines the impact of firms' digital transformation on management earnings forecasts with a sample of Chinese firms. Using a deep learning model and textual analysis, we create a proxy for digital transformation based on the frequency of keywords related to digitization in firms' annual reports. Our empirical results reveal that firms that engage in more digital transformation are more likely to issue management earnings forecasts voluntarily, more often, and with greater precision. The findings are robust to alternative metrics of management earnings forecasts and digital transformation, after accounting for endogeneity, and after considering firms' future forecasts. Additional analyses on the transmission mechanisms suggest that digital transformation improves firms' information environment, enhances internal controls, and alleviates agency problems.

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1. Introduction

In the digital era driven by information technology, firms are motivated to digitize their intangible assets in order to gain a competitive advantage (Škare and Soriano, 2021; Vial, 2019; Wu et al., 2019). Digital technology, such as the internet of things, big data, and cloud computing, has improved firms' production and business models. Digital transformation (DT) has become an engine for economic development and plays an important role in consumption, production, investment, and employment. According to Zhai et al. (2022), DT means the

use of new digital technologies to enable major business improvements. Essentially, DT refers to employing digital assets in the operations, business models, and business strategies of a firm in order to increase its value. In developed economies, such as the United States, the digital economy increased at an annual rate of 6.3 percent from 2012 to 2020. The digital economy contributes 10.2 percent of the US gross domestic product (GDP). In China, the value of the digital economy increased from RMB 22.4 trillion in 2016 to 35.8 trillion in 2019.

Prior studies have investigated the effect of DT on productivity, product categories, innovation, customer value, and firm value (Battisti & Stoneman, 2010; Blichfeldt & Faullant, 2021; Chen & Srinivasan, 2019; Li et al., 2013; Zhai et al., 2022). In the context of capital markets, several studies examine the impact of DT on stock price crash risk (Jiang et al., 2022; Wu et al., 2022). In addition, several recent studies

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examine how DT impacts organizational transformation (Wessel et al., 2021), firm profits (Teece, 2018), and analyst forecast accuracy (Chen et al., 2022). However, the impact of firms' DT on financial reporting is underexplored. We consider the quality of accounting information disclosure a cornerstone of the capital market that impacts all involved parties for two reasons. First, high-quality information disclosure (management earnings forecasts [MEFs] are an important form of disclosure) can effectively mitigate the agency problem caused by information asymmetry in the capital market and promote more efficient allocation of resources (Healy & Palepu, 2001). In the United States, voluntary MEFs have become an important source of investor information in the capital market, and they are an important tool used by many firms to transmit information and influence stock prices and analyst forecasts (Beyer et al., 2010). Second, a corporate performance forecast is an important form of information disclosure for firms. Firms' active disclosure of high-quality performance forecasts (i.e., MEFs) not only help investors understand the company's prospects but also help them to evaluate investment decisions (Hirst et al., 2008) and contribute to stock liquidity (Boone et al., 2015). Other corporate disclosures, such as annual and quarterly reports, while useful, do not serve the purposes discussed by Healy and Palepu (2001), Beyer et al. (2010), Hirst et al. (2008), and Boone et al. (2015). Hence, it is imperative to study how DT affects disclosure quantity and quality. To circumvent the challenge of quantifying a firm's DT, we leverage recent advances in textual analysis to gauge the extent of DT based on the frequency in firms' annual reports of keywords related to digitization, such as artificial intelligence, blockchain, cloud computing, and big data (Chen et al., 2022; Zhai et al., 2022). Although the approach is indirect, it is a consistent measure of firms' use of digital assets and therefore accurately captures the extent of a firm's DT.

We argue that when firms use digital assets to engage in DT, they mention it frequently in their annual reports.¹ Most important, the increase in DT mitigates agency problems between management and shareholders and strengthens internal control (Jiang et al., 2022; Wu et al., 2022). As a result, firms improve their disclosures such as management earnings forecasts (MEFs). When firms engage in more voluntary disclosure, information intermediaries—such as financial analysts, industry experts, and financial media—further enhance the efficiency of the capital market (Healy & Palepu, 2001).

The objective of this paper is to examine the impact of corporate DT on MEFs from the perspective of disclosure quantity and quality. We perform our analyses using a sample of Chinese firms for two reasons. First, the availability of digital assets has grown rapidly in China, and therefore it is likely that firms have been undergoing significant DT. In terms of government policy, China has proposed the development of advanced manufacturing industries and promoted deep

integration between the digital economy and the real economy. Second, the stock market is less efficient in emerging markets. Low levels of corporate disclosure naturally impede the healthy development of the Chinese capital market. Moreover, agency problems due to information asymmetry between management and shareholders are more severe in China. Thus, China provides a good setting for our study of the impact of DT on MEFs.

Our findings suggest that when a firm engages in more corporate DT, it is more likely to release MEFs and release them more often. In addition, the MEFs are more precise. Hence, DT contributes to higher disclosure quantity (the likelihood and frequency of disclosure) and quality (greater disclosure precision). The results are robust to alternative metrics of DT, an instrumental variable approach, and a consideration of future MEFs. In the mechanism analyses, we find that DT improves firm transparency, enhances internal control, and reduces agency problems between the management team and shareholders. These improvements mediate the impact of DT on MEFs. In the cross-sectional analysis, we document that firms are more likely to disclose both good news and bad news in their MEFs after DT and the impact of DT on MEFs is more pronounced at non-state-owned firms.

We contribute to the literature in two major ways. First, we document a new determinant of voluntary MEFs. The decision to make voluntary MEFs has a DT component. Hence, it is a good public policy that a government can use to encourage corporate DT so as to drive firms to make more voluntary disclosures. Second, we advance the literature on the impact of DT on capital markets in general and in Chinese capital markets in particular. Previous studies report a positive impact of DT on the corporate information environment of the capital market from analysts' earnings forecast performance (Chen et al., 2022; Jiang et al., 2022; Wu et al., 2022). We provide a new perspective: firms' voluntary disclosure. The paper provides empirical evidence that firms that are more digitized are more likely to issue MEFs, issue them more frequently, and issue them with better precision. When firms use more DT and strategically pay more attention to the trend toward digitization, they are more willing to disclose their MEFs voluntarily. Corporate DT improves the internal information environment, enhances internal control, and mitigates agency problems, leading to more efficient capital markets. The coexistence of voluntary and mandatory MEFs in China provides an opportunity for empirically investigating the relative impacts of voluntary and mandatory MEFs on corporate decisions. Chinese firms are required to provide MEFs when expected earnings changes meet predetermined disclosure requirements. At the same time, firms can voluntarily offer MEFs when expected earnings changes do not meet the disclosure threshold. Hence, our findings suggest that a firm's DT plays a role in voluntarily provided MEFs in China. In an emerging market such as China, sound economic development requires the development of a healthy capital market, which requires high-quality corporate information disclosure (Tucker & Zhang, 2016; Wang et al., 2021; Wang & Wu, 2011). Hence, revealing the determinants of MEFs is helpful.

¹ Digital assets are tangible or intangible assets with some digital content. They typically allow a firm to use digital applications. For instance, a firm can enhance its operations through the use of its social media platform, mobile devices, and analytics.

The remainder of the paper is organized as follows. Section 2 reviews the literature and develops our hypotheses. Section 3 describes the research design. Section 4 presents our detailed empirical findings. Section 5 summarizes the findings and presents concluding remarks.

2. Literature review and hypothesis development

Based on the rules by China's Shanghai and Shenzhen Stock Exchanges, firm MEFs are either mandatory or voluntary. MEFs are mandatory when managers' earnings expectations meet specific thresholds and are voluntary in other circumstances (Huang et al., 2018). Disclosure is mandatory under three circumstances: (1) when managers anticipate a loss for the entire current year; (2) when managers anticipate a profit for the current year after a loss in the prior year; and (3) when managers anticipate a large change in earnings (increase or decrease of over 50%) from the previous year. Managers may voluntarily issue MEFs in other circumstances, and the management team can make its own decisions about the frequency and content. Internal and external corporate governance characteristics in China greatly influence this decision. Management teams tend to release financial reports near the deadline for their accounting period instead of following an expected schedule. Sometimes, the team postpones the release of good news and discloses bad news ahead of the expected schedule due to their shareholding (Cheng & Lo, 2006). Firms are more willing to issue MEFs and make more accurate disclosures in them when they face high litigation risk and when they have more analysts following (Baginski & Hassell, 1997; Rogers & Stocken, 2005; Skinner, 1994).

A firm can be in different categories from one year to the next based on specific earnings levels and change cutoffs. In the literature, it is found that this mixed approach generally has both positive and negative effects in China (Huang et al., 2018). The positive effect is a learning effect, implying that mandatory MEFs stimulate voluntary MEFs in later periods as managers become familiar with the process. The negative effect is earnings manipulation to avoid the forecast threshold of large declines in earnings.

In general, prior studies find that the Chinese stock market is less informationally efficient than developed markets such as the United States. The information asymmetry between managers and investors is significant because of inadequate disclosure and the limited role of financial analysts (Chan & Hameed, 2006; Jin & Myers, 2006; Morck et al., 2000). Enforcement of regulations is generally weak. Regulators may penalize firms that omit, delay, or issue inaccurate MEFs by publicly denouncing those with violations as well as their executives and directors (Huang et al., 2018).

Previous studies find that financial analysts are less effective in the Chinese stock market than elsewhere (Xing et al., 2019). Chen et al. (2022) find that, during COVID-19, firms manipulated the disclosure of MEFs. Firms tended to hide preexisting firm-specific bad news, especially those with high managerial ownership, those that were not state owned, and those that were in financial distress.

Overall, limited studies have been done on the impact of corporate DT on MEFs. We argue that MEFs are important disclosures that offer information to capital market participants. We contend that the improved corporate governance and reduced agency problems resulting from corporate DT positively influence the information efficiency of listed firms. We link the two strands of literature by testing our hypothesis.

2.1. Hypothesis development

Corporate DT comprises a company-wide change that stimulates the development of new business models and implements a new business logic to create and capture value (Pagani & Pardo, 2017; Verhoef et al., 2021; Zott & Amit, 2008). Digital technologies increase digital competition, which results in more digitization by customers. Hence, digital technologies not only demand greater digital resources from firms but also require changes in a firm's organizational structure, growth strategies, and metrics. Firms transform internal and external signals into digital information, which improves the effectiveness and efficiency of information transmission. Using digital technology, such as digital networking, open innovation, and big data analytics, can effectively reduce intermediation in business processes (Nambisan, 2017).

Digital technologies have profoundly reduced market friction and the cost of information search, transportation, and production and offer tremendous new opportunities for achieving higher market efficiency (Chen et al., 2022). Therefore, we predict that DT has a positive effect on corporate information disclosure for three reasons. First, corporate DT reduces information asymmetry between firms and stakeholders. Using corporate DT, such as social media, firms can more easily transmit information to external stakeholders (Feng & Johansson, 2019). External stakeholders can gain more information about the firm, thus reducing information asymmetry. Internal stakeholders benefit when digital organization, digital institutional infrastructure, and digital institutional building blocks reduce internal opportunistic activities by the firm's managers. After implementing DT, firms can listen to customers and closely follow market trends. DT also strengthens the relationship between managers and external stakeholders (Hinings et al., 2018; Wu et al., 2022).

Second, corporate DT strengthens internal controls, improves information disclosure, and further enhances information transparency between the firm and external stakeholders. On the one hand, the management team needs to timely disclose information to each organizational level. On the other hand, DT reduces human error and human emotion in information processing. Managers and staff at every level have less power and fewer opportunities to manipulate data and hide critical information. Therefore, corporate DT raises the efficiency and effectiveness of internal controls and external audits, resulting in better corporate governance (Bloom et al., 2014; Manita et al., 2020).

Third, corporate DT reduces the likelihood of EM by creating obstacles for a firm that wants to use accounting techniques to make its financial reports look better. DT changes

the passive role played by external stakeholders. The corporate information database of customers and suppliers has more inputs. Digital networking encourages information sharing and improves collaboration. Higher trust among the various stakeholders reduce the motivation for EM and increases the likelihood of more-precise MEFs (Kraus et al., 2021; Wang et al., 2022). Overall, we contend that corporate DT motivates the management team to provide more disclosure that is of better quality. Thus, firms are more likely to make MEFs voluntarily with greater frequency and precision. Therefore, we propose the following hypotheses.

Hypothesis 1. Corporate digital transformation positively affects the quantity of information disclosure in terms of the likelihood that a firm will issue management earnings forecasts and the number of forecasts issued.

Hypothesis 2. Corporate digital transformation positively affects the quality of information disclosure in terms of precision in management earnings forecasts.

3. Research design

3.1. Data

We include in our sample all A-share firms from the Shanghai and Shenzhen Stock Exchanges for 2007–2020. The initial sample consists of 38,835 firm-years from 4475 firms. Then, we delete firms in the financial industry (775), financially distressed firms (4,264), firms with missing accounting and financial data (2,037), and firm-years in which the firm was subject to mandatory MEFs (13,780). The final sample comprises 18,052 firm-years. The data are retrieved from the China Stock Market and Accounting Research (CSMAR) database and the Wind database. We winsorize all continuous variables at the 1 percent and 99 percent levels.

3.2. Specification of variables

3.2.1. Corporate digitization

To gauge a focal firm's DT level, we follow Wu et al. (2022) and Zhai et al. (2022) in deriving a quantifiable DT metric from the annual reports of listed firms. Specifically, we develop a dictionary of digital keywords based on a manual reading of 200 annual reports. Then, we conduct a textual analysis using Python software to determine the frequency of the digital keywords in firms' annual reports. Then, we use the natural logarithm of 1 plus the number of keywords used (denoted *DIG*) to proxy for the extent of a firm's DT. We present the specific keywords in Appendix A. We exclude a term if it is preceded by negative tone words such as “no,” “not,” “non,” or “nothing.”

3.2.2. Management earnings forecasts (MEFs)

We primarily use two metrics to proxy for disclosure quantity. First, we define *VOLDIS* as a dummy variable that

takes a value of 1 if a firm issues an MEF in a given year, and 0 otherwise. Second, we define *DISFREQ* as the natural logarithm of the number of times that a firm issues an MEF in a given year.

3.2.3. Management earnings forecasts precision (MEFP)

To gauge a firm's disclosure quality, we use MEF precision. Specifically, we follow Wang and Zhu (2022) and Zhai et al. (2022) in deriving a quantifiable MEF metric of firms. We define *PRECISION* as taking a value of 3 for an MEF with a point estimate, 2 for an interval estimate, or 1 for a qualitative estimate, respectively. The larger the number is, the more precise the information disclosure is.

3.2.4. Multiple regression model

We conduct our analysis using the following multiple regression model:

$$\begin{aligned} VOLDIS_{i,t} \text{ (or } DISFREQ_{i,t} \text{ or } PRECISION_{i,t}) \\ = \alpha_0 + \alpha_1 DIG_{i,t} + CONTROL + YEAR + INDUSTRY + \varepsilon_{i,t} \end{aligned} \quad (1)$$

CONTROL is a set of control variables, including firm size (*SIZE*), financial leverage (*LEV*), return on assets (*ROA*), revenue growth (*GROWTH*), cash holdings (*CASH*), board independence (*INDEPENDENT*), state ownership (*SOE*), a chairperson who is also the CEO (*DUAL*), board size (*BOARD*), the standard deviation of return on assets in the previous five years (*STDEARN*), operating loss (*LOSS*), firm age (*AGE*), the standard deviation of monthly stock returns (*MRETVOL*), and industry competitiveness (*HHI*). In Equation (1), we use logistic (ordinary least squares, or OLS) regression when the dependent variable is *VOLDIS* (*DISFREQ* and *PRECISION*). We control for year and industry fixed effects, and the standard errors are clustered at the firm level to mitigate the impact of missing control variables on MEFs. Table 1 presents detailed definitions of all the variables.

4. Results and discussion

4.1. Summary statistics and correlation coefficients

We present the summary statistics of the sample in Table 2. The means of *VOLDIS* and *DISFREQ* are 0.406 and 0.715, suggesting MEFs are issued in approximately 40.6 percent of the firm-years, with a mean of 0.715 times a year. The mean of *PRECISION* is 1.335, indicating that most firms only offer open-interval MEFs. The mean of *DIG* is 2.482, indicating that, on average, each annual report has approximately 11 keywords (before natural logarithm).

4.2. Findings of the baseline regression

We present the baseline results for Equation (1) in Table 3 using *VOLDIS*, *DISFREQ*, and *PRECISION* as dependent variables. In all columns, the coefficients of *DIG* are positively significant at the 1 percent level, suggesting that when a firm has

Table 1
Variable definitions.

Variables	Definitions	Source
<i>VOLDIS</i>	Indicator that equals 1 if firm <i>i</i> discloses management earnings forecasts (MEFs), and 0 otherwise.	WIND
<i>DIS_FREQ</i>	The natural logarithm of the number of times a firm issues an MEF in a given year	WIND
<i>PRECISION</i>	A measure of forecast precision that equals 0 for qualitative, 1 for open-interval, 2 for range, and 3 for point forecasts	WIND
<i>DIG</i>	Digitization level of enterprises calculated based on the frequency of words related to digitization in the company's annual report	WIND
<i>SIZE</i>	The natural logarithm of total assets	CSMAR
<i>LEVERAGE</i>	The ratio of total liabilities to total assets	CSMAR
<i>ROA</i>	The ratio of net earnings to total assets	CSMAR
<i>GROWTH</i>	The growth rate of revenue	CSMAR
<i>CASH</i>	The ratio of cash and marketable securities to total assets	CSMAR
<i>INDEPENDENT</i>	The ratio of the number of independent directors to board size	CSMAR
<i>SOE</i>	If a firm is state owned, the value is 1, and 0 otherwise	CSMAR
<i>DUAL</i>	If a firm's chairperson and CEO are the same individual, the value is 1, and 0 otherwise	CSMAR
<i>BOARD</i>	The natural logarithm of board size	CSMAR
<i>STDEARN</i>	Standard deviation of the return on assets in the previous five years	CSMAR
<i>LOSS</i>	If a firm incurs a loss, the value is 1, and 0 otherwise	CSMAR
<i>AGE</i>	The natural logarithm of one plus the listing years	CSMAR
<i>MRETVOL</i>	Standard deviation of monthly market returns in a year	CSMAR
<i>HHI</i>	Herfindahl-Hirschman Index of a firm's revenue in a given year	CSMAR

Note: Table 1 presents definitions of all the variables.

Table 2
Statistical summary.

Variable	N	Mean	Std. dev.	Min	p25	p50	p75	Max
<i>VOLDIS</i>	18,052	0.406	0.491	0	0	0	1	1
<i>DIS_FREQ</i>	18,052	0.715	0.67	0	0	0.693	1.386	1.609
<i>PRECISION</i>	18,052	1.335	0.497	1	1	1	2	3
<i>DIG</i>	18,052	2.482	1.366	0	1.386	2.485	3.434	5.684
<i>SIZE</i>	18,052	22.144	1.35	19.917	21.134	21.938	22.9	26.398
<i>LEV</i>	18,052	0.408	0.204	0.048	0.242	0.399	0.563	0.859
<i>ROA</i>	18,052	0.052	0.04	−0.075	0.025	0.046	0.073	0.184
<i>GROWTH</i>	18,052	0.133	0.244	−0.414	0.002	0.104	0.226	1.258
<i>CASH</i>	18,052	0.02	0.104	−0.234	−0.027	0.008	0.05	0.478
<i>INDEPENDENT</i>	18,052	0.373	0.053	0.3	0.333	0.333	0.429	0.571
<i>SOE</i>	18,052	0.422	0.494	0	0	0	1	1
<i>DUAL</i>	18,052	0.256	0.437	0	0	0	1	1
<i>BOARD</i>	18,052	3.206	0.585	2	3	3	3	5
<i>STDEARN</i>	18,052	0.07	0.092	0.009	0.028	0.044	0.073	0.674
<i>Loss</i>	18,052	0.025	0.157	0	0	0	0	1
<i>Age</i>	18,052	1.972	0.956	0	1.386	2.197	2.773	3.296
<i>MRETVOL</i>	18,052	0.134	0.074	0.041	0.088	0.116	0.157	0.509
<i>HHI</i>	18,052	0.055	0.085	0.008	0.013	0.016	0.062	0.453

Note: Table 2 presents the statistical summary of the sample. The variables are defined in Table 1.

a high level of DT, it is more likely to issue MEFs, its MEFs are issued more frequently, and its MEFs are more precise. The results are economically significant. Column (1) shows that when a firm has one more unit of *DIG*, its probability of issuing an MEF increases approximately 14.9 percent ($e^{0.139}-1$). The control variables in Table 3 and if significant, have the expected signs. For instance, the coefficients of *SIZE*, *LEV*, *ROA*, *CASH*, *SOE*, and *HHI* are negatively significant in all columns. Hence, to protect its operational information, when a firm is larger, more profitable, has more cash, or is in a competitive industry, it is less likely to issue an MEF, issues fewer MEFs, or issues vague MEFs. Similarly, a state-owned enterprise is less likely to issue an MEF, issues fewer of them, or issues less precise MEFs given their low incentives to do so.

4.3. Robustness checks

We conduct several robustness checks to confirm our baseline findings. First, we use an alternative metric of DT. Specifically, we use the ratio of the number of digital keywords to total intangible assets and denote it as *DIG3*. Then, we replace *DIG* with *DIG3* in Equation (1) and present the findings in Panel A of Table 4. The coefficients of *DIG3* continue to be positively significant at the 5 percent level.

Second, we examine Equation (1) using an instrumental variable (IV) approach. We use the mean DT for other firms in the province as an instrument (denoted as *MEAN_PRO*) to predict a value of *DIG* (*PRED_DIG*). Then, we use *PRED_DIG* to replace *DIG* in Equation (1). The results in Panel B

Table 3
The impact of enterprise digitization on management earnings forecasts.

Variables	(1) <i>VOLDIS</i>	(2) <i>DIS_FREQ</i>	(3) <i>PRECISION</i>
<i>DIG</i>	0.139*** (5.24)	0.024*** (3.61)	0.028*** (6.38)
<i>SIZE</i>	−0.194*** (−5.27)	−0.061*** (−7.38)	−0.033*** (−5.87)
<i>LEV</i>	−0.840*** (−4.13)	−0.131** (−2.57)	−0.164*** (−4.72)
<i>ROA</i>	−3.909*** (−4.11)	−1.112*** (−4.80)	−0.534*** (−3.27)
<i>GROWTH</i>	0.808*** (9.15)	0.216*** (10.99)	0.134*** (8.56)
<i>CASH</i>	−1.320*** (−7.89)	−0.487*** (−12.16)	−0.225*** (−7.26)
<i>INDEPENDENT</i>	0.709 (1.25)	0.224 (1.64)	0.132 (1.40)
<i>SOE</i>	−0.805*** (−9.16)	−0.212*** (−9.35)	−0.130*** (−9.50)
<i>DUAL</i>	0.081 (1.21)	0.024 (1.38)	0.020* (1.69)
<i>BOARD</i>	−0.015 (−0.26)	−0.012 (−0.88)	−0.006 (−0.70)
<i>STDEARN</i>	−0.129 (−0.64)	−0.058 (−1.17)	−0.030 (−0.83)
<i>LOSS</i>	2.770*** (15.36)	0.444*** (12.77)	0.316*** (9.31)
<i>AGE</i>	−0.604*** (−14.41)	−0.128*** (−11.90)	−0.071*** (−9.64)
<i>MRETVOL</i>	−0.036 (−0.10)	0.405*** (5.46)	0.223*** (3.72)
<i>HHI</i>	−1.199** (−2.17)	−0.451*** (−3.17)	−0.180** (−2.05)
Constant	4.146*** (5.12)	2.351*** (13.66)	2.206*** (18.72)
Observations	18,052	18,052	18,052
Year	Y	Y	Y
Industry	Y	Y	Y
Pseudo R^2	0.254		
Adj. R^2		0.268	0.274
F		109.0	74.11

Note: Table 3 presents the logistic and ordinary least squares regression results for the impact of digital transformation on management earnings forecasts. t -statistics are reported in parentheses. The standard errors are clustered at the firm level. Variable definitions are presented in Table 1. ***, **, and * indicate 1%, 5%, or 10% significance, respectively.

of Table 4 show that the coefficients of *PRED_DIG* continue to be positively significant at the 1 percent level.

Third, we use *VOLDIS*, *DIS_FREQ*, and *PRECISION* at $t + 1$ to replace the same variables at t in Equation (1). The results in Panel C of Table 4 indicate that the coefficients of *DIG* remain positively significant at the 1 percent level.

Last, some studies suggest that if a firm is required to issue MEFs at $t-1$ or $t + 1$, the firm's MEF behavior is affected at t (Huang et al., 2018; Zhu et al., 2022). To account for the effect, we define *MANDIS_BEFORE* (*MANDIS_AFTER*) as a dummy variable with a value of 1 if the China Securities and Regulatory Commission (CSRC) requires a firm to issue an MEF at $t-1$ ($t + 1$), and 0 otherwise. Then, we add *MANDIS_BEFORE* or *MANDIS_AFTER* to Equation (1). We present the findings in Panel D of Table 4. The coefficients of

DIG continue to be positively significant at the 1 percent level in all columns.

Collectively, our baseline findings are robust to alternative metrics for DT, after accounting for endogeneity, after considering subsequent MEFs, and after controlling for the effect of mandatory MEFs.

4.4. Mechanism analysis

4.4.1. Stock price informativeness

We hypothesize that DT can enhance the information embedded in stock prices. To confirm the hypothesis, we follow Amihud (2002) in calculating the liquidity of a stock as follows:

$$LIQUID_{i,t} = \frac{1}{N_{i,t}} \sum_{d=1}^{N_{i,t}} \frac{dvol_{i,d}}{|R_{i,d}|} \times 10^{-6},$$

where $R_{i,d}$ and $dvol_{i,d}$ are the return and trading volume of stock i at day d , and $N_{i,t}$ is the number of trading days for the stock in year t . The logic is that, when a stock is liquid, its trading volume is generally large, and the stock price changes less. If *LIQUID* is small, the information embedded in the stock is greater. We define *AMIVEST* as stock price informativeness; it has a value of 1 if *LIQUID* is above its median, and 0 otherwise. When *AMIVEST* is 0, the stock price is more informative and vice versa.

We then add *AMIVEST* and *DIG*AMIVEST* to Equation (1) to gauge the moderating effect of stock price informativeness. The findings in Panel A of Table 5 show that the coefficients of *DIG*AMIVEST* are positively significant in all columns. Hence, conditional on the level of DT, high stock price informativeness leads DT to have an even stronger impact on a firm's voluntary MEFs.

4.4.2. Internal controls

We argue that a firm can leverage its DT to enhance its internal control effectiveness. According to CSRC regulations, firms must disclose certain things in a timely manner so that investors can better understand the firm's internal operations. DT facilitates the disclosure process and makes the process more efficient. In addition, DT circumvents the interference caused by some executives and reduces the ability of managers to hoard bad news. In addition, DT enhances data-driven management decision systems that allow a firm to strengthen its oversight and detect internal control weaknesses in a timely way.

To confirm our hypothesis, we follow Liu et al. (2022) in using the internal control index from DIB to gauge the effectiveness of a firm's internal control. Because the internal control index is from 0 to 1,000, we transform the raw score into a standard normal score and denote it as *ICZ*. Then, we add *ICZ* and *DIG*ICZ* to Equation (1) to gauge the moderating effect of the effectiveness of a firm's internal control. We present the findings in Panel B of Table 5. The coefficient of *DIG*ICZ* is positively significant at the 5 percent level in column (1) using *VOLDIS* as the dependent variable, but insignificant in columns (2) and (3) using *DIS_FREQ* and *PRECISION* as the dependent

Table 4
Robustness checks.

Panel A: Alternative metrics of digitization						
Variables	(1)		(2)		(3)	
	<i>VOLDIS</i>		<i>DIS_FREQ</i>		<i>PRECISION</i>	
<i>DIG3</i>	0.061** (2.07)		0.016** (2.23)		0.012** (2.40)	
Control var.	Yes		Yes		Yes	
Constant	3.490*** (3.93)		2.317*** (12.10)		2.170*** (16.02)	
Observations	14,244		14,244		14,244	
Year	Y		Y		Y	
Industry	Y		Y		Y	
Pseudo R^2	0.239					
Adj. R^2			0.259		0.256	
F			78.42		49.85	
Panel B: Instrumental variable						
Variables	(1)	(2)	(3)	(4)		
	First stage	Second stage	Second stage	Second stage		
	<i>DIG</i>	<i>VOLDIS</i>	<i>DIS_FREQ</i>	<i>PRECISION</i>		
<i>MEAN_PRO</i>	0.373*** (0.026)					
<i>PRED_DIG</i>		0.217*** (0.031)	0.355*** (0.046)	0.262*** (0.034)		
Control var.	Yes	Yes	Yes	Yes		
Constant	−3.054*** (0.193)	1.696*** (0.125)	3.047*** (0.182)	2.555*** (0.133)		
Observations	18,048	18,048	18,048	18,048		
R^2	0.452	0.139	0.015	0.044		
Panel C: Considering subsequent management earnings forecasts						
Variables	(1)		(2)		(3)	
	<i>VOLDIS</i> _{t+1}		<i>DIS_FREQ</i> _{t+1}		<i>PRECISION</i> _{t+1}	
<i>DIG</i>	0.186*** (5.44)		0.038*** (4.54)		0.033*** (6.38)	
Control var.	Yes		Yes		Yes	
Constant	5.414*** (4.74)		2.281*** (11.15)		2.113*** (15.11)	
Observations	10,779		10,779		10,779	
Year	Y		Y		Y	
Industry	Y		Y		Y	
Pseudo R^2	0.274					
Adj. R^2			0.286		0.304	
F			65.39		61.56	
Panel D: Accounting for mandatory MEFs before or after current year						
Variables	(1)	(2)	(3)	(4)	(5)	(6)
	Control for mandatory MEFs one year before			Control for mandatory MEFs one year after		
	<i>VOLDIS</i>	<i>DIS_FREQ</i>	<i>PRECISION</i>	<i>VOLDIS</i>	<i>DIS_FREQ</i>	<i>PRECISION</i>
<i>DIG</i>	0.101*** (4.23)	0.012** (2.09)	0.020*** (5.46)	0.106*** (4.30)	0.014** (2.40)	0.021*** (5.61)
<i>MANDIS_BEFORE</i>	−2.106*** (−36.20)	−0.544*** (−42.03)	−0.354*** (−33.62)			
<i>MANDIS_AFTER</i>				−2.637*** (−35.63)	−0.534*** (−37.77)	−0.393*** (−34.60)
Control var.	Yes	Yes	Yes	Yes	Yes	Yes
Constant	5.062*** (7.17)	2.374*** (16.77)	2.222*** (22.85)	6.026*** (8.50)	2.573*** (17.60)	2.370*** (24.48)
Observations	18,052	18,052	18,052	18,052	18,052	18,052
Year FE	Y	Y	Y	Y	Y	Y
Ind FE	Y	Y	Y	Y	Y	Y

(continued on next page)

Table 4 (continued)

Panel D: Accounting for mandatory MEFs before or after current year						
Variables	(1)	(2)	(3)	(4)	(5)	(6)
	Control for mandatory MEFs one year before			Control for mandatory MEFs one year after		
	<i>VOLDIS</i>	<i>DISFREQ</i>	<i>PRECISION</i>	<i>VOLDIS</i>	<i>DISFREQ</i>	<i>PRECISION</i>
Pseudo R^2	0.335			0.354		
Adj. R^2		0.366	0.350		0.352	0.357
F		291.0	215.1		288.0	230.2

Note: Panels A–D present the results of several robustness checks for the impact of digital transformation on management earnings forecasts. In Panel A, we replace *DIG* with *DIG3*, which is the ratio of the number of digital keywords to total intangible assets. Panel B uses an instrumental variable. *MEAN_PRO* is the mean DT for other firms in the province. We use it to generate a predicted value of *DIG* (*PRED_DIG*) to replace *DIG*. In Panel C, we use management earnings forecasts at $t + 1$ to replace those at t . Panel D accounts for mandatory management earnings forecasts at $t-1$ or $t + 1$. We define *MANDIS_BEFORE* (*MANDIS_AFTER*) as a dummy variable with a value of 1 if a firm is asked by the China Securities and Regulatory Commission to issue a mandatory MEF at $t-1$ ($t + 1$), and 0 otherwise. For brevity, we do not present the coefficients of control variables. t -statistics are reported in parentheses. Standard errors are clustered at the firm level. Variable definitions are presented in Table 1. ***, **, and * indicate 1%, 5%, or 10% significance, respectively.

Table 5

Mechanism analysis.

Panel A: Stock price informativeness			
Variables	(1)	(2)	(3)
	<i>VOLDIS</i>	<i>DIS_FREQ</i>	<i>PRECISION</i>
<i>DIG*AMIVEST</i>	−0.186*** (−5.63)	−0.031*** (−3.86)	−0.014** (−2.49)
<i>DIG</i>	0.234*** (7.24)	0.040*** (5.02)	0.035*** (6.64)
<i>AMIVEST</i>	0.333*** (3.33)	0.057** (2.36)	0.011 (0.69)
Control var.	Yes	Yes	Yes
Constant	4.447*** (5.14)	2.406*** (13.13)	2.296*** (17.64)
Observations	18,052	18,052	18,052
Year	Y	Y	Y
Industry	Y	Y	Y
Pseudo R^2	0.256		
Adj. R^2		0.269	0.275
F		98.02	67.78

Panel B: Internal controls			
Variables	(1)	(2)	(3)
	<i>VOLDIS</i>	<i>DIS_FREQ</i>	<i>PRECISION</i>
<i>DIG* IC_Z</i>	0.039** (2.19)	0.004 (0.90)	0.001 (0.33)
<i>DIG</i>	0.134*** (4.78)	0.023*** (3.29)	0.025*** (5.49)
<i>IC_Z</i>	−0.232*** (−4.59)	−0.031*** (−2.83)	−0.016* (−1.66)
Control var.	Yes	Yes	Yes
Constant	2.652*** (3.11)	2.069*** (11.31)	2.030*** (16.12)
Observations	16,466	16,466	16,466
Year	Y	Y	Y
Industry	Y	Y	Y
Pseudo R^2	0.275		
Adj. R^2		0.274	0.289
F		94.37	72.21

Panel C: Agency conflicts

Variables	(1)	(2)	(3)
	<i>VOLDIS</i>	<i>DIS_FREQ</i>	<i>PRECISION</i>
<i>DIG*AC</i>	−0.107** (−2.40)	−0.038*** (−3.58)	−0.024*** (−3.61)
<i>DIG</i>	0.165*** (5.96)	0.034*** (4.81)	0.034*** (7.14)
<i>AC</i>	0.302** (2.29)	0.100*** (3.24)	0.049*** (2.68)
Control var.	Yes	Yes	Yes
Constant	4.109*** (4.98)	2.331*** (13.22)	2.169*** (17.96)
Observations	18,052	18,052	18,052
Year	Y	Y	Y
Industry	Y	Y	Y
Pseudo R^2	0.254		
Adj. R^2		0.269	0.275
F		97.84	66.12

Note: Panels A–D present the results for the mediating effects of information transparency, internal controls, and agency costs for the impact of digital transformation on management earnings forecasts. In Panel A, we define *AMIVEST* as stock price informativeness, and it has a value of 1 if *LIQUID* is above its median and 0 otherwise, where $LIQUID_{i,t} = \frac{1}{N_{i,t}} \sum_{d=1}^{N_{i,t}} \frac{dvol_{i,d}}{|R_{i,d}|} \times 10^{-6}$. In Panel B, *ICZ* is the standard normal transformation of the internal control index of a firm. In Panel C, *AC* is a firm's agency costs using the ratio of management expense to total revenue. For brevity, we do not present the coefficients of control variables. t -statistics are reported in parentheses. Standard errors are clustered at the firm level. Variable definitions are presented in Table 1. ***, **, and * indicate 1%, 5%, or 10% significance, respectively.

variables. Thus, improvement in internal controls can further enhance the impact of DT on voluntary MEFs in terms of *VOLDIS*.

4.4.3. Agency costs

We contend that DT can reduce a firm's agency costs, which makes a firm more likely to issue MEFs. We proxy a firm's

Table 6
Heterogeneity analysis.

Panel A: Disclosure of good news and bad news

Variables	(1) <i>Good news</i>	(1) <i>Bad news</i>
<i>DIG</i>	0.094*** (3.53)	0.094*** (3.53)
Control var.	Yes	Yes
Constant	2.655*** (3.03)	2.655*** (3.03)
Observations	18,049	18,049
Year	Y	Y
Industry	Y	Y
Pseudo R^2	0.196	0.235

Panel B: State ownership

Variables	(1) <i>VOLDIS</i> State-owned firms	(2) <i>VOLDIS</i> Non-state owned firms	(3) <i>DIS_FREQ</i> State-owned firms	(4) <i>DIS_FREQ</i> Non-state owned firms	(4) <i>PRECISION</i> State-owned firms	(5) <i>PRECISION</i> Non-state owned firms
<i>DIG</i>	0.054 (1.13)	0.184*** (5.63)	0.001 (0.11)	0.036*** (4.42)	0.010 (1.63)	0.036*** (6.14)
Control var.	Yes	Yes	Yes	Yes	Yes	Yes
Constant	4.491*** (3.65)	4.810*** (4.11)	2.163*** (9.42)	2.670*** (9.37)	2.022*** (13.10)	2.540*** (13.41)
Year	Y	Y	Y	Y	Y	Y
Industry	Y	Y	Y	Y	Y	Y
Observations	7616	10,424	7616	10,435	7616	10,435
Pseudo R^2	0.191	0.216				
Adj. R^2			0.148	0.231	0.127	0.279
F			40.17	32.98	15.55	23.38

Note: Panels A and B present the results for the mediating effects of good news vis-à-vis bad news and state ownership of a firm on the impact of digital transformation on management earnings forecasts. In Panel A, we define *GOODNEWS* as a dummy variable with a value of 1 if management issues MEFs related to turning negative earnings into positive earnings or an earnings increase, and 0 otherwise. We define *BADNEWS* as a dummy variable in a similar fashion when a firm acknowledges positive earnings turning into negative earnings or an earnings decrease. *t*-statistics are reported in parentheses. Standard errors are clustered at the firm level. Variable definitions are presented in Table 1. ***, **, and * indicate 1%, 5%, or 10% significance, respectively.

agency costs using the ratio of management expenses to total revenue (*AC*). Then, we add *AC* and *DIG*AC* to Equation (1). The results in Panel C of Table 5 show that the coefficients of *DIG*AC* are negatively significant at the 1 percent or 5 percent level in all columns. Hence, conditional on DT, lower agency costs drive a firm to issue more MEFs.

4.5. Heterogeneity analysis

4.5.1. Nature of disclosure

We further examine good and bad news MEFs. Prior studies suggest that managers may hide bad news to protect their careers (Kothari et al., 2009). To disentangle good from bad news in our analysis, we define *GOODNEWS* as a dummy variable with a value of 1 if the management issues an MEF related to turning negative earnings into positive earnings or an earnings increase, and 0 otherwise. We define *BADNEWS* as a dummy variable in a similar fashion when a firm issues an MEF related to turning positive earnings into negative earnings or an earnings decrease. Then, we replace the two MEFs variables in Equation (1) with *GOODNEWS* or *BADNEWS*. We present the findings in Panel A of Table 6. The coefficients of *DIG* are positively significant in both columns. Interestingly, DT drives more disclosure, irrespective of whether the disclosure contains

good or bad news. The findings corroborate our hypothesis that DT enhances stock price informativeness and internal controls and reduces agency costs. All these benefits lead to a higher probability that a firm will issue an MEF or will issue MEFs more frequently, even if it contains bad news.

4.5.2. State ownership

Managers of state-owned firms (*SOEs*) are less motivated to issue MEFs because *SOEs* face fewer financial constraints. In contrast, non-*SOEs* face more financial constraints. Thus, after DT, non-*SOEs* find it easier to issue MEFs to attract financing. We divide the full sample into subsamples for *SOEs* and non-*SOEs* and rerun Equation (1). The results in Panel B of Table 6, as expected, show that the coefficients of *DIG* remain positively significant at the 1 percent level for the non-*SOE* subsample, and the same coefficients are insignificant for the *SOE* subsample.

5. Conclusions

We examine the impact of corporate DT on MEFs in China. Our results suggest that corporate DT enhances a firm's likelihood of issuing MEFs with better disclosure quantity and quality, increases their frequency, and having better precision.

The findings are robust to alternative metrics of DT and MEFs and after accounting for endogeneity. In addition, we document that corporate DT improves internal control, increases information transparency, and reduces firms' agency problems. In the heterogeneity analysis, we find that the effect is equally pronounced for both good news and bad news. Non-state-owned firms issue more MEFs after DT.

The results in our paper have implications for capital market development in emerging markets. We document the benefits of corporate DT on capital market efficiency in China by showing that DT encourages firms to issue more and better MEFs. We provide insights on one of the most important and recent trends in DT. The evidence is useful for regulators, managers, and investors in other economies, especially other emerging markets.

Declaration of competing interest

We do not have any conflict of interests.

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Appendix A. Keywords in the textual analysis

Categories	Keywords
Artificial intelligence	Artificial intelligence, business intelligence, image understanding, investment decision support system, intelligent data analysis, intelligent robot, machine learning, deep learning, semantic search, biometric technology, face recognition, speech recognition, identity verification, automatic driving, and natural language processing
Block chain	Digital currency, smart contract, distributed computing, decentralization, Bitcoin, alliance chain, differential privacy technology, and consensus mechanism
Cloud computing	Memory computing, cloud computing, stream computing, graph computing, Internet of Things, multiparty secure computing, brain-inspired computing, green computing, cognitive computing, converged architecture, billion-level concurrency, EB-level storage, and cyberphysical systems
Big data	Big data, data mining, text mining, data visualization, heterogeneous data, credit reporting, augmented reality, mixed reality, and virtual reality
Digital technology application	Mobile internet, industrial internet, mobile internet, internet health care, e-commerce, mobile payment, third-party payment, NFC payment, B2B, B2C, C2B, C2C, O2O, internet connection, smartwear, smart agriculture, smart transportation, smart health care, smart customer service, smart home, smart investment, smart cultural tourism, smart environmental protection, smart grid, smart energy, smart marketing, digital marketing, unmanned retail, internet finance, digital finance, fintech, financial technology, quantitative finance, and open banking

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